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COMPARATIVE ANALYSIS OF THE USE OF AI IN THE EU AND MIDDLE EASTERN AIRPORTS SUPPLY CHAIN

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Abstract

In recent years, the adoption of Artificial Intelligence has significantly increased, particularly in the aviation sector. AI has transformed perspectives on the operational efficiency within the airport supply chain. This paper primarily focuses on a Comparative Analysis of AI use within the airport supply chains of Europe (Amsterdam Schiphol and Frankfurt International Airport) and the Middle East (Dubai International Airport and Hamad International Airport). A mixed-method approach is employed, combining quantitative analysis of data from the two key airports, DXB and FRA, alongside qualitative analysis derived from industry reports, webinars, and various secondary sources. The primary emphasis is on comparing two approaches: Rule-Based AI applied to DXB data and XG Boost applied to FRA data to predict taxi time. This comparative analysis points out the variations in strategy and operational results, which can be beneficial for airport managers and policymakers in this sector.

Abstract German

In den letzten Jahren ist die Verwendung von Künstlicher Intelligenz (KI) erhöht und hat den Luftfahrtsektor stark beeinflußt.Diese Studie spezialisiert sich auf die vergleichende Analyse des KI-Einsatzes in der Flughafen-Supply Chain in Europa (Amsterdam Schiphol und Frankfurt International Airport) und des Nahen Ostens (Dubai International Airport und Hamad International Airport). Es verwendet einen gemischten Methodenansatz und ein Inferenzsystem für die Datenanalyse von DXB auf der Grundlage der regelbasierten KI-Methode und des XGBoost-Algorithmus zur Vorhersage der Taxizeit in FRA-Daten. Diese Untersuchung zeigt Unterschiede im strategischen und operationellen Verhalten auf und bietet so wertvolle Implikationen für Flughafen-Manager und politische Entscheidungsträger in den beiden Regionen.

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List of Abbreviations

AI Artificial intelligence

AOBT Actual off-block time

AMS Amsterdam Airport Schiphol

DOH Hamad International Airport

DXB Dubai International Airport

ETA Estimated time of arrival

FRA Frankfurt Airport

LTO Landing and take-off cycle

SOBT Scheduled off-block time

1. Introduction

1.1. Main Topic

This study focuses on this topic due to its relevance for both academic research and practical application. Nowadays, society faces various challenges, and many are finding solutions using AI.

This study compares EU and Middle Eastern Airports, with a main focus on how boarding, baggage services, and the flight experience have changed with the use of AI. The main point of the case study will be reducing taxi time and finding ways, using AI, to improve it and reduce the delays caused by long taxi time.

1.2. Organisation of the paper

The next sub-chapters will be dedicated to the concept of Airport and AI, first information about the chosen airports then going on with the use of AI in the AMS, DOH, DXB and FRA. The next chapter will be a description of the research methodology, case study approach and data collection methods. Chapter 2.5 will present detailed case studies of AI implementation and some insights in the codes used, implemented in Python. In the last chapter, the results of each method will be presented and compared. The next paragraph explains some of the most important concepts that will be used later. This section aims to familiarize the reader with the topic and make it understandable not only to the experts but also to everyone.

1.3. Concepts

Abnormal flights: flights arriving or departing in advance or late, it refers to a flight that cannot be served according to the scheduling time due to deviation between the actual arrival time and the planned arrival time (Zhu, Sun & Guo, 2022).

Airport Operations: direct and facilitate all aspects of flight and aircraft handling, including luggage, bus transport, take-off, and landing (van Slobbe, 2020). In the context of surface movement operations, aircraft are distinguished between arrival and departing aircraft. The goal of arriving aircraft is to travel from runway to their assigned gate in an optimal manner with respect to fuel burn and taxi time. For departing aircraft their goal is to reach the runway from their gates in an optimal manner (Delft University of Technology, 2023).

Airport Slot: It is a scheduled day and time casually defined within a 15- or 30-minutes period for an airline flight to arrive and depart from an airport (Ashford, Mumayiz and Wright, 2011, p. 579)

With the reference to the book by Kazda & Caves (2015, p.119); Aprons are designed areas for parking aeroplanes and turning them around between flights. They should permit the on- and off-loading of passengers, baggage, and cargo, and the technical servicing of aeroplanes, including refuelling. These are the most heavily loaded of all the movements area pavements (Kazda & Caves, 2015, p.119)

ASTAIR-Auto Steer Taxi at AirPort

Delay: Actual Off-Block Time (AOBT) minus Scheduled Off-Block Time (SOBT) (Assaia, 2024).

End-Around is a maneuverer or procedure where an aircraft-taxis or moves around the end of a runway or taxiway to reach the opposite end or a different part of the airfield. It occurs when an aircraft cannot use a direct taxi route.

Ground Delay: Delay minus arrival delay (Assaia, 2024).

Head-on conflicts: Two aircrafts are meeting head-to-head in the same taxi way segment (Liu et al., 2024).

Node conflicts: Also called as the intersection conflict, and is encountered at the key intersections entering or exiting runways (Liu et al., 2024).“Number of flights unable to depart on time refers to the number of flights whose ground- handling service end time is later than the originally planned departure time.”(Zhu, Sun & Guo, 2022).

Overtaking conflicts: The trailing aircraft overtaking or taxiing closely to the leading aircraft (Liu et al., 2024).

Punctuality: referring to outbound traffic is the percentage of commercial flights that depart on time (van Slobbe, 2020).

Rostering: The process of planning and scheduling crew members and sometimes aircrafts to meet operation needs while complying with regularity, contraction and safety requirements. Airline scheduling is difficult from that of buses, railways and passenger ferries because the timetable is developed first and routing afterward. Airline scheduling has four basic elements: timetable development, aircraft assignment, aircraft routing, and crew scheduling (de Neufville & Odoni, 2013, p. 539).

Runway capacity: The hourly rate of aircraft operations on a single runway or combination of runways that can reasonably be expected to meet by system capacity under certain conditions (Güven, Çetek & Çeçen, 2024). “The final runway capacity should meet the predicted demand in the typical peak hour traffic in the far future.” (Kazda & Caves, 2015, p.46). The capacity of the runway subsystem is expressed as the number landings and take-offs that can be performed safely per hour (de Neufville & Odoni, 2013, p.580). Two types of capacity are known in air travel: capacity along flight routes and capacity at airports.

Taxiways are designed to provide the shortest and most direct connections between runways, aprons and other operational areas in airport (Kazda & Caves, 2015, p.107).

Turnaround: from the arrival of the aircraft to gate until push-back for departure (Assaia, 2024). Normally the push-back takes in average two to four minutes depending on the size of aircraft, type of push-back tractor and on the position where are engines started up at the stand or after push-back (Kazda & Caves, 2015, p.131).

1.4. Airport concept and reason of choosing

We got familiar with some of the concepts but the main for this paper and aviation industry is 'Airport'. What is an airport, how can we define it? After explaining the main concept of the study, it will focus on four chosen airports and the reason behind that decision. For the concept of airport there is not an official definition from IATA. Airports are the vital arteries of trade, commerce and connectivity. One of the main concepts that is taking a lot of attention is smart airport, according to ACI World Director General Justin Erbacci (ACI World, 2025);to address challenges in air traffic management during the last years initiatives like the Single European Sky (SESAR) in Europe and Next Generation Air Transportation System (NextGen) in the United States have been implemented (Delft University of Technology, 2023).The fundamental airport infrastructure includes runways, taxiways, apron space, gates, passenger and freight terminals and ground transport interchanges (Horn, 2010). Each airport operator has a unique identity, but all have to assume overall control and responsibility at the airport (El Makhloufi, 2023). "The airports using AI technology is defined as a smart airport or Airport 4.0. At smart airport, the Internet of Things (IoT) is used as smart application to mobilize, identify, and process tasks to identify passengers together with RFID to provide advanced security service." (Aruna Rajapaksha & Dr.Nisha Jayasuriya,2020)

Another definition that should be clear for the paper is the supply chain management. As outlined by Toorajipour et al. (2021) is the management of a network of relationships within a firm and between interdependent organizations and business units. From the original producer to the final customer with the benefits of adding value, maximizing profitability through efficiencies, and achieving customer satisfaction (Xue, Dou and Shang, 2020).

The main objective of this paper is based on the case study for the chosen airports, but the decision to work with them is not occasionally, it is based on the following criteria:

1. AI adoption level
2. Size and traffic volume, later in this paragraph some insights related to this point will be given.
3. Data availability: It was somehow difficult to find them for the chosen airports regarding the use of AI and the cost of its implementation.
4. Strategic importance: All the four chosen airports are very important because they are main hubs of connection and through them passes a high percentage of the passengers which travel around the world.

5. In the FTE Airport Digital Transformation List can be found all of the chosen airports in the list of the airports with the highest level of AI adoption; Amsterdam in the second place, Doha in the third place followed by Frankfurt on the fourth place and Dubai International Airport is on the sixth place. ACI World (2025) reports that Dubai International Airport is the second busiest airport in the world with a total of 92331506 passengers in 2024, this represents an increase of 6.1% compared to 2023.DXB is ranked also the first airport in the world for the number of the international passengers, followed by AMS ranked on the fifth place, FRA on the eighth place and DOH ranked on the 10-th place. In the top 20 cargo airports for 2024 DOH is ranked on the 8-th place in the world for the volume of the cargo handled in 2024 which is 2616849 representing a 11.1% increase compared to 2023,DXB stays on the 11-th place with a volume of 2176843 and FRA on the 16-th place with a volume of 1991048. They have been in the same list also in 2019-2021.

Before going to details for each of airports, all of them four are airports for lager aircrafts; they can meet the usability requirements without relying on multiple taxiway directions (Kazda & Caves, 2015, p.47)

1.5. Introduction of airports

AMS

AMS- Amsterdam International Airport known also as Schiphol is part of Schiphol Group and it is the main airport in Netherlands. On 2024; 66.8 million passengers in 473,815 flights flew via Schiphol from them 91% went through the security check within 10 minutes. In 2024 Amsterdam Airport Schiphol saw an 8% increase reaching 1.49 million tonnes. There were 15,661 cargo- only flights. This is a decrease of almost 2% compared to 2023, and an increase of 11% compared to 2019. (Schiphol Group, 2025). In the first half of 2025 668000 tons of cargo has been processed which represents 6.8% increases compared to the same period on 2024 (Schiphol, 2025). It is one of the four best connected airports in the world and the third busiest airport of Europe.

Figure 1.1 AMS Airport (Source: International Airport Review, 2018)


Figure 1.2 AMS Airport Outside (Source: Amsterdam Schiphol Airport: Future Focused – Airport World,2024)

Amsterdam International Airport or known as Schiphol has 5 long take-off and landing runways and one shorter. This airport has one terminal concept which is then divided into 3 sections: 1, 2, 3, it has 223 boarding gates. The 3 departure halls are divided into pier and each of them has their own gates which are used differently for Schengen and non-Schengen flights. It takes about 25 minutes from self-drop-off to the aircraft, and the longest distance a suitcase can travel is 2.5 km.

The names and all the specifications of the runways are as following:

1. 18R/36L which is 3800x60 and its name is Polderban, it takes 10 to 20 minutes taxi to and from terminal.

1. 06/24 which is 3500x45 and its name is Kaagban

2. 09/27 which is 3453x45 and its name is Buitenvelderban

3. 18L/36R which is 3400x45 and its name is Aalsmeerban

4. 18C/36C which is 3300x45 and its name is Zwarenburgban

5. 04/22 which is 2014x45 and its name is Oostban.

Figure 1.3 Amsterdam Airport runways (Source: Wikipedia contributors, 2025)

During inbound peaks, Schiphol operates 2 landing runways and 1 take-off runway. Similarly, during outbound peaks, 1 runway is used for landing and 2 for take-offs. In periods where the inbound and outbound peaks overlap, a configuration of 2 runways per each traffic flow is used (Graham, 2023).

DOH

DOH or known as Hamad International Airport was voted by Skytrax as the "World's Best Airport" in 2021,2022. (Qatar Airways,2024). DOH is also known for the largest hangar in the world which can repair 13 aircrafts at once.

In 2024, Hamad International Airport (DOH) handled 52.7 million passengers, which is a 15% increase compared to 2023. Aircraft movements increased to 279,000, a 10% rise year-on-year in, while 2.6 million tonnes of cargo is handled, up 12% from the previous year. Additionally, the airport processed 41.3 million bags, improving baggage handling efficiency by 10%. (Hamad International Airport, 2025)

Figure 1.4: Doha International Airport (Source: International Airport Review, 2017)

Figure 1.5 DOH Outside (Source:Hamad International Airport Passenger Terminal Complex - HOK,2021)

Doha International Airport has 2 parallel runways which are located 2km from each other and are used to perform simultaneous take-off and landing; western one 34R/16L which is one of the eight longest in the world; 4850x60 meters and the other one is 34L/16R which is 4250x60 meters.

DOH has one terminal which is divided into five concourses: A, B, C, D, E; they have respectively 10,10 and 24 gates. Concourse D and E are opened in March 2025. It has 3 parallel taxiways and 12 parking aprons. At this airport, unlike the other 3 airports, nose-in parking is mandatory and pushback is restricted.

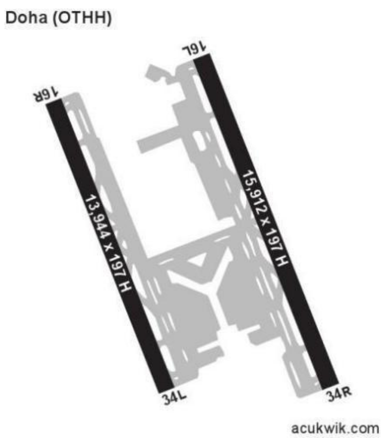

Figure 1.6 Runways DOH airport (Source: OTHH/Doha/Hamad International General Airport Information, 2025)

DXB

Dubai International Airport leads in CO_2 emission (16.6 million tons), which is also one of the reasons they would like to improve their ground operations and reduce the taxi time.

Surveys have shown that Dubai International Airport consistently provides passengers with smooth experience of moving in the airport (Kazda & Caves, 2015, p.241). Dubai International (DXB) has maintained its position as the world's busiest airport for international passengers for 11 consecutive years, according to Airports Council International (ACI) (Dubai Airports, 2025).

Dubai International (DXB) welcomed 23.4 million guests in the first quarter of 2025 and the traffic was up 1.5% compared to the same period in 2024. January 2025 alone welcomed 8.5 million guests. Cargo volumes registered a small decline of 3.6% year-on-year during the first quarter, with DXB handling 517,000 tonnes of cargo.
DXB also recorded 111,000 flight movements in Q1 2025, which is 1.9% more than the same period last year, with an average of 215 guests per flight. Despite growing passengers number, DXB sustained high levels of operational efficiency. In Q1 2025 over 21 million bags were processed in, with baggage mishandled rate fewer than 1.95 bags per 1,000 guests, which is a success rate of 99.8%. The airport connects travellers to 269 destinations across 106 countries, served by 101 international carriers. (Dubai Airports, 2025)

In 2024 DXB handled 92 million passengers which is 6% up compared with 2023. 20/12/2024 was the busiest day on this airport with 296000 guests and between 20-22/12 nearly 880000 guests passed through it. These numbers make December also the busiest month for 2024 which counts 8.2 million guests. In 2024 2.2 million ton of cargo has been handled which represents a 20% increase compared to 2023. In 2024 there was also an increase of 5.7% in the aircraft's movements counting 440300.

Figure 1.7: Dubai International Airport (Source:Aviation Airport Wiki; International Airport Review, 2018).

DXB has 3 terminals: T1, T2, and T3.. Terminal one is used for diverse range of international flights and has a capacity of 45 million passengers and in 520000 m^2 it has 221 check- in desks. Terminal 2 is used for regional flight and low cost; it has a surface of 47000 m^2 and a capacity of 10 million passengers and it counts 37 checks in counters. This terminal does not have any jet bridge. Passing to the last terminal; Terminal 3 which is the most important one because in this terminal Emirates Airline operates, it has 3 concourses: A, B and C. Terminal 3 have a capacity of 65 million passengers and in 1713000 m^2 it has 180 check-ins and 14 baggage carousels.

DXB has a parallel runway design which is useful for simultaneous take-off and landing, each of them is 4km long and 60 wides. The two runways are named: 12L/ 30R ,4000x60 and 12R/30L, 4447x60. They have a gap between centre-lines 385 meters. As it has two parallel runways it uses the End-Around and also when one runway is congested, the aircraft may taxi around the runway- end to reach the holding point, in this way it reduces the taxi delay.

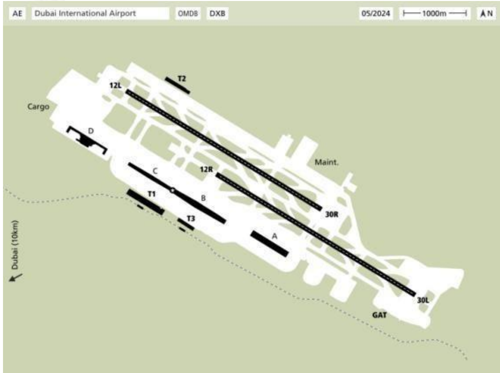

Figure 1.8 Runway DXB (Source: Central Jets, n.d.)

FRA

Frankfurt is among the largest airports in the world, and ranks as one of the busiest cargo airports; and it has also an history that makes it special; the first official mail flight was from Frankfurt to Darmstadt operated by Lufthansa on 10.06.1912 (Kazda & Caves, 2015, p.213). In 2024, 61.6 million passengers travelled through Frankfurt Airport (FRA), an increase of 3.7% from 2023.Cargo volumes in Frankfurt (including airfreight and airmail) grew by 6.2 % totaling 2.1 million metric tons in 2024. The number of aircraft movements climbed by 2.4 percent to 440,853 take-offs and landings. Likewise, total maximum take-off weights (or MTOWs) increased by 2.8 percent to approximately 27.8 million metric tons. (FRAPORT 2025). In 2024 Fraport remained as the leading airport for global hub connectivity.

Figure 1.9: Frankfurt Airport (Source: Fraport AG, 2019; Kampmark, 2025).

Frankfurt International Airport has 2 large terminals: T1 and T2. Terminal 1 has 103 gates with a capacity of 50 million passengers. T2 with 42 gates and a capacity of 15 million passengers. Here is the same configuration as in AMS where there are different gates for the Schengen and non-Schengen flights.

FRA has 4 runways; 3 of them are in 2 directions, only Runway 18 is in one direction. It has two outer parallel runways which are 07L/25R, 2800x45 and it is used only for landing and 07R/25L, 4000x45 and it used for landing and take-off. It has a central parallel runway; 07C/25C, 4000x60 and it is used only for take offs. Runway 18 is 4000x45 and it is used only for take offs in the southbound direction. FRA uses the END-Around routinely to access holding points or during peak hours, it is managed via advanced A-CDM procedures and AI supported ground traffic monitoring.

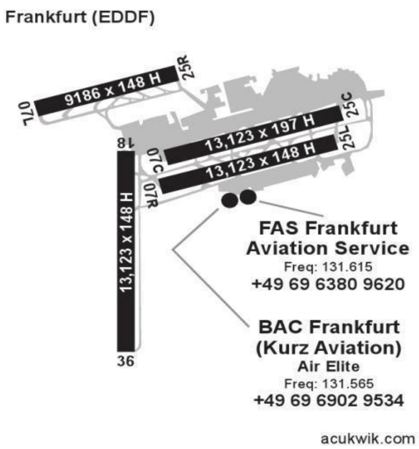

Figure 1.10 Runway Frankfurt Airport (Source: AC-U-KWIK, n.d.)

In the paragraph above the main focus was the runway system, their number because the number and their orientation should provide at least 95% usability factor. Usability factor for the types of aircraft which are intended to use the aerodrome, presuming very conservative crosswind capability of the aircraft (Kazda and Caves, 2015, p. 47). All the four airports taken into this study should and must cope with longer airplanes like Boeing

737 and Airbus A380, it is usually necessary to provide additional pavements at the end of the runway to allow the aircraft to turn around (Kazda and Caves, 2015, p. 108). Referring to the cargo aircrafts it is important to be parked as near as possible to the freight terminal in order to reduce the amount of ground traffic movements (Kazda and Caves, 2015, p. 221).

DXB uses A-Stair (used when aircraft do not put a jet bridge/gate) occasionally. DOH uses them only for cargo and VIP jets, another perspective is in AMS when they use them regularly for low cost, charter flights, in FRA we have the same view as in DXB where A-Stair is used occasionally in overflow situations or regional flights.

1.6. Definition of AI and its division

For the artificial intelligence are hundreds of thousands of definitions but in this paper will be presented the ones that are more appropriate to the topic of the paper; According to Atwani *et al.* (2022); “AI is the design of intelligent systems that learn from data and can make decisions and predictions”. One of expression that I have read in the paper “Artificial Intelligence Systems in Aviation” and which has taken my attention is: “AI is about ‘man-and-machine’; not ‘man-versus machine’ (Kashyap, 2019).

During the phase of literature searched I have worked also with the paper “ AI Application in Transport and Logistics Opportunities and Challenges (An Exploratory Study)” by (El Makhloufi, 2023), which has the most appropriate definition for Artificial Intelligence regarding the scope of this paper: “ Artificial Intelligence (AI) refers to systems that display intelligent behaviour by analysing their environment and taking actions- with some degree to autonomy- to achieve specific goals” This definition was taken from European Commission 2019.

The development of AI can be divided into 5 different phases respectively:

1. Foundation which is before 2010 when the new digital tools were introduced, encountering here the rule-based systems and basic scheduling software.

2. First wave from 2010-2015 having the early AI experiments used to predict maintenance and for delay forecasting. One of the airports that has used AI in this phase is Frankfurt International Airport.

3. AI Adoption from 2016 to 2019, started using it in the chat-bots, machine learning for baggage handling. Main examples in this period are Schiphol using it for the baggage handling and Emirates together with Lufthansa using in chat-bots.

4. Integration and intelligence which is the period we are living and working in; it is known for full AI integration in operation and logistics. Examples: smart gates, digital twins, predictive cargo and maintenance and turnaround optimization.

Compared to 2015, 52% of global airports had implemented unassisted bag drop in 2021, and 40% of airports had implemented self-boarding, and 35% had implemented automated border control. 25% of airports in the world were planning to offer flight status notifications on mobile devices in 2021 (Delft University of Technology, 2023).

AI is a broad field, the next sub-chapter gives some of its subsets which are also the main focus in the case study part of this paper. Referring to the definitions of (Atwani,Hlyal and Elalami,2022);

1. Genetic Algorithms (GAs) are random research algorithms that imitates natural genetics.
2. Machine Learning (ML) consists in predicting the behaviour, so it is widely used to solve several supply chain issues in forecasting and planning. Another explanation from Struk (2023), computers learn from data to make decisions without being explicitly programmed. ML is a suitable candidate to overcome limitations in prediction

imprecision (Delft University of Technology, 2023). It is used for example to predict flight delays, manage air traffic, and tailor the travel recommendations based on passengers' previous reference. Its adoption can significantly improve operational decision-making by providing more accurate and timely predictions. It is focused on developing algorithms and models that enable computers to learn and make data driven decisions. Machine learning algorithms depending on the type of learning in can be classified:

a) Supervised Learning which are used for prediction and metric validation.

b) Unsupervised learning, used to explore unknown patterns in unlabelled data.

c) Semi-supervised learning; used for processing partially labelled data.

d) Reinforcement learning used to achieve a specific goal. (Lozano Tafur et al., 2025)

3. Deep Learning is a subset of machine learning that uses neural networks inspired by the human brain's structure to analyze complex data patterns (Tafur et al., 2025). Struck (2023) defines it as a more sophisticated form of machine learning, which interprets data through complex, layered processes akin to those of the human brain because it employs neural networks. Deep Learning methods require thousands of data records for models to become relatively good at classification tasks and, in some cases, millions of them to perform at the level of humans. The neural network algorithm dominates several characteristics. Random Forest appears as a popular choice across multiple characteristics, suggesting its effectiveness and reliability in predictive and classification analyses. It excels on tasks requiring precise predictions based on labelled data, making them well-suited for applications like predicting estimated time of arrival or assessing collision risks in air traffic. (Lozano-Tafur et al., 2024).

During the research phase I encountered an highly relevant paper that explains the use of AI and this will be presented in the figure 1.11.

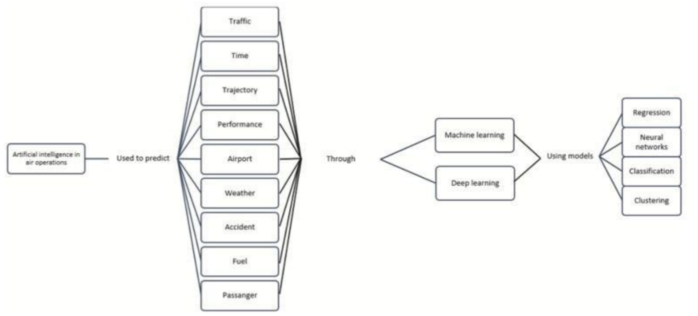

Figure 1.11 Applications of AI (Source: Lozano Tafur et al., 2025)

Referringtofigure1.11theartificialintelligenceisusedintheaviationindustrytopredict: traffic, taxi time; performance, passenger volume, weather and airport performance. AI does all of this through machine learning and deep learning, as explained in detail above. The algorithms used in machine learning and deep learning use models such as regression, neural networks, classification, and clustering. (Lozano Tafur et al., 2025)

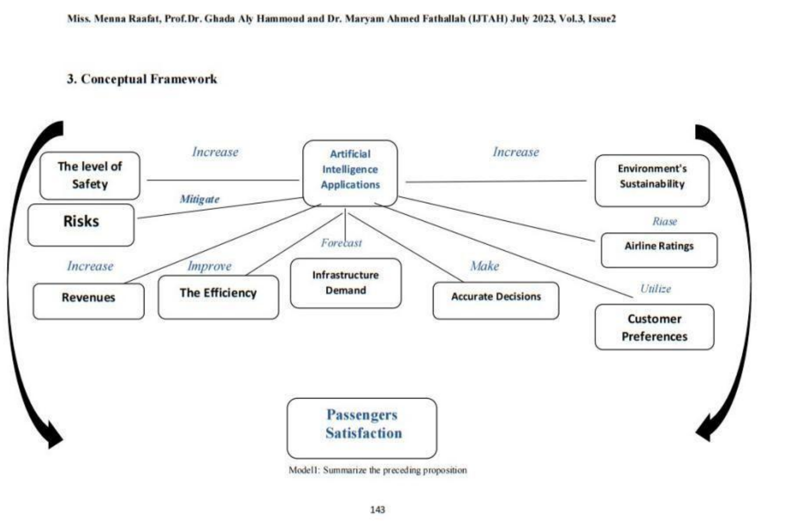

Figure 1.12 Conceptual Framework (Raafat, Hammoud & Fathallah, 2023)

The framework given in figure 1.12 gives an overview of the application of artificial intelligence and its improvements; it increases: the level of safety, revenues, environment's sustainability. It mitigates the risks; and improves: the efficiency and what is the most important in the airport supply chain it helps in making accurate decisions.

The main field where AI is used in the airport operation are:

1. Baggage handling: the use of robotics and machine learning has reduced the delays (McKinsey, 2021).

2. Smart Gates: the use of biometrics has influenced positively the speed of processing (Gursoy et al., 2020).

3. Operational Centres

4. The chat-bots which have enhanced passenger assistance (Wanf & Xiang, 2022).

5. Airports use it for speech and image recognition to identify the travellers or luggage and interpret the customer feedback.

6. Neural Networks simulating human vision identify runway numbers and predict delays with high accuracy, demonstrating practical applications for operational efficiency.

7. AI is not only used in the airports and their operation, but it is also used in the aircrafts, they are using AI before the clients get to the airplane terminal, to up sell devotion program travellers on business class updates (Kashyap, 2019).

ASTAIR AI can forecast 20 minutes of vehicle trajectories, deconflicted by speed regulations, centralizing information from stakeholders to inform routing computations. ASTAIR will consider estimated arrival times confirmed 10 to 15 minutes in advance, allowing parking assignments to be modified similarly. ASTAIR seeks to automate routing and guidance services, enabling airport operators to share information and supervise ground movements (Garcia et al., 2025).

After outlining the physical and operational characteristics of the airport the following section examines how AI technologies are currently integrated into its processes.

1.7. Use of AI in the chosen Airports

1. In 2006 AMS was one of the first airports in the world which used the robot for baggage handling. AMS uses for baggage handling a system that is powered by SITA and AI analytic. An AI powered theft detection system which is called Vessia/TRSS is used in AMS shops having a positive effect of preventing more than 50 thefts, about 163000 Euros. AMS has implemented Apron AI that is used for the optimization of the turnaround process.

2. DOH uses the AI in self-service kiosks which are faster than the traditional modes and process a bag in less than 50 seconds. Hamad International Airport is using across all airport operations the software of Aerofficial Intelligence, a company specialized in supporting airport and air traffic management. DOH on 02/07/2024 was awarded with the Best AI Solution award. MATAR, the responsible company for the management of the Hamad International Airport, won the Best-AI Solution Corporate prize for its Digital Twin for customer service. The latest AI advancements in this airport are the use of autonomous vehicle trials for the stuffy bus and the Digital Twin in the airport management; it tackles long-standing challenge and optimizes the decision process. It integrates machine learning and AI to simplify the complex data analysis (Hamad International Airport, 2025). Hamad International Airport has adopted AI-driven technologies to increase operational efficiency, but we do not have specific use of Apron AI system as we have seen by Amsterdam International Airport. In the figure 1.13 is Sama 2.0, that is the first robot that service in the Qatar Airways Aircrafts.

Figure 1.13 Sama 2.0 (Souce: (Ostwal, n.d.)

3. At DXB the smart tunnel uses artificial intelligence and facial recognition to allow passengers to go through passport control in only 15 seconds and with no need of human intervention. The smart gates at DXB are cutting-edge biometric technology that precisely identifies passengers by their facial features. (Mäkelä, 2024)

Emirates Airline was the first company in the Middle East to use CMR software (KIS), it created its own business application, Knowledge-driven In-flight Service (KIS), which allows pursers to use laptops to take stock of what is transported on a flight and how to better serve passengers. (Alshurideh, Alsharari & Al Kurdi, 2019).

Dubai International Airport has adopted Six Sigma principles to improve its operations like: baggage handling and customer service. It tracks passenger baggage from check-in to aircraft; in this way it reduces the lost baggage incidents. It has also applied the DMAIC (Define, Measure, Analyse, Improve, Control) framework to reduce baggage mishandling from 5 to 2 per 1000 passengers. DXB is using the Passport Free AI Corridor which process 10 passengers simultaneously through facial recognition (Dubai Airports, 2025.)

DXB is one of the airports that uses MRP Tools to improve the inventory management and its use has reduced excess stock by 12% and improved the forecast for spare parts by 30%. In this way the maintenance tasks are addressed properly and it has minimized the downtime and helped to maintain high standards of airport operation.

4. Frankfurt International Airport uses Lean Six Sigma strategies to improve baggage handling process. Frankfurt is also the world's first airport to regularly employ walk through scanners for passengers' security checks; QPSWeb 2000 which can process 18000 departing passengers per day. Bags ID: use high speed computer vision and AI to identify bags in a system that makes traveling with all bags at the airport much more direct for a passenger. The main technologies include RFID tagging, AI predicting analytic and real time monitoring (Mäkelä, 2024).

FRA in 2023 introduced a deep learning neural network system to predict turbulence impacts on specific routes, resulting in a 20% improvement in flight punctuality (Lozano Tafur et al., 2025). In this airport another use is SEER, a computer vision combined with AI system that monitor and analyse each stage of aircraft handling, ground turnaround etc. It has been deployed in 5 gates, with plans to expand to 20 gates later.

2. Main Part

2.1. Study Objective

The focus of this paper is on the airport supply chain because the airports and air traffic, besides the hospitals are the places where the response must be very fast and where a small change needs hours or days to be put back at normality. As indicated in the thesis title the comparative analysis is the main point of it; comparative analysis of various artificial intelligence techniques is crucial for identifying the most effective methodologies in aviation operations. The analysis conducted in this study involves the implementation of two different techniques; the Rule Based AI to predict the taxi time for Dubai International Airport and XG Boost to predict the taxi time in Frankfurt International Airport. After the implementation of two different techniques in two different airports; I decided to use two different methods for the same data and in the same airports to see how the result will change.

Research Questions:

1. Which are the key AI applications in airport supply chain in EU and Middle East selected airports?

2. What are the differences in AI implementation between the EU and Middle East airports?

3. What will happen if the Frankfurt International Airport will use the XG Boost to predict the taxi time and in this way to regulate the ground movements?

4. How will the use of Rule Based AI change the prediction about the taxi time in Dubai International Airport?

The central topic of this paper and all the master thesis is the reduction of the taxi time. Before predicting it is essential to clarify how taxi time is defined and calculated. In this paper the definition is based in the definition by von der Burg & Sharpanskykh (2025), referring to the taxi time of an aircraft as the time it travels over the airport surface from runway to gate or the other way around. In this paper the exact calculation of taxi time is distinguished between the taxi time for departure which is the difference between the gate leaving and take off and for the arrival as the difference between the landing and gate arrival.

Another concept which is also very important is the delay, referring in this paper as the time difference between the scheduled landing and the real landing and for the departure as the difference between the scheduled time for take-off and the real take off time.

Why is it important to reduce the taxi time and the ground operations; the primary reason; the airplanes earn only while flying. Even minor disruptions of 2 to 5 minutes can result in hours by the end of the day (Kazda & Caves, 2015, p.173,188). Understanding ground operations is essential before evaluating how AI can improve efficiency, as these influences directly the taxi time, delay and overall airport performance. The following section provides an overview of the activities included in ground operations and their relevance for airport performance.

2.2. Ground Operation of Aircraft

An arrival flight that has just landed, it slows down and leaves the runway from the designated fast lane and taxis to the designated gate (Sun *et al.*, 2022). For a departure one it pushes back and start up first then taxis to wait outside the designated runway and finally enters the runway and accelerates until leaving the ground.

Push-back time delay is the delay of push-back for a period of time after the expected time, to prevent the aircraft from stopping to wait to detouring on the taxiway due to collision (Sun et al., 2022). According to (Dönmez, 2024) the aircraft is considered to be on ground if their altitude was recorded as zero. The taxi time is calculated as the difference between the first and last recorded ground positions of each aircraft.

Table 2. Aircraft separation requirements (seconds)

Leading/Following	Heavy	Medium	Light
Heavy	90	120	120
Medium	60	60	60
Light	60	60	60

Table 2.1 Aircraft separation requirement (Liu et al., 2024, Table 2)

Referring to Farhadi, Ghoniem, and Al Salem (2014); the ICAO standard classifies aircraft along three main weight classes (Heavy, Medium and Light) based on their maximum take-off weight. This is also one of the classifications used to predict the taxi time with the XG Boost method in this paper, presented in detail in the next chapter. It requires a minimum separation of 2 min between any pair of operation for any weight class unless a light landing follows a heavy or medium landing, in which case a 3 min minimum separation time must be enforced. (Farhadi, Ghoniem & Al Salem, 2014)

2.3. Methodology

This study uses a mixed approach combining case studies for the chosen airports and also descriptive statistics like the average delay per each airport, the number of flights per each aircraft type, the average taxi time for per each terminal. Using the following keywords for online search; Airport, Artificial Intelligence, AI in airports, SCM, Airport Supply Chain, Blockchain Technology, Technology and Airport, Managerial Solution, Operation Management and Technology Strategies, Frankfurt, Doha, Dubai, Amsterdam. The platforms used are Isi web of Science; Google Scholars; Usearch; Jstor; Elsevier, borrowed books from Hauptbibliothek der Universität Wien, focusing on the articles from 2008 and on. For the case study part, its protocol has been followed:

1. Aim of the study: to reduce the taxi time and improve airport operations.
2. Issues to address: delays.
3. Case Study sites: four different airports; AMS, FRAU, DXB and DOH.
4. Source of information: websites of the chosen airports, different papers regarding the use of AI in the Airport Supply Chain.
5. Format of narrative: The case study protocol explained the research design, the locations of the case studies, and how data would be collected and analysed.

2.4. Data Collection

In this paper the used method for data collection is the ADS-B, it has three key phases: data collection, the data are collected from flight-radar and flight-aware, preprocessing; the data were manually collected and subsequently put into structured Excel datasets, formatting as a table and analysis. The data has the following structure per each airport on each day one excels file and this is separated in different sheets for: Morning Departure, Morning Arrival, Afternoon Departure and Afternoon Arrival. Each of the sheets has the following columns: Flights which refers to the flight number, aircraft refereeing to the aircraft model, from the third column we can distinguish between arrival and departure flights. For the arrival we have: Terminal, Landing which is used for the time the aircraft is landed and from that point the taxi time starts to be calculated, Gate Arrival referring to the time the aircraft is ready to be disembarked, Delay; if this column is empty than there is no delay the flight has arrived and is leaving on time and the last columns is the Taxi Time which is the most important for the objective of this paper, in table 2.2 and 2.3 there is a small representation of the data in excel. I started first to collect the data for 25/12/2024 for both airports in the two different time of the day; morning from 06:00 to 09:00 and afternoon from 16:00 to 19:00 these are also the peak hours for the airport movements. I have chosen to work with 25/12, 29/12, 22/08, because 25/12 is Sunday which represents the weekend and 29/12, 22/08 are Wednesday and Friday to represent weekdays. On 29/12/2024 I also collected the data but, in this day, there were a lot of distortion in both airports, because on that day there was a high number of airplane accidents. 29/12/2024 is the day with the most incidents in 2024.

Flight	Aircraft	Terminal	Landing	Gate Arrival	Delay	Taxi Time
FDB718	737 MAX 8	T2	16:00	16:06	36	6
FDB1026	737 MAX 8	T3	16:03	16:10	10	7
FDB8626	737 MAX 8	T2	16:06	16:14	39	8
DAO184	737-300	-	16:09	16:19	19	10
KNE221	A320 NEO	T1	16:17	16:26	-	9
IGO1473	A320 NEO	T1	16:19	16:30	-	11
FDB1464	737 MAX 8	T3	16:22	16:27	22	5

Table 2.2: Afternoon Arrival DXB 22082025

Flight	Aircraft	Gate	Terminal	Gate Leaving	Take-off	Delay	Taxi Time
UAE125	777-300	B25	T3	15:49	16:04	-	15
UAE5	A380-800	A24	T3	15:51	16:06	11	15
UAE803	A380-800	B15	T3	16:00	16:15	20	15
UAE721	777-300 ER	A17	T3	15:53	16:20	15	27
UAE648	777-300 ER	B22	T3	16:09	16:24	4	15

FDB178 1	737 MAX 8	C13	T3	15:43	16:27	42	44
AEE959	A320 NEO	D7	T1	14:55	16:29	84	94

Table 2.3: Afternoon Departure DXB 220822025

After gathering the data, the next step was to find the average delay per each airport in each day. I will present here the code used in Python 3.13.1 with main libraries: panda, numoy, matplotlib, XG-Boost inside PYCHARM virtual environment, I have used a Macbook Air 13.3 inch, M1 chip with 8GB RAM, MacOS Sequia 15.2 and in the Appendix A Table 5.3 Average Delay for DXB&FRA you can find and read all the results.

```
# Calculate average delay
avg_delay = df['delay_minutes'].mean()
print(f"Average delay in minutes: {avg_delay:.2f}" if pd.notna(avg_delay) else "No
delay data available")
```

Code 2.1.1 Average Delay Calculation

As we can see from the results that the largest delay is in the FRA on 29/12/2024 in the morning with a value of 31.37 minutes followed by the DXB on 22/08/2025 with an average delay on arrival afternoon of 29.86 minutes. The smallest delay we encounter in FRA on 25/12/2024 Morning Departure of 8.17 minutes. As it can be seen from these results is difficult to make predictions because the same operation in the same part of the day, with almost the same number of flights can have different values for the delay.

In the following paragraph it will be presented a short overview of the code used to find the number of the flights per each aircraft type and later representing the results as a table. In the appendix B you can find all table with all results.

```
for sheet in sheets:
    df = pd.read_excel(file_path,

    sheet_name=sheet) if "Aircraft" not in

    df.columns:

        print(f"Sheet '{sheet}' does not have an 'Aircraft'

        column.") continue

    counts = df["Aircraft"].value_counts()                    // it add to the list of flights per

aircraft and counts

    for aircraft_model, num in counts.items():

        results.append([sheet, aircraft_model, int(num)])
```

Code 2.1.2 Read the excel

Sheet	Aircraft Model	Flights
Morning Departure	737 MAX 8	23
Morning Departure	777-300 ER	22
Morning Departure	A380-800	15
Morning Departure	737-800	8
Morning Departure	A321	3
Morning Departure	A350-900	2
Morning Departure	A320 NEO	2
Morning Departure	A321 NEO	1
Morning Departure	A330-300	1
Morning Departure	A320	1
Morning Departure	737 MAX 9	1
Morning Departure	777-200 LR	1
Morning Arrival	777-300 ER	22

Morning Arrival	737 MAX 8	19
Morning Arrival	A380-800	16
Morning Arrival	737-800	7

Table 2.4 Flights per aircraft DXB 22082025

After computing the average taxi time and the average delay going through the next chapters; the core of the paper and explain each of the methods and the codes that I have implemented in Python and see their use with real data.

2.5. Case Study Methods

2.5.1. Rule Based AI

Rule Based AI algorithm work is based on the, if then statement. The model predicts taxi time by combining historical averages with predefined reference values using weight coefficients. For the case study; it is IF Aircraft Model x, THEN Taxi Time =y. The first try was the rule-based AI code with average taxi taken from internet for each aircraft type but the results that came out were; MAE=3.62 and RMSE=5.12 and for departure; MAE=11.08 and RMSE= 14.80 that are not good predictions especially for the departure. The next step was to include also the terminal and average taxi time per terminal, but still there was no improvement in the results. In this situation another point was added; the time interval split in 30 minutes, but this gave no change in the result.

In the next part it will be presented the code, its philosophy and its main parts:

1. It finds the train files which are 25/12/2024 and 22/08/2025, the test file which is 29/12/2024.
2. The average taxi time for the arrival and departure was computed which gave the following results: arrival reference value is 7.67 and departure reference value is

17.33 minutes.

3. In the Rule Based Algorithm will not only be used the train files but will use also the reference values given in point 2. The weight of the model with 2 train files is 0.7 and the weight of the reference values is 0.3. During the computation and the work with the python code, different values for the weight have been tried.

   # === Reference taxi times and their weights ===

   arrival_ref = 7.67

   departure_ref = 17.33

   weight_model = 0.7

   weight_ref = 0.3

   Code 2.2 Reference and weight in taxi time

4. The model excludes all the empty cells without taxi time the next step is to load and prepare the training data.

5. After loading and reading the training data it computes the average taxi time for the model grouped by the operation type and aircraft model.

   # Compute average taxi per Aircraft Model from training data

   avg_taxi_model = train_df.groupby(['OperationType',

   'Aircraft'])['TaxiTime'].mean().to_dict()

   Code 2.3 Computation of average taxi time

6. In this phase the taxi time is computed, and the test data is loaded.

7. The main part of the code and the most important point of the model is the rule based ai prediction. First the function is defined, get the computed taxi time before and it is made separately for the arrival and departure.

   # define the function for the prediction and get the average taxi time

   def predict_taxi(row):

   key = (row['OperationType'], row['Aircraft'])

model_avg = avg_taxi_model.get(key, np.nan)

if pd.isna(model_avg):

Code 2.4 Definition of Rule Based Function

Calculate the value which is the sum of the products of model average*weight of the model and the reference value*weight that the reference has for this model.

 # blend model avg with reference

ref_value = arrival_ref if row['OperationType'] == 'Arrival' else departure_ref

*return model_avg * weight_model + ref_value * weight_ref*

8. Call the function which loaded the test data and add to that the following columns: Predicted Taxi,Difference which is the difference between the actual taxi time and the predicted taxi time.

test_df['Predicted_Taxi'] = test_df.apply(predict_taxi, axis=1)

test_df['Difference'] = test_df['TaxiTime'] - test_df['Predicted_Taxi']

Code 2.5 Call the function

9. After predicting the taxi time, it should be evaluated how good the model is and for this the following metrics: RMSE and MAE have been used.

mae = mean_absolute_error(df['TaxiTime'], df['Predicted_Taxi'])

rmse = np.sqrt(mean_squared_error(df['TaxiTime'],

Code 2.6 Evaluation Rule Based AI

10. Save all the results and predictions in the excel.

After working with Rule Based AI which is one of the first AI algorithms, the next part of the thesis will be focused on XG Boost, that is a more advanced algorithm.

2.5.2. XG BOOST

XG Boost is part of gradient boosting algorithms which are part of the category supervised algorithm. It is highly efficient and can operate on standard CPUs, making them ideal to deal with scenarios with limited computational resources. This supervised algorithm has an accuracy between 90 to 95% and it needs medium costs for computational. It is used to predict the ETA, collision risk detection with main advantages: the high accuracy with labelled data but it has also a disadvantage that it requires labelled datasets. The models based on Gradient Boosting have proven particularly effectiveness in predicting climb trajectories and dynamically controlling speed in Extended Arrival Management systems, which reduces emissions and improve efficiency (Lozano Tafur et al., 2025). Gradient Boosting builds model sequentially, and each model tries to correct the errors made by the previous ones (Paquette, 2023). The algorithm starts with a simple decision tree, makes predictions and compute the errors. A new tree is then trained to predict those errors. The reason for choosing it; is because predicting the taxi time is a regression task and the goal is to estimate a continuous value. One of the main points, which needed a lot of attention is the reproduction of the data and the code; was that all the columns have the same names and that they do not have any extra space at the end because if they have then the code cannot read that column and as result do not read also the data in that column.

Different models and codes all related to XG Boost have been used; for example, to group the aircrafts according to their weight and run the model to predict the taxi time, another model was to ignore the taxi time greater than 50 minutes and do not consider the delay more than 50 minutes because this means that something abnormal is happening.

The following section will present some parts of the code and some explanations why they are used.

1. Locating the 2 train files, one try was also with three train files, but the problem was that on 29/12/2024 there were a lot of delays, and this makes distortions in the model

2. Ensure that we have a file where the results will be saved.
3. The categorical variables for departure and arrival which defines which columns are non- numeric.
4. Prepare the data for training when it keeps only the useful columns and split the data into X-Inputs and Y-Target variable which in our case is the Taxi Time.

```
def prepare_X_y(df, categorical_cols):
  df = df.copy()
  cols_to_keep = categorical_cols + ['TaxiTime', 'OperationType']
  df = df[[col for col in cols_to_keep if col in df.columns]]
  df_encoded = pd.get_dummies(df, columns=categorical_cols + ['OperationType'])
  X = df_encoded.drop(columns=['TaxiTime'])
  y = df_encoded['TaxiTime']
  X = X.apply(pd.to_numeric, errors='coerce').fillna(0).astype(float)
  return X, y
```

Code 2.7 Define the preparation function

5. The train model which is composed in the following way 80% is training and 20% is validation to test the accuracy of the model is defined. The key parameters of it are: 200 trees which is the number of estimators, 0.05 is the learning rate; how fast the model learns, 8 is the max depth which is the complexity of each tree. It will calculate the metrics MAE and RMSE and the output will be the trained model.

```
def train_model(X, y):
  X_train, X_val, y_train, y_val = train_test_split(X, y, test_size=0.2, random_state=42)
  y_train = y_train.squeeze().astype(float)
```

```
  y_val = y_val.squeeze().astype(float)
model = XGBRegressor(n_estimators=200, learning_rate=0.05, max_depth=8,
random_state=42)
  model.fit(X_train, y_train)
  y_val_pred = model.predict(X_val)
  val_mae = mean_absolute_error(y_val, y_val_pred)
  val_rmse = sqrt(mean_squared_error(y_val, y_val_pred))

  print(f"Validation MAE: {val_mae:.3f}, RMSE: {val_rmse:.3f}")
  return model, X_train.columns.tolist()
```

Code 2.8 Define the train files

6. The model prepares the new data.
7. Train and save the model

```
# === Train models ===
X_arrival, y_arrival = prepare_X_y(train_arrival, categorical_cols_arrival)
X_departure, y_departure = prepare_X_y(train_departure, categorical_cols_departure)
```

Code 2.9 Train model is saved

8. Predict on new data

```
# Predict Arrival
if not df_arrival.empty:
  X_arrival_pred = prepare_for_prediction(df_arrival, categorical_cols_arrival,
features_arrival)
  preds_arrival = model_arrival.predict(X_arrival_pred)
```

```
  df_arrival.loc[:, 'TaxiTime_Predicted'] = np.round(preds_arrival, 2)
# Predict Departure
if not df_departure.empty:
  X_departure_pred = prepare_for_prediction(df_departure, categorical_cols_departure,
features_departure)
  preds_departure = model_departure.predict(X_departure_pred)
  df_departure.loc[:, 'TaxiTime_Predicted'] = np.round(preds_departure, 2)
# Combine predictions
df_predicted = pd.concat([df_arrival, df_departure])
if df_predicted.empty:
  print(f"No valid rows to predict in sheet {sheet}")
  continue
```

Code 2.10 Prediction of taxi time

9. Save the results in excel

After having the first insights and understood the basic codes the next chapter will be more advanced. All the codes and all their explanations can be found in Appendix B.

2.6. Concepts Advancements

In chapter 1.3 we got to know to some concepts that were very important to understand the thesis, now in the chapter 2.6 we will go further and take some extra information for these concepts.

The perfect turnaround does not just save time, but it drives down costs, reduces environmental impact and enhances the overall passenger experience (Benchmarket

Report, 2024.4). The Deep Turnaround algorithm monitor all activities on the apron, providing high performance event at new stands. Its data-centric AI approach also reduces implementation time at the airport (Amsterdam Airport Schiphol, 2024).
According to the EUROCONTOL Performance Review Report, the largest source of primary delay are ground operations with 33% followed by 21% air traffic flow management regulations while secondary delays make up 44% (Evler, Asadi, Preis & Fricke, 2021).) Going back to the concept of block chain technology; Airport Collaborative Decision Making (A-CDM) is one of the most relevant block chain technology applications in the airport industry. It promotes cooperation between the main players in the aviation industry and the air traffic controllers to reduce in efficiency, fragmentation and uncoordinated operations and to stimulate and manage information and data sharing. The A-CDM initiative marks a shift in the turnaround management practices moving from first come, first served to first ready, first served. It is an integrated platform that, in real time, transfers information on the status of all departing flights to the EUROCONTROL Management Operations Centre, which in turn transmits it to other partner airports (Di Vaio & Varriale, 2020). Collaborative Decision-Making systems can optimize the available limited resources that prevail in the terminal (Mäkelä, 2024). The measure of the efficiency of the airport management is divided in the structural efficiency and operational efficiency. The structural efficiency measures by incorporating inputs such as the number of runways, the capacity of car parks, the terminal area; whether immovable assets like land utilization are used productively and measures whether terminal land is used efficiently.
Operational efficiency reflects the capability of an airport to generate outputs relative to its operating inputs (Ozsoy and Orkcu, 2021). A-CDM represents a standardized network based approach to managing airport operations. Examples of the use of it in the aviation industry are: Airbus Sky-wise uses AI to optimize flight paths for airlines like Lufthansa,

considering weather patterns, air traffic control restrictions, and fuel efficiency, DXB and FRA uses it (Airbus, 2017). Another example is GEAviation's Predict system, which evaluates sensor data from aircraft engines to forecast maintenance requirements and plan preventive repairs (GE Aviation, 2016).

Connecting now to the airports chosen for this paper which of them uses it and which still not, I will go through them one by one:

1. AMS: has fully implemented it and it is integrated with the EUROCONTROL Network Manager, it is welcomed as the 28th full A-CDM airport.

2. IBG extended its contract with DOH to support it under advanced air traffic management strategies, DOH is in the process of being part of the A-CDM.

3. DXB approached between 2019-2020, now it is actively involved in it and in Total Airport Management Initiatives.

4. FRA has fully implemented A-CDM to improve air traffic flow and capacity management by reducing delays and optimizing resource utilization.

THE GOAL IS TO FORECAST WELL FORWARD NOT TO PERFECTLY FIT THE PAST.

(EDX Lecture 2025)

3. Results

After understanding the methods and their work, the next section presents the results per each implemented method. The first shown are the results about the average taxi time per aircraft model and followed by the average delay per each airport on each day.

3.1. Average Taxi Time

In this subchapter, the results about the Average Taxi Time per aircraft model in each day, in each of the chosen airports will be presented.

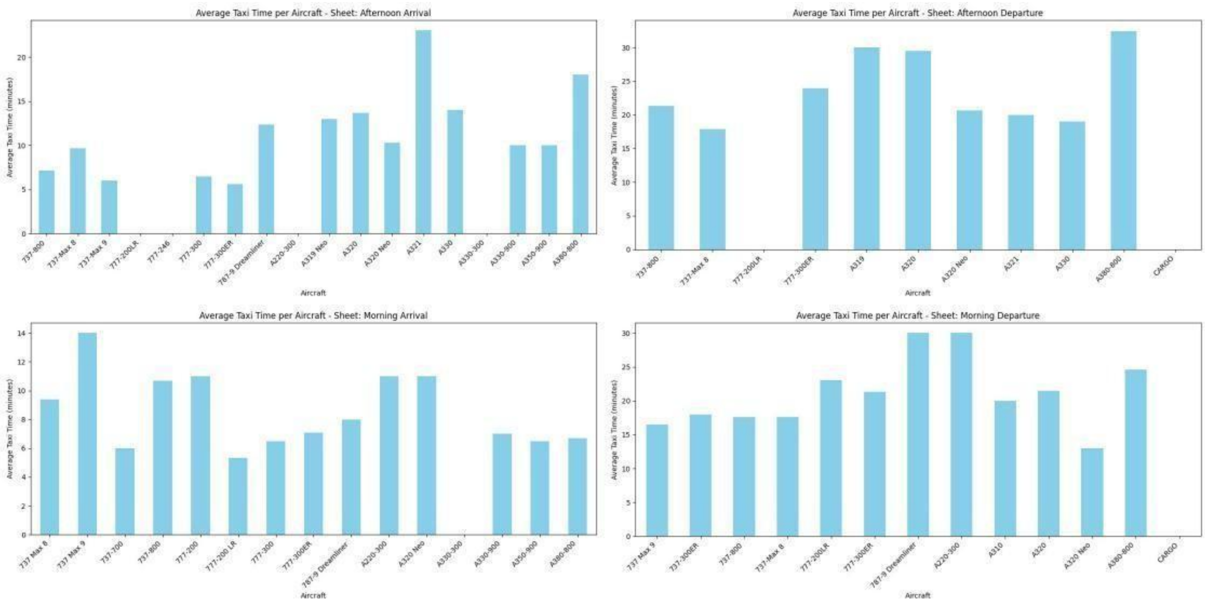

Figure 3.1: Avg Taxi Time DXB 25122024

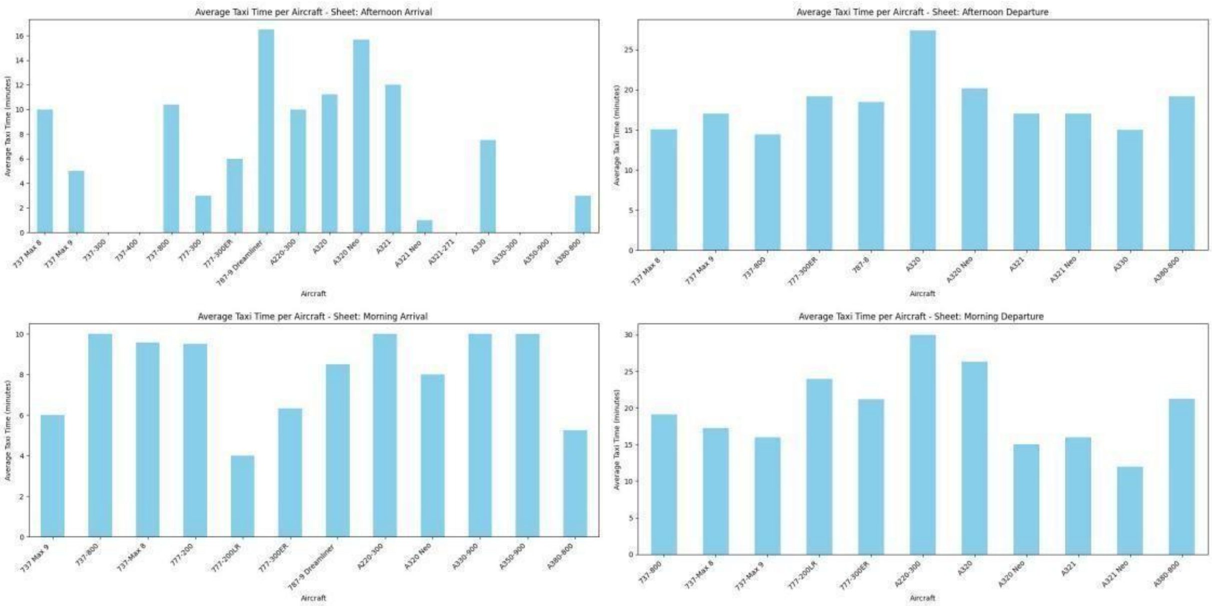

Figure 3.2: Avg Taxi Time DXB 29122024

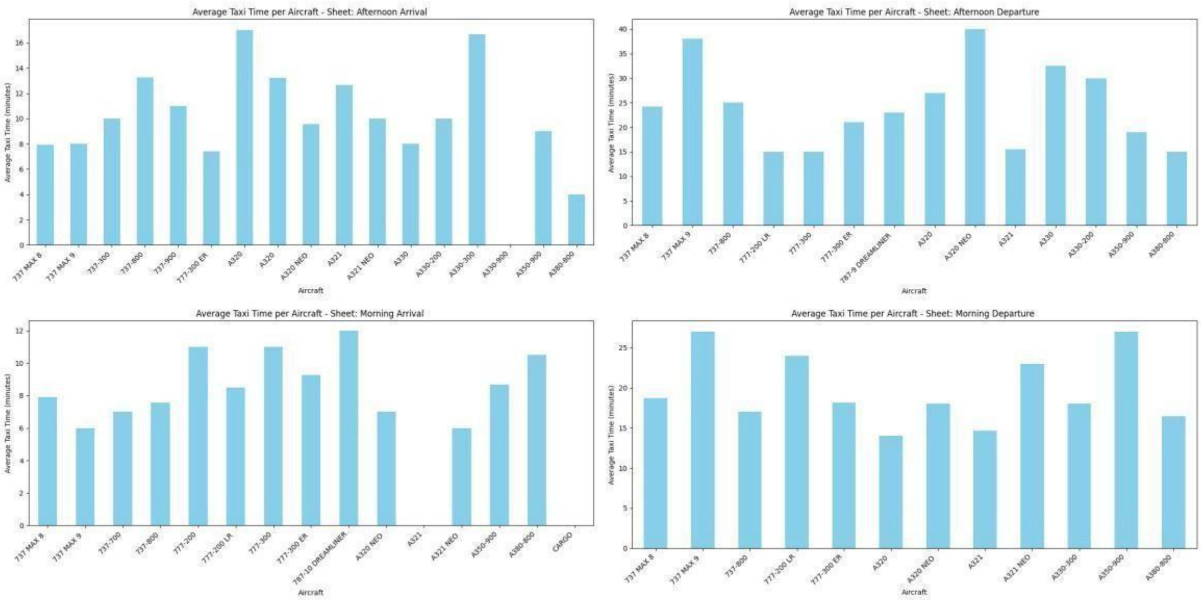

Figure 3.3 Avg Taxi Time DXB 22082025

In the next pages will be presented the same situation for Frankfurt International Airport.

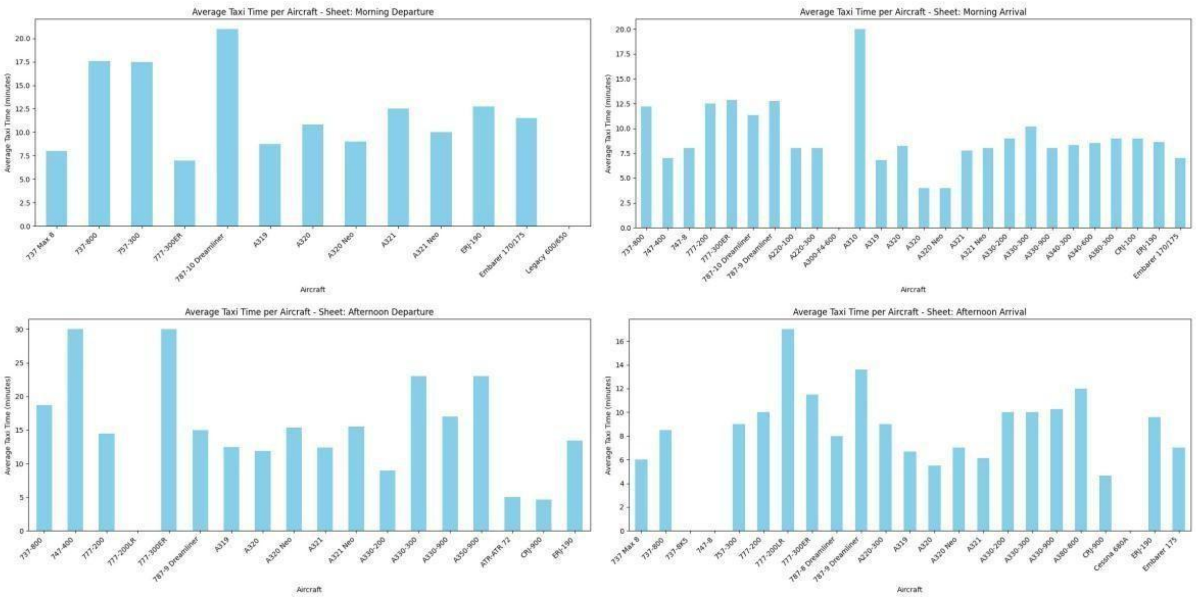

Figure 3.4 Avg Taxi Time FRA 25122024

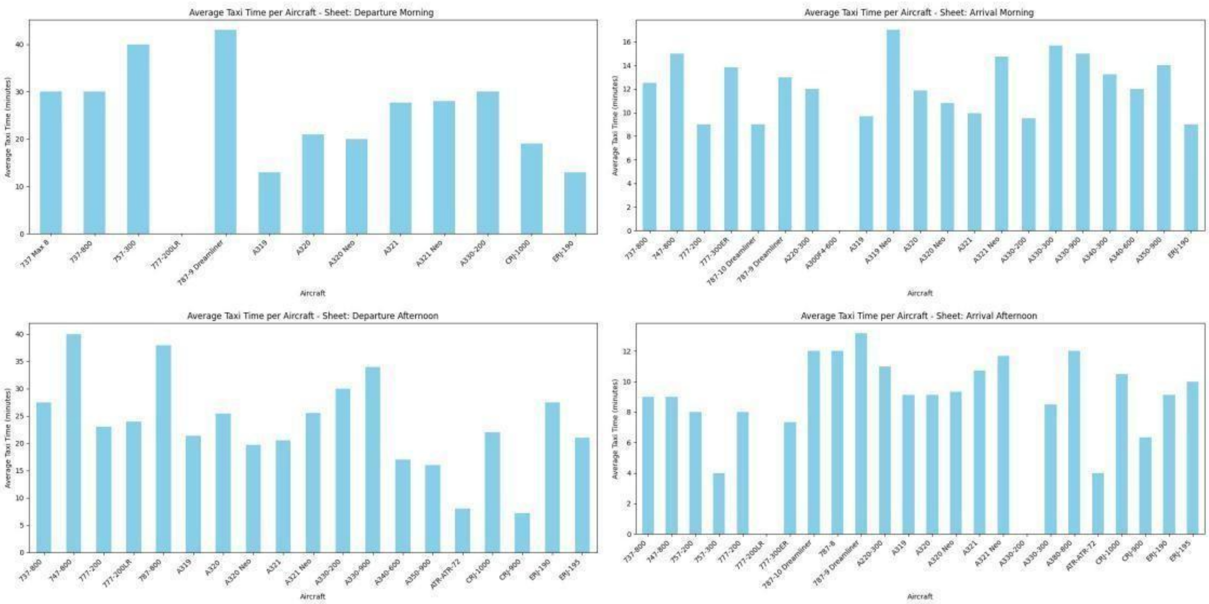

Figure 3.5 Avg Taxi Time FRA 29122024

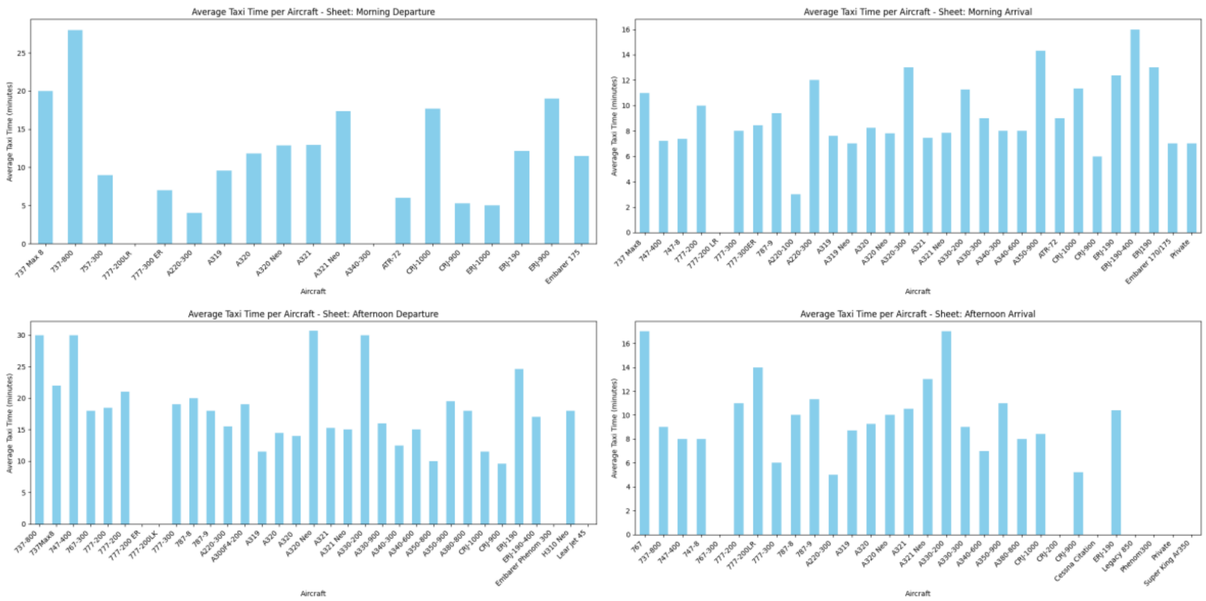

Figure 3.6 Avg Taxi Time FRA 26052025

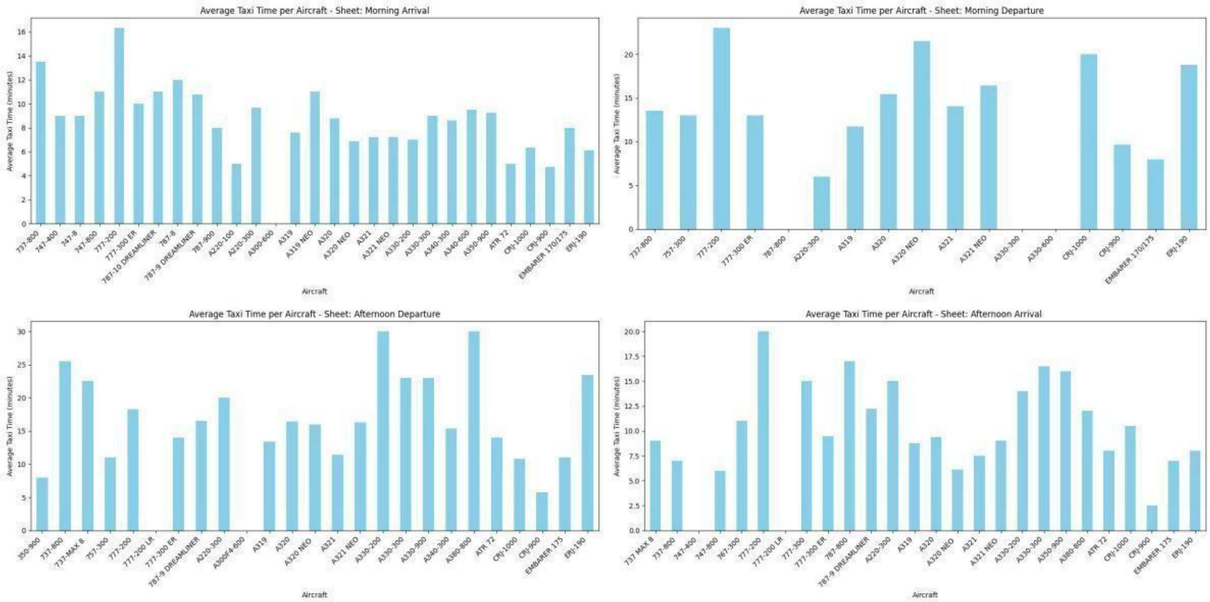

Figure 3.7 Avg Taxi Time FRA 22082025

In the following figure will be presented the taxi time in each terminal in each airport. As already noted in the first chapter the taxi time of the aircrafts despite being an arrival or departure it is influenced by the terminal where the operations will take place.

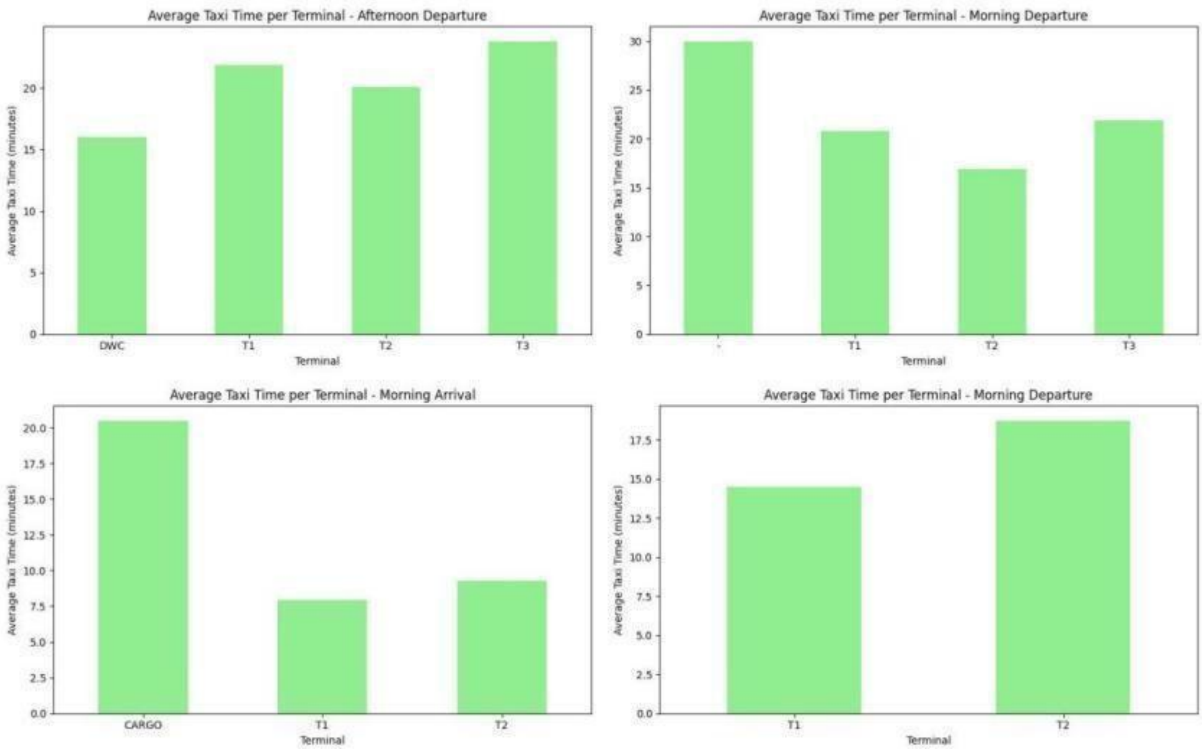

Figure 3.8: Avg Taxi Terminal DXB 25122024

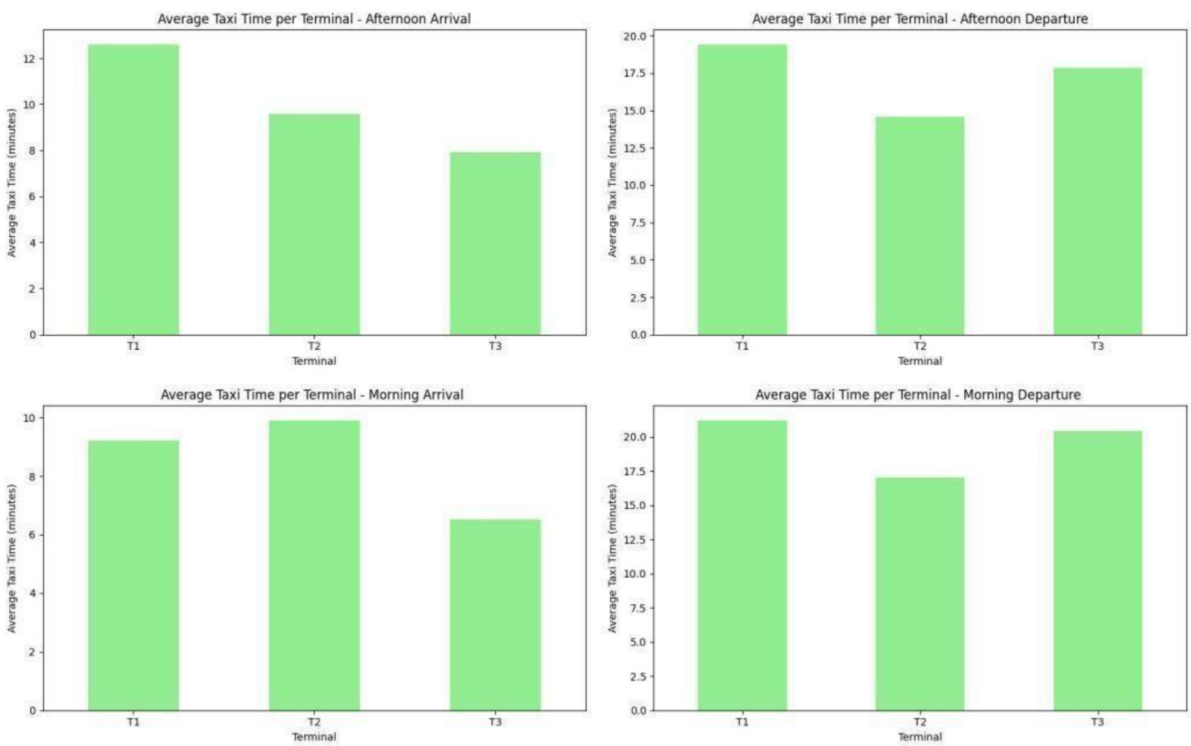

Figure 3.9: Avg Taxi Terminal DXB 29122024

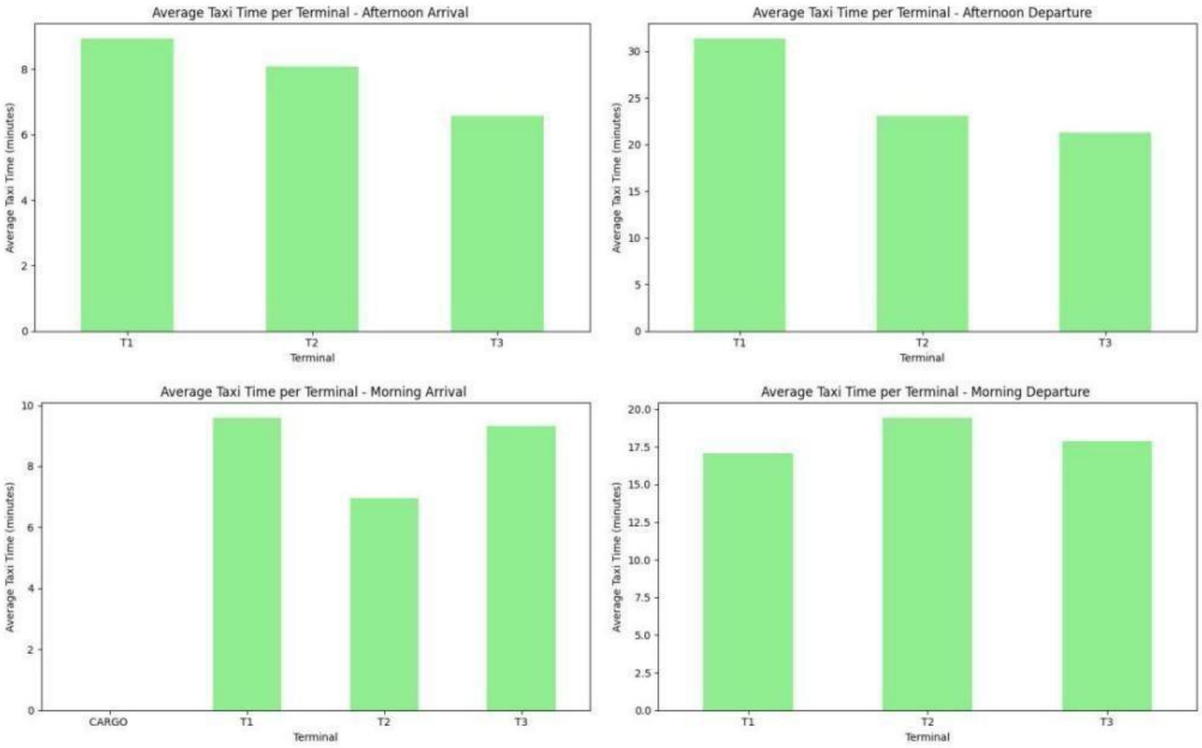

Figure 3.10 Avg Taxi Terminal DXB 22082025

In the following figures 3.11 to 3.14 the average taxi time per terminal in each day for Frankfurt International Airport is presented. The results will not be the same because the number of the terminals is not the same.

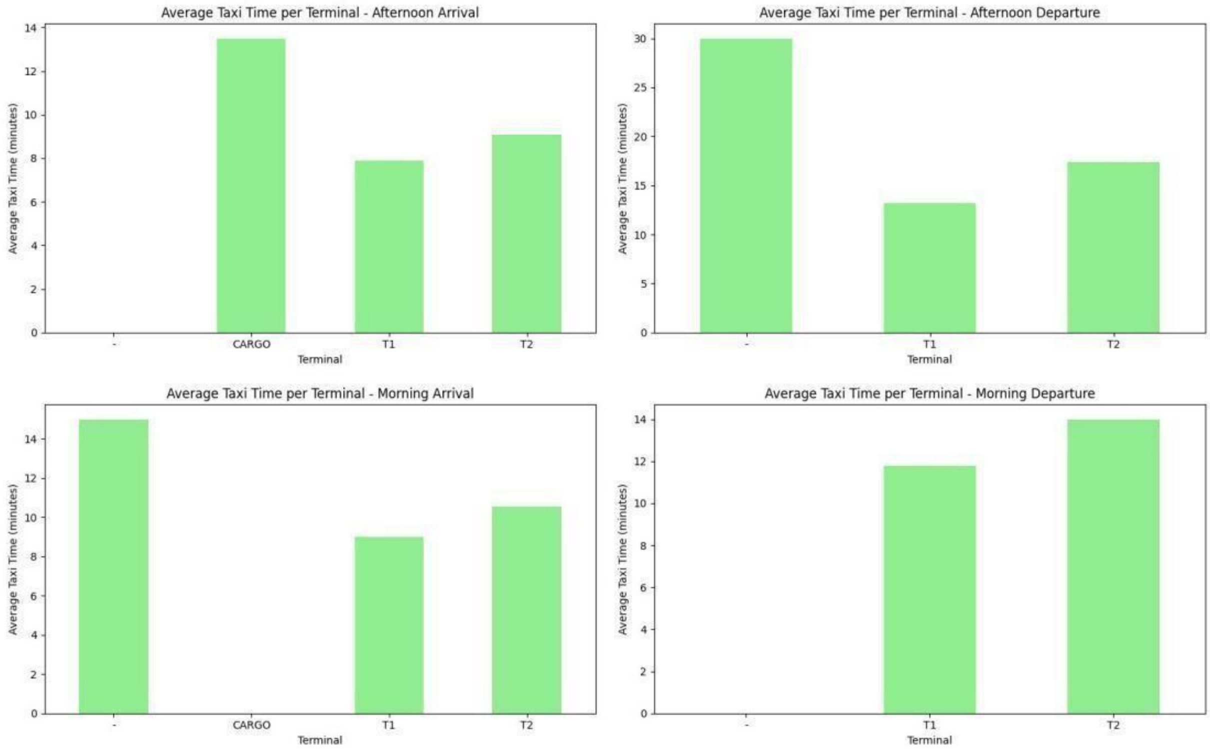

Figure 3.11 Avg Taxi Terminal FRA 25122024

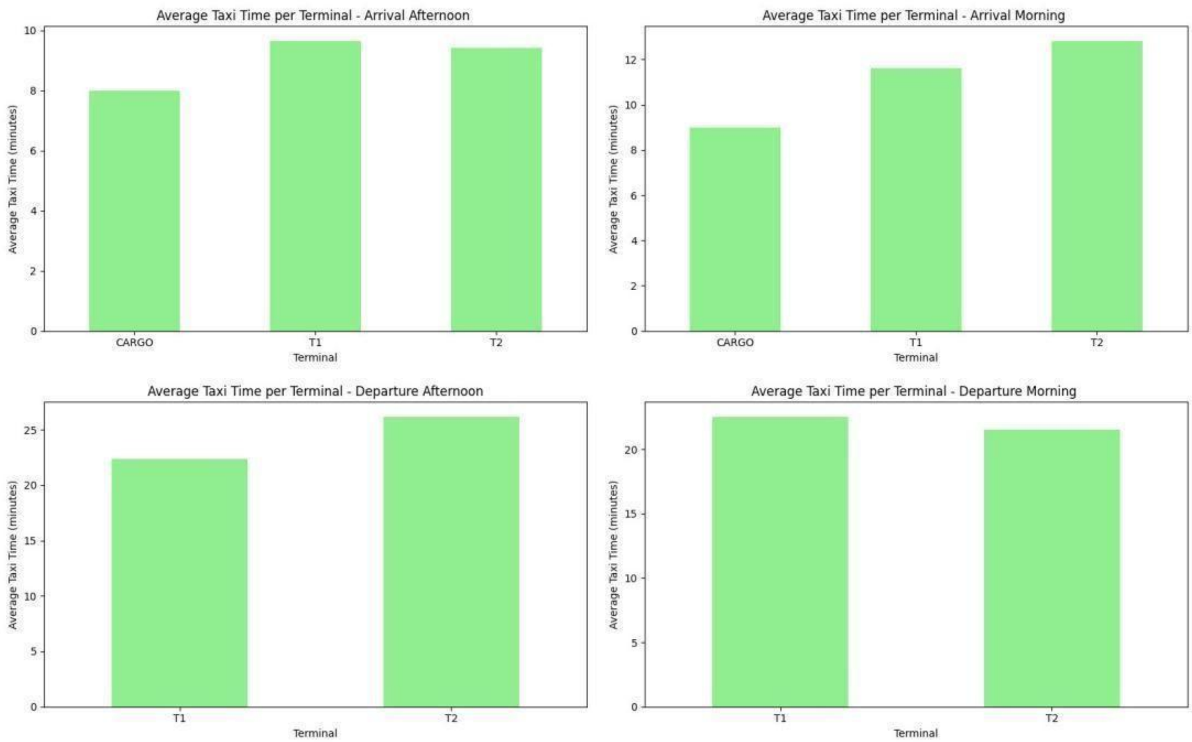

Figure 3.12 Avg Taxi Terminal FRA 29122024

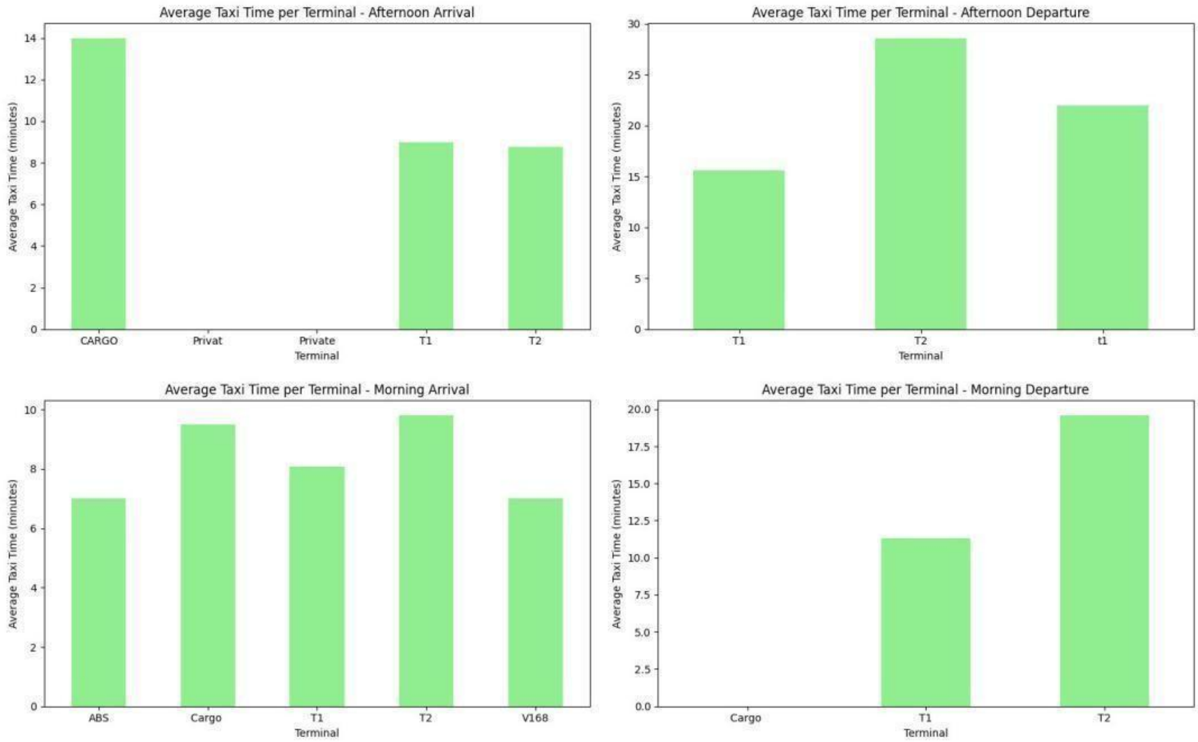

Figure 3.13 Avg Taxi Terminal FRA 26052025

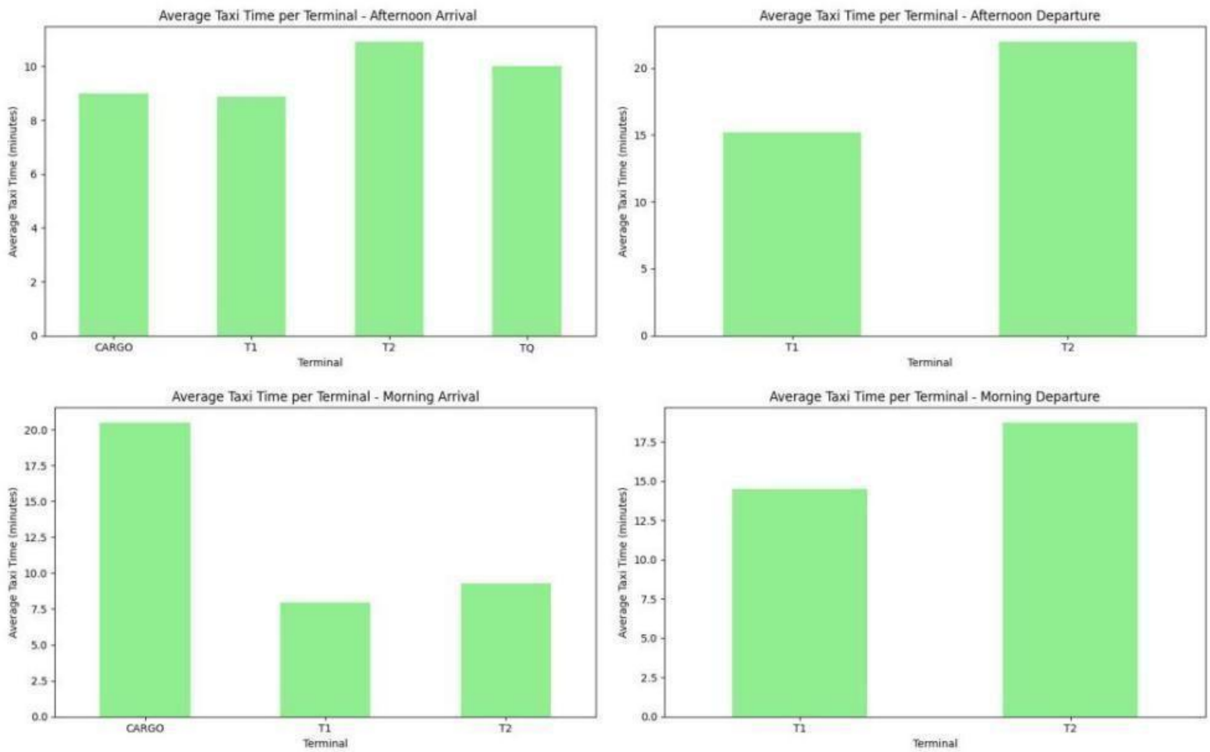

Figure 3.14 Avg Taxi Terminal FRA 22082025

In the last chapter, the main graphs showing the average taxi time per airport, per operation, for each part of the day are presented. Table 3.1 is a resume of the graphs presented in this chapter. In this table is represented the average taxi time on each day for both operations: arrival and departure in the chosen airports for this case study.

Airport	Date	Operation	Average Taxi Time
DXB	25/12/2024	Arrival	8.71
DXB	25/12/2024	Departure	21.22
DXB	29/12/2024	Arrival	8.86
DXB	29/12/2024	Departure	18.99
DXB	22/08/2025	Arrival	9.47
DXB	22/08/2025	Departure	21.09
FRA	25/12/2024	Arrival	8.94
FRA	25/12/2024	Departure	13.24
FRA	29/12/2024	Arrival	10.58
FRA	29/12/2024	Departure	23.25
FRA	26/05/2025	Arrival	9.11
FRA	26/05/2025	Departure	15.29
FRA	22/08/2025	Arrival	8.72
FRA	22/08/2025	Departure	15.54

Table 3.1 Average Taxi Time

Confirming also the statement that the departure has higher taxi time than arrival; 15.54-23.25 minutes for departure and 8.71-9.47 minutes for arrival.

3.2. Case Study Results

After taking the first insights and results about the average taxi time per each airport in chapter 3.2 will be presented the results of the methods: XG Boost and Rule-Based AI.

During the implementation of the code for XG Boost Method, for the seek of improvement of the results; different derivations of the main methods have been implemented such as:

1. Grouping the aircraft based on the weight gave the result for arrival: RMSE= 3.391 and MAE=
2. 589 but for departure: RMSE= 12.087 and MAE=7.001 which are not better than the result that we had in this way the basic model will be kept.

2. The model not considering the delay and taxi time greater than 50 minutes the results are as following: for arrivals: MAE=2.492 and RMSE=3.183 and for departures: RMSE= 5.069 and MAE=3.770. There is an improvement but still the final model has better results. The results of the main model are presented in table 3.2.

To define if the model has performed good or bad we need the statistics elements, to see and to arrive to one conclusion; the metrics used are: RMSE and MAE. RMSE stands for the root mean squared error and MAE stand for mean absolute error. In the next paragraph will be presented the values of these metrics.

Table 3.2 presents metrics for both methods and different scenarios for both airports.

Method	Airport	MAE Arrival	RMSE Arrival	MAE Departure	RMSE Departure
XG Boost Group by Weight	FRA	2,589	3,391	7,001	12,087

XG Boost Taxitime <40	FRA	2,492	3,183	3,77	5,069
XG Boost Final	FRA	2,492	3,183	3,683	4,773
XG Boost Final	DXB	3,362	5,744	4,26	5,325
Rule Based AI	DXB	2.96	4.66	3.75	4.73
Rule Based AI	FRA1	2,674	3,623	5,792	6,997
Rule Based AI	FRA	3,093	4,231	10,67	13,42

Final model for XG Boost for the data taken from Frankfurt International Airport gave us the following results for Arrival: MAE=2.492, RMSE=3.183 and for Departure MAE=3.683 and RMSE=4. 773.If a comparison of these values has been made; this model is predicting more accurately and for final analysis will be based on that.

The results coming for the Rule Based AI in the data of DXB are as following for arrival: MAE=2.96, RMSE=4.66 and for the departure: MAE=3.75, RMSE=4.73, which shows that the model is predicting very well for arrival and departure. It has a difference of 2.96 minutes up or down in the prediction of the arrival taxi time and 3.75 for the departure taxi time.

Table 3.3 Comparison of final results

Method	Operation	Airport	Normal	Prediction
XG Boost	Arrival	FRA	8,72	8,76
XG Boost	Departure	FRA	15,54	12,9
Rule Based	Arrival	DXB	8,86	8,44
Rule Based	Departure	DXB	18,99	19,13

XG Boost	Arrival	DXB	9,47	8,68
XG Boost	Departure	DXB	21,09	19,99
Rule Based	Arrival	FRA	8,72	9,62
Rule Based	Departure	FRA	15,54	16,69

Table 3.3 Comparison of the taxi time

After carefully implementation of the XG Boost for the data of FRA and the data of DXB, it can conclude that XG Boost is more appropriate for FRA and DXB. If we will use these methods to predict the taxi time and later to regulate the ground operations, then we will have an improvement on the average taxi time in departure in FRA by 2.64 minutes and in DXB for arrival 0.42 minutes.

3.3. Sensitivity Analysis

Sensitivity analysis is used to see how sensitive the predictions; are to changes in the input variables. The results are read in the following way; if the number that we get per each parameter is high then it influences more; if the number is smaller than also its influence is less. The sensitivity analysis can be only implemented for the XG Boost algorithm because Rule Based AI applied fixed rules and there is not any learned model.

The following represents a code for sensitivity analysis.

```
# === Sensitivity Analysis ===

print("\n Sensitivity Analysis (Feature Importance)")

# Arrival

arr_importance = model_arrival.get_booster().get_score(importance_type='gain')
```

```
arr_sorted = sorted(arr_importance.items(), key=lambda x: x[1], reverse=True)

print("\n FRA Arrival Taxi Time Sensitivity:")
for feat, score in arr_sorted:

    print(f"{feat}: {score:.3f}")

# Departure

dep_importance = model_departure.get_booster().get_score(importance_type='gain')

dep_sorted = sorted(dep_importance.items(), key=lambda x: x[1], reverse=True)

print("\n FRA Departure Taxi Time Sensitivity:")

for feat, score in dep_sorted:

    print(f"{feat}: {score:.3f}")

# Optional: Save to file for your thesis

with open(os.path.join(output_folder, 'FRA_sensitivity.txt'), 'w') as f:

   f.write(" FRA Arrival Taxi Time Sensitivity:\n")

   for feat, score in arr_sorted:

       f.write(f"{feat}: {score:.3f}\n")

   f.write("\n FRA Departure Taxi Time

   Sensitivity:\n") for feat, score in dep_sorted:
```

```
    f.write(f"{feat}: {score:.3f}\n")

print("\n✅ Sensitivity analysis saved!")
```

Code 3.1 Sensitivity analysis

The sensitivity analysis is performed separately for arrivals and departures. And from the results can be concluded that the departure is highly influenced by the aircraft type where A320 Neo has a gain value of 495.836. Another influence factor is the terminal. For the arrival the main influence factor with a gain value of 36.386 is the aircraft type especially 787-9 Dream-liner. As we can see also from gain values, we can confirm that the departure is influenced higher than the arrival from the aircraft type and the terminal.

The results presented in chapter 3 are in the same direction with the results from other papers like: Dönmez (2024), (Lozano Tafur et al., 2025).

The integration of AI techniques in air traffic management has shown potential improving operational efficiency and decision making. The use of neural networks to predict the estimated time of arrival of aircraft has been proven to be both accurate and efficient, allowing for better planning and management of airport sources (Lozano Tafur et al., 2025)

The results of Dönmez (2024) show that while parallel runways effectively increase an airport's throughput, they also introduce complexities, especially in managing aircraft ground movements. The results from the paper are the following: the average taxi time for arrival aircraft using end-arounds is about 17 minutes, while those not using them the average taxi time is calculated to be around 9 minutes. For departure flights, the average taxi time for aircraft using end-arounds is calculated to be 22.4 minutes, while it is calculated to be 20.6 minutes for those not using it.

4. Discussion

The results presented above require further interpretation to understand their operational significance. Although the main objective of the airports is to reduce the taxi time, in the paper of (Graham, 2023), it says that the shortest taxi time is not always the optimal and often longer routes are used to avoid areas of congestion or crossing busy runways.

Still the results presented in table 3.3 can be better improved after implementing the metrics in large data sets. Another limitation in the preparation and witting of this paper was to find the cost of the implementation of the newest developments in both airports.

5. Conclusion

This thesis examined the role of artificial intelligence in improving airport supply chain operations through a comparative analysis of four major airports in EU and the Middle East: Amsterdam International Airport (AMS), Frankfurt International Airport (FRA), Dubai International Airport (DXB), and Hamad International Airport (DOH).
The findings indicate that the use of AI has significantly increased in recent years and the chosen airports are among the first implementers using it to predict the maintenance of the spare parts, to reduce the percentage of mishandled bags etc. We have a large volume of information for the EU airports and some limitation in the information for the Middle East Airports. Both parts of the world are using AI in the same direction, but their difference is in the type of algorithms that they use. The primary objective of this paper was to evaluate methods for reducing taxi time and improving ground operations. The XG Boost Method applied to FRA data demonstrated a stronger improvement in the taxi time prediction, particularly for departures. In the DXB data the Rule Based AI method has been used, showing an improvement, but if the two methods are compared

can clearly be concluded that the improvement coming from XG Boost algorithm is higher than the one of Rule Based AI.

Furthermore, the results of the sensitivity analysis indicate that taxi time is significantly influenced by factors such as aircraft type and terminal allocation.

This paper demonstrates that more sophisticated models such as XG-Boost, provide more accurate and reliable predictions compared to traditional rule-based approaches.

6. Future Research

While the swift evolution of artificial intelligence is noteworthy, it is crucial to ensure that its implementation adheres to key performance indicators related to cybersecurity and prioritizes the safety of all parties involved.

By 2030 the use of AI will be in every step and process of the process at the airport supply chain. This paper can be useful for the managers working in the aviation sector in order to make their job easier and to improve the operation in the chosen airports but not only.

These methods can be used also in other airports data and see how it will improve the overall operation compared with the model that they are using now.

Future research could extend this study by incorporating optimization models to reduce taxi time, while integrating constraints such as runway capacity, aircraft separation, and terminal allocation. This would enable more precise operational decision-making and greater efficiency in airport ground operations.

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Appendix A

Airport	Date	Operation	Time	Taxi Time	Terminal
DXB	**25/12/2024**	**Arrival**	**Morning**	9.57	T1
				10.25	T2
				7.25	T3
DXB	**25/12/2024**	**Departure**	**Morning**	20.77	T1
				16.9	T2
				21.86	T3
DXB	**25/12/2024**	**Departure**	**Afternoon**	21.85	T1
				20.05	T2
				23.8	T3
DXB	**25/12/2024**	**Arrival**	**Afternoon**	11.29	T1
				8.61	T2
				8	T3
DXB	**29/12/2024**	**Departure**	**Morning**	21.21	T1
				17	T2
				20.44	T3
DXB	**29/12/2024**	**Arrival**	**Morning**	9.2	T1
				9.9	T2
				6.52	T3
DXB	**29/12/2024**	**Arrival**	**Afternoon**	12.6	T1
				9.57	T2
				7.9	T3
DXB	**29/12/2024**	**Departure**	**Afternoon**	19.42	T1

				14.57	T2
				17.85	T3
DXB	**22/08/2025**	**Departure**	**Morning**	17.08	T1
				19.45	T2
				17.89	T3
DXB	**22/08/2025**	**Arrival**	**Morning**	9.6	T1
				6.94	T2
				9.31	T3
DXB	**22/08/2025**	**Departure**	**Afternoon**	31.41	T1
				23.05	T2
				21.29	T3
DXB	**22/08/2025**	**Arrival**	**Afternoon**	8.94	T1
				8.07	T2
				6.58	T3

Table A.1 Taxi Time Terminal DXB

Airport	Date	Operation	Time	Taxi Time	Terminal
FRA	**25/12/2024**	**Departure**	**Morning**	11.75	T1
				14	T2
FRA	**25/12/2024**	**Arrival**	**Morning**	9.01	T1
				10.57	T2
FRA	**25/12/2024**	**Departure**	**Afternoon**	13.21	T1
				17.4	T2
FRA	**25/12/2024**	**Arrival**	**Afternoon**	7.9	T1
				9.09	T2

FRA	**29/12/2024**	**Departure**	**Morning**	22.54	T1
				21.5	T2
FRA	**29/12/2024**	**Arrival**	**Morning**	11.62	T1
				12.81	T2
FRA	**29/12/2024**	**Departure**	**Afternoon**	22.38	T1
				26.18	T2
FRA	**29/12/2024**	**Arrival**	**Afternoon**	9.65	T1
				9.41	T2
FRA	**26/05/2025**	**Departure**	**Morning**	11.31	T1
				19.6	T2
FRA	**26/05/2025**	**Arrival**	**Morning**	8.06	T1
				9.81	T2
FRA	**26/05/2025**	**Departure**	**Afternoon**	15.62	T1
				28.61	T2
FRA	**26/05/2025**	**Arrival**	**Afternoon**	9	T1
				8.77	T2
FRA	**22/08/2025**	**Departure**	**Morning**	14.5	T1
				18.75	T2
FRA	**22/08/2025**	**Arrival**	**Morning**	7.96	T1
				9.28	T2
FRA	**22/08/2025**	**Departure**	**Afternoon**	15.2	T1
				22	T2
FRA	**22/08/2025**	**Arrival**	**Afternoon**	8.89	T1
				10.92	T2

Table A.2 Taxi Time Terminal FRA

Airport	Date	Operation	Time	Average Delay	Number of flights
DXB	25/12/2024	Arrival	Morning	20.79	91
DXB	25/12/2024	Departure	Morning	18.27	82
DXB	25/12/2024	Departure	Afternoon	16.63	70
DXB	25/12/2024	Arrival	Afternoon	13.9	70
DXB	29/12/2024	Departure	Morning	16.82	76
DXB	29/12/2024	Arrival	Morning	18.22	70
DXB	29/12/2024	Departure	Afternoon	13.77	56
DXB	29/12/2024	Arrival	Afternoon	20.85	64
DXB	22/08/2025	Departure	Morning	20.61	80
DXB	22/08/2025	Arrival	Morning	22.9	80
DXB	22/08/2025	Departure	Afternoon	25.71	64
DXB	22/08/2025	Arrival	Afternoon	29.86	62
FRA	25/12/2024	Departure	Morning	8.17	35
FRA	25/12/2024	Arrival	Morning	20.05	71
FRA	25/12/2024	Departure	Afternoon	10.41	55
FRA	25/12/2024	Arrival	Afternoon	14.5	66
FRA	29/12/2024	Departure	Morning	31.37	34
FRA	29/12/2024	Arrival	Morning	20.06	84
FRA	29/12/2024	Departure	Afternoon	28.38	76
FRA	29/12/2024	Arrival	Afternoon	26.77	98
FRA	26/05/2025	Departure	Morning	10.97	85
FRA	26/05/2025	Arrival	Morning	24.76	144
FRA	26/05/2025	Departure	Afternoon	27.98	132

FRA	26/05/2025	Arrival	Afternoon	26.17	110
FRA	22/08/2025	Departure	Morning	12.2	85
FRA	22/08/2025	Arrival	Morning	15.73	133
FRA	22/08/2025	Departure	Afternoon	25.36	123
FRA	22/08/2025	Arrival	Afternoon	22.69	101

Table A.3 Average Delay DXB&FRA

Sheet	Aircraft Model	Flights
Morning Departure	777-300ER	24
Morning Departure	737-Max 8	19
Morning Departure	A380-800	16
Morning Departure	737-800	10
Morning Departure	A320	4
Morning Departure	737 Max 9	2
Morning Departure	CARGO	1
Morning Departure	A310	1
Morning Departure	737-300ER	1
Morning Departure	A320 Neo	1
Morning Departure	777-200LR	1
Morning Departure	787-9 Dreamliner	1
Morning Departure	A220-300	1
Afternoon Departure	737-Max 8	21
Afternoon Departure	777-300ER	17
Afternoon Departure	737-800	10
Afternoon Departure	A320 Neo	9

Afternoon Departure	A380-800	5
Afternoon Departure	A321	2
Afternoon Departure	A320	2
Afternoon Departure	A319	1
Afternoon Departure	A330	1
Afternoon Departure	CARGO	1
Afternoon Departure	777-200LR	1
Morning Arrival	777-300ER	26
Morning Arrival	737 Max 8	20
Morning Arrival	A380-800	16
Morning Arrival	737-800	12
Morning Arrival	777-200 LR	3
Morning Arrival	777-300	2
Morning Arrival	A320 Neo	2
Morning Arrival	A350-900	2
Morning Arrival	787-9 Dreamliner	2
Morning Arrival	737 Max 9	1
Morning Arrival	777-200	1
Morning Arrival	A330-300	1
Morning Arrival	A220-300	1
Morning Arrival	A330-900	1
Morning Arrival	737-700	1
Afternoon Arrival	737-Max 8	14
Afternoon Arrival	737-800	13

Afternoon Arrival	A320 Neo	13
Afternoon Arrival	777-300ER	7
Afternoon Arrival	A320	4
Afternoon Arrival	A330	3
Afternoon Arrival	787-9 Dreamliner	3
Afternoon Arrival	777-300	2
Afternoon Arrival	A330-300	2
Afternoon Arrival	737-Max 9	1
Afternoon Arrival	A321	1
Afternoon Arrival	A220-300	1
Afternoon Arrival	A350-900	1
Afternoon Arrival	777-246	1
Afternoon Arrival	A319 Neo	1
Afternoon Arrival	A330-900	1
Afternoon Arrival	777-200LR	1
Afternoon Arrival	A380-800	1

Table A.4 Flights per aircraft 25122024

Sheet	Aircraft Model	Flights
Morning Departure	777-300ER	21
Morning Departure	737-Max 8	21
Morning Departure	A380-800	15
Morning Departure	737-800	8
Morning Departure	A320	3
Morning Departure	A321	2
Morning Departure	A321 Neo	2

Morning Departure	A220-300	1
Morning Departure	737-Max 9	1
Morning Departure	A320 Neo	1
Morning Departure	777-200LR	1
Afternoon Departure	737 Max 8	13
Afternoon Departure	777-300ER	12
Afternoon Departure	737-800	9
Afternoon Departure	A380-800	5
Afternoon Departure	A320	5
Afternoon Departure	A320 Neo	5
Afternoon Departure	787-8	2
Afternoon Departure	A330	2
Afternoon Departure	A321 Neo	1
Afternoon Departure	737 Max 9	1
Afternoon Departure	A321	1
Afternoon Arrival	737 Max 8	15
Afternoon Arrival	737-800	11
Afternoon Arrival	A320 Neo	11
Afternoon Arrival	A320	6
Afternoon Arrival	777-300ER	4
Afternoon Arrival	A330	3
Afternoon Arrival	787-9 Dreamliner	2
Afternoon Arrival	A321	2
Afternoon Arrival	737-300	1

Afternoon Arrival	A220-300	1
Afternoon Arrival	A350-900	1
Afternoon Arrival	A330-300	1
Afternoon Arrival	A380-800	1
Afternoon Arrival	A321 Neo	1
Afternoon Arrival	777-300	1
Afternoon Arrival	737-400	1
Afternoon Arrival	737 Max 9	1
Afternoon Arrival	A321-271	1

Table A.5 Flights per aircraft DXB 291222024

Sheet	Aircraft Model	Flights
Morning Departure	737 MAX 8	23
Morning Departure	777-300 ER	22
Morning Departure	A380-800	15
Morning Departure	737-800	8
Morning Departure	A321	3
Morning Departure	A350-900	2
Morning Departure	A320 NEO	2
Morning Departure	A321 NEO	1
Morning Departure	A330-300	1
Morning Departure	A320	1
Morning Departure	737 MAX 9	1
Morning Departure	777-200 LR	1
Morning Arrival	777-300 ER	22

Morning Arrival	737 MAX 8	19
Morning Arrival	A380-800	16
Morning Arrival	737-800	7
Morning Arrival	A350-900	3
Morning Arrival	777-200 LR	3
Morning Arrival	737 MAX 9	2
Morning Arrival	A321	1
Morning Arrival	777-300	1
Morning Arrival	737-700	1
Morning Arrival	A320 NEO	1
Morning Arrival	787-10 DREAMLINER	1
Morning Arrival	CARGO	1
Morning Arrival	777-200	1
Morning Arrival	A321 NEO	1
Afternoon Departure	737 MAX 8	23
Afternoon Departure	777-300 ER	10
Afternoon Departure	A320 NEO	6
Afternoon Departure	737-800	6
Afternoon Departure	A380-800	4
Afternoon Departure	A320	4
Afternoon Departure	777-200 LR	2
Afternoon Departure	A330	2
Afternoon Departure	A321	2
Afternoon Departure	777-300	1

Afternoon Departure	737 MAX 9	1
Afternoon Departure	787-9 DREAMLINER	1
Afternoon Departure	A350-900	1
Afternoon Departure	A330-200	1
Afternoon Arrival	737 MAX 8	15
Afternoon Arrival	737-800	8
Afternoon Arrival	A320 NEO	7
Afternoon Arrival	777-300 ER	7
Afternoon Arrival	A320	5
Afternoon Arrival	A321	3
Afternoon Arrival	A330-300	3
Afternoon Arrival	A321 NEO	3
Afternoon Arrival	A330	2
Afternoon Arrival	A330-900	1
Afternoon Arrival	A320	1
Afternoon Arrival	737-900	1
Afternoon Arrival	A330-200	1
Afternoon Arrival	A380-800	1
Afternoon Arrival	737-300	1
Afternoon Arrival	737 MAX 9	1
Afternoon Arrival	A350-900	1

Table A.6 Flights per aircraft model DXB 22082025

Sheet	Aircraft Model	Flights
Morning Departure	A320	6

Morning Departure	737-800	6
Morning Departure	A320 Neo	4
Morning Departure	ERJ-190	4
Morning Departure	A319	4
Morning Departure	Embarer 170/175	2
Morning Departure	A321	2
Morning Departure	757-300	2
Morning Departure	Legacy 600/650	1
Morning Departure	A321 Neo	1
Morning Departure	737 Max 8	1
Morning Departure	777-300ER	1
Morning Departure	787-10 Dreamliner	1
Afternoon Departure	A319	11
Afternoon Departure	A320	8
Afternoon Departure	ERJ-190	7
Afternoon Departure	A321	5
Afternoon Departure	737-800	4
Afternoon Departure	A320 Neo	3
Afternoon Departure	CRJ-900	3
Afternoon Departure	777-200	3
Afternoon Departure	A321 Neo	2
Afternoon Departure	787-9 Dreamliner	1
Afternoon Departure	777-300ER	1
Afternoon Departure	A350-900	1

Afternoon Departure	ATR-ATR 72	1
Afternoon Departure	A330-300	1
Afternoon Departure	747-400	1
Afternoon Departure	777-200LR	1
Afternoon Departure	A330-900	1
Afternoon Departure	A330-200	1
Morning Arrival	777-300ER	7
Morning Arrival	A319	5
Morning Arrival	A330-300	5
Morning Arrival	ERJ-190	5
Morning Arrival	737-800	5
Morning Arrival	A320	5
Morning Arrival	787-9 Dreamliner	4
Morning Arrival	A321	4
Morning Arrival	787-10 Dreamliner	3
Morning Arrival	A320 Neo	3
Morning Arrival	A340-300	3
Morning Arrival	747-8	3
Morning Arrival	777-200	2
Morning Arrival	A220-100	2
Morning Arrival	747-400	2
Morning Arrival	A220-300	2
Morning Arrival	A340-600	2
Morning Arrival	A300-F4-600	1

Morning Arrival	A330-200	1
Morning Arrival	A320	1
Morning Arrival	A321 Neo	1
Morning Arrival	CRJ-100	1
Morning Arrival	A310	1
Morning Arrival	A330-900	1
Morning Arrival	A380-300	1
Morning Arrival	Embarer 170/175	1
Afternoon Arrival	A321	8
Afternoon Arrival	A320	7
Afternoon Arrival	A319	6
Afternoon Arrival	ERJ-190	5
Afternoon Arrival	787-9 Dreamliner	5
Afternoon Arrival	A330-900	4
Afternoon Arrival	A320 Neo	4
Afternoon Arrival	CRJ-900	3
Afternoon Arrival	777-200LR	3
Afternoon Arrival	737-800	3
Afternoon Arrival	777-300ER	3
Afternoon Arrival	787-8 Dreamliner	2
Afternoon Arrival	A380-800	2
Afternoon Arrival	777-200	2
Afternoon Arrival	Cessna 680A	1
Afternoon Arrival	A330-200	1

Afternoon Arrival	A330-300	1
Afternoon Arrival	747-8	1
Afternoon Arrival	737 Max 8	1
Afternoon Arrival	737-8K5	1
Afternoon Arrival	Embarer 175	1
Afternoon Arrival	A220-300	1
Afternoon Arrival	757-300	1

Table A.7 Flights per aircraft FRA 251222024

Sheet	Aircraft Model	Flights
Departure Morning	A320	12
Departure Morning	A320 Neo	5
Departure Morning	777-200LR	3
Departure Morning	A321	3
Departure Morning	CRJ-1000	2
Departure Morning	A330-200	2
Departure Morning	737-800	1
Departure Morning	737 Max 8	1
Departure Morning	787-9 Dreamliner	1
Departure Morning	A319	1
Departure Morning	ERJ-190	1
Departure Morning	A321 Neo	1
Departure Morning	757-300	1
Arrival Morning	A321	14
Arrival Morning	A319	12

Arrival Morning	A320	8
Arrival Morning	777-300ER	7
Arrival Morning	787-9 Dreamliner	5
Arrival Morning	A340-300	5
Arrival Morning	A320 Neo	5
Arrival Morning	ERJ-190	4
Arrival Morning	A321 Neo	4
Arrival Morning	A330-300	4
Arrival Morning	A340-600	2
Arrival Morning	747-800	2
Arrival Morning	A330-200	2
Arrival Morning	737-800	2
Arrival Morning	A330-900	2
Arrival Morning	787-10 Dreamliner	1
Arrival Morning	777-200	1
Arrival Morning	A350-900	1
Arrival Morning	A319 Neo	1
Arrival Morning	A220-300	1
Arrival Morning	A300F4-600	1
Departure Afternoon	A320	14
Departure Afternoon	A319	10
Departure Afternoon	A320 Neo	8
Departure Afternoon	ERJ-190	8
Departure Afternoon	A321	7

Departure Afternoon	777-200LR	4
Departure Afternoon	CRJ-900	4
Departure Afternoon	737-800	4
Departure Afternoon	A330-200	3
Departure Afternoon	CRJ-1000	2
Departure Afternoon	A330-900	2
Departure Afternoon	777-200	2
Departure Afternoon	A321 Neo	2
Departure Afternoon	A340-600	1
Departure Afternoon	747-800	1
Departure Afternoon	ATR-ATR-72	1
Departure Afternoon	ERJ-195	1
Departure Afternoon	787-800	1
Departure Afternoon	A350-900	1
Arrival Afternoon	A320	19
Arrival Afternoon	A321	15
Arrival Afternoon	A319	10
Arrival Afternoon	ERJ-190	8
Arrival Afternoon	A320 Neo	6
Arrival Afternoon	787-9 Dreamliner	6
Arrival Afternoon	737-800	4
Arrival Afternoon	A321 Neo	4
Arrival Afternoon	CRJ-900	3
Arrival Afternoon	777-300ER	3

Arrival Afternoon	777-200	2
Arrival Afternoon	CRJ-1000	2
Arrival Afternoon	A380-800	2
Arrival Afternoon	757-300	2
Arrival Afternoon	747-800	2
Arrival Afternoon	A330-300	2
Arrival Afternoon	A220-300	1
Arrival Afternoon	787-10 Dreamliner	1
Arrival Afternoon	777-200LR	1
Arrival Afternoon	757-200	1
Arrival Afternoon	ERJ-195	1
Arrival Afternoon	ATR-ATR-72	1
Arrival Afternoon	A330-200	1
Arrival Afternoon	787-8	1

Table A.8 Flight per aircraft FRA29122024

Sheet	Aircraft Model	Flights
Morning Departure	A320	18
Morning Departure	A319	17
Morning Departure	A321	12
Morning Departure	ERJ-190	9
Morning Departure	A320 Neo	7
Morning Departure	CRJ-900	4
Morning Departure	A321 Neo	3
Morning Departure	CRJ-1000	3

Morning Departure	Embarer 175	2
Morning Departure	777-300 ER	1
Morning Departure	ATR-72	1
Morning Departure	A220-300	1
Morning Departure	737 Max 8	1
Morning Departure	737-800	1
Morning Departure	A340-300	1
Morning Departure	757-300	1
Morning Departure	ERJ-900	1
Morning Departure	777-200LR	1
Morning Departure	ERJ-1000	1
Morning Arrival	A321	18
Morning Arrival	A320	17
Morning Arrival	A319	14
Morning Arrival	ERJ-190	11
Morning Arrival	A320 Neo	10
Morning Arrival	747-8	8
Morning Arrival	777-300ER	7
Morning Arrival	A330-300	6
Morning Arrival	A321 Neo	6
Morning Arrival	747-400	5
Morning Arrival	787-9	5
Morning Arrival	777-200	4
Morning Arrival	A330-200	4

Morning Arrival	CRJ-900	4
Morning Arrival	CRJ-1000	3
Morning Arrival	A350-900	3
Morning Arrival	A340-600	3
Morning Arrival	A220-300	2
Morning Arrival	777-300	2
Morning Arrival	A340-300	2
Morning Arrival	ERJ-190-400	1
Morning Arrival	777-200 LR	1
Morning Arrival	A319 Neo	1
Morning Arrival	A320-300	1
Morning Arrival	737 Max8	1
Morning Arrival	ERJ190	1
Morning Arrival	ATR-72	1
Morning Arrival	A220-100	1
Morning Arrival	Private	1
Morning Arrival	Embarer 170/175	1
Afternoon Departure	A320	26
Afternoon Departure	A319	19
Afternoon Departure	ERJ-190	15
Afternoon Departure	A321	10
Afternoon Departure	A320 Neo	9
Afternoon Departure	CRJ-900	5
Afternoon Departure	CRJ-1000	4

Afternoon Departure	A321 Neo	4
Afternoon Departure	777-200LK	3
Afternoon Departure	737-800	3
Afternoon Departure	777-200	2
Afternoon Departure	A220-300	2
Afternoon Departure	A340-300	2
Afternoon Departure	747-400	2
Afternoon Departure	777-200 ER	2
Afternoon Departure	767-300	2
Afternoon Departure	777-200	2
Afternoon Departure	A380-800	2
Afternoon Departure	A330-200	2
Afternoon Departure	737Max8	2
Afternoon Departure	ERJ-190-400	2
Afternoon Departure	A350-900	2
Afternoon Departure	A340-600	1
Afternoon Departure	787-8	1
Afternoon Departure	Embarer Phenom 300	1
Afternoon Departure	Lear Jet 45	1
Afternoon Departure	A300F4-200	1
Afternoon Departure	777-300	1
Afternoon Departure	H310 Neo	1
Afternoon Departure	A330-900	1
Afternoon Departure	A320	1

Afternoon Departure	A350-800	1
Afternoon Departure	787-9	1
Afternoon Arrival	A320	20
Afternoon Arrival	A319	12
Afternoon Arrival	ERJ-190	12
Afternoon Arrival	A321	12
Afternoon Arrival	A320 Neo	7
Afternoon Arrival	CRJ-1000	5
Afternoon Arrival	CRJ-900	5
Afternoon Arrival	787-9	4
Afternoon Arrival	737-800	3
Afternoon Arrival	A321 Neo	3
Afternoon Arrival	A330-200	2
Afternoon Arrival	777-200LR	2
Afternoon Arrival	A350-900	2
Afternoon Arrival	767-300	2
Afternoon Arrival	777-300	2
Afternoon Arrival	A330-300	2
Afternoon Arrival	Legacy 850	1
Afternoon Arrival	A380-800	1
Afternoon Arrival	Private	1
Afternoon Arrival	747-8	1
Afternoon Arrival	A340-600	1
Afternoon Arrival	767	1

Afternoon Arrival	Super King Ar350	1
Afternoon Arrival	747-400	1
Afternoon Arrival	CRJ-200	1
Afternoon Arrival	A220-300	1
Afternoon Arrival	Cessna Citation	1
Afternoon Arrival	777-200	1
Afternoon Arrival	Phenom300	1
Afternoon Arrival	787-8	1

Table A.9 Flights per aicraft 26052025

Sheet	Aircraft Model	Flights
Morning Departure	A321	18
Morning Departure	A320	15
Morning Departure	A319	12
Morning Departure	ERJ-190	9
Morning Departure	CRJ-900	6
Morning Departure	A321 NEO	5
Morning Departure	A320 NEO	4
Morning Departure	CRJ-1000	3
Morning Departure	757-300	3
Morning Departure	777-200	2
Morning Departure	737-800	2
Morning Departure	787-800	1
Morning Departure	EMBARER 170/175	1
Morning Departure	A220-300	1

Morning Departure	A330-300	1
Morning Departure	777-300 ER	1
Morning Departure	A330-600	1
Morning Arrival	A320	18
Morning Arrival	A319	17
Morning Arrival	A321	14
Morning Arrival	A320 NEO	10
Morning Arrival	ERJ-190	9
Morning Arrival	A330-300	8
Morning Arrival	777-300 ER	5
Morning Arrival	A340-300	5
Morning Arrival	A321 NEO	5
Morning Arrival	CRJ-900	4
Morning Arrival	A350-900	4
Morning Arrival	787-9 DREAMLINER	4
Morning Arrival	747-400	4
Morning Arrival	777-200	3
Morning Arrival	A220-300	3
Morning Arrival	CRJ-1000	3
Morning Arrival	737-800	2
Morning Arrival	A340-600	2
Morning Arrival	747-800	2
Morning Arrival	A330-200	2
Morning Arrival	ATR 72	1

Morning Arrival	787-8	1
Morning Arrival	747-8	1
Morning Arrival	A220-100	1
Morning Arrival	A319 NEO	1
Morning Arrival	787-900	1
Morning Arrival	787-10 DREAMLINER	1
Morning Arrival	A300-600	1
Morning Arrival	EMBARER 170/175	1
Afternoon Departure	A320	25
Afternoon Departure	A319	19
Afternoon Departure	A321	14
Afternoon Departure	ERJ-190	12
Afternoon Departure	A320 NEO	8
Afternoon Departure	777-200	7
Afternoon Departure	CRJ-900	5
Afternoon Departure	CRJ-1000	5
Afternoon Departure	A321 NEO	4
Afternoon Departure	A340-300	3
Afternoon Departure	787-9 DREAMLINER	2
Afternoon Departure	737-MAX 8	2
Afternoon Departure	777-200 LR	2
Afternoon Departure	A220-300	2
Afternoon Departure	A330-300	2
Afternoon Departure	737-800	2

Afternoon Departure	757-300	1
Afternoon Departure	A330-900	1
Afternoon Departure	350-900	1
Afternoon Departure	777-300 ER	1
Afternoon Departure	A300F4-600	1
Afternoon Departure	A330-200	1
Afternoon Departure	ATR 72	1
Afternoon Departure	A380-800	1
Afternoon Departure	EMBARER 175	1
Afternoon Arrival	A320	26
Afternoon Arrival	A321	13
Afternoon Arrival	A319	10
Afternoon Arrival	ERJ-190	7
Afternoon Arrival	A320 NEO	7
Afternoon Arrival	787-9 DREAMLINER	5
Afternoon Arrival	777-200 LR	4
Afternoon Arrival	A321 NEO	3
Afternoon Arrival	A330-300	2
Afternoon Arrival	A220-300	2
Afternoon Arrival	777-300	2
Afternoon Arrival	737-800	2
Afternoon Arrival	CRJ-1000	2
Afternoon Arrival	CRJ-900	2
Afternoon Arrival	777-300 ER	2

Afternoon Arrival	747-800	1
Afternoon Arrival	787-800	1
Afternoon Arrival	EMBARER 175	1
Afternoon Arrival	767-300	1
Afternoon Arrival	ATR 72	1
Afternoon Arrival	A380-800	1
Afternoon Arrival	737 MAX 8	1
Afternoon Arrival	A330-200	1
Afternoon Arrival	A350-900	1
Afternoon Arrival	777-200	1
Afternoon Arrival	747-400	1

Table A.10 Flights per aicraft 22082025

Appendix B

Code flights per aircraft type

```
Import pandas as pd
import os
# File path of Excel where the data is stored
file_path = "/Users/rejanakarapiti/Desktop/FRA 22082025.xlsx"
# Output path;where the results will be saved
output_path = os.path.expanduser("~/Downloads/flights_per_aircraft_model_FRA2208.xlsx")
# Sheet names in  Excel
sheets = ['Morning Departure', 'Morning Arrival', 'Afternoon Departure', 'Afternoon Arrival ']
#We open a new list to store the results
results = []
# We go over all the sheets that we have and read their data
for sheet in sheets:
  df = pd.read_excel(file_path, sheet_name=sheet)
  if "Aircraft" not in df.columns: //if the aircraft column does not exist that i twill print
    following print(f"Sheet '{sheet}' does not have an 'Aircraft' column.")
    continue
  counts = df["Aircraft"].value_counts()
  for aircraft_model, num in counts.items():
    results.append([sheet, aircraft_model, int(num)])
# Convert to DataFrame
final_df = pd.DataFrame(results, columns=["Sheet", "Aircraft Model", "Flights"])
# Save to Excel
final_df.to_excel(output_path, index=False)
```

print(f"Done! Results saved to {output_path}")

Code Rule Based AI

```
import pandas as pd

import numpy as np

from sklearn.metrics import mean_absolute_error,

mean_squared_error import re

import os

# ===Paths of the train files===

train_files = [

    '/Users/rejanakarapiti/Desktop/Master zum Lessen /DXB 25122024.xlsx',

    '/Users/rejanakarapiti/Desktop/DXB 22082025.xlsx',

]

test_file = '/Users/rejanakarapiti/Desktop/Master zum Lessen /DXB29122024.xlsx'

output_file =

'/Users/rejanakarapiti/Downloads/RuleBasedAI_Full/RuleBasedAI_Evaluation_12102025.xlsx'

# === Reference taxi times and their  weights in the model ===

arrival_ref = 7.67

departure_ref = 17.33

weight_model = 0.7

weight_ref = 0.3

# ===Function which determine the operation===

def assign_operation_type(sheet_name):

    sheet_lower = sheet_name.lower()

    if 'arrival' in sheet_lower:
```

```
return 'Arrival'
elif 'departure' in
sheet_lower: return
'Departure'

else:
return 'Unknown'
def extract_numeric_taxi(x):
match = re.search(r'\d+',
str(x))
return int(match.group(0)) if match else
pd.NA def load_and_prepare(file_path):
all_sheets = []
xls =
pd.ExcelFile(file_path) for
sheet in xls.sheet_names:
df = pd.read_excel(file_path, sheet_name=sheet)
df.columns = df.columns.astype(str).str.strip()
# Skip sheets without Aircraft column
if 'Aircraft' not in df.columns:
continue
# Extract numeric Taxi Time
taxi_col_candidates = ['Taxi Time', 'Taxi', 'Taxi Actual Min',
'TaxiTime'] found_col = next((c for c in df.columns if c in
taxi_col_candidates), None) if found_col:
df['TaxiTime'] =
```

```
df[found_col].apply(extract_numeric_taxi) else:

   df['TaxiTime'] = pd.NA

# === Exclude rows without TaxiTime ===

df =

df.dropna(subset=['TaxiTime'])

if df.empty:

   continue

# Assign operation type

df['OperationType'] = assign_operation_type(sheet)

if 'Terminal' not in df.columns:

   df['Terminal'] = ''


all_sheets.append(df)

return pd.concat(all_sheets, ignore_index=True) if all_sheets else pd.DataFrame()

# === Load training data ===

train_df = pd.concat([load_and_prepare(f) for f in train_files],

ignore_index=True) train_df = train_df[train_df['OperationType'].isin(['Arrival',

'Departure'])]

# === Compute average taxi per Aircraft Model from training data ===

avg_taxi_model = train_df.groupby(['OperationType', 'Aircraft'])['TaxiTime'].mean().to_dict()

# === Load test data ===

test_df =

load_and_prepare(test_file) if

test_df.empty:

   print("No test data found.

   Exiting.") exit()
```

```
# === Rule-Based AI Prediction

def predict_taxi(row):

    key = (row['OperationType'], row['Aircraft'])

    model_avg = avg_taxi_model.get(key, np.nan) //find the average for the

    model if pd.isna(model_avg):

        return arrival_ref if row['OperationType'] == 'Arrival' else

    departure_ref else:

        # blend model avg with reference

        ref_value = arrival_ref if row['OperationType'] == 'Arrival' else

        departure_ref return model_avg * weight_model + ref_value *

        weight_ref

test_df['Predicted_Taxi'] = test_df.apply(predict_taxi, axis=1)

test_df['Difference'] = test_df['TaxiTime'] -

test_df['Predicted_Taxi']

# === Exclude any rows with empty TaxiTime for metrics ===

test_valid = test_df.dropna(subset=['TaxiTime', 'Predicted_Taxi'])

# Separate arrivals and departures

arrivals = test_valid[test_valid['OperationType'] == 'Arrival']

departures = test_valid[test_valid['OperationType'] ==

'Departure'] # === Compute metrics ===

def compute_metrics(df,

    label): if df.empty:

        print(f"{label} -> No valid

        data") return {}

    mae = mean_absolute_error(df['TaxiTime'], df['Predicted_Taxi'])

    rmse = np.sqrt(mean_squared_error(df['TaxiTime'],
```

```
    df['Predicted_Taxi'])) print(f"{label} -> MAE: {mae:.2f}, RMSE:
    {rmse:.2f}")
    return {'OperationType': label, 'MAE': mae, 'RMSE': rmse, 'Flights': len(df)}
summary = [compute_metrics(arrivals, 'Arrival'), compute_metrics(departures, 'Departure')]
# === Mean taxi per Aircraft Model ===
arrival_model_avg = arrivals.groupby('Aircraft')['TaxiTime'].mean()
departure_model_avg =
departures.groupby('Aircraft')['TaxiTime'].mean()

arrival_flags = arrival_model_avg.apply(lambda x: 'Above 11 min' if x > arrival_ref else
'Below 11 min')
departure_flags = departure_model_avg.apply(lambda x: 'Above 20 min' if x >
departure_ref else 'Below 20 min')

# === Overall mean taxi times ===
overall_arrival_mean = arrivals['TaxiTime'].mean()
overall_departure_mean = departures['TaxiTime'].mean()


print("\nAverage Taxi Time per Aircraft Model (Arrival):")
print(pd.DataFrame({'MeanTaxi': arrival_model_avg, 'Flag': arrival_flags}))

print("\nAverage Taxi Time per Aircraft Model (Departure):")
print(pd.DataFrame({'MeanTaxi': departure_model_avg, 'Flag': departure_flags}))

print(f"\nOverall mean taxi time (Arrival): {overall_arrival_mean:.2f} min (Reference:
{arrival_ref} min)")
```

print(f"Overall mean taxi time (Departure): {overall_departure_mean:.2f} min (Reference: {departure_ref} min)")

=== Detect outliers ===

test_valid['Error'] = test_valid['TaxiTime'] - test_valid['Predicted_Taxi']

mean_err = test_valid['Error'].mean()

std_err = test_valid['Error'].std()

*test_valid['Outlier'] = test_valid['Error'].abs() > 3 * std_err*

 # === Save all results to Excel ===

os.makedirs(os.path.dirname(output_file), exist_ok=True)

with pd.ExcelWriter(output_file) as writer:

test_df.to_excel(writer, sheet_name='Details', index=False) # keep all rows including empty

pd.DataFrame([s for s in summary if s]).to_excel(writer, sheet_name='Summary', index=False)

pd.DataFrame(

{'Aircraft': arrival_model_avg.index, 'MeanTaxi': arrival_model_avg.values, 'Flag': arrival_flags.values}

).to_excel(writer, sheet_name='Arrival_Model_Avg', index=False)

pd.DataFrame(

{'Aircraft': departure_model_avg.index, 'MeanTaxi': departure_model_avg.values, 'Flag': departure_flags.values}

).to_excel(writer, sheet_name='Departure_Model_Avg', index=False)

print(f"\n Rule-Based AI evaluation complete. Results saved to '{output_file}'")

XG Boost

import pandas as pd

```
from xgboost import XGBRegressor
import joblib
import os
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_absolute_error,
mean_squared_error import numpy as np
from math import sqrt
# Old Files
# === Parameters ===
old_files = [
    '/Users/rejanakarapiti/Desktop/Master zum Lessen /FRA 25122024.xlsx',
    #/Users/rejanakarapiti/Desktop/Master zum Lessen /FRA291222024.xlsx',
    '/Users/rejanakarapiti/Desktop/FRA 26052025.xlsx',
]  # Two training files
new_file = '/Users/rejanakarapiti/Desktop/FRA 22082025.xlsx' # New data for prediction
output_folder =
'/Users/rejanakarapiti/Downloads/Taxi_Predictions_FRA_taxitime<50.xlsx'
os.makedirs(output_folder, exist_ok=True)
categorical_cols_arrival = ['Aircraft', 'Terminal', 'Sheet']  # For arrivals
categorical_cols_departure = ['Aircraft', 'Terminal', 'Gate', 'Sheet']  # For
departures

# === Helper functions ===
def assign_operation_type(sheet_name):
    sheet_name_lower =
    sheet_name.lower() if 'arrival' in
```

```
    sheet_name_lower:
        return 'Arrival'
    elif 'departure' in
        sheet_name_lower: return
        'Departure'
    else:
        return 'Unknown'
def prepare_X_y(df,
    categorical_cols): df = df.copy()
    cols_to_keep = categorical_cols + ['TaxiTime',
    'OperationType'] df = df[[col for col in cols_to_keep if col
    in df.columns]]
    df_encoded = pd.get_dummies(df, columns=categorical_cols +
    ['OperationType']) X = df_encoded.drop(columns=['TaxiTime'])
    y = df_encoded['TaxiTime']
    X = X.apply(pd.to_numeric,
    errors='coerce').fillna(0).astype(float) return X, y
def train_model(X, y):
    X_train, X_val, y_train, y_val = train_test_split(X, y, test_size=0.2,
    random_state=42) y_train = y_train.squeeze().astype(float)
    y_val = y_val.squeeze().astype(float)
    model = XGBRegressor(n_estimators=200, learning_rate=0.05, max_depth=8,
random_state=42)
    model.fit(X_train, y_train)
    y_val_pred =
    model.predict(X_val)
```

```
    val_mae = mean_absolute_error(y_val, y_val_pred)
    val_rmse = sqrt(mean_squared_error(y_val, y_val_pred))
    print(f"Validation MAE: {val_mae:.3f}, RMSE:
    {val_rmse:.3f}") return model, X_train.columns.tolist()
def prepare_for_prediction(df, categorical_cols,
    features): df = df.copy()
    for col in categorical_cols +
        ['OperationType']: if col not in
        df.columns:
            df[col] = ''

    if 'Gate' in df.columns and 'Gate' not in
        categorical_cols: df = df.drop(columns=['Gate'])
    df_encoded = pd.get_dummies(df, columns=categorical_cols + ['OperationType'])
    missing_cols = [c for c in features if c not in df_encoded.columns]
    for c in missing_cols:
        df_encoded[c] = 0
    df_encoded = df_encoded[features]
    df_encoded = df_encoded.apply(pd.to_numeric,
    errors='coerce').fillna(0).astype(float) return df_encoded
# === Load and prepare training data ===
all_data = []
for old_file in old_files:
    old_excel =
    pd.ExcelFile(old_file) for sheet in
    old_excel.sheet_names:
```

```
        df = pd.read_excel(old_file, sheet_name=sheet)

        df.columns = df.columns.str.strip()

        if 'Taxi Time' not in df.columns or 'Aircraft' not in df.columns:

            print(f"Skipping sheet {sheet} in {old_file} because required columns missing.")

            continue

        df['Taxi Time'] = df['Taxi

        Time'].astype(str).str.extract(r'(\d+)') df['Taxi Time'] =

        pd.to_numeric(df['Taxi Time'], errors='coerce') df =

        df.dropna(subset=['Taxi Time', 'Aircraft'])

        df['OperationType'] = assign_operation_type(sheet)

        df['Sheet'] = sheet

        desired_cols = ['Aircraft', 'Terminal', 'Gate', 'Taxi Time', 'Sheet', 'OperationType']

        existing_cols = [col for col in desired_cols if col in df.columns]

        df = df[existing_cols]

        df = df.rename(columns={'Taxi Time': 'TaxiTime'})

        all_data.append(df)

train_df = pd.concat(all_data, ignore_index=True)

train_df = train_df[train_df['OperationType'].isin(['Arrival',

'Departure'])] train_arrival = train_df[train_df['OperationType'] ==

'Arrival'].copy() train_departure = train_df[train_df['OperationType']

== 'Departure'].copy() # Drop Gate for arrivals if exists

if 'Gate' in train_arrival.columns:

    train_arrival = train_arrival.drop(columns=['Gate'])

# === Train models ===

X_arrival, y_arrival = prepare_X_y(train_arrival, categorical_cols_arrival)

X_departure, y_departure = prepare_X_y(train_departure,
```

categorical_cols_departure)

print(f"Training samples Arrival: {X_arrival.shape[0]}, Departure:

{X_departure.shape[0]}") print("\nTraining Arrival Model:")

model_arrival, features_arrival = train_model(X_arrival, y_arrival)

print("\nTraining Departure Model:")

model_departure, features_departure = train_model(X_departure, y_departure)

joblib.dump(model_arrival, 'xgb_taxi_model_arrival.joblib') #save here for reuse

joblib.dump(features_arrival, 'model_features_arrival.joblib')

joblib.dump(model_departure,

'xgb_taxi_model_departure.joblib')

joblib.dump(features_departure,

'model_features_departure.joblib') print("\nBoth models

trained and saved.")

 # === Predict on new data===

new_excel = pd.ExcelFile(new_file)

for sheet in new_excel.sheet_names:

df = pd.read_excel(new_file,

sheet_name=sheet) df.columns =

df.columns.str.strip()

 # Skip sheet if completely empty

if df.empty:

print(f"Skipping empty sheet: {sheet}")

continue

 # Drop completely empty rows

```
df = df.dropna(how='all')

# Skip if required columns are missing

required_cols = ['Aircraft', 'Terminal']

if not any(col in df.columns for col in required_cols):

    print(f"Skipping sheet {sheet} because required columns are

    missing") continue

print(f"\n Processing Sheet: {sheet}")

# Assign operation type

df['OperationType'] = assign_operation_type(sheet)

# Ensure all categorical columns exist

for col in ['Aircraft', 'Terminal', 'Gate', 'Sheet']:
    if col not in df.columns:

        df[col] = ''

# Handle Taxi Time column

if 'Taxi Time' in df.columns:

    df['Taxi Time'] = df['Taxi

    Time'].astype(str).str.extract(r'(\d+)') df['Taxi Time'] =

    pd.to_numeric(df['Taxi Time'], errors='coerce')

else:

 df['Taxi Time'] = pd.NA

df_orig = df.rename(columns={'Taxi Time': 'TaxiTime'})

 # Split by operation type

df_arrival = df_orig[df_orig['OperationType'] == 'Arrival'].copy()

df_departure = df_orig[df_orig['OperationType'] ==

'Departure'].copy() # Predict Arrival

if not df_arrival.empty:
```

X_arrival_pred = prepare_for_prediction(df_arrival, categorical_cols_arrival,

features_arrival) preds_arrival = model_arrival.predict(X_arrival_pred)

df_arrival.loc[:, 'TaxiTime_Predicted'] = np.round(preds_arrival, 2)

 # Predict Departure

if not df_departure.empty:

X_departure_pred = prepare_for_prediction(df_departure, categorical_cols_departure,

features_departure)

preds_departure = model_departure.predict(X_departure_pred)

df_departure.loc[:, 'TaxiTime_Predicted'] =

np.round(preds_departure, 2)

 # Combine predictions

df_predicted = pd.concat([df_arrival,

df_departure]) if df_predicted.empty:

print(f"No valid rows to predict in sheet {sheet}")

continue

df_predicted = df_predicted.sort_index()

 # Display average predicted taxi times

print("Average predicted taxi time by Aircraft:")

print(df_predicted.groupby('Aircraft')['TaxiTime_Predicted'].mean().sort_va

lues()) **# Save predictions**

output_path = os.path.join(output_folder, f"taxi_predictions_{sheet.replace(' ', '_')}.xlsx")

df_predicted.to_excel(output_path, index=False)

print(f" Saved predictions to: {output_path}")