

Use of Digital Twins in Commercial Aviation to Mitigate Unplanned Maintenance and Downtime to Increase Efficiency and Profitability

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1. Abstract

This research project delves into the application of Digital Twins (DTs) to tackle unplanned maintenance challenges in the aviation industry. Unplanned maintenance disrupts airline operations and incurs substantial financial losses. The study aims to investigate how DT technology can offer innovative solutions to these challenges. By examining current maintenance practices and their limitations, the research identifies a pressing need for new approaches to enhance maintenance efficiency and minimize disruptions. Through a structured research approach, the study explores the feasibility and potential applications of DTs in addressing unplanned maintenance. Various DT-integrated solutions, including Predictive Maintenance and Integrated Aircraft Health Management technologies, are analyzed to identify promising frameworks that leverage DTs for predictive analytics and optimization of maintenance operations. The study's results underscore the significant potential of DT technology in revolutionizing maintenance practices within the aviation industry. By harnessing real-time data and predictive analytics, DTs offer opportunities to enhance maintenance efficiency, reduce downtime, and optimize resource utilization. The implications of the research extend beyond the aviation industry, with potential applications in other sectors requiring proactive maintenance strategies. Key conclusions highlight the need for continued investment in DT development and integration, as well as collaboration between industry stakeholders to drive adoption. Overall, the project underscores the transformative potential of DT technology in improving maintenance practices and ensuring seamless operations in the aviation industry.

Declaration

I, Efe Bertan Butev, solemnly declare that no portion of the work referred to in the dissertation titled “Use of Digital Twins in Commercial Aviation to Mitigate Unplanned Maintenance and Downtime to Increase Efficiency and Profitability” has been submitted in support of an application for another degree or qualification of this or any other university or institute of learning.

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2. Introduction

2.1. Summary

Digital Twin is a mirror image of a physical process that is articulated alongside the process in question, usually matching exactly the operation of a physical process which takes place in real time (Batty, 2018). First type of digital twins was found by Michael and since then has rapidly become a crucial part of many processes that shape the modern world. During the 22 years of its existence, the uses of digital twins penetrated numerous industries.

Even though the DT technology has been widely adopted by many different industries, there are only few cases where the full potential of the technology has been taken advantage of. With increased computational budgets, enhanced data analysis techniques and innovations in machine learning and artificial intelligence the potential that digital twins have, has been increasing exponentially. By investigating the possible integration of upcoming technologies and digital twins, unprecedented systems that can help industries optimize their processes can be found.

One of the largest industries that benefit from the digital twins is the commercial aviation industry, which was valued at \$841.44B (Statista, 2024). The use of digital twins in the industry mostly focuses on the design phase of aircraft parts, however there are few examples where the technology is utilized during further phases in the products' life cycle. Limited use of digital twins in this area is a notable point as, operational inefficiencies cost billions of dollars each year to airline companies. One of the most prominent loss factors related to operational inefficiencies is unplanned maintenance and downtime. Advanced capabilities of digital twins paired with different techniques promise to address and mitigate related issues.

2.2. Scope

The scope of the research is focused on exploring the use of digital twins in commercial aviation to mitigate unplanned maintenance and downtime. The possible applications of digital twins combined with methods such as Integrated Vehicle Health Management (IVHM) and Predictive

Maintenance will be examined. The research will be done on relevant literature, case studies, and research to assess the effectiveness of the digital twins in mitigating unplanned maintenance and reducing related downtime.

While the scope is primarily focused on the digital twins' role in commercial aviation, it is important to note that similar applications are being done in different industries. Due to lack of literature that is directly related to aviation, applications in other industries may be examined to enhance understanding of possible benefits and challenges of using digital twins in similar areas. Additionally, while the focus is primarily on digital twins' use in mitigating unplanned maintenance, potential extensions of the research may include exploring their role in other aspects of the aircraft operations or their integration with emerging technologies.

2.3. Background

Commercial aviation industry stands as one of the largest industries with a combined market cap of \$841.44B in the year 2023 (Statista, 2024). Facilitating the movement of over 3.5 billion passengers in 2022 alone (IATA, 2023) it serves as a cornerstone of global economies. Operating for billions of people all around the year comes with big responsibilities. Most important ones being safety of passengers and shareholder profits. Efficiency plays a pivotal role in achieving these objectives, as streamlined processes not only enhance operational performance and profitability but also contribute to the overall safety of passengers. Every incremental improvement in efficiency not only translates into cost savings but also enables airlines to allocate more resources towards ensuring the highest standards for safety. Every year stakeholders allocate substantial portions of their budgets towards research and development aiming to increase efficiency, since any incremental improvement on efficiency yield substantial gains.

Currently different airlines and aircraft manufacturers are working on ways to increase operational efficiency by digitalizing current systems and employing current and emerging fuel, fleet health and crew management techniques. With many companies shifting towards more and more digitalized processes. These efforts mostly include utilizing digital twins, as digital twins promise

faster ways of processing and interpreting data to optimize each process as it undertakes. With each stakeholder focusing more on increasing efficiency within the industry and digitalization being the most promising way, digital twins have the potential to be the main factor in this change.

One of the key aspects of commercial aviation where efficiency is extremely valuable because of significant costs related to it is maintenance, with each aircraft in an airline's fleet requiring periodic maintenances to ensure airworthiness. Scheduled and unscheduled maintenance are two main types of maintenance, both ensuring safe and reliable operations. Direct costs related to aircraft maintenance accounts for approximately 11% of an airline's operational costs, encompassing labor, materials, and parts repairs and replacements (Dupuy, et al., 2011). With technological advancements onboard aircrafts and increasing component numbers and complexity, maintenance costs show a trend of increasing. Factors such as growing fleet sizes and increases in operational hours further contribute to the growing significance of maintenance expenses each year. To address increased costs airlines, seek various maintenance strategies, such as predictive maintenance, to optimize maintenance operations. The objective to increase efficiency in maintenance operations calls for digital twin utilization. With the combination of digital twins, current and emerging operational management methods, the cost burden of maintenance on airlines can be minimized to unprecedented levels.

However, while efficiency is important in ensuring the smooth operation of processes within the aviation industry and safeguarding passenger safety, achieving these goals is further complicated by the strict regulations governing the sector. Regulations impose rigorous standards on any new system integration, requiring meticulous compliance checks and procedures before any can be made. These regulations not only increase the costs related to R&D but also demands higher workload for system integration processes. It is crucial to consider these regulatory challenges when examining the applicability of digital twins and other methods in the aviation industry, as the requirements and challenges can differ significantly from those in other sectors.

2.4. Motivation

Digital twins have been a part of most engineering processes, which have been widely used in many different industries, especially in product design. However, their application diminishes significantly as products transition through the later stage of their life cycle, including the commercial aviation sector. Despite being proven in reducing costs and timeframes during the design phase, the full potential of digital twins remains untapped in later stages of the product life cycle. This lack of utilization stands out. Digital twins remain one of the best ways to utilize data in an era where data creation increases every day.

An industry where data is abundant but valuable is the commercial aviation industry. Efficiency as discussed before is one of the key parameters in aviation, as every second and every small action can have immense impacts on operations, and in a digitalized world one of the best ways of ensuring efficient operations is utilizing data. In the year 2018 global commercial aviation industry has created approximately 1,325PB of data where only 1.5% was recorded (Frost & Sullivan, 2019). Most of the data that is created is sourced from aircraft performance data such as engine parameters, flight paths, airspeeds, etc. These are valuable data that can be utilized to enhance performance of aircraft and track the health of each component.

Even, though there are several companies and research institutions that invest resources to the development of systems that can leverage the features of digital twins within the industry, the developments are slow and insufficient. The motivation of this research is the lack of digital twin utilization in the support and service phase of the lifecycle within the commercial aviation industry. The focal point of research within the support and service phase of the lifecycle will be the maintainability of the components as this aspect is one of the costliest operational processes that is caused by inefficiencies, and which can be addressed using digital twin technologies.

2.5. Aims & Objectives

With the motivation of this project being the information and practice gap of the use of digital twins during the support and service phase of the product lifecycle within the aviation industry, specifically during maintenance operations, the aim of this project has been decided as:

To investigate the potential roles of Digital Twins in addressing unplanned maintenance during the support and service phase of a product's lifecycle within the aviation industry.

To achieve the aim, set out for this research, four different objectives have been designated, and for each objective research questions were written to guide the research in a direction that would satisfy the related objectives.

1. Examine how unplanned maintenance affects airline operations, and investigate current techniques that are being used to address this.

RQ1 - How does unplanned maintenance affect airlines operational efficiency and profitability?

RQ2 - What are some current and emerging methods that airlines use to mitigate issues regarding unplanned maintenance?

2. Assess the current utilization of Digital Twins within the aviation industry, particularly in managing unplanned maintenance during the service and support phase.

RQ3 - In what specific areas of aviation operations are digital twins currently applied, with a focus on managing unplanned maintenance during the service and support phase?

RQ4 - What are some examples across the industry for digital twin utilization in managing unplanned maintenance within the support and service phase of the lifecycle?

3. Explore potential applications of digital twins to address unplanned maintenance, and how promising features can be integrated with current systems.

RQ5 - How can digital twins capture and utilize real-time data from operational aircraft in order to accurately represent the current condition of components?

RQ6 - What data interpretation methods and tools can be employed to enhance the capabilities of digital twins in analyzing and interpreting complex datasets related to aircraft performance and maintenance?

RQ7 - How can digital twins be integrated with emerging maintenance operation techniques to optimize maintenance processes and minimize unplanned maintenance and downtime in aviation operations?

4. Identify key challenges and knowledge gaps that are being faced while integrating digital twins to existing systems.

RQ8 - What are the knowledge gaps in terms of skill requirements and workforce training for the effective implementation of digital twins?

RQ9 - What are regulatory constraints and industry standards that pose challenges to the integration of digital twins into existing aviation systems?

3. Methodology

3.1. Introduction

The purpose of this research is to examine and assess the possible uses of existing and emerging digital technologies in addressing unplanned maintenance and downtime within the aviation industry, in combination with current and upcoming methods that are being used in airline companies to address unplanned maintenance. The primary research methodology employed for this research is a comprehensive literature review of existing literature and other credible sources. A broad range of sources such as articles from different databases (Google Scholar, ABI Inform), white papers done by research companies and online articles that are written by investigative reporters are included in the research of the topic at hand.

The literature review method is selected over alternative methodologies due to the complex and non-experimental nature of the subject under research. Choosing to gather data from existing sources allow for the compilation of comprehensive dataset, thus enabling a thorough analysis of the topic. Utilizing the available data optimizes the resource allocation towards a detailed analysis and interpretation. Additionally, the knowledge gap in the specific area that is chosen calls for interpolation and interpretation of data and information from similar fields. As a result, keyword searches that are done do not only consist of industry focused searches but rather area focused searches that involves numerous industries.

To ensure a systematic approach, the literature review is conducted using both systematic keywords searching and the PRISMA flow diagram. The initial phase of the search involves identifying relevant articles with the help of designated keywords which are listed in a hierarchical way. Second stage will involve the screening of the identified sources where each source is analyzed for relevance by reading the abstract. After the screening process the sources that are left are thoroughly analyzed and all useful sources will be included in the review. Any eliminated sources at this stage will be justified on the PRISMA flow chart.

3.2. Systematic Keyword Search

During the identification phase of the sources, a systematic keyword search approach is done to ensure that predetermined research questions are satisfied. For these purposes the following table is designed so that keywords are sorted in a way that helps with the flow of the research. First research questions are listed in a way in which wider scoped ones are listed first and as the list progresses more specific ones are addressed. After this process each research question is matched with keywords search phrases that would satisfy the question. It is important to note that keywords were added through the research as research yielded new findings.

Table 1: Systematic Keyword Search

Systematic Keyword Search	
Research Questions	Keywords/phrases
RQ1 How does unplanned maintenance affect airlines operational efficiency and profitability?	• Unplanned maintenance • Operational losses in airlines • Unplanned maintenance in commercial aviation • Unplanned maintenance effects on airline operations • Unplanned maintenance cost for airlines • Main causes for unplanned maintenance
RQ2 What are some current and emerging methods that airlines use to mitigate issues regarding unplanned maintenance?	• How do airlines address unplanned maintenance • Methods of maintaining an airline fleet • Predictive maintenance in aviation • Fleet health management in aviation • Operational structure of maintenance in aviation • Comprehensive Data Analysis • Exploratory Data Analysis • Condition Monitoring • Integrated Aircraft Health Management • Condition Based Maintenance
RQ3 In what specific areas of aviation operations are digital twins currently applied, with a focus on managing unplanned maintenance during the service and support phase?	• Digital twins and aviation • Digital twin use in airlines • Digital twin use in airline operational phases • Integrated Vehicle Health Management

RQ4 What are some examples across the industry for digital twin utilization in managing unplanned maintenance within the support and service phase of the life cycle?	• Digital twin-based technologies addressing unplanned maintenance • US Airforce digital twin research • Airbus digital twin use • 3DEXPERIENCER TWIN Dassault • Siemens DT • Asset monitoring systems • F35 Digital Twins
RQ5 How can digital twins capture and utilize real-time data from operational aircraft in order to accurately represent the current condition of components?	• Online airplane parameter tracking • Data collection methods • Interpretations of airplane parameters • Airplane maintenance predicting, key data • Indicators of required maintenance
RQ6 What data interpretation methods and tools can be employed to enhance the capabilities of digital twins in analyzing and interpreting complex datasets related to aircraft performance and maintenance?	• Data interpretation methods • Data Fusion • Current data fusion techniques • Current and emerging data analysis tools • Data fusion method in aviation • Data Integration

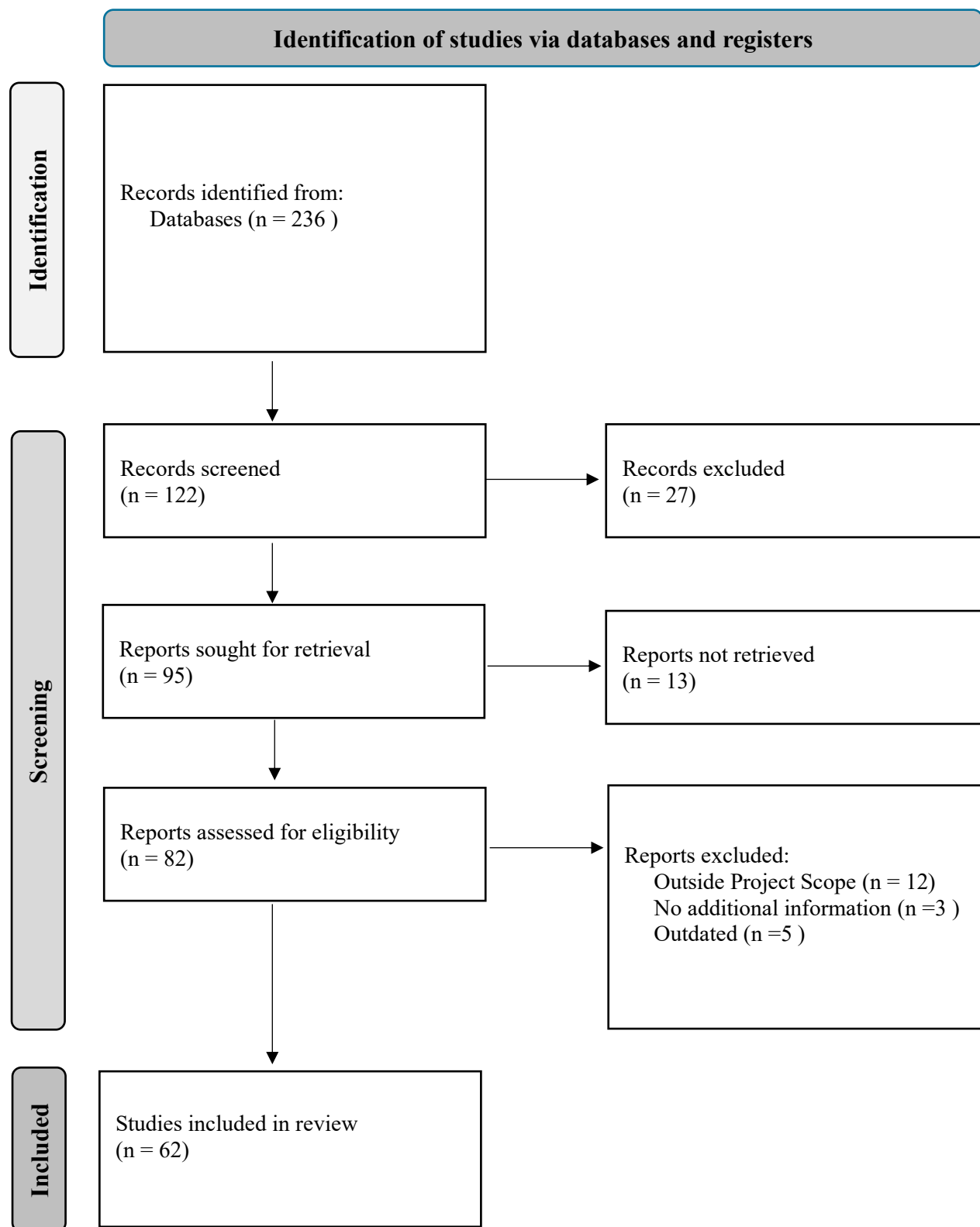
RQ7 How can digital twins be integrated with emerging maintenance operation techniques to optimize maintenance processes and minimize unplanned maintenance and downtime in aviation operations?	• Digital twins and Predictive Maintenance • Digital twins and Integrated Vehicle Health Management • Digital twins and Fleet Health Management
RQ8 What are the knowledge gaps in terms of skill requirements and workforce training for the effective implementation of digital twins?	• Challenges in digital twin use in aviation • Airline companies' data management/ analysis capabilities • Airline companies' investments and research in data analysis • Skills required to maintain a data driven model
RQ9 What are regulatory constraints and industry standards that pose challenges to the integration of digital twins into existing aviation systems?	• Cost of integration of digital twins in the aviation industry • Cost of integration of digital twins in • Regulatory bodies in play in aviation • Regulatory requirements to implement new technology in airline operations • Timeframe for implementing a new system into airline systems

3.3. PRISMA 2020 (Preferred Reporting Items for Systematic reviews and Meta- Analysis) Flowchart

PRISMA is a flowchart that was founded in 2009 by Cochrane authors. It is a systematic review which aim to extensively scan available reports published on the subject to answer defined research questions (Selcuk, 2019). PRISMA 2020 is an enhanced version of the PRISMA method, and it is the method that is used. This method is chosen to approach the literature review in a systematic and transparent way as the flowchart conveys how the research was done at each point and lays a framework for a standardized research approach.

The PRISMA 2020 consists of three main sections: identification, screening, and included. Each section consists of several sections. Each section indicates the number of articles, reports that were used. The identification section defines the number of records identified after doing keyword searches. Later the duplicates or ineligible reports are removed, and the number of the removed reports are conveyed at the cell on the right-hand side. In the screening phase the remaining eligible reports are screened based on different parameters as stated within each cell. At the first phase of screening, the only check is done by reading the abstract to verify the relevance of the report to the topic at hand, no further review is done at this stage. Later, at the second cell the reports are sought for retrieval, using the institution access, any inaccessible reports are eliminated at this stage. Lastly, eligibility of each report is checked by thoroughly analyzing the report. Any reports excluded at this phase due to ineligibility is justified in the cell on the right hand. In the last phase of the flowchart, which is included, all included reports and studies are shown. These are the sources that are used to answer the research questions.

Down below is the PRISMA 2020 flowchart used. There are several versions of the flowchart where this version is selected due to its compatibility with the research being done.



4. Literature Review

This section consists of sections which aim to answer the predetermined research questions. The information conveyed on each section is based on the compiled reports. The sections are sorted by relevance to each research question. The aim of this section is to layout, analyze and understand the topics at hand with the information gathered.

4.1. Unplanned Maintenance

There are two types of maintenance including the aviation industry, which are planned and unplanned maintenance. Planned maintenance is performed with regards to the requirements set by the manufacturer. Within the aviation sector there are three main criteria which affect planned maintenance, these are: Calendar Time, Flight Hours, and Cycles. Calendar Time depends on the time that has passed over since the start of operation of the equipment, which effects any component that degrades over time regardless of how much that component is used (Jenvald & Howmöller, 2020). A good example would be the fire extinguishers, regardless of it not being used over time it degrades and needs to be replaced. Flight Hours refer to the actual number of hours flown by the aircraft over a specific period from the end of takeoff until the beginning of landing (Guzhva, et al., 2018). On the other hand, Flight Cycles includes all the period within Flight Hours as it refers to the total time from engine start through engine shutdown (Mofokeng, et al., 2020).

On the other hand, “unplanned maintenance is initiated by technical failures, reported defects, and faults identified during inspection” (Ayeni, et al., 2011). The unpredictable nature of unplanned maintenance poses challenges for fleet operations. Along many costs that airlines incur during operation, approximately 12% of all costs come from maintenance related costs making it the third cost center behind fuel and cost of operations (Potter, et al., 2015). Even though some of this cost is incurred from planned maintenance, the majority is attributed to unplanned maintenance as unplanned maintenance causes more costs to be incurred apart from the costs related to the maintenance itself. The disruption it causes through operations causes flight delays and cancellations, while in some cases causing unplanned and costly aircraft location changes, where another spare airplane is flown from another area to keep the route operational. Furthermore, the necessity to compensate customers adds to the financial burden. Airlines also incur indirect costs

associated with maintenance. When an aircraft is operating, it produces revenue. When the aircraft stop operating to go out for maintenance, the airline does not only incur costs of performing the maintenance, but also faces the opportunity cost of no longer producing revenue for the time that the aircraft is in maintenance (Dupuy, et al., 2011).

Apart from the financial damages, it complicates already complex flight schedules. As any replacement aircraft might also cause delays on its predetermined routes and so on. These effects can sometimes cause butterfly effect crippling the ability of the airline to operate. Fortunately, most of these incidents can be isolated and taken care of by airlines. However, the costs related to it does not go away with good management. According to a study done in 2023 reveals that delayed and cancelled flights due to unplanned maintenance has cost airlines globally \$21B in the year 2017. According to projections, that number is expected to surpass \$40B by the year 2035 (Statista, 2023) as depicted below in figure 1.

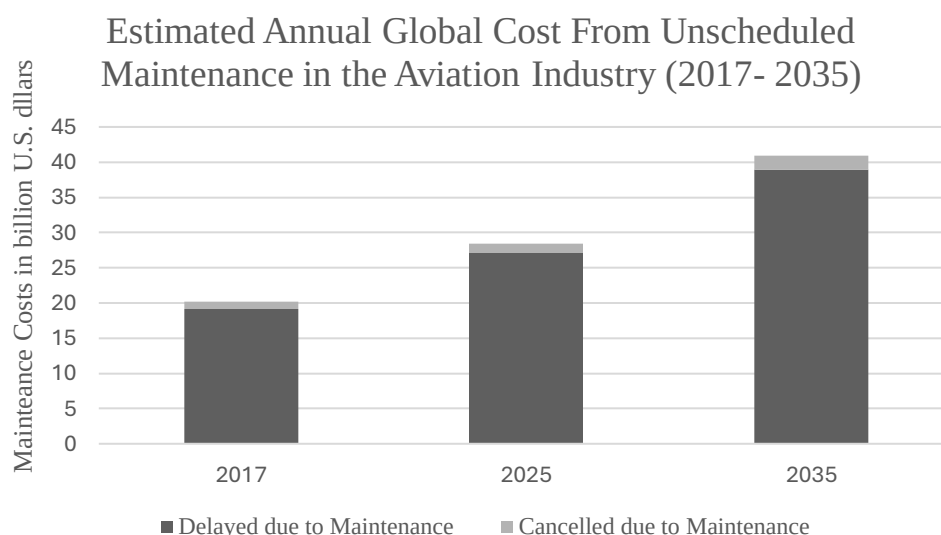


Figure 1: Estimated Annual Global Cost from Unscheduled Maintenance in the Aviation Industry (2017- 2035) (Statista, 2023)

There are several reasons for the costs related to unplanned maintenance to increase. The increasing fleet sizes and the number of operational aircrafts is one of the more obvious reasons. However, a forecast done by Airbus suggests that “...demand for passenger traffic will grow

annually by 3.6%. (2019-2042 CAGR – Compound Annual Growth Rate) over the next 20 years.” (AIRBUS, 2023). Which indicates that growing demand contributes minimally to the expected increase in costs related to unplanned maintenance which is expected to double within the next 10 years. Secondly, the increasing complexity of aircrafts introduce new systems with each model development, these systems help increase efficiency of the components however these systems and additional components are also prone to maintenance and increase the workload. Additionally, scheduling is another factor, with every airline aiming to reduce operational costs, their schedules must ensure that every aircraft within their fleet has high annual utilization as fixed costs related to aircraft ownership diminish with higher output. However, high aircraft utilization can increase the need for maintenance (Camilleri, 2017). Another effect of high aircraft utilization and consequently tight scheduling is that any local disruptions to operations can have bigger effects throughout airline operations. A single airline being grounded during a leg can cause a much bigger stress on scheduling as finding available aircraft to replace the inoperative one can be harder, and these types of incidents can have cascading effects.

With all these effects in play the costs of unplanned maintenance will become more significant over the year. One of the biggest operational costs, fuel costs are slowly decreasing as new technologies are introduced and airlines aim to reduce environmental footprints, by investing more into these emerging technologies. A case study done on fuel burn of an AIRBUS A320-200, one of the most common aircraft used in the market, expects the fuel burn to decrease approximately 40% within the next 10 years (Kharina, et al., 2016). With most cost drivers being addressed through the industry, like fuel burn costs, it is crucial to also address related maintenance costs and especially unplanned maintenance costs to increase the efficiency.

It is evident that unplanned maintenance poses significant challenges for the aviation industry, in terms of operational disruptions and financial burdens. With the projected increase in costs related to unplanned maintenance globally, it is crucial for airlines to explore and invest in innovative strategies and technologies to address these issues.

4.2. Current and Emerging Technologies to Address Unplanned Maintenance

Unplanned maintenance is not a new issue for airlines, dating back to the start of the aviation industry. Engineers and operation managers have sought to mitigate the impact of the issue over the years, resulting in the development of various approaches. Understanding these current methods is vital for identifying areas in need of improvement. In addition, some of these current methods have the potential to be integrated into newer systems. Following are methods that are being used throughout the industry.

4.2.1. Discrete Event Simulation (DES)

Discrete Event Simulation method is a method that airlines use to mitigate adverse effects of unplanned maintenance. DES is a simulation model used as a network of queues and entities. The system runs by using individual elements to simulate and create numbers of activities to help users understand the distribution of the output. DES method is a widely used method through different industries (Albakkoush, et al., 2021). In the aviation context input data consist of maintenance schedules, aircraft availability, resource constraints, and operational parameters. With these inputs the simulation can predict the potential impacts of unplanned maintenance on different aspects of airline operations (Robinson, 2014).

Using DES, airlines can simulate the effects of unplanned maintenance events on flight schedules, crew assignment, passenger services, and ground operations. The observation of these outputs helps airlines to identify potential bottlenecks and disruptions to service. The identification of these effects can be used to optimize resource allocation, by allocating maintenance resources to disrupted areas. Allocations can be done on the workforce, equipment, and facilities.

In addition, DES can be used to simulate different maintenance scenarios to monitor key performance indicators such as aircraft utilization, on-time performance, and maintenance costs. The different maintenance scenarios can then be used to develop contingency plans and test these plans to evaluate the effectiveness of each plan (Pidd, 1998). In addition to contingency planning the simulations of scenarios at hand enable informed decision making.

DES Inputs and Outputs

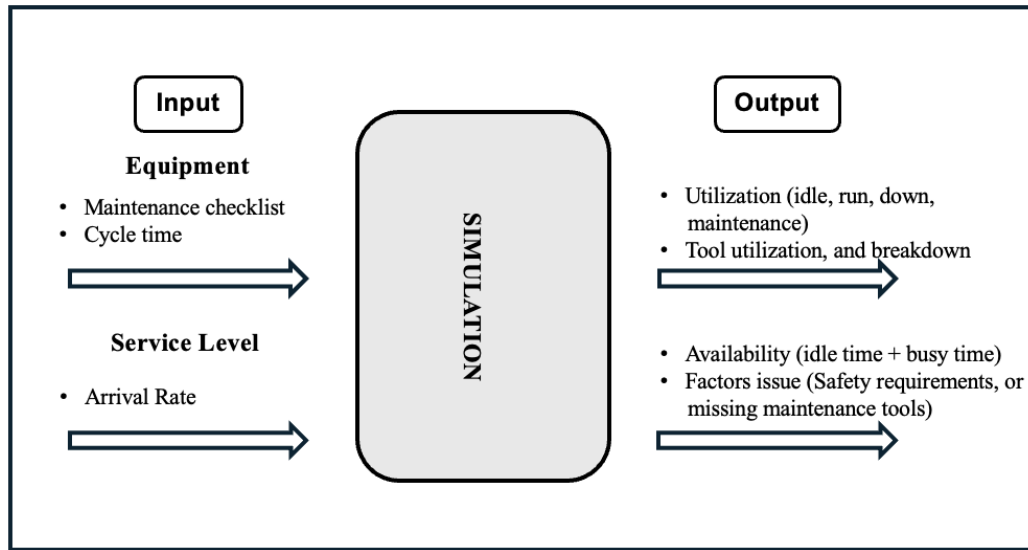


Figure 2: DES input and output (Albakkoush, et al., 2021)

Figure 2 is the simple flowchart of a DES, showing what the potential inputs and outputs. It can be observed that crucial information such as utilization, tool utilization, availability, and factors issues can be obtained from the output by inputting maintenance checklist values, cycle times and the arrival rates. The outputs can be altered by changing the inputs or the simulated parameters.

4.2.2. Comprehensive Data Analysis (CDA)

Comprehensive data analysis plays a pivotal role in the aviation industry. It is used to systematically analyze complex historical datasets. By monitoring and evaluating key performance indicators, airlines can extract meaningful patterns that can help identify potential areas of concern and predict maintenance based on these historical patterns before the maintenance need escalates. Furthermore, identification of rare events, such as unexpected failure of parts can be made possible by detecting the meaningful outliers in large data sets. However, due to the complex nature of these datasets different machine learning methods must be applied, such as Isolation Forest and Logistic Regression (Apostolidis, et al., 2020).

CDA consist of different phases which include:

- **Data Collection**

Airlines gather relevant data from different sources, such as sensors, maintenance records, flight logs, and operational databases to compile datasets for analysis.

- **Data Cleaning and Preprocessing**

Data needs to be cleaned and preprocessed to ensure reliability. This process involves removing inconsistencies, errors, and missing values, as well as normalizing and aggregating data for analysis (Wang, et al., 2022).

- **Exploratory Data Analysis**

Two main goals of the exploratory data analysis are data description and model formulation, both of which are essential to understanding the data that was gathered. This first step is crucial because it enables analysts to understand the importance of the available data. This phase involves several techniques, such as residual analysis and model validation, in addition to the computation of fundamental indicators like standard deviation (Chatfield, 1986). Tukey (1977) established the groundwork for this stage, and analysts in this field continue to rely heavily on his work. Although there are frameworks available to make this process more efficient, analysts frequently look for various metrics to extract insights from the dataset, leading to a wide variety of approaches during this stage (Morgenthaler, 2009).

- **Data Visualization**

Data visualization is a critical stage where the collected data is visually illustrated to comprehend the patterns and trends. Tufte (1983) laid principles for scientific illustration, emphasizing its significance as one of the most effective methods for interpreting datasets. Comparable to holding a specimen, scientific illustrations, including data visualization, offer insights into the entirety of the compiled data (Webster, 1994).

- **Interpretation and Reporting**

The last stage is to interpret analysis results in the context of the research objectives and to prepare comprehensive reports to communicate findings to stakeholders.

4.2.3. Condition Based Maintenance (CBM)

CBM can be explained as “a maintenance program that recommends maintenance actions based on the information collected through condition monitoring.” (Jardine, 2006). CBM technologies help identify and prevent unplanned maintenance, facilitate substitution or extension of task intervals, and help optimize maintenance schedules throughout the entire fleet. CBM has the potential to become one of the most common techniques used to address unplanned maintenance through the aviation industry, however, even though the technology has been available for decades the practices currently lack the ability to exploit its full potential (Verhagen, et al., 2023).

CBM consists of three main elements:

- **Condition/ Health Monitoring**

This stage involves the direct and indirect collection of health data of the related equipment. The data can be collected using signals from on-board sensors or various Non-destructive Tests, which is done by ground inspection crews. These data can be collected periodically to produce up-to-date condition reports of each aircraft or component (Verhagen, et al., 2023).

- **Integrated Aircraft Health Management (IAHM)**

IAHM is a process that utilizes data collected through condition/health monitoring. The main goal of this process is to predict the degradation and aging of each component onboard to produce a comprehensive health condition data about an aircraft (Verhagen, et al., 2023). “The technologies developed under the IAHM program may be used to increase aircraft system reliability, safety, maintainability, availability, and affordability.” (Ortiz, et al., 2008).

- **Maintenance Planning**

In this final stage the gathered data and analysis done through IAHM is used to make informed decisions on resource allocation to perform maintenance, maximizing fleet utilization, availability and increasing profitability.

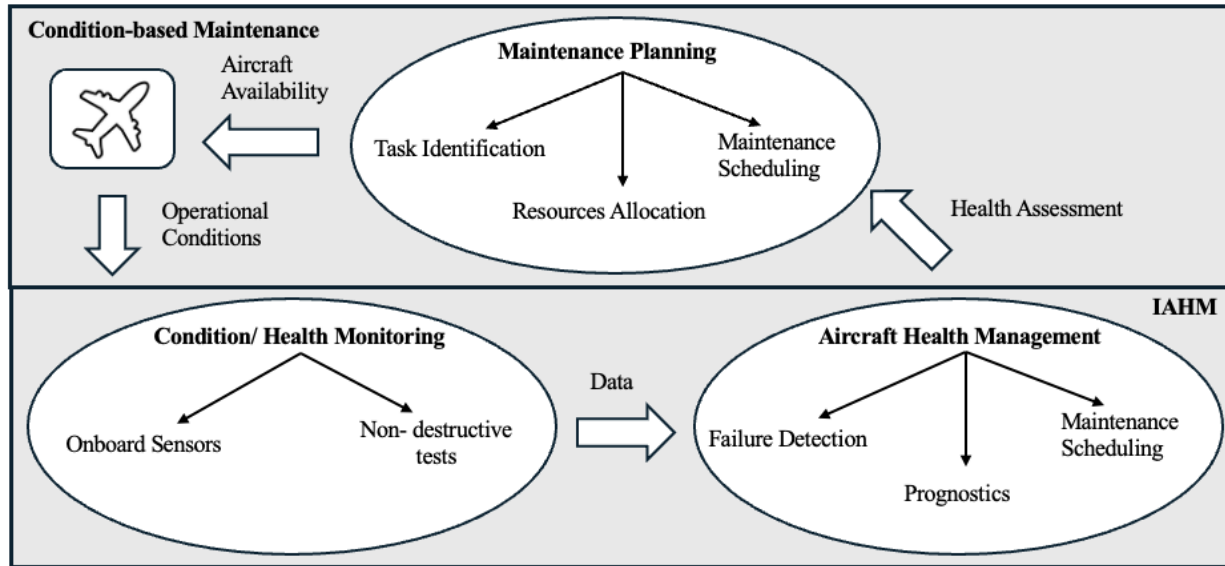


Figure 3: Condition-based Maintenance Flowchart (Verhagen, et al., 2023)

Figure 3 illustrates how 3 main elements of CBM work in a combined way. Condition health monitoring gathers data from the physical aircraft then transfers the gathered data to aircraft data management systems. The AHM system processes and analyzes the data and transfers interpretations and analysis on aircraft health to maintenance planning, which uses the information provided to amend schedules on the physical aircraft. It is a closed-loop system where each phase feeds information to the next phase all around the loop. This closed loop structure ensures that the system is up-to-date and aware of any conditions including the effects of amendments done by maintenance processes.

4.2.4. Predictive Maintenance (PM)

Predictive maintenance is the strategy of proactively maintaining the equipment at hand, by leveraging data analytics, machine learning, and sensor technology to predict related failures

before they occur. In the context of the aviation industry, predictive maintenance plays a pivotal role in ensuring the safety reliability and efficiency of aircraft operations (Smith, 2019). “The integration of Cloud-based analytics with industrial machinery has driven the advent of a new “Industrial Internet” – and with it, opportunities for huge productivity gains. Industrial machines equipped with a growing number of electronic sensors can see, hear, and feel a lot more than ever before – and deliver enormous amounts of data to be analyzed. Sophisticated algorithms then provide insights that allow us to operate machines – fleets of engines, airplanes and network entire systems like airlines and airports – in entirely new more efficient ways.” (Daily & Peterson, 2017).

Sensors embedded within the aircraft systems collect data on various parameters such as temperature, pressure, vibrations, and fluid levels, providing insight into the health and performance of these components. With the use of complex algorithms, the collected data is analyzed and is used to enhance the understanding of the aircraft’s componential and overall health. The analysis and the data are later used to predict impending failures of the components. These predictions are then used schedule maintenance before the failures happen. A simple predictive maintenance approach has a flow diagram as follows.

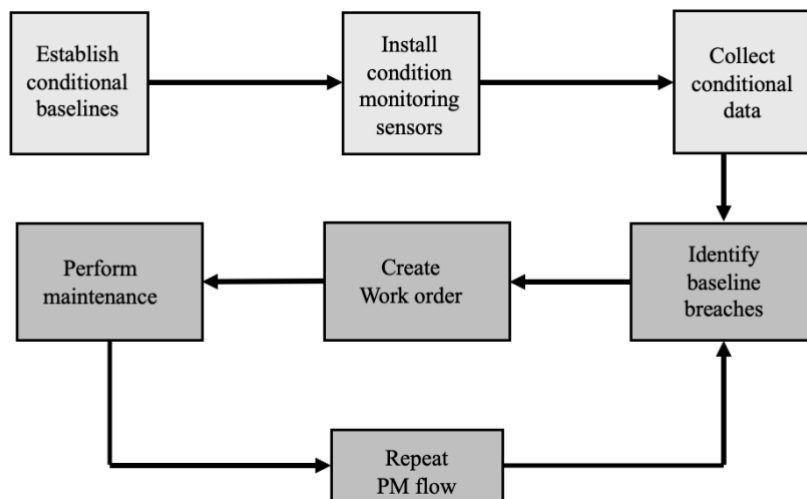


Figure 4: Predictive Maintenance Flow Diagram (Upkeep, 2024)

Predictive maintenance has a simple flow however certain models and parameters are needed to be set beforehand. Firstly, baseline conditions are set to replicate the scenario at hand, later sensors

are installed into the areas and components where desired parameters can be monitored. Using these sensors data collection of pre-determined parameters begins. After this phase the Predictive Maintenance system can start to analyze real-time data. When the parameters that are being monitored surpass or fall short of the preset values the system is triggered, which creates a work order to address the detected anomaly. Following the work order, related maintenance is conducted, which in turn brings the parameters back within the limits. At this stage the model is back to the baseline and the system continues to monitor the data. The closed loop nature of the system ensures constant monitoring.

While predictive maintenance offers benefits, such as reduced downtime and cost savings, it also presents limitations and challenges. One of the major challenges comes with data quality related issues. The quality of the data can be low if the data acquired is incomplete or inaccurate, which can lead to incorrect predictions and reduced effectiveness of predictive maintenance efforts (Láinez, et al., 2018). Moreover, implementing predictive maintenance can be complex and resource-intensive, requiring large investments in sensor technology, data analytics capabilities, and personnel training (Mokhtari, et al., 2018). Another challenge arises with the integration of predictive maintenance systems with existing maintenance workflows and IT infrastructure. The compatibility and operability between predictive maintenance and current systems may increase costs and workforce needed for integration (Peterson, et al., 2014). Lastly, regulatory and compliance considerations to address, particularly regarding security and data privacy. Overcoming these challenges are essential to exploit the full potential of predictive maintenance in the aviation industry.

4.3. Digital Twins (DT) Utilization in Aviation

4.3.1. DT Background

Digital twins can be defined as “a mirror image of a physical process that is articulated alongside the process in question, usually matching exactly the operation of the physical process which takes place in real time.” (Batty, 2018). The development and enhancement of DT benefits from the progress achieved in the internet of things (IoT), artificial intelligence (AI), cloud computing, edge computing, 5G, etc. (Xiong & Wang, 2022). “DT can provide real-time, high-fidelity virtual

model for its aviation counterparts.” (Li, et al., 2021). There are numerous companies who are investing in developing DT systems, which will satisfy a wide range of needs through the industry.

4.3.2. DT Utilization Areas in Aviation

As discussed before DT has been used in many industries, since its discovery. There are many different applications of DTs that are being used in different companies around the aviation industry. Understanding current methods that leverage DT technology and analyzing the positive and adverse effects is crucial to deduce which areas can be enhanced about the technology. There is a wide scope for DT in the aviation industry and companies leverage the power of DT to enhance processes that affect them most. It is reasonable to assume that most of the times a manufacturing company focuses on leveraging DT in their manufacturing processes whereas an airline would like to use the technology to increase operational efficiency.

General Electrics have been developing a DT framework for the last ten years. It is one of the most advanced of its type. “GE believes that the DT represents the software form of assets and processes and can be employed to understand, predict , and optimize performance.” and the purpose is to improve the performance of assets and processes (Parris, 2017). With this approach and developed DT frameworks, GE now tracks more than 7000 assets globally, giving probabilistic predictions on the assets to the users. This system also tracks down the systems value addition by calculating the savings accumulated by the help of predictive maintenance approach employed with the use of DTs. An example can be given by the latest prediction done by GE, which was an early warning of increased enclosure temperature on an aeroderivative gas turbine. This was made possible by monitoring real-time temperature of the asset and detecting an anomaly that could imply this failure. This detection was then notified to the customer and countermeasures was taken to minimize disruption. It was calculated that this early warning has saved approximately \$475,000 to the customer (GE, 2024). This system leverages both the power of digital twins and predictive maintenance.

Siemens also came into the Digital Twin scene with their own product, and put forward the term *comprehensive DT*, and pointed out that an ideal product can be delivered by the mapping of DT products. (Xiong & Wang, 2022). With advanced asset monitoring and mapping of each interaction

of assets, Siemens aims to increase the real-time knowledge about assets at hand within the whole vertical team, ranging from the designer to the operation manager, to increase workforce efficiency, and improve coherence between teams.

Airbus is another main player in the shift towards a digitalized future, with the focus on production. First applications were seen with the production of A350, where DTs were used in the assembly line (Sadeghi, et al., 2024). The main driver was the increasing demand from customers for shorter order delivery times. Airbus started to work on applying DTs in the production lines. The digital transformation lead Juan Ignacio Castro has explained the approach by saying: “To achieve this requires an overall view of the processes (design, development sales, services etc.) and connecting all data generated during associated operations, from beginning to end.” (lantek, 2014) In order to create an ecosystem which encapsulates all of the processes related to production, all the data gathered from the beginning of the assembly line until the day of delivery have to be sorted, modeled, and demonstrated. With these organized datasets at hand each process can be accelerated. With digital models at hand, manufacturing of components can be done by cheap and fast methods such as additive manufacturing which serves the main purpose of reducing production time and increasing profitability. In addition to the production phase, with increased data utilization more and more tests can be conducted on digital models which were once done on the physical aircrafts, which were more costly and time consuming. Furthermore, with any unsatisfactory results it is trivial to make changes on the digital twin to understand effects of the amendment. This way the whole production line becomes faster, cheaper, and safer as design iteration and amendments enable increased development intervals. With these developments Airbus aims to improve production quality, shorten production time, and offer new services or business models. In addition to these developments Airbus has also started to work with automated robots and drones which work alongside engineers and inspectors, where robots help with assembly and drones inspect parts for quality testing, these advancements are all made possible by the ecosystem created by the data centered digitalization.

Apart from the implementation of digital twins to the production and assembly lines, Airbus has also introduced a DT for the latest model A321XLR where it is expected reduce fuel burn by 30%. While also focusing on defense industry with the latest Future Combat Air System (FCAS) which

aims to improve defense technology of Europe and the spillovers into the civilian world (Sadeghi, et al., 2024).

One of the most important developments in the DT area has been made by Lufthansa's new software product AVIATAR, which is an aircraft fleet management DT (Sadeghi, et al., 2024). The aim of this product is to use previous fleet management solutions, and data related to science and engineering to provide integrated services and products to airlines (Careless, 2021). Lufthansa explains this platform as "...a platform for the entire aviation industry, offering extensive variety of digital products and services for airlines." (Lufthansa Technik , 2024). The platform includes a range of products, such as Condition Monitoring, MRO Management, Predictive Health Analytics, Technical Logbook, Reliability Solutions, and more are currently being developed. Each app is a standalone product, able to operate on its own however the use of all apps offers to create an ecosystem that increase the power and effectiveness of the platform. (Lufthansa Technik , 2024). With the help of these apps the aim is to increase operational efficiency of airlines.

Several other applications of DT can be seen through the industry such as Boeing's application of DT in the production lines of 737MAX, 777X, and 787 in order to increase production quality and asses the whole production line, which helped reduce assembly time by 80% (Sadeghi, et al., 2024). The joint venture of GKN Aerospace and GE aims to develop DT for manufactured aircrafts which will reduce inefficiencies in traditional prototyping, Dassault Systems are developing an all-around system: 3DEXPERIENCER TWIN which aims to leverage digital twins' data capabilities to create an all-around data centered work environment, which is aimed to keep each vertical team member up to date with real time data to increase informed decision making, this system is also being developed for specific aviation industries with the joint work done between Dassault and Airbus (Sadeghi, et al., 2024). Lastly, KLM Royal has developed 104 DTs which allow to reduce travel movements of crew, increase customer satisfaction, and reduce environmental impact of the airline (Matterport).

While the examples discussed above showcase the extensive utilization of digital twins (DTs) in various aspects of aviation, it is important to note that most applications currently focus on the manufacturing phase rather than operational aspects except AVIATAR and DTs of KLM. This

highlights a significant opportunity for further development and expansion of DT technology in the operational domain of the aviation industry. While DTs have demonstrated their value in optimizing manufacturing processes, enhancing quality control, and reducing production times, their potential in streamlining operational activities, such as maintenance, fleet management, and flight operations, remains as an intriguing area for DT utilization. By harnessing the power of DTs to create virtual replicas of aircraft systems and assets, airlines can gain real-time insights into performance, health, and operational status, enabling proactive decision-making, predictive maintenance, and optimized resource allocation. As the industry continues to evolve and embrace digital transformation, there is room for innovation and collaboration to drive the adoption of DTs in operational workflows, ultimately leading to improved efficiency, safety, and reliability in aviation operations.

4.3.3. DT Use in Addressing Unplanned Maintenance

Digital Twin technology is revolutionizing the aviation industry by enhancing safety, reliability, and operational efficiency. DT technology provides virtual representation of aircrafts and components, enabling real-time monitoring, simulation, and optimization of aircraft systems (Xiong & Wang, 2022). Together with different maintenance methods, DTs offer a holistic approach to maintenance management and operational decision-making in aviation.

“The development of maintenance has undergone the transition from “post-event maintenance” and “preventative maintenance “ to “predictive maintenance” and the future development direction is precise maintenance.” (Xiong & Wang, 2022). To further enhance the approach towards maintenance, and eliminate unplanned maintenance, Digital Twins, and maintenance methods, such as predictive maintenance (PM), Integrated Aircraft Health Management, Discrete Event Simulation (DES), and Comprehensive Data Analysis can be used in integration.

4.3.3.1. Digital Twins and Predictive Maintenance

Predictive maintenance is one of the most promising methods out of the methods listed above, as the needs of Predictive Maintenance and developing digital twins overlap. Predictive maintenance needs constant real-time parameter monitoring, similarly digital twins require the same information to construct and update the virtual replica. With the use of both technologies a real-

time model, with the ability to predict any maintenance, can be created. When the possibility of DT working in tandem with PM is further investigated, a system that can work in harmony between DT and PM can be possible. The system can consist of two main stages, where the first stage is the creation of a DT and data acquisition to maintain a real-time DT. Later predictive maintenance algorithms can work on the DT to gather data where needed, to spot anomalies and deduce the overall health of the equipment. By combining the needs of DT and PM a more efficient model can be developed. The output of this combined system will have a highly useful information while also not using computational power as much as using these two systems separately.

An example to how this system will work can be explained through a scenario. When an aircraft lands and takes-off at high speeds, the condition can cause stress to the tires on the landing gear, which can cause a phenomenon called a flat spot. Flat spots can cause faster wear to the tires and can increase the possibility of a tire blow up (Xiong & Wang, 2022). This issue can be tracked and can be acted upon using DTs and PM. To develop the process, experimental data of the tire characteristics in ideal and non-ideal conditions will be needed to be collected (Zakrajsek & Mall, 2017). The collected data will serve as a baseline for the model. The baseline model will then receive crucial parameters in real-time from the aircraft which will monitor the desired component, in this case the tires. The system will monitor the condition of the physical aircraft, updating the current condition of the DT. When an anomaly is spotted, data will go through the predictive maintenance process to predict the magnitude of the anomaly and using the algorithms, will decide if an action needs to be taken. In a case where action needs to be taken, related maintenance runs will be scheduled before the failure occurs to reduce the disruption caused to the operations. After the maintenance is complete, the health state of the aircraft will again be monitored by the sensors and the changes will appear real-time on the DT. This way the maintenance quality can also be controlled. When every process is done the physical aircraft goes back to service, while still being constantly monitored for any other failure. This process can be used for the identification of failures in many other components apart from tires. The system can either be used to monitor the overall health of the aircraft or selected crucial components. Following is a flow diagram depicting how each system and process can be structured.

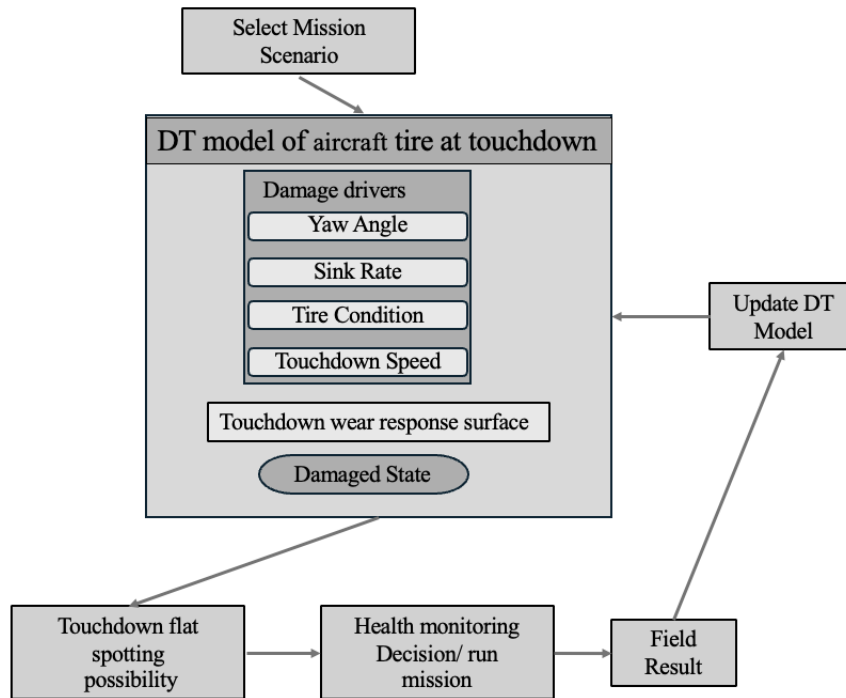


Figure 5:DT for tire health management (Zakrajsek & Mall, 2017)

By monitoring different parameters which are listed as damage drivers, a preset DT is updated constantly. When a damage occurs, or possible parameter anomalies happen the system runs this through health monitoring. During this stage predictive maintenance methods are used to assess the situation and suggest actions. After conducting necessary operations, the DT is again updated with the live data. This flow is structured for tire health management however, same structure can be used for monitoring different components simply changing the inputs, and preset DT.

4.3.3.2. Digital Twins and Integrated Aircraft Health Management

Integrated Aircraft Health Management (IAHM) is the paradigm shift to support condition-based maintenance (Xiong & Wang, 2022). DT combined with IAHM technology can assess the overall health of components and systems. IAHM is based on continuous interaction and update of data, to diagnose, predict and mitigate failures (Ezhilarasu, et al., 2019).

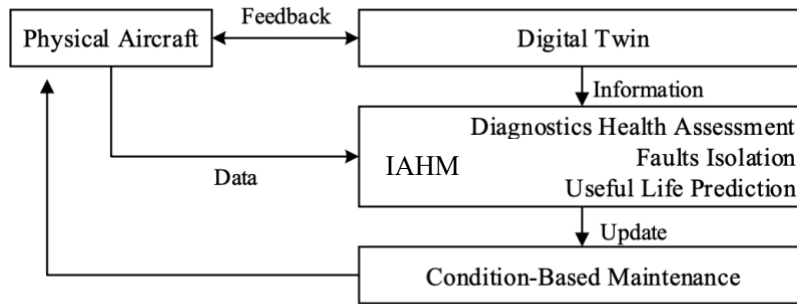


Figure 6:DT in a IAHM framework (Ezhilarasu, et al., 2019)

The framework illustrates how the IVHAM system can seamlessly integrate with a DT model. While traditional condition-based maintenance remains prevalent for addressing maintenance needs, focusing on past faults, there is potential for synergy between IAHM, DT, and traditional methods. Both the Digital Twin and the IAHM system receive data from the physical aircraft: the former uses this data to update DT properties, while the latter analyzes overall health. IAHM systems also leverage additional information from the DT to enhance analysis accuracy. Predictions and assessments by the IAHM system proactively update the condition of the physical aircraft, allowing for preemptive action before observable issues arise. This continuous flow of data through the framework ensures ongoing monitoring of the aircraft's overall health.

4.4. Current and Emerging Technologies for Data Collection and Processing

4.4.1. Real- Time Data Capturing

Real-time data update is crucial for maintaining the accuracy and quality of Digital Twins, as it ensures that the virtual representation remains synchronized with the real-world counterpart. According to Xiong and Wang (2022), constant data acquisition and updates enable Digital Twins to reflect the current state of physical assets accurately, allowing for timely analysis and decision-making based on real-time conditions. Real-time data capturing involves the integration of various sensors, data acquisition systems, and communication networks installed on the aircraft to continuously collect and transmit operational data to the Digital Twin model. The sensors installed on the aircraft collect crucial performance parameters, such as temperature, pressure, vibration, and engine performance, providing a comprehensive insight into the health and the performance

of the aircraft of critical components. The real time data that is collected later gets communicated to the Digital Twin through wireless networks, ensuring the synchronization between the DT and its physical counterpart (Laínez, et al., 2018). Additionally, the utilization of edge-computing and onboard processing capabilities allows for data pre-processing and analysis onboard the aircraft, reducing latency and enhancing the efficiency of real-time data capturing processes (Daily & Peterson, 2017).

To collect crucial data accurately, the selection of parameters that will be monitored is crucial. The parameters should be decided according to the components that are intended to be monitored. Different performance parameters can be utilized to analyze the health of the components. Following is an example parameter- component pairing framework.

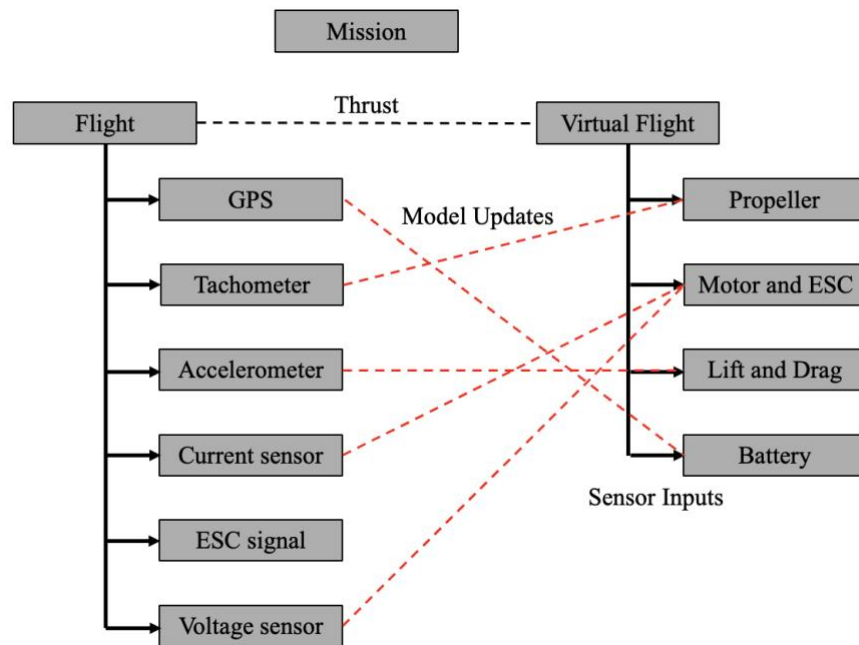


Figure 7: Updating procedures of the models used in the virtual domain (Leishman , 2006)

The virtual flight keeps track of the parameters selected (Propeller, Motor and ESC, Lift and Drag, Battery) using different data sources as listed on the left-hand side. Each source provides data input to the system to update the monitored components on the virtual flight. A crucial step in this process is the modelling structure used to design the DT. For the data to be meaningful to the DT model,

it needs to be trained using historical data. This provides information about the normal component parameters limits, so that the system can understand the values that are being fed in it. The modelling process and parameter data feed can be illustrated as seen in Figure 8.

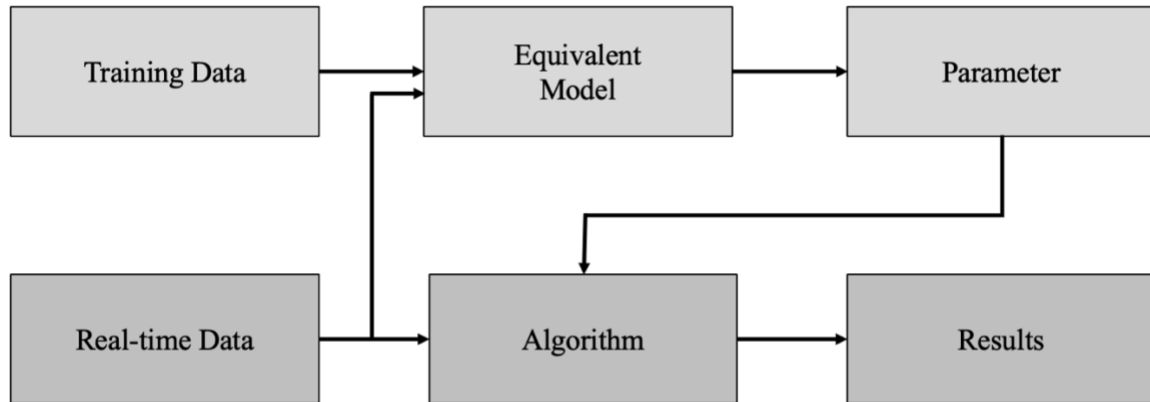


Figure 8:DT Real-time data update framework (Sadeghi, et al., 2024)

Firstly, an equivalent model is created, and is trained with historical data. The model consists of parameters that are fed into the algorithm, which also receives data from real-time events. The algorithm used, compiles, and analyses all the data produces a report, which in the context of maintenance, are the health information about the components.

Overall, this structure is an effective way to collect and transmit data to the virtual counterpart. Real-time data capturing plays a crucial role in driving efficiency and competitiveness in aviation maintenance practices. However, there are several challenges that can arise when these systems are being used. Data latency, bandwidth limitations and cybersecurity concerns are some of them. These challenges emphasize the importance of edge-computing and data preprocessing as discussed before (Daily & Peterson, 2017). Additionally, stringent cybersecurity measures are essential to safeguard data integrity and prevent unauthorized access to critical flight data. Continuous development, innovation and investment in data capturing and communication is crucial to harness the full potential of DTs and realize the benefits of predictive maintenance in the aviation industry.

4.4.2. Data Processing and Fusion Methods (Data Integration Methods)

Data processing and fusion methods are two crucial elements that support the functionality of both DTs and Predictive Maintenance technologies within the aviation industry. These methods are instrumental in merging and combining data streams originating from diverse sensors and sources, thereby facilitating in-depth analysis and informed decision making. Information integrations systems ensures that the user can obtain the complete yet concise overview of all existing data without needing to access all data sources separately. (Bleiholder & Naumann, 2008). The use of data processing and fusion techniques increase the interpretability of the available datasets by humans and algorithms. Thus, they serve as one of the most important phases through the data process. In this article it is assumed that the data integration process consists of three phases as depicted in Figure 9 (Naumann, et al., 2004).

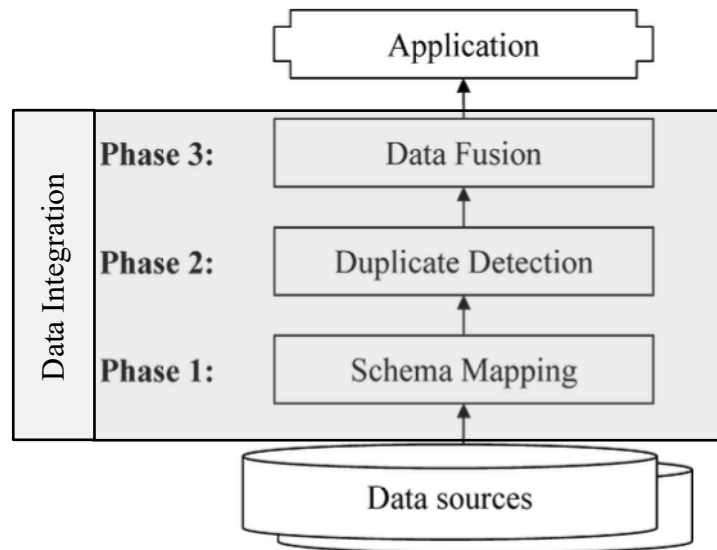


Figure 9: Data Integration Process (Naumann, et al., 2004)

Data sources include wide range of different sources, that can produce different kinds of data which needs to be integrated. In the context of aviation, the large component number of aircrafts result in a wide range of different types of data making the data integration process even more important.

The data integration process happens in three main stages:

4.4.2.1. Schema Mapping

Schema Mapping is a process which involves the process of defining correspondences or relationships between schemas of different data sources. The mapping facilitates the transformation and alignment of data from different sources, to ensure compatibility and consistency within the integrated dataset. With the use of schema mapping heterogenous data sources can be integrated and seamless data exchange and analysis can be made possible.

4.4.2.2. Duplicate Detection (Record Linkage)

This phase aims to identify multiple representations of the same real-world object. This process is done by comparing each pair of objects using a similarity measure and apply a threshold. If a pair is detected to be more similar than the set threshold it is declared as a duplicate. As simple as the process is there are two main challenges related to duplicate identification: effectiveness and efficiency. Effectiveness is affected by the quality of the set similarity measure and the set threshold. A high threshold results in high precision (nonduplicates are not found) but low recall (not all duplicates are found), conversely a too low threshold will result in a high recall but reduced precision. Tuning the threshold to an optimized value can prove difficult because of its domain and event specific nature (Bleiholder & Naumann, 2008). Efficiency becomes an issue as the datasets are often large, calculating and storing all pairs of objects can become an obstacle. Another obstacle is the complexity of the similarity measure itself. Using intelligent partitioning of the objects and comparison of pairs of objects can overcome the first obstacle. Additionally, second obstacle can be avoided by computing the upper bounds of the similarity and the actual distance for pairs whose bounds are higher than the upper bound (Weis & Naumann , 2004).

4.4.2.3. Data Fusion

Data fusion is a critical phase in data integration, aiming to merge and reconcile data from heterogenous sources, maximizing the benefits of diverse information to provide a unified perspective (Piantella, 2013). Key aspects of data fusion include resolving conflicts and inconsistencies between dataset, handling redundancy and enriching data by combining information from numerous sources (Ahamed & Ramkumar, 2016). There are several challenges

related to data fusion, which include: addressing heterogeneity, ensuring data quality, scalability, semantic integration, and security and privacy concerns (Lahat, et al., 2015). The effective application of prior phases such as data cleaning, conflict resolution, schema mapping, and record linkage is crucial for the seamless integration of data from diverse sources, enabling users to leverage their data assets and gain valuable insights.

Overall, data integration plays a crucial role in turning the acquired data into useful data. The output from DTs and IAHM systems can be as good as the data that has been fed in them, thus using the data integration procedures before feeding the data into the DT/IAHM systems can largely impact the useful output generated from the method depicted in Figure 6. Incorporation of data integration and DT/IAHM framework can be depicted as:

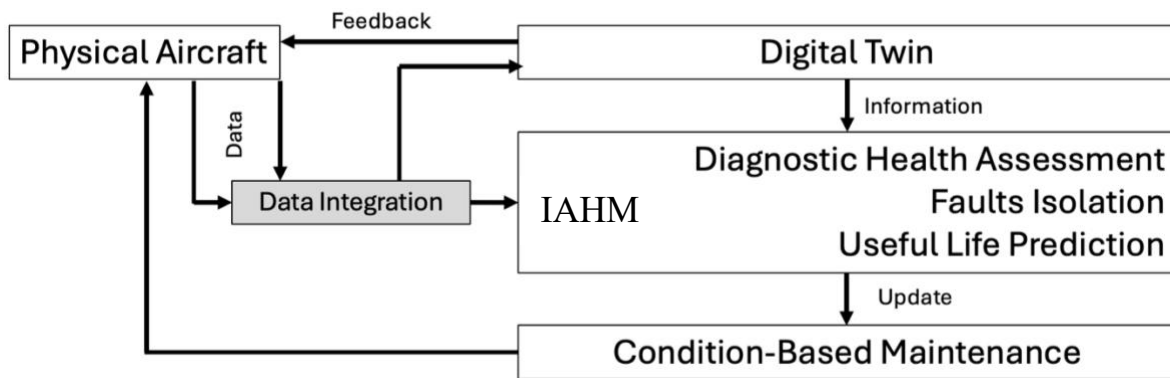


Figure 10: DT/IAHM Framework Interaction with Data Integration Interpreted from: (Ezhilarasu, et al., 2019)

This setup resembles the model depicted in Figure 6, but with an added layer of data integration. As discussed earlier, ensuring the quality of data fed into both DTs and IAHM systems is paramount for optimizing their performance. To refine data quality and simplify any complexities, a data integration step precedes the flow of data into both the DT and IAHM. It's important to note that the data integration component consists of three primary stages of data integration, as illustrated in Figure 9. Feedback in this structure bypasses the data integration process. However, if necessary, data from the DT can also undergo integration. The feedback received from the DT is generally directed to on-site personnel and scheduling departments. When integrating the data, it's crucial to ensure that the recipients can easily interpret it.

4.5. Limitations, Regulations and Challenges Related to DT Integration

DTs used in integration with current and emerging methods have the potential to mitigate and eliminate disruptions due to unplanned maintenance. However, the integration of DTs into current maintenance methods within the aviation industry poses several challenges that need to be addressed. Implementing DTs in aviation maintenance faces hurdles related to data compatibility, system complexity, and organizational readiness (Suh & Magar, 2019). Furthermore, the aviation sector operates within a highly regulated environment where the safety and reliability are paramount, adding another layer of complexity to DT integration efforts. Understanding the challenges is crucial for developing effective strategies to overcome them and harness the full potential of DTs in aviation maintenance.

4.5.1. Technical Limitations

There are numerous technical challenges related to integrating DTs into current and emerging maintenance methods. The standing out challenges can be listed as:

- **Data Integration**

As discussed before data integration is a crucial step to ensure high quality information. There are many current and emerging technologies to address data related problems, however there are many problems that need to be addressed further, such as effectiveness and efficiency. In addition to these problems, as the aircrafts get more complex, datasets become more complex with them.

The diverse origins of aircraft maintenance data, stemming from sensors, maintenance logs, and operational records, present a challenge due to their varying formats and structures. Harmonizing these heterogeneous data sources into a cohesive digital twin model proves to be a significant hurdle (Bisanti, et al., 2023) (Casian, et al., 2022). Furthermore, maintaining the quality of the integrated data is paramount. Accuracy, completeness, and consistency are crucial aspects to ensure reliable representations and sound maintenance decisions, as poor data quality can undermine the effectiveness of the systems. Lastly, establishing procedures to safeguard data security and privacy of large datasets can pose

difficulties. The data collected within these systems are real-time crucial data for the flights. To ensure the safety of the tracked flights, strict security measures should be taken (Casian, et al., 2022).

- **Scalability**

One important challenge when implementing DTs in aircraft maintenance is scalability, due to the immense volume of data generated by multiple systems and components across an entire fleet. Managing and processing this vast amount data in real-time poses significant technical challenges. From monitoring engine performance to tracking structural health, DTs must efficiently handle data streams from numerous sources while maintaining responsiveness and reliability. Ensuring scalability involves designing robust data infrastructure, employing advanced analytics tools, and implementing scalable cloud computing solutions, which can require large investments, and complex workloads (Bisanti, et al., 2023).

- **Real- Time Synchronization**

Real-time data capturing is crucial to maximize the benefits of DTs. This feature enables related systems to receive and process the data to react to the constant changes in the condition of the components. However, communicating with flights all over the world constantly requires advanced communication tools which are costly. Even if the costs are covered current communication technologies can have unwanted delays and cutoffs while communicating. Investment to further enhance communication technologies is crucial (Bisanti, et al., 2023).

- **Model Fidelity**

Developing high-fidelity digital twin models that accurately represent the behavior and degradation of aircraft components over time is a significant challenge, requiring advanced modelling techniques and domain expertise (Bisanti, et al., 2023).

4.5.2 Regulatory Limitations

The aviation industry is continuously evolving and innovating, with the adoption of new technologies making flying safer and more efficient. However, innovation, in an industry where any small mistake can cause catastrophic outcomes, is highly regulated. Even though these regulations are placed to ensure the safety of the industry, they can also hinder and decelerate progress and innovation. While DTs are not a new technology, the use of DTs in maintenance is a new and innovative approach. To use this technology in the aviation industry ensuring compliance to the regulations is crucial. However, this can greatly impact the speed and costs of implementing DTs.

The regulations are governed by regulatory bodies. Most countries or regions have their own regulatory bodies. Federal Aviation Administration (FAA) is the primary regulatory body for civil aviation in the United States. European Aviation Safety Agency (EASA) is the European counterpart to the FAA, both responsible for setting regulations to maintain safety of air travel within their regions. On the other hand, International Civil Aviation Organization (ICAO) is a United Nations agency that creates international standards and recommended practices for civil aviation globally (Srivastava, 2024). Airlines need to comply with international and regional regulations to fly within the airspace of those regions. Thus, compliance is inescapable for airlines to continue operations and ensure safety. Some of the main regulations that must be complied to adopt DT technologies can be listed as:

- **Airworthiness Regulations**

Guidelines must be established to ensure the airworthiness of aircrafts equipped with DT systems. These include validating the accuracy and reliability of DT models used in maintenance decision making (Monroy, 2023).

- **Maintenance Program Regulations**

Regulators need to update maintenance program regulations to incorporate DT technology. This includes setting guidelines for using DT insights to optimize maintenance schedules

and procedures (Lufthansa Technik , 2024). Used models and recommendations from those models need to be investigated to detect any errors that might cause any safety concerns.

- **Liability and Responsibility Regulations**

Regulators must address liability and responsibility issues related to maintenance decisions made based on DT data. Clear guidelines must be set to determine accountability for any failures or incidents related to DT systems (Lufthansa Technik , 2024) (Srivastava, 2024).

- **Pilot Training Regulations**

Another requirement could be placed on pilot training. Even though pilots are not directly involved with the processes of DT systems, they should be aware of the sensors and how the system functions to make educated decisions about in-flight faults (Lufthansa Technik , 2024). When a failure occurs on the flight, pilots often contact maintenance hubs of their airlines to save the issue at hand. In a DT based maintenance structure, maintenance centers will receive live data from the aircraft, however pilots will need to double check and communicate any errors spotted on the data. This will require rigorous training of pilots that will operate DT equipped aircrafts. This training will cost likely be regulated by the regulatory bodies and will require substantial funds and intricate training scheduling for operating pilots. The additional trainings can increase the workload of pilots.

Regulations are a common aspect of the aviation industry and are not new for airlines. However, a significant hurdle in the adoption of DT technology is the absence of specific regulations tailored to it. The technology is new for both airlines and regulatory bodies. Thus, there are no definite regulations to be followed while developing the technology. Regulations will need to be updated or new regulations will need to be introduced. This process can be long, as the regulatory bodies are likely not familiar with the technology. The regulations will have to be developed with the cooperation of regulatory bodies and the airlines, and new iterations will need to be done. Historically, the certification of new aircrafts takes between 5 to 9 years (FAA, 2023). Given the complexity of obtaining approval for new technologies, achieving regulatory compliance for DTs across multiple jurisdictions may require a similarly extensive timeframe. Approving a brand-new technology with many different regulatory bodies will likely take as much as an approval of a new

aircraft. This timeframe can be lengthy and costly, as the development of the technology could change directions with the updates coming to the requirements.

4.5.3. Organizational Challenges

Apart from the challenges regarding the implementation of the technologies, adapting the organization to a new technology is another challenge. Some related challenges are:

- **Cultural Shift**

Adopting DT and other new technologies represents a significant cultural shift in aircraft maintenance practices. Overcoming resistance to change and creating a digital mindset within the departments is as crucial challenge (Bree, 2023).

- **Workforce Training and Addition**

Introducing a brand-new technology to an existing system can cause problems, related to knowledge gaps and cultural habits. Addition of new personnel, expert in the field of data analytics, internet of things, communication networks is crucial. Furthermore, current personnel need to undergo rigorous training aiming to familiarize the personnel with the new systems. These are crucial steps that need to be taken to create a knowledgeable workforce that will help with the upkeep and maintenance of the systems itself. Training staff and hiring field experts can incur significant costs (Bree, 2023).

- **Infrastructure and Investments**

Implementing DT technology across an entire fleet requires substantial investment towards procuring hardware, software, and infrastructure. The comprehensive implementation incurs substantial financial burden for airlines and maintenance organizations, posing a significant challenge in terms of budgetary considerations (Bisanti, et al., 2023).

5. Conclusions

This project aimed to explore the potential of Digital Twins (DTs) in addressing unplanned maintenance during the support and service phase of a product's lifecycle within the aviation industry. While DT technology itself is not new and has been in existence for over 30 years, its application in aviation is gradually gaining traction, with various manufacturers and airlines investing in DT technologies. However, current utilization of DTs in aviation primarily focuses on the design and manufacturing phases of the product lifecycle, leaving a notable gap in support and maintenance-based applications. Upon investigating operational challenges, it became evident that maintenance inefficiencies contribute significantly to disruptions in service and financial losses for airlines, stemming from outdated practices. This research thus sought to bridge this gap by exploring how DT technology and emerging maintenance methods could offer potential solutions to these challenges, while also acknowledging associated limitations and obstacles.

Initially, four primary objectives were established to guide the research toward its aim. Each objective was carefully chosen after thorough investigation and identification of key areas that required exploration to comprehensively understand the opportunities and limitations of the technology. These objectives were then aligned with relevant research questions (RQs) intended to address them. Subsequently, the RQs were used to derive keywords capable of answering the questions. These keywords were utilized across various databases to identify relevant articles for inclusion in the extensive literature review. Through continuous database searches and research efforts, the findings were organized into different sections within the literature review, aimed at gathering sources and presenting insights related to the objectives. As the objectives were structured to complement each other progressively, the literature review was likewise organized to follow the flow of these objectives. This approach ensured that the content of the review aligned with the goals of the research, allowing for a coherent exploration of relevant literature in a manner that addressed each objective in sequence. By maintaining this alignment, the literature review provided a comprehensive understanding of the research landscape while addressing the key objectives set forth at the outset of the study. To convey the conclusions effectively, the objectives will serve as the structural framework. Each objective will be elaborated upon, and related findings will be discussed accordingly. This approach ensures that the conclusion is organized and aligned

with the original aims of the research, facilitating a clear and systematic presentation of key findings and their implications.

The first objective was *examining how unplanned maintenance affects airline operations and investigating current techniques that are being used to address this*. This initial step proved pivotal as it facilitated a comprehensive understanding of the significant challenges posed by unplanned maintenance within the aviation industry. By scrutinizing existing strategies employed to mitigate these challenges, insights were gained into the current operational landscape. This, in turn, enabled to identify areas with a potential for enhancement and assess how the proposed technological solution could effectively address inefficiencies differently from the current methods.

RQ1 was satisfied by researching the effects of unplanned maintenance on airlines' operations. Firstly, unplanned maintenance was found to be a huge loss factor for airlines. Research revealed that each year airlines lost \$21B due to disruptions stemming from unplanned maintenance, making it the second largest loss factor related to operational inefficiencies. The biggest disruption caused by unplanned maintenance was identified as related canceled and delayed flights. Unplanned maintenance actions on operating aircrafts increased the stress on scheduling flights as the malfunctioning aircrafts must be replaced by any other available aircraft, this can in turn disrupt other unrelated flights causing a cascading effect through flight operations. In addition to the current effects of unplanned maintenance, findings suggested that the costs related to unplanned maintenance are likely to rise over the next ten years. The most alarming evidence was found on research done by Statista (2023) suggesting that the costs related to unplanned maintenance will likely double, reaching \$40B by the year 2035. Two main reasons were found to this trend, which were increasing fleet sizes, and increasing component number and complexity of the systems used on new generation aircrafts. These findings underscored the critical need to address unplanned maintenance promptly to mitigate future disruptions effectively.

To satisfy **RQ2**, current and emerging technologies were investigated through articles, and reports and white papers published by companies operating in the aviation industry. In this section four different methods were investigated. It was found that Condition Based Maintenance (CBM) is a dominating approach over the industry towards maintenance operations. CBM was found to be the

most basic approach out of the analyzed methods. CBM relies on on-site inspections and fault indicators to detect any failures that need to be addressed. This approach is the method to address maintenance over different industries and is a common practice. CBM heavily relies on human input to detect faults, this aspect makes this method prone to errors and undetected faults. Nevertheless, Integrated Aircraft Health Management (IAHM), one of the three main elements of CBM, is a promising method which can be enhanced further with the use of DTs. IAHM utilizes data which was acquired through condition monitoring to assess and predict the wear and degradation of the aircraft components.

Another widely adopted approach was found to be Discrete Event Simulation (DES), which simulates specified scenarios. DES runs by using individual elements to simulate and create numbers of activities to help users understand the distribution of the outputs. The user of DES can select the inputs to create case-based scenarios which will output the resulting conditions. This approach is a valuable method to explore and experiment new cases and see their effects over both individual aircrafts and entire fleets. One of the main advantages of this method is the ability to run experiments at a low cost which would have costed a significant amount if it was done in real life. However, this method lacks the ability to react to constantly changing conditions and processing real-life events.

Predictive Maintenance (PM) was another promising method, as it had the potential to be integrated with DT technologies. Different approaches were explored for Predictive Maintenance among different industries and the structure that was depicted in Figure 4 was adopted. This structure served as a baseline model for further integration between DTs and PM technologies. This method, promised to address unplanned maintenance in an unprecedented way, predicting upcoming maintenance needs based on up-to-date data.

These findings satisfied the needs of the first objective and gave insight on the problem in question, while also exploring methods that are being used or are being developed. Providing grounds to explore topics related to objective 2.

Second objective was to *assess the current utilization of Digital Twins within the aviation industry, particularly in managing unplanned maintenance during the service and support phase*. This objective played a crucial role in exploring the current landscape of DTs within the aviation sector, specifically focusing on their application in managing unplanned maintenance during the service and support phase. This objective was deemed essential due to the increasing interest and investment in DT technologies across various industries, including aviation. Understanding the extent to which DTs are currently utilized in addressing maintenance challenges provided valuable insights into the readiness of the aviation industry to adopt such innovative solutions. Additionally, exploring ongoing developments and emerging trends in DT applications helped to identify opportunities and potential barriers for integrating DTs into existing maintenance practices within aviation.

RQ3 and **RQ4** was addressed by investigating new technologies that are being developed by different companies within the aviation industry, ranging from manufacturers to airline operators. Some promising projects were found during this stage. General Electric's development of DT framework aiming to understand, predict, and optimize performance of all their assets, Lufthansa's new AVIATAR software aimed at managing large fleets, Airbus's effort to digitalize manufacturing lines, and Siemens's comprehensive DT approach to map their assets to increase educated decision making were the most promising projects. By the investigation of systems and applications that use DTs, identified knowledge gaps were further endorsed. The up and running systems of GE and Lufthansa offered useful insight on functions such as, asset tracking, condition monitoring, MRO management (Maintenance Repair Operations), predictive health analytics, technical logbook, and reliability solutions, which could be incorporated in a DT/ Maintenance framework. The only DT model that aims to tackle unplanned maintenance was found to be Lufthansa's AVIATAR. The evidence found on the lack of DT application to address unplanned maintenance once again verified the motivation of this research.

The third objective of *exploring potential applications of digital twins to address unplanned maintenance, and how promising features can be integrated with current systems* intended to explore potential applications of DTs in addressing unplanned maintenance within the aviation industry. This objective aimed to investigate the promising features of DT technology and examine

how these features could be integrated with current maintenance systems. By doing so, the research sought to identify feasible integration methods for DTs and maintenance technologies, with the goal of enhancing maintenance practices and mitigating the impact of unplanned maintenance events. This objective was crucial in bridging the gap between theoretical possibilities offered by DTs and practical implementation strategies within real-world maintenance operations.

RQ7 was dedicated to exploring potential integration strategies of DTs with various maintenance methods discussed in the research. Two distinct models were examined, each leveraging predictive maintenance (PM) and integrated aircraft health management (IAHM) methods, respectively. The PM/DT framework emerged as a promising system, offering users the capability to develop models for different aircraft components. This approach demonstrated significant potential in predicting imminent maintenance needs for specified components. By utilizing the DT's ability to model physical objects, this framework facilitated the creation of virtual models of aircraft components, enhancing the accuracy of maintenance predictions. Furthermore, the PM/DT framework integrated real-time data processing, a feature that distinguishes it as an advanced version of discrete event simulation (DES). On the other hand, the IAHM and DT framework also capitalized on the DT's modelling and data organization capabilities. By compiling data within the DT, seamless data transfer to IAHM systems was enabled, working together with condition-based maintenance (CBM) methods. Both frameworks exhibited promising approaches to addressing unplanned maintenance, offering versatile solutions adaptable to different operational scenarios and maintenance needs.

Real-time data capturing is a crucial stage in utilizing DTs, **RQ5** aimed to explore the real-time data capturing ability of DTs, analyzing the needs and relevant framework for this function. Real-time data capturing has two stages. Firstly, the data must be acquired from the operational aircraft via sensors, and this data must be communicated to the cloud for processing. The sensors need to be placed in components that will give in-flight performance parameters. This is crucial to model and interpret the data. However, the volume of the data collected is large and can pose difficulties to transfer. Thus, onboard edge computing systems can be used to preprocess the data before communicating with the cloud. This process can reduce the volume by refining the data, which in turn will increase the speed of data transfer. **RQ6** complemented **RQ5** by further analyzing data

related hurdles, namely data integration. Data integration method was found as a useful approach for processing the acquired data. Other crucial elements such as data fusion and related emerging technologies were investigated to explore options to integrate with DTs. The findings led to the incorporation of data integration processes within the IAHM/DT framework.

Identifying key challenges and knowledge gaps that are being faced while integrating DTs to existing systems was the fourth and last objective, set to investigate potential limitations and challenges related to DT integration to maintenance methods. This objective was crucial to understand the feasibility of DT use in aviation maintenance.

RQ8 intended to uncover the knowledge gaps, within organizations, in implementing data driven DT technologies. Findings suggested that significant challenges stemmed from cultural habits, including resistance to change and reluctance towards adopting new technologies, hindering the seamless integration of these systems within organizations. Moreover, the intricate nature of DT technology, coupled with the requirement for specialized expertise, was found as a further obstacle for companies. With many organizations still adopting traditional maintenance approaches, the task of finding personnel capable of adapting to the transition towards DTs was identified as a major challenge. Additionally, the shortage of skilled professionals familiar with DT technology may impede the integration process, underscoring the critical need for investment in hiring and training personnel to bridge this gap.

Apart from the knowledge gaps, regulatory constraints were also analyzed to satisfy **RQ9**. Results of the research revealed that main hurdle in using DT in maintenance stems from the lack of regulations tied to it. New regulations will need to be introduced as the systems are being integrated thus constant changes to the models will need to be applied as the regulations change. This will be a costly and a lengthy process.

Overall, this research has shed light on the detrimental impact of unplanned maintenance on airline companies, delved into existing methodologies for mitigating these issues, explored various Digital Twin integrated solutions, and assessed the feasibility of these systems. It is evident that DTs offer robust data-driven capabilities that can effectively address and minimize disruptions

caused by unplanned maintenance when coupled with Predictive Maintenance and Integrated Aircraft Health Management technologies. Moreover, advancements in data processing techniques and tools further enhance the potential of DTs. While current communication technologies may impose limitations on DTs by impeding real-time data transfer, emerging innovations in communication technology hold promise for resolving this challenge.

With notable investments from industry leaders like Lufthansa and General Electric in the development of digital twin solutions, there is a notable shift towards digital approaches to unplanned maintenance. However, it is crucial to acknowledge the substantial hurdles that must be overcome, including technical complexities, organizational readiness, and regulatory constraints. Overcoming these challenges necessitates significant financial investments in framework development, which may pose challenges for smaller organizations. Consequently, the responsibility falls largely on larger entities to drive the adoption and development of DT solutions. However, the high demand for investment can deter even large companies to start shifting towards DT technologies, nevertheless the increasing costs due to unplanned maintenance and fleet sizes will call for this shift soon, and even though investments might seem large, after robust integration, the technology in question has the potential to reduce major costs for airlines. A long-sighted vision is crucial to understand and act on the advantages that this technology will bring.

Furthermore, the widespread adoption of DT systems is expected to encounter delays due to their complexity. The extensive deployment of sensors across fleets, a prerequisite for these systems, is a time-consuming and costly endeavor. Nonetheless, despite these challenges, DTs stand out as the most promising technology for enhancing efficiency and safety in aviation maintenance. Through continued innovation, collaboration, and strategic investment, the aviation industry can unlock the full potential of DTs to revolutionize maintenance practices and ensure seamless operations.

6. Limitations and Recommendations for Further Research

6.1. Limitations

While this project aimed to comprehensively explore the utilization of DTs for predictive maintenance in the commercial aviation sector, it is important to acknowledge certain limitations

inherent in the research process. Firstly, the scope of the study was limited by the availability and accessibility of relevant literature and data, which impacted the depth of the analysis. Additionally, the project's timeline constraints have restricted the ability to conduct extensive primary research or fieldwork, limiting the depth of insights gained. Moreover, depending solely on existing literature and case studies might have introduced biases or left gaps in understanding, especially if certain perspectives or methodologies are underrepresented in the available sources. These limitations should be considered when interpreting the results and implications of the research.

6.2. Recommendations for Further Research

This research has revealed promising avenues for further exploration into the utilization of DTs to address unplanned maintenance within the aviation industry. While offering valuable insights, it has also surfaced a multitude of questions, suggesting that the journey has just begun. Indeed, the investigation has opened more questions than it has answered, due to the complexity of the subject and the need for continued inquiry. Future research should aim to delve into the details of DT integration with existing maintenance systems. A more detailed understanding of how complex data can be effectively modeled within the DT framework is essential to enhance predictive capabilities and decision-making processes. Additionally, regulatory challenges emerged as a significant challenge to DT integration, calling for further research. Investigating the nuances of regulatory frameworks and devising strategies to navigate these constraints will be important to ensure compliance while using the full potential of DT technology.

Moreover, organizational dynamics play a crucial role in facilitating the adoption of DT systems. Thus, exploring effective organizational structures and change management strategies is imperative to create a culture of innovation and expedite the integration process. Communication challenges surrounding real-time data transfer also demand attention, necessitating the development of communication frameworks to facilitate seamless data transmission between physical assets and their digital counterparts. Lastly, expanding the scope of maintenance methods and conducting detailed component-level analyses by broadening the horizons of research in these areas, further studies can uncover new opportunities for optimizing maintenance practices and enhancing the efficiency of DT-enabled systems. In conclusion, addressing these research

recommendations holds the key to advancing the field of DT-enabled maintenance in aviation, leading the way for transformative breakthroughs in the industry.

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Plan for Individual Project		Semester 1										Semester 2										
Week	Week Commencing	Week 5-14	Week 5-15	Week 5-16	Week 5-17	Week 5-18	Week 5-19	Week 5-20	Week 5-21	Week 5-22	Week 5-23	Week 5-24	Week 5-25	Week 5-26	Week 5-27	Week 5-28	Week 5-29	Week 5-30	Week 5-31	Week 5-32	Week 5-33	Week 5-34
		18th Dec	25th Dec	1st Jan	8th Jan	15th Jan	22nd Jan	29th Jan	5th Feb	12th Feb	19th Feb	26th Feb	4th March	11th March	18th March	25th March	1st April	8th April	15th April	22nd April	29th April	6th May
Key Dates - Individual Project																						
Key Dates - Other Modules							Exam Period					Poster Submission		Poster Presentation					Sample Writing Submission			Final Report Submission (2 May Thursday)
Objectives																						
Literature Review:																						
What is a Digital Twin?																						
Current uses of Digital Twins in any industry																						
Potential DT use in supply and support phase of the product																						
Current uses of Digital Twins in the aviation industry																						
Current techniques that are used to address problems related to unplanned maintenance																						
What is predictive maintenance																						
How can DT be utilised for predictive maintenance																						
Key challenges of integrating DT technology into current systems																						
Initial Project Plan:																						
Write, submit and reflect on feedback																						
Project Proposal:																						
Write, submit and reflect on feedback																						
Write a draft Literature Review:																						
Review With Advisor:																						
Get feedback on your first draft of literature review																						
Get feedback on the final report draft																						
Semester 1 Other Deliverables:																						
Control Engineering Report																						
Design System Requirements Report																						
Aerodynamics Quiz																						
Vibrations Quiz																						
Operations Management CW																						
Vibrations Report																						
Design Poster Submission																						
Design Final Report																						
Design Tradeshow																						
Exam preparation																						
Project Poster:																						
Plan poster content and create first draft																						
Final draft and submission																						
Prepare for presentation day																						
Final Report:																						
Plan report structure and compile relevant resources																						
Write a draft and review feedback																						
Write final report and submit																						
Semester 2 Other Deliverables:																						
Semester CWs and projects																						
Exam preparation																						

8.3. Revised Gantt Chart (04.04.2024)

Week	Week 5-14		Week 5-15	Week 5-16	Week 5-17		Week 5-18	Week 5-19	Week 5-20	Week 5-21	Week 5-22	Week 5-23	Week 5-24	Week 5-25	Week 5-26	Week 5-27	Week 5-28	Week 5-29	Week 5-30	Week 5-31	Week 5-32	Week 5-33	Week 5-34
Week Commencing	18th Dec	25th Dec	1st Jan	8th Jan	15th Jan	22nd Jan	29th Jan	5th Feb	12th Feb	19th Feb	26th Feb	5th March	12th March	19th March	26th March	2nd April	9th April	16th April	23rd April	30th April	7th May	14th May	
Key Dates - Individual Project																							
Key Dates - Other Modules																							
Exam Period																							
Objectives																							
Literature Review:																							
What is a Digital Twin																							
Current uses of Digital Twins in any industry																							
Potential DT use in supply and support phase of the product																							
Current uses of Digital Twins in the aviation industry																							
Current techniques that are used to address problems related to unplanned maintenance																							
What is predictive maintenance																							
How can DT be utilized for predictive maintenance																							
Key challenges of integrating DT technology into current systems																							
Initial Project Plan:																							
Write, submit and reflect on feedback																							
Project Proposal:																							
Write, submit and reflect on feedback																							
Write a draft Literature Review:																							
Review With Advisor:																							
Get feedback on your first draft of literature review																							
Get feedback on the final report draft																							
Semester 2 Other Deliverables:																							
Structures Coursework																							
Airframe Inspection Lab Report																							
Flight Dynamics Coursework																							
Modelling and Simulation Lab																							
Exam preparation																							
Project Poster:																							
Plan poster content and create first draft																							
Final draft and submission																							
Prepare for presentation day																							
Final Report:																							
Plan report structure and compile relevant resources																							
Write a draft and review feedback																							
Write final report and submit																							

8.4. Risk Assessment and Mitigation

Risk	Description	Likelihood (1-3)	Severity (1-3)	Overall Risk = Likelihood x Severity
	There might be a lack of literature available, focusing			

Limitation of literature	on the use of DT in the aviation industry	3	2	6
Bias in Literature	Even though the use of the scientific method reduces the likeliness of bias in research the researcher can't fully mitigate bias. Examples of this bias are confirmation bias, availability bias, selection bias	2	2	4
Out-dated literature	DT technology is a rapidly advancing field where some literature that are available might be outdated.	2	1	2
Biased Literature Selection	As any other research, even though I try to escape my own biases, my research won't be without any bias. The selection of literature that will be analyzed could be biased towards some specific literature	2	1	2
Time constraints	Doing a wide literature review can be time consuming, so there is a risk of not being able to cover all the literature available where this might lead to an uncomprehensive product.	1	2	2
Workload management	Even though this project is a priority for the year, task from other modules might interfere with the project's timeline.	3	2	6
Health	Personal health problems might clash with important due dates and might also interfere with the project plan.	1	2	2

Risk	Mitigation	Result
Limitation of literature	While there may be a scarcity of literature specifically addressing the application of digital twins for predictive maintenance within the commercial aviation industry, relevant data can be extrapolated and interpreted from analogous implementations in diverse industrial sectors.	Reduced
Bias in Literature	The potential of reviews being biased can be eliminated by widening the resource base. Also identifying biases might allow to address the biases later to mitigate their distortion.	Reduced
Out-dated literature	The effect of outdated literature would not be a major concern within the field of this study as it would assist in the understanding and development of the maintenance techniques within the aerospace field. The “outdated” literature can be used to gain an understanding of the progression in the techniques as long as it is assisted with the newer research within the field.	Reduced
Biased Literature Selection	To minimize selection, bias the pre-explained method of using a systematic keyword search approach will be adopted.	Reduced
Time constraints	With the detailed Gantt Chart above the time allocated for each research question and their respective research durations, this issue will be mitigated. Even though there might be modifications to the plan the allocated time for each area will not be surpassed noticeably ensuring	Reduced

	sufficient time allocation for each research are.	
Workload management	This risk can be eliminated as there is a thorough project plan that considers the timeline of other deadlines in place. In addition, this plan will be updated as new key dates are obtained to ensure the compliancy of the plan to real life.	Reduced
Health	Any delays caused by health problems will be considered when updating the project plan so that they can be addressed, and essential changes can be done.	Reduced

8.5. Initial Reflection

The successful completion of this dissertation project is contingent upon the careful identification, assessment, and mitigation of potential risks that may impede the thorough analysis of the use of digital twins for predictive maintenance within the commercial aviation industry. In the risk identification table, each risk was allocated with two different numbers between 1 and 3 representing the severity and the likeliness of each risk. These numbers were then multiplied to obtain the overall risk score ranging from 1 to 9. A higher overall risk score represents a higher magnitude of effect for the related risk. In the second table each risk was matched with a potential way of overcoming it and each solution was then declared reduced or eliminated. This systematic approach is useful since it demonstrates each risk with a relevant grading so that they will be considered throughout the project.

Efforts will have been made to mitigate the limitation of literature by drawing on analogous applications from diverse industrial sectors, ensuring a comprehensive understanding of digital twin utilization. Additionally, the risk of bias in the literature review will be addressed through an expanded resource base and the identification of potential biases for subsequent mitigation. To

counter the impact of outdated literature, emphasis has been made on integrating historical perspectives to track the evolution of maintenance techniques within the aerospace field. Moreover, the systematic keyword search approach has been adopted to minimize any potential bias in the literature selection process. Health-related concerns have also been factored into the project plan, allowing for necessary adjustments to accommodate any potential delays due to unforeseen health issues.

Furthermore, a detailed Gantt Chart has been devised, carefully considering the interplay between research components and other project deadlines, thereby ensuring effective workload management and adherence to the outlined project timeline. Specific research areas are allocated time slots to ensure even coverage of each area. Buffer time slots were added before certain key dates so that sufficient time can be spent to get feedback from the advisor and to amend related fields. Even though the plan was made thoroughly and as detailed as possible there is a high possibility of the key dates changing or new key dates and tasks appearing. To preserve the reliability of the plan, constant updates to the plan should be done. As demonstrated above the Gantt Chart has been updated from its initial phase, where the updated version includes detailed dates and task allocations to each milestone of the project. In addition, any deadline from other modules have been added to ensure that time management is done well so that the tasks involved to the project does not clash with other modules. Even though the Gantt Charts are detailed there is a high probability that various changes would need to be done later.

8.6. Final Reflection

Upon reflecting on the completion of this project, several key insights can be gained for future works. Firstly, the objectives set at the outset of the project underwent multiple modifications throughout its duration. These changes were motivated by the belief that the revised objectives would offer a more comprehensive understanding of the topic at hand. However, this process highlighted the importance of clarity and specificity in defining research objectives, as frequent modifications can potentially impact the project's coherence and focus.

Secondly, the initial scope of the project was ambitiously wide-ranging, reflecting a desire to explore various facets of the subject matter. However, as the research progressed, it became apparent that a narrower scope would allow for a more in-depth analysis of the topic. While the scope was subsequently refined, this experience showed the importance of balancing ambition with realism in project planning. Moving forward, a more careful approach to defining the scope would be beneficial in ensuring that research efforts are effectively concentrated on addressing the details of the subject.

Thirdly, despite careful planning and the creation of multiple Gantt charts to outline deadlines and workload distributions, there were instances where the actual progress deviated from initial expectations. This difference highlighted the dynamic nature of research projects and the need for flexibility in adapting to changing circumstances. Moreover, the experience underscored the importance of contingency planning and proactive management of unexpected challenges.

The late discovery of the PRISMA method during the research process presented obstacles in conducting the literature review, slowing down the research progress. This experience emphasized the importance of conducting thorough methodology research at the project's start. Early familiarity with methodologies can systematically organize crucial processes and improve overall efficiency.

Finally, the risk assessment conducted proved invaluable in identifying and mitigating potential challenges, with most risks addressed. However, managing workload emerged as a persistent challenge, particularly as the dissertation deadline coincided with other coursework deadlines. This experience underscored the importance of effective time management and highlighted areas for improvement in future projects.

Overall, while the planning process served as a crucial initial step in guiding the research, the project revealed valuable lessons regarding the importance of adaptability, methodology research, and workload management. Moving forward, these insights will inform more informed and effective approaches to future research endeavors.