Generalized Flight Path Modeling Based on Key Airport Parameters

Improving climb and descent phase emission estimations

Jeltes de Weerd

Generalized Flight Path Modeling Based on Key Airport Parameters

Thesis Report

by

Jeltes de Weerd

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Thesis committee:	
Chair:	Dr. Junzi Sun
Supervisors:	Dr. I.C. Dedoussi
	ir. Eneko Rodríguez - To70
External examiner:	Dr. Fabrizio Oliviero
Place:	Faculty of Aerospace Engineering, Delft
Project Duration:	July, 2023 - June, 2024

Faculty of Aerospace Engineering · Delft University of Technology

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With this thesis, I am concluding my time as a student after nine years. My journey began with a year in nursing, followed by four years pursuing a bachelor's degree in Aeronautical Engineering at the university of applied sciences. I then completed a pre-master and dedicated three additional years to obtaining my master's degree in Aerospace Engineering. I am proud to have reached this milestone in my life, but I could not have done it without the guidance and support of many people.

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Contents

Nomenclature

List of Abbreviations

ADS-B Automatic Dependent Surveillance–Broadcast

AIP Aeronautical Information Publication

ANSP Air Navigation Service Providers

ATC Air Traffic Controller

ATM Air Traffic Management

BADA Base of Aircraft Data

BR Bayesian Regression

CAS Calibrated Air Speed

CO Carbon Monoxide

FAA Federal Aviation Administration

FEAT Fuel Estimation in Air Transportation

HC Hydro-Carbons

IATA International Air Trasport Association

ICAO International Civil Aviation Organization

K-S Kolmogorov-Smirnov

KPI Key Performance Indicator

LTO Landing and Take-off

MAE mean Absolute Error

MC Monte Carlo

MLE Maximum Likelihood Estimation

MLR Multiple Linear Regression

MSE Mean Squared Error

NNR Neural Network Regression

nvPM non-volatile Particulate Matter

OLS Ordinary Least Squares

PDF Probability Distribution Function

PLS Partial Least Squares

PRC Performance Review Commission

RMSE Root Mean Squared Error

RoC/D Rate of Climb/Descent

RR Ridge Regression

SE Standard Error

TMA Terminal Maneuvering Area

TOC Top of Climb

TOD Top of Descent

VIF Variance Inflation Factor

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Executive Summary

This research describes the relationship between airport parameters and aircraft flight path during climb and descent phases. The study focuses on employing statistical methods on open sourced ADS-B data to relate airport parameters to flight path, aiming to address uncertainties and assumptions in flight path specific factors within the research of *Quadros et al.*[1].

Problem Statement
A thorough literature study preceded the thesis after which a research plan laid the groundwork for the main research, describing the scope, research questions and research goal. The research focuses specifically on the non-LTO (Landing and Take-Off) emissions. This encompasses 3000 feet above the airport elevation, up to the cruise altitude of the aircraft and visa versa. The primary goal is to develop an alternative method of determining the aircraft position during the climb and descent phase to enhance the model of Quadros. The goal is as follows:

To develop a method to estimate the global emissions of civil aircraft within the climb and descent phases, using generalized flight path modeling based on key airport parameters.

Proposed Solution
The proposed solution centers on the application of statistical methods to analyze extensive data sourced from ADS-B transponders. Through the analysis of climb and descent segments, the research identified parameters affecting flown distance at airports: flight movements, number of runways, and airport elevation. These parameters were related to the flown distance during climb and descent using various regression types, with Multiple Linear Regression (MLR) emerging as the most promising. MLR achieved a Mean Absolute Error (MAE) of 9.23% on arrival distances and 15.77% on departure distances on unseen data, and effect sizes of 12.8% and 6% for arrivals and departures, respectively.

Furthermore, the proposed method uses actual flight distances rather than optimal climb or descent profiles for arriving and departing flights causing a difference in emissions. For the climb, overall NO_2 emissions increase from 17.1 to 18.2 g/kg of fuel burned, while CO emissions decrease from 506 to 424 mg/kg. This is due to the constant slope assumption, requiring higher thrust later in the climb. Although this method provides a better estimation based on flight distance, it lacks the accuracy of a real climb and descent profile in which there is a steeper climb at the beginning compared to end of climb. The descent phase shows a similar pattern: increased NO_2 emissions from 4.65 to 8.2 g/kg of fuel burned and decreased CO emissions from 27.9 to 6 g/kg, again due to increased engine thrust during the extended descent.

The. Although MLR showed about a 10% deviation in its predictions, using the real mean distances and comparing them with the predicted means indicated almost no difference in the emissions. the 95% confidence interval for the mean was used to calculate low, mean, and high estimates. In the climb phase, the differences were negligible, with nearly identical results across the estimates. In the descent phase, the variations were slightly more significant, with a discrepancy of about 3%. Also note the flight distance generalization might be well estimated, the estimation does not represent the real world scenario due to the lack of level flights within the profile. A better estimation would be able to include the level flights at their respective heights and include the standard climb and descent rate.

Conclusion
This research offers new insights into the position estimation of aircraft in generalized global emission models by linking flight paths to airport parameters using ADS-B data. This research argues that, within the boundaries of this research, the suitable method to improve emissions estimation is to use MLR to relate the distances flown at airports to attributes such as annual flight movements, the number of runways, and airport elevation. This approach provided a more accurate estimate, bringing it closer to real-world scenarios. However, there is still room for improvement by incorporating level flight segments at specific altitudes and considering airspace complexity as an additional airport parameter.

1 Introduction

Over the last few decades, global emissions have experienced a significant surge, leading to mounting concerns about their impact on the environment. Academics have dedicated considerable effort to researching the effects of emissions on the planet, resulting in the development of predictive models for their transport patterns [1], regional sensitivities [2], and global effects [3]. This research contributes to understanding the consequences of emissions on both the global climate and the well-being of regional populations.

This thesis focuses on generalizing flight paths using key airport parameters to enhance global aviation emissions models. More specifically, it aims to generalize the climb and descent phase as they are, at least partly, dependent on the airport parameters and airspace around it. By focusing on the specific flight phases of climb and descent within the emission estimation model created by *Quadros et al.* [1] and using Automatic Dependent Surveillance–Broadcast (ADS-B) data, this study aims to enhance the accuracy of the emission model of Quadros. The existing method relies on great circle distance and Top of Climb or Descent with an uncertainty factor, leading to potential inaccuracies, especially within the climb and descent phases.

The report is divided into three parts. Part I - Thesis Work, which includes the methodology, results of the airport analyses and emissions, conclusion and recommendations. Part II - Appendices, includes the related appendices, including the sample list and additional results. And finally Part III - Literature Review and Research Plan, onto which the thesis is build upon.

Part I

Thesis

2
Methodology

This chapter discusses the used methods throughout the thesis. Covering the research objective and questions, data acquisition and preparation, code definitions, airport parameters, used statistical methods, sample flight list for the comparison of emission and the integration into the current model of Quadros et al. [1].

2.1. Research objective and question

A thorough literature study preceded the thesis after which a research plan laid the groundwork for the main research, describing the scope, research questions and research goal. The research focuses specifically on the non-LTO (Landing and Take-Off) emissions. This encompasses 3000 feet above the airport elevation, up to the cruise altitude of the aircraft and visa versa. The primary goal is therefore to develop an alternative approach of determining the aircraft position during the climb and descent phase. The goal of the thesis is to develop a specific approach to enhance the model of Quadros. The goal is as follows:

To develop a method to estimate the global emissions of civil aircraft within the climb and descent phases, using generalized flight path modeling based on key airport parameters.

The intent of this goal is to improve the aircraft position estimation method used by *Quadros et al.* in their study, *"Global Civil Aviation Emissions Estimates for 2017–2020 Using ADS-B Data"* [1]. A more precise research question is defined to capture the core objective of this thesis, contributing to the field of civil aviation emission modeling. The primary research question is as follows:

Research Question

How can emission estimation during the climb and descent phases in global models using ADS-B data be enhanced by generalizing the flight path based on key airport parameters, resulting in a quantifiable improvement in accuracy?

This main question is separated into three sub-questions, which are as follows:

- **SQ-1: Which airport parameters have an impact on the flight path during climb and descent?**
- **SQ-2: What is the quantified relation between the airport parameters and flight path and what are the sensitivities?**
- **SQ-3: How does the flight path length emission estimation compare to other research in accuracy and speed?**

Figure 2.1 shows the flow chart for the work within this thesis, covering the different sub-questions in a structured manner. First, literature review and airport analyses using ADS-B data were conducted to identify key airport parameters and the flight distances flown to various airports. The output of the airport analyses was then used to quantify the relationship between these parameters and flight distances. During the statistical analysis, it became evident that incorporating additional parameters could further strengthen this relationship, making the process iterative between airport analysis and statistics. Finally, the quantified relationship was integrated into the model, and the resulting emissions were compared with those produced by the current method, providing an indicative measurement of the new method's accuracy and uncertainty.

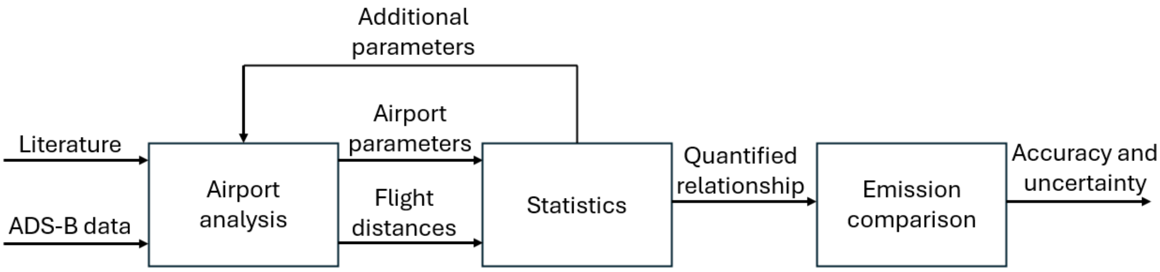


Figure 2.1: Flow chart of thesis work

2.2. Data acquisition and preparation

The data used in this project primarily consists of ADS-B data. This data source is particularly advantageous because of its widespread availability from various channels. The selection of ADS-B data is underpinned by its precision and prevalence. Notably, all civil aircraft equipped with a transponder actively emit and receive ADS-B data, facilitating effective communication with other aircraft and ground stations.

2.2.1. Data Acquisition

The ADS-B data utilized in this research is obtained from OpenSky [4], a public database specifically designed for scientific research. The OpenSky platform has gained popularity due to its open access to aircraft data, contributed by aviation enthusiasts who share their ADS-B receivers with the network. As the OpenSky network expands, so does its coverage, offering a comprehensive view of aircraft movements around the world.

The data set from OpenSky contains a wealth of information about aircraft in flight, provided that they are within the range of a receiver connected to the network. This data set includes state information such as aircraft position, velocity, vertical speed, time, and both geometric and barometric altitudes. It also contains semi-fixed data like callsigns and the unique ICAO24 identification numbers for each aircraft. These features make OpenSky's ADS-B data a robust and versatile resource for aviation-related research.

The data set used within this research are the state data of 06-06-2022 and 13-06-2022. State data is a data which contains the state of an aircraft at a given moment. This includes altitude, velocity, climb or descent rate, etc. These data sets contain thousands of flights, therefore taking significant time in the processing of the data. The data used within the research is within the busiest time of the year and could contain a seasonal offset because of it.

2.2.2. Data cleaning and preparation

The acquired ADS-B data undergoes a cleaning and preparation process to ensure it is suitable for analysis. It is critical to clearly define each step in the code to accurately extract, process, and interpret the data, yielding meaningful results.

To identify the flights related to a specific airport, a bounding box is created around the airport's coordinates. This box extends 25 km in each direction from the airport's decimal degree coordinates. Any data point within this boundary and below 3,000 feet above the airport's elevation triggers a flag, marking that particular ICAO24 identification for extraction. This process allows for the isolation of aircraft activity related to the targeted airport.

The next step is to extract the complete set of data for each identified ICAO24 number, ensuring that all relevant tracks are retrieved. Since aircraft fly multiple routes, the data require careful segmentation to distinguish individual flights. This step involves identifying the start and end points of specific flights and separating them from the larger data set.

Following segmentation, the data undergoes a thorough cleaning process to remove corrupted or redundant data points. This step is required to maintain data integrity and ensure accurate analysis.

The final cleaned data set provides a solid foundation for further examination, helping to ensure that the extracted flights are relevant to the research objectives and that the data is accurate and reliable.

2.3. Definitions

This section discusses the definitions used within the code.

2.3.1. Climb/descent definition

Once the flights are categorized into segments coming to or leaving from the target airport, the data is broken down into climb and descent phases. This segmentation is performed using a sliding window of 30 data points, typically covering about 300 seconds, and a minimum vertical rate of 2.5 meters per second (approximately 500 feet per minute). This rate aligns with the minimum required climb/descent rate as outlined in the FAA Instrument Procedures Handbook [5].

The handbook provides specific guidance on rate of descent: ”*ATC may ask the pilot to descend to and maintain a specific altitude. Generally, this clearance is for en route traffic separation purposes, and pilots need to respond to it promptly. Descend at the optimum rate for the aircraft being flown until 1,000 feet above the assigned altitude, then descend at a rate between 500 and 1,500 fpm to the assigned altitude. If at any time, other than when slowing to 250 KIAS at 10,000 feet MSL, the pilot cannot descend at a rate of at least 500 fpm, advise ATC.*”

Similarly, for climb, the handbook states: ”*Climb at an optimum rate consistent with the operating characteristics of the aircraft to 1,000 feet below the assigned altitude, and then attempt to climb at a rate of between 500 and 1,500 fpm until the assigned altitude is reached. If at any time the pilot is unable to climb at a rate of at least 500 fpm, advise ATC. If it is necessary to level off at an intermediate altitude during climb, advise ATC.*”

Thus, the cut-off points for climb and descent segments are determined by these criteria. If the aircraft maintains a vertical rate of 500 fpm (2.5 m/s) or more within the sliding window, it indicates an active climb or descent phase. These segments are then isolated from the overall flight data to facilitate further analysis, allowing for a focused examination of climb and descent behaviors within the defined parameters.

Departures are adjusted for longitude differences based on the absolute latitude of the airport, meaning that the climb is considered finished if the aircraft has passed certain longitude threshold. This threshold is variable for the latitude degree of the airport and is introduced to prevent flights with missing data skewing the data set. Furthermore for analysis, only data points with altitudes below 13,000 meters are considered, which corresponds to just above the service ceiling of 42,000 feet, thus filtering out potential faulty data. Tracks with insufficient data points are excluded, with the required data volume depending on the airport's elevation. The climb segment starts when the average vertical rate within a 300-second sliding window is above 2.5 meters per second, provided the altitude has reached at least 75% of the maximum altitude achieved by the aircraft. The segment ends when the average vertical rate falls below the threshold and when certain latitude and longitude conditions are met.

For arrivals, longitude differences are adjusted in relation to latitude just as for departures. Tracks with insufficient data are filtered out. The descent segment begins when the average vertical rate in the 300-second sliding window falls below -2.5 meters per second. This segment concludes when the rate exceeds the threshold or the altitude drops below 500 meters above the airport's elevation.

2.3.2. Distance

Flight distances for climb and descent segments are calculated using the longitude and latitude along with the aircraft's altitude. The distance measurements starts and end at 3000ft for departures and arrivals respectively as this research focuses on non-LTO emissions, which occur exclusively above 3,000 feet above airport elevation.

2.4. Airport parameters

The airport parameters selected for this study are annual flight movements, number of runways and airport elevation. These parameters were chosen because they are specific enough for each airport and are publicly available. Earlier suggested parameters, such as distance between airports and regional procedures and practices, were not considered because the data is either difficult to obtain, unavailable, or too vague. Regional procedures and practices are typically not publicly accessible and are challenging to quantify. The distance between airports parameter is also vague because the effect of nearby airports depends on their own specific characteristics, making it hard to measure and quantify their impact on the airport where the estimation is being made.

Selected airports

The airports listed in Table 2.1 were selected to ensure a diverse set of parameters for all airports. Choosing a dataset with varying airport characteristics allows a regression model to better estimate the individual and collective effects of these parameters. Additionally, the airports had to be covered by the OpenSky network to ensure data availability.

Table 2.1: Airport parameter information

Airport ICAO	Airport City	Flight Movements	Runways	Airport Elevation
EHAM	Schiphol	462600	5	-3
SKBO	El Dorado	296777	2	2548
EBBR	Brussels	178930	3	56
FACT	Cape Town	98666	2	46
YSSY	Sydney	177646	3	6
OMDB	Dubai	373261	1	19
EGPH	Edinburgh	93004	1	41
KDEN	Denver	615733	6	1656
VIDP	Delhi	429964	4	237
KLAS	Las Vegas	581000	4	665
LEMD	Madrid	351906	4	609
SBGR	São Paulo	242881	2	750
LIRF	Rome	113972	3	5
KIAH	Houston	399805	5	30
KMCI	Kansas	102905	3	313
KMIA	Miami	458478	4	3

Complexity metric

In addition to the selected airport parameters, the airspace complexity has a large influence on the flown distance at airports. Therefore, an attempt at incorporating airspace complexity was made such that the effect size might increase.

In 2006, the Performance Review Commission (PRC) of EUROCONTROL published a technical report dedicated to assessing complexity and developing metrics for benchmarking analyses in Air Navigation Service Providers (ANSP) [6]. The report outlines four complexity indicators, summarized in Table D.1. It's important to note that the airspace complexity in this context is assessed based on arrival data only.

Table 2.2: Complexity indicators [6]

Complexity dimension	Indicator	Description
Traffic density	Adjusted density	A measure of the potential number of interactions between aircraft in a given volume of airspace.
Traffic in evolution	Potential vertical interactions (VDIF)	Captures the potential interactions between climbing, cruising and descending aircraft.
Flow structure	Potential horizontal interactions	Provides a measure of the potential interactions based on the aircraft headings.
Traffic mix	Potential speed interactions	Assesses the potential interactions based on the aircraft speeds.

To incorporate airspace complexity into the statistical model, it is necessary to establish pre-set variables to estimate distances for airports not included in the original data. The EUROCONTROL report indicates that the route structure significantly influences airspace complexity. The route structure is defined as follows:

- **Route structure:**
  - **Influence on productivity and costs:** Route structure reflects and organises the underlying demand of traffic. And the route structure together with the constraints put on its utilisation (Letters of Agreement, flight level restrictions, bi or uni-directional routes, etc) can contribute to reducing controller workload and increasing capacity and efficiency.
  - **Candidate indicators:** Number of routes within a given volume of airspace, number of crossing and merging points within a given volume, direction of flows - uni, or bi-directional.

Within the code a radius of 150 km is drawn around the airport and the number of crossing points, merging points and the amount of airways are counted. This adheres to the candidate indicators laid out within the report of the PRC.

Selected airports and complexity metrics
By counting the number of crossing and merging points from the Aeronautical Information Publication (AIP) of a country within a certain range of the airport, candidate indicators related to the number of routes, and the number of merging and crossing points within a volume of airspace, are utilized. However, a significant issue with this method is the limited availability of route structure data from AIPs. Many countries do not make this information freely accessible and often require monetary compensation for it. Consequently, only airports from the dataset with accessible AIPs are considered. The list of these airports is provided in Table 2.3.

Table 2.3: Airports with complexity metrics

Airport ICAO	Flight Movements	Runways	Airport Elevation	Merg./Cross. points	Airways
EHAM	462600	5	-3	46	59
SKBO	296777	2	2548	19	43
EBBR	178930	3	56	23	41
FACT	98666	2	46	14	59
EGPH	93004	1	41	25	34
LEMD	351906	4	609	53	42

2.5. Statistical methods considered

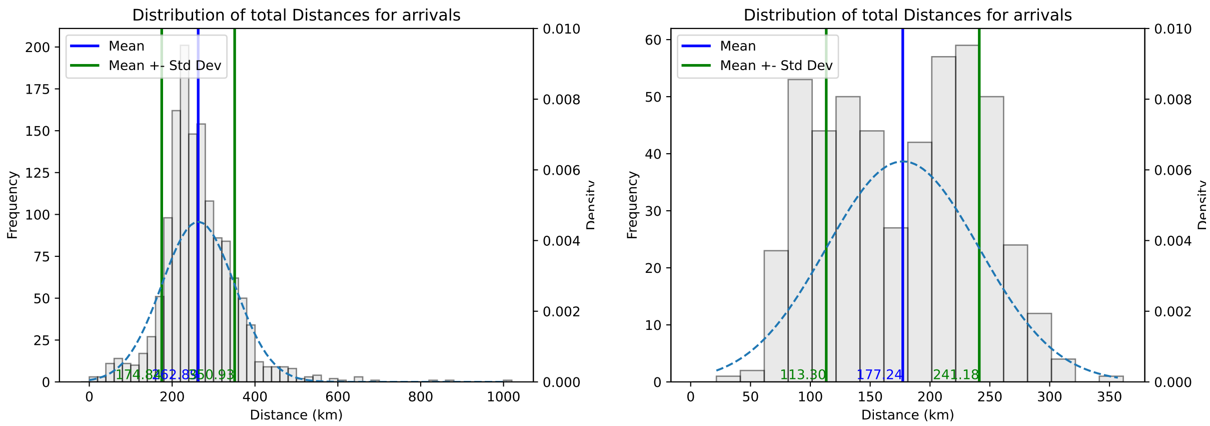
Various statistical methods are used to analyze the sample data and to establish relationships between airport parameters and flight paths. This section provides an overview of the statistical techniques applied in this study.

2.5.1. Data manipulation

A verification has been done to judge the accuracy of the method used for the analysis and to gain an initial understanding of the data. Figure 2.2 illustrates the data for arrivals, with Fig. 2.2a representing Denver Airport and Fig. 2.2b representing El Dorado Airport. This figure shows the results obtained from that verification.

Trimmed mean

As shown in the data, some airports like Denver in Fig. 2.2a, exhibit skewness. This skewness is due to outliers in the data, which can arise from lacking or wrong data which the code is not always able to catch out, leading to incorrect distances being included in the dataset. To address this issue, the data is trimmed at both ends by 5%, so that 90% of the data is used for analysis. This statistical approach is known as a "robust method" and is referred to as the "trimmed mean," as described by *Field*[7].



(a) Arrival distances at Denver

(b) Arrival distances at El Dorado

Figure 2.2: Verification results of arrivals at Denver and El Dorado airport showing outliers and sample difference

Sample size

Additionally, there is a difference in the frequency (left axis) between Denver and El Dorado airports. This poses a problem for regression analysis, as it treats each calculated distance (x axis) as an independent sample. This can lead to a bias toward airports with more data points, resulting in inaccurate variables for estimating distances at various airports. Since the regression analysis is skewed toward airports with more samples, it fails to accurately account for the characteristics of smaller airports, thereby introducing bias.

To address this issue, each airport's sample distribution is resampled 5,000 times. This resampling creates a more balanced distribution, with similar means and standard deviations, and an equal number of samples for each airport. Although the distributions might differ slightly, the large number of samples ensures that the means and standard deviations remain closely aligned, reducing the potential for bias in the regression analysis.

2.5.2. Regression

This subsection discusses the different regression types used in this study and the methods for evaluating their results. The study applies Multiple Linear Regression (MLR), Bayesian Regression (BR), Ridge Regression (RR), and Neural Network Regression (NNR).

Multiple Linear Regression

Linear regression, also known as Ordinary Least Squares (OLS), is one of the most widely used methods for analyzing relationships in data. When there are multiple input variables, the approach is called Multiple Linear Regression (MLR). In this study, MLR is the initial method used to evaluate the relationship between airport parameters, such as elevation and the number of runways; and the distance flown during climb and descent. Even if the relationship might not be strictly linear, MLR is a logical starting point because it is straightforward to interpret and provides a foundational understanding of how much variance in the data can be explained through linear relationships.

MLR produces a function that consists of a constant (intercept) and coefficients (Beta values) corresponding to each input variable. When applied to the associated airport parameters, the resulting function estimates the expected distance for climb or descent. This simplicity allows for a clear view of the impact each parameter has on the overall outcome, which is helpful when building predictive models or gaining insights into the factors affecting flight paths.

Assessment of MLR results

To evaluate the regression models' fit to the sample data, several methods are used to assess the quality and reliability of the results. The methods are outlined below:

- **Confidence interval:** This indicates which airport parameters significantly contribute to predicting flight paths. A 95% confidence interval represents the range where the Beta value is likely to fall. If zero is not within this interval, the null hypothesis can be discarded. This means that the parameter is considered statistically significant, suggesting it has a notable effect and does not include the possibility that it has 0 effect on distance estimation.
- **T-value:** The T-value is a dimensionless metric that shows the relative strength of a parameter's influence on the regression results compared to other parameters. This value can be used to identify which factors have a significant impact and which have a negligible effect, allowing for the removal of parameters that contribute little to the overall result.
- **Variance Inflation Factor (VIF):** The Variance Inflation Factor (VIF) quantifies the level of multicollinearity in a regression analysis, indicating how strongly one variable is related to others in the model. High VIF values can suggest that multicollinearity is affecting the regression results, potentially leading to misleading conclusions about variable relationships. If the VIF exceeds 5, it signals the need for further investigation. A VIF value above 10 is a warning of severe multicollinearity, possibly indicating critical issues with the regression model, as noted by Myers [8] and Bowerman et al. [9].
- **Effect size (R^2):** The effect size represents the proportion of variance in the dependent variable that is explained by the model. It ranges from 0 to 1, with a higher value indicating a better fit and a greater ability of the model to explain the data its variance. A value of 1 implies that the model accounts for all variance, while a value of 0 suggests that the model explains none of the variance. Alongside the confidence interval and T-value, the effect size helps determine whether a parameter has a meaningful impact on the outcome.

Bayesian regression

Bayesian regression is a linear regression approach that integrates uncertainty into the modeling process, providing probability distributions for the parameters to reflect their inherent uncertainty. To build the

Bayesian regression model, a prior distribution is required. For this work, TensorFlow is used to develop the Bayesian regression model. TensorFlow is an open-source machine learning framework and is widely used for developing and training machine learning methods. Initially, the predictors are scaled using a standard scaler to ensure consistent input across the model. A normal distribution is selected, as it's one of the most commonly used distributions, providing a straightforward approach for first estimations and because it is also representative of the distribution seen in the data.

The Bayesian model undergoes a training process, with the number of epochs, or iterations through the dataset, set at 50,000. This high number allows the model to properly converge. However, the model uses a loss function to identify when it has achieved a satisfactory level of accuracy, stopping the training process when further iterations do not reduce the loss, offering a balance between training and efficiency. Additionally the data is split into a 4/5 training and 1/5 validation set, as is a common practise data split to train the model and test the outcome.

Ridge regression

Ridge regression is a regression technique that is particularly useful when dealing with multiple variables. *Frank and Friedman*[10] introduced a penalty term into the approach that consists of the sum of the squares of the regression coefficients, scaled by a constant α. This constant, known as the regularization parameter, regulates the strength of the penalty term and helps to mitigate overfitting by promoting simpler models with smaller coefficients. The mathematical formulation of ridge regression is presented in Eq. (2.1), where y_i represents the target variable for the i^{th} observation, x_{ij} is the value of the j^{th} feature for the i^{th} observation, β_j denotes the coefficient for the j^{th} feature, α is the regularization parameter, and p is the total number of features. The first summation term represents the squared differences between the actual target values and the predicted values, while the second summation term denotes the sum of the squares of the coefficients, scaled by α.

$$minimize(\sum_{i=1}^{n}(y_i - \sum_{j=1}^{p} x_{ij}\beta_j)^2 + \alpha \sum_{j=1}^{p} \beta_j^2) \tag{2.1}$$

Ridge regression helps to stabilize the model and reduce the impact of multicollinearity by shrinking the coefficients towards zero. Unlike lasso regression, which tends to produce sparse models with some coefficients exactly zero, ridge regression keeps all features in the model but penalizes their magnitude. Tuning the regularization parameter α is crucial in ridge regression to find the right balance between bias and variance, where a higher α leads to more regularization, while a lower α reduces the regularization effect, potentially leading to overfitting.

This method is applied through using RidgeCV within the scikit-learn library. It uses cross validation to find the best model parameters, in this case alpha. Through bootstrapping it determines the distribution of the coefficients and calculate confidence intervals.

Neural Network regression

The study conducted by *Wong et al.* [11] compares various regression techniques to evaluate their accuracy in modeling. The research examines several models, including Artificial Neural Network (ANN), Generalized Regression Neural Network (GRNN), Support Vector Regression (SVR), Multiple Linear Regression (MLR), and Response Surface Model (RSM). The models were tested on two distinct non-linear cases. From these tests, ANN, GRNN, and SVR were found to be reliable, as the other models failed to accept the null hypothesis in one of the two quadratic scenarios.

Based on Wong et al.'s findings, this thesis employs a Neural Network approach to quantify the relationship between selected airport parameters and flight distance, aiming to explore its applicability. The key advantage of a Neural Network is its capacity to model non-linear relationships between input variables and outputs, potentially leading to a higher explained effect size (R^2) or better predictive capabilities for unseen data. A typical neural network consists of multiple layers: an input layer, one or more hidden layers, and an output layer. The input layer's nodes correspond to the number of input variables, the hidden layers contain a variable number of nodes to model non-linear relationships, and the output layer has a single node that provides the regression prediction.

Optimizing the neural network involves adjusting the number of layers and the number of nodes within each layer. An excessive number of layers or nodes can lead to overfitting, while too few can result in underfitting. Determining the optimal configuration requires trial and error. In this study, various configurations are explored, with the number of hidden layers and their respective node counts specified as follows; layers - (nodes layer 1: nodes layer 2: ...). starting with one-layer models containing 3, 5, and 10 nodes. Double-layered models are also examined with node configurations of 3:2, 3:3, 5:3, 5:5, and 10:5. Finally, triple-layered models with 5:3:2 and 10:5:3 configurations are tested. Figure 2.3 illustrates a neural network architecture with two hidden layers using a 2-(3:2) configuration.

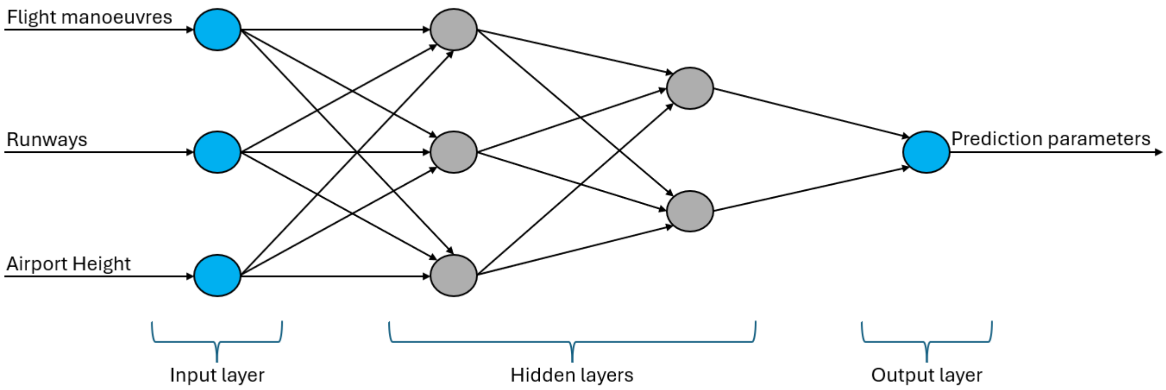


Figure 2.3: Standard Neural Network architecture with 3:2 node configuration.

Through backpropagation, the neural network aims to minimize the loss function, which, within this study, is the Mean Squared Error (MSE), as is standard within the *scikit-learn* module in Python. During training, the neural network adjusts its weights and biases to minimize the MSE, typically using optimization algorithms like stochastic gradient descent or its variants. The optimization process involves iteratively updating the model parameters to move towards the minimum of the loss function, thereby improving the model's accuracy on the training data.

To train and test the model, the dataset is split into two parts, with 4/5 allocated for training and 1/5 for testing. The network uses the *relu* activation function, which is frequently used in neural networks due to its computational efficiency and ability to mitigate the vanishing gradient problem. The *adam* solver, an adaptive learning rate optimization algorithm, is employed for its robustness and efficiency. Additionally, a fixed random state of *42* is used to ensure reproducibility of results.

2.5.3. Regression Comparison

The regression models are all evaluated using the training dataset. To identify which regression method is most effective at predicting unseen data, a separate test dataset consisting of five airports with sufficient range in the airport parameters is created. This test dataset is used to assess and compare the predictive capabilities of each regression model to determine which one performs best within the context of this study. The regression method that demonstrates the highest predictive accuracy on the test dataset is chosen for the final part of the thesis. This final section, which focuses on integration and comparison, involves applying the selected regression method to generate emission results using the new approach.

2.6. Sample flight list

A sample flight list is used to compare emissions from the current method with those from the new method described in this thesis. The list is limited to flights involving the airports assessed in this study, ensuring more accurate uncertainty quantification because the error margins of the mean values are known. The type of aircraft used in the analysis is also important. The share of B737 and A320 aircraft is significant, but to integrate the new method accurately—which is designed for all types of aircraft—a representative fleet composition is needed within the sample. Data from Cirium[1] indicates the percentage of flights flown by the ten most common aircraft types, as shown in Table 2.4.

[1] Obtained from: https://simpleflying.com/most-used-commercial-aircraft-types-2022/

Table 2.4: Aircraft flights and airlines in 2022

Aircraft	2022 Flights	% of World's Flights	Top 3 Airlines by Flights
A320ceo	6.35 million	20.5%	IndiGo, easyJet, China Eastern
737-800	5.53 million	17.9%	Ryanair, Southwest, American
A321ceo	2.12 million	7.0%	American, Delta, China Southern
A319ceo	1.42 million	4.6%	American, easyJet, United
737-700	1.16 million	3.7%	Southwest, United, WestJet
Embraer 175	969,200	3.1%	American, United, Delta
ATR-72	909,800	2.9%	Wings Air, Binter Canarias, Azul
A320neo	831,500	2.7%	Volaris, Frontier, Spirit
737 MAX 8	723,100	2.3%	Southwest, Ryanair, Gol
CRJ-900	634,900	2.0%	Delta, American, Lufthansa

Considering the requirements for the sample set, the flight list used for comparison is provided in Appendix B. The flights in this list are chosen to ensure an accurate fleet composition, in accordance with the percentage distribution of aircraft types shown in Table 2.4. However, these flights only involve routes between the airports analyzed in the regression study. Note that the ATR-72 and A320neo aircraft are not included. The A320neo is not available in the used version of BADA, and the ATR-72 encountered issues with the code. The error indicated stall issues which is expected to be caused by the aircraft descent speed, taken from the BADA files, which could not match the descent slope for the aircraft.

To create the flight list, the percentages of each aircraft type are multiplied by 10 to estimate the number of aircraft corresponding to each percentage of all flights. This means there are e.g. $20.5 * 10 = 205$ A320 aircraft and $17.9 * 10 = 170$ 737-800 etc. Additionally, the total number of annual flights (total flight movements) for each departure airport is taken and multiplied by the number of aircraft, then divided by the total sum of all flight movements for all considered airports. This yields a scaled flight number associated with each departure airport. This process is repeated for each aircraft type and each airport, resulting in the flight list presented in Appendix B. The equation for this calculation is given in Equation 2.2, where $N_{aircraft}$ represents the number of aircraft of a specific type, $FM_{airport}$ is the total flight movements for the considered airport, and FM_{total} is the total flight movements for all airports in the dataset.

$$flights = \frac{N_{aircraft} * FM_{airport}}{\sum FM_{total}} \tag{2.2}$$

The method described above generates a sample dataset for comparing flight emissions. As noted, certain aircraft types are excluded from the dataset, and a specific route between KDEN (Denver Airport) and SBGR (São Paulo) was not considered due to code errors. Figure 2.4 presents the aircraft included in the sample set, along with the respective percentages as given in Table 2.4 in which 61.1% of the total global flights are represented. The adjusted percentages do not perfectly align with the percentages for all flights globally, but they are within an acceptable range for the purposes of this research. Appendix B shows the table related to the aircraft flights within the sample set.

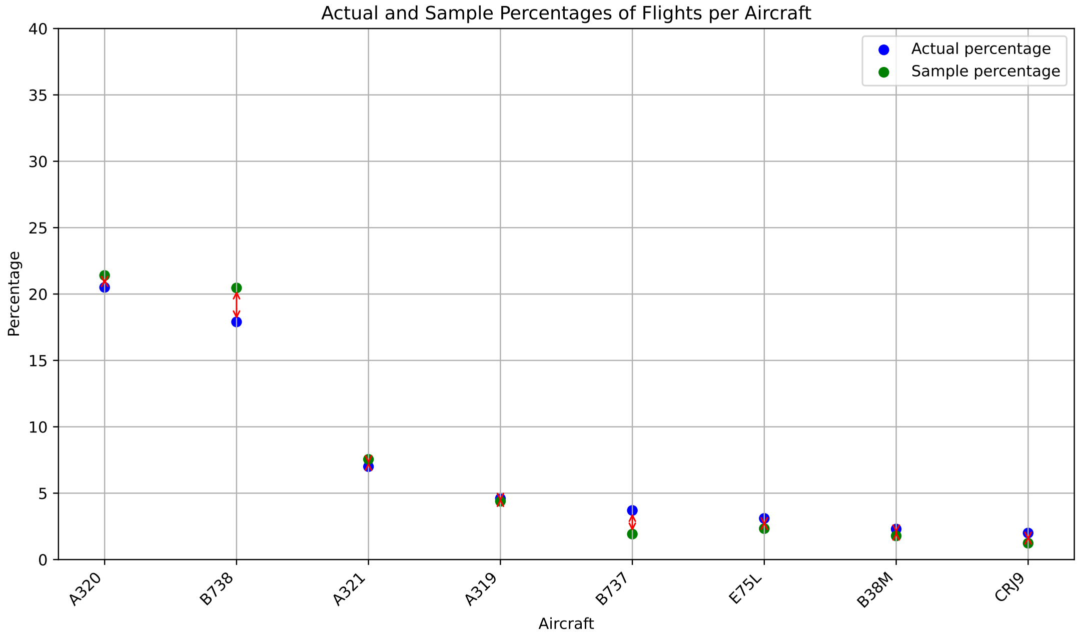


Figure 2.4: Percentages of aircraft in actual and sample data

The objective is to ensure that the percentages of flights to and from each airport in the sample set closely mirror the percentages of actual annual flight movements at each airport. Figure 2.5 displays the percentages relative to the total annual flights for all airports and the corresponding percentages within the sample data. While these percentages may not perfectly match, they sufficiently represent the real-world scenario for the purposes of this research, which focuses on comparing two analytical approaches. This level of representation is adequate given the study's aim of comparing emission estimates from different methodologies. The table with exact percentages is given in Appendix C.

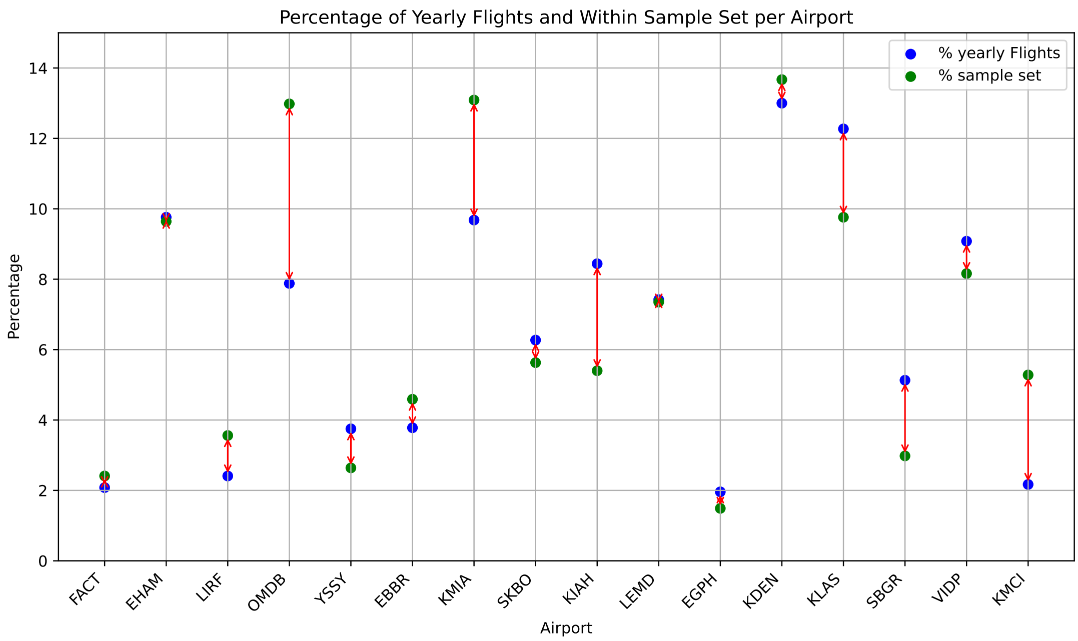


Figure 2.5: Percentage of annual flights and Within sample set per Airport

2.7. Integration into openAVEM

The parts requiring modification in the openAVEM code are specifically related to climb and descent. The code in the model by Quadros et al. separates climb, cruise, and descent, and determines the starting mass with a 5% extra fuel reserve, additional fuel for diversion (depending on whether it is a long-haul or short-haul flight), and the estimated payload mass. For each phase of the flight—climb, cruise, and descent—it adds a lateral inefficiency factor.

After determining the best method to relate the flight path to airport parameters, the method is implemented into the model of Quadros. The developed method specifically replaces the current method of estimating the aircraft position. By calling the function described in the 'readme' file, the process is triggered, loading a CSV document with the sample flight list.

2.7.1. Aircraft position estimation

In the current estimation approach, BADA calculates the Top of Climb/Descent (TOC/TOD). It calculates fuel flow and aircraft position based on a speed schedule, using the destination elevation and descent speed schedule, as detailed in the Instrument Procedures Handbook of the FAA [5]. However, descent from the TOD is typically not followed strictly due to air traffic management or airspace design constraints.

Consequently, the climb and descent calculated by the standard BADA may not be accurate in certain cases. To adjust the openAVEM model, the code that calculates fuel flow during climb and descent has been altered to account for additional distance flown. For this, pyBADA is used, which offers a function called 'constantspeedslope'. This function determines the fuel flow of an aircraft at a constant velocity and slope. This function is offered within pyBADA which means that it is validated and is not allowed to be altered. The fuel flow is determined each 1000 feet step, just like with the original method, and the speed is taken from the 'PTD' files of the aircraft from BADA.

2.7.2. Emission Comparison

The comparison of emissions between the current approach and the developed approach within this thesis is a central part of this research. By comparing the emissions from both approaches and providing a related uncertainty analysis, the applicability of the new approach can be evaluated.

Sample Dataset

The sample dataset described in Section 2.6 is applied to compare the methods. The goal is to achieve a comparable fleet composition to the real world for each airport, and scale the number of sample flights to each airport according to the annual flight movements at the airport. This approach ensures a realistic sample, which minimizes bias in the results.

Emission Comparison

The model is run several times to obtain the emissions for the climb and descent phases separately, using both the original approach and new, proposed approach. The total fuel consumption is expected to increase, but because of different operating conditions, the emissions may vary, potentially decreasing for some specific emissions.

Uncertainty Quantification

To evaluate the accuracy of the new approach, the predicted values are compared to the actual mean values for each airport. The difference between the estimated mean value and the actual mean value indicates how far the prediction deviates for the entire sample set. Additionally, upper and lower estimates, derived from the confidence interval or uncertainty of the flight distance prediction, quantify the uncertainty in the emissions.

3

Airport Analysis and Statistical Results

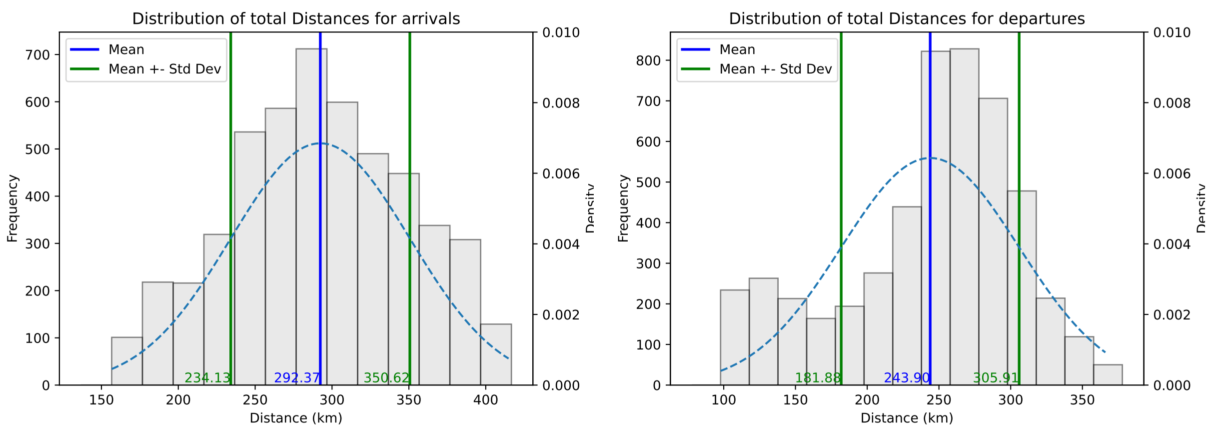
This chapter discusses the analyses performed on the airports to identify key parameters and the methods used to relate these parameters to flight distance. It compares different regression techniques to determine the most suitable approach for the application within the scope of this thesis.

3.1. Analysis of flight distances

This section presents the outcomes of the analyses and the statistical assessment. It synthesizes the findings and discusses the subsequent steps that were taken based on these results. It encompasses focused analyses of the airports to identify patterns in the data which includes analysis of the flown distance, aircraft type, and flight direction.

3.1.1. Arrivals and departures

Figure 3.1 illustrates the difference in distances between arrivals and departures at Schiphol Airport. The mean distance for arrivals is approximately 290 kilometers, while for departures it is about 240 kilometers. This difference could be attributed to aircraft converging as they approach an airport, which requires additional separation and vectoring, thereby increasing the distance during descent. In contrast, departing aircraft disperse as they head to various destinations. This natural dispersion reduces the need for vectoring during ascent, resulting in shorter distances for departures but with a larger spread compared to arrivals.



(a) Arrival distances at Schiphol

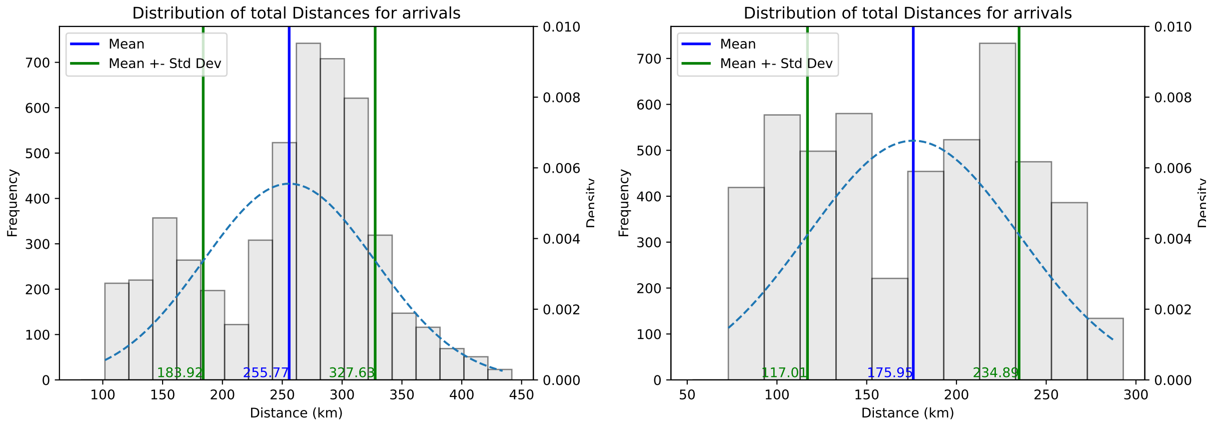
(b) Departure distances at Schiphol

Figure 3.1: Arrival and departure distances at Schiphol

3.1.2. Airport elevation

The difference in arrivals, as shown in Fig. 3.2, is likely due to the substantial disparity in airport elevation. Sydney Airport is situated at 6 meters above sea level, while El Dorado Airport is located at 2,548 meters.

This notable difference in elevation affects the total distance flown to and from each airport as there is less vertical distance between cruise and the airport. While there could be other contributing factors, the large gap in elevation indicates that airport elevation plays a significant role in flight path distances.

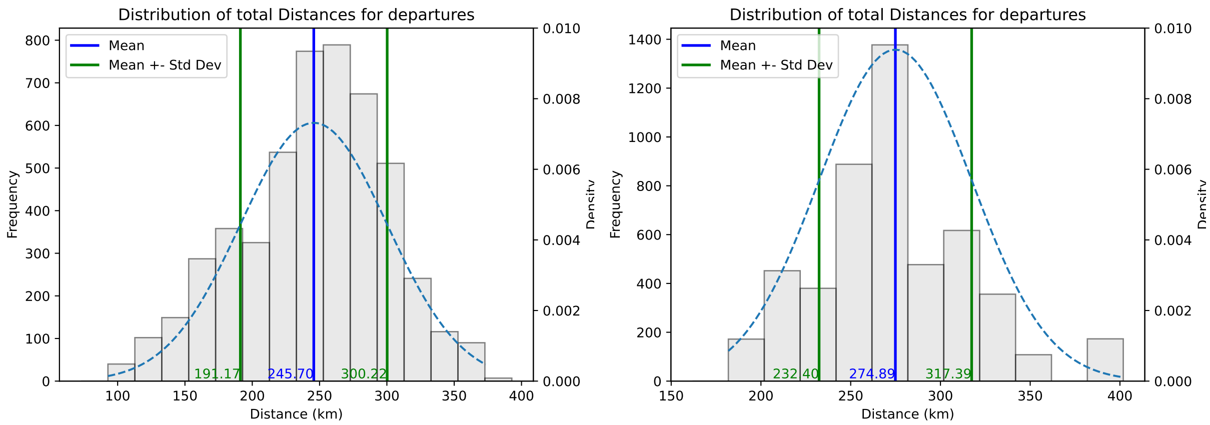


(a) Arrivals Sydney

(b) Arrivals El Dorado

Figure 3.2: Arrivals Sydney and El Dorado

In the departures shown in Fig. 3.3, there is a noticeable difference between the flights departing from Madrid and those departing from Cape Town. This is especially evident at the lower end of the spectrum, where flights from Cape Town generally cover a greater distance compared to those from Madrid. This discrepancy could be due to Cape Town's relatively isolated location, which leads to a greater proportion of long-range flights. Long-range flights cruise at higher altitudes compared to short-range flights and therefore the geographic location of an isolated airport contributes to longer distances flown during climb and descent. This is why Cape Town has a higher mean distance compared to Madrid, which is a network with a greater proportion of short-range flights.



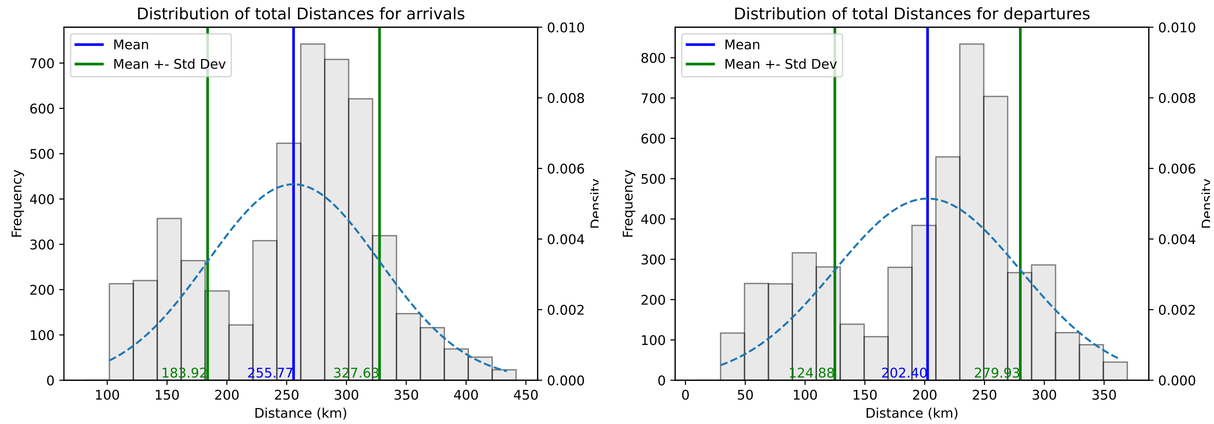
(a) Departures Madrid

(b) Departures Cape Town

Figure 3.3: Departures Madrid and Cape Town

3.1.3. Aircraft type

Sydney Airport exhibits a similar distribution for both its arrivals and departures, though there's a difference of about 50 kilometers in the mean distances. The graphs display a slight bimodal distribution in the flown distances, indicating that there might be two common flight patterns or routing strategies for this airport.

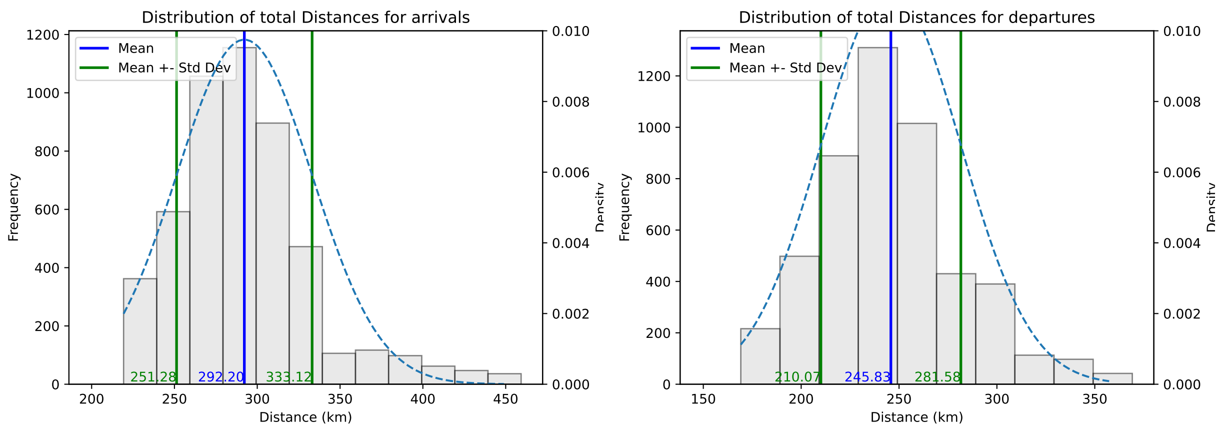


(a) Arrivals Sydney

(b) Departures Sydney

Figure 3.4: Arrivals and Departures at Sydney

Figure 3.5 depicts the distances flown by aircraft categorized as *large narrow-body*. These aircraft operate both long and short routes, depending on airline practices or airport location. The main peak in the data is explained by large narrow-body aircraft, but the aircraft categorized as narrow-body and wide-body, typically used for short-haul and long-haul flights, do not fully explain the rest of the distribution. This suggests that further investigation may be needed to understand which aircraft types are responsible for shorter distances, leading to the secondary peak at lower distances. A comprehensive list of wide-body, large narrow-body, and narrow-body aircraft is provided in Appendix A, obtained from MIT[1].



(a) Large narrow-body arrivals Sydney

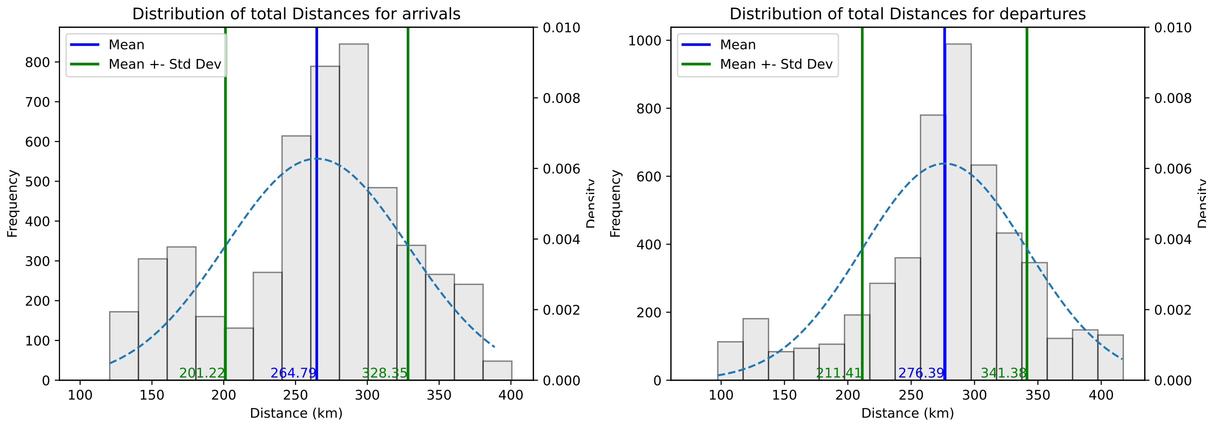
(b) large narrow-body departures Sydney

Figure 3.5: Large narrow-body Arrivals and Departures at Sydney

3.1.4. Flight direction

Figure 3.6 illustrates the distribution of flown distances at Miami Airport. This airport exhibits a slight deviation from a typical normal distribution, with a small peak observed just before and around the 150-kilometer mark for both departures and arrivals.

[1]Obtained from: https://web.mit.edu/airlinedata/www/Aircraft%20Categorization.pdf



(a) Arrivals Miami

(b) Departures Miami

Figure 3.6: Arrivals and Departures at Miami

Further analysis of flight directions, by determining which quadrant around the airport the aircraft flew from or to, revealed a significant drop in flown kilometers in the southeast direction. Quadrants are a simple way to assess whether there are recognizable deviations in the departure or arrival routes. The analysis results shown in Table 3.1 indicate that the southeast direction has a significantly lower mean compared to other flight directions. Upon further investigation, as shown in Fig. 3.7, the cause was found to be insufficient data. To address this, the code was slightly adjusted by increasing the minimum required data points to 70 for altitudes above 1,500 meters and to 100 points for altitudes below 1,500 meters. The graph in Fig. 3.6 and the corresponding table below already reflect this adjustment.

Table 3.1: Flight directions of arrivals at Miami airport per quadrant

Quadrant	Sample size	Mean (km)	Standard deviation (km)
South East	103	155	34
South West	112	277	47
North East	252	287	61
North West	303	284	55
Unclassified	15	247	69

The decision to include only data with a minimum length introduces additional uncertainty, as it leads to excluding more data points. Despite this precaution, there are still instances where data points exceed the considered threshold but still terminate at the same coordinates during climb or descent. This indicates that incorrect data persists despite efforts to minimize it, highlighting the limitations of open-source data in terms of coverage. These limitations are not only due to the absence of receivers in certain regions but also because the range of these receivers may not always be sufficient.

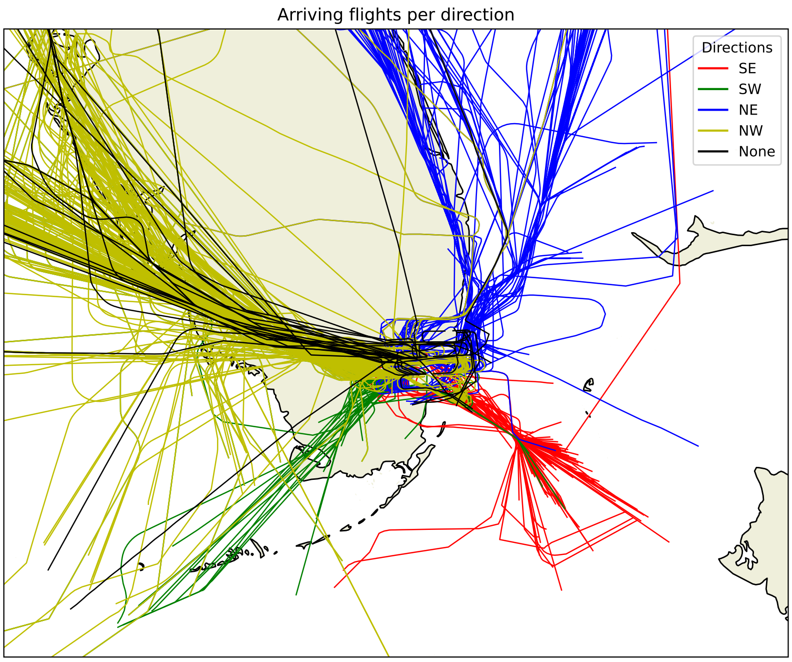


Figure 3.7: Arriving flights at Miami airport.

3.2. Statistical results

Various statistical techniques have been applied to obtain a quantified relationship between the airport parameters and flight path. The preliminary airport parameters selected for the analysis are total flight Movements, airport elevation, and number of runways.

3.2.1. Multiple Linear Regression

Three input variables used within the regression analysis include flight movements, the number of runways and airport elevation. The output variable is the distance flown.

Beta coefficients and their significance

Table 3.2 and Table 3.3 show the values of the Beta coefficients with the related confidence intervals. The confidence intervals do not include zero which means that the null hypothesis can be discarded and the Beta coefficients have a statistically significant effect.

Table 3.2: Beta coefficients and their confidence intervals for arrivals

Variable	Beta Coefficient	95% Confidence Interval
constant	267.32	(266.12, 268.51)
Flight movements	0.000104	(0.000100, 0.000108)
Runways	-1.96	(-2.42, -1.49)
Airport elevation	-0.0373	(-0.0378, -0.0368)

Table 3.3: Beta coefficients and their confidence interval for departures

Variable	Beta Coefficient	95% Confidence Interval
constant	247.29	(245.92, 248.66)
Flight movements	0.000117	(0.000113, 0.000122)
Runways	-6.55	(-7.09, -6.02)
Airport elevation	-0.0264	(-0.0272, -0.0256)

T-values and VIF
Table 3.4 shows that the VIF values are within an acceptable range for all but one of the Beta coefficients. The constant has a VIF value slightly above 6, which might be due to the low effect size of the statistical model.

Table 3.4: T-values and Variance Inflation Factor (VIF) for Arrivals and Departures

Variable	T-value (Arr)	T-value (Dep)	VIF
constant	437.55	353.30	6.68
Flight movements	50.84	49.91	2.14
Runways	-8.24	-24.06	1.96
Airport elevation	-103.08	-63.67	1.13

Additionally, from the T-values it is seen that airport elevation has a larger effect on the flown distance during descent compared to climb which could be due to vectoring and a higher airport might require less vectoring as the descent phase is smaller.

Effect size
Effect size, often represented as R^2, measures the proportion of the variance in the dependent variable that is explained by the independent variables in the regression model. It ranges from 0 to 1, where 0 means none of the variance is explained by the model, and 1 indicates that the model explains all variance.

Each parameter was added to the model separately to test its effect size independently. Table 3.5 shows that airport elevation has the most significant effect on the distance flown, explaining 8.5% of the variance. This is significantly higher than the effect of flight movements and runways, which have effect sizes of 1.2% and 1.0%, respectively.

Table 3.5: Effect sizes for variable combinations

Variables	R^2 (Arr)	R^2 (Dep)
Flight movements	0.0120	
Runways	0.0096	
Airport elevation	0.0848	
Flight movements, Runways	0.0130	
Flight movements, Airport elevation	0.1274	
Runways, Airport elevation	0.1001	
Flight movements, Runways, Airport elevation	0.1282	0.0599

While it's logical that the combined effects of multiple variables would result in a higher explained variance in a linear model, the combined effects are not simply the sum of the individual effects. This discrepancy is likely due to a common underlying factor among the selected variables. For example, the combined effect of flight movements and runways is lower than the sum of their individual effects, accounting for only 1.3% of the explained variance. However, the combined effect of runways and airport elevation, and especially of flight movements and airport elevation, is higher, with explained variance percentages of 10% and 12.7%, respectively. These combinations actually increase the explained variance more than the sum of their individual effects, supporting the hypothesis that an underlying factor influences both flight movements and runways. These factors are largely unrelated to airport elevation, which is a static metric independent of, for example, airport capacity.

As the flight movements variable is added to the model, the relevance of the number of runways diminishes, as it does not significantly explain variance in the model. With a total of 13% explained variance, it may be worth exploring other related factors to improve the model's accuracy. One possible area of investigation could be airspace complexity, which might play a significant role in the large unexplained variance of the current model.

MLR estimates

Figure 3.8 shows the estimated distances for each airport and compares those to the actual mean of the airport. The results show that MLR over and under-estimates the actual distances flown. The average error margin of MLR on the training data set is 8.17%. The exact values and error margins are given in Appendix C.

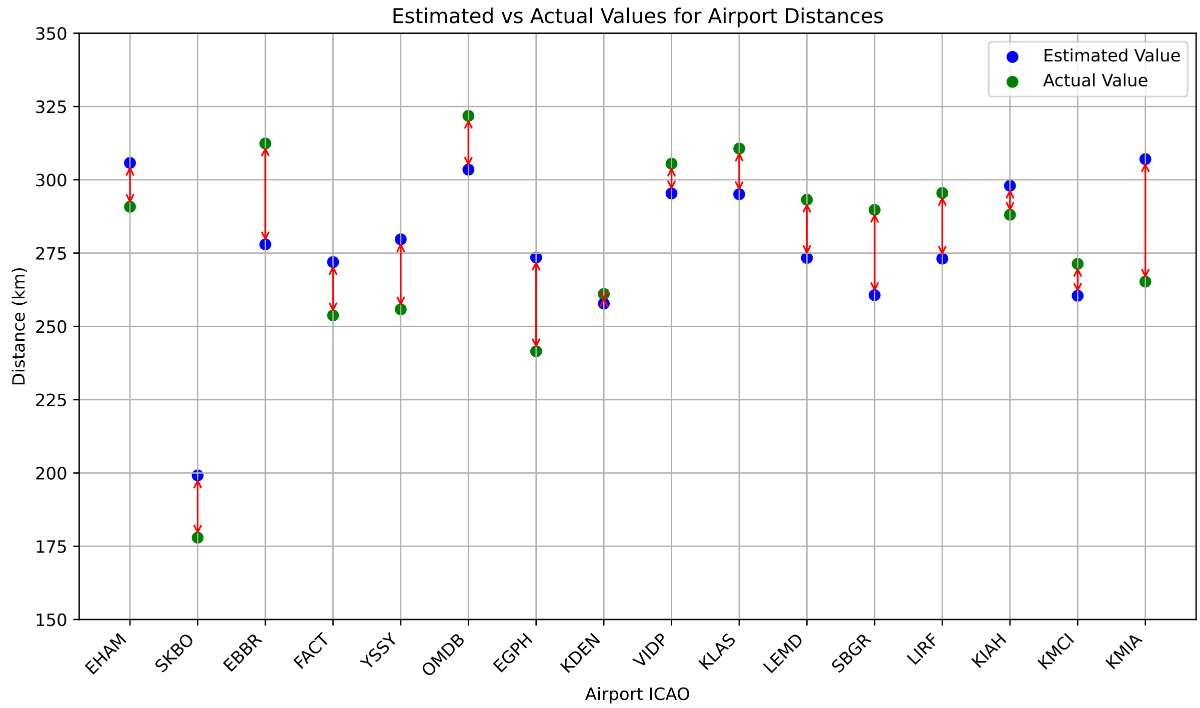


Figure 3.8: Estimated values and actual values per airport using MLR

3.2.2. Multiple Linear Regression with airspace complexity

As explained by *Zhu et al.* [12], "Airspace complexity serves as an objective metric for evaluating the operational condition of the airspace." This metric is crucial in the design of airspace within Air Traffic Management (ATM), but its assessment is complex due to non-linear relationships among various independent factors.

Airport selection

For this analysis only the six airports given in Table 2.3 were taken to evaluate the feasibility of incorporating airspace complexity into the model due to data availability constraints as explained in Section 2.4. When another linear regression is applied to just these six airports, using flight movements, runways, and airport elevation as parameters, the effect size increases to 38%. This is likely because many of these airports share similar characteristics. However, some of the tests applied to the MLR show significant differences, as illustrated in Table 3.6 and Table 3.7.

Table 3.6: Beta coefficients and their confidence intervals of selected airports

Variable	Beta Coefficient	95% Confidence Interval
constant	216.20	(214.36, 218.03)
Flight movements	-0.000319	(-0.000335, -0.000303)
Runways	46.38	(44.79, 47.97)
Airport elevation	-0.0131	(-0.0141, -0.0121)

Table 3.7: T-values and Variance Inflation Factor (VIF) of selected airports

Variable	T-value	VIF
constant	230.90	8.91
Flight movements	-39.39	12.26
Runways	57.09	12.11
Airport elevation	-21.22	3.28

The influence of the runway parameter has notably increased in its impact on the results, indicating that an additional runway would add 46 kilometers of distance. This is a significant deviation from the original regression results. Moreover, it is surprising to see that more flight movements now have a diminishing effect on the total distance flown. Additionally, the VIF values for flight movements and runways are very high. These outcomes are likely due to the limited number of airports considered. However, these values are not realistic, as more flights should typically increase distance, and runways are expected to decrease distance, as observed in the regression results from the full dataset.

Removal of runways parameter
Due to the high VIF values and unrealistic beta values associated with the runway parameter, it has been discarded. This decision is further supported by the fact that this parameter barely contributed to the variance (0.1%) in the effect size of the full dataset. The revised results are shown in Table 3.8 and Table 3.9 below.

Table 3.8: Beta coefficients and their confidence intervals of selected airports without runway parameter

Variable	Beta Coefficient	95% Confidence Interval
constant	254.43	(253.08, 255.79)
Flight movements	0.000123	(0.000118, 0.000128)
Airport elevation	-0.0422	(-0.0430, -0.0415)

Table 3.9: T-values and Variance Inflation Factor (VIF) of selected airports without runway parameter

Variable	T-value	VIF
constant	369.36	4.35
Flight movements	49.11	1.06
Airport elevation	-114.23	1.06

The results now seem more plausible, aligning closely with the initial linear regression outcomes shown in Table 3.2 and Table 3.4. The effect size of the model drops to 31.2%.

Regression results with airspace complexity parameters

The additional value of including airspace complexity metrics in the regression is evaluated by individually examining the effect size of each variable. Table 3.10 illustrates the effect sizes for various combinations of airport parameters.

Table 3.10: Effect sizes for variable combinations with airspace complexity metrics

Variables	R^2
Flight movements	0.0124
Airport elevation	0.2565
Merg./cross. points	0.1118
Airways	0.0100
FM, H	0.3118
FM, H, MCP	0.3177
FM, H, A	0.3249
FM, H, MCP, A	0.3249

The results suggest that the chosen complexity parameters contribute little to the explained variance in the model. Given the minimal additional variance explained, the current approach to defining airspace complexity seems inadequate. Further analysis and research are needed to effectively incorporate airspace complexity into the model.

3.2.3. Bayesian Regression

Bayesian Regression (BR) shares similarities with multiple linear regression, but it offers an additional dimension by quantifying uncertainty. The Bayesian regression used in this study is implemented with TensorFlow, as described in Section 2.5.

Beta coefficients

Just like in linear regression, beta coefficients in Bayesian regression represent the change in the output variable for each unit change in the associated input variable. However, in Bayesian regression, these coefficients come with an uncertainty measure, offering additional insight into their reliability. Table 3.11 and Table 3.12 show the beta coefficients obtained from the Bayesian regression, along with their associated uncertainty quantification.

Table 3.11: Beta coefficients and their confidence intervals for arrivals

Variable	Beta Coefficient	95% Confidence Interval
constant	295.71	-
Flight movements	0.000104	(0.000102, 0.000107)
Runways	-1.96	(-2.43, -1.49)
Airport elevation	-0.0373	(-0.0376, -0.0370)

Table 3.12: Beta coefficients and their confidence intervals for departures

Variable	Beta Coefficient	95% Confidence Interval
constant	263.84	-
Flight movements	0.0000209	(0.0000144, 0.0000273)
Runways	−0.047	(−5.13, 5.04)
Airport elevation	−0.0240	(−0.0369, −0.0112)

Table 3.11 demonstrates that the results of Bayesian regression align with those obtained from multiple variable linear regression. Table 3.12, on the other hand, shows quite different outcomes compared to the MLR. The runways parameter in this case has a large confidence interval, ranging from -5 to 5, which encompasses zero. This suggests that we cannot reject the null hypothesis for this parameter, indicating that it might not be significant in this context. The reason behind such a wide confidence interval for this parameter is not entirely clear.

Model performance

Table 3.14 provides metrics related to the performance of the Bayesian regression model. The BR is an iterative process within which the maximum epoch number was set at 50,000, with a loss function that would automatically halt the training loop if no significant improvement was observed over 100 epochs. This setup indicates that the model has achieved convergence in terms of validation loss and training loss. However, the validation loss (VL) remains relatively high, around 90 thousand, whilst the training loss (TL) is higher at 360 thousand suggesting that the model might struggle to capture the underlying patterns in the data and that the way this data is setup, is hard to train to for the model. As shown in Table 3.13 and visually in Fig. 3.9, the training loss starts around 2.6 billion, going down to 360 thousand, whilst the validation loss goes down from 656 million to 90 thousand. Departures show a similar outcome with the validation loss ending significantly below the training loss of the model.

Table 3.13: Validation and training loss

Flight type	VL_{start}	VL_{end}	TL_{start}	TL_{end}
Arrivals	656.145.000	89.934	2.624.834.000	359.803
Departures	552.031.800	92.095	2.216.532.700	368.524

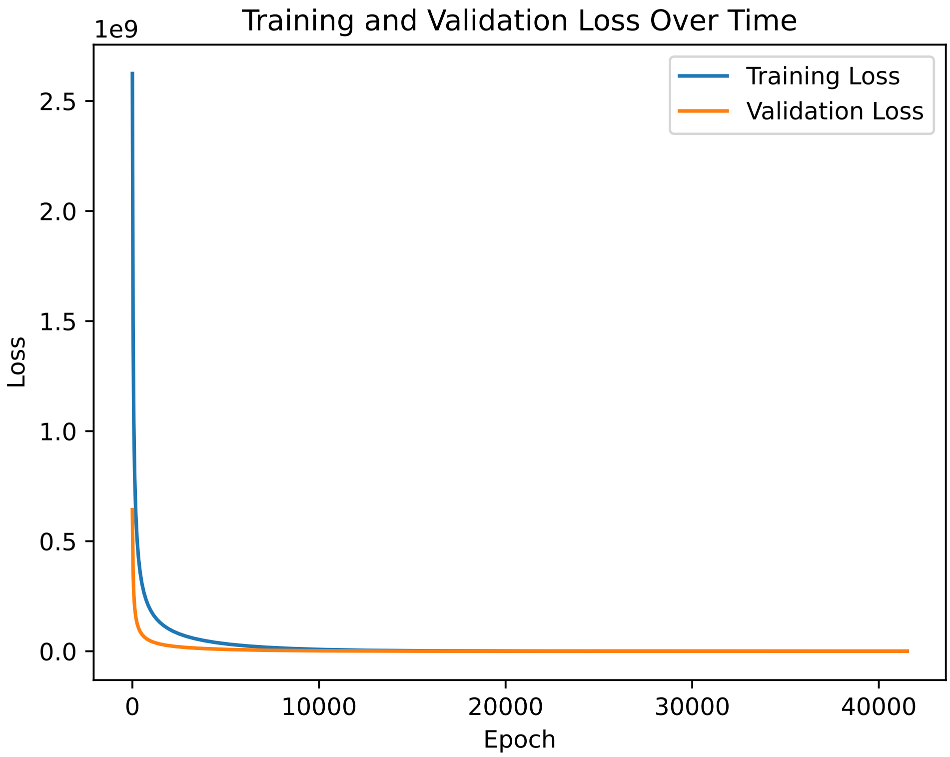


Figure 3.9: Training an validation losses for arrivals in Bayesian Regression.

This is also reflected in the low effect size of 12.6%, which is in the same range as the multiple variable linear regression conducted earlier, indicating that the Bayesian model does not provide a significant improvement in performance.

Table 3.14: Model performance

Flight type	Early Stopping Epoch	Log Standard Deviation	Effect size (R^2)
Arrivals	42203	4.203 (67 km)	12.60%
Departures	39674	4.339 (76 km)	6.47%

The log standard deviation from the BR model is 4.203, which translates to approximately 67 kilometers. This suggests that the predicted distances can vary by as much as 67 kilometers above or below the mean estimate. For departures, the standard deviation is even higher at 76 kilometers, which is considerable given that departure distances are generally shorter. This higher variation could be attributed to the significantly lower effect size of the departures model compared to the arrivals model.

Bayesian Regression results

Figure 3.10 presents the estimated distances from the BR model. When comparing these results with those from the MLR, it becomes evident that the error margins are generally larger with BR, with the average error margin being up at 11.5% compared to the 8.17% of the MLR. This might indicate that the Bayesian model has a higher degree of uncertainty or that it's overfitting certain aspects of the data. Notably, most error margins from the BR are greater than those from the MLR, although the Bayesian model does provide a clear estimate of the uncertainty.

This uncertainty, around 67 kilometers, encapsulates almost all of the airport estimations, except for Miami airport (KMIA), where the estimate appears to be an outlier. It's also interesting to note that nearly all distances in the Bayesian model are overestimated. This tendency towards overestimation could suggest that the model's intercept needs adjustment, which might help correct the overall direction of the estimates and improve accuracy. The exact values and error margins are given in Appendix C. This is further supported by the similar beta coefficients and shape of the estimation graph of the arrivals compared with the MLR, which is simply higher due to the constant.

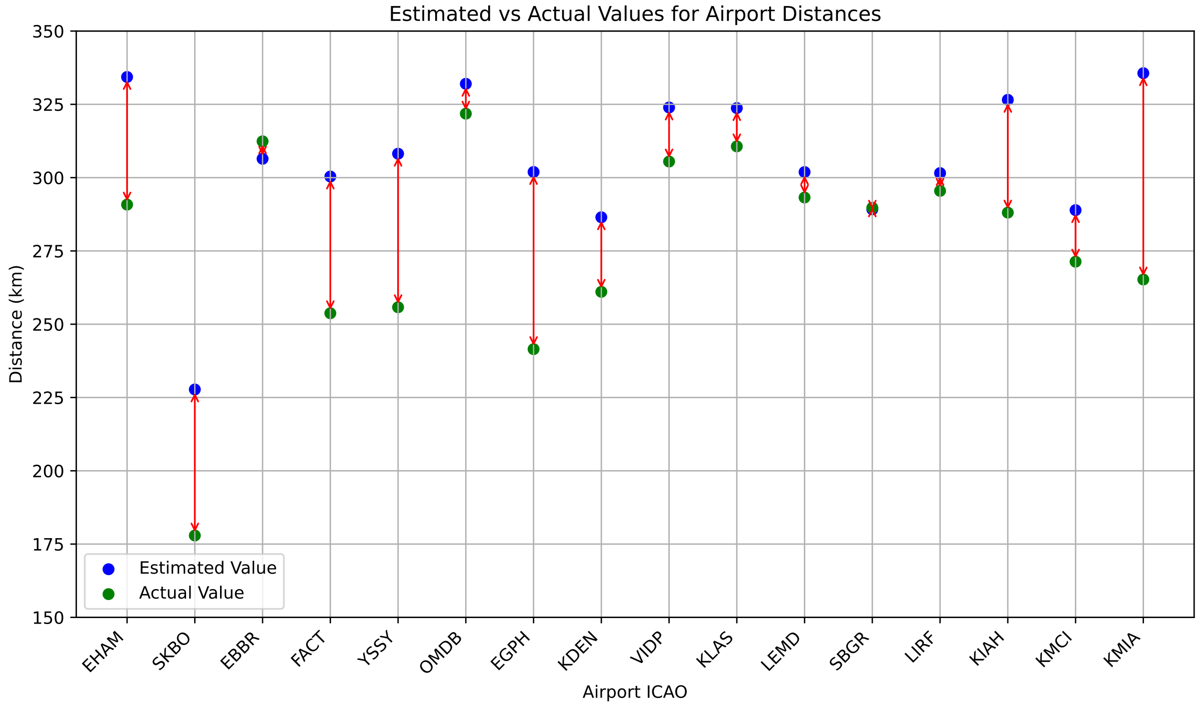


Figure 3.10: Estimated values and actual values per airport using BR

3.2.4. Ridge Regression

The results of the Ridge Regression for arrivals are presented in Table 3.15. The results indicate that the beta coefficients from Ridge Regression are very similar to those obtained from MLR, suggesting that Ridge Regression provides a comparable fit to the data, but with potentially better generalization due to regularization. The alpha value with the best performance is selected, indicating the optimal level of regularization. In the given context, an alpha value of 10 was chosen from the range of available alpha values (0.1, 1, 10, 20, 50, 100) as the best fitting for the model.

Table 3.15: Ridge Regression coefficients and their confidence intervals for arrivals

Variable	Beta Coefficient	95% Confidence Interval
constant	281.71	(-)
Flight movements	0.000104	(0.000100, 0.000109)
Runways	-1.95	(-2.54, -1.40)
Airport elevation	-0.0373	(-0.0378, -0.0368)

Table 3.16: Ridge Regression coefficients and their confidence intervals for departures

Variable	Beta Coefficient	95% Confidence Interval
constant	266.25	(-)
Flight movements	0.000117	(0.000113, 0.000122)
Runways	-6.57	(-7.09, -6.06)
Airport elevation	-0.0264	(-0.0271, -0.0256)

The results from Fig. 3.11 indicate that RR, while designed to generalize better on unseen data, may lead to a wider range of error in some cases. This table reveals that underestimation errors have decreased, suggesting better accuracy for airports initially underestimated by linear regression. However, the same table shows that overestimation errors have increased, with several airports exhibiting errors above 20%. RR is designed to generalize better on unseen data, potentially offering improved accuracy over MLR, however the overall error margin on the training set is 8.21%, which is comparable to the 8.17% of the MLR. This could mean that Ridge Regression might be more reliable in predicting unknown data, which is tested within Section 3.3. The effect sizes for the Ridge Regression arrival and departure models are 12.9% and 6%, respectively. The exact values and error margins are given in Appendix C. Similar to the BR, the RR also reflects the performance of the MLR with regards to the beta coefficients in the arrivals. The constant is still estimated too high however, and therefore exhibits a greater error on the complete data set.

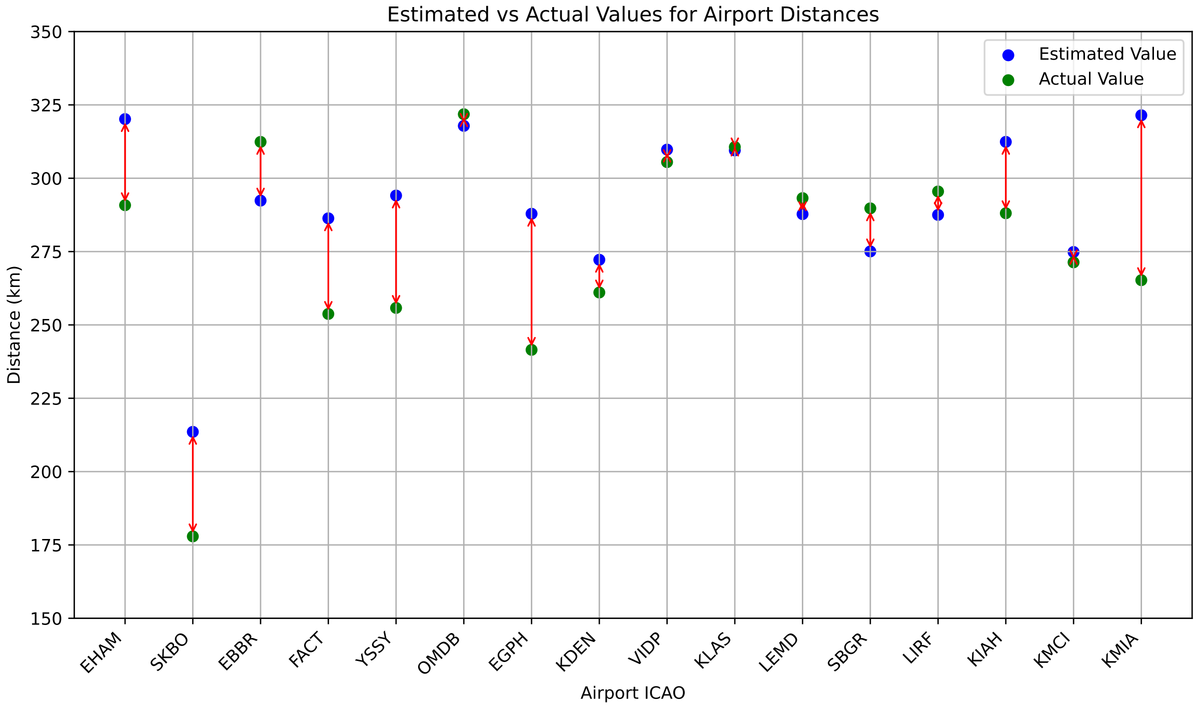


Figure 3.11: Estimated values and actual values per airport using RR

3.2.5. Neural Network Regression

The Neural Network Regression (NNR) was tested with various configurations. In Table 3.17, the configurations are detailed, with the number of hidden layers and their respective node counts specified (e.g., layers - (nodes layer 1: nodes layer 2: ...)). The optimal configuration balances accuracy with complexity, ensuring that the network does not overfit or underperform. By examining the MAE and R^2 values, the predictive capabilities of each configuration is assessed to determine the best structure for estimating flight emissions.

Table 3.17: Neural Network regression results per configuration for arrivals and departures

Configuration	Effect size (R^2_{arr})	MAE (%)	Effect size (R^2_{dep})	MAE (%)
1-(3)	0.127	7.47	0.066	6.49
1-(5)	0.127	7.46	0.066	6.49
1-(10)	0.132	7.15	0.078	5.77
2-(3:2)	0.127	7.46	0.066	6.52
2-(3:3)	-8.904	76.54	-5.572	74.25
2-(5:3)	0.158	4.62	0.066	6.41
2-(5:5)	0.143	6.02	0.071	5.97
2-(10:5)	0.192	2.98	0.126	1.84
3-(5:3:2)	0.139	6.18	0.109	3.57
3-(10:5:3)	0.195	2.92	0.126	1.77

The results demonstrate that various neural network configurations yield different performance levels. Adding a large number of nodes to a single-layer setup doesn't significantly increase the explained variance. Similarly, increasing the number of layers, as in the 5:3:2 configuration, does not guarantee improved outcomes and may lead to overfitting, where the model becomes too specific to the training data, hindering its generalization to unseen data.

Another observation is that having two layers with the same number of nodes seems to reduce performance, as seen in the 5:5 configuration and further supported by the poor results from the 3:3 configuration, indicating that the neural network struggled to find discernible patterns.

The best-performing structure seems to be the 5:3 configuration, striking a balance between complexity and risk of overfitting. Nonetheless, the potential for overfitting remains a concern and requires further examination. In Section 3.3, a comparison between different neural network configurations and between various regression methods is conducted to better understand the prediction capabilities of these models. Because of the high explained variance and low error margin, the 10:5 configuration is also used in the comparison.

3.3. Regression prediction capabilities

In this section, the focus is on assessing which regression method best predicts data that wasn't used during training, which helps determine whether the models can generalize beyond their training data. To evaluate the predictive capabilities of various regression models, a test dataset of additional airports is used. This dataset contains airports not included in the initial regression analysis, providing a fresh set of data points for evaluating the accuracy and robustness of the predictions.

3.3.1. Test dataset

The test dataset includes a selection of airports that vary across the three key parameters: elevation, number of runways, and flight movements. This variety helps ensure that the regression models do not overfit on specific patterns from the training dataset and can handle a broader range of input data. The list of additional test airports is shown in Table 3.18.

Table 3.18: Airports within regression test dataset

Airport ICAO	Airport City	Flight Movements	Runways	Airport elevation
RJTT	Tokyo	388100	4	11
EDDB	Berlin	164293	2	48
CYYZ	Toronto	338577	5	173
EGCC	Manchester	151460	2	78
KATL	Atlanta	724145	5	313

3.3.2. Regression performances

Table 3.19 and Table 3.20 show the error margins for different regression models applied to a test dataset. They provide a comparison of how well each model predicts distances for new airports, with separate results for arrivals and departures. These error margins, given for individual airports and as an overall mean, offer insights into the accuracy of the models.

Table 3.19: Error margins (%) comparison of considered regression methods for arrivals

Airport ICAO	MLR	BR	RR	NNR(5:3)	NNR(10:5)
RJTT	13.22	4.95	9.05	16.05	40.17
EDDB	5.63	4.00	0.76	6.67	30.22
CYYZ	10.80	21.85	16.38	10.48	27.44
EGCC	7.75	18.86	13.37	7.24	19.27
KATL	10.75	20.64	15.72	34.04	43.44
Mean error margin	9.23	14.66	11.46	14.70	32.11

Table 3.20: Error margins (%) comparison of considered regression methods for departures

Airport ICAO	MLR	BR	RR	NNR(5:3)	NNR(10:5)
RJTT	32.45	35.08	41.86	32.16	38.98
EDDB	11.32	17.44	19.67	11.85	10.43
CYYZ	13.90	21.63	22.52	13.21	16.02
EGCC	4.87	11.24	12.81	5.37	6.43
KATL	16.24	8.34	23.79	15.11	8.22
Mean error margin	15.77	18.25	24.53	15.74	16.02

The results indicate that despite the NNR achieving a higher effect size on the training dataset, its predictive accuracy is significantly lower than that of Multiple Linear Regression when predicting on unseen arrival data. However, for departures, the Neural Network Regression's predictive accuracy is only marginally better than MLR. This suggests that the effectiveness of a neural network in this context may lie in memorizing specific patterns in the training data rather than generalizing well, an indication for overfitting.

A neural network might still be useful if additional airport parameters are included in the dataset, which could improve the ability of the model to generalize by capturing more of the underlying variation. However, the current results suggest caution when using neural networks, as overfitting could lead to inaccurate predictions on new data.

The BR, intended to improve generalization, shows some success in reducing errors for underestimated distances, particularly for the first two arrival airports. However, it struggles with overestimated distances, leading to larger error margins. For departures, the Ridge regression generally overestimates but shows some improvement in accuracy for the last three airports.

The RR results also show considerable variation in predictive accuracy. For example, in the case of arrivals, the last three airports are significantly overestimated, while the first two are underestimated. For departures, all predictions show notable error margins, especially for Haneda Airport (RJTT), which has an error exceeding 40%. Manchester Airport (EGCC) is somewhat of an exception, with a smaller but still significant error margin of almost 13%.

Among the tested regression methods, MLR seems to offer the best predictive performance, maintaining a balance between model simplicity and accuracy on unseen data. Although the model's effect size is low, indicating that it doesn't capture all the underlying variation, its generalization capabilities are the most promising among the regression methods tested. This suggests that when the underlying factors are not fully understood, simpler models may be more robust for predictive purposes.

3.4. Synthesis

This chapter presents the findings from the data analysis and explores the suitability of various regression models for understanding the relationship between airport parameters and flight paths. Within this section, the first and second sub-questions of the thesis are addressed.

3.4.1. Findings of sub-question 1

The first sub-question delves into understanding the factors influencing flight paths during the ascent and descent phases. The first sub-question asks *"Which airport parameters impact flight paths during climb and descent?"*. By analysing airport data and discerning recurring patterns within flight distances, several key parameters emerge as influential, including fleet composition, airport elevation, flight direction, flight movements, runways, and airspace complexity.

Fleet composition

Analysis, as depicted in Figures 3.4 and 3.5, reveals that aircraft type influences flight paths at certain airports. Notably, at Sydney airport, departures exhibit distinct patterns based on aircraft classification. Large narrow-body aircraft demonstrate a peak in departure data, suggesting specific flight characteristics associated with these aircraft types. Conversely, short-haul aircraft show a smaller peak, likely indicative of their shorter flight distances and lower cruising altitudes during descent.

Airport elevation

Airport elevation significantly impacts the distance flown during descent and climb phases. A comparison between Sydney and El Dorado airports in Figure 3.2 illustrates this effect. El Dorado, situated over 2500 meters above sea level, requires less distance for descent compared to Sydney, nearly at sea level. This suggests that higher altitude airports necessitate shorter descent distances due to standard descent rates and additional level flight segments.

Flight direction

Initial observations suggest a correlation between flight direction and total flight distance, as indicated in Figure 3.6. However, further analysis reveals that this discrepancy stems from limitations in available data beyond a certain point. This shortfall may be attributed to data being out of range from receiving stations or failing to meet accuracy standards for inclusion in the dataset.

Flight movements and runways

Total yearly flight movements and the number of runways at an airport serve as additional indicators for flight distance. Increased flight movements is associated with longer flight distances owing to heightened congestion and ATC interventions, whilst increased runway count is associated with lower distances. However, runway inclusion in the analysis marginally impacts the predictive model, with airport elevation and flight movements emerging as primary influencing parameters on flight distance.

Airspace complexity

The analysis reveals a low effect size across all models, with only a 13% variance explained by the MLR for arrivals and about 6% for departures, indicating inadequate predictive capabilities. Consulting with ATM experts at To70 suggests that airspace complexity could enhance predictive accuracy due to its influence on flight distances to airports. However, attempts to integrate airspace complexity into the analysis did not improve prediction accuracy; instead, they worsened it. Further research is needed to refine methods for incorporating airspace complexity, potentially leading to significant advancements in predictive modeling for this thesis.

Conclusion
Given the findings and the focus of the first sub-question, three key parameters are selected for further analysis: total flight movements, runway quantity, and airport elevation. Fleet composition and flight direction, though influential, pose challenges in pre-determination for predictive purposes. Additionally, while airspace complexity remains unexplored in this analysis, its potential contribution to unexplained variance underscores the need for future research integration into predictive models for improved accuracy

3.4.2. Findings of sub-question 2

The analysis also addresses the second sub-question, which seeks to quantify the relationship between airport parameters and flight paths. This research inquiry poses the question: *"What is the quantified relation between airport parameters and flight path, and what are the sensitivities?"* A comparison between regression methods is conducted to identify the most appropriate approach for relating airport parameters to flight paths.

Multiple Linear Regression
The Multiple Linear Regression yielded results supported by confidence intervals, allowing rejection of the null hypothesis for all beta coefficients, indicating statistical significance. Comparison between arrivals and departures reveals differences in coefficients due to the difference in flight movements. Departures exhibit a lower intercept compared to arrivals, with flight movements showing a higher difference per flight for departures. Additionally, runway quantity exerts a more substantial influence on departures, while airport elevation has a lesser impact.

The influence of each parameter, as indicated by the T-value, varies between arrivals and departures. Flight movements and runway quantity exhibit increased influence relative to other parameters. Conversely, the constant value and airport elevation demonstrate decreased significance. VIF values remain consistent between arrivals and departures.

Effect size analysis highlights significant differences between arrivals and departures. The chosen airport parameters explain approximately 13% of variance in the model for arrivals, compared to only 6% for departures.

Furthermore, inclusion of the airspace complexity metric does not significantly improve explained variance on the test set. The original MLR test, explaining 31% of variance, marginally increases to 32% with airspace complexity metrics. Given the challenges in obtaining and availability of airspace complexity metrics, they are discarded from the analysis.

Bayesian Regression
The Bayesian regression exhibits similar coefficient results to the MLR for arrivals, albeit with a notably higher estimated constant. Conversely, for departures, an anomalous value is observed for the runway parameter, indicating a reduction of flown kilometers by -0.0467 per runway, with a confidence interval ranging between -5 and 5. Consequently, the null hypothesis cannot be dismissed, meaning the runway parameters might be statistically insignificant in departure predictions. However, the Bayesian regression approach provides more insight into data variability, with standard deviations of 67 kilometers for arrivals and 76 kilometers for departures. Despite departure distances being shorter, the larger standard deviation can be attributed to the model's lower effect size of merely 6.89% for departures, compared to 12.8% for arrivals.

Ridge Regression
The ridge regression yields results closely resembling those of the MLR method for both arrivals and departures, with the exception of the intercept term, which is higher for both models. Effect sizes for the arrival and departure models are 12.9% and 6% respectively.

Neural Network Regression
Neural network regression is good in modeling non-linear relationships among variables through the definition of layers and their constituent nodes. While a single layer fails to outperform the standard linear model in estimation accuracy, triple layers demonstrate the most precise distance estimations. However, employing triple layers adds a risk of overfitting due to the limited number of parameters. Therefore, the double layer configuration emerges as the optimal choice, balancing improved estimations over the single layer while mitigating the risk of overfitting. Among the tested configurations, the 5:3 configuration is deemed the most effective option.

Conclusion
The determination of the most suitable method for relating airport parameters to flight path and predicting distances flown towards different sized airports involves assessing each regression method's predictive capability on data outside of the training dataset. In this evaluation, five new airports with diverse parameter sets are introduced. Error margins, as detailed in Table 3.19 and Table 3.20, underscore the multiple linear regression's superior predictive accuracy compared to the other methods.

Notably, departure error margins surpass those of arrivals significantly. This and the lower effect size of the departure models suggests that parameters such as flight movements and runway quantity may yield lesser influence on departure outcomes. The influence of flight movements may be mitigated as aircraft divert towards different routes, thereby experiencing lesser impact from airspace congestion as flights converge to the airport, as is the case for arrivals. Thus, different parameters are warranted to accurately define the relationship between airports and departure distances as compared to arrivals.

4 Emission Comparison Results

This chapter compares the results obtained from this thesis to the existing model by *Quadros et al.* [1]. The sample as described in Section 2.6, is used to address the differences between the two methods for aircraft position estimation. This chapter discusses the implementation of the quantified relationship between airports parameters and flight distance into the model and the resulting emission estimations using the new method.

4.1. Emission comparison

Table 4.1 displays the difference in total emissions between the original approach, which is based on TOC and TOD, and the approach suggested in this research. The results indicate a total fuel burn difference of 0.3 Gg (10^9 grams) between the two methods which also includes the cruise phase. This discrepancy is expected, as the new approach includes additional distance during the climb and descent phases, leading to greater fuel consumption.

Table 4.1: Emissions Results - Climb and Descent

Species	**TOD/TOC based(Quadros)**		**Flight-path based**	
FUELBURN	10.3 Gg	1.00 kg/kg	10.6 Gg	1.00 kg/kg
NO_2	116 Mg	11.3 g/kg	121 Mg	11.4 g/kg
HC	659 kg	63.9 mg/kg	616 kg	58.2 mg/kg
CO	21.7 Mg	2.10 g/kg	21.3 Mg	2.01 g/kg
nvPM	55.5 kg	5.38 mg/kg	78.7 kg	7.43 mg/kg
nvPM_N	4.60e+21	4.46e+14 /kg	4.93e+21	4.66e+14 /kg

The fuel burn differs by approximately 3%, which is significant. However, some of this fuel burn might be overestimated, as the cruise phase has remained unchanged. The uncertainty regarding this overestimation is discussed in Section 4.2. Figure 4.1 and Figure 4.2 visually shows the increase in fuel burn for three aircraft, Type1, Type2 and Type3, for both the departure and arrival. Both show an increase in the fuel burned, but what is important to notice is that the mid-point of the fuel burned in the climb has shifted up in altitude, indicating an increased fuel burn further in the climb.

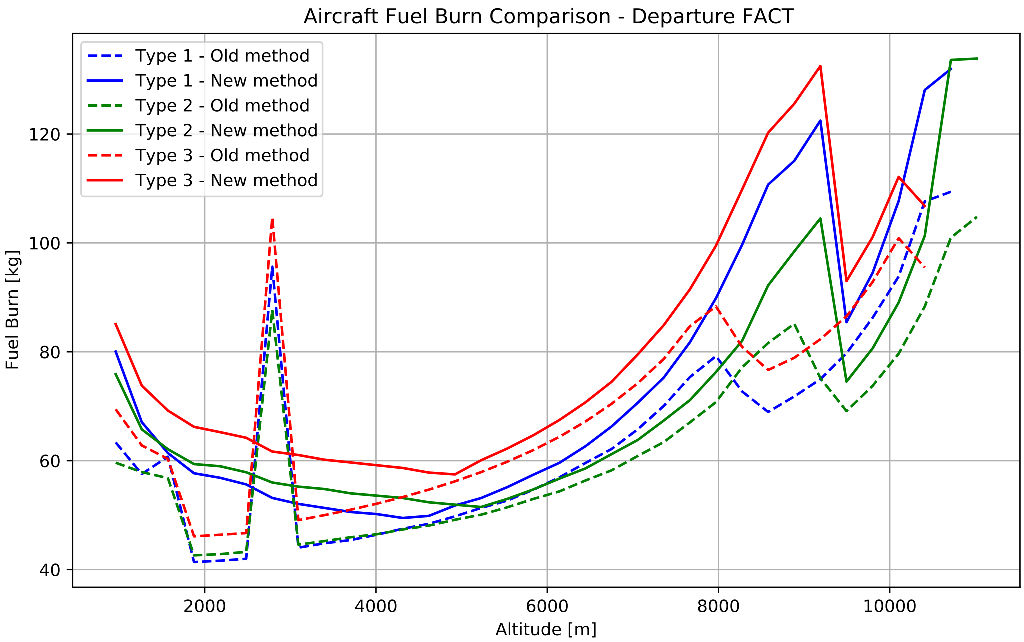


Figure 4.1: Fuel burn per height - Departures FACT

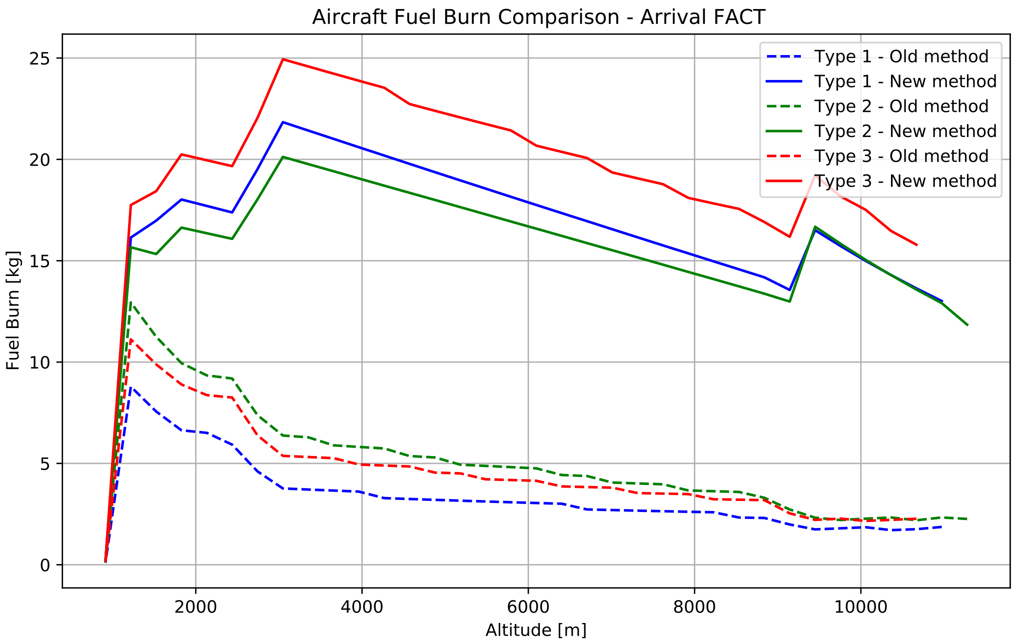


Figure 4.2: Fuel burn per height - Arrivals FACT

As shown in Table 4.1, the impact on total flight emissions is noticeable, but to understand the effect better, it's essential to compare emissions for each flight phase separately. Within Appendix C, Table C.6 and Table C.7 provide a detailed comparison of emissions, as seen in Figure 4.3 and Figure 4.4, based on the flight path adjustments. The overall emissions of NO_2 increased, both in absolute terms and relative to each kilogram of fuel burned. During the climb phase, NO_2 emissions rose from 17.1 to 18.2 g/kg, and during descent, from 4.65 to 8.2 g/kg.

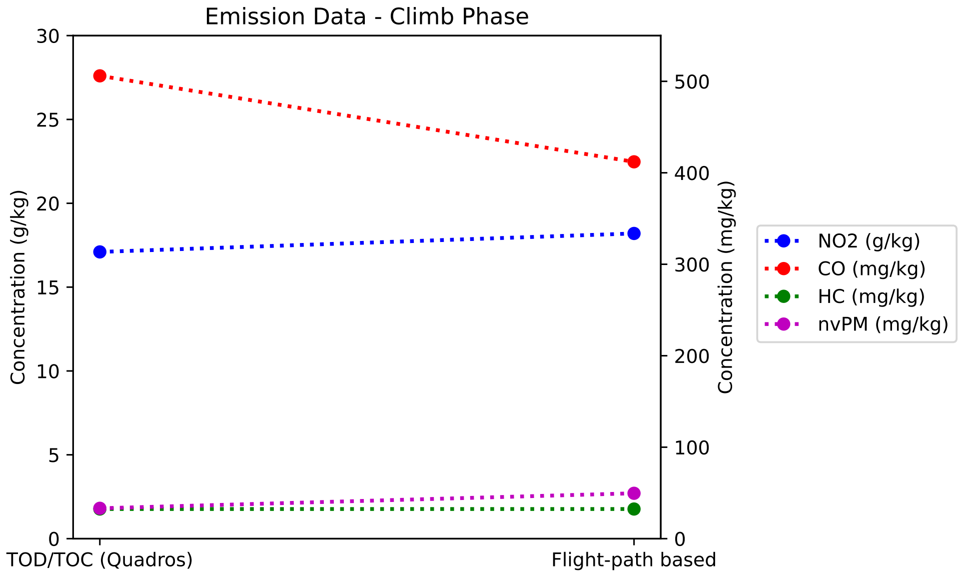


Figure 4.3: Comparison of TOD/TOC approach and flight-path based method - climb phase.

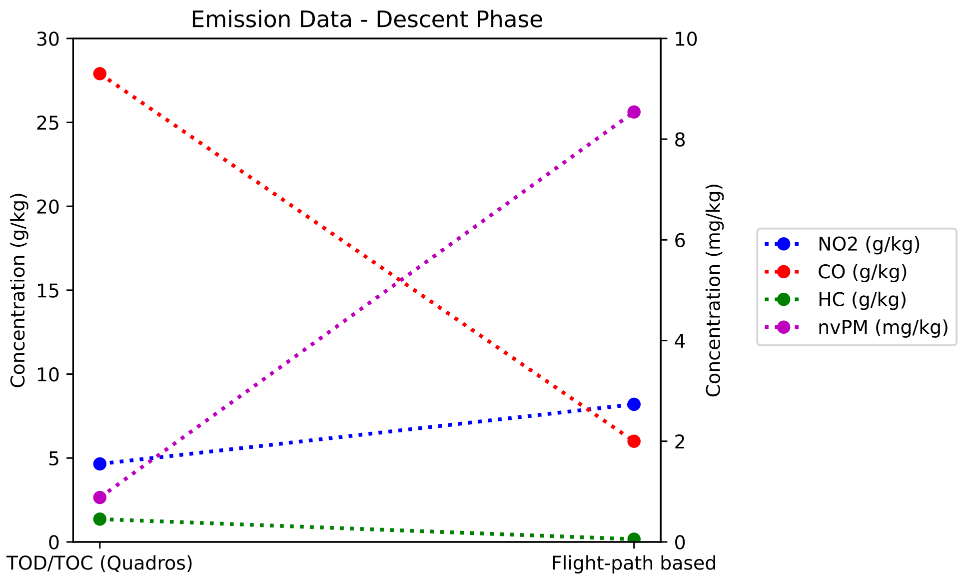


Figure 4.4: Comparison of TOD/TOC approach and flight-path based method - descent phase.

To achieve a constant climb slope at higher altitudes, the aircraft requires increased thrust, causing the engine to run hotter. This higher operating temperature results in greater NO_2 emissions per kilogram of fuel burned, explaining the increase in the emission index. This trend is illustrated in the total NO_2 emissions in Figure 4.5 and in Figure 4.6, which shows the NO_2 emissions per kilogram of fuel burned. The NO_2 per kg of fuel burned for the new method is initially lower but surpasses the old method just beyond the 3000 meter mark. This is also the case for the arrivals of which the figures are included in Appendix C in Figure C.3 and Figure C.4. Also note that duration for the climb and descent have increased, as the new method requires additional time for both the climb and descent phases. The time plot for departures is shown in Appendix C in Figure C.1, and for arrivals in Figure C.2.

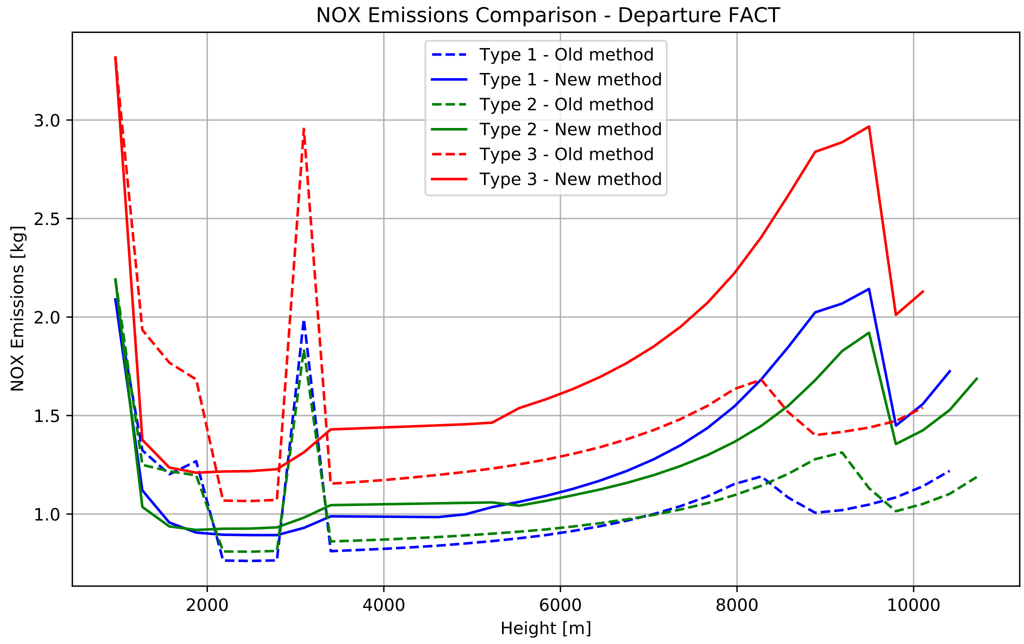


Figure 4.5: NO_2 emissions per height - Departures FACT

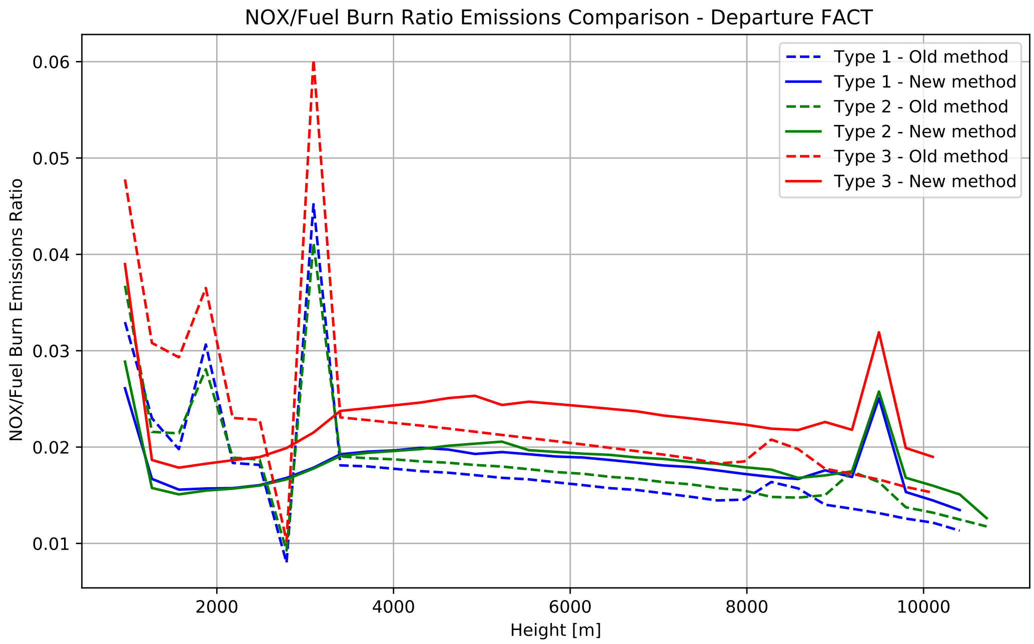


Figure 4.6: NO_2 emissions per kg of fuel burned - Departures FACT

Conversely, the emissions of HC (hydrocarbons), which represent un-burned fuel, and CO (carbon monoxide) per kilogram of fuel decreased. This can be attributed to steadier engine operation. As the engine operates closer to its optimal efficiency, typically during cruise, it produces fewer emissions such as HC and CO. HC emissions tend to be higher in idle continuous descent operations in the TOC/TOD-based approach, but because the engine generates more thrust in the new approach, overall HC emissions are reduced. CO emissions decrease when the engine operates at a higher power setting. This is supported by the research of Turgut et al. [13], which found that higher thrust settings are strongly associated with a decrease in CO and HC emissions. This trend is also evident in Figure 4.7, where an increased power setting at the higher altitudes results in lower average CO emissions. Note that the new method for Type3 exhibits higher CO emissions during climb compared to the old method but this is not the case for the descent as is shown in Figure C.5. In the new method, the CO ratio in the climb phase dropped from 506 to 424 mg/kg and in the descent phase from 27.9 to 6 g/kg.

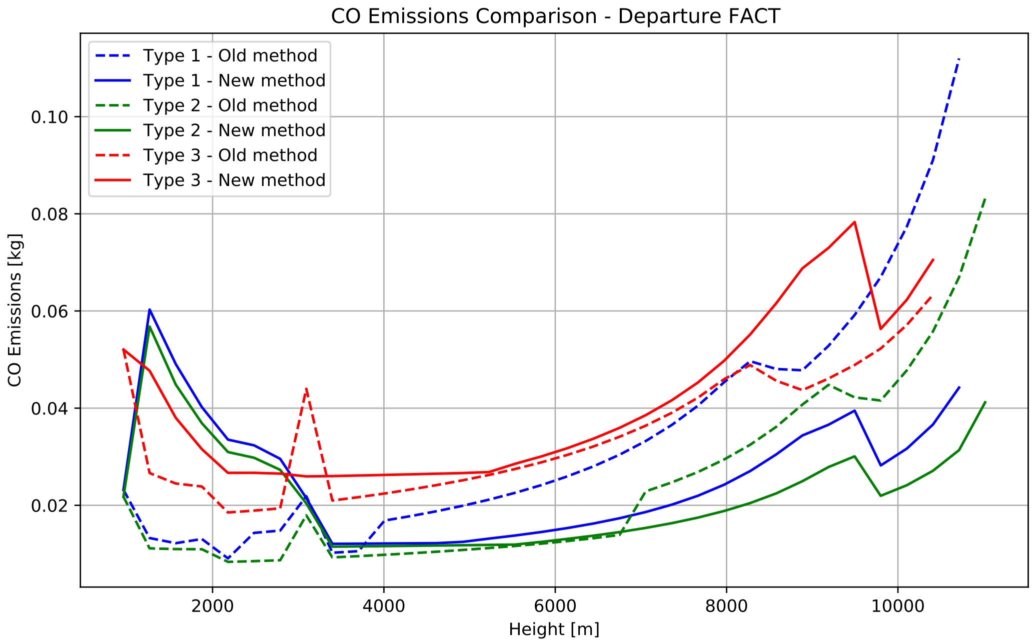


Figure 4.7: CO emissions per height - Departures FACT

Emissions of non-volatile particulate matter (nvPM) increased significantly during descent, from 883 µg/kg to 8.54 mg/kg, and in the climb phase, from 31.1 mg/kg to 42.3 mg/kg. The increase during descent is likely due to greater soot formation in the primary engine zone as the engine operates at a higher thrust level. The slight increase during the climb phase could be due to reduced diluting effects of high-temperature regions downstream as argued by Mishra et al. in their study on soot emissions [14]. The creation and dilution of nvPM are more optimal during cruise, as noted in Table 4.1, where total nvPM creation is just 7.43 mg/kg for the entire flight.

4.2. Uncertainty quantification

The method used in the flight-path-based approach estimates the flown distance by considering the yearly flight movements, number of runways, and airport elevation. This approach demonstrated a 10% absolute deviation when tested on a sample set of airports. However, this method is designed to generalize airports and enhance global emission models, making it suitable for large datasets with diverse airports. As such, the absolute error might not be critical, since underestimations and overestimations can balance each other out. Given this context, emissions calculated for the climb and descent are compared using both the regression-based flight distance estimates and the actual distances, as shown in Table 4.2 and Table 4.3.

Table 4.2: Emissions Results - Mean Estimate vs. Real Value - Climb Phase

Species	Mean Estimate		Real Value	
FUELBURN	1.03 Gg	1.00 kg/kg	1.03 Gg	1.00 kg/kg
NO_2	18.8 Mg	18.2 g/kg	18.8 Mg	18.2 g/kg
HC	33.4 kg	32.4 mg/kg	33.4 kg	32.4 mg/kg
CO	424 kg	412 mg/kg	423 kg	411 mg/kg
nvPM	51.0 kg	49.6 mg/kg	51.0 kg	49.6 mg/kg
nvPM_N	1.08e+21	1.05e+15 /kg	1.08e+21	1.05e+15 /kg

Table 4.3: Emissions Results - Mean Estimate vs. Real Value - Descent Phase

Species	Mean Estimate		Real Value	
FUELBURN	220 Mg	1.00 kg/kg	221 Mg	1.00 kg/kg
NO_2	1.81 Mg	8.20 g/kg	1.82 Mg	8.23 g/kg
HC	36.2 kg	164 mg/kg	36.6 kg	165 mg/kg
CO	1.32 Mg	6.00 g/kg	1.33 Mg	6.01 g/kg
nvPM	1.88 kg	8.54 mg/kg	1.97 kg	8.90 mg/kg
nvPM_N	1.43e+20	6.49e+14 /kg	1.45e+20	6.56e+14 /kg

The results from Table 4.2 and Table 4.3 indicate that the impact of error in distance prediction is minimal when comparing emissions based on actual mean values from the airport analysis. This can be attributed to the linear regression model's capacity to generalize across all airports within the dataset. Since the sample dataset represents all airports, with scaling based on the annual number of flight movements, the error margins tend to balance out. The slight variations in emissions could be due to the decision to represent all airports equally by artificially sampling each one an equal number of times, without distributing flights equally among them. Overall, this result shows that the sample is representative to the data when using MLR.

The beta values used to estimate the mean have confidence intervals that define the range within which the true mean is likely to fall with 95% certainty. The low and high estimates account for uncertainty in the estimated flight distance mean. The beta values used for these low and high estimates are provided in Table 3.2 and Table 3.3. These low and high estimates for the beta values lead to the results presented in Table 4.4 and Table 4.5.

Table 4.4: Flight-path based - Climb Phase

Species	Low Estimate		Mean Estimate		High Estimate	
FUELBURN	1.03 Gg	1.00 kg/kg	1.03 Gg	1.00 kg/kg	1.03 Gg	1.00 kg/kg
NO_2	18.7 Mg	18.3 g/kg	18.8 Mg	18.2 g/kg	18.8 Mg	18.2 g/kg
HC	33.3 kg	32.5 mg/kg	33.4 kg	32.4 mg/kg	33.5 kg	32.4 mg/kg
CO	419 kg	409 mg/kg	424 kg	412 mg/kg	429 kg	415 mg/kg
nvPM	50.8 kg	49.5 mg/kg	51.0 kg	49.6 mg/kg	51.3 kg	49.6 mg/kg
nvPM_N	1.07e+21	1.05e+15 /kg	1.08e+21	1.05e+15 /kg	1.08e+21	1.05e+15 /kg

Table 4.5: Flight-path based - Descent Phase

Species	Low Estimate		Mean Estimate		High Estimate	
FUELBURN	213 Mg	1.00 kg/kg	220 Mg	1.00 kg/kg	227 Mg	1.00 kg/kg
NO_2	1.73 Mg	8.11 g/kg	1.81 Mg	8.20 g/kg	1.88 Mg	8.28 g/kg
HC	37.0 kg	174 mg/kg	36.2 kg	164 mg/kg	35.5 kg	156 mg/kg
CO	1.33 Mg	6.24 g/kg	1.32 Mg	6.00 g/kg	1.32 Mg	5.80 g/kg
nvPM	1.75 kg	8.21 mg/kg	1.88 kg	8.54 mg/kg	2.02 kg	8.87 mg/kg
nvPM_N	1.36e+20	6.37e+14 /kg	1.43e+20	6.49e+14 /kg	1.50e+20	6.60e+14 /kg

The impact of the low and high estimates on fuel burn during climb is negligible due to the high initial fuel consumption. However, slight differences in emissions can be observed. For the descent, the differences are more noticeable because a larger percentage-wise variation in fuel required for the high and low distances estimates, although the overall impact remains minor. These differences are shown within Figure 4.8 and Figure 4.9.

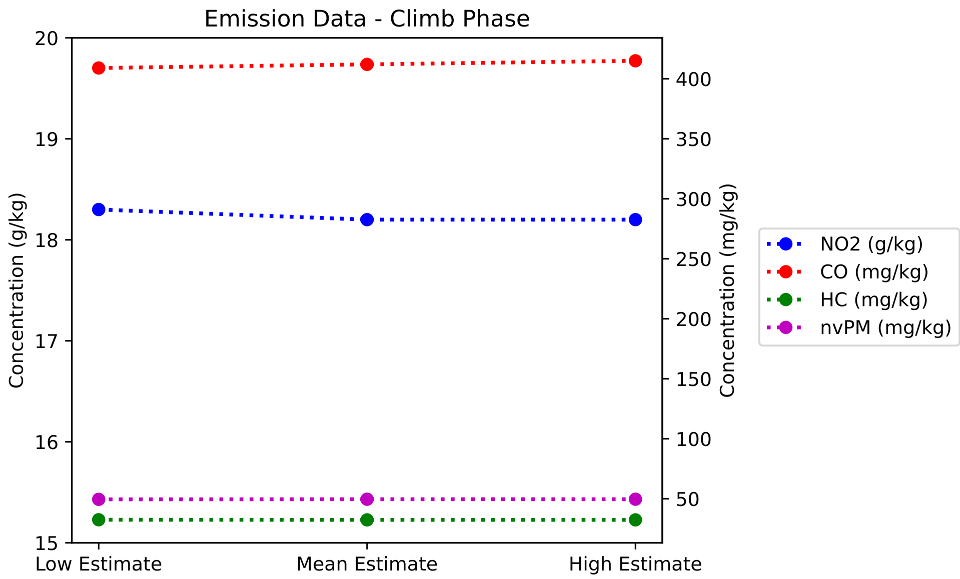


Figure 4.8: Low, Mean and High emission estimate of climb phase.

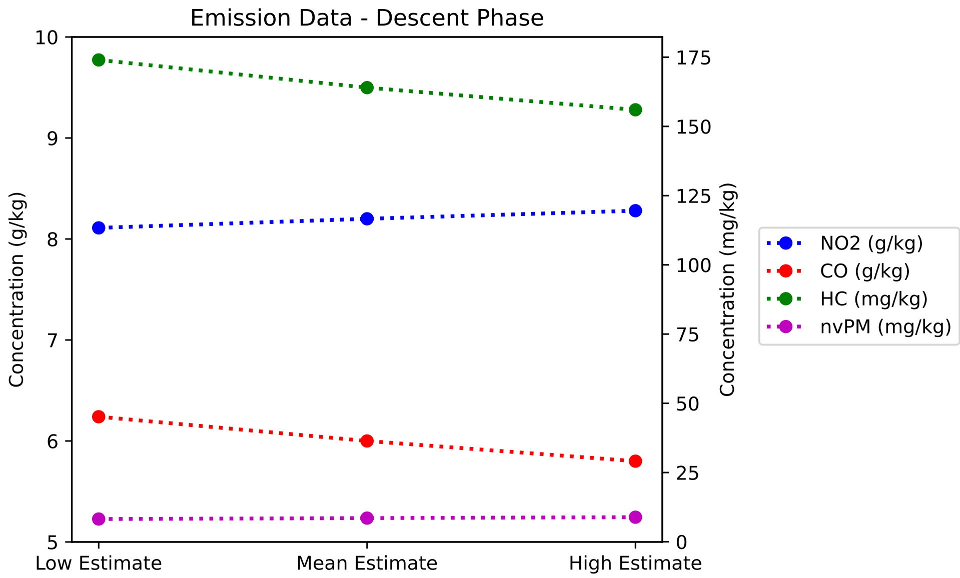


Figure 4.9: Low, Mean and High emission estimate of descent phase.

Not considered within this analysis but also important is uncertainty due to level flights flown in actual paths during the climb or descent. The level flights would likely add additional fuel due to more variation in the thrust settings and especially during descent requires extra thrust. Additionally, the height at which a level flight is conducted affects the amount and type of emissions of the level flight. Therefore, not incorporating the emissions due to the level flights adds an error to the actual emissions of the aircraft.

The flight-path-based approach focuses solely on the additional distance flown during climb and descent and replaces the approach of Quadros. This implies that the cruise segment is still defined as the distance between the end of the TOC and the start of the TOD. This leads to additional distance flown during the cruise phase, as not all the estimated distance in the new approach occurs before TOC or after TOD. The climb phase might be longer due to turns around the airport or if it ends beyond the originally designated TOC. Similarly, the descent is likely to start earlier than the assumed TOD, impacting the emissions and fuel consumption during these phases.

4.3. Synthesis

The third sub-question in this research aims to compare the developed approach with the existing model to assess its accuracy and efficiency. This sub-question is stated as: *"How does the flight path length emission estimation compare to other research in terms of accuracy and speed?"*. By comparing the emissions produced by the original approach with those of the new approach, the impact of the new method on emissions is quantified. This comparison helps determine whether the new approach yields more accurate results and if it does so in a timely manner.

Using a sample dataset that includes a representative fleet composition for global civil air traffic and a proportionate number of sample flights per airport, based on the annual flight movements, the emissions resulting from the increased fuel burn are compared. While the revised approach is longer flight paths resulted in higher fuel consumption, it did not necessarily lead to increased emissions for certain gases. The newly developed and integrated approach is not very efficient, requiring more processing time. Since the necessary parameters are pre-set and airport data is loaded before analysis, only a few operations are required to calculate the new flight distances however these operations add about 40-50% to the time required for the analysis of the sample set.

The use of MLR provides a better estimation of the distance flown during the climb and descent phases, enhancing the accuracy of global and local emissions predictions in global civil aviation. This method shows a close correlation with the emissions based on the real mean distances flown at specific airports, supporting the hypothesis of a more representative approach for modeling the climb and descent phases within a global emission model. Despite some uncertainty in the data used for distance estimation, the new approach still outperforms Quadros' original method.

However, the new approach does not fully represent real-world scenarios, as many level flight segments occur during the climb and particularly the descent phases, which require varying thrust levels, contributing to additional emissions. The climb and descent phases have been revised to better align with real-world operations, while the cruise phase remains unchanged. This suggests that the additional distance flown using the new approach occurs before the TOC and after the TOD points in the model. Nonetheless, some of this additional distance might also be flown before reaching the TOC or after the TOD, suggesting that the cruise phase might be shorter. Further investigation is required to determine the extent to which the cruise phase is affected.

5 Conclusion

To reiterate, the primary research question within this thesis is as follows:

Research Question

How can emission estimation during the climb and descent phases in global models using ADS-B data be enhanced by generalizing the flight path based on key airport parameters, resulting in a quantifiable improvement in accuracy?

The goal of this thesis can be considered achieved as a new approach has been developed that links a generalized flight path to airport parameters. As a result, the main research question can also be addressed. Through several sub-questions, these aspects have been examined and the key insights are provided in the following section. The addressed sub-questions are:

- **SQ-1: Which airport parameters have an impact on the flight path during climb and descent?**
- **SQ-2: What is the quantified relation between the airport parameters and flight path and what are the sensitivities?**
- **SQ-3: How does the flight path length emission estimation compare to other research in accuracy and speed?**

5.1. Sub-question 1 - Airport parameters

The airport attributes, referred to as airport parameters in this thesis, are fixed data points for each airport. The parameters considered in this study include annual flight movements, the number of runways, and airport elevation. There was an attempt to include airspace complexity, but due to the challenges in quantifying it accurately, further work in this area was set aside. However, integrating airspace complexity has the potential to significantly increase the explained variance in the model, which could lead to better performance with other regression models like Neural Network Regression (NNR).

5.2. Sub-question 2 - Quantified relationship

Generalizing the flight path can be achieved using a statistical model that relates various airport attributes to distances flown towards an airport. The model considered most suitable for this purpose is MLR, as it effectively captures and generalizes trends and due to the relatively low effect size (R^2)—12.8% for arrivals and 6% for departures. Other, more sophisticated models like NNR, did not show improvements over MLR, whilst NNR exhibiting overfitting.

Using MLR with these airport parameters provides a mean estimate for the flight distances at each airport. A 95% confidence interval defines the uncertainty of this mean estimation. While some airports fall outside of this confidence interval, when considering a global scale, overestimations and underestimations tend to balance each other out. On a local scale, though, such deviations could result in inaccurate metrics for emissions. When applied to a test dataset of airports not included in the training set, the MLR yielded an uncertainty in flight distance estimation of 9.2% for arrivals and 15.8% for departures compared to the actual flown distances from the analyses.

5.3. Sub-question 3 - Comparison and uncertainty

Addressing the third sub-question; To further investigate the differences between Quadros' original approach [1] and the newly developed approach in this thesis, a comparison of emissions was conducted. A test dataset was used that featured a representative global fleet distribution and was scaled according to the annual flight movements at all considered airports. The emissions comparison revealed that total fuel burn increased by about 3%, but non-CO2 emissions did not necessarily follow the same trend. Due to engine operating conditions, total emissions of hydrocarbons (HC) and carbon monoxide (CO) actually decreased throughout the entire flight. However, emissions of nitrogen dioxide (NO_2) and non-volatile particulate matter (nvPM) increased, both in total and per unit of fuel burned.

The descent phase showed the highest percentage increase in fuel burned, with a 263% increase in total fuel burn compared to a 15.6% increase during the climb. This significant increase during descent is due to the original Top of Descent (TOD) approach, where the engines operate at (or near) idle, whereas the new approach requires more thrust to cover the additional distance. Emissions in the climb phase generally increased for all pollutants except for CO, while the descent phase showed increased emissions except for HC and CO. This is due to the constant glide slope requiring higher thrust as the power required increases at higher altitudes. A hotter running engine results in higher NO_2 emissions and lower CO emissions as laid out by Turgut et al. [13].

To estimate the range of possible emissions, the 95% confidence interval for the mean was used to calculate low, mean, and high estimates. In the climb phase, the differences were negligible, with nearly identical results across the estimates. In the descent phase, the variations were slightly more significant, with a discrepancy of about 7 megagrams (Mg) in fuel burn (plus or minus) from the mean of 220 Mg for the low and high estimates. Additionally, the actual mean distances at airports were taken and compared to the estimated means. Although MLR showed about a 10% deviation in its predictions, using the real mean distances and comparing them with the predicted means indicated almost no difference in the emissions. This finding suggests that the new approach closely resembles the real-world scenario, assuming that the airport analyses are accurate.

The minimal difference in emissions can be attributed to the generalization of airport parameters, where overestimations tend to counterbalance underestimations, resulting in a representative global emissions estimate. The slight differences could be due to the MLR treating all airports equally to avoid bias toward larger airports, while the sample dataset represents the actual flight activity at each airport.

5.4. Synthesis

The goal of the thesis can be considered achieved. A new approach has been developed that uses a generalized flight path based on airport parameters to estimate the distance flown to an airport. Through analyses, it was observed that the revised flight paths indicated increased distance during the climb and descent phases, which was modeled using MLR that takes into account annual flight movements, the number of runways, and airport elevation. Although the explained variance was relatively low—12.8% for arrivals and 6% for departures— and the mean error margin was significant—9.2% for arrivals and 15.8% for departures—the estimation approach demonstrated close resemblance to actual flown distances when tested with a dataset featuring a representative fleet composition and route distribution, indicating an improvement in accuracy.

Sources of inaccuracy in the estimated emissions lie in defining the climb and descent phases as the code can not always identify them correctly due to faulty or insufficient data, despite efforts to minimize their impact. Additionally, level flights within the descent phase contribute to increased emissions because the engine operates at a higher thrust setting to maintain altitude before further descent. Similar to the original approach that uses a fixed Top of Descent, this new approach has not accounted for these level flights during descent. Another factor related to the increased distance is the points at which the cruise phase starts and ends, which were not explicitly defined in this thesis. This uncertainty can lead to overestimation of the cruise phase its contribution to overall emissions. Future studies should address these issues to better determine the beginning and end of the cruise phase to improve the accuracy of emission estimates using the suggested approach from this thesis.

The new method does not follow a regular climb or descent profile but instead follows a constant slope. This approach better reflects the actual flown distance during these phases, though it does not accurately reflect a typical climb profile. During a standard climb, an aircraft initially follows a steeper gradient, which gradually decreases as available power diminishes. The constant slope method results in increased thrust requirements later in the climb, significantly adding to the emissions. This introduces a source of uncertainty and underscores the necessity for an accurate representation of level flight segments within the climb and descent phases.

6 Recommendations

This chapter provides a brief overview of the primary recommendations for the future continuation of this research project.

Recommendation 1 - Use of ’traffic’ library for track analyses
In this thesis, the flights analyzed were sourced from data files available on the openSKY website, from which the required flights were extracted and analyzed. This analysis involved developing a code capable of identifying the climb and descent segments of a flight. To further improve the code’s robustness and efficiency, the ’traffic’ library could be used. This library is designed to work in conjunction with the openSKY database and ADS-B data, offering a wide variety of functions for processing airport and flight data. Utilizing this library could enhance the efficiency of the code and facilitate the integration of new airport parameters, which could further improve the new approach. Additionally, the library can connect to the openSKY API, enabling direct and targeted data retrieval, which might reduce the uncertainty arising from limited data used in the analysis within this thesis, potentially accounting for any seasonal offset in the distance calculations.

One example of how this library could be used is to quantify air traffic density, which can be modeled with the ’traffic’ library’s built-in functionalities. This could contribute to the quantification of the airspace complexity parameter, which has been identified as a potential area for further research and improvement in the estimation of flight paths and emissions.

Recommendation 2 - Cruise start/end points
As noted in the conclusion, the current start and end points for the cruise phase are still assumed to be at the Top of Climb (TOC) and Top of Descent (TOD). This assumption does not always reflect reality and needs correction. To improve the accuracy of the model, further analysis should be conducted using the same dataset used to determine the distances flown to and from each airport. This analysis should calculate the direct distance from the first point where an aircraft begins its descent to the last point where it completes its climb.

By plotting this information similarly to the flight distances, the average direct route distance can be determined, providing a clearer indication of when the cruise phase should start and end. This would allow for the adjustment of the cruise phase in the model to represent the actual points where it begins and ends. Such an adjustment would directly improve the accuracy of emissions estimated by the model, leading to more reliable and realistic results.

Recommendation 3 - Inclusion of level flight segments
Another step to enhance the model’s accuracy is to include level flight segments in the analysis, and to create a method to estimate level flights at other airports. Additionally, it is important to find a reliable way to estimate the altitude of these level flights, as this influences thrust settings and, consequently, the aircraft’s total emissions.

Integrating the total distance of level flights should be straightforward. However, categorizing them into different altitude segments and developing a predictive method for other airports is a more challenging task, yet it could significantly improve the model’s accuracy.

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Part II

Appendices

A

Aircraft Categories

The aircraft categorization list is displayed on the following page.

Widebody

BTS Aircraft Type ID	Aircraft
339	AIRBUS A330-900
359	AIRBUS A350-900
624	BOEING 767-400/ER
625	BOEING 767-200/ER
626	BOEING 767-300/ER
627	BOEING 777-200
637	BOEING 777-300/ER
683	BOEING B777-F
687	AIRBUS A330-300
690	A300B/C/F-100/200
691	A300-600/R/CF/RCF
692	A310-200C/F
696	A330-200/220F
697	A340
730	DOUGLAS DC-10-10
731	DOUGLAS DC-10-20
732	DOUGLAS DC-10-30
733	DOUGLAS DC-10-40
735	DOUGLAS DC-10-30CF
740	MD-11
760	L-1011-1/100/200
765	L-1011-500 TRISTAR
816	BOEING 747-100
817	BOEING 747-200/300
818	BOEING 747C
819	BOEING 747-400
820	BOEING 747-4F
821	BOEING B747-8
822	BOEING 747SP
823	BOEING 747-200F
836	A350-1000
837	B787-10 DREAMLINER
871	A340-300
872	A340-500
873	A340-200
874	A340-600
882	A380-800
887	B787-8 DREAMLINER
889	B787-9 DREAMLINER

Large Narrow-body

BTS Aircraft Type ID	Aircraft
614	BOEING 737-800
622	BOEING 757-200
623	BOEING 757-300
634	BOEING 737-900
694	A320-100/200
699	A321
721	A321-200N
722	A320-200N
838	B737 MAX 800
839	B737 MAX 900
888	B737-900ER

Small Narrow-body

All aircraft types not listed as widebody or large narrowbody

B

Sample List

The complete sample flight list is displayed on the following page.

typecode	origin	destination	count	typecode	origin	destination	count
A320	FACT	EHAM	4	B738	EGPH	KIAH	3
A320	LIRF	OMDB	4	B738	OMDB	SKBO	13
A320	YSSY	OMDB	7	B738	SKBO	KLAS	10
A320	EBBR	KMIA	7	B738	EBBR	KLAS	6
A320	SKBO	KMIA	12	B738	KLAS	KMCI	20
A320	KIAH	OMDB	16	B738	VIDP	EHAM	15
A320	KMIA	LEMD	18	B738	KIAH	KMIA	14
A320	EHAM	OMDB	19	B738	FACT	KMCI	3
A320	EGPH	KDEN	3	B738	YSSY	LIRF	6
A320	LEMD	OMDB	14	B738	LEMD	KMIA	12
A320	KLAS	KDEN	23	B738	KMCI	KDEN	3
A320	SBGR	VIDP	10	B738	EHAM	KDEN	16
A320	OMDB	KDEN	15	B738	SBGR	LIRF	8
A320	KMCI	VIDP	4	B738	LIRF	KMIA	4
A320	VIDP	KDEN	17	B738	KMIA	KDEN	16
A321	SBGR	FACT	3	B738	SBGR	EBBR	1
A321	LEMD	YSSY	4	B738	EBBR	KMCI	1
A321	KIAH	LIRF	5	B738	KMIA	KMCI	3
A321	LIRF	SKBO	1	B738	OMDB	KMCI	2
A321	KLAS	KMIA	8	E75L	KLAS	EGPH	3
A321	EBBR	KMCI	2	E75L	SBGR	LIRF	1
A321	YSSY	FACT	2	E75L	OMDB	VIDP	2
A321	KMCI	VIDP	1	E75L	LEMD	VIDP	2
A321	EGPH	VIDP	1	E75L	SKBO	YSSY	1
A321	VIDP	KDEN	6	E75L	YSSY	EBBR	1
A321	SKBO	OMDB	4	E75L	VIDP	EHAM	2
A321	EHAM	OMDB	6	E75L	KMIA	EGPH	2
A321	FACT	KDEN	1	E75L	EHAM	KMCI	2
A321	OMDB	KDEN	5	E75L	EBBR	LIRF	1
A321	KMIA	KDEN	6	E75L	KIAH	KDEN	2
A319	LIRF	KMIA	1	B38M	KIAH	FACT	1
A319	KMIA	LEMD	4	B38M	SKBO	EBBR	1
A319	YSSY	EBBR	1	B38M	VIDP	LEMD	1
A319	KLAS	KMCI	5	B38M	KMIA	EHAM	2
A319	LEMD	VIDP	3	B38M	EHAM	LEMD	2
A319	OMDB	EBBR	3	B38M	KLAS	FACT	2
A319	KIAH	EHAM	3	B38M	OMDB	FACT	1
A319	EHAM	EBBR	4	B38M	SBGR	EBBR	1
A319	SBGR	SKBO	2	B38M	LEMD	KDEN	1
A319	VIDP	EBBR	3	CRJ9	EHAM	FACT	1
A319	SKBO	KDEN	2	CRJ9	VIDP	OMDB	1
A319	EBBR	KDEN	1	CRJ9	KIAH	KLAS	1
A737	YSSY	EGPH	1	CRJ9	SKBO	EBBR	1
A737	KIAH	EBBR	2	CRJ9	LEMD	EBBR	1
A737	KLAS	KMIA	4	CRJ9	KMIA	KLAS	1
A737	LEMD	EHAM	2	CRJ9	OMDB	EBBR	1
A737	VIDP	EHAM	3	CRJ9	KLAS	EBBR	2
A737	SKBO	KDEN	2	-	-	-	-

C
Additional Results

C.1. Regression results

C.1.1. MLR airport estimation arrivals

Table C.1: Estimated Values, Actual Means, Errors, and Error Margins for arrivals

Airport ICAO	Estimated Value(km)	Actual Mean(km)	Absolute Error(km)	Error Margin(%)
EHAM	305.75	290.80	14.95	5.14
SKBO	199.16	177.92	21.24	11.93
EBBR	277.96	312.39	-34.44	11.02
FACT	271.94	253.74	18.20	7.17
YSSY	279.69	255.79	23.90	9.34
OMDB	303.47	321.82	-18.35	5.70
EGPH	273.50	241.50	32.00	13.25
KDEN	257.79	261.05	-3.26	1.25
VIDP	295.35	305.50	-10.14	3.32
KLAS	295.08	310.66	-15.58	5.01
LEMD	273.35	293.22	-19.88	6.78
SBGR	260.66	289.74	-29.08	10.04
LIRF	273.11	295.49	-22.38	7.57
KIAH	297.98	288.07	9.91	3.44
KMCI	260.46	271.33	10.88	4.01
KMIA	307.05	265.25	41.80	15.76
MAE	-	-	-	**8.17**

C.1.2. BR airport estimation arrivals

Table C.2: Estimated Values, Actual Means, Errors, and Error Margins for arrivals

Airport ICAO	Estimated Value(km)	Actual Mean(km)	Absolute Error(km)	Error Margin(%)
EHAM	334.33	290.80	43.53	14.97
SKBO	227.74	177.92	49.82	27.10
EBBR	306.43	312.39	-5.96	1.91
FACT	300.38	253.74	46.64	18.38
YSSY	308.16	255.79	52.37	20.47
OMDB	332.01	321.82	10.20	3.17
EGPH	301.93	241.50	60.43	25.02
KDEN	286.48	261.05	25.43	9.74
VIDP	323.93	305.50	18.43	6.03
KLAS	323.73	310.66	13.07	4.21
LEMD	301.90	293.22	8.68	2.96
SBGR	289.18	289.74	-0.56	0.19
LIRF	301.55	295.49	6.06	2.05
KIAH	326.54	288.07	38.47	13.36
KMCI	288.91	271.33	17.57	6.48
KMIA	335.63	265.25	70.38	26.53
MAE	-	-	-	**11.5**

C.1.3. RR airport estimation arrivals

Table C.3: Estimated Values, Actual Means, Errors, and Error Margins for arrivals

Airport ICAO	Estimated Value(km)	Actual Mean(km)	Absolute Error(km)	Error Margin(%)
EHAM	320.16	290.80	29.37	10.10
SKBO	213.55	177.92	35.62	20.02
EBBR	292.37	312.39	-20.03	6.41
FACT	286.34	253.74	32.61	12.85
YSSY	294.10	255.79	38.31	14.98
OMDB	317.86	321.82	-3.95	1.23
EGPH	287.89	241.50	46.39	19.21
KDEN	272.21	261.05	11.15	4.27
VIDP	309.76	305.50	4.27	1.40
KLAS	309.49	310.66	-1.17	0.38
LEMD	287.76	293.22	-5.47	1.86
SBGR	275.06	289.74	-14.68	5.07
LIRF	287.51	295.49	-7.97	2.70
KIAH	312.40	288.07	24.33	8.45
KMCI	274.86	271.33	3.53	1.30
KMIA	321.46	265.25	56.21	21.19
MAE	-	-	-	**8.21**

C.2. Sample tables

Table C.4: Aircraft Flights and Adjusted Percentages

Aircraft	Non-adjusted Percentage	Adjusted Percentage
A320	35.06%	21.40%
B738	33.48%	20.46%
A321	12.36%	7.55%
A319	7.19%	4.39%
B737	3.15%	1.92%
E75L	3.82%	2.33%
B38M	2.92%	1.78%
CRJ9	2.02%	1.23%

Table C.5: Percentage of Yearly Flights and Within Sample Set per Airport

Airport	% yearly Flights	% sample set
FACT	2.08%	2.41%
EHAM	9.76%	9.64%
LIRF	2.41%	3.56%
OMDB	7.88%	12.98%
YSSY	3.75%	2.64%
EBBR	3.78%	4.59%
KMIA	9.68%	13.09%
SKBO	6.27%	5.63%
KIAH	8.44%	5.40%
LEMD	7.42%	7.35%
EGPH	1.96%	1.49%
KDEN	13.00%	13.67%
KLAS	12.27%	9.76%
SBGR	5.13%	2.98%
VIDP	9.08%	8.16%
KMCI	2.17%	5.28%

C.3. Emission results

C.3.1. Emission results tables

Table C.6: Emissions Results - Climb Phase

Species	TOD/TOC based (Quadros)		Flight-path based	
FUELBURN	891 Mg	1.00 kg/kg	1.03 Gg	1.00 kg/kg
NO2	15.2 Mg	17.1 g/kg	18.8 Mg	18.2 g/kg
HC	28.9 kg	32.4 mg/kg	33.4 kg	32.4 mg/kg
CO	451 kg	506 mg/kg	424 kg	412 mg/kg
nvPM	29.5 kg	33.2 mg/kg	51.0 kg	49.6 mg/kg
nvPM_N	8.66e+20	9.72e+14 /kg	1.08e+21	1.05e+15 /kg

Table C.7: Emissions Results - Descent Phase

Species	TOD/TOC based (Quadros)		Flight-path based	
FUELBURN	60.6 Mg	1.00 kg/kg	220 Mg	1.00 kg/kg
NO2	281 kg	4.65 g/kg	1.81 Mg	8.20 g/kg
HC	82.5 kg	1.36 g/kg	36.2 kg	164 mg/kg
CO	1.69 Mg	27.9 g/kg	1.32 Mg	6.00 g/kg
nvPM	53.5 g	883 µg/kg	1.88 kg	8.54 mg/kg
nvPM_N	1.22e+19	2.01e+14 /kg	1.43e+20	6.49e+14 /kg

C.3.2. Fuel burn per time

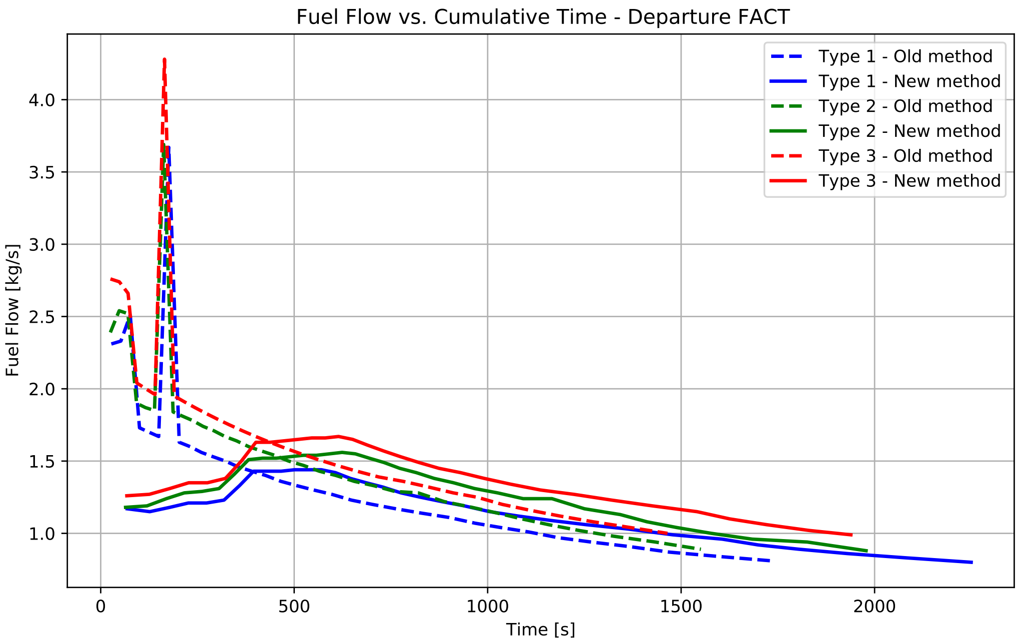

Figure C.1: Fuel burn per time - Departures FACT

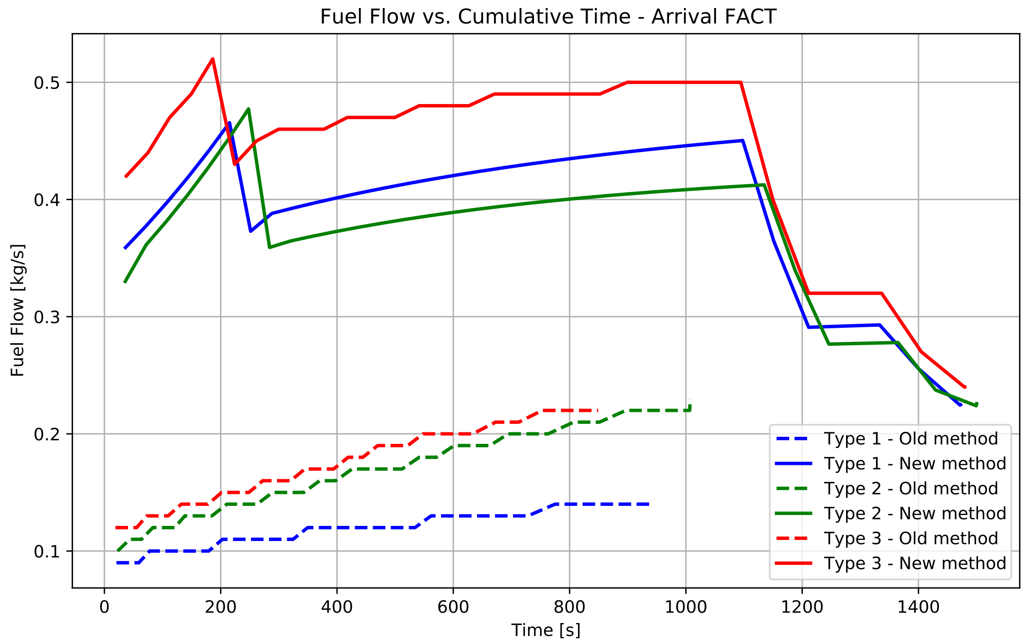

Figure C.2: Fuel burn per time - arrivals FACT

C.3.3. Other arrival route results

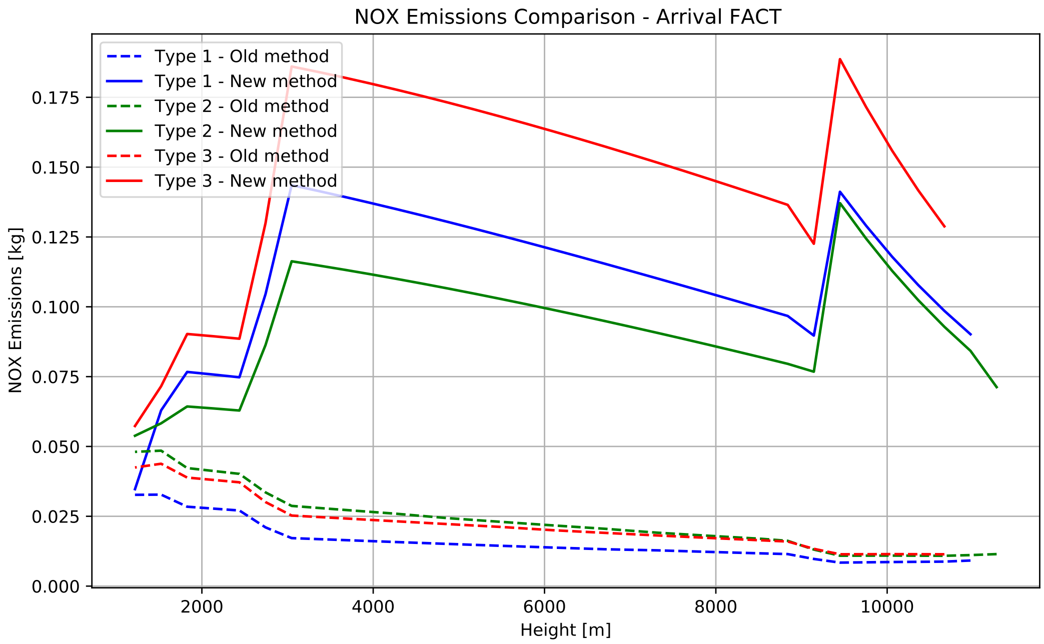

Figure C.3: NO_2 emissions per height - Arrivals FACT

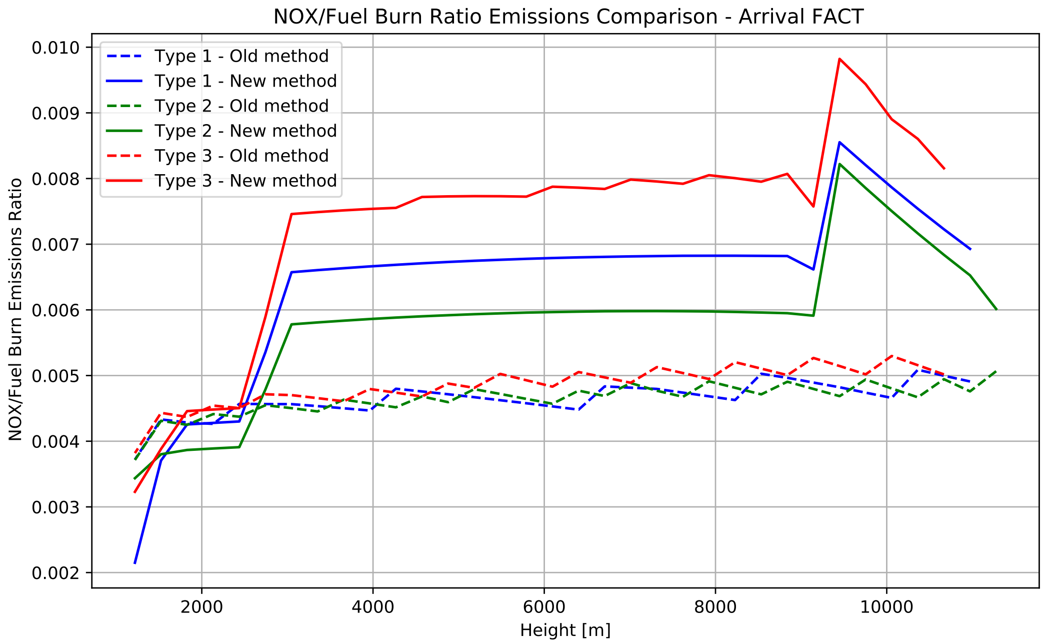

Figure C.4: NO_2 emissions per kg of fuel burned - Arrivals FACT

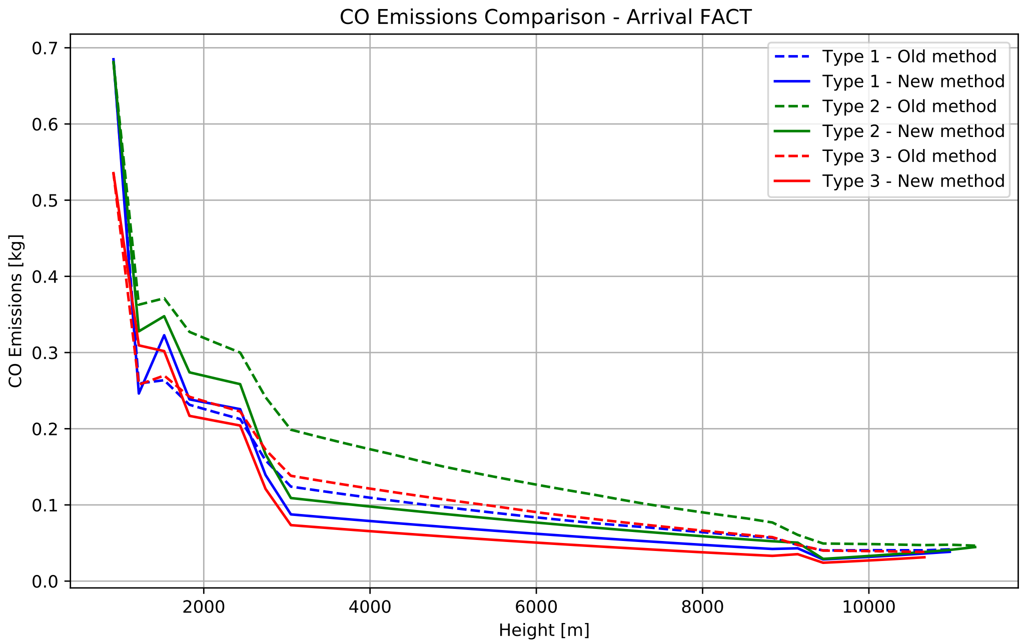

Figure C.5: CO emissions per height - Arrivals FACT

*The literature review and research plan have been assessed for the course AE4020 Literature Study.

Part III

Literature Review and Research Plan

*The literature review and research plan have been assessed for the course AE4020 Literature Study.

D

Literature Review

This chapter covers the relevant literature for the thesis. Based on this literature review, the research plan is setup, forming the basis of the thesis.

***The literature review and research plan have been assessed for the course AE4020 Literature Study.**

D.1. Introduction

This paper outlines the literature review for a thesis focused on developing a generalized Terminal Maneuvering Area (TMA) operations model to improve the distance estimations of the climb and descent phases. The TMA operations model is based on key airport parameters for integration into the global estimation model of *Quadros et al.* [1].

The study titled *'Global Civil Aviation Emissions Estimates for 2017–2020 Using ADS-B Data'* [1] considers Landing and Take-Off (LTO) and non-LTO emissions separately. LTO emissions are modeled based on *Stettler et al.*[15] for altitudes between ground level and 3000 feet. Non-LTO emissions are simulated using an aircraft performance model, evaluating climb and descent in 1000-feet increments until reaching a cruise altitude set at 7000 feet below the aircraft type's maximum operating altitude. The flight's great circle distance, representing the direct route between two locations, is considered. To account for deviations due to weather, Air Traffic Control (ATC) instructions, or other factors, an uncertainty factor is applied to the total flight distance, affecting emission estimations' precision. Most uncertainty arises within the TMA, making more precise estimations of aircraft descent and climb essential for improving emission estimations locally and globally.

This document is organized into six chapters, each addressing a distinct aspect of the literature review. In Chapter D.2, the focus is on the current literature regarding global civil aviation emissions. Subsequently, Chapter D.3 delves into the literature related to aircraft position data. Chapter D.4 covers literature concerning the definition of airport parameters, with a particular emphasis on TMA design. In Chapter D.5, the discussion centers on potential data analysis approaches for identifying patterns. Chapter D.6 explores correlation techniques, establishing connections between flight paths and airport parameters. Finally, Chapter E sets out the research plan for the thesis, including the objective and research questions.

D.2. Research base

This chapter provides a more in-depth exploration of the research presented in *Quadros et al.*'s primary paper and other connected emissions estimation research. It covers the operational procedures of alternative emission models, drawing comparisons, and explains the methodologies employed in handling and refining ADS-B data.

D.2.1. Previous work

The research conducted by *Seymour et al.* [16], titled Fuel Estimation in Air Transportation: Modeling global fuel consumption for commercial aviation, serves as a precursor to Quadros et al.'s *Global Civil Aviation Emissions Estimates for 2017-2020* [2]. Seymour's study is integral to the foundation of the 2017-2020 emissions estimates and delineates the creation of an aviation emission model, known as Fuel

Estimation in Air Transportation (FEAT). This model is designed to minimize the required variable input data and computational cost while upholding a high level of modeling accuracy.

The approach to estimating emissions in both studies is notably similar, employing the BADA model and Boeing Fuel Flow Method 2, along with the ICAO database to establish fuel flow and emitted emissions. The key distinction lies in the method of data acquisition. Both Seymour and Quadros draw upon the groundwork laid by *Wasiuk et al.* [17], where the BADA Aircraft Performance Model (APM) and the Boeing Fuel Flow method, along with the ICAO database, were utilized.

Unlike Wasiuk, who utilized the 'CAPSTATS Database of Commercial Air Traffic Movements, 2005-2011,' a commercial database with detailed flight information, Seymour and Quadros opted for ADS-B data. Seymour purchased data for the fourth weeks of January and August from AirNav Systems to model emissions, while Quadros utilized full-year coverage from Flightradar24 and OpenSky for its model. This shift in data sources highlights a significant evolution in methodology, moving towards real-time ADS-B data for enhanced accuracy and coverage.

D.2.2. Research of Quadros et al.

This section provides a thorough evaluation of the openAVEM software's functionality. It covers the trajectory simulation based on an aircraft performance model and proceeds to explain how emissions are determined from the simulated trajectory. The model's foundation is comprehensively detailed in the research by *Quadros et al.* [1] and is summarized within this section.

Origin-Destination Pairs

The model acquires real flight track data from three primary sources. Schedule data, encompassing both passenger and cargo flights (excluding those by FedEx, UPS, and some owned by DHL), is obtained from OAG(a market intelligence company). To eliminate duplicate entries arising from code sharing, which represents the same aircraft, data is cleaned. The other two sources include ADS-B data from Flightradar24, a commercial service, and data from OpenSky, a nonprofit organization that manages tracker data from a collaborative network of volunteers.

For flights concluding at an altitude of 2500 m or lower, trajectories are extrapolated to the ground, reaching the nearest airport within a 10 km radius. To accommodate flights with only partial recordings, conditions are relaxed to a 500 km radius from the extrapolated landing location. All flights are assigned both an origin and destination.

The coordinates and elevation of each airport are determined by referencing either the International Air Transport Association (IATA) or ICAO code, obtained from the OpenFlights database.

Airport, Aircraft, and Engine Data

Aircraft performance is characterized using the Base of Aircraft Data (BADA) 3.15 [18]. Military aircraft are excluded from the ADS-B data, aligning with the study's scope.

The fuel mass flow rates and emission indices (NO_x, CO, HC, and $nvPM$), along with additional engine information, is primarily sources from the certification data in the ICAO Engine Emission Databank [19]. This databank specifically covers turbofans with thrust greater than 26.7 kN. To complement, piston engine data is sourced from the Swiss Federal Office of Civil Aviation [20], and for some older engines and turboprops, information is derived from the U.S. Environmental Protection Agency [21] or as used by *Stettler et al.* [15].

Due to the inability of ADS-B data to identify engine models, the research manually incorporates engine types. Data provides each aircraft along with its respective engine models and their market share percentages. Emissions are calculated for each engine, and a weighted sum, considering each engine's market share, is then computed. The lack of precise knowledge about engine versions introduces some uncertainty. However, for the evaluation of climb and descent phases in the model, the engine assignment does not impact the results significantly, as the BADA model calculates fuel burn rates based on its Aircraft Performance Model for non-LTO emissions. The relevance of engine versions might become apparent during the thesis if it enhances result accuracy. Nevertheless, the supplemental material notes in S8.3 that for full-flight, fuel burn changes at most by 3.3% [1].

Flight model
The flight model comprises two distinct components: LTO (Landing and Takeoff) and non-LTO emissions. LTO encompasses various phases, including taxi-out, taxi-out acceleration, hold, takeoff, initial climb, climbout, approach, landing, reverse thrust, taxi-in acceleration, and taxi-in, as per the model proposed by *Stettler et al.* [15]. Non-LTO emissions, covering climb, cruise, and descent, are simulated above 3000 ft from the origin and destination airport, utilizing the BADA 3 model. BADA assesses aircraft performance in terms of total energy, treating the aircraft as a point of varying mass subject to drag, lift, and thrust [18]. It incorporates aerodynamic coefficients, operational parameters, and other properties necessary for determining fuel mass flow rates under different flying conditions. Wind speed is applied throughout non-LTO phases, utilizing year-specific monthly average wind vectors from the MERRA-2 reanalysis product [22].

Although wind influences each flight by affecting its direction, no flight path optimization is performed. Climb is evaluated in 1000-feet increments until the most common cruise altitude observed in the first 70 days of 2020 is reached, provided it is at least 200 NM and done in the climb speed schedule of the aircraft. In cases where ADS-B data is insufficient, cruise altitude is set 7000 feet below the aircraft type's maximum operating altitude. For short flights, the average cruise altitude is determined based on flight length categories (50-100 NM, 100-150 NM, 150-200 NM) for turbojets or turboprops, as reported by *Kim et al.* [23]. Cruise is simulated at a constant altitude in steps of 50 NM, while descent is simulated in 1000-feet increments and done according to the descent speed schedule of the aircraft.

Fuel Burn and Emissions Model
Both LTO and non-LTO emissions are simulated, generating flight segments with associated fuel flow rates and durations. During LTO, the fuel flow rate at a given thrust is interpolated piece-wise linearly from available engine data. In the non-LTO phases, BADA pre-calculates fuel flow as a function of thrust and speed, maintaining energy and mass balance as the aircraft adheres to a modeled schedule of speed, climb, or descent rates [18]. The Boeing Fuel Flow Method 2, as employed by *Kim et al.* [23] with additional considerations for edge cases, is then used to calculate emissions.

The initial aircraft mass for each flight follows the method used by Eyers et al., incorporating fuel for reserve, diversions, and time in a holding pattern based on flight classification (short- or long-haul). Payload mass is determined as a fraction of the maximum payload capacity, relying on annual weight load factor statistics [24]. Takeoff mass is the sum of aircraft empty mass, estimated fuel for the entire flight distance, fuel reserves, and payload.

To adjust for the actual flight distance exceeding the geodesic simplification, emissions for the non-LTO portion are multiplied by a lateral inefficiency factor derived from a trajectory analysis by *Seymour et al*.[16] of ADS-B telemetry data. This scaling factor, equivalent to adding 3.87% plus 40.5 NM to the great circle distance, is consistent with the findings by Seymour et al.

Model sensitivity, Uncertainty, and Limitations
The primary uncertainty parameter addressed in this thesis is the lateral inefficiency factor. This factor adjusts emissions to account for variations between the actual flown trajectory and the modeled trajectory, where the latter assumes a constant cruise altitude for each aircraft type and horizontal trajectories following the shortest path between origin and destination. It acknowledges that the actual spatial distribution of emissions may differ from the geodesic trajectory employed in the model. The study does not evaluate the potential effects of reduced air traffic in 2020 on cruise.

D.3. Aircraft position data

As highlighted in the preceding chapter, the forefront of data employed in the analysis of aircraft movements is now occupied by ADS-B data. Consequently, this research integrates ADS-B data to contribute further to the research fields of both ADS-B and emission estimation modeling.

With the growing availability of ADS-B data from an expanding network of ground stations, ADS-B is emerging as a reliable and widely accessible source for ATM investigations that rely on operational data and statistics. *Sun et al.* [25], titled *Large-scale Flight Phase Identification from ADS-B Data Using Machine Learning Methods*, underscores this trend.

D.3.1. ADS-B in research

In recent years, ADS-B has taken a prominent role in academic research utilizing aircraft position data, surpassing traditional radar-based methods. This shift is attributed to the real-time nature and heightened accuracy of ADS-B compared to its radar counterparts. As articulated by Gui et al. [26], "*The accuracy and comprehensiveness of the ADS-B message make it a high-quality data source for air route flow statistics.*" Gui et al. exemplified this by creating an aviation big data platform employing ADS-B data to map air traffic flow between cities. Furthermore, the study employed two machine learning methods for predicting such traffic flow, emphasizing the limitations of traditional air traffic surveillance techniques with their lower tracking accuracy, deemed inadequate for the demands of future congested airspace. This underscores a pivotal shift in the preference for ADS-B based data, indicating its contemporary status as the state-of-the-art in positional data for aviation research.

D.3.2. Data Acquisition

The input data comprises information on all aircraft equipped with an ADS-B transponder, within the coverage of an OpenSky receiver. The coverage, as of the specified date (06-06-2022), is depicted the Figure D.1. All areas marked red has Open-Sky coverage on this date.

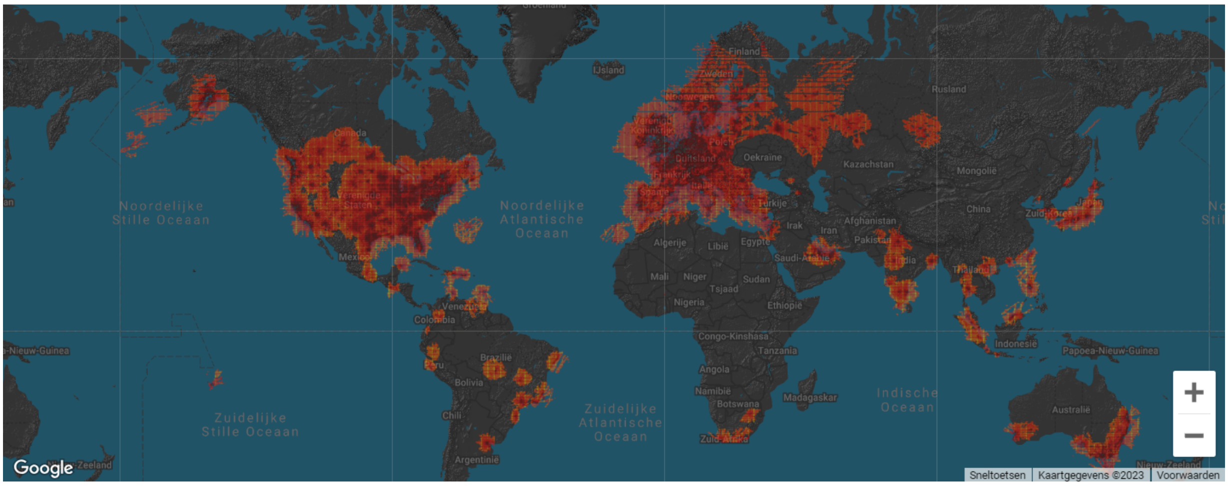

Figure D.1: OpenSky coverage on 06-06-2022 by OpenSky [27]

D.3.3. Data preparation

In order to acquire suitable data for analysis, extensive preprocessing was conducted to generate a dataset suitable for the research analysis.

Firstly, the airport under analysis needs to be defined. A bounding box of 25 km in each direction around the airport is established, within which an aircraft must have been below 3000 feet to be considered. If any data point of an aircraft is detected within this bounding box, all data points for that aircraft are extracted. Subsequently, the data of an aircraft is cut where the flight concludes and a new flight commences, after which the individual flights are cut into segments.

The segments are divided into two phases: climb and descent. The climb is identified as the point where the aircraft has a vertical rate of at least 2.5 m/s, up to the point where the aircraft is at least at 75% of its highest recorded altitude, and the average vertical rate drops below 2.5 m/s over 30 data points (equivalent to 5 minutes, given a data point recorded every 10 seconds).

The descent is defined in a reversed manner compared to the climb. If the average of 30 data points drops below -2.5 m/s, the descent segment begins, continuing until landing. In order to be considered a climb or descent segment the length of the track has to be at least 50 data points.

Both the climb segment end and descent segment initiation occur if the difference between the latitude of the airport and the current data point is below three degrees, or four degrees longitude when the absolute airport latitude is below 40 degrees, eight degrees longitude if it is between 40 and 70 degrees, and twenty degrees longitude if the absolute airport latitude is above 70 degrees. This criterion is established to exclude unintended data, such as instances where an aircraft adjusts to a lower cruise altitude midway during cruise.

If an aircraft is flying at an exact longitudinal degree, the descent is initiated 333 km away from the airport, a distance more than sufficient to fully encompass the descent. Particularly noteworthy is the nominal range at which an aircraft begins descent, typically falling within 100-150 NM (185-280 km), known as the '3 to 1 formula' according to the Federal Aviation Administration (FAA) [5]. This formula stipulates that three NM of travel should be allocated for every 1000 feet of descent, implying that an aircraft flying at FL350 would require 105 NM of flown distance.

D.4. Airport parameters

To identify which parameters are of relevance, it is important to understand the scope of the research and the physical and societal factors like ATC, influencing the flight path of an aircraft as laid out within the reserach plan Appendix E. The climb and descent phases, especially within US airspace, are partially, and at times entirely, situated within a TMA. Consequently, the design of the TMA becomes a factor influencing the three-dimensional flight path of an aircraft, potentially offering valuable insights into key airport parameters. However, this relationship is not always straightforward. Flight physics also contribute significantly to this thesis, given the three-dimensional nature of the flight path. For instance, a descending aircraft following a continuous descent trajectory experiences lower fuel burn compared to an aircraft maintaining level flight at a constant speed. Similarly, an aircraft flying at higher velocities demands increased fuel flow to generate the necessary thrust, a consideration particularly relevant at airports situated at higher altitudes.

To comprehend the factors impacting emissions estimation during the specified climb and descent phases, a comprehensive understanding of the parameters and methods employed by the 'openAVEM' model developed by Quadros et al. [1] is necessary. This model, which forms the basis of the investigation, provides a framework for assessing aviation emissions and serves as a valuable reference for aligning the analysis with established methodologies in the field.

D.4.1. Trajectory prediction studies

Trajectory prediction holds significant relevance to this research as it explores the search for a generalized flight path based on airport parameters. An insightful study by *Wang et al.* [28] focuses on a 4-D prediction of the flight trajectory within the Beijing TMA. Their prediction primarily targets estimating the arrival time using a Neural Network model developed in a previous study by *Wang et al.* on short-term 4D trajectory prediction using Machine Learning methods [29]. While such predictions may not be feasible on a global scale due to vast amounts of data, the concept of generalized flight path lengths becomes imperative. Nonetheless, the key factors influencing the estimation of arrival time within these studies could potentially indicate key airport parameters that influence the flight path length.

D.4.2. TMA design

Chandra et al. [30] underscore the significant role of TMA within the air transportation and ATM system, playing a non-trivial role in determining the throughput and operational efficiency. Their research addresses this aspect by utilizing accessible data types, such as flight records, to characterize TMA flows through a simplified approach. Employing four key performance indicators—flight distance, flight time, track distance, and track time—they analyze and characterize air traffic flows within the TMA. These parameters, defined by investigating flow counts, operational and performance differences of arrivals and departures in the TMA, offer insights into the intricacies of TMA dynamics.

In a complementary study by Netjasov et al. [31], a generic metric is developed to measure the complexity of a given TMA. Six primary factors influencing TMA complexity are identified, including the number and length of arrival/departure trajectories, airport runway system capacity, air traffic volume, aircraft fleet mix, spatial distribution of traffic, and air traffic control separation rules. The study reveals that dynamic complexity exhibits a more than proportional increase with air traffic intensity (demand/capacity ratio(s)) and slightly increases with the heterogeneity of the aircraft fleet. This highlights non-linear relationships among parameters influencing airspace complexity.

TMA design factors
In TMA design, numerous factors impact the layout, shaping the operational characteristics. This section explores the intricacies of designing a Terminal Maneuvering Area, required for comprehending the research environment and extracting essential airport parameters. The potentially influential factors, drawn from research such as that by Chandra and Netjasov ([30], [31]), as well as rational considerations, are outlined below.

- **Air traffic volume:** the volume of air traffic at an airport influences TMA design. Airports with higher traffic will often require larger and more complex TMAs to accommodate the flow of arriving and departing aircraft.
- **Obstacle avoidance:** the surrounding terrain, obstacles, and geographic features play a significant role in TMA design. Airspace and flight-procedure designers need to ensure that flight paths are clear of obstructions and that aircraft can navigate safely in the designated airspace.
- **Aircraft types:** different aircraft types have varying performance characteristics, such as climb rates, approach speeds and turn rates. TMAs must be designed to accommodate these differences while maintaining safe separation.
- **Air traffic control procedures:** TMAs are designed to facilitate air traffic control operations. Procedures for managing aircraft during the approach, landing, departure, and climb-out phases are established to ensure safe and orderly traffic flow.
- **Noise abatement:** TMA design may also consider noise abatement measures, such as minimizing aircraft overflight of populated areas during critical phases of flight.
- **Airspace classifications:** different segments of the TMA may have different airspace classifications (e.g., Class B, C, or D airspace) based on the level of control required.
- **Air traffic flow management:** modern TMA design incorporates air traffic flow management techniques to optimize the sequencing and spacing of arriving and departing aircraft, reducing congestion and delays.
- **Communication and navigation aids:** TMAs are equipped with communication and navigation aids to assist pilots and air traffic controllers in maintaining safe and precise operations. This includes designated instrument approach procedures that guide aircraft safely from the en-route phase to the final approach and landing.
- **Route separation:** route separation is another key factor in TMA design. Aircraft are required to maintain a horizontal distance of 5 nautical miles or a vertical distance of a 1000 feet.

The airspace around airports including the TMA are designed to accommodate air traffic as efficiently as possible for their descent towards, or arrival at, an airport. This generally means that as airports grow bigger and the air traffic towards the airports increases, the airspace has to be designed such that the traffic can be sequenced with minimal delay and maximum capacity, whilst adhering to the safety requirements.

Airspace complexity
As articulated by *Zhu et al.* [12], ”Airspace complexity serves as an objective metric for evaluating the operational condition of the airspace.” This metric plays a pivotal role in the design of airspace within Air Traffic Management (ATM), yet its assessment is intricate due to the non-linear correlations among various independent factors. Zhu et al. introduce a learning model aimed at measuring air traffic complexity within a sector, particularly when dealing with limited samples. This approach aligns with the broader literature in the field, where research on airspace complexity predominantly focuses on evaluating specific sectors, driven by the inherent challenges in precisely quantifying the complexity of an entire airspace.

In 2006, the Performance Review Commission (PRC) of EUROCONTROL published a technical report dedicated to assessing complexity and developing metrics applicable for benchmarking analyses in Air Navigation Service Providers (ANSP) [6]. The report outlines four complexity indicators, as illustrated in Table D.1.

Table D.1: Complexity indicators [6]

Complexity dimension	Indicator	Description
Traffic density	Adjusted density	A measure of the potential number of interactions between aircraft in a given volume of airspace.
Traffic in evolution	Potential vertical interactions (VDIF)	Captures the potential interactions between climbing, cruising and descending aircraft.
Flow structure	Potential horizontal interactions	Provides a measure of the potential interactions based on the aircraft headings.
Traffic mix	Potential speed interactions	Assesses the potential interactions based on the aircraft speeds.

The analysis utilizes data from a two-week period in 2003, enabling a comparative evaluation of 67 Area Control Centers (ACCs) and 34 ANSPs. The findings, illustrated in Figure D.2, present a unified metric termed 'complexity score,' amalgamating the individual indicators. It is essential to acknowledge that the chosen indicators are specifically tailored for calculating en-route complexity and may not be universally applicable to terminal areas. Nevertheless, within the scope of this study, these indicators may exert a noteworthy influence on assessing distances for climb and descent.

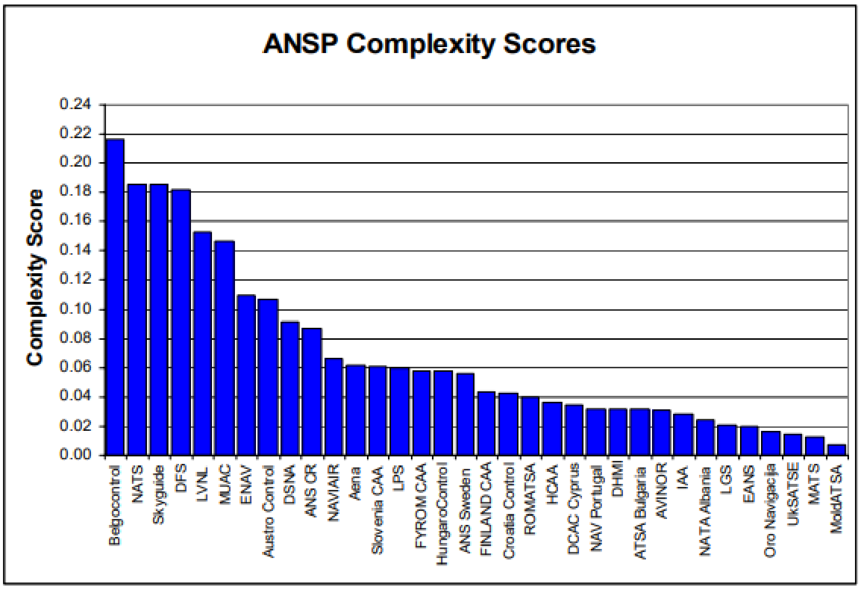

Figure D.2: ANSP Complexity Scores by *EUROCONTROL* [6]

Incorporating elements from the EUROCONTROL report, the thesis stands to gain valuable insights by integrating selected indicators to evaluate airspace complexity into the airport parameters. Notably, the complexity dimension related to airspace, as outlined by EUROCONTROL, could significantly enhance the thesis. While the parameters considered in the thesis may not precisely capture airspace complexity, their inclusion could contribute to a more comprehensive understanding of the variance within the applied statistical model. The supplementary parameters extracted from the EUROCONTROL report for assessing airspace complexity are enumerated as follows:

- **Sector:**
  - **Influence on productivity and costs:** For a given volume of airspace, the higher the number of sectors, the more resources are needed and the higher the costs. This should be related to the traffic density.
  - **Candidate indicators:** Number of sectors, characteristics/dimensions (shape and size)
- **Route structure:**
  - **Influence on productivity and costs:** Route structure reflects and organises the underlying demand of traffic. And the route structure together with the constraints put on its utilisation (Letters of Agreement, flight level restrictions, bi or uni-directional routes, etc) can contribute to reducing controller workload and increasing capacity and efficiency.
  - **Candidate indicators:** Nb of routes within a given volume of airspace, Nb of crossing and merging points within a given volume, Direction of flows - uni, or bi directional.

D.4.3. Preliminary airport selection

This section describes the criteria for airport selection based on the considered airport parameters: Total flight movements at an airport (FM), the number of runways (R), the height of the airport (H), distance within 'X' of another airport ($AtoA$), and regional procedures and practices (RPP).

Key Performance Indicators rationale

Considering the aspects related to TMA design, the preliminary parameters are the following:

- **Total flight movements (FM):** the total flight movements is related to the traffic volume at an airport. More flights is partly an indicator for elevated procedural airspace and possibility of conflicts and therefore causing more ATC instructions and consequently more distance flown.
- **Number of runways (R):** more runways could be an indicator for an increased required capacity, more routes and flights and therefore a increase in ATC interference.
- **Distance within 'X' of another airport ($AtoA$):** interference with surrounding airports or airways could lead to an increase in ATC instructions to prevent conflict with crossing traffic.
- **Regional procedures and practices (RPP):** a more arbitrary parameter, but difference in traffic handling around the world might cause difference in flown distance from the top of descent point of aircraft or show a difference in level flight flown during the climb or descent at specific heights, also influencing the emissions.
- **Airport elevation (H):** airport elevation is a slightly more significant factor and easy to define. An airport at significant elevation would intuitively mean a shorter flown distance as less horizontal distance is required during its descent to an airport at 8000 feet compared to an airport at 0 feet elevation.

Airspace complexity, potentially coupled with ATC interference, may serve as the root cause for certain selected airport parameters. This aspect requires thorough investigation during the thesis work. Moreover, it is probable that some airport parameters influencing the distance covered by aircraft cannot be pre-identified. As flights at various airports are analyzed, patterns may emerge that are not directly attributable to or explicable by the predetermined parameters. These effects are subsequently analysed and, where feasible, incorporated into the model through the relevant airport parameter

Selected airports

The primary Key Performance Indicators (KPIs) selected for their significant influence on the flight path are utilized in the initial airport selection for the preliminary Terminal Maneuvering Area (TMA) analysis. The chosen airports are required to exhibit both comparable and distinct values for these KPIs. Geographical diversity is considered to account for local variations, and initially, six airports are selected. As differences are identified and necessitate quantification, additional airports within similar regions may be added to comprehensively capture local variations or practices. The initially selected airports are the following:

Table D.2: Airport main parameter data

Airport	Altitude (m)	Runways	Flight Movements	Closest Airport (km)
Schiphol A	-3	5(6)	462,600 (2022)	158 (Brussels)
El Dorado IA	2548	2	296,777 (2022)	216 (Medellin)
Brussels A	56	3	178,930 (2022)	158 (Schiphol)
Cape Town IA	46	2	98,666 (2022-23)	1257 (Johannesburg)
Sydney A	6	3	177,646 (2022-23)	180 (New castle A)
Dubai IA	19	1	373,261(2021)	17 (Sharjah IA)
Edinburgh A	41	1	93,004 (2022)	79 (Glasgow)
Denver IA	1656	6	615,733 (2022)	853 (Salt lake city IA)

D.5. Data analysis

This chapter discussed various techniques for the analysis of the sample data. To identify patterns within the sample data, various techniques and analyses are discussed to obtain them. Additionally, key performance indicators which fundamentally differentiate the the different airports are defined within this section.

D.5.1. ADS-B data

Researched performed by *Sun et al.* [25], titled *Large-scale Flight Phase Identification from ADS-B Data Using Machine Learning Methods*, highlights the growing effectiveness of ADS-B within ATM investigations, whilst primarily developing Machine Learning Methods based on fuzzy logic.

In a subsequent study in 2017, *Sun et al.* [32], in Modeling Aircraft Performance Parameters with Open ADS-B Data, delves further into the utilization of ADS-B data for generating parametric models describing flight phases. Approximately 3000 flights were analyzed for each assessed aircraft, using ADS-B data from Flightradar24, a commercial ADS-B network known for its extensive coverage.

The study employs Maximum Likelihood Estimation (MLE) to derive the best unbiased values of parameters based on observations. Three continuous Probability Distribution Functions (PDF) – Normal, Gamma, and Beta distributions – are assumed for each performance parameter, and MLE is applied to obtain the best estimates for each PDF from sample data. In addition, *Rudnyk et al.* [33] employed a similar technique of using MLE with PDFs to get a distribution which fit the data well. Their research focused on trajectory prediction using Monte Carlo simulations. Employing the same method within this research should help in performing a good analysis on the data.

The research identifies seven flight phases: takeoff, initial climb, climb, cruise, descent, final approach, and landing. Of particular interest for this research are the climb and descent phases, which are comparable. The climb segment initiates when the aircraft reaches a clean configuration and continues until it reaches the designated cruise altitude. Typically, aircraft accelerate to a target Calibrated Airspeed (CAS) and then maintain a constant CAS during the climb. As altitude increases, the speed of sound decreases, leading to an increasing Mach number. Upon reaching a specific Mach number, the aircraft transitions to flying at a constant Mach number until it reaches cruising altitude. The Mach climb segment results in a decreasing CAS due to decreasing air density. The climb CAS profile is illustrated in Figure D.3. The descent phase essentially mirrors the climb phase.

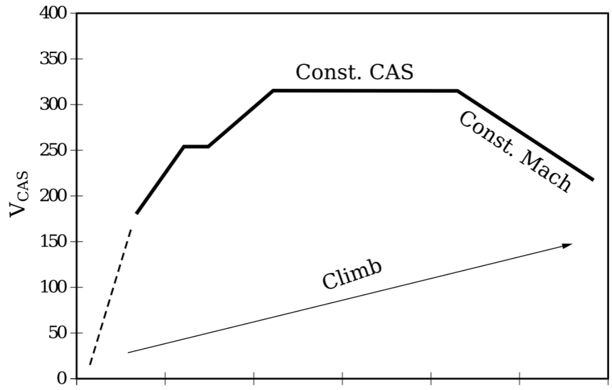

Figure D.3: Standard climb profile by *Sun et al.* [32]

The outcomes are presented in the form of mean, gamma, or beta distributions, from which the optimal estimate is derived. These estimations depict a parameter distribution specific to the aircraft, featuring a central tendency and mean variance. Illustrated parameters are speed in both CAS and Mach, Transition altitude at constant CAS and Mach, mean Rate of Climb (RoC, or RoD for descent) at pre-CAS, constant CAS, and constant Mach. Additionally, the climb range, representing the total distance covered by the aircraft during its ascent, is included in the analysis. Exemplifying this methodology, the results for the Airbus A320 are delineated in Figure D.4.

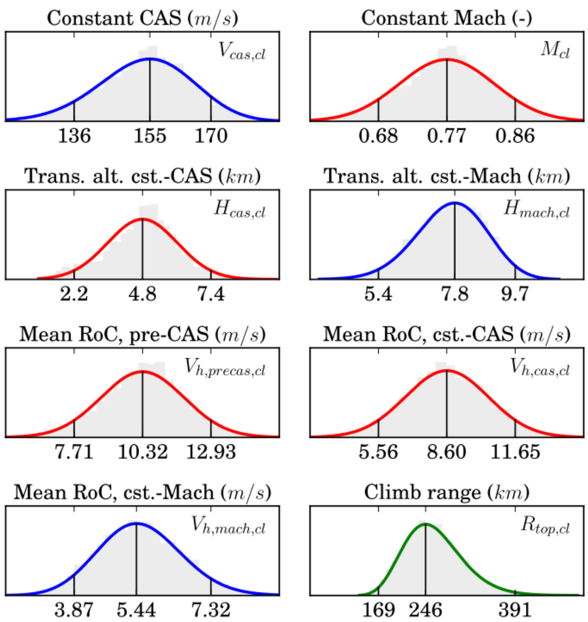

Figure D.4: Climb parameters by *Sun et al.* [32]

These findings hold significant relevance for this thesis, which aims to evaluate the impact of airport parameters on an aircraft's flight path. Employing a methodology comparable to that of *Sun et al.* [32], a robust distinction can be established concerning the mean value and variance of various parameters influencing the flight performance during the climb and descent phases. This approach proves versatile for the examination of diverse aircraft types, mirroring the methodology applied by Sun et al. in their comprehensive study. The discerned variations among the considered aircraft in their study serve as a valuable tool to mitigate the uncertainties associated with aircraft-specific factors in flight paths, facilitating a more precise analysis of the airport-related effects.

Within the validation segment of the paper, the researchers conduct a comparative analysis with the BADA3 model, clarifying disparities observed between the two. While potential contributors to these variations include differences in transition altitude, flight strategy, and aircraft weight, it is important to recognize the broader relevance of these uncertainties to the present research. The applicability lies in the fact that similar uncertainties may influence this study due to shared considerations in assessing the impact of airport parameters on climb and descent phases. By acknowledging and addressing these uncertainties, the research aims to enhance the robustness of its findings and ensure a more accurate evaluation of airport-related effects on flight paths.

D.5.2. Statistics related to data analysis

This section discusses some statistical methods to for assessment and analysis of the data. These include the maximum likelihood estimation together with probability density function, and a K-S test to assess the correctness of the estimation. Additionally to remove outliers, a trimmed mean is discussed.

Maximum Likelihood Estimation

The MLE, as described by *Aldrich* [34], is a statistical method for estimating the parameters of an assumed probability distribution. By maximizing a likelihood function, under an assumed model, the most probable solution can be found for the observed data. The MLE can be used along the regression model as assumed model to obtain the most likely estimate rather than one which minimizes the sum of squares.

As described by *Rudnyk et al.* [33], first N observations are taken from an unknown probability distribution $f(\cdot)$, like distance flown during climb from a specific airport, and denoted as $X : \{x_1, ..., x_n\}$. Defined as a vector of parameters θ, $f(X|\theta)$. Under the assumption that the observations are independent and identically distributed, their joint distribution can be expressed as:

$$f(X|\theta) = f(x_1, ..., x_n|\theta) = \Pi_{i=1}^{n} f(x_i|\theta) \tag{D.1}$$

The likelihood $\mathcal{L}$ is a probability of obtaining observed values given certain values of parameters:

$$\mathcal{L}(\theta|X) = \Pi_{i=1}^{n} f(x_i|\theta) \tag{D.2}$$

This can be simplified to:

$$log\mathcal{L}(\theta|X) = log\Pi_{i=1}^{n} f(x_i|\theta) = \sum_{i=1}^{n} logf(x_i|\theta) \tag{D.3}$$

Consequently, the MLE of θ (θ_{MLE}) is the value of θ maximizing $\mathcal{L}$:

$$\theta_{MLE} = argmax_{\theta} log\mathcal{L}(\theta|X) = argmax_{\theta} \sum_{i=1}^{n} logf(x_i|\theta) \tag{D.4}$$

Kolmogorov–Smirnov test and significance testing

These tests are utilized to assess the fit of a distribution to the data, determining if a data sample corresponds to a specific population distribution. In this thesis, they may be applied to examine whether airport distances exhibit a normal distribution. The K-S test, as employed by Rudnyk et al. [33], is also used to select the most suitable fit for the probability distribution function obtained through MLE.

Trimmed mean

An effective method under consideration is the 'trimmed mean' procedure. Essentially, a trimmed mean is the average of a distribution where a specified percentage of data is excluded from both ends. For instance, a trimmed mean of 10% involves removing 5% from each side of the distribution, effectively eliminating outliers within the dataset.

D.5.3. Airport analysis

This section describes what type of analyses could be performed on the sample data to identify patterns. Additionally, key performance indicators for the comparison of airports are defined within this section.

Short, long and medium haul flights

In the analysis of descent and climb distances in aviation, it is crucial to distinguish between short-haul and long-haul flights due to the inherent differences in their operational characteristics. Combining these two categories can lead to a distorted representation, resulting in a bimodal distribution rather than a unimodal one. Additionally, 'medium' haul flights would be the most common and/or modern aircraft types which fly both short and long haul flights.

Short-haul flights typically involve lower cruising altitudes whilst long-haul flights involve higher cruising altitudes. When these two types of flights are combined, the resultant graph may exhibit two distinct peaks, reflecting the dissimilarity in operational patterns. The consequences of such a bimodal distribution extend to the calculation of statistical measures, particularly the mean and standard deviation. A bimodal distribution violates the assumption of normality required for the accuracy of the normal distribution, rendering them unreliable for drawing meaningful conclusions. The mean value, in particular, loses its interpretative significance as it fails to capture the central tendency of the data in the presence of multiple modes.

To mitigate these challenges and ensure a more accurate representation, it is imperative to analyze short-haul and long-haul flights separately. By doing so, the resulting graphs are more likely to exhibit a unimodal distribution, allowing for a valid application of statistical measures like mean and standard deviation. This separation enhances the precision and reliability of the analysis, providing a clearer insight into the descent and climb distances specific to each flight category.

Key Performance Indicators within flight path
Effective analysis of the flight performance relevant within this study requires consideration of KPIs associated with flight path. The selected KPIs—distance during climb/descent, vertical rate during climb and descent, and the amount of level flights—have been chosen to provide a comprehensive understanding of the aircraft's behavior during the climb/descent phases. Each KPI offers unique insights into the overall quality of flight trajectories associated with the airport.

Distance during climb and descent The distance covered during climb and descent serves as a straightforward metric to evaluate aircraft performance at a specific airport. Understanding the distance traversed during the climb and descent phases allows the model to account for variations in operational profiles across different airports.

During the data preparation phase, the climb and descent segments are extracted. Subsequently, the distance is computed by taking the difference between two data points. The cutoff for both the climb and descent distance is set at 3000 feet above the airport. Beyond this altitude, the flight is deemed to be in the LTO phase, falling outside the scope of this study.

Vertical rate during climb and descent The vertical rate during climb and descent is an additional easily quantifiable metric for performance assessment. Using basic trigonometry, one can anticipate that as the distance during climb or descent increases, the vertical rate decreases. While these parameters can be viewed as comparable metrics, this specific metric provides additional information on the influence of airport parameters, particularly when considering the presence or absence of level flights.

Level flights The quantity of level flights is a key performance indicator directly influencing emission estimation. For instance, during descent, a level flight at a lower altitude implies that the aircraft must increase its power output, elevating fuel flow and, consequently, emissions. Since the type of emissions is dependent on atmospheric conditions, it becomes crucial to identify the atmospheric layer within which the aircraft is flying at a constant altitude.

D.6. Statistics

This chapter focuses on statistical methods, specifically regression and Monte Carlo Simulation, applied within the thesis. It touches upon aspects related to regression like predictors, residuals, and errors, with an emphasis on assessing the statistical significance of the beta coefficient with the confidence interval and effect size for the statistical significance of the model. The Monte Carlo Simulation is introduced as a valuable tool for estimating flight distances at airports.

D.6.1. Quantifying relationship techniques

There are many different techniques to quantify a relationship between variables. The most commonly known is the linear regression technique, also known as ordinary least squares (OLS). This technique is a well proven way of quantifying the linear relationship between two, or more, variables.

The study of *Wong et al.* [11] compares different regression techniques in terms of modeling accuracy. The research compares Artificial Neural Network (ANN), Generalised Regression Neural Network (GRNN), Support Vector Regression (SVR), Multiple Linear Regression (MLR), and Response surface Model (RSM). The models were tested on two different non-linear cases. From this the ANN, GRNN and SVR were deemed reliable as the other models did not accept the null-hypothesis in one of the two complex models.

This study showed that ANN and GRNN methods were more reliable than SVR, although their modelling abilities were comparable. A NN regression type could therefore possibly prove valuable compared to MLR. However, as a first iteration MLR would provide a good indicative benchmark of the percentage of explained variance due to solely linear relationships. Just as was done within the research of *Wong et al.* [11].

D.6.2. Regression

Understanding regression analysis is essential, given the nature of predictive challenges. This analytical approach relies on several key predictors, encompassing both continuous and potentially categorical variables. The difficulty lies in selecting the most appropriate model from a spectrum of available options. *Field* [7] offers an in-depth explanation of the procedures involved in regression analyses, detailing the required tests and steps to assess the statistical outcomes.

Regression types

An array of regression types caters to various applications, with linear regression, often referred to as ordinary least squares (OLS), standing out as the most commonly used method. While linear regression exclusively deals with continuous variables, several other techniques accommodate regression involving categorical variables or a combination of both. The following overview outlines various continuous regression methods, specifically relevant to the envisaged airport parameters.

- **Linear Regression (OLS):** Most common for continuous variables. Gives the mean change for a one-unit change in the independent variable.
- **Advanced Types of Linear Regression:** Ridge regression, Lasso regression, Partial Least Squares (PLS) regression to address issues like multicollinearity and overfitting.
- **Nonlinear Regression:** Greater flexibility for fitting curves, recommended if linear regression doesn't provide a good fit.

Within advanced linear regression methods, Ridge regression primarily addresses multicollinearity and prevents overfitting by introducing a penalty term, thereby enhancing the stability of variables. Similarly, Lasso regression employs a penalty term, but it possesses the capability to eliminate variables in the presence of high multicollinearity. PLS regression, while serving the same purpose, proves particularly valuable when there are more predictors than observations, a condition not applicable to this research.

Non-linear regression models, such as polynomial regression and exponential regression, also merit consideration. Polynomial regression introduces polynomial terms to predictors, facilitating improved curve fitting. However, it is sensitive to outliers and may be prone to overfitting, rendering it accurate for test data but less reliable for unseen data. On the other hand, exponential regression is especially suited for data exhibiting an exponential function. Nonetheless, if the underlying relationship is not exponential, this method may yield inaccurate predictions, and its sensitivity to initial values must be noted.

Predictors

Adopting a hierarchical entry approach proves advantageous for theory testing. Initiating the model with the most impactful predictor and progressively introducing other relevant variables ensures a methodical exploration of potential relationships.

Predictors vary in type, including continuous variables and dichotomous/categorical factors. It's important to evaluate and address issues of multicollinearity, aiming for predictors with Variance Inflation Factors (VIF) below 10 and steering clear of predictors with zero variance. VIF is useful in assessing how strong the relationship between two independent variables is.

Residuals and Cook's Distance

Beyond predictor selection, a robust regression analysis necessitates a thorough examination of residuals. The standard residuals' distribution should ideally see 95% falling within ± 1.96 in an average sample, with 99% residing within ± 2.5. Outliers, characterized by a residual of 3 or more, demand careful consideration as potential influential data points.

Cook's distance measures the impact of individual cases on the overall model. A value surpassing 1 raises concern, signifying that a particular outlier significantly shapes the beta coefficients, potentially impacting the validity of the regression model.

Errors

Uncorrelated errors are fundamental for a reliable regression analysis. The assumption of independent and normally distributed errors ensures the robustness of the statistical inferences drawn from the regression model.

As a sampling set gets large (usually above 30 samples), the sampling distribution has a normal distribution with a mean equal to the population mean, and a standard deviation of:

$$\sigma_{\bar{X}} = \frac{s}{\sqrt{M}} \tag{D.5}$$

In which $\sigma_{\bar{X}}$ is the standard error of the mean, s the standard deviation of the sample data, and N the sample size.

Confidence intervals

Confidence intervals are to quantify the uncertainty of an estimate, providing a range within which the results parameters are likely to fall. within regression analysis, confidence intervals help in the assessment of the precision and reliability of the coefficients.

Confidence intervals help in assessing multiple aspects within a regression analysis. For example:

- **Precision of estimates:** Estimates are prone to sampling variability. Confidence intervals give a range around the point estimate, indicating how precise the estimate is and how much it might vary.
- **Statistical significance:** If the confidence interval does not include 0, the coefficient is considered statistically significant at the chosen confidence level. This means that it is likely that the coefficient has a non-zero effect on the outcome.
- **Direction and magnitude:** The sign of the coefficient indicates the direction of the relationship, while the width of the confidence interval indicates the precision. A narrow interval suggests more precise estimation, while a wide interval suggests greater uncertainty.

Within the context of this thesis, the confidence interval indicates which airport parameters describe the flight path of an aircraft within the climb or descent phase.

To calculate the confidence interval, the limits at which 95% of the means fall are necessary. The limits are therefore -1.96 and 1.96 for z-scores, determined by using D.6.

$$z = \frac{X - \bar{X}}{s} \tag{D.6}$$

In which z is the z-score, X the boundary limit, $\bar{X}$ the mean and s the standard deviation. The equation can be rearranged and is easily calculated as follows:

$$X = (\pm 1.96 \times s) + \bar{X} \tag{D.7}$$

However, for smaller sample sizes the distribution might not be normal and therefore requires a different technique for calculating the confidence interval. The confidence interval is then as follows:

$$X = \bar{X} \pm (t_{n-1} \times SE) \tag{D.8}$$

In this equation X is the lower/upper boundary, $\bar{X}$ the mean, SE the standard error, and $n-1$ the equations degrees of freedom, telling which t-distribution to use. The degrees of freedom is the amount of observations minus one.

D.6.3. Monte-Carlo simulation

The Monte Carlo Simulation is a method that helps anticipate a range of possible outcomes for an uncertain event by analyzing past or similar data. This technique allows for factoring in uncertainty when making predictions, offering a more realistic view compared to fixed predictions without any variation. The simulation runs multiple iterations, producing random outcomes that together form a probability distribution. While conducting more simulations yields a more accurate distribution, it requires increased computational power and time.

Rudnyk et al. [33] described how a Monte Carlo Simulation is used to perform a Global Sensitivity Analysis. It explains how there are three steps involved with applying it: 1) sample inputs from the distribution functions; 2) compose input vectors containing sampled inputs; 3) run a model for all input vectors. Using chosen metrics for a model output evaluation, an uncertainty analysis can be performed by computing output distribution and statistics. Then, scatter plots can be used to inspect the sensitivity of output to each input and a sensitivity measure can be obtained by computing a correlation coefficient.

In the context of this study, the Monte Carlo Simulation can be applied to estimate the distribution of flight distances at an airport using results from regression analysis. The goal is to use the simulation to project an expected range of distances at an airport based on selected parameters. The average flight distance should fall within the predicted range suggested by the Monte Carlo simulation, verifying the findings of the regression analysis.

E

Research Plan

***The literature review and research plan have been assessed for the course AE4020 Literature Study.**

E.1. Introduction

This chapter aims to outline the research plan for a thesis focused on developing a generalized Terminal Maneuvering Area (TMA) operations model to improve the distance estimations of the climb and descent phases. The TMA operations model is based on key airport parameters for integration into global emission models.

E.1.1. Problem statement

The study titled *'Global Civil Aviation Emissions Estimates for 2017–2020 Using ADS-B Data'* [1] considers Landing and Take-Off (LTO) and non-LTO emissions separately. LTO emissions are modeled based on *Stettler et al.*[15] for altitudes between ground level and 3000 feet. Non-LTO emissions are simulated using an aircraft performance model, evaluating climb and descent in 1000-feet increments until reaching a cruise altitude set at 7000 feet below the aircraft type's maximum operating altitude. The flight's great circle distance, representing the direct route between two locations, is considered. To account for deviations due to weather, Air Traffic Control (ATC) instructions, or other factors, an uncertainty factor is applied to the total flight distance, affecting emission estimations' precision. As such the position estimation within the research of Quadros et al. contains key assumptions which add considerable uncertainties for the emission estimation. Especially within the climb and descent these assumptions model the aircraft in an ideal path which deviates significantly from the actual flown path.

E.1.2. Relevance

The research presented in this thesis addresses critical gaps in the scientific understanding of global civil aviation emissions estimation. By focusing on the specific flight phases of climb and descent within the emission estimation model produced by *Quadros et al.* [1] using Automatic Dependent Surveillance–Broadcast (ADS-B) data, this study aims to enhance the accuracy of current emission estimation models. The existing model relies on great circle distance with an uncertainty factor, leading to potential inaccuracies, especially within the TMA.

This research seeks to establish a quantifiable relationship between key airport parameters and flight path during climb and descent using ADS-B data. By doing so, it bridges the gap in knowledge regarding the impact of airport-specific factors on the flown distance of aircraft. The proposed model offers a more precise estimation, particularly in the TMA, where significant uncertainty lies.

This research falls within the context of the broader research area of global emission estimation models. It aims to improve the estimation of aircraft emissions during specific flight phases within the TMA by considering key airport parameters. By doing so, the study contributes to the advancement of accurate and comprehensive global emission estimation methodologies, aligning with the overhanging objective of understanding and mitigating the environmental impact of aviation emissions on a local and global scale.

E.1.3. Scope

This study focuses on the climb and descent phases within the study of *Quadros et al.* [1]. The climb and descent phases are defined within the non-LTO emissions, enclosed between 3000 feet above airport elevation and cruise altitude.

Within this research, it is important to note that the intended goal is to improve the emissions estimation within the climb and descent phases. A 2D/3D flight path should be considered due to the impact of altitude and distance flown on the total emissions. Air Traffic Control (ATC) instructions or Air Traffic Management (ATM) considerations are of primary influence on that flight path. This is because the engine produces the emissions based on its engine settings, which differ per height and flight operation. Considering these aspects, this research focuses primarily on developing an alternative approach of estimating the position of the aircraft during the climb and descent phases which should be implemented into the existing model of *Quadros et al.* [1] for comparison purposes.

E.2. Research Objective

The main goal of this research is to enhance current civil aviation emission estimation models that use ADS-B data. Currently, these models rely on great circle distance and incorporate an uncertainty factor to account for estimation variations. However, the primary source of uncertainty lies within the TMA of airports, specifically during the climb and descent phases of aircraft. As each airport exhibits unique characteristics due to terrain and air traffic density, a more accurate estimation approach is necessary for the estimation of these flight phases within the TMA. Improving these estimates will lead to enhanced global emission models.

Therefore, the primary objective of this research is:

To construct a model to estimate the global emissions of civil aircraft within the climb and descent phases, using generalized flight path modeling based on key airport parameters.

E.3. Research Questions

With the research objective defined, a research framework is determined to assist the formulation of the main and sub research questions. This results in the following main research question:

How can emission estimation during the climb and descent phases in global models using ADS-B data be enhanced by generalizing the flight path based on key airport parameters, resulting in a quantifiable improvement in accuracy?

Multiple steps are required to answer this in structured manner. The sub-questions are setup with their associated tasks. The sub-questions which help answer the main research question are as follows:

- **SQ-1: Which airport parameters have an impact on the flight path during climb and descent?**
  - **SQ-1.1:** Acquiring and preparing ADS-B data for analysing airports.
  - **SQ-1.2:** Analysing airport specific distances of incoming and outgoing flights in various configurations.
  - **SQ-1.3:** Defining preliminary airport parameters of influence for flown distance during climb and descent.
- **SQ-2: What is the quantified relation between the airport parameters and flight path and what are the sensitivities?**
  - **SQ-2.1:** Defining different methods to quantify a relationship between airport parameters and flight path.
  - **SQ-2.2:** Apply most promising method in accordance with scope and goal thesis.
  - **SQ-2.3:** Reiterate influential airport parameters.
  - **SQ-2.4:** Defining metrics for assessing accurateness and correctness of relationship analysis.
  - **SQ-2.5:** Testing relationship on data outside the data-set.
  - **SQ-2.6:** Quantify deviation from actual flown path and assess the sensitivities.

- **SQ-3: How does the flight path length emission estimation compare to other research in accuracy and speed?**
  - **SQ-3.1:** Understand code of current model and define dataset for comparison.
  - **SQ-3.2:** Integration into existing emission model of *Quadros et al.* [1].
  - **SQ-3.3:** Comparison of emission estimation of existing model and with the implemented relationship of flight path and airport parameters.

E.4. Methodology

This section describes the technical framework and methodology followed throughout the research. As previously mentioned in Section 3, the sub-questions are divided into tasks. Each task is described, and additional information on the methodology and methods is provided.

E.4.1. SQ-1: Data Collection and preliminary analysis

Sub-Question 1: *Which airport parameters have an impact on the flight path during climb and descent?*

This part aims to understand and describe the airport parameters impacting the flight path of an aircraft by acquiring data and performing airport specific analyses. In order to achieve this, ADS-B data needs to be obtained which has a sufficient enough resolution for the purpose within this research. Sources logging ADS-B data such as Flightradar24 and OpenSky or To70's own ADS-B data are qualifying resources, depending on how freely available the data is, the resolution and the amount of available data within the dataset. The data also needs to be cleaned and prepared for the analyses within the thesis, which is expected to be time consuming. Preparing the data includes correctly cutting flights, and defining the cut-off for the climb and descent.

The data is used to determine the distance flown from and to different airports. A comparison will who the difference between airports and by relating the differences to airport specific factors by finding additional airports or creating sub-sets within the data will consequently show what kind of factors influence the distance flown. From this preliminary parameters can be selected. These parameters could include runway amount or length, airport elevation, weather conditions, air traffic control constraints, and regional aspects. The determination of these parameters entails a literature review, and additional factors may be identified during the course of the research from the analyses, further extending this phase. Notably, the consideration of Air Traffic Management (ATM) design is crucial, as it aims to optimize trajectories, and the design parameters within TMA design might align with those influencing increased flight path length. Also ADS-B based research as done by Junzi Sun would be very useful during the data cleaning, preparing and analyses. An example is his paper on modeling aircraft performance parameters with open ADS-B data [32]. In this paper open sourced ADS-B data is used to determine the performance parameters of different types of aircraft during different flight phases. Employing a similar analysis on the range of the climb and descent phase.

E.4.2. SQ-2: Data Analysis and Interpretation

Sub-Question 2: *What is the quantified relation between the airport parameters and flight path and what are the sensitivities?*

This part aims to answer what the quantified relationship is between the airport parameters and flight path by employing a to-be-determined statistical method for obtaining a quantification of the influence of the selected parameters from the previous part, SQ-1. After relating the airport parameters to flight path it will become clear whether the relationship is strong and how much of the variance can be explained by the method. This will indicate how much the chosen airport parameters actually influence the flight path and whether additional parameters should be added to get a more accurate result. A quantified relationship is the output of this part of the thesis.

Employing the Spearman Rank Correlation is one approach, adjusting the data to highlight variations in a specific airport parameter to deduce correlations with path length. Other statistical techniques, including regression analysis and correlation tests, may also be utilized. A regression analysis is a well established technique, especially the linear regression is a proven method, but requires a somewhat linear relationship. However a linear regression is often a good way to start to get an indication of the variance and accuracy of the linear model. This could then be enhanced by employing a more sophisticated regression technique.

For each type of regression type there are different ways of determining whether the results from the analyses are (statistically) significant. For determining the variance in the prediction coefficients, called the Beta values, confidence intervals give a distribution within which the Beta values are predicted to lie. If these values fall outside of the 0, the null hypothesis can be discarded as the predictors have a statistically significant effect on the output with a 95 percent accuracy. Other test could include the T-test, which test how much effect each Beta has and the effect size (R-squared) which explains how much of the variance is explained by the model.

E.4.3. SQ-3: Emission Estimation and Comparison

Sub-Question 3: *How does the flight path length emission estimation compare to other research in accuracy and speed?*

This part will apply the relationship found to the already existing model of *Quadros et al.*[1] to find whether the relationship is a promising method to determine the emissions during the climb and descent phase and how accurate it is compared to the current method of determining the emissions. This requires a good understanding of the exact code used within the paper before integration of the method from this research can be implemented. After implementation a comparison of a sample dataset will be performed to measure the differences in the estimation and argue whether the new method is a promising alternative way of determining the emissions during climb and descent.

The comparison process includes various methods such as cross-validation. Cross-validation partitions the data into multiple subsets, trains the model on different subsets, and then validates it on the remaining subsets. This helps in evaluating the model’s robustness and ability to generalize to new data. Berrar introduced the most common cross-validation techniques and discussed the applicability of them in various scenarios [35]. The uncertainty of the model can be assessed by performing a Monte Carlo Simulation. This simulation generates random samples from probability distributions of input parameters, such that the range of possible outcomes and uncertainties can be established, as was used in the research of *Rudnyk et al.* [33], in which this method was used for a trajectory prediction Sensitivity Analysis.

Moreover, error metric such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), or Percentage Error to quantify the accuracy of the emission estimation compared to ground truth or reference data could be performed to further validate the model.

E.5. Hypotheses

The central hypothesis tested in this thesis proposes that generalized path lengths derived from key airport parameters will enhance the accuracy of global emission calculations. This hypothesis was formulated based on prior research indicating strong associations between delays and TMA density, as evidenced by *Dhief et al.* [36].

SQ-1 Hypothesis

Although relating airport parameters to flight path could prove to be arbitrary, it is expected that there will be about three to six parameters required for the estimation of the distance flown during the climb or descent. Less parameters risks insufficient variables to accurately estimate the distances, whilst too many variables might not be feasible as more data for each airport is required and a the intent of the thesis for a simple distance indication might be compromised.

SQ-2 Hypothesis

Quantifying the relationship between the airport parameters and flight path done by regression would satisfy the intent for a simplistic well proven method for relating the parameters to flight path. Regression outputs weights for each of the variables considered within the analysis. These weights multiple with airport parameters of an arbitrary airport form a formula for the distance flown during climb or descent. Statistical test will indicate whether the estimation is accurate in terms of assumptions and errors and whether the statistical model explains the variance in the data. It is expected that this is an iterative process with SQ-1 as within this part it becomes clear how much of the variance is explained by the model and therefore whether the chosen airport parameters are significant or not.

SQ-3 Hypothesis

The aim of the thesis is to provide a new and more accurate method to estimate the location of the aircraft during the climb and descent phases. However, it is expected that this thesis lays the ground work for the new method and that the chosen airport parameters could possibly not explain enough of the variance and inaccuracies in the result and the analysis make it less accurate than the existing model.