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Alessandro Giacotto

HOLISTIC OPTIMIZATION FRAMEWORK FOR PRESCRIPTIVE MAINTENANCE

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HOLISTIC OPTIMIZATION FRAMEWORK FOR PRESCRIPTIVE MAINTENANCE

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I dedicate this work to my father, Marcello Giacotto, who has taught me the value of discipline, hard work, and respect since an early age.

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"If I have seen further, it is by standing on the shoulders of giants".

(Isaac Newton)

Abstract

Prescriptive maintenance (PsM) is a proactive approach enabled by the Internet of Things (IoT), asset health prognostics, and prescriptive analytics that aims to optimize maintenance by prescribing a course of action. In a challenging context, in which industries face shortage of workforce and fierce competition, complex systems operating in dynamic operations are supported by traditional maintenance practices, that based on reactive or preventive approaches, often result in inefficiencies, high costs, and unexpected equipment failures. To address these challenges, a new PsM-based optimization framework is required to process the information available and recommend possible maintenance actions holistically, considering both operation and support. Therefore, the purpose of this research is to demonstrate that maintenance efficiency and effectiveness can be improved through the implementation of a PsM framework that provides optimal course of action, is adaptable across different industries and extensible to assets with different technological maturities. To achieve these objectives and highlight the novelty of this work, a comprehensive review of existing literature on prescriptive maintenance is presented, followed by the design and verification of a PsM Mixed-Integer Linear Programming (MILP) based optimization framework. The framework is tested in real-world case scenarios, through three experiments, that include a Brazilian regional airline operation and the São Paulo state health system's pandemic response. The two experiments with the airline demonstrated the framework’s efficacy, achieving increases of 36.16% and 26.41% in fleet availability, along with profitability improvements of 0.81% and 406%, respectively. The health system experiment further highlighted the framework’s adaptability, showing a potential 65% increase in patients’ survivorship. These results provide valuable insights and guidance for researchers and practitioners, emphasizing the viability and potential of the prescriptive maintenance paradigm.

Resumo

A manutenção prescritiva (PsM) é uma abordagem proativa possibilitada pela Internet das Coisas (IoT), prognósticos de saúde dos ativos e análises prescritivas que objetiva otimizar a manutenção recomendando ações. Num contexto desafiador, em que as indústrias enfrentam escassez de mão de obra e forte competição, sistemas complexos que operam em operações dinâmicas são apoiados por estratégias tradicionais de manutenção, que baseadas em abordagens reativas ou preventivas, muitas vezes resultam em ineficiências, custos elevados e falhas inesperadas de equipamentos. Para enfrentar estes desafios, é necessária uma nova abordagem de otimização baseada em PsM para processar as fontes de informação disponíveis e recomendar possíveis ações de manutenção de forma holística, considerando tanto a operação como o suporte. Portanto, o objetivo desta pesquisa é demonstrar que a eficiência e a eficácia da manutenção podem ser melhoradas através da implementação de um arcabouço baseado em PsM que forneça a melhor recomendação possível, seja adaptável a diferentes indústrias e extensível a ativos com diferentes maturidades tecnológicas. Para atingir estes objetivos e destacar a novidade deste trabalho, é apresentada uma revisão da literatura existente sobre manutenção prescritiva, seguida pela apresentação e verificação de um arcabouço de otimização baseado em PsM e programação linear inteira-mista. O arcabouço é testado em situações vivenciadas no mundo real, por meio de três experimentos, que incluem a operação de uma companhia aérea regional brasileira e a resposta à pandemia do sistema de saúde do estado de São Paulo. Os dois experimentos com a companhia aérea demonstraram a eficácia do arcabouço, conseguindo aumentos de 36,16% e 26,41% na disponibilidade da frota, juntamente com melhorias na rentabilidade de 0,81% e 406% respetivamente. O experimento no sistema de saúde destacou ainda mais a adaptabilidade do framework, mostrando um aumento potencial de 65% na sobrevivência. Estes resultados fornecem informações e orientações valiosas para pesquisadores e profissionais, enfatizando a viabilidade e o potencial do paradigma da manutenção prescritiva.

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List of Acronyms

AI	Artificial Intelligence
AC	Aircraft
AR	Augmented Reality
ATA	Air Transportation Association
ATR	Avions de Transport Régional
CBM	Condition Based Maintenance
COVID	Coronavirus disease
CPPS	Cyber-Physical Production Systems
Dr.	Doctor
F	Female
FTE	Full Time Equivalent
GB	Giga Byte
GSE	Ground Support Equipment
KBM	Knowledge Based Maintenance
IATA	International Air Transportation Association
IDE	Integrated Development Environment
ICU	Intensive Care Units
IETP	Integrated Electronic Technical Publication
IoT	Internet of Things
ITA	Instituto Tecnológico de Aeronáutica
LRU	Line Replaceble Unit
Max	Maximum
M	Male

MAT	Material
MILP	Mixed-Integer Linear Programming
MON	Monday
MRO	Maintenance, Repair and Overhaul
MTBF	Mean Time Between Failure
MTBUR	Mean Time Between Unscheduled Removals
N	No
OF	Objective function
OEE	Overall Equipment Efficiency
OEM	Original Equipment Manufacturer
macOS	Macintosh operating system
Prof.	Professor
PdM	Predictive Maintenance
PHM	Prognostic Health Management
PM	Preventive Maintenance
PsM	Prescriptive Maintenance
Rev	Revenue
RCM	Reliability Center Maintenance
RUL	Remaining Useful Life
SAT	Saturday
SPMF	Smart prescriptive maintenance framework
TAT	Turn Around Aime
TLC	Total Lide Cycle Cost
TPM	Total Production Maintenance
TUE	Tuesday

USD	United States Dollars
VR	Virtual Reality
Y	Yes

List of Symbols

$X(t)$	degradation at time t
h	drift coefficient
$L(t)$	proportional coefficient
$\boldsymbol{s}$	diffusion coefficient
B	Brownian constant
t	time
X_k	degradation level at instant k
X_{k+}	degradation level at instant k+
α_k	degradation limit
$	US dollars
>	Larger than
<	Smaller than
%	Percentage
$\sum x$	Sum of x
∈	Pertains to
≤	Smaller than or equal to
≥	Larger than or equal to
←	Corresponds to
✓	Yes / check / addressed
-	Not applicable

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1 Introduction

Prescriptive Maintenance (PsM) is an emerging strategy that aims to optimize maintenance by utilizing data-driven, model-driven techniques and prescriptive analytics [22, 23, 24, 27, 78]. Legacy maintenance practices are based on reactive or preventive approaches, where maintenance actions are triggered by failures or predefined time-based intervals respectively. These approaches can be inefficient and costly, as they may lead to unnecessary maintenance activities or unexpected equipment failures [24, 58, 64, 104, 108, 109, 110].

In recent years, the advent of the Internet of Things (IoT) and the proliferation of sensor technologies have enabled the collection of large volumes of data from equipment, systems, and resources. This data, when properly analyzed, can provide valuable insights, allowing for a more proactive and targeted maintenance approach. PsM leverages this data and employs techniques such as machine learning, statistical modeling, and optimization algorithms to optimize maintenance decisions, reduce downtime, and improve overall asset performance, which is particularly useful in dynamic operations of complex systems such as the aerospace and health [6, 54, 56].

Despite the potential benefits of PsM and examples of PsM-based solutions with development recently announced[113], its implementation in industrial 4.0 settings, which operates complex systems in highly dynamic environments, poses several challenges. Firstly, Industry 4.0 organizations, often struggle with the integration and management of heterogeneous data sources from different equipment and systems. This includes data from sensors, maintenance logs, historical records, and other relevant sources [5, 6, 8, 9, 30, 32, 52, 55, 58, 60, 65, 84]. Secondly, there is a need for developing accurate and reliable models that can effectively predict equipment failures or degradation[5, 23, 32, 52, 54, 55]. Additionally, decision-making algorithms and optimization techniques must be developed to identify the most suitable maintenance actions based on the predicted outcomes, costs, operating parameters, maintenance activities, and maintenance resources. And, finally, developers are struggling to propose extensible or scalable frameworks, undermining large industrial adoption.

The successful implementation of PsM has the potential to revolutionize the field of maintenance management, since, by adopting a data-driven and proactive approach, organizations can optimize not only maintenance activities but also operations, increasing equipment availability.

1.1 Context, Research Problem and Motivation

The aviation industry is one of the most important transportation sectors, having a significant impact on the socio-economic development of society[1]. However, as presented by [6], the aviation market is also characterized by very strong competition and rapid changes brought by deregulation, fast technology improvements, and industry consolidation. On top of that, the main aeronautical players, such as original equipment manufacturers (OEMs) and maintenance repair and overhaul (MRO) organizations, are facing a lack of workforce [8, 9, 132, 133] and pressure to lower emissions to boost sustainability[1, 2, 3]. Despite the competition, operational costs raise, workforce crisis, and the sustainability new requirements, affordable airfares continue to be expected by passengers[6] putting more pressure on the industry and resulting in a challenging context capable of putting 34 airliners out of business in 2021 alone[7], in the midst of the COVID pandemic. In 2024, although airlines are expected to transport almost 5 billion people globally, and reap a record net profit high of USD 25,7 billion, the net profit margin is as low as 2,7%, that is, 4% less than the cost of capital[134], emphasizing even more how challenging the operational environment is.

In this context, a new maintenance strategy is needed to overcome these challenges by augmenting current workforce capability and skills, lowering asset life cycle cost, and optimizing maintenance resources while increasing asset availability and boosting sustainability: Prescriptive Maintenance (PsM) is becoming the strategy to follow that could solve at least part of the challenge. Although what PsM entails might not be clear as several definitions have been presented over the years - authors have not agreed on a unified concept - for the sake of setting the grounds this author defines PsM as *a proactive maintenance strategy enabled by the internet of things (IoT), asset health prognostics and prescriptive analytics, provides a course of action prescription to optimize maintenance and maximize asset availability.*

Figure 1.1 depicts the potentialities of this new paradigm. Unlike traditional maintenance processes, which rely on fixed, scheduled tasks, the proposed prescriptive maintenance approach considers the current predicted aircraft's health status, support resources, and operation requirements. This allows for proactive scheduling of tasks during preferred time slots, based on available resources at the designated maintenance base, thereby avoiding operational disruptions such as flight delays. By extending the window for necessary maintenance tasks, it is possible to reduce waiting times for occupied resources, as the increased number of maintenance opportunities allows for greater flexibility in task allocation.

Figure 1.1 also introduces the main differences between predictive maintenance scheduling and prescriptive maintenance scheduling. While the predictive allows us to find maintenance windows so that the asset receives adequate maintenance, does not care about the issue of maintenance logistics. Only informs the remaining useful life windows of each asset. Meanwhile, prescriptive maintenance evaluates the capacity of maintenance logistics to decide to advance maintenance of aircraft 1 (AC 1) so that all resources are available and do not impact the maintenance and operation of other fleet assets (AC 2). This advantage of prescriptive maintenance has a price, which is to deal with a larger number of variables and therefore a smaller horizon to maintain the same ability to find satisfactory results in a timely time.

Another example of PsM implementation would be in a situation in which not all hangars at the destination have the same support capability: in this context, what would the best action be in terms of operation and support resources in case of asset failure? To perform the original flight to the location with no support capability and spend more to direct labor and material to repair the aircraft? Or divert the flight to an airport with the necessary support and reassign the rest of the fleet?

The proposed PsM approach also aligns seamlessly with the concept of a digital twin environment, which serves as a real-time virtual replica of the physical fleet, its operational ecosystem and support resources. This integration enables a bidirectional flow of information, where data from the digital twin informs the optimization framework for PsM, and the optimization decisions made by the framework are reflected back into the twin. This dynamic interaction allows for real-time monitoring, predictive insights and course of action recommendation within a shorter time horizon. As a result, the adoption of a Mixed-Integer Linear Programming (MILP) model becomes not only feasible but also practical for capturing the complexities of fleet-wide operations in dynamic and constrained environments. By incorporating the digital twin's real-time data, the MILP framework can process uncertainties, adapt to evolving conditions, and propose optimized solutions that balance immediate operational demands and maintenance requirements with resources availability.

Reducing maintenance-related downtimes and at the same time maximizing operation, enables aircraft operators to improve asset utilization rates and minimize costs associated with operational irregularities, such as passenger compensation. Extending this concept to other complex systems, PsM emerges as a transformative solution that leverages the latest advancements in IoT, analytics, and proactive strategies to address the critical needs of Industry 4.0.

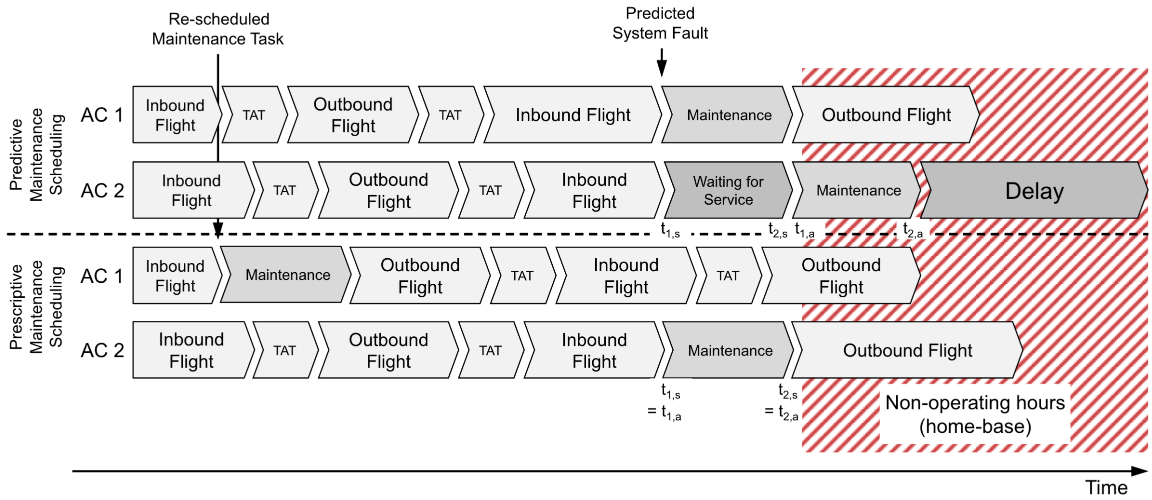

Figure 1.1 – Differences between predictive and prescriptive maintenance scheduling.

Source: Reproduced with permission from Meissner, 2021

The challenging context described at the beginning of this chapter is the author's motivation behind the idea of implementing the prescriptive maintenance philosophy. The following research problem justifies this research:

Industry 4.0 is changing the perception of maintenance: from monitoring the degradation state of components and anticipating their failures to prescribing the most suitable action to optimally manage the whole system considering the dynamic operation environment in which it is embedded[104, 56, 106, 107]*. This requires the development of an optimization framework suitable to process all sources of information available, with the associated uncertainties, manage different system states, and recommend possible maintenance actions* [104, 107].

As will be shown in chapter 2.2 Literature Review, an optimization framework capable of processing all information related to maintenance such as labor, tooling, infrastructure, material repair, operational requirement, maintenance imperfections, and scalability has not been proposed so far..

This is a problem worth solving since, as described, at the beginning of this chapter, the scarcity of labor accompanied by dynamic operations, the competitive environment, and the operation's high performances expected by customers, constitute challenges that pose a threat to the existence of entire organizations and their business models. Thus, since maintenance ranges from 40% to 70% of the industry operations costs[105], finding a way to reduce maintenance expenditures while maximizing operation is paramount.

1.2 Research Question

The research question was identified by analyzing the research problem. Thus, the first part of the research question addresses the necessity of providing an optimization framework capable of prescribing a maintenance course of action considering all resources involved and maintenance imperfections. Thus, the first part of the research question addresses the necessity of providing an optimization framework capable of prescribing a maintenance course of action considering all resources involved, maintenance imperfections, and uncertainties.

Additionally, the Literature Review, as it will be showcased in Chapter 2, has revealed that other open issues related to the research problem need to be addressed: the framework's extensibility to assets with different maturities and adaptability to different industries, which is relevant since it affects the scalability of the framework and its generalizability.

The research question is presented in Table 1.1.

Table 1.1 – Research question.

How maintenance efficiency can be improved through an optimization framework for prescriptive maintenance which:	
Considers	1. Maintenance resources involved namely labor, tools, and infrastructure?
	2. Maintenance imperfections?
Is	3. Extensible to different assets with different technological maturities?
	4. Adaptable to different industries, namely aerospace, and health?
Provides	5. Optimized maintenance course of action?

1.3 Hypothesis

The hypothesis is that the problem described in Chapter 1.2 can be solved with an optimization framework for prescriptive maintenance, enabled by the IoT, failure prognosis and prescriptive analytics and capable of maximizing maintenance efficiency and effectivity through optimized course of action prescription.

1.3.1 Hypothesis Justification

PsM solutions have provided significant results in recent research works: prescriptive maintenance has been successfully implemented framework for an automated pressure monitoring system of an Airbus A320[54], in which four different maturities levels in terms of automation and prognostics capabilities were considered. The results presented a decrease of 34% in maintenance cost compared to conventional maintenance strategies[54] and an increase in aircraft availability[56]. PsM on a railway infrastructure system it has been also implemented[49], obtaining a reduction of total completion time and an improvement of the balance of maintenance teams' workloads in terms of number of activities executed and length of the paths covered by each maintenance team, in comparison to the previous preventive maintenance strategy[49]. In another work PsM framework has been implemented on a brake system of industrial automotive vehicles obtaining consistently lower maintenance costs, through the exploitation of a dynamic schedule, while respecting operational constraints[62]. This author also has shown that a PsM, adopted in a wing assembly line, could improve Overall Equipment Effectiveness (OEE) by almost 5% and assembly robot availability by almost 3% once the PsM-based system took into consideration technicians' skills for maintenance scheduling[55].

1.4 General Objective

The general objective of this work is *to demonstrate that maintenance efficiency and effectiveness can be improved by implementing and verifying a smart optimization framework for Prescriptive Maintenance, which provides an optimal course of action, is extensible across industries, is adaptable to assets of different technological maturities, considers maintenance resources and imperfections*.

Further details about how to achieve the general objective are provided in Section 1.5 focuses on describing the specific objectives.

1.4.1 General Objective Justification

As stated in Section 1.1, dynamic operations, such as the aviation industry, are facing ever-increasing competition pushing organizations to lower their operating costs[56] making maintenance, that contributes from 40% to 70% of the overall industry operation cost[105] and at least 20% of airline operations cost[56], one of the major concerns of the industry and transportation sectors[24]. However, existing maintenance philosophies, as stated in Section 1.1, do not meet current Industry 4.0 complex systems and their dynamic operation requirement.

These limitations, thus, represent important opportunities for improvement that can be addressed by this research and partly left for future work as the objective of PsM implementation.

1.5 Specific Objectives

The specific objectives must be non-trivial, and verifiable and constitute the general objective subproducts[111]. Thus, this author has selected specific objectives that will support the demonstration of maintenance efficiency improvement by the adoption of the PsM framework described in Section 1.4:

1. Specific objective 1: verify maintenance cost decrease because of PsM implementation in aeronautical operation.
2. Specific objective 2: verify, for aeronautical operation, if asset availability is greater or equal to the availability obtained using traditional maintenance strategies.
3. Specific objective 3: verify if results obtained in specific objectives 1 and 2 are adaptable to other dynamic operations, namely, the health industry.

1.6 Original Contribution

This research presents original contributions that expand the practical application of PsM across industries and operational settings. Through a series of real-world experiments and the development of a comprehensive framework, this study demonstrates how PsM can be valuable. The following contributions highlight the innovative aspects and implications of this work:

1. The implementation of the PsM framework in an experiment based on a real case scenario constituted by more than 200 aircraft, and 9 different platforms, simulating the operation in more than 150 destinations considering the variability of support capability across Depot, Intermediate, and Organizational hangars, and different maintenance requirements (A-check, C-check and unscheduled), considering Prognostics Health Management (PHM).
2. The test of the framework adaptability from aeronautical to the health industry addresses a real case scenario of more than 1000 patients admitted in more than 200 public hospitals during the COVID-19 pandemic response in 2021.
3. The implementation of an optimization algorithm that considers 14 days of operation, variability of support capability by ATA chapter and by hangar, and that is capable of prescribing tasks and ground support equipment (GSE) based on the specific failure and resources (labor and GSE) availability. It is important to clarify that the ATA Chapter system is a way to organize the aircraft systems into numbered chapters and subchapters for easy reference[161]. Chapter 2.1.2 will further explain the ATA Chapter's concept.
4. The proposal of a generic prescriptive maintenance framework that can be used in all industries.

The experimental implementation in both aeronautical and healthcare settings highlight the method's adaptability. The development of an optimization algorithm capable of prescribing tasks based on resource availability adds a layer of practical value.

1.7 Thesis Organization

This thesis presents in Chapter 2 the theoretical framework and literature review, Chapter 3 discusses the research development methods and materials used, Chapter 4 presents the experiments, in Chapter 5 showcases the experiments' results, limitations, and future work recommendations. In Chapter 6 the references are listed and in Chapter 7 the appendix is presented. Table 1.2 presents this organization.

Table 1.2 – Thesis organization.

Chapter	Description
2	Theoretical framework and literature review
3	Materials and methods
4	Case studies
5	Conclusion and future work
6	References
7	Appendix

2 Theoretical Framework and Literature Review

The theoretical framework, presented in Section 2.1, introduces the maintenance concepts, optimization problem definitions, airline operations characteristics, and public health system similarities to aeronautics operations. Section 2.2 is focused on presenting a systematic literature review directly related to PsM, the prominent future work, and the research gaps addressed by this work to highlight its original contribution.

2.1 Theoretical Framework

2.1.1 Maintenance

Maintenance is defined as the combination of technical and administrative actions, that ensure that a system is in its required functioning state, and it is related to actions such as repairing, replacing, overhauling, inspecting, servicing, adjusting, testing, measuring, and detecting faults[18]. Maintenance is classified according to the following strategies[19]:

- **Total Production Maintenance (TPM):** it is production-based and implemented by all employees, from senior management to operators encompassing all the organization's departments. It has 5 pillars namely, improving equipment effectiveness, improving maintenance equipment and effectiveness, ensuring early equipment management and maintenance prevention, and providing training to all people involved in routine maintenance[19].
- **Total Life Cycle Cost (TLC):** it is a systemic approach to managing maintenance from asset inception to disposal. The Program Manager is the single point of accountability for accomplishing maintenance program objectives, consequently, he is responsible for the implementation, management,

and/or oversight of activities associated with the system's development, production, sustainment, and disposal[20].

- **Reliability Centered Maintenance (RCM):** it is based on preserving functions, identifying failure modes that can defeat the functions, prioritizing functions (via the failure modes), and selecting effective preventive maintenance tasks[21].
- **Corrective Maintenance:** it is a maintenance strategy where maintenance is performed after equipment failure. Unlike reactive maintenance, run-to-failure maintenance is adopted deliberately for some assets which would be too costly for the adoption of a proactive or preventive strategy[18].
- **Preventive maintenance (PM):** it was introduced in the 1950s, after the recognition of the need to prevent failure, PM has been adopted for more complex assets than those usually maintained through run to failure strategy. The basic principle of a PM system is that it involves predetermined maintenance tasks that are derived from machine or equipment functionalities and component lifetimes. Accordingly, tasks are planned to change components before they fail and are scheduled during machine stoppages or shutdowns[14].
- **Condition Based Maintenance (CBM):** it is a maintenance strategy that monitors the actual condition of an asset to decide what maintenance needs to be done. Based on the concept of Remaining Useful Life (RUL), CBM dictates that maintenance can only be performed when certain indicators show signs of decreasing performance or upcoming failure. Checking a machine for these indicators may include non-invasive measurements, visual inspection, performance data, and scheduled tests. Condition data can then be gathered at certain intervals, or continuously (as it is done when a machine has internal

sensors). CBM can be applied to mission-critical and non-mission-critical assets[23].

- **Predictive Maintenance (PdM):** by using knowledge about degradation mechanisms, extends the degradation propagation into the future to project system failures. This approach combines insights coming from the observation of experienced degradation with anticipated operating loads in the future to predict when the asset will fail and support the maintenance decision-making process[14].

Some authors characterize CBM[72, 100] and PdM[79] as a sub-classification of the preventive strategy. Other researchers prefer to regard corrective, preventive, CBM, and PdM as distinct classes[104, 108, 109, 110]. The former approach stresses the moment of intervention concerning the failure (before or after the failure), while the latter focuses on the technology involved in each strategy and is the one adopted in this work. Table 2.1.1 provides an overview of these maintenance strategies, highlighting their characteristics, applicability, and limitations.

Table 2.1 – Maintenance strategies and their limitations.

Maintenance strategy		**Characteristics & applicability**	**Limitations**
Corrective		Also known as reactive or unscheduled, it restores functionality of the asset after failure, through repairing or replacement procedures. Suitable for non-safety, non-critical items for which maintenance can be performed quickly and at a low cost[104]	Avoided in complex and dynamic systems whose failures induce costly and severe consequences [108] such as unscheduled operations stops and poorly optimized maintenance resources[109]
Preventive	Age-dependent[110]	The maintenance time is determined according to the	Leaves equipment prone to insufficient

Maintenance strategy		Characteristics & applicability	Limitations
		service age of the components. This method is applicable for components whose service age is known[110]	maintenance[110] or over-maintenance, since actual degradation is not known[24, 58, 64]
	Periodic[110]	The interval between two maintenances is constant. This method is suitable for components with small fluctuations in degradation rate[110]	The risk of failure due to an increase in the rate of component degradation cannot be avoided[110, 58, 64]
	Sequential[110]	The maintenance interval decreases step by step. This method applies to components with significant change characteristics of degradation rules[110]	Prone to a mismatch between maintenance requirements and maintenance operations[110]
	Failure limit[110]	The maintenance time is determined according to the relationship between component reliability and failure threshold. This method is suitable for components with high-reliability requirements[110]	The threshold is difficult to determine[110] leading to unexpected failures or over-maintenance
Condition-based		It incorporates status information of the asset obtained from sensors, early detection of failures, and diagnosis of different anomalies[23, 72]. This method applies to components whose condition parameters can be monitored.	It cannot be applied to non-monitorable components[110, 23]. High volume and quality data to be managed[23].
Predictive		The maintenance opportunity is determined according to the	It does not prescribe maintenance actions to

Maintenance strategy	Characteristics & applicability	Limitations
	predicted component degradation trend by calculating the remaining useful life (RUL). This method applies to components whose degradation parameters can be monitored[110] and failure predicted with assertively[72]	prevent or mitigate asset unavailability[135, 136]. It cannot be applied to non-monitorable components[110]. Data-driven RUL models are not viable when the necessary quantity or quality of data is not available[23] resulting in unreliable failure prognostics. Models can be a black box without providing deterministic information on their behavior[23]. It does not consider varying technological maturity levels[26] and the effect of maintenance intervention on the risk of failure[64]. It solely focuses on the asset itself, allowing limited consideration of multi-stakeholders' scenarios and asset's behavior in its ecosystem[26, 137].

It is important to note that the limitations presented in Table 2.1 do not imply that traditional maintenance strategies adoption must be avoided. On the contrary, depending on the asset's technological complexity and operation size and requirements, traditional strategies may well be the most cost-effective option. These limitations, however, represent opportunities for improvement that can be addressed as the objective of PsM implementations.

Additionally, it is paramount to highlight the differences between PsM and PdM as the concepts are often blurred in the literature. Table 2.2 presents the differences in terms of objective, method, and outcome while Figure 2.1 showcases the comparison in terms of maintenance philosophy outcomes and analytics used.

Table 2.2 – Traditional maintenance strategies and their limitations.

Maintenance philosophy	**Objective**	**Method & analytics**	**Outcome**
PdM	It aims to predict when equipment failure might occur. The primary goal is to perform maintenance at the most opportune time – just before failure is likely to happen but not so early that it's unnecessary[23, 26, 110, 137]	It leverages predictive analytics using data from various sources like equipment sensors, operation history, and maintenance records. Techniques such as statistical analysis, vibration analysis, thermal imaging, and oil analysis are commonly used[23, 26, 110, 137]	The result is failure prediction that can be used by the maintainer to make a maintenance schedule more efficient than routine or time-based maintenance, minimizing the risk of unexpected breakdowns and reducing unnecessary maintenance activities[23, 26, 110, 137]
PsM	It goes a step further than predicting failures. It not only forecasts potential	It leverages advanced analytics, including predictive analytics, but combines this with	The outcome is not just a prediction of when something will fail, but a set of recommendations or

Maintenance philosophy	Objective	Method & analytics	Outcome
	issues but also prescribes specific actions to prevent or mitigate them. The goal is to not just anticipate failures but also to optimize maintenance operations and decision-making[1, 5, 7, 15, 16, 17, 48, 54, 55, 56, 61]	prescriptive analytics. It uses machine learning, optimization algorithms, and complex system models to analyze the data and provide specific recommendations[1, 5, 7, 15, 16, 17, 48, 54, 55, 56, 61, 52]	decisions on what to do about it – whether it's adjusting operations, scheduling maintenance, ordering parts, or even redesigning components. It's a more holistic approach that seeks to optimize the entire maintenance process and improve overall asset performance and operations[1, 5, 7, 15, 16, 17, 48, 54, 55, 56, 61, 52]

Figure 2.1 visually differentiates between PdM and PsM across two dimensions: analytics and outcome. The x-axis represents the “analytics”, indicating a spectrum from predictive analytics to more advanced prescriptive analytics[56]. The y-axis measures the “outcome”, illustrating a progression from simple failure prediction to comprehensive course of action prescription.

Moving rightward along the x-axis, the complexity of analytics increases[56], and we reach PsM that encompasses the predictive aspect and advances it by answering "When will it fail & what can we do about it?"[56, 1, 5, 7, 15, 16, 17, 48, 54, 55, 56, 61]. It not only anticipates equipment failure but also uses complex analytics to prescribe specific actions that can prevent or mitigate potential issues[1, 5, 7, 15, 16, 17, 48, 54, 55, 56, 61, 52]. This leads to a higher level of outcome where the actions are not just reactive but optimized for better maintenance operations and decision-making[56].

As analytics become more complex, transitioning from predictive to prescriptive, the potential benefits of outcomes increase[56], especially when dealing with complex systems operating in dynamic environments[51]. This reflects the more holistic approach of PsM[7], which leverages both predictive and prescriptive analytics to deliver actionable insights, thereby enhancing the overall efficacy.

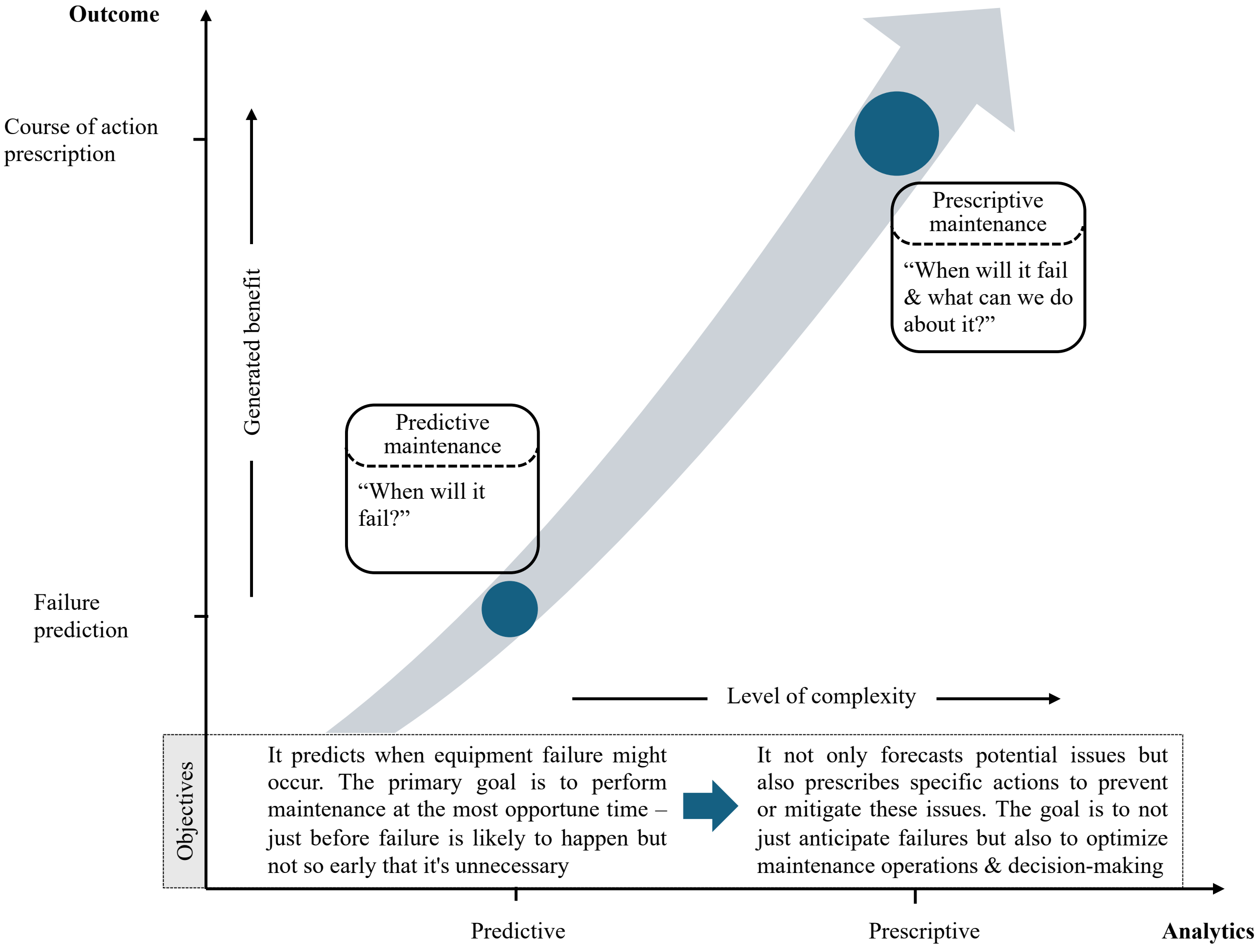

Figure 2.1 – Differences between PsM and PdM. (Source: this author)

2.1.2 ATA Chapter System

The ATA Chapters system, developed by the Air Transport Association (now Airlines for America), organizes aircraft systems into numbered chapters and subchapters for easy reference and it is widely accepted in the industry[161]. Each chapter corresponds to a specific system, such as “Chapter 22: Auto Flight” for autopilot or “Chapter 33: Lights” for lighting systems. This standardized coding streamlines technical information management, aiding maintenance personnel and engineers in ensuring consistency and efficiency in aircraft maintenance and operations[161]. This system was used to model the maintenance events in the experiments 2 and 3, as seen in Chapter 4.1 and Chapter 4.3.

An extract of the ATA chapter list is presented in Table 2.3. The whole list is presented in Appendix E.

Table 2.3 – ATA Chapters list.

ATA Chapter	ATA Chapter Description
ATA 66	FOLDING BLADES/PYLON
ATA 67	ROTORS AND FLIGHT CONTROLS
ATA 70	STANDARD PRACTICES - ENGINE
ATA 71	POWER PLANT
ATA 72	ENGINE
ATA 72	ENGINE - TURBINE/TURBOPROP, DUCTED FAN/UNDUCTED FAN
ATA 72	ENGINE - RECIPROCATING
ATA 73	ENGINE - FUEL AND CONTROL
ATA 74	IGNITION
ATA 75	BLEED AIR

ATA Chapter	ATA Chapter Description
ATA 76	ENGINE CONTROLS
ATA 77	ENGINE INDICATING

2.1.3 Optimization Problem

Optimization problem is the process of selecting the best possible solution (the maximum or minimum of an objective function) from a feasible set, under constraints that represent limitations or requirements on the decision variables[146]. The objective function can represent cost, time, or another performance measure and its constraints are restrictions represented by mathematical equations. Optimization problems can be categorized as:

1. **Linear Programming**: the objective function and constraints are linear. The goal is to find the best decision variables that maximize or minimize the objective function while satisfying the linear constraints.
2. **Nonlinear Optimization**: the objective function and/or constraints are nonlinear. These types of problems are more complex and require specialized methods for the solution. An example of a nonlinear optimization problem could involve maximizing profit under conditions where production costs vary nonlinearly with the volume of goods.
3. **Discrete Optimization**: in these problems, some or all the decision variables are restricted to discrete values, often integers. This is common in situations like scheduling, resource allocation, or routing, where you need to make whole-number decisions (it is not possible to assign half-machine to a task).
4. **Multi-objective Optimization**: Here, more than one objective needs to be optimized simultaneously, such as balancing cost and quality. Since these objectives often conflict, the solution typically involves trade-offs and approaches like the weighted sum method can be used to handle these.

In general, optimization provides a structured way to improve decision-making by helping to identify the best possible action given certain conditions and limitations.

In this research, as will be presented in Chapter 3.2 and mentioned in Chapter 1.1, MILP is the class of optimization that has been adopted. It is a hybrid method that combines elements of linear programming, discrete optimization, and multi-objective approach in a single framework, allowing for a broad range of applications across these optimization types. MILP addresses problems where the objective function and constraints are linear, but some variables are integer values, making it ideal for problems that involve discrete decisions (binary choices) such as whether to take certain actions and how many units to produce or how many resources to allocate, enabling complex real-world applications. MILP can also be extended to multi-objective frameworks, where a weighted sum approach or other techniques can balance conflicting objectives, such as cost minimization and availability maximization, within the same model. This versatility makes MILP a powerful method for optimizations in contexts that need decision-making across a range of criteria and constraints.

2.1.4 Airliner Operations

Airline operations are complex and dynamic, involving the coordination of numerous interconnected processes to ensure safety, efficiency, and profitability. Key characteristics include high-frequency scheduling, adherence to safety regulations, and the need for flexibility in response to unpredictable factors such as weather conditions, air traffic control constraints, and maintenance requirements. One of the main challenges is maintaining optimal aircraft utilization while minimizing delays and disruptions, which can lead to increased operational costs and passenger dissatisfaction. In this context, tail assignment is the process of assigning specific aircraft (or "tails") to scheduled flights over a given planning period[147]. Tail assignment is a critical component of airline operational scheduling, as it must account for each aircraft's maintenance requirements, seating configurations, range limitations, market demands, and efficiency. Operational optimization is an important aspect of the Holistic Framework for PsM as mentioned in Section 3.2 as it allows us to consider the operational side of the optimization.

2.1.5 Widebody and Narrowbody Aircraft

Narrowbody and widebody aircraft are classifications based on the width of the fuselage, which directly impacts seating arrangements and operational use. Narrowbody aircraft have a single aisle and typically accommodate between 4 to 6 passengers per row, supporting a total capacity of 100 to 240 passengers. The fuselage width generally ranges from 3 to 4 meters. These aircraft are most used for short to medium-haul flights, such as domestic or regional routes, and include models like the Airbus A320 family and Boeing 737 series.

In contrast, widebody aircraft feature a dual-aisle configuration and can seat 7 to 10 passengers per row, allowing for a larger total capacity of 200 to over 850 passengers. Their fuselages are wider, typically between 5 to 6 meters, and they are optimized for long-haul and international flights due to their extended range and fuel capacity. Examples include the Boeing 787 Dreamliner, Airbus A350, and the Airbus A380. Table 2.4 compares the aircraft.

Table 2.4 – Narrowbody and widebody features.

Feature	Narrowbody	Widebody
Aisles	Single	Dual
Seating Capacity	100-240	250-850
Fuselage Width	3-4 meters	5-6 meters
Range	Short to medium-haul	Long-haul

2.1.6 Public Health Operations

Public hospital operations, especially in emergencies, face significant challenges in managing high patient volumes, limited resources, and strict timing demands[164]. During peak times or crises, such as a pandemic, hospitals must treat an overwhelming number of inpatients with diverse and critical health needs, all while dealing with constraints on available beds, intensive care units (ICUs), ventilators, and medical staff [164]. This demand requires hospitals to efficiently prioritize care, allocate scarce resources, and minimize patient wait times to improve survival rates. Emergency operations in public hospitals, therefore, rely heavily on effective resource management and real-time adjustments to accommodate the inflow of critical cases[164].

Drawing a parallel with airline operations[165, 166], we can view each patient in the hospital as an aircraft in an airline fleet, each requiring tailored treatment and care. In this analogy, hospitals resemble (MRO) hangars, where resources are organized to maintain operational readiness. Doctors and nurses operate as technicians, providing the care and expertise needed to “restore” the patient to health, much like technicians ensuring an aircraft’s airworthiness. Key resources like ventilators and ICU beds parallel Ground Support Equipment (GSE) and hangar slots in MRO facilities, are critical for keeping aircraft (patients) safely “grounded” until they are fit to return to operation.

In both settings, maximizing asset availability and minimizing downtime—whether a patient’s recovery time or an aircraft’s turnaround—is crucial to maintaining an effective, responsive operation. This parallel highlight the extensibility concept of the Holistic Framework for Prescriptive Maintenance presented in detail in Chapter 3. Table 2.5 summarizes this parallelism.

Table 2.5 – Parallel between health and aeronautics transportation.

Asset/attribute	Health	Aeronautics transportation
Asset	Patient	Aircraft
Station	Hospital	MRO hangar
Tools	Ventilators and ICUs	GSE
Personnel	Doctors and nurses	Technicians
Station vacancies	Beds	Slots

2.1.7 Mean Time Between Unscheduled Removal (MTBUR)

The Mean Time Between Unscheduled Removal (MTBUR) is an indicator used in reliability studies and represents the average time, often measured in operational hours, between unplanned removals of components due to failure. It is calculated by dividing the operating time by the number of unscheduled removals. It can be calculated for a single component, systems, or systems of systems depending on the operating times and removals considered.

As presented in Chapter 4 the MTBUR will be used in experiments 1 and 3 to estimate degradation and calculate the probability of failure of each system in function of flight hours flown.

2.1.8 Prognostics and Health Management (PHM)

It is a multidisciplinary field aimed at predicting the future health of a system while managing its maintenance needs to optimize reliability, safety, and cost efficiency[158]. PHM integrates advanced diagnostics and prognostics tools to monitor systems in real-time and estimate the Remaining Useful Life (RUL) of components or systems[158, 159, 160]. By leveraging data from sensors, operational history, and environmental conditions, PHM systems provide insights into potential failures before they occur, allowing for proactive maintenance decisions[159, 160].

At its core, PHM involves two main components: diagnostics and prognostics[158, 159]. Diagnostics identifies the current health state of a system by detecting and isolating faults, while prognostics predicts the future state and health of the system based on current conditions and degradation trends. These predictions are made using a combination of statistical models, machine learning algorithms, and physics-based simulations, depending on the nature of the system and the data available[158, 159].

The value of PHM lies in its ability to transition from reactive to predictive maintenance, minimizing unscheduled downtime and reducing operational risks. By enabling CBM, PdM and PsM, PHM helps organizations balance performance and cost by replacing components only when needed rather than on a fixed schedule[160]. This approach is particularly beneficial in complex sustems' industries such as aerospace, automotive, and manufacturing, where system failures can have significant safety and financial repercussions. Ultimately, PHM enhances system availability, extends asset lifecycles, and fosters resource allocation optimization, making it an essential component of PsM.

2.1.9 Maintenance Levels

To comprehensively assess and model the maintenance capabilities within the framework, it is essential to understand the different levels of maintenance performed across the various airliner locations. The maintenance capability model considers three primary levels of maintenance: depot, intermediate, and organizational as follows:

- Depot maintenance: it refers to the highest level of maintenance, typically performed at specialized facilities with extensive capabilities. This type of maintenance, also referred to as C-check in commercial aviation, involves major repairs, overhauls, and extensive inspections that require specialized equipment and highly skilled personnel. Depot maintenance is usually planned and scheduled well in advance and is conducted less frequently compared to other maintenance levels. Examples include complete engine overhauls, structural repairs, and significant upgrades or modifications. These facilities often support multiple operational units and provide capabilities that are beyond the scope of organizational and intermediate maintenance levels[172].

- Intermediate maintenance: it is the middle level of maintenance, performed at a maintenance facility or unit that is typically closer to the operational environment than a depot but more specialized than the organizational level. This level, called A-check in commercial aviation, includes tasks such as troubleshooting, parts replacement, minor repairs, calibrations, and scheduled inspections that cannot be accomplished at the organizational level but do not require the extensive resources of depot maintenance. Intermediate maintenance aims to support operational units by providing timely repairs and ensuring that equipment remains in good working condition, reducing the need for depot-level interventions[172].
- Organizational maintenance: It is the lowest level of maintenance, performed by the operational units using the equipment. This level includes routine, day-to-day maintenance tasks such as inspections, lubrication, adjustments, troubleshooting, and repairs limited to remove and replace activities. Organizational maintenance is designed to be quick and efficient, allowing for immediate corrections to minor issues[172].

2.2 Literature Review

2.2.1 Introduction

Typically described as the “most advanced” or the “most mature” maintenance concept, Prescriptive Maintenance (PsM) consists of asset data acquisition, prediction of failure capability, and prescription of actions based on the data acquired and the prediction of failure, all this taking place in an integrated and automatic or semi-automatic workflow. PsM is increasingly being explored as a means of improving production and operational efficiency, by maximizing asset availability and minimizing maintenance costs. Enabled by a wide variety of prescriptive analysis techniques and leveraged by the Internet of Things (IoT), the interest in the PsM has greatly increased in the past five years across both academia and industry, accompanied by a growth in the number of related publications. It is missing from the literature, however, a consolidated, consistent, and systematic literature review on what the PsM is, and how the concept is evolving to meet the needs of the many use cases to which it is being tied. This lack of consistency has led to a wide variety of characterizations, definitions, and processes that lead to a risk of diluting the concept and missing the benefits that the PsM was originally devised to deliver. This literature review consolidates concepts presented in the research published until January 2024 to identify a common understanding of PsM and ensure that the research effort addressed by this study is based on solid foundations.

2.2.2 Methodology

The research presented follows a systematic approach, as illustrated in Figure 2.2, ensuring a comprehensive and repeatable process. The review focused on identifying relevant works related to prescriptive maintenance (PsM) through a structured search conducted on the

Google Scholar platform. The search, performed between August 2022 and January 2024 using the query "Prescriptive Maintenance," initially yielded 983 publications. After applying the relevance criteria which was based on the paper directly address PsM frameworks or maintenance and operations optimizations, 56 papers directly related to PsM were selected for in-depth analysis. Additionally, seminal works were identified using citation-based analysis methods, as outlined in[3], further refining the review by pinpointing contributions that have shaped the evolution of PsM research. The results of this literature review not only provide a foundation for understanding the current state of PsM but also guide the subsequent analysis and experiments detailed in this study.

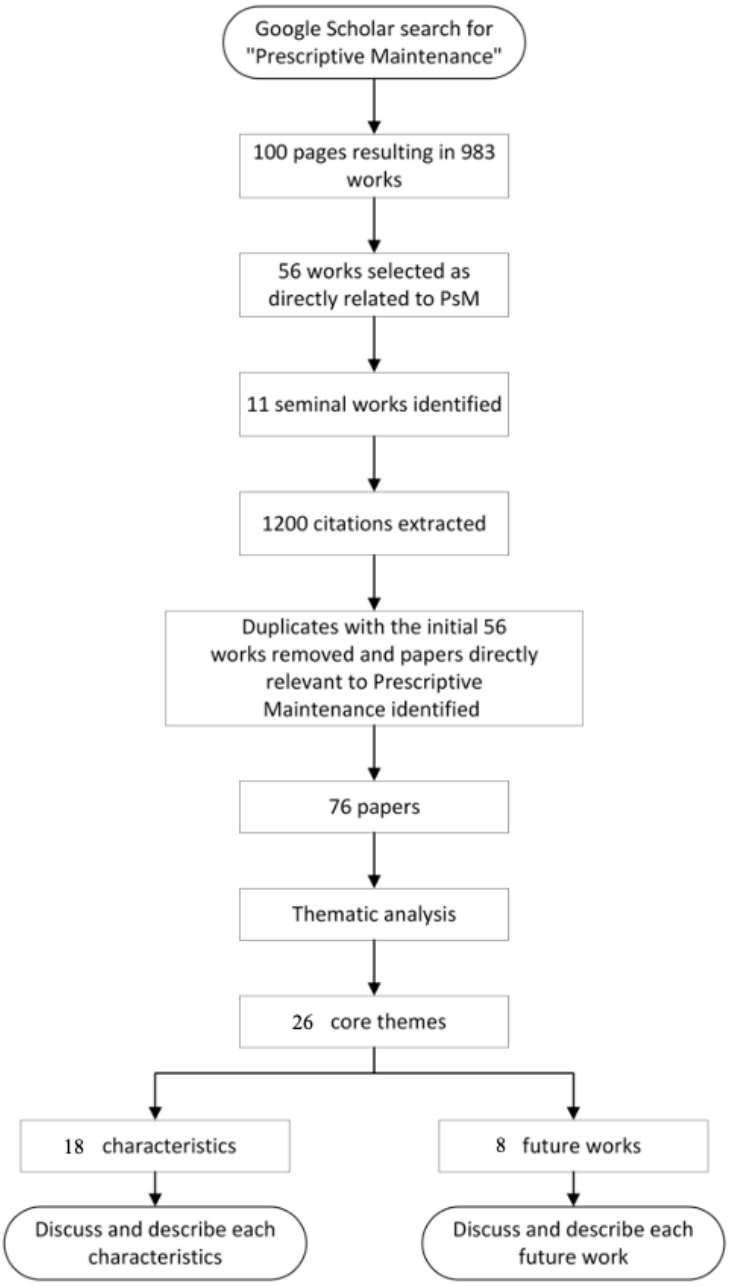

Figure 2.2 – Literature review methodology diagram.

Source: Jones (2020).

The seminal works, as mentioned at the beginning of this chapter, have been identified using the methodology presented by[3]. It consists of evaluating the "peaks" in terms of deviation from a 5-year median of the yearly citations' sums. The result is the spectrogram of Figure 2.3.

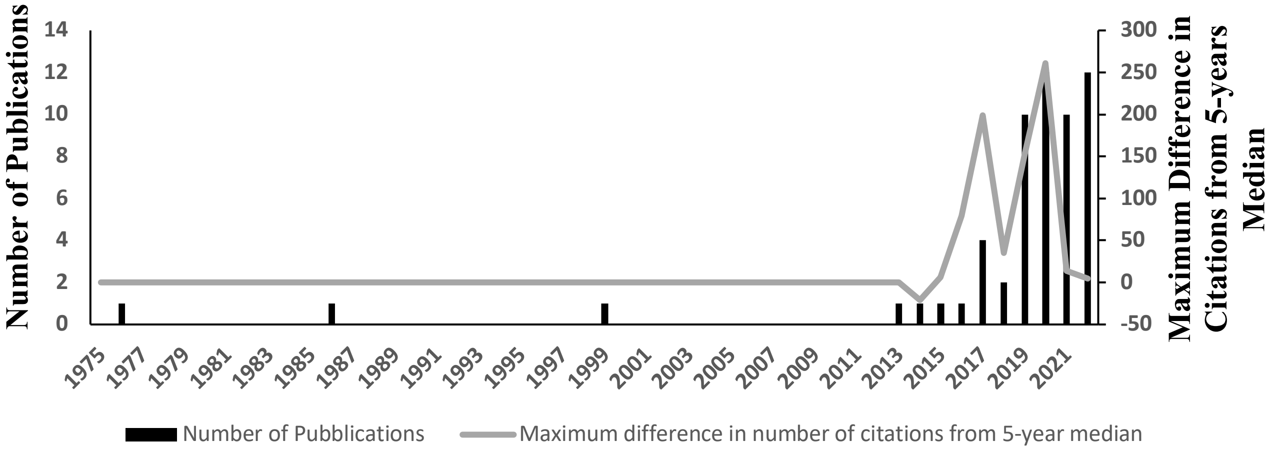

Figura 2.3 – Identification of seminal work between 1975 and January 2024 PsM-related publications (this author).

2.2.3 The Origin of PsM

It is only in 2014, that Olaf Sauer mentioned in his paper the work of Alexandre Linden who in 2013 described PsM as maintenance anticipation and action proposition through decision support systems and decision automation systems enabled by sensing capabilities, machine condition monitoring and diagnostic analysis, drastically differentiating PsM from scheduled maintenance[14, 15].

One year later, Setrag Khoshafian and Carolyn Rostetter expanded the concepts presented by Sauer and Linden[16]. In their work, the authors described PsM as “the sum of Total Productive Maintenance”, “descriptive, preventive, and predictive analytics of equipment data for maintenance”, and “automated end-to-end process”. Calling this flow the “Process of Everything” the authors mentioned that PsM provides the “orchestration of end-to-end dynamic cases involving people, applications, trading partners and things (including robots) as participants”. Khoshafian and Rostetter saw a world where machines predict potential failures and autonomously trigger maintenance — all with minimal human intervention. The machines (or things) that are covered by the “Process of Everything” become self-learning and over time can "take care of themselves," reducing the need for rework and manual efforts that are typical of traditional maintenance.

Thus, PsM is adaptive: it continuously learns from the events or the behavior of the device or its components, leveraging the business by continuous real-time analysis to provide actionable maintenance decisions.

These concepts were reinforced two years later by Ansari, Glawar, and Sihn who introduced the notion of knowledge-based maintenance (KBM) to describe PsM[17]. In this work, the authors mentioned that the digital transformation brought by the Cyber-Physical Production Systems (CPPS) leveraged the importance of data for production and maintenance processes alike through the deployment of decision support systems to booster machine availability and production process stability. The authors suggested a framework model that supports the implementation of a prescriptive maintenance strategy, facilitates the integration of data and the deployment of a technique based on a Dynamic Bayesian Network (DBN) for predicting future events[17]. Table 2.6 summarizes the PsM core concepts discussed in this chapter[5, 15, 16].

Table 2.6 – PsM core concepts.

Concept	**Description**	**Reference**
Holistic	It is the sum of diagnostics, preventive and predictive maintenance orchestrating end-to-end dynamic maintenance cases involving people, applications, trading partners, and things as participants.	16, 17
Actions prescription	PsM automatically creates a maintenance case or prescribes tasks that can be assigned to things or people.	15, 16, 17
Self-learning & Adaptive	With PsM machines become self-learning and over time can predict failures and "take care of themselves". By self-learning, PsM adapts to the events or the behavior of assets achieving continuous real-time analysis to provide actionable decisions.	15, 16, 17
Automated	End-to-end processes enabled by IoT with machines predicting potential failures and autonomously triggering maintenance.	15, 16, 17

Concept	Description	Reference
Optimized	Optimized maintenance is provided	15, 16, 17
KBM	Knowledge-based maintenance: structured and unstructured knowledge as well as data collected through sensors from machines, people, and processes are used as a base for failure prediction and maintenance recommendation	15, 17

Table 2.7 shows the identified themes and their description, Table 2.8 presents the themes and their respective sub-themes and Figure 4.1 (this author) showcases PsM defining characteristics, enablers, and desired outputs.

Each theme presents a key concept identified across the literature as part of the PsM characterization. Sub-themes 1 to 6 answer "What PsM is", while sub-themes 7 to 12 list PsM enablers, sub-themes 13 to 18 present PsM outcomes and expected results, and finally sub-themes 19 to 25 form the basis for future directions and gaps in research.

The next chapter explores each theme and relative sub-themes mapped to related papers according to the codes identified in the corpus review.

Table 2.7 – Theoretical framework themes.

Number	Theme	Description
1	PsM definition	It answers to the question: "What is PsM?". It lists PsM's building blocks and main constitutive concepts.
2	PsM enablers	It presents enablers in terms of processes, technologies, methods, and best practices that make PsM implementation possible.
3	PsM outputs	PsM's results are obtained from actual implementations, business cases, or expected by conceptual frameworks and theories.
4	Future work	Recommended open questions and research possibilities according to the authors

Table 2.8 – Theoretical framework themes and sub-themes.

Theme number	Theme	Sub-theme number	Sub-theme
1	PsM definition	1	The most mature maintenance process
		2	Knowledge-based
		3	Predictive
		4	Holistic
		5	Self-learning
		6	Adaptive
2	PsM enablers	7	Prescriptive analytics
		8	Internet of things
		9	Failure prognosis systems
		10	Data analysis
		11	Decision support system
		12	Ontology
3	PsM outputs	13	The course of action prescription
		14	Life cycle cost minimization and asset availability maximization.
		15	Optimized maintenance
		16	Automated maintenance workflow
		17	Maintenance recommendation continuous improvement
		18	Integration between operation and maintenance
4	Future work	19	Prescriptive Analytics methodology considering all resources
		20	Extensibility/adaptability/scalability
		21	Prototype development/real-case scenario
		22	Process integration
		23	Algorithm feedback & maintenance imperfection
		24	Improve prediction quality
		25	Improve data availability
		25	Appropriate objective function development

Figure 2.4 presents a clear progression from the definitions of maintenance strategies to their practical enablers, and finally, the desired outputs. It starts with foundational characteristics, such as predictive and knowledge-based maintenance, advancing through to holistic, adaptive, and self-learning approaches. These characteristics are powered by enablers

like prescriptive analytics, IoT, and decision support systems, which leverage data to provide the desired outputs: actionable prescriptions, minimized costs, maximized availability, optimized routines, automated workflows, continuous improvement, and seamless integration of operations and maintenance.

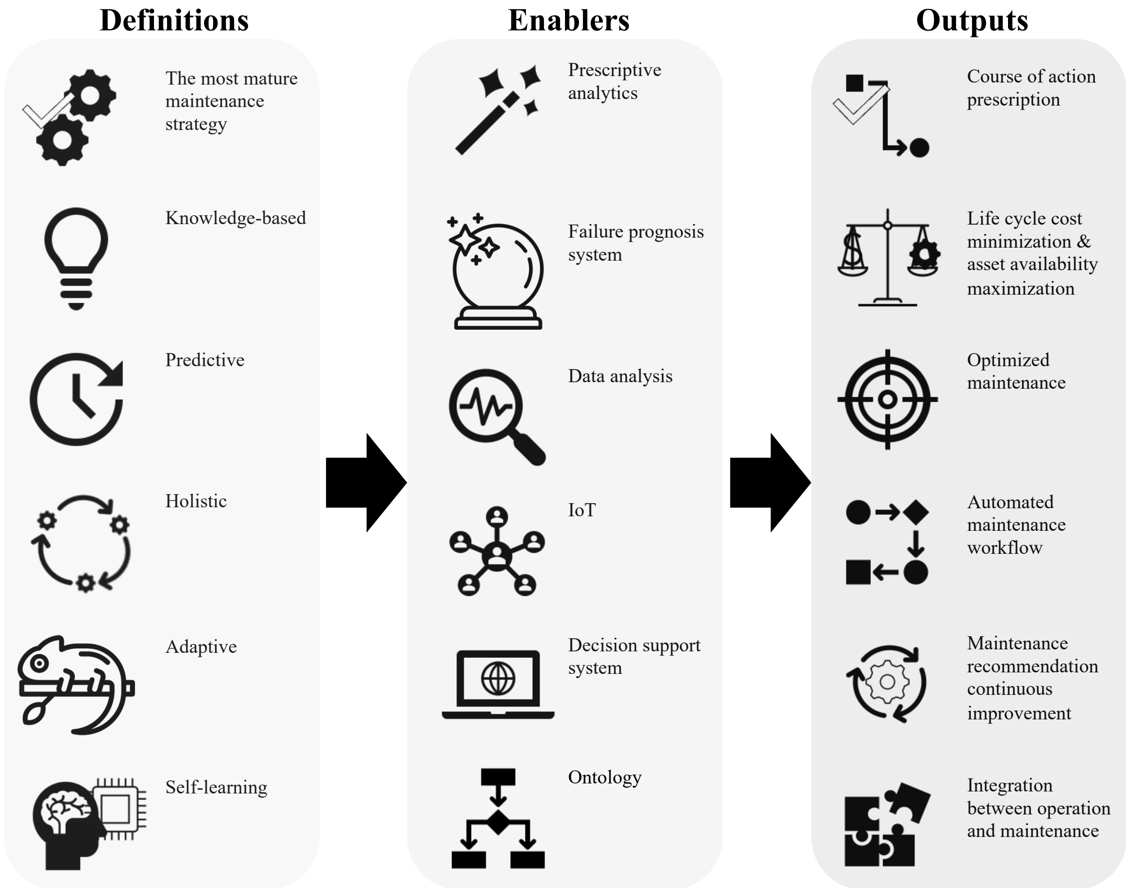

Figure 2.4 – PsM definitions, enablers, and outputs. (Source: this author)

2.2.4 Research Gap Identification

This chapter is dedicated to analyzing, within the corpus, what has been done and proposed in terms of the research question addressed in this thesis, as seen in Section 1.2 the following also proposed in Table 2.9:

Table 2.9 – Research question.

How maintenance and operations efficiency can be improved through an optimization framework for prescriptive maintenance that:	
considers	1. Maintenance resources involved namely labor, tools, and infrastructure?
	2. Maintenance imperfections?
is	3. Extensible to different assets with different technological maturities?
	4. Adaptable to different industries, namely aerospace, and health?
provides	5. Optimized maintenance course of action?

Agent-based simulation that considers aspects of maintenance, operations, and fleet different technological maturity to provide maintenance optimization based on asset real-time condition and health prognosis have been implemented[54, 56]. However, resource-wise, the author considers only human line maintenance resources, while leaving for future work an algorithm capable of extending the optimization approach to consider prognostics' low accuracy, evaluation of maintenance schedule robustness over unexpected events such as bad weather, the scheduling of different tasks that might compete for the same resources, ground support equipment, shop repair resources and material logistics as maintenance process constraints. In subsequent work, the simulation to cover maintenance imperfections and uncertainties in prognostics has been developed[56], however, the model did not cover resources other than labor as in his previous work[56]. Maintenance imperfections have been modeled proposing a methodology to consider their effects on maintenance scheduling using simulation[43], however, this study leaves out resources' constraints and assets' different technological maturities from the equation. Similarly, other approaches define maintenance imperfection and model how it affects scheduling but do not consider resource stakeholders or the option of having human-cobot interaction[66, 67]. The prescriptive methodologies that provide the base for the hypothesis are agent-based simulation[67, 66], machine learning, and Markov Decision Process[67].

As prescriptive analytics methodology to optimally schedule maintenance, authors have used mixed integer programming (linear and nonlinear)[7, 91, 57, 49, 92, 62, 94, 95, 82, 97, 98, 64, 81], Markov Decision Process[20, 63, 67], machine learning[8, 23, 92, 22, 67, 64, 65], Monte-Carlo simulation[43, 92, 62, 50], Heuristics[60, 79, 91, 92, 95, 50, 96, 30], discrete-event simulation[54, 56, 79], agent-based simulation[54, 56, 79, 66, 67] and ontology[5, 8, 9, 17, 30, 60, 79], however, no work has considered resource constraints other than human labor or human-robot collaboration.

Regarding the theme of human-cobots collaboration, the issue is mentioned as future work or trend[5, 17, 22, 100, 101, 102] and addressed by[77, 89, 99] but not as a constraint in the PsM model. Specifically, Deng et al.[77] proposed an ontological framework to map out and describe how knowledge is shared and increases among humans and cobots, while Ansari[89, 99] models the interaction and how it affects a production line supported by cyber-physical production system (CPPS), however, in both cases there is no integration between the model of the system proposed, all maintenance resources and maintenance imperfections.

Regarding the extensibility between industries or different systems, authors refer to it as future work[5, 7, 22, 24, 30, 35, 48, 49, 51, 52, 54, 58, 60, 62, 64, 65, 81] and as a crucial step to assess the actual scalability and applicability of PsM concepts, however, it is an issue that is not addressed. Other studies propose methodologies based on simulation[30] and machine learning[65] however do not provide experimentation to evaluate the proposals.

Table 2.10 summarizes this author's approach concerning the research question. It can be noted that although the focus has been maintenance optimization, no work considers maintenance imperfection, different types of labor resources (airframe, avionics, and powerplant), different assets of different technological maturities, different support capabilities, failures per system, in the same work. Similarly, no work effectively assesses and demonstrates how the prescription algorithm could cover different industries, demonstrating its scalability and adaptability to different scenarios. This is where this work is positioned.

Table 2.10 – PsM works related to the research gaps.

Approached by	Resources constraint	Asset maturity	Maintenance imperfections	Maintenance optimization	Tested on a real case scenario	Different technological maturities	Different support capabilities	Different type of failures	Prognostics uncertainties	Scalability to different industries	Main Goal
Meissner[54]	◐	○	○	●	○	○	○	○	○	○	Cost
Meissner[56]	◐	◐	◐	●	◐	○	○	○	○	○	Cost
Ansari et al.[5]	◐	○	○	●	○	○	○	○	○	○	Framework
Choubey[7]	◐	○	○	●	○	○	○	○	○	○	Framework
Mattioli et al.[8]	○	○	○	◐	●	○	○	○	○	○	Framework
Glawar et al.[9]	◐	○	○	◐	○	○	○	○	○	○	Framework
Ansari et al.[17]	◐	○	○	◐	○	○	○	○	○	○	Framework
Silvestri[100]	○	○	○	○	○	○	○	○	○	○	Concept
Cisterna[101]	○	○	○	○	○	○	○	○	○	○	Concept
Ameri[102]	○	○	○	○	○	○	○	○	○	○	Concept
Gao et al.[20]	○	○	○	●	○	○	○	○	○	○	Cost
Kovacs[23]	○	○	○	●	○	○	○	○	○	○	Cost
Strack[30]	○	○	○	◐	○	○	○	○	○	○	Framework
Strack[39]	◐	○	○	◐	○	○	○	○	○	○	Framework
Koops[43]	○	○	●	●	●	○	○	○	○	○	Cost
Padovano[60]	◐	○	○	●	○	○	○	○	○	○	Framework
Deng et al.[77]	○	○	○	●	○	○	○	○	○	○	Framework
Garcia[79]	◐	○	○	●	○	○	○	○	○	○	Cost & avail.
Ansari[89]	○	○	○	◐	○	○	○	○	○	○	Framework
Ansari[99]	○	○	○	●	○	○	○	○	○	○	Framework
Aramon[91]	◐	○	○	●	○	○	○	○	○	○	Cost & avail.
Cho et al.[57]	◐	○	○	●	○	○	○	○	○	○	Cost
Consilvio[49]	◐	○	○	●	●	○	○	○	○	○	Cost
Consilvio[92]	◐	○	○	●	●	○	○	○	●	○	Concept
Dias et al.[62]	○	○	○	●	○	○	○	○	○	○	Concept
Filo et al.[22]	○	○	○	●	○	○	○	○	○	○	Concept
Gavranis[94]	◐	○	○	●	○	○	○	○	○	○	Cost & avail.
Kozanidis[95]	◐	○	○	●	○	○	○	○	○	○	Cost & avail.
Liu et al.[50]	○	○	○	●	○	○	○	○	○	○	Cost
Nakousi[82]	○	○	○	●	○	○	○	○	○	○	Cost
Nejad[66]	◐	○	●	●	○	○	○	○	○	○	Cost
Robert[96]	○	○	○	●	○	○	○	○	○	○	Cost
Schrotenb[97]	●	○	○	●	○	○	○	○	○	○	Cost

Approached by	**Resources constraint**	**Asset maturity**	**Maintenance imperfections**	**Maintenance optimization**	**Tested on a real case scenario**	**Different technological maturities**	**Different support capabilities**	**Different type of failures**	**Prognostics uncertainties**	**Scalability to different industries**	**Main Goal**
Safei et al.[98]	◐	○	○	●	○	○	○	○	○	○	Availability
Tham et al.[63]	○	○	○	●	○	○	○	○	○	○	Cost
van de Loo[67]	○	○	●	●	○	○	○	○	○	○	Cost
Vandersch[64]	○	○	○	●	○	○	○	○	○	○	Cost
Venkatach[81]	○	○	○	●	○	○	○	○	○	○	Cost
Mao et al.[142]	◐	○	○	●	○	○	○	○	◐	○	Cost & availa
Pinciroli[139]	○	○	○	●	○	○	○	○	○	○	Cost & avail.
Sun et al.[137]	○	○	○	●	○	○	○	○	○	○	Cost
Goby[145]	◐	○	○	●	○	○	○	○	○	◐	Cost
Zhao[135]	○	○	○	●	○	○	○	○	○	○	Cost
Esposito[145]	○	○	○	●	○	○	○	○	○	○	Cost
This work	●	●	◐	●	●	●	●	●	○	●	Profit

○ Regarded ◐ Partially regarded ○ Not regarded

3 Materials and Methods

3.1 Materials

This chapter details the hardware and software resources utilized in the development and implementation of this research. The selection of hardware aimed to meet the computational demands essential to the study, while the software tools were chosen to enable efficient analysis, modeling, and validation of results. Together, these resources allowed to carry out experiments, managing data, and achieving the objectives of this research. Each component is discussed in detail in the following chapters.

3.1.1 Hardware

The hardware utilized for this research was a 2023 MacBook Pro, equipped with the Apple M2 Pro chip and 16 GB of memory. It was noted that this set up generally could handle experiments efficiently, although processing time usually increased up to 4 hours as for more complex experiments – especially for the health case study.

Table 3.1 – Hardware characteristics.

Characteristics	**Description**
Chip	Apple M2 Pro
Ram memory	16 GB
Hard disck memory	500 GB

3.1.2 Software

The software environment for this research consisted of macOS Sonoma 14.5 as the operating system and Microsoft Excel (version 16.9) used for preliminary data organization and results analysis. For complex modeling and coding tasks, PyCharm 2023.2.3 served as the primary Integrated Development Environment (IDE), enabling development in Python 3.12.0. Core computations and optimization tasks were executed using the Gurobi Optimizer (version 11.0.3), an industry-standard tool for solving linear optimization problems. Key Python libraries, included pandas for data manipulation, gurobipy for interfacing with Gurobi, and matplotlib for data visualization. Table 3.2 summarizes the software used.

Table 3.2 – Software used and their attributes.

Attributes	**Description**
Environment	macOS Sonoma 14.5
Data pre/post analysis	Microsoft Excel 16.9
Modeling & coding	PyCharm 2023.2.3
Development environment	Python 3.12.0
Optimization solver	Gurobi Optimizer 11.0.3
Pandas	Python library for data manipulation
Gurobipy	Python library to use gurobi solver in python
Numpy	Python library for Monte Carlo simultion
Time	Python library to track processing time

3.2 Methods

This chapter is dedicated to the heart of this research, presenting the development and methods, that resulted in the Holistic Optimization Framework for PsM. The work is linked to the Smart Prescriptive Maintenance Framework (SPMF), an implementation approach for PsM[51] first introduced by Marques et al. in 2019 and later reproposed[55] by this author in 2021. This framework places a strong emphasis on holistic optimization, integrating operation, maintenance, and maintenance resources into a unified strategy. It goes beyond the aerospace industry, associating diverse assets such as aircraft and human health, for a cross-industry PsM paradigm shift.

3.2.1 Holistic Optimization Framework for PsM

The Holistic Optimization Framework for PsM, shown in Figure 3.1 is designed to address the challenges of maintaining complex systems in dynamic operational environments. As illustrated in the flowchart, the framework integrates various elements that influence maintenance and operation decisions, including the asset's characteristics, external factors and operation disruptions (both scheduled and unscheduled). The framework considers maintenance resources such as stations, equipment, personnel, and materials, alongside other constraints like maintenance uncertainties and time. By leveraging a prescriptive algorithm aimed at maximizing performance and minimizing costs, this framework processes these inputs and constraints to recommend optimal maintenance actions and operation recommendation. This holistic approach ensures that all relevant factors are accounted for, leading to more efficient and effective operation and maintenance that can be scaled across different industries.

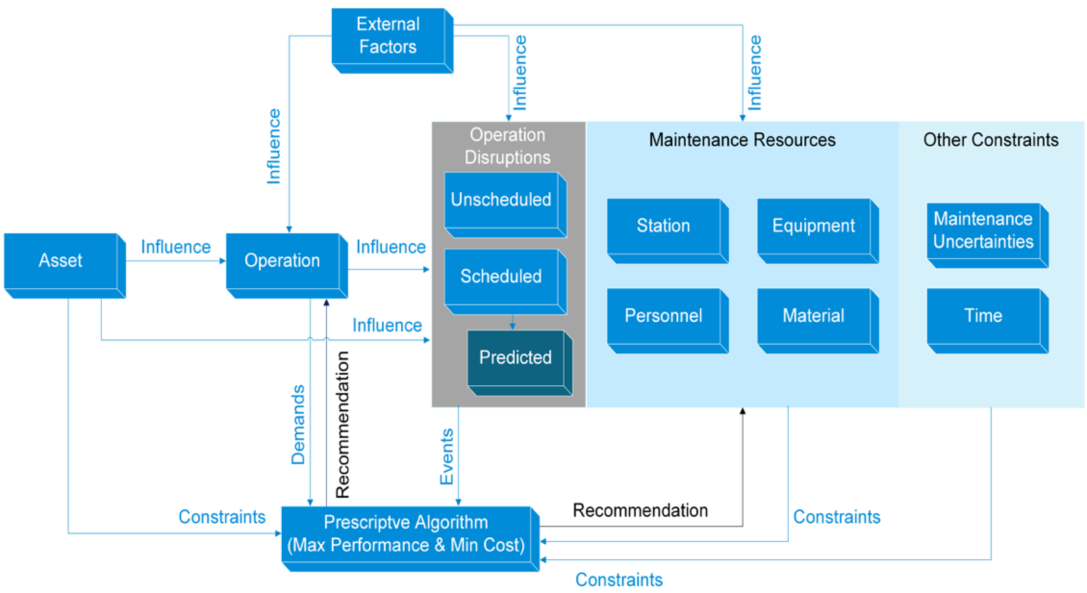

Figure 3.1 – Holistic Optimization Framework for PsM. (Source: this author)

The asset can encompass a single aircraft, a fleet, a set of production machines in the manufacturing industry, a fleet of ships, an oil extraction platform, a fleet of urban air mobility vehicles, a wind farm, or humans and its characteristic influences how the operation occurs.

Operations can be disrupted for various reasons, including the wear and tear or degradation of systems that cause interruptions or reduced efficiency. When these disruptions happen unexpectedly, they result in unscheduled events, leading to increased operational and maintenance costs due to the unplanned nature of the event and the necessary use of resources that must be deployed to continue operation or mitigate the effects of the disruption. This scenario pertains to unscheduled maintenance. Examples of unscheduled events include sudden failures in aircraft or machines and health emergencies like pandemics, heart attacks, cerebral vascular accidents and many others.

To mitigate costly operational stoppages, complex assets are often maintained proactively to prevent sudden failures. In this context, assets are removed from operation in a planned manner, potentially during periods of lower demand or less intensive operation, for inspection or preventive activities. This strategy is more efficient than reactive maintenance but can lead to over-maintenance as it does not consider the asset's actual health state. In humans, this can be compared to elective surgeries and preventive health check-ups.

A more refined subset of scheduled maintenance is PdM. For continuously monitored assets, it is possible not only to assess the current health state but also to predict future states. This allows maintenance to be planned based on the predicted state, ensuring it is performed when necessary. Although predictive maintenance does not provide course of action, it is the optimal strategy in comparison to the unscheduled and the more general scheduled strategy. Predictive strategies are still evolving as not all complex systems have this capability. Human health systems currently lack this capability, but the rapid evolution of wearables and other sensing devices could lead to significant health benefits by enabling state prognostics for humans, thereby optimizing healthcare system support. These operation disruptors are events that need to be managed to resume operations as quickly as possible at the required quality and costs. They provide information on when the event should occur, its estimated duration, and scope while maintenance resources provide the state and quantity of available personnel, physical space, material and equipment.

Maintenance resources include physical spaces (hangars, hospitals, repair shops, plants, etc.), equipment and tools, spare parts, and personnel such as technicians, engineers, nurses, doctors and all human capital involved in maintenance. These resources are finite, making their optimization critical for sustainable operations, especially in highly dynamic and demanding environments.

Additional constraints include maintenance uncertainties, as maintenance may not always restore the asset to a "good as new" state, but rather to a condition somewhere between "new" and "old"[43]. Time is also a critical constraint, as it dictates the pace of operations and maintenance.

External events, which are often beyond the system's control, can be human-made (wars, strikes, labor shortages) or natural (floods, heavy rains, seismic activities, volcanic ash clouds). They directly affect the operation and can cause unscheduled events creating great impacts to the system performance and maintenance activities.

The prescriptive algorithm considers constraints defined by the asset, such as its reliability. For human assets, this includes genetic information, innate resistance to infections, responsiveness to specific treatments or survival probability. The operation attributes provide asset's performance requirements, indicating what is expected from the asset in terms of quality of the product, service level and costs.

Through these constraints and requirement, the algorithm provides the best recommendations for deploying the assets and support resources to holistically enhance operational performance and maintenance implementation.

To provide a clear understanding of the interconnected components within the Holistic Optimization Framework for PsM, Table 3.3 outlines the key elements and their correlations.

This Table illustrates how each element influences and constrains the others, highlighting the dynamic interactions between assets, their operations, external factors, disruptions, maintenance resources, and the prescriptive algorithm.

Table 3.3 – Holistic and scalable smart optimization framework elements and their correlations.

Element	Action	Element	Description
Asset	Influences	Operation	Asset's characteristics determines the operations' characteristics
	Influences	Operation disruptions	Asset's reliability and health directly determines possible operations' disruptions such as stoppage for maintenance
	Constraints	Prescriptive algorithm	Assets characteristics such as reliability and performance capability define optimization restrictions
Operation	Influences	Operation disruptions	Variability, level and intensity of operation influences when disruptions happen
	Demands	Prescriptive algorithm	The specific of operation determines what is expected from the optimization such as availability maximization, cost minimization or better performance and quality
External factors	Influences	Operation	Uncontrollable environmental or human caused events may affect operation
	Influences	Operation disruptions	Uncontrollable environmental or human caused events may cause disruptions such as maintenance event
Operation disruptions	Determine events to	Prescriptive algorithm	Disruptions in operation are the events to be managed by the prescriptive algorithm to fulfil operation demands. They can be unscheduled or scheduled. Predicted events are considered a sub-category of scheduled events
Maintenance resources	Constraints	Prescriptive algorithm	They are finite operation's support assets, such as physical space, machinery, equipment, personnel and material that are constraints to the prescriptive algorithm. They usually need to be optimized to ensure efficiency and effectiveness
Other constraints	Constraints	Prescriptive algorithm	Time and other maintenance uncertainties that also generate restrictions to the maintenance resources, and in turn, to the

Element	Action	Element	Description
			prescriptive algorithm
Prescriptive algorithm	Recommends	Operation	The prescriptive algorithm generates recommendations to the operation to increase holistic operation-maintenance performance while pursuing cost minimization
Prescriptive algorithm	Recommends	Maintenance resources	The algorithm recommends how to deploy maintenance resources optimally to leverage holistic performance of the system operation-maintenance resources

By considering the relationships between the elements, the PsM algorithm enables informed decision-making that enhances maintenance and operation seamlessly.

To illustrate how the framework can be extended across industries, Figure 3.2 presents the association between two very different assets: aircraft and humans. The characteristics of these assets are associated based on the framework presented in Figure 3.1. and will be further explained through the case studies in next chapters. For humans, operations include life activities, while operations for aircraft encompass transportation. Unscheduled events like COVID-19 pandemic admissions parallel unscheduled maintenance events for aircraft, such as equipment failure. Scheduled events for humans, such as elective procedures, align with planned aircraft maintenance checks like A-check and C-check. PdM, a future work area for humans, involves anticipating human health issues or aircraft failures through predictive analytics.

Maintenance resources for humans involve hospital ICUs (stations), ventilators (equipment), doctors and nurses (personnel), and hospital consumables (material). Similarly, aircraft maintenance resources include hangar slots (stations), tool sets (equipment), maintenance technicians (personnel), and spare parts units (material). Both domains face constraints from maintenance uncertainties and time. For humans, this includes uncertainties in medical treatments and time constraints, while for aircraft, it involves maintenance imperfections and time limitations. Figure 3.2 illustrates these concepts.

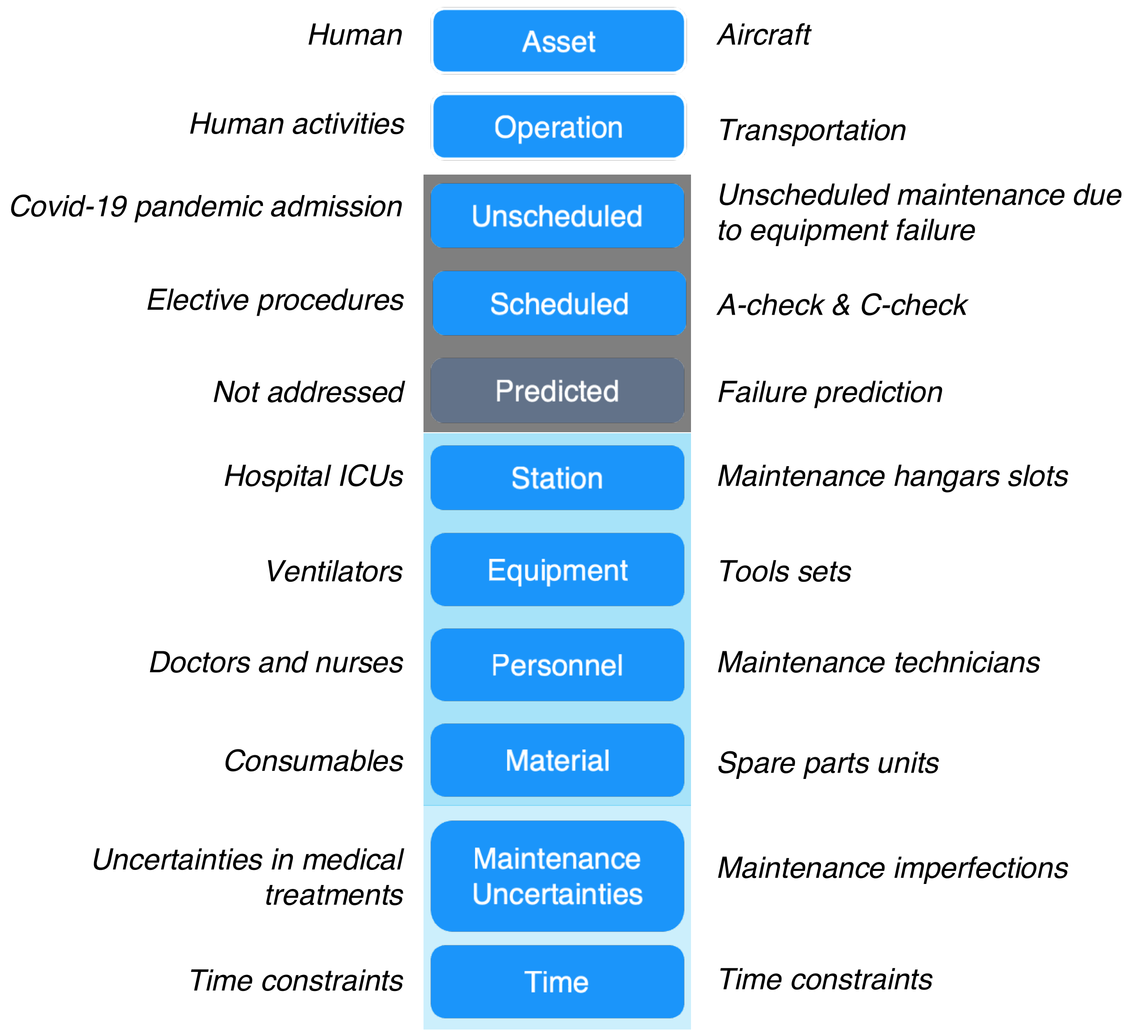

Figure 3.2 – Human and aircraft framework parallel. (Source: this author)

Figure 3.3 introduces the mathematical structure that will further be detailed in next chapters. The Figure presents the association between assets, parameters, constraints, and objective functions. For both humans and aircraft, the assets (individuals and aircraft) engage in operations (human activities and transportation). Unscheduled events include COVID-19 pandemic admissions for humans and equipment failures for aircraft, while scheduled events cover elective medical procedures and planned maintenance checks. Both events are time constrained as they must happen up to a certain date in the case of A-check, C-check and predicted events, while unscheduled maintenance happen, as per definition, in specific dates according to unforeseen failures or COVID-19 pandemic spread.

Key constraints are then highlighted, such as the availability of hospital ICUs, ventilators, doctors, and nurses for human patients, and the availability of maintenance slots, tools, and technicians for aircraft. Additionally, constraints related to materials, such as consumables for humans and spare parts for aircraft, are considered. The framework also accounts for maintenance uncertainties, where stochastic methods are applied post-optimization for humans to account for medical errors or treatments failures while Mean Time Between Unscheduled Removal (MTBUR) are updated to account for degradation accumulation due to imperfect maintenance for aircraft.

Time constraints are crucial, ensuring that patient admissions and aircraft maintenance occur promptly to maintain operational viability. The objective function for both domains focuses on maximizing the difference between revenue and cost, ensuring that the optimization process enhances efficiency and effectiveness. In the case of humans, revenue is directly related to the maximization of the probability of saving life with greatest life expectancy while costs are correlated to the daily hospitalization expenditures. For aircraft fleet, revenue is related to the maximization of number of flights and cost to the maintenance cost. Detailed mathematical models are presented in the next chapters.

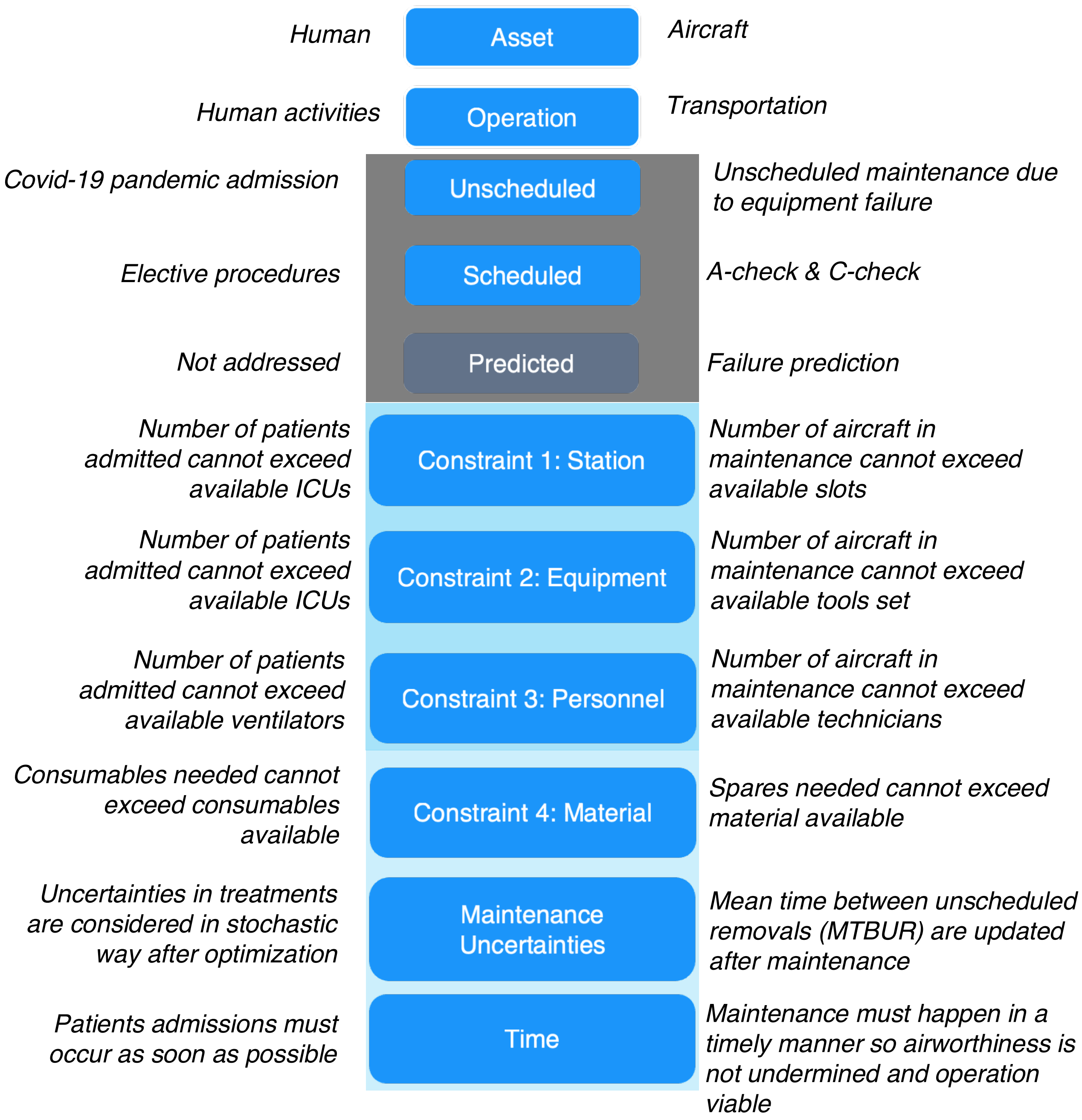

Figure 3.3 – Framework mathematical structure. (Source: this author)

As this chapter concludes, the framework's adaptability has been exemplified by drawing parallels between the maintenance of complex systems like aircraft and the health care provided to humans. Moving forward, next chapter will present the core mathematical model of the framework and the description of the prescriptive algorithm to outline the elements that are context sensitive that need adaptation according to the context, and the elements that are structural, that is, do not vary according or need only minor adaptations to the context.

3.2.2 Prescriptive Algorithm

This chapter is dedicated to describing the prescriptive algorithm mathematically and conceptually presenting its elements and their characteristics.

Figure 3.4 presents this overview and highlights the prescriptive algorithm flow designed towards the optimization and decision-making processes across various industries, including air transport, health, oil and gas, energy, and transportation. The algorithm integrates context-sensitive elements and structural elements. The former elements need to be modeled according to the business and operational contexts the assets operate in, while the latter need little or no adaptation across different operations.

1. Real-World Context and Assets: this element represents the diverse domains, such as air transport, healthcare, oil & gas infrastructure operations and other industry-specific assets that can be addressed by the algorithm.

2. Data Input Pre-Processing: the algorithm begins with cleaning and organizing relevant data collected about the assets. Mathematical and statistical simulations, such as Monte Carlo simulation, may be needed to describe current operation. This step ensures the reliability of input data for downstream processes.

3. Asset and Operations Characteristics: the cleaned data is analyzed to define asset's maintenance requirements, operational requirements, existing support resources, and asset-specific characteristics such as Mean Time Between Failure (MTBF), MTBUR, RUL and failure modes.

4. Decision Variables: decision variables X, Y, and O indicate the scheduling or occurrence of maintenance (scheduled vs. unscheduled) and operations. X = 1 or Y = 1 signifies the occurrence of a maintenance, whereas O = 1 denotes operational activities. Variables X may be in function of triggers such as time, operational cycles and predicted degradation, while Y is related to unforeseen events and failures thus linked to statistic behavior. Variables may be a function of time, location and asset.

Unscheduled interventions are not programmed, as the name suggests. They can be caused by incidents or accidents due to external factors or unforeseen asset failures.

Scheduled interventions are the ones that are programmed to prevent sudden failures. Predictive maintenance tasks end up being scheduled tasks as well, with the difference that the interval is based on the actual degradation of the asset instead of a fixed interval.

Table 3.4 specifically lists these decision variables.

Table 3.4 – Example of decision variables.

Variable	State	Type
X_{idh}	• Equal to 1 if programmed activity is scheduled for asset *i* on day *d* and hangar *h* • *0* otherwise	Binary
Y_{idh}	• Equal to 1 if unscheduled activity happens for asset *i* on day *d* and hangar *h* • *0* otherwise	Binary
O_{idh}	• Equal to 1 if operation occurs for asset *i* on day *d* and hangar *h* • *0* otherwise	Binary

5. Constraint Formulation:

- **Material Constraint**: ensures that both scheduled and unscheduled maintenance do not exceed the available material resources. In the example shown below (equation 3.1), for each day *d,* asset *i* and event *m*, materials quantity used cannot be larger than the quantity available at station *H* at each day *d*. In this case, materials used for scheduled and unscheduled maintenance task are the same.

$$\sum_{h \in H} \sum_{i \in F} \sum_{d \in D} (X_{idh} + Y_{idh}) * MAT_{idm} \leq MAT_{Hd} \tag{3.1}$$

- **Tool/GSE Constraint**: limits maintenance activities based on the availability of required tools or GSE. In the example below (equation 3.2), for each day *d,* asset *i* and event m, GSE quantity used cannot be larger than the quantity available at station *H* at each day *d*.

$$\sum_{h\in H}\sum_{i\in F}\sum_{d\in D}(X_{id} + Y_{id}) * GSE_{idm} \leq GSE_{Hd} \tag{3.2}$$

- **Labor Constraint**: ensures tasks are aligned with the available full-time equivalents (FTEs) for scheduled and unscheduled tasks. It might be broken down in terms of technician's skills such as avionics, powerplant, airframe, engineering, doctors, nurses and so on. The example shown in equation 3.3 establishes that for each day *d,* asset *i* and event m, the FTE quantity used cannot be larger than the quantity available at station *H* at each day *d*.

$$\sum_{h\in H}\sum_{i\in F}\sum_{d\in D}(X_{idh} + Y_{idh}) * FTE_{idm} \leq FTE_{Hd} \tag{3.3}$$

- **Station Constraint**: it limits the amount of assets that undergoes maintenance to the stations' capacity and unit of space. It can be expressed in area, slots, intensive care units (ICUs), shops and any physical space where maintenance needs to take place. The limitation imposed by the number of available stations is described in equation 3.4. For any given day *d*, the number of assets slated to receive maintenance must not exceed the physical space available, denoted by H_d. This stipulation enforces a cap on the maximum number of assets undergoing maintenance at any one time, ensuring that the physical space available is not exceeded.

$$\sum_{h\in H}\sum_{i\in F}\sum_{d\in D}(X_{idh} + Y_{idh}) \leq H_d \tag{3.4}$$

6. Revenue and Cost Equations: this element expresses that maintenance and operation are mutually exclusive. If an asset is operating, maintenance cannot happen and vice versa.

7. Revenue and Cost Equations:

- **The Revenue Equation:** evaluates the monetary gain derived from service or product delivery over a period. It is a context-dependent element since depending on the business service or product are provided.
- **The Cost Equation:** accounts for the costs associated with providing services, considering different scenarios such as quality delivery, delays or not delivery of a product or service. As revenue, it is a context-dependent equation since delay related cost, for example, are not always applicable.

8. Objective Function: the optimization goal is defined as the maximization of profit, calculated as revenue minus cost, as also shown in equation 3.5. This function ensures that operations achieve the highest efficiency and profitability. This equation defines the prescriptive approach since it ensures optimization is holistic, considering both revenue, which linked to operation, and cost, which is attached to maintenance and support.

$$ObjectiveFunction = Max(Revenue - Cost) \tag{3.5}$$

9. Results Post-Processing: the optimized results are analyzed to provide actionable insights, such as strategies to increase system efficiency or prescribe a course of action. Simulations, such as Monte Carlo simulation, may also be conducted to validate and visualize the recommendations depending on the context.

The algorithm offers a comprehensive framework for balancing operational constraints and maximizing value creation. It leverages data-driven insights, mathematical modeling, and optimization techniques to prescribe actionable strategies.

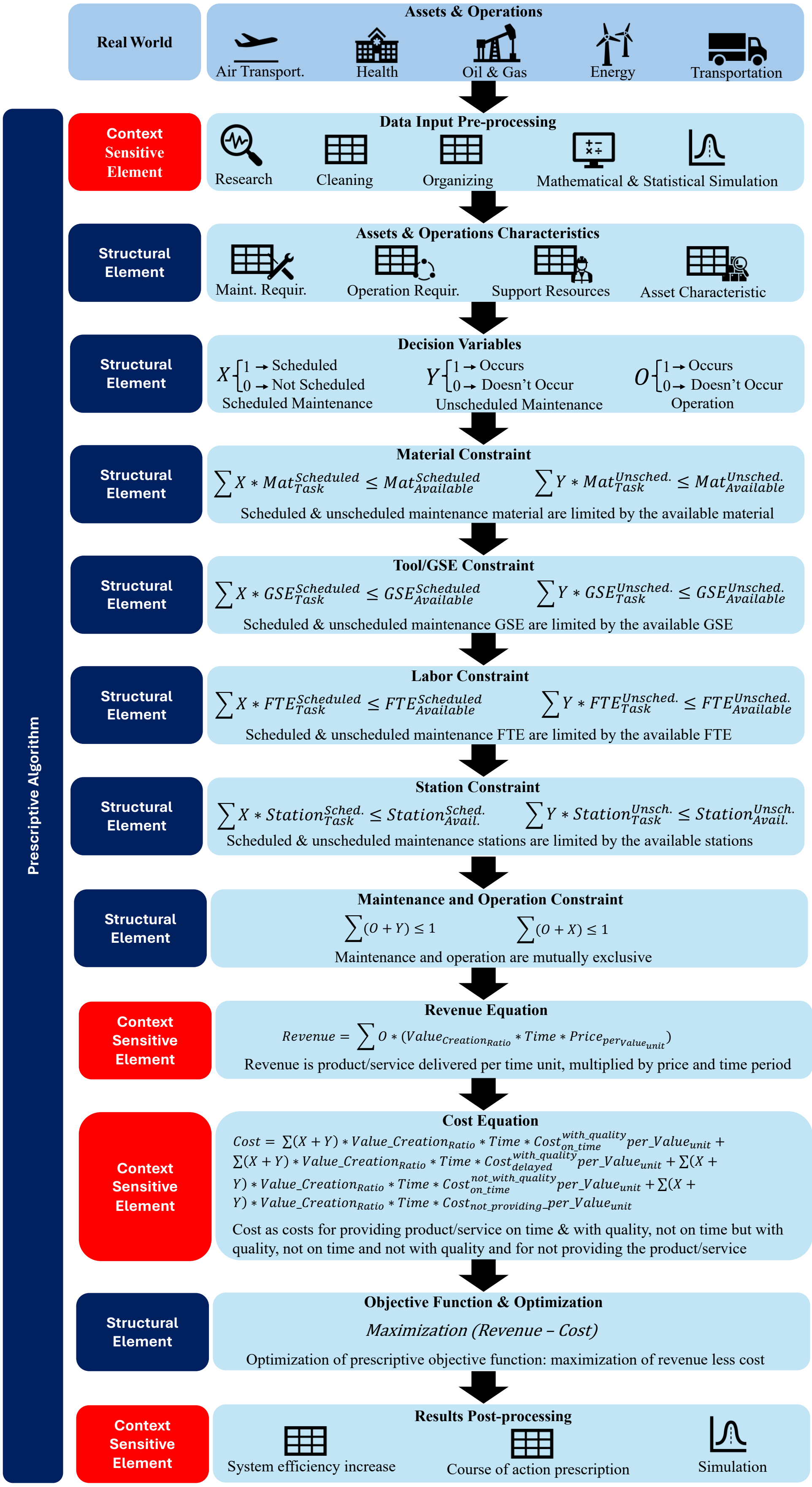

Figure 3.4 – Prescriptive algorithm. (Source: this author)

To further clarify the algorithm, pseudocode 3.5 outlines the process of optimization beginning with input parameters, including asset requirements, operational constraints, and available resources, and iterates over assets (*i* in *I*) and days (*d* in *D*). The key constraints, mentioned in Figure 3.4, are applied, such as station availability, tooling, personnel, and material limitations, ensuring that scheduled and unscheduled maintenance do not overlap with operations. After defining the revenue and cost equations, the optimization process calculates the optimal set of actions to maximize efficiency and profitability while adhering to all constraints. This pseudocode will be further reviewed in chapter 4.

Pseudocode 3.5 – Optimization algorithm.

Input: asset maintenance requirements, operational requirement, maintenance cost, available resources, revenue parameters

Output: asset availability, revenue and set of actions or recommendations

procedure: objective function definition

OF← *ObjectiveFunction = Max(Rev-Cost)* ▻ *Objective function definition (eq. (1))*

for each $i \in I$ ▻ *Iterate through assets*

  for each $d \in D$ ▻ *Iterate through days*

  $\sum_{i \in F} \sum_{d \in D} (X_{id} + Y_{id}) \leq H_d$ ▻ *Station constraint*

  $\sum_{i \in F} \sum_{d \in D} X_{id} \geq K_A$ ▻ *Temporal constraint*

  $\sum_{i \in F} \sum_{d \in D} (X_{id} + Y_{id}) * GSE_{idm} \leq GSE_{Hd}$ ▻ *Tooling constraint*

  $\sum_{i \in F} \sum_{d \in D} (X_{id} + Y_{id}) * FTE_{idm} \leq FTE_{Hd}$ ▻ *Personnel constraint*

  $\sum_{i \in F} \sum_{d \in D} (X_{id} + Y_{id}) * MAT_{idm} \leq MAT_{Hd}$ ▻ *Material constraint*

  $\sum_{i \in F} \sum_{d \in D} (X_{id} + O_{id}) \leq 1$ ▻ *If scheduled maintenance happens, operation cannot happen and vice versa*

  $\sum_{i \in F} \sum_{d \in D} (Y_{id} + O_{id}) \leq 1$ ▻ *If unscheduled maintenance happens, operation cannot happen*

  end for ▻ *End iteration through assets*

end for ▻ *End iteration through days*

Restrictions ← [rest1; rest2; rest3; rest4; rest5] ▻ *Build restriction matrix*

model.A ← restrictions ▻ *Definition of restrictions within gurobi*

model.OF ← OF ▻ *Definition of OF in solver*

$Rev = \sum_{i \in F} \sum_{d \in D} (O_{id} * Rev\_per\_service\_prod)$ ⊳ *Revenue equation*

$Cost = \sum_{i \in F} \sum_{d \in D} (X_{id} * Cost_{sched_{main}} + Y_{id} * Cost_{unsched_{main}})$ ⊳ *Cost equation*

Optimize(Rev-Cost) ⊳ *Objectiva Function Optimization*

3.2.3 Algorithm Functional Check

Let's suppose aircraft A suffers an unscheduled failure still on-ground, at Confns, before the flight from Confins to Campinas, as shown in Figure 3.7. The failure is related to ATA Chapter 21 and São Paulo hangar has the personnel, material and tool capabilities to repair such a failure but not in that specific day. Without the algorithm, the decision could be complete the flight and facing a stoppage of 5 days for the complete repair to be concluded.

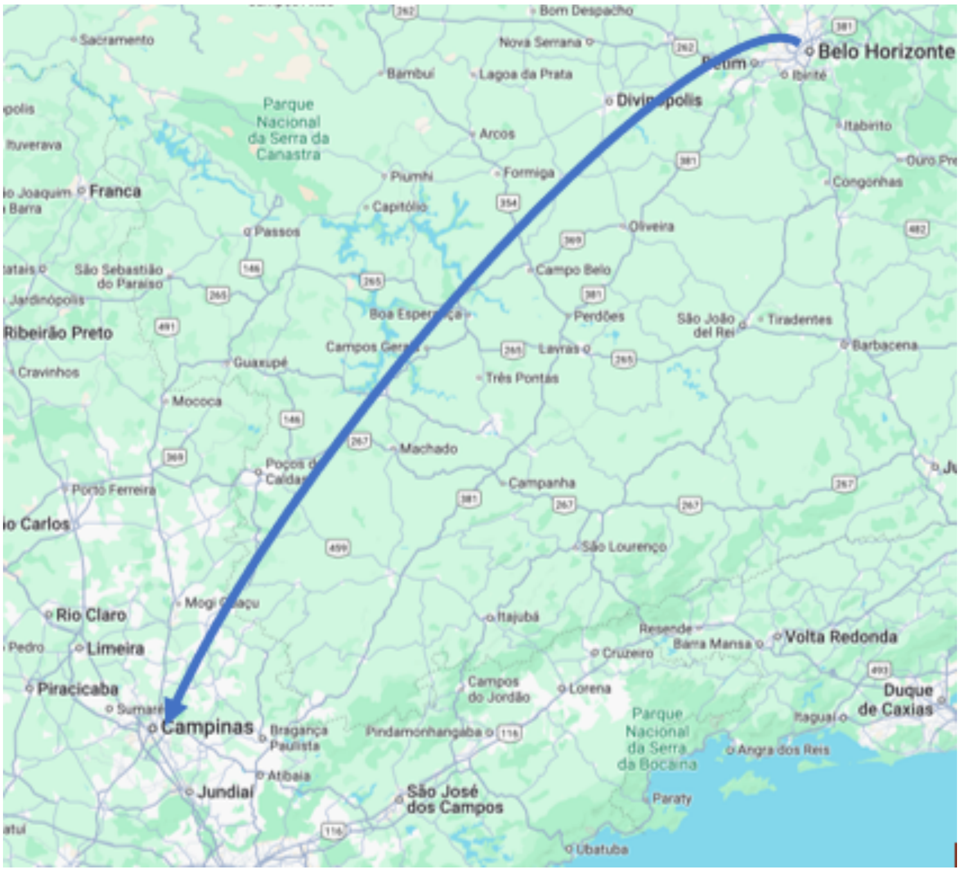

Figure 3.6 – Original aircraft A flight path.

Implementing the algorithm in this scenario, the optimization would scan, among all stations, to verify which one has available resources, slots and capability of repairing the aircraft the soonest. However, São José dos Campos has the capability but not the slot availability. Ribeirão Preto have both capability and availability has so it could represent a good choice to speed up the repair. However, it is still needed to take another decision: is it better to cancel the flight and repair the aircraft at Ribeirão Preto? Divert the technicians from Ribeirão Preto or Campinas to repair the aircraft at Confins? Or maybe we could select another aircraft, aircraft B, to complete the flight from Belo Horizonte to Campinas and assign the aircraft A to complete the flight from Confins to Ribeirão Preto and get the necessary repair?

The last option is in this case the optimal option, as depicted in Table 3.5.

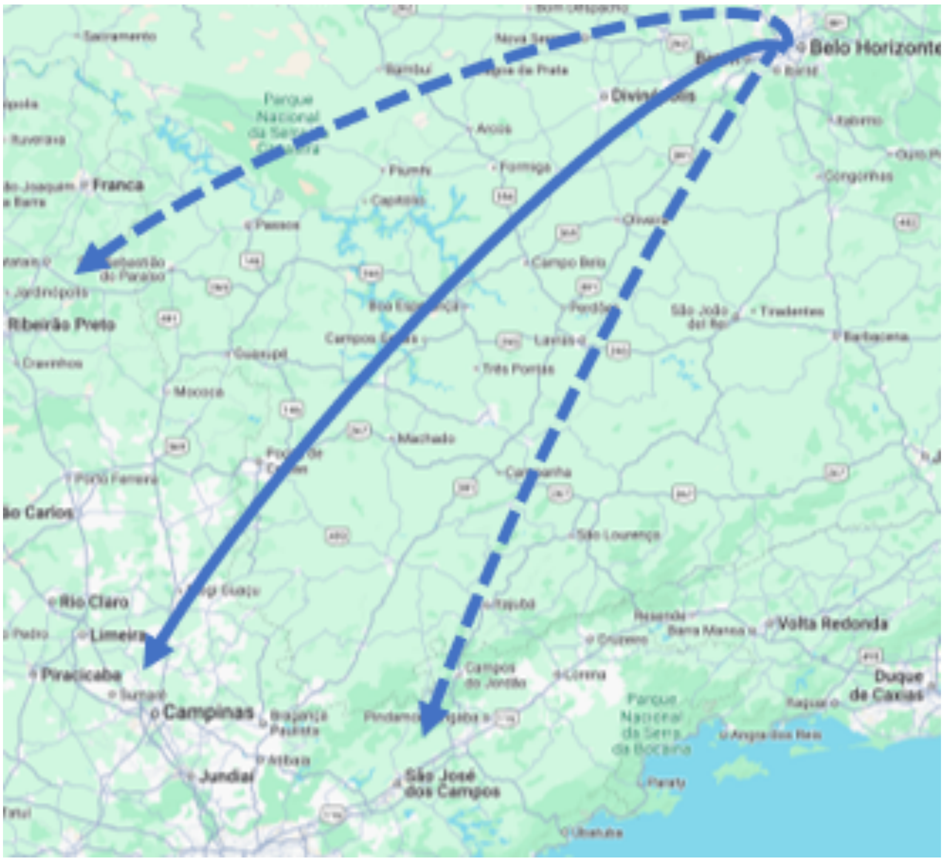

Figure 3.7 – Original aircraft A flight path.

Although aircraft B was not assigned in that specific day to any flight, so its deployment ensured revenue and system availability maximization.

Table 3.5 – Results comparison with and without use of prescriptive optimization.

Attribute	Non-prescriptive	Prescriptive	Comments
Availability	99.70%	99.89%	Aircraft A stays on-ground for 5 days in the non-prescriptive scenario
Profit	- USD 63.000,00	+ USD 14.200,00	In the non-prescriptive scenario Aircraft A completes the flight to Campinas but then stays on ground 5 days waiting for maintenance. In the prescriptive scenario Aircraft A completes a flight to Ribeirao Preto while Aircraft B is assigned to complete the flight from Belo Horizonte to Campinas
Course of action prescription	Not available	Aircraft A undergoes maintenance in day 12 Task 21.1: perform troubleshooting Task 21.2: remove and replace LRU GSE utilization: 21.1 Tool to remove and replace LRU	In the non-prescriptive scenario, no course of action is provided.

Attribute	Non-prescriptive	Prescriptive	Comments
		Avionics FTE: 8 Powerplant FTE: 0 Airframe: 0	

4 Case Studies

To test the framework and its mathematical model, three case studies were conducted. The first case study is related to a regional Brazilian airliner with more than 150 destinations and a fleet constituted by 9 different platforms of different technological maturities and operation types. The objective was to test whether the prescriptive approach of optimizing operations requirements and maintenance stoppages holistically (as a unique system) could yield better results, in terms of availability and profitability, than the traditional approach of prioritizing operations and overspending in maintenance if necessary. To do so two objective functions were adopted: the first one, named “non-prescriptive”, pursued to minimize maintenance, and the second one, denominated “prescriptive”, focused on maximizing the difference between the revenue coming from operation and the cost caused by maintenance.

The second experiment was focused on testing the extensibility of the framework in the health ecosystem. It was considered a real case scenario that occurred in 2020, during the COVID-19 pandemic response in the São Paulo state public hospitals network. In this scenario, more than 3800 patients and 70 hospitals were considered. The differences between this case study and the first one are that in this health real case scenario scheduled maintenance is not applicable, duration of maintenance was variable, and patients could be treated in any of the 3800 hospitals. Additionally, the objective function adopted was the prescriptive one, trying to maximize survivability and minimize costs. Results were then compared to real-case scenario mortality.

The third and last experiment considered operations of the Brazilian regional airliner of case study 1 adding variability in hangar supportability in terms of ATA chapters, the constraints of technical personnel, and ground support equipment for each hangar. The objective was to test if the framework could not only increase operations profitability recommending for each aircraft the best holistic strategy in terms of where to provide maintenance and when, but also recommend maintenance task course of action prescription providing full-time equivalents personnel, date, location, tasks, ATA Chapter to be repaired and aircraft information. As for experiment 1, the results were compared using two objective functions: the “non-prescriptive”, that pursued minimizing maintenance, and the second one, denominated “prescriptive”, which focused on maximizing the difference between the revenue coming from the operation and the cost caused by maintenance.

For each case study assumptions, results, and limitations are presented and discussed.

4.1 Case Study 1: Regional Airliner Operation Scenario

4.1.1 Scope and Assumptions

This simulation was designed to optimize maintenance scheduling and tail assignment for an airline fleet, considering both scheduled and unscheduled maintenance events. The primary goal is to maximize the difference between revenue and cost ensuring regulatory compliance while yielding better results than the traditional approach that prioritizes operations over maintenance. The model integrates multiple factors, including flight schedules, maintenance durations, and hangar capacities.

The next sections present the operation simulation assumption, the optimization mathematical model, the pseudocode, and the results.

4.1.2 Operation Simulation

The simulation was based on a Brazilian regional airliner operation with the fleet summarized in Table 4.1[148, 152, 153]. This airliner operates in more than 150 cities scattered across all Brazilian territory and in 7 cities internationally as depicted in Figure 4.1.

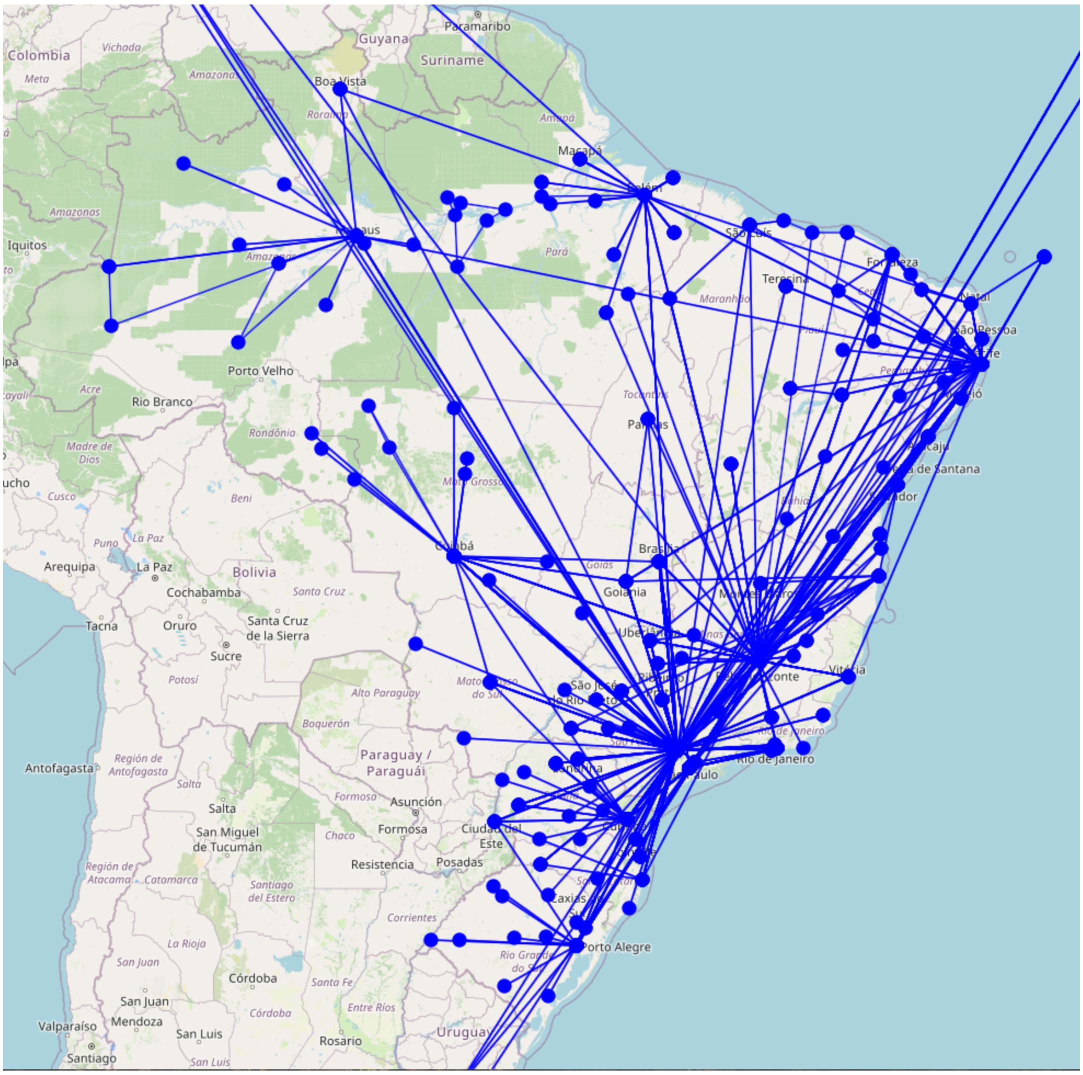

Figure 4.1 – Airliner hub network (Source: this author)

Table 4.1 – Fleet characteristics.

OEM	Aircraft	Qty.	PHM enabled	Average age (years)	Seats	Wingspan x length (m^2)	Slot occupation (m^2)
Airbus	A320neo	54		5	174	1345	942
Embraer	E-195	41		9	118	1111	778

OEM	Aircraft	Qty.	PHM enabled	Average age (years)	Seats	Wingspan x length (m^2)	Slot occupation (m^2)
ATR	72-600	46		8	70	735	515
Cessna	Caravan 208B	23		16	9	91	64
Embraer	E195-E2	27	✓	2	136	1457	1020
Airbus	A321neo	8		3	214	1593	1115
Airbus	A330-900	3	✓	3	298	4074	2852
Airbus	A330-200	1	✓	18	272	3547	2483
Airbus	A350-900	2	✓	6	334	4325	3028
	Total	205	-	5	-	-	-

The fleet characteristics encompass several key parameters for each aircraft model, including the OEM, the number of aircraft in the fleet, whether PHM is enabled for that model, the average age of the aircraft, the seating capacity, the physical dimensions (expressed as wingspan multiplied by length), and the slot occupation area in square meters. The slot occupation was obtained considering that the parking of aircraft in MRO is done in such a way that aircraft wings are interleaved, allowing a more optimized usage of the available area. Thus, the assumption is that the effective occupied slot area by each aircraft is equal to 70% of the area obtained by multiplying the aircraft wing span and lengths.

The fleet includes 54 Airbus A320neo aircraft, each with an average age of 5 years, a seating capacity of 174 passengers, and a slot occupation of 942 square meters. In contrast, the fleet also includes smaller aircraft like the Cessna Caravan 208B, which has a seating capacity of 9 and occupies just 64 square meters of slot space. The tables highlight the presence of PHM capabilities in certain aircraft models such as the Embraer E195-E2 and the Airbus A330-900, which support advanced predictive maintenance strategies. The diversity in aircraft sizes, technological maturity, ages, and capabilities requires an adaptable approach to maintenance as presented in the research question of Table 2.4.

Flight paths (origin-destination) and flight hours flown per day by each aircraft were collected directly from the airliner website for all 150 destinations[151]. Table 4.2 presents an example of the data collected in terms of flight hours per trip, flight path, and flight frequency, based on weekdays, over 365 days. The entire airliner operation is available in Appendix B.

Table 4.2 – Operation characteristics.

Aircraft	**Serial**	**Origin**	**Destination**	**Flight duration (hours)**	**Departure**	**Frequency**
A320neo	1063	Campinas	Confins	1.17	6:15	MON TUE SAT

After defining the assumptions related to the operation, the assumptions related to the product maintenance requirements and reliability were mapped out. Firstly, the maintenance intervals for A-check and C-check were identified[160, 161] as presented in Table 4.3.

Table 4.3 – Fleet maintenance characteristics.

Aircraft	**Maintenance check interval**					
	A-check			**C-check**		
	Flight hours (hours)	**Calendar (months)**	**Duration (days)**	**Flight hours (hours)**	**Calendar (months)**	**Duration (days)**
A320neo	750	4	7	7500	24	30
E-195	750	4	7	7500	24	30
ATR-72-600	750	4	7	8000	24	30
208B Caravan	500	3	5	7000	18	30
E195-E2	1000	6	7	10000	24	30
A320neo	750	4	7	7500	24	30
A321neo	750	4	7	7500	24	30
A330-900	1000	6	7	10000	24	30
A330-200	1000	6	7	10000	24	30
A350-900	1000	6	7	10000	24	30

Regarding the unscheduled maintenance, the MTBURs were used to calculate the probability of failure per each ATA Chapter in the function of time *t* corresponding to the accumulated sum of flight hours while the probability distribution utilized is the exponential distribution[155] as shown in equations 4.1 and 4.2. Specialists were consulted to validate the estimated MTBUR for each ATA Chapter for each model. Table 4.4 lists an overview of the MTBUR values per each model and ATA Chapter. The complete list is available in Appendix B.

Table 4.4 – MTBUR per each model and ATA Chapter.

Model	**MTBUR**			
	ATA 21	**ATA 22**	**ATA 23**	**ATA 24**
E-195	1098	5953	1469	1140
E195-E2	1440	1098	5953	1469
A330-900	2000	2300	6500	2300
A320neo	1650	9617	2062	2104

The unscheduled maintenance duration was estimated as 1 day if the maintenance was performed in a hangar with corrective maintenance capability, and 2 days if the aircraft was in a hangar with organizational-level maintenance capability, due to the necessity of deploying technicians and materials from other hangars to repair the aircraft, as validated by the specialists consulted. It is important to notice that unscheduled maintenance probability is a probability that, when identified in the real world, must be updated so the model is able to provide recommendations that reflect the up-to-date asset state. This is particularly true when the model is integrated to a digital twin of the fleet and support resources, allowing the framework to run whenever there is a disruption due to situations found in the real world. The framework needs to be agile and run within businesses' decision time.

The full list of maintenance events used to estimate the degradation is presented in Appendix B.

- *F(t)*: probability of failure

- $\boldsymbol{\lambda}$: failure ratio
- $\boldsymbol{t}$: accumulated flight hours

$$\boldsymbol{F(t) = 1 - e^{-\lambda t}} \tag{4.1}$$

$$\boldsymbol{\lambda = 1/MTBUR} \tag{4.2}$$

Regarding the PHM failure prediction, no data was available or identified about the degradation ratio in function of the accumulated flight hours per ATA Chapter and because of this, degradation was estimated using the MTBUR as baseline and reference values mapped in the literature[157, 158]. Outcomes are presented in results Section while the algorithm developed to estimate the maintenance imperfection is presented in Section 4.1.4.

The simulation provided for each aircraft the dates, within the period considered, of maintenance occurrences according to their intervals and accumulated flight hours for scheduled events, while the unscheduled events were mapped out through the exponential probability through equation 4.1, considering the failure ratio for each ATA chapter calculated through equation 4.2, adjusted according to PHM forecasts estimation for those assets with prognostics systems. Table 4.5 presents an extract of the operational simulation results. All the maintenance events are presented in the Appendix B.

Table 4.5 – Extract of operational simulation results in terms of maintenance occurrences days according to the simulation temporal assumptions.

Aircraft	**Serial**	**A-check days**	**C-check days**	**Unscheduled maintenance estimated days**
E195-E2	1158	15	215	2
		40		22
		80		32
		122		44
		160		56

Aircraft	Serial	A-check days	C-check days	Unscheduled maintenance estimated days
				58 85 95 130 200 220 243 280 300

In conclusion, the operational simulation effectively provided maintenance schedules and estimated unscheduled events days, in the 365 days considered (one-year period), for each aircraft in the fleet, representing the events that must be managed by the optimization algorithm.

The next Section will present the maintenance capability model that addresses the maintenance resources used to perform maintenance—such as hangar slots, tooling, personnel, and materials.

4.1.3 Maintenance Capability Model

Table 4.6 illustrates the main maintenance hangar locations and their capabilities across these three levels of maintenance described in Chapter 2. For instance, the Campinas facility (VCP) supports organizational, intermediate, and depot maintenance, whereas locations like Manaus (MAO) and Cuiaba (CGB) are equipped for organizational and intermediate maintenance only[152, 154, 162, 163, 166, 167, 168]. Regarding the main hub Campinas, its slot area was defined indirectly since it is reported that Campinas can accommodate up to 8 narrow bodies or 2 wide bodies at the same time during basic checks[163, 166]. As presented in equations 4.3, 4.4 and 4.5, the largest narrowbody and widebody were used to estimate the slot area. The whole hangar network maintenance capability is presented in Appendix C.

$$\boldsymbol{Largest\ narrow\ body\ area = 1028m^2} \tag{4.3}$$

$$\boldsymbol{Largest\ wide\ body\ area = 3028m^2} \tag{4.4}$$

$$\boldsymbol{Estimated\ Campinas\ hub\ slot\ area \geq MAX \begin{cases} 1028\ x\ 8 = \ 8224m^2 \\ 3028\ x\ 2 = \ 6056m^2 \end{cases}} \tag{4.5}$$

Similarly, for the Pampulha hub, it is estimated that its capability is at least 5 narrow bodies[166, 167]. Equations 4.6 and 4.7 present the estimating calculations for Pampulha's hub slot area.

$$\boldsymbol{Largest\ narrow\ body\ area = 778m^2} \tag{4.6}$$

$$\boldsymbol{Estimated\ Pampulha\ hub\ slot\ area \geq 778\ x\ 5 = 3885m^2} \tag{4.7}$$

Table 4.6 – Main maintenance hangar locations and their maintenance capability.

Location	**IATA code**	**Slots area (m^2)**	**Maintenance level capability**		
			Organizational	**Intermediate**	**Depot**
Campinas	VCP	8224	✓	✓	✓
Pampulha	PLU	3885	✓	✓	✓
Manaus	MAO	2800	✓	✓	
Cuiaba	CGB	2800	✓	✓	
Recife	REC	2800	✓	✓	

This distribution of capabilities across various locations is crucial for planning and executing maintenance activities efficiently, ensuring that each facility is utilized to its full potential according to operation demands.

Table 4.7 provides an overview of the maintenance locations available for each aircraft in the fleet, detailing where basic and intermediate checks (A-check and C-check), as well as unscheduled maintenance, can be performed. The Table highlights specific bases where the C-check maintenance activities are conducted, reflecting the operational flexibility and capacity of the maintenance network.

For instance, the Airbus A320neo and the Embraer E195-E2 can undergo C-check maintenance at the Campinas facility, with an additional 30 locations available for A-check maintenance and over 120 locations for unscheduled maintenance. Similarly, the ATR 72-600 is serviced for C-check at Pampulha, with a similar spread of additional locations for A-check and unscheduled maintenance.

Table 4.7 – Fleet C-check and A-check locations.

Aircraft	**Locations and Maintenance Levels**		
	Depot	**Intermediate**	**Organizational**
	C-check **A-check** **Unscheduled**	**A-check** **Unscheduled**	**Unscheduled**
A320neo	Campinas	+30 locations	+120 locations
E-195	Pampulha	+30 locations	+120 locations
72-600	Pampulha	+30 locations	+120 locations

Aircraft	Locations and Maintenance Levels		
	Depot	Intermediate	Organizational
	C-check A-check Unscheduled	A-check Unscheduled	Unscheduled
Caravan 208B	Pampulha	+30 locations	+120 locations
E195-E2	Campinas	+30 locations	+120 locations
A321neo	Campinas	+30 locations	+120 locations
A330-900	Campinas	+30 locations	+120 locations
A330-200	Campinas	+30 locations	+120 locations
A350-900	Campinas	+30 locations	+120 locations

4.1.4 Optimization Algorithm and Mathematical Model

The algorithm integrates operations management and maintenance by acknowledging the influence of operations on maintenance and vice versa.

This holistic approach highlights that for PsM to be fully effective, it must not only optimize maintenance activities but also shape operational decisions. This indicates a more dynamic and interconnected system where the optimization of maintenance activities is carried out in tandem with operational adjustments. This strategy ensures that both maintenance and operations are aligned, leading to enhanced efficiency, reduced downtime, and improved overall performance of complex systems. As mentioned in Chapter 4, results between the prescriptive and non-prescriptive approaches were compared using two different objective functions.

This Chapter presents the mathematical model and pseudocode focusing on the scheduling of fixed interval maintenance checks and unscheduled maintenance.

Constants & parameters

- F: fleet size;
- $Acft_{payload}$ = number of seats;
- $\boldsymbol{Revenue_{per\_seat}}$= average ticket price;
- $\boldsymbol{Occupation_{ratio}}$= average fleet aircraft occupation ratio;
- $Flight_{day}$ = number of flights per day;
- $Tot_{possible\_op\_days}$ = total possible operational days;
- $Tot_{downtime}$ = total downtime due to maintenance;
- J: set of maintenance team;
- H: set of stations;
- h: station in set H;
- A_{dh}: area of station h at each day d;
- D: number of operational days;
- i: aircraft of the fleet F;
- d: day of the period D;
- d_A: day in which A-check should be scheduled according to the interval $\boldsymbol{I_A}$;
- d_B: day in which unscheduled maintenance should be executed according to operation simulation results
- d_C: day in which C-check should be scheduled according to the interval $\boldsymbol{I_C}$;
- A: A-check duration;
- B: unscheduled maintenance duration;
- C: C-check duration;
- I_A: A-check interval;
- I_C: C-check interval;
- ${C_{baseline}}_A$: daily maintenance cost when A-check maintenance occurs in the baseline interval;
- ${C_{early}}_A$: daily maintenance cost when A-check maintenance occurs before the baseline;
- ${C_{late}}_A$: daily maintenance cost when A-check maintenance occurs after the baseline;
- ${C_{baseline}}_B$: daily unscheduled maintenance cost when maintenance is executed on the day of the event;
- ${C_{late}}_B$: daily unscheduled maintenance cost when maintenance is executed later than 1 day after the event;
- ${C_{baseline}}_C$: daily maintenance cost when C-check maintenance occurs in the baseline interval;
- ${C_{early}}_C$: daily maintenance cost when C-check maintenance occurs before the baseline;

- C_{late_C}: daily maintenance cost when C-check maintenance occurs after the baseline;
- $C_{forgone_{id}}$: cost, or revenue loss, due to forgone flight for each serial *i* and day *d*;
- K_A: number of A-check intervals in the period *D* considered;
- K_C: number of C-check intervals in the period *D* considered;
- d_{late_A}: day after d_A in which A-check is scheduled;
- d_{late_B}: day after d_B in which unscheduled maintenance is scheduled;
- d_{late_C}: day after d_C in which C-check is scheduled;
- d_{early_A}: day in which A-check is scheduled, before d_A;
- d_{early_C}: day in which C-check is scheduled, before d_C;
- E_A: quantity of days before d_A in which A-check is scheduled;
- E_C: quantity of days before d_C in which C-check is scheduled;
- F_A: quantity of days after d_A in which A-check is scheduled;
- F_B: quantity of days after d_B in which unscheduled maintenance is scheduled;
- F_C: quantity of days after d_C in which C-check is scheduled;
- *m:* maintenance type

Decision variables

Table 4.8 – Decision variables.

Variable	State	Type
X_{idh}	• Equal to 1 if A-check is scheduled for aircraft *i* on day *d* and hangar *h* • 0 otherwise	Binary
Y_{idh}	• Equal to 1 if unscheduled maintenance is executed for aircraft *i* on day *d* and hangar *h* • *0* otherwise	Binary
Z_{idh}	• Equal to 1 if C-check is scheduled for aircraft *i* on day *d* and hangar = Campinas or Pampulha • 0 otherwise	Binary
O_{idh}	• Equal to 1 if flight is assigned for aircraft *i* on day *d* • 0 otherwise	Binary

Objective Function Parameters Calculation

$$Cost = \sum X_{idh} * C_{early_A} * days\_before_A + \sum X_{idh} * C_{late_A} * days\_after_A + \sum X_{idh} * C_{baseline_A} + \sum X_{idh} * C_{forgone_{id}} + \sum Z_{idh} * C_{early_C} * days\_before_C + \sum Z_{idh} * C_{late_C} * days\_after_C + \sum Z_{idh} * C_{baseline_A} + \sum Z_{idh} * C_{forgone_{id}} + \sum Y_{idh} * C_{baseline_B} + \sum Y_{idh} * C_{late_B} * days\_after_B + \sum Y_{idh} * C_{forgone_{id}} \tag{4.8}$$

$$Revenue = \sum O_{id} * \left(Revenue_{per\_seat} * Flight_{day} * Acft_{payload} * Occupation_{ratio}\right)_{id} \tag{4.9}$$

Non-Prescriptive Objective Function

$$ObjectiveFunction = Min(Cost) \tag{4.10}$$

Prescriptive Objective Function

$$ObjectiveFunction = Max(Revenue - Cost) \tag{4.11}$$

Calculations

Equations 4.12 and 4.13 define that d_A and d_C are multiples of the respective A-check and C-check intervals. Equations 4.14 and 4.15 determine the number of intervals, which is given by the division between D and the interval I_A for A-check and I_C for C-check. Equations 4.16, 4.18, and 4.19 define d_{late} while equations 4.17 and 4.20 present the calculation for d_{early} since, if no slots are available, maintenance may be pushed back or pulled forward. Equations 4.21 and 4.22 calculate the number of days in which A-check is scheduled before or after d_A. Similarly, equations 4.23 and 4.24 calculate the number of days in which C-check is scheduled before or after d_C.

$$d_A = n \times I_A \mid n{:}\ 1 \rightarrow K_A,\ n \in \mathit{Integer} \tag{4.12}$$

$$d_C = n \times I_C \mid n{:}\ 1 \rightarrow K_C,\ n \in \mathit{Integer} \tag{4.13}$$

$$K_A \geq \frac{D}{I_A},\ K_A \in Integer, K_A > 0 \tag{4.14}$$

$$K_C \geq \frac{D}{I_C},\ K_C \in Integer, K_C > 0 \tag{4.15}$$

$$d_A < d_{late_A} \leq d_A + I_A - A \tag{4.16}$$

$$d_A - I_A + A \leq d_{early_A} < d_A \tag{4.17}$$

$$d_B < d_{late_B} \leq d_B + I_B - B \tag{4.18}$$

$$d_C < d_{late_C} \leq d_C + I_C - C \tag{4.19}$$

$$d_C - I_C + C \leq d_{early_C} < d_C \quad (4.20)$$

$$E_A = d_A - d_{early_A} \qquad \text{for } d_A > d_{early_A} \quad (4.21)$$

$$F_A = d_{late_A} - d_A \qquad \text{for } d_{late_A} > d_A \quad (4.22)$$

$$E_C = d_C - d_{early_C} \qquad \text{for } d_C > d_{early_C} \quad (4.23)$$

$$F_C = d_{late_C} - d_C \qquad \text{for } d_{late_C} > d_C \quad (4.24)$$

For this experiment, it has been assumed that anticipation of maintenance does not generate additional costs or penalties thus as seen in equations 4.25 and 4.26:

$$C_{early_A} = C_{baseline_A} \quad (4.25)$$

$$C_{early_C} = C_{baseline_C} \quad (4.26)$$

<u>*Constraints*</u>

A key consideration is the limitation imposed by the number of available maintenance slots described in Equation 4.27. For any given day *d*, the number of aircraft slated to receive maintenance — be it an A-check, C-check, or unscheduled — must not exceed the hangar area available, denoted by A_h. This stipulation enforces a cap on the maximum number of aircraft undergoing maintenance at any one time, ensuring that the physical space available is not exceeded. Equations 4.28 and 4.29 enforce that for each aircraft *i* on each day *d*, the cumulative number of A-checks and C-checks conducted is bound by a non-negotiable OEM requirement. These requirements, denoted as K_A, K_C, serve as the minimum thresholds for A-checks and C-checks that must be performed to uphold the safety and performance standards.

Similarly, Equations 4.30 and 4.31 enforce the intervals between maintenance checks. For A-checks, the left hand of the Equation 4.30, $X_{(idh)n} - X_{(idh)\,n-1}$, captures the interval between two consecutive checks for an aircraft i and ensures that it does not exceed I_A, as mandated by the OEM. Similarly, for C-checks, the intervals are represented by $Z_{(idh)n} - Z_{(idh)\,n-1}$, adhering to the OEM-specified limits I_C.

Constraints 4.32, 4.31, and 4.32 enforce that each maintenance event must happen while equations 4.33, 4.34, and 4.35 enforce that an aircraft cannot fly and receive maintenance at the same time.

$\sum_{h \epsilon H}\sum_{i \in F}\sum_{d \in D}(X_{idh} + Y_{idh} + Z_{idh}) \leq A_{dh}$	for each day *d,* aircraft *i* and station *h*	(4.27)
$\sum_{h \in H}\sum_{i \in F}\sum_{d \in D} X_{idh} \geq K_A$	for each day *d,* aircraft *i* and station *h*	(4.28)
$\sum_{h \in H}\sum_{i \in F}\sum_{d \in D} Z_{idh} \geq K_C$	for each day *d,* aircraft *i* and station *h* = Campinas or Pampulha	(4.29)
$X_{(idh)n} - X_{(idh)\,n-1} \leq I_A$	for each *d, i, h* and *n*	(4.30)
$Z_{(idh)n} - Z_{(idh)\,n-1} \leq I_C$	for each *d, i, n h* = Campinas or Pampulha	(4.31)
$\sum_{h \in H}\sum_{i \in F}\sum_{d \in D} Y_{idh} \geq 1$	for each *d, h* and *i*	(4.32)
$\sum_{h \in H}\sum_{i \in F}\sum_{d \in D}(X_{idh} + O_{idh}) = 1$	for each *d, h* and *i*	(4.33)
$\sum_{h \in H}\sum_{i \in F}\sum_{d \in D}(Y_{idh} + O_{idh}) = 1$	for each *d, h* and *i*	(4.34)
$\sum_{h \in H}\sum_{i \in F}\sum_{d \in D}(Z_{idh} + O_{idh}) = 1$	for each *d, i* and *h* = Campinas or Pampulha	(4.35)

<u>*Maintenance Imperfections*</u>

Maintenance imperfections are estimated pos-optimization by using the methodology that considers the Brownian motion to calculate accumulated degradation after each maintenance event[43]. Koops (2020) describes the degradation before and after repair using a stochastic model that is modeled as drifted Brownian motion. This process is characterized by two coefficients: the drift coefficient (η) which represents the expected rate of degradation, and the diffusion coefficient (σ) which accounts for the magnitude of Gaussian noise perturbing the trend. The Wiener process can be expressed as shown in equation 4.36.

$$\boldsymbol{X(t) = hL(t) + \ sB(L(t))} \tag{4.36}$$

Being $X(t)$ the degradation at time *t,* $L(t)$ =*t* assuming a linear degradation model, $h > 0$ is the drift coefficient, s denotes the diffusion coefficient, and *B(t)* is the constant for Brownian motion[43]. In the context of imperfect repairs, Koops (2020) utilizes an improvement factor α_k to describe the degradation level before and after the *K-th* repair. The degradation levels X_k and X_{k+} before and after the *K-th* repair are expressed as presented in equation 4.37:

$$\boldsymbol{X_{k+} = (1 - \alpha_k)X_k} \tag{4.37}$$

where $0 \leq \alpha_k \leq 1$. The two limiting cases correspond to minimal repair ($\alpha_k = 0$), "as bad as old" and perfect repair (α_k =1), "as good as new". The effect of repair is subject to randomness and the improvement factor α_k is modeled by a truncated normal distribution in the range [0,1]. The assumption is that for an almost perfect maintenance procedure based on replacement and removal, as the ones addressed by this simulation, $\alpha_k = 0{,}9, \mathrm{h} \ = 1, \sigma = 0{,}3$, $B = 1$ which is the maximum degradation allowed (threshold). Considering as number of iterations the total number of maintenance events per model, and as t the MTBUR values, the accumulated degradations were calculated. As a result, a decrease of MTBUR values of around 10% by the end of one year was achieved.

Pseudocode 4.2 presents the algorithm used to calculate the degradation due to maintenance imperfection based on each model's MTBURs. Here's a breakdown of each part:

1. **Inputs and Outputs**:
   a. **Inputs**: operational data, maintenance events, MTBUR list.

   b. **Outputs**: new MTBURs and degradations.

2. **Data Loading (Steps 1-3)**:
   a. Load data from Excel files into data frames.
3. **Parameters Definition (Steps 4-9)**:
   a. Define wiener model parameters
4. **Degradation and MTBUR Calculation (Steps 10-15)**:
   a. Define the wiener equation
   b. Run the equation through flight hours and repair events to calculate degradation per aircraft model
   c. Calculate new MTBURs
5. **Print Results (Steps 16-17)**:
   a. Print new MTBURs per model and degradations

Pseudocode 4.2 – Case study 1: maintenance imperfection evaluation.

Input: operational data, maintenance events, MTBUR list
Output: new MTBURs and degradations

1: **operation_df**← operation.xlsx ⊳ *Load operational data*
2: **maintenance_df**← maintenance_events.xlsx ⊳ *Load maintenance events*
3: **mtbur_df**← MTBUR_list.xlsx ⊳ *Load MTBUR list*
4: $\alpha_k \leftarrow 0{,}9$ ⊳ *Improvement factor (repair efficiency)*
5: h ←1 ⊳ *Drift coefficient (rate of degradation over time)*
6: $\sigma \leftarrow 0{,}3$ ⊳ *Diffusion coefficient (volatility in degradation)*
7: B ← 1 ⊳ *Degradation threshold*
8: Initial_degradation ← 0 ⊳ *Initial degradation*
9: $d_t \leftarrow 1$ ⊳ *Time step in flight hours*
10: **for each** $\boldsymbol{d_t} \in \boldsymbol{T}$ ⊳ *Iterate through time*
11: **for each** $\boldsymbol{repair} \in \boldsymbol{Main\_events}$ ⊳ *Iterate through repairs*

$X(t) = hL(t) + sB(L(t))$ ▻ *Degradation calculation*

new_mtbur = *mtbur**(1- $X(t)$) ▻ *New MTBUR calculation*

end for ▻ *End iteration through maintenance events*

end for ▻ *End iteration through time*

Print results ← *Print_new_mtbur* ▻ *Present new MTBURs*

Print results ← *Print_degradation* ▻ *Present degradation*

New MTBURs are presented in the Results Section.

Optimization Algorithm Pseudocode

The pseudocode 4.3 outlines the steps for implementing the optimization model for aircraft maintenance scheduling, focusing on a non-prescriptive objective function that seeks to minimize maintenance costs. Here's a breakdown of each part:

6. **Inputs and Outputs**:
    a. **Inputs**: operational, maintenance, support, and fleet data.
    b. **Outputs**: fleet availability, revenue, maintenance costs, and a non-prescriptive objective function's performance.
7. **Data Loading (Steps 1-4)**:
    a. Load data from Excel files into data frames.
8. **Model Setup (Steps 5-9)**:
    a. Define a Gurobi optimization model.
    b. Define decision variables for different types of maintenance and flight assignments:
        i. X_{idh} for A-checks (intermediate-level maintenance).
        ii. Y_{idh} *for* unscheduled maintenance.
        iii. Z_{idh} for C-checks (depot-level maintenance).

iv. O_{idh} for flight assignments.

9. **Constraints**:

    a. **Station Capacity Constraint (Steps 10-16)**:

        i. Iterate over assets (i), days (d), and stations (h) to ensure that the total number of maintenance events (A-check, C-check, and unscheduled) does not exceed the station's capacity (A_h).

    b. **Minimum Maintenance Constraints (Steps 17-25)**:

        i. Ensure that a minimum number of C-checks (K_C) and A-checks (K_A) are scheduled. Unscheduled maintenance events must occur

10. **Cost Calculation (Steps 26-33)**:

    a. Define Cost as a linear expression to minimize. It is calculated by iterating through assets and days to accumulate it, including:

        i. Baseline costs for A-checks, C-checks, and unscheduled maintenance.

        ii. Cost components for early and late maintenance penalties, and

        iii. Forgone revenue due to missed flights.

11. **Objective Function and Optimization (Steps 34-35)**:

    a. Set the objective function to minimize the Cost.

12. **Post-Optimization Calculations and Output (Steps 36-40)**:

    a. Calculate fleet availability based on dispatch reliability.

    b. Print results: fleet availability, maintenance cost, revenue generated, and detailed maintenance schedule.

Pseudocode 4.3 – Case study 1: non-prescriptive objective function.

Input: operational data, maintenance requirements, support data, fleet data

Output: fleet availability, operational revenue. Maintenance cost and revenue for the non-prescriptive objective function

operation_df← operation.xlsx ▻ *Load operational data*

fleet_df← fleet.xlsx ▻ *Load fleet data*

maintenance_df← maintenance.xlsx ▻ *Load maintenance data*

stations_df← stations.xlsx ▻ *Load support data*

model←gp.model ▻ *Optimization start*

X_{idh} ←a_check(days, serial, hangar binary) ▻ *A-check variable definition*

Y_{idh} ←unscheduled(days, serial, hangar binary) ▻ *Unscheduled maint. variable definition*

Z_{idh} ←c_check(days, serial, hangar binary) ▻ *C-check variable definition*

O_{idh} ←Flight_assigned(days, serial, hangar binary) ▻ *Flight variable definition*

for each $i \in F$ ▻ *Iterate through assets*

  for each $d \in D$ ▻ *Iterate through days*

    for each $h \in H$ ▻ *Iterate through stations*

$\sum_{h \in H} \sum_{i \in F} \sum_{d \in D} (X_{idh} + Y_{idh} + Z_{idh}) \leq A_{dh}$ ▻ *Station area constraint*

    end for ▻ *End of iteration through stations*

  end for ▻ *End of iteration through days*

end for ▻ *End of iteration through serials*

for each $i \in F$ ▻ *Iterate through assets*

  for each $d \in D$ ▻ *Iterate through days*

    for each $h \in H$ ▻ *Iterate through hangars*

  $\sum_{h \in H} \sum_{i \in F} \sum_{d \in D} Z_{idh} \geq K_C$ ▻ *C_check minimum events constraint*

  $\sum_{h \in H} \sum_{i \in F} \sum_{d \in D} X_{idh} \geq K_A$ ▻ *A_check minimum events constraint*

  $\sum_{h \in H} \sum_{i \in F} \sum_{d \in D} Y_{idh} \geq 1$ ▻ *Unscheduled maint. must happen*

    end for ▻ *End iteration through hangars*

  end for ▻ *End iteration through days*

end for ▻ *End iteration through assets*

Cost = gp.LinExpr() ▻ *Cost defined as a linear expression*

for each $i \in F$ ▻ *Iterate through assets*

for each $d \in D$ ▻ *Iterate through days*

for each $h \in H$ ▻ *Iterate through hangars*

$Cost = \sum X_{idh} * C_{early_A} * days\_before_A + \sum X_{idh} * C_{late_A} * days\_after_A + \sum X_{idh} * C_{baseline_A} + \sum X_{idh} * C_{forgone_{id}} + \sum Z_{idh} * C_{early_C} * days\_before_C + \sum Z_{idh} * C_{late_C} * days\_after_C + \sum Z_{idh} * C_{baseline_A} + \sum Z_{idh} * C_{forgone_{id}} + \sum Y_{idh} * C_{baseline_B} + \sum Y_{idh} * C_{late_B} * days\_after_B + \sum Y_{idh} * C_{forgone_{id}}$ ▻ *Cost calculation*

end for ▻ *End of iteration through hangars*

end for ▻ *End of iteration through days*

end for ▻ *End of iteration through assets*

model.setObjective(Cost, GRB.MINIMIZE) ▻ *Objective definition*

model.optimize() ▻ *Optimization start*

Availability ← *Dispatch_reliability* ▻ *Post-optimization availab. calculation*

Print results ← *Print_availability* ▻ *Availability ouput*

Print results ← *Print_maintenance_cost* ▻ *Maintenance cost output*

Print results ← *Print_revenue* ▻ *Revenue output*

Print results ← *Print_maintenance_schedule* ▻ *Maintenance schedule output*

The diagram shown in Figure 4.4 provides a structured overview of the non-prescriptive experiment process:

1. **Data research:** inputs from specialists, web sources, and papers are collected to inform the model.
2. **Data structuring:** collected data is organized into four categories, namely, operation, fleet, station, and maintenance.
3. **Algorithm structure:**

a. **Data Loading:** loads operation, fleet, support, and maintenance data and transforms it on data frames for processing ease.

b. **Gurobi Model Creation:** a Gurobi optimization model is established called "Maintenance_Scheduling". Constraints are defined and objective function is determined.

4. **Post-Optimization Calculation and Results:** the model optimizes the cost and outputs results.

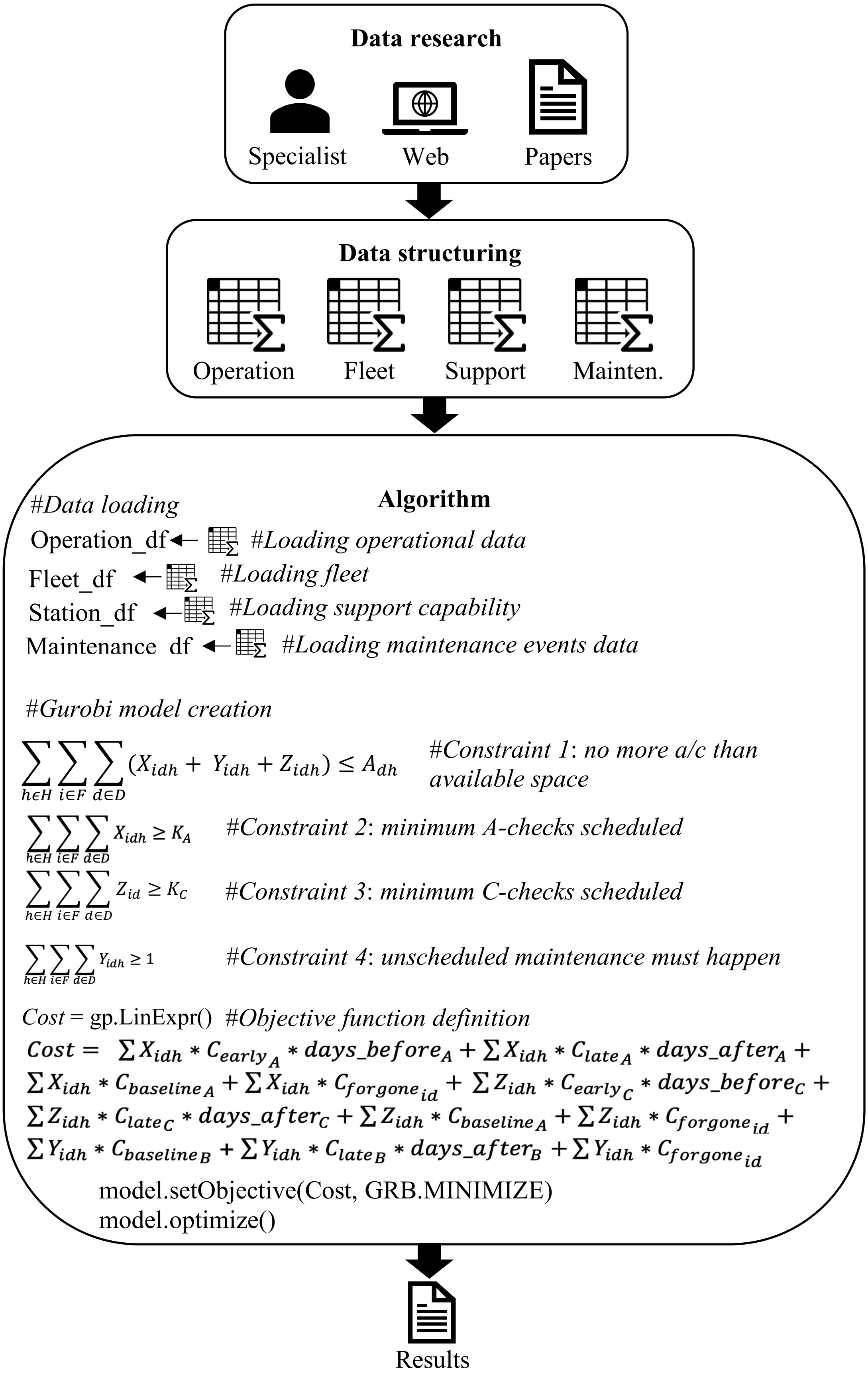

Figure 4.4 – Case study 1: non-prescriptive experiment process.

The pseudocode 4.5 presents the steps for implementing the optimization model focusing on a non-prescriptive objective function that seeks to maximize maintenance profit, that is the difference between revenue and cost. Here's a breakdown of each part:

1. **Inputs and Outputs**:
    a. This section is equal to the one in Pseudocode 4.3.

2. **Data Loading (Steps 1-4)**:
    a. This section is equal to the one in Pseudocode 4.3.

3. **Model Setup (Steps 5-9)**:
    a. Define a Gurobi optimization model.
    b. Define decision variables for different types of maintenance and flight assignments:
        i. X_{id} for A-checks (intermediate-level maintenance).
        ii. Y_{id} *for* unscheduled maintenance.
        iii. Z_{id} for C-checks (depot-level maintenance).
        iv. O_{id} for flight assignments.

4. **Constraints**:
    a. **Station Capacity Constraint (Steps 10-16)**:
        i. Iterate over assets (i), days (d), and stations (h) to ensure that the total number of maintenance events (A-check, C-check, and unscheduled) does not exceed the station's capacity (A_h).
    b. **Minimum Maintenance & Operations vs. Maintenance Events (Steps 17-26)**:
        i. Ensure that a minimum number of C-checks (K_C) and A-checks (K_A) are scheduled. Unscheduled maintenance events must occur.

ii. If the aircraft is flying it cannot undergo maintenance and vice versa.

5. **Cost & Revenue Expression (Steps: 27-28)**
    - **a.** Cost and Revenue are defined as linear expressions.
6. **Cost & Revenue Calculation (Steps: 29-34)**
    - **a.** Revenue is equal to the sum of the number of flights per day multiplied by aircraft seats, average revenue per seat, and occupation ratio.
    - **b.** Cost is defined as showcased in Pseudocode 4.3.
7. **Objective Function (Steps 35-36)**:
    - **a.** Set the objective function to maximize the difference between Revenue and Cost.
8. **Post-Optimization Calculations and Output (Steps 37-41)**:
    - **a.** As defined in Pseudocode 4.3.

Pseudo-code 4.5 – Case study 1: prescriptive objective function.

Input: operational data, maintenance requirements, hangars data, fleet data

Output: fleet availability, operational revenue. maintenance cost, revenue and profit for the prescriptive objective function

1: **operation_df**← operation.xlsx	▻ *Load operational data*
2: **fleet_df**← fleet.xlsx	▻ *Load fleet data*
3: **maintenance_df**← maintenance.xlsx	▻ *Load maintenance data*
4: **stations_df**← stations.xlsx	▻ *Load hangar data*
5: model←gp.model	▻ *Optimization start*
6: X_{idh} ←a_check (days, serial, hangar binary)	▻ *A-check variable definition*
7: Y_{idh} ←unscheduled (days, serial, hangar binary)	▻ *Unscheduled maint. variable definition*
8: Z_{idh} ←c_check (days, serial, hangar binary)	▻ *C-check variable definition*
9: O_{idh} ←*Flight_assigned* (days, serial, hangar binary)	▻ *Flight variable definition*

for each $i \in F$ ⊳ *Iterate through assets*
  for each $d \in D$ ⊳ *Iterate through days*
    for each $h \in H$ ⊳ *Iterate through stations*
$\sum_{h\epsilon H} \sum_{i\in F} \sum_{d\in D} (X_{id} + Y_{id} + Z_{id}) \leq A_{dh}$ ⊳ *Station area constraint*
    end for ⊳ *End of iteration through stations*
  end for ⊳ *End of iteration through days*
end for ⊳ *End of iteration through serials*
for each $i \in F$ ⊳ *Iterate through assets*
  for each $d \in D$ ⊳ *Iterate through days*
    for each $h \in H$ ⊳ *Iterate through hangars*
  $\sum_{h\in H} \sum_{i\in F} \sum_{d\in D} Z_{idh} \geq K_C$ ⊳ *C_check minimum events constraint*
  $\sum_{h\in H} \sum_{i\in F} \sum_{d\in D} X_{idh} \geq K_A$ ⊳ *A_check minimum events constraint*
  $\sum_{h\in H} \sum_{i\in F} \sum_{d\in D} Y_{idh} \geq 1$ ⊳ *unscheduled maintenance must happen*
  $\sum_{h\in H} \sum_{i\in F} \sum_{d\in D} (X_{idh} + O_{idh}) = 1$ ⊳ *No flight if a_check happens*
  $\sum_{h\in H} \sum_{i\in F} \sum_{d\in D} (Y_{idh} + O_{idh}) = 1$ ⊳ *No flight if unscheduled maint. happens*
  $\sum_{h\in H} \sum_{i\in F} \sum_{d\in D} (Z_{idh} + O_{idh}) = 1$ ⊳ *No flight if c_check happens*
      end for ⊳ *End hangar iteration*
    end for ⊳ *End day iteration*
  end for ⊳ *End assets iteration*
Cost = gp.LinExpr() ⊳ *Cost defined as a linear expression*
Revenue = gp.LinExpr() ⊳ *Revenue defined as a linear expression*
for each $i \in F$ ⊳ *Iterate through assets*
  for each $d \in D$ ⊳ *Iterate through days*
  for each $h \in H$ ⊳ *Iterate through hangars*
$Revenue = \sum O_{idh} * \left(Revenue_{per\_seat} * Flight_{day} * Acft_{payload} * Occupation_{ratio} \right)_{idh}$ ⊳ *Revenue calculation*

$Cost = \sum X_{idh} * C_{early_A} * days\_before_A + \sum X_{idh} * C_{late_A} * days\_after_A + \sum X_{idh} * C_{baseline_A} + \sum X_{idh} * C_{forgone_{id}} + \sum Z_{idh} *$ ⊳ *Cost calculation*

$C_{early_C} * days\_before_C + \sum Z_{idh} * C_{late_C} * days\_after_C + \sum Z_{idh} * C_{baseline_A} + \sum Z_{idh} * C_{forgone_{id}} + \sum Y_{idh} * C_{baseline_B} + \sum Y_{idh} * C_{late_B} * days\_after_B + \sum Y_{idh} * C_{forgone_{id}}$

```
        end for                                          ⊳ End of iteration through hangars
    end for                                              ⊳ End of iteration through days
end for                                                  ⊳ End of iteration through assets
model.setObjective(Revenue - Cost, GRB.MAXIMIZE)         ⊳ Objective definition
model.optimize()                                         ⊳ Optimization start
Availability ← Dispatch_reliability                      ⊳ Post-optimization availab. calculation
Print results ← Print_availability                       ⊳ Availability ouput
Print results ← Print_maintenance_cost                   ⊳ Maintenance cost output
Print results ← Print_revenue                            ⊳ Revenue output
Print results ← Print_maintenance_schedule               ⊳ Maintenance schedule output
```

The diagram shown in Figure 4.6 provides a structured overview of the prescriptive experiment process:

1. **Data research:** inputs from specialists, web sources, and papers are collected to inform the model.
2. **Data structuring:** collected data is organized into four categories, namely, operation, fleet, station, and maintenance.
3. **Algorithm structure:**
   a. **Data Loading:** loads operation, fleet, support, and maintenance data and transforms it on data frames for processing ease.
   b. **Gurobi Model Creation:** a Gurobi optimization models is established. Constraints are defined and objective function determined.
4. **Post-Optimization Calculation and Results:** the model optimizes the cost and outputs results.

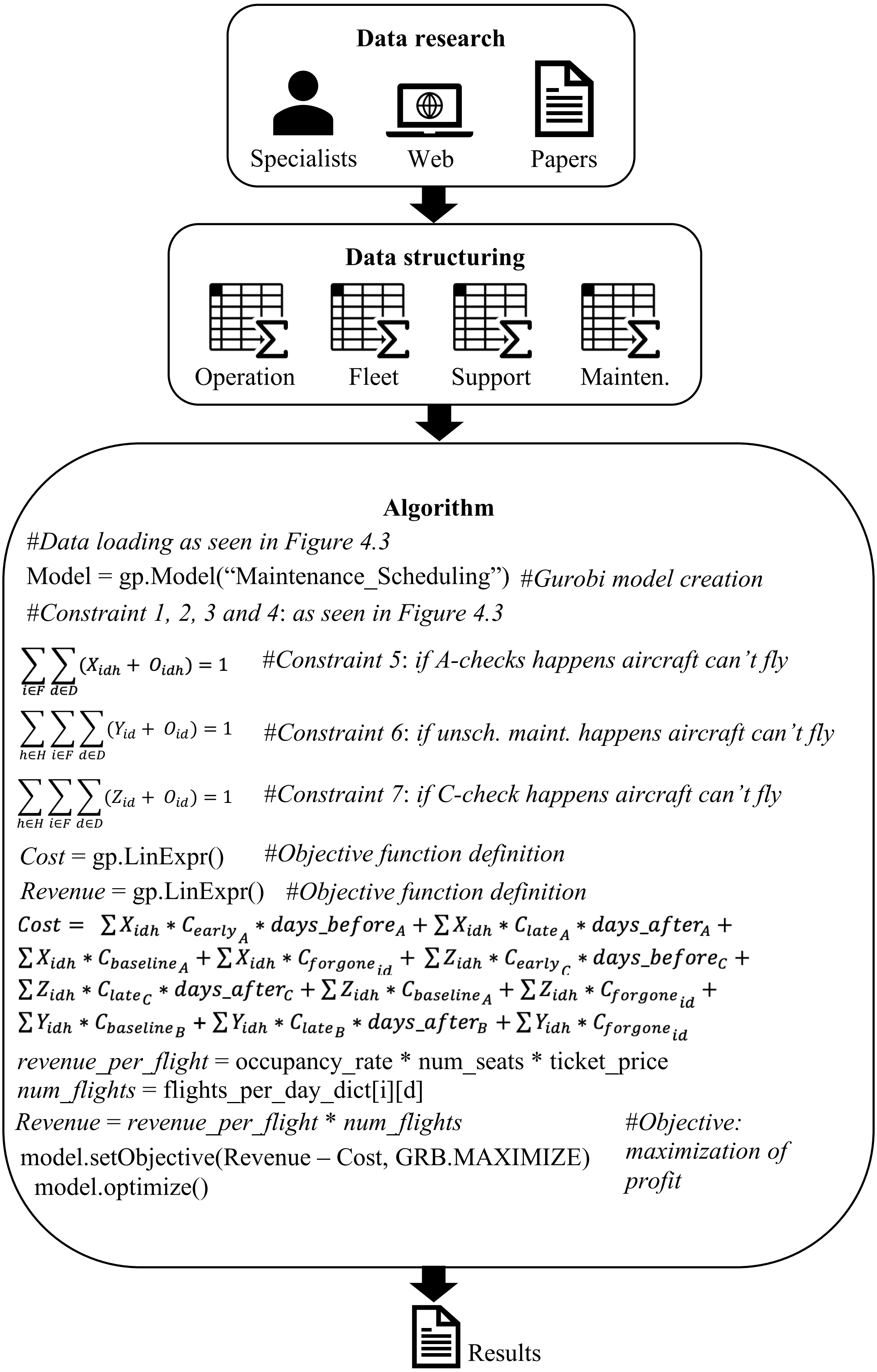

Figure 4.6 – Case study 1: prescriptive experiment process.

4.1.5 Results

This Chapter presents the results of this 1st case study. Table 4.9 showcases an extract of the C-check maintenance schedule optimized considering only cost minimization, as the first part of the experiment accounted for a non-prescriptive objective function. The result lists the aircraft serial numbers, model, maintenance start day, end day, and station. Table 4.10 presents A-checks schedules while Table 4.11 showcases unscheduled maintenance occurrence. Appendix A presents the full results. Table 4.12 presents the non-prescriptive results in terms of dispatch reliability, revenue, cost, and profit.

Table 4.9 – Case study 1 result extract, non-prescriptive C-check schedule.

C-check periods
Serial: 1161, Model: A321neo, Start Day: 107, End Day: 137, Hangar: Campinas
Serial: 1057, Model: A320neo, Start Day: 96, End Day: 126, Hangar: Campinas
Serial: 1036, Model: A320neo, Start Day: 65, End Day: 95, Hangar: Campinas

Table 4.10 – Case study 1 result extract, non-prescriptive A-check schedule.

A-check periods
Serial: 1158, Model: E195-E2, Start Day: 1, End Day: 8, Hangar: Campinas
Serial: 1160, Model: E195-E2, Start Day: 153, End Day: 160, Hangar: Campinas
Serial: 1157, Model: E195-E2, Start Day: 153, End Day: 160, Hangar: Campinas

Table 4.11 – Case study 1 result extract, non-prescriptive unscheduled occurrences.

Unscheduled maintenance
Serial: 1024, Model: E-195, Start Day: 16, End Day: 17, Hangar: Manaus
Serial: 1024, Model: E-195, Start Day: 41, End Day: 42, Hangar: Manaus
Serial: 1025, Model: E-195, Start Day: 12, End Day: 13, Hangar: Manaus

Table 4.12 – Case study 1 non-prescriptive results in terms of cost, revenue, profit, and dispatch reliability.

Cost (USD)	**Revenue (USD)**	**Profit (USD)**	**Dispatch Reliability**
$ 164.497.612,92	$ 2.046.415.098,00	$ 1.881.917.485,08	73,90%

Table 4.13 presents an extract of the C-check maintenance scheduled optimized considering the maximization of the difference between revenue and cost, as this second part of the experiment was based on a prescriptive objective function. The result lists the aircraft serial numbers, model, maintenance start day, end day, and station. Table 4.14 presents A-checks schedules while Table 4.15 showcases unscheduled maintenance occurrence. Appendix A presents the full results.

Table 4.13 – Case study 1 result extract, prescriptive C-check schedule.

C-check periods
Serial: 1161, Model: A321neo, Start Day: 98, End Day: 128, Hangar: Campinas
Serial: 1057, Model: A320neo, Start Day: 93, End Day: 123, Hangar: Campinas
Serial: 1036, Model: A320neo, Start Day: 71, End Day: 101, Hangar: Campinas

Table 4.14 – Case study 1 result extract, prescriptive A-check schedule.

A-check periods
Serial: 1158, Model: E195-E2, Start Day: 30, End Day: 37, Hangar: Campinas
Serial: 1160, Model: E195-E2, Start Day: 204, End Day: 211, Hangar: Campinas
Serial: 1157, Model: E195-E2, Start Day: 150, End Day: 157, Hangar: Campinas

Table 4.15 – Case study 1 result extract, prescriptive unscheduled occurrences.

Unscheduled maintenance
Serial: 1024, Model: E-195, Start Day: 16, End Day: 17, Hangar: Manaus
Serial: 1024, Model: E-195, Start Day: 41, End Day: 42, Hangar: Manaus
Serial: 1025, Model: E-195, Start Day: 12, End Day: 13, Hangar: Manaus

Comparing non-prescriptive and prescriptive C-check and A-check schedules it can be noted that they are slightly different as the objective function in the second case also takes into account the operation, trying to maximize availability, and as a consequence, it may pull back or push forward maintenance attempting to improve fleet availability. Appendix A presents the full results. Table 4.16 presents the results of the prescriptive experiment in terms of costs, revenue, profit, and dispatch reliability.

Table 4.16 – Case study 1 prescriptive results in terms of total cost, total revenue, net profit, and dispatch reliability.

Cost (USD)	**Revenue (USD)**	**Profit (USD)**	**Dispatch Reliability**
164.818.082,40	2.061.959.502,60	1.897.141.420,20	99,89%

Table 4.17 presents a comparison between the results of the two case study approaches: non-prescriptive and prescriptive maintenance scheduling. Key metrics analyzed include processing time, dispatch reliability, profit, revenue, and cost. The prescriptive approach requires more processing time (75,40 seconds) compared to the non-prescriptive approach (31,10 seconds), a difference of 44,3 seconds, representing a 142,44% increase. Dispatch reliability improves significantly with the prescriptive model, reaching 99,89% compared to 73,90% in the non-prescriptive model, marking a 25,99% improvement comparable to airliners' best practices[162, 163]. Financially, the prescriptive approach yields higher profit, revenue, and cost. Profit increases by $15.223.935,12 (0,81%), and revenue rises by $15.544.404,60 (0,76%), indicating a favorable economic outcome. However, the cost also slightly increases by $320.469,48 (0,19%) with the prescriptive approach. This comparison highlights that while the prescriptive method is more computationally intensive, it enhances operational reliability and financial returns.

Table 4.17 – Comparison between case study 1 results.

Metric	**Non-prescriptive**	**Prescriptive**	**Difference (Prescriptive – non-prescriptive)**
Processing time	31 sec.	75 sec.	44 sec. (+142,44%)
Dispatch reliability	73,90%	99,89%	25,99% (+35,16%)
Profit	$ 1.881.917.485,08	$ 1.897.141.420,20	$ 15.223.935,12 (+0,81%)
Revenue	$ 2.046.415.098,00	$ 2.061.959.502,60	$ 15.544.404,60 (+0,76%)
Cost	$ 164.497.612,92	$ 164.818.082,40	$ 320.469,48 (+0.19%)

To take into account the maintenance imperfections the wiener equation has been implemented. Degradation due to imperfection has been calculated in terms of MTBURs as described in Section 4.1.4 and pseudocode 4.2. Table 4.18 presents lists an extract of the new MTBURs per ATA Chapter. Full list is available on Appendix A.

Table 4.18 – Maintenance Imperfection in Terms of New MTBURs.

Model	ATA Chapter	New MTBUR
E195-E2	21	1147,94
E195-E2	22	875,30
E195-E2	23	4745,62

4.2 Case Study 2: Hospital Public Network Epidemic Response

4.2.1 Scope and Assumptions

This study case is based on the historical data, provided by the Caraguatatuba city's Health Department, related to more than 900 patients admitted in 56 public hospitals of São Paulo state during the COVID-19 pandemic of 2021, who had to be assisted with the use of intensive care units (ICUs). The data lists patients' age, gender, day of admission, hospital of admission, duration of admission, and if the patients were deceased. An extract of this historical data is presented in Appendix C. The network of public hospitals considered is shown in Figure 4.7.

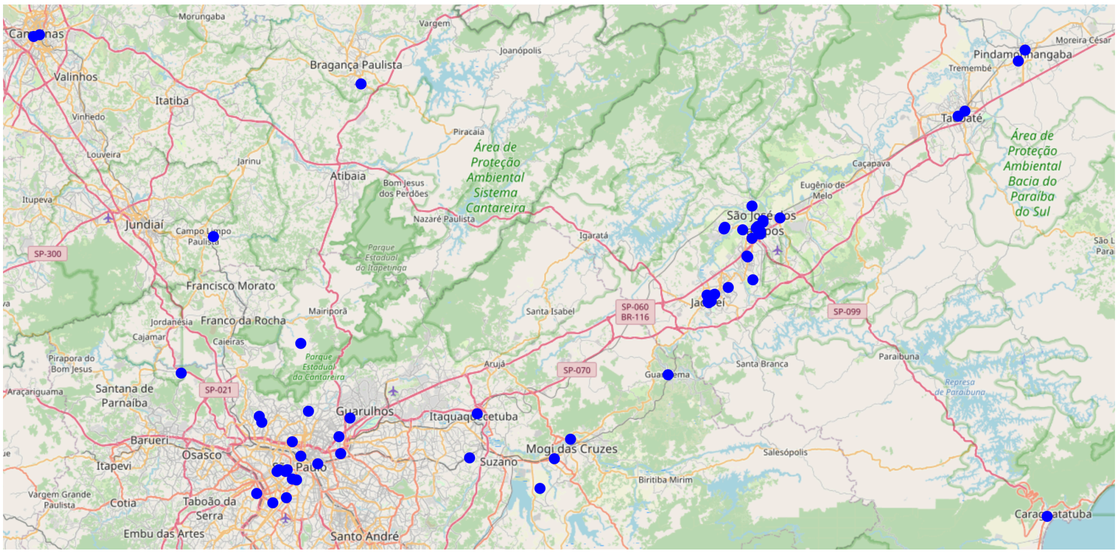

Figure 4.7 – Hospital network location considered in the experiment. (Source: this author)

4.2.2 Survivability Statistical Study Result

Analyzing the historical data, the admission durations that should ensure the highest chances of survival were identified for each age group. To identify these admission durations, the algorithm described in the pseudocode 4.8, was used. The program begins by loading historical patient data from historical_data.xlsx into a data frame. Then it defines a binary survival variable S_{id} that equals 1 if a patient i survives a given duration d, and 0 otherwise. The code then iterates through each gender g in set G, each age range a in set A, and each duration d inset D, analyzing survival probabilities for different groups. For each combination, it checks if the sum of survival outcomes S_{id} for that duration equals the maximum survival count $Smax_{id}$. If this condition is met, it calculates the probability of maximum survival $Pmax_d$ by dividing the maximum survival count by the total count of patients in that group. After completing these iterations across genders, age ranges, and durations, the program outputs the durations and their associated survival probabilities, allowing for the identification of time frames that offer the best survival chances across demographic groups.

Constants & parameters

- I: patients set;
- i: patient of set I;
- D: set of durations;
- $\boldsymbol{d}$: duration of set D;
- G: = gender set;
- g: gender of set G;
- A: age ranges set;
- a: age range of set A;
- $\boldsymbol{Smax_{id}}$: maximum number of survivors within gender g and age range a;
- $\boldsymbol{Pmax_d}$: maximum survival probability corresponding at a specific duration d, age range a and gender g;
- $\boldsymbol{i_d}$: patient admitted for a duration d;

Variable

Table 4.19 – Decision variables.

Variable	State	Type
S_{id}	• Equal to 1 if patient *i* survived at admission duration *d* • 0 otherwise	Binary

Pseudocode 4.8 – Case study 2: identification of the durations that offer the best chances of survival.

Input: historical data

Output: durations per gender and age that offer the biggest chance of survival

1: **historical_data_df**← historical_data.xlsx ⊳ *Load historical data into a data frame*

S_{id} ←binary variable equal to 1 if patient i survives on duration d, 0 otherwise	▻ $Survival\ variable\ definition$
for each $g \in G$	▻ *Iterate through gender*
for each $a \in A$	▻ *Iterate through age ranges*
for each $d \in D$	▻ *Iterate through stations*
if $\sum_{d \epsilon D} S_{id} = Smax_{id}$ **Then**	▻ *Identification of admission durations that offer survival best chances*
$Pmax_d = Smax_{id} / \sum i_d$	▻ *Maximum survival probability calculation*
end for	▻ *End of iteration through durations*
end for	▻ *End of iteration through age ranges*
end for	▻ *End of iteration through gender*
Print best durations and probabilities	▻ *Print results*

The duration of maximal survivability is listed in Table 4.20 for each age range and gender. For example, male patients aged 0-4 had an optimal admission duration of 14 days with a probability of survival of approximately 0.9008. In contrast, female patients in the same age range had an optimal duration of 12 days with a probability of survival of 1. This data is critical for an optimization algorithm to tailor the admissions schedules toward patient survival maximization. The assumption is that admission duration plays a critical role in survivability chances, that is, there is a direct correlation between how long patients have access to health care and their chances of survival. This is a simplification since other factors such as the patient's genetics, patients' pre-conditions, and medical errors among others[151] are not considered in this experiment.

Table 4.20 – Survival statistical analysis to identify optimal duration.

Age range	Gender	Patients	Optimal admission duration (days)	Optimal probability of survival
0-4	M	47	14	0.90083875
0-4	F	36	12	1
5-9	M	18	26	1
5-9	F	12	15	1
10-14	M	10	51	0.893
10-14	F	6	3	0.893
15-19	M	5	17	0.95966667
15-19	F	6	7	0.893
20-24	M	5	13	1
20-24	F	5	9	0.893
25-29	M	10	9	0.95966667
25-29	F	7	8	0.893
30-34	M	21	7	0.893
30-34	F	15	12	0.893
35-39	M	39	22	0.89460256
35-39	F	27	11	0.893
40-44	M	52	8	0.893
40-44	F	38	8	0.893
45-49	M	55	9	0.893
45-49	F	35	10	0.893
50-54	M	60	12	0.893

Age range	Gender	Patients	Optimal admission duration (days)	Optimal probability of survival
50-54	F	28	10	0.95816291
55-59	M	58	14	0.893
55-59	F	46	36	0.95944791
60-64	M	47	12	0.893
60-64	F	43	10	0.893
65-69	M	52	9	0.58
65-69	F	37	20	0.80850123
70-74	M	45	14	0.59851852
70-74	F	32	14	0.81106061
75-79	M	36	16	0.893
75-79	F	24	7	0.893
80-84	M	27	10	0.893
80-84	F	33	17	0.65744108
85-89	M	18	99	0.83448029
85-89	F	21	24	0.80887865
90-94	M	11	9	0.58
90-94	F	15	8	0.58
95-99	M	1	8	0.58
95-99	F	2	0	0.58

In conclusion, the statistical analysis provided in Table 4.20 offers insights into the optimal admission durations required to enhance patient survival rates. By leveraging this data, and with the assumption that survivability is directly related to admissions' durations, it is possible to optimize admissions and resource allocation. The next Chapter will address the healthcare infrastructure capability and build upon the considerations related to optimal durations by introducing the optimization algorithm to schedule patient admissions and allocate healthcare resources effectively.

4.2.3 Hospitals Capability

Table 4.21 presents the healthcare infrastructure capabilities of four hospitals (names of the hospitals are preserved to ensure data privacy), detailing the availability of the critical resource ICU[148]. The complete list is available in Appendix B.

This information is essential for understanding the capability of each hospital to handle patient admissions and provide adequate care, especially in scenarios involving high demand or emergencies such as a pandemic.

This Table serves as a foundational element for the subsequent optimization algorithm, which aims to schedule patient admissions and allocate healthcare resources based on historical data and optimal duration insights.

Table 4.21 – Healthcare infrastructure capability.

Hospital	**ICU**
Hospital 1	15
Hospital 2	30
Hospital 3	41
Hospital 4	24

4.2.4 Admissions Optimization

This Section introduces the mathematical model used for the optimization algorithm in the healthcare context. The model is designed to optimize the scheduling of patient admissions based on available ICUs. To achieve this, the model incorporates a range of constants and parameters that define the system's operational constraints and objective function that maximizes the difference between Revenue and Cost as implemented in case study 1. These parameters include sets of patients and hospitals, admission periods, optimal treatment durations, and the availability of ICU beds. Additionally, cost factors and life expectancy metrics are included to ensure that the model not only optimizes resource use but also aligns with broader healthcare objectives which is saving lives.

Constants & parameters

- I: patients set;
- H: hospitals set;
- h: hospital of set H;
- i: patient;
- d_{fi}: final day of admission for patient i;
- d_{ai}: day of admission for patient i;
- d_{oi}: optimal duration per patient i;
- $\boldsymbol{ICU_{dh}}$: quantity of ICUs available in the hospital h and day d;
- $Yearly_{salary}$: patient yearly average salary, estimated at USD 11.000,00 per year [154];
- $Life\_expectancy_i$: life expectancy for patient i;
- $Life\_expectancy_{average}$: population average life expectancy, roughly equal to 75 years [153];
- $C_{admission_{day}}$: cost of admission per day[152], roughly equal to USD 2.170,00;
- $C_{non\_admission_i}$: cost of non-admission for patient i;
- $R_{optimal_i}$: revenue due to optimal admission for patient i;
- R_{late_i}: revenue due to late admission for patient i;
- $C_{optimal_i}$: cost of admission when admission is on optimal date and duration for patient i;
- C_{late_i}: cost of admission when admission is after optimal date and duration for patient i;

Decision variable

Table 4.22 – Decision variable.

Variable	State	Type
X_{idh}	• Equal to 1 if patient i is admitted on day d in hospital h • 0 otherwise	Binary

Objective Function

$$C_{non_{admission_i}} = Life\_expectancy_i * Yearly_{salary} \tag{4.38}$$

$$Cost = \sum X_{idh} * C_{admission_{day}} * d_{o_i} + \sum (1 - X_{idh}) C_{non_{admission_i}} \tag{4.39}$$

$$R_{optimal_i} = \sum X_{idh} * \left(Life\_expectancy_i * Yearly_{salary}\right) \tag{4.40}$$

$$R_{late_i} = 0.5 * R_{optimal_i} \tag{4.41}$$

$$Revenue = \sum (R_{optimal_i} + R_{late_i}) \tag{4.42}$$

$$ObjectiveFunction = Max(Revenue - Cost) \tag{4.43}$$

Calculations

Table 4.23 presents the calculation of the life expectancy. When the age is larger than the average life expectancy then the logistic equation was adopted to estimate the life expectancy of the patient. The logistic equation, commonly used in population dynamics, is a mathematical model used to describe growth that starts exponentially but slows as it approaches a maximum value[155], a behavior that fits the life expectancy variation over time.

Table 4.23 – Life expectancy calculation.

Variable	State
$Life\ expectancy_i$	$= Life\_expectancy_{average} -$ age if age $\leq Life\_expectancy_{average}$ $= \frac{age - Life\_expectancy_{average}}{1+e^{(age - Life_{expectancy_{average}})}}$ if age $\geq Life\_expectancy_{average}$

Constraints

Equation 4.44 enforces that admission must happen while constraint 4.45 enforces that for each admission event, the available ICUs are not exceeded.

$$\sum_{h\in H}\sum_{i\in I}\sum_{d\in D}(X_{idh}) = 0 \qquad \text{for each day } d \text{ patient } i \text{ and hospital } h, \text{ if } d < d_{oi} \tag{4.44}$$

$$\sum_{h\in H}\sum_{i\in I}\sum_{d\in D}(X_{idh}) \leq ICU_{dh} \qquad \text{for each day } d, \text{ patient } i \text{ and hospital } h \tag{4.45}$$

Pseudocode

The pseudocode 4.9 presents the steps for implementing the optimization model focusing on a prescriptive objective function that seeks to maximize the difference between Revenue and Cost. The revenue equation tries to maximize the number of optimal admissions while the cost is related to the admission costs, increasing significantly whenever a patient is admitted not at the optimal date or not admitted. Here's a breakdown of each part:

1. **Data Loading (Steps 1-3)**:
    a. In these steps patients' optimal admissions, survival probability, and hospitals' ICU capabilities are loaded.

2. **Model Setup (Steps 4-5)**:
   - **a.** Define a Gurobi optimization model.
   - **b.** Define decision variables:
     - i. X_{idh} for patient admissions.
3. **Constraints**:
   - **a. Station Capacity Constraint (Steps 6-12)**:
     - i. Iterate over assets (*i*), days (*d*), and stations (*h*) to ensure that the total number of patients admitted does not exceed the station's (hospital) capacity (ICU_h).
   - **b. Admission cannot occur before historical data admissions (Steps 13-19)**:
     - i. For every day, patient and hospital, admission day cannot be smaller than the optimal admission day which is the one recorded on the historical data.
4. **Cost & Revenue Calculation (Steps: 21-30)**
   - **a.** Revenue is equal to the sum of the number of patients admitted times the number of expected life years times the yearly average income. If the patient is admitted after the optimal date, revenue is half the value it would be if admission were on the optimal date.
   - **b.** Cost is proportional to the number of days of admission. If a patient is not admitted then the cost is equal to the yearly average earnings times the life expectancy.
5. **Objective Function (Steps 31-32)**:
   - **a.** Set the objective function to maximize the difference between Revenue and Cost.

6. **Output (Step 33)**:

   Print results.

Pseudocode 4.9 – Case Study 2 optimization model.

Input: patient admission data, ideal patient admission duration, hospitals data,

Output: location and duration of admission

1: **admission_data**← admission data ▻ *Load admission data*

2: **admission_duration**← admission duration ▻ *Load admission duration*

3: **stations_data**← hospitals_data ▻ *Load hospital data*

4: model←gp.model ▻ *Optimization start*

5: X_{id} ← patient_admitted(patient,days, hospital, binary) ▻ *Admission variable definition*

6: **for each** $i \in I$ ▻ *Iterate through patients*

7: **for each** $d \in D$ ▻ *Iterate through days*

8: **for each** h $\in H$ ▻ *Iterate through hospitals*

9: $\sum_{h \in H} \sum_{i \in I} \sum_{d \in D} (X_{idh}) \leq ICU_{dh}$ ▻ *The number of patients cannot be larger than the available ICUs*

10: **end for** ▻ *End of iteration through hospitals*

11: **end for** ▻ *End of iteration through patients*

12: **end for** ▻ *End of iteration through days*

13: **for each** $i \in I$ ▻ *Iterate through patients*

14: **for each** $d \in D$ ▻ *Iterate through days*

15: **for each** h $\in H$ ▻ *Iterate through hospitals*

16: $\sum_{h \in H} \sum_{i \in I} \sum_{d \in D} (X_{idh}) = 0$ if $d < d_{oi}$ ▻ *Patient admission cannot occur before real admission according to historical data*

17: **end for** ▻ *End hospital iteration*

18: **end for** ▻ *End day iteration*

19: **end for** ▻ *End patients iteration*

20: **for each** $i \in I$ ▻ *Iterate through patients*

21: **for each** $d \in D$ ▻ *Iterate through days*

for each h $\in H$ ▻ *Iterate through hospitals*

$Cost = \sum X_{idh} * C_{admission_{day}} * d_{o_i} + \sum(1 - X_{idh}) * C_{non_{admission_i}}$ ▻ *Cost equation*

if $d_{a_i} = d_{o_i}$ **then** ▻ *If admission day is equal to the optimal day*

$R_{optimal_i} = \sum X_{idh} * (Life\_expectancy_i * Yearly_{salary})$ ▻ *Optimal revenue*

else if ▻ *If admission day is not equal to the optimal day*

$R_{late_i} = 0.5 * R_{optimal_i}$ ▻ *Sub-optimal revenue*

end if ▻ *Conditional logic closing*

end if ▻ *Conditional logic closing*

$Revenue = \sum(R_{optimal_i} + R_{late_i})$ ▻ *Revenue is defined as the sum of optimal and late revenues*

model.setObjective(Revenue-Cost, GRB.MAXIMIZE) ▻ *Objective function definition*

model.optimize() ▻ *Optimization start*

Print results ← *Print_admission_recommendation* ▻ *Admission recommendation output*

The optimization aims to distribute the patients' admission across the hospitals to maximize the chances of survival, as shown in Table 4.24. It is important to note that if the admission duration assigned was optimal after the optimization, it means that the patient has been assigned the optimal probability of survival presented in Table 4.18. Full algorithm results are presented in Appendix A, Section A.2. As previously stated, many unforeseeable factors play crucial roles in humans' survivability, being survivability statistical in nature rather than deterministic[156]. It is necessary thus to evaluate survivorship using a statistical approach such as Monte Carlo simulation[156, 157], as presented in the next Chapter.

Table 4.24 – Case study 2 results extract.

Patient	Gender	Age	Admitted? (Y/N)	Admission			Duration (optimal /sub-optimal)
				Hospital	Day	Duration (days)	
316286817512	F	1	Y	1	96	12	Optimal
316246448213	M	19	Y	1	37	17	Optimal
316286805191	M	79	N	-	-	-	-

4.2.5 Monte Carlo Simulation for Survivorship Estimation

To evaluate the most probable quantity of surviving patients the Monte Carlo approach has been implemented, due to the statistical nature of survivorship[156, 157]. Parameters used, and pseudocode are presented below. A value (seed) used to initialize the random number generator (RNG) was adopted to ensure reproducibility.

Parameters

N_simulations: 100.000
Seed: 42

Pseudocode

The pseudocode 4.10 presents the steps for implementing the Monte Carlo model focusing. Here's a breakdown of each part

1. **Load Input Data (Step 1)**
   - Load the dataset into a data frame using read_excel.
2. **Set Monte Carlo Simulation Parameters (Steps 2 - 3)**
   - Define the number of simulations.
   - Set a random seed for reproducibility.
3. **Run Monte Carlo Simulation (Steps 4 - 6)**
   - For each iteration:
     - Generate random numbers for each individual.
     - Compare random numbers to survival probabilities to determine survivors.
     - Count the number of survivors and store the result.
4. **Analyze Simulation Results (Step 7)**
   - Compute the average number of survivors across all simulations.
   - Generate the survival probability distribution as a frequency Table.
5. **Print Summary (Step 8)**
   - Display the average number of survivors.
   - Display the top entries of the survival probability distribution

Pseudocode 4.10 – Case study 2 Monte Carlo simulation to evaluate survivors number.

Input: patient list and their admission cure probability

Output: most probable quantity of survivors

1: **survivorship_data**← list of patients and their probability of survival ⊳ *Load survivorship probability data*

2: n_simulations = 100000 ⊳ *Number of simulations*

3: np.random.seed(42) ⊳ *Calling of random function with seed equal to 42*

4: **for each simulation** ⊳ *Iterate through patients*

5: survived = np.random.rand(len(serials)) < survival_chances	⊳ *Condition for survival*
6: survival_counts.append(survived.sum())	⊳ *Count the number of survivors*
7: average_survivors = np.mean(survival_counts)	⊳ *Mean calculation of all results*
8: Print results ← *Print_mean and most probable values*	⊳ *Admission recommendation output*

Table 4.25 presents the results in terms of the most probable survivor quantities. It is possible to note that the most probable value is 706 while the overall mean is 707 people.

Table 4.25 – Monte Carlo simulation most probable number of survivals.

Survivors
707

4.2.6 Results

Survivability in the health industry depends on many factors, ranging from patient existing pre-condition, genetics to drug availability, efficient medical techniques, infrastructure and order of arrival at the hospital. However, for this experiment, to evaluate the initial hypothesis, the following assumptions was adopted: the optimal admission duration maximizes survivorship.

Thus, the prescriptive algorithm implementation was focused on recommending the best course of action in terms of patients' allocation to hospitals' ICUs and admissions durations, seeking to maximize the patients 'community survivorship, without considering order of arrival and patients 'possible preconditions. Table 4.26 shows that the prescriptive approach potentially might be more effective under the experiment assumptions, indicating that more people could be assisted for longer than the historical data showed, increasing the probability of survivorship.

Table 4.26 – Case study 2 potential results.

Indicator	Historical data	Prescriptive approach
Survivors	429	707

Table 4.27 presents the results in terms of Revenue, Cost, and Profit comparing the values obtained considering the evaluated cost of life losses, according to average yearly salary and average life expectancy, and the values obtained without considering these losses.

Table 4.27 – Case study 2 results in terms of revenue, cost, and difference between revenue and cost.

Attributes	Not considering loss of lives as a cost	Considering loss of lives as a cost
Revenue (USD)	3.730.496.000,00	3.734.192.000,00
Cost (USD)	427.344.610,00	7.508.602.974.457,81
Revenue – Cost (USD)	3.303.151.390,00	-7.504.868.782.457,81
Processing time (seconds)	232,86	8104,64
Survivorship (persons)	707	707

Although the computational time for the approach that considers loss of lives as cost is much longer in comparison to the approach that does not consider it, both approaches yield the same results, meaning that the constraint of ICU beds is insurmountable even when the costs rise almost exponentially.

The prescriptive approach, which considers operation and maintenance, in this experiment years of life versus costs of healthcare, offers promising results and, under the assumption of the study, a potential increase in survivorship.

4.3 Case Study 3: Regional Airliner Operation Scenario – 14 Days Window

4.3.1 Scope and Assumptions

For this case all the operational assumptions in terms of fleet typology, number of aircraft, flights, stations, and maintenance capability were adopted from case study 1. In this experiment, however different capabilities of repairing systems were randomically distributed among the 150 plus stations, while full-time equivalents (FTE) and GSE were also assigned to each base. The repairing capability is in terms of readiness to repair systems per ATA Chapter, allowing the prescriptive recommendation and holistic analysis mentioned in Chapter 3, Section 3.2.3. Time period considered is 14 days to test the algorithm performance in a tactical operational context.

4.3.2 Maintenance Capability

As mentioned in Section 4.3.1, the depot and intermediate maintenance hangars and their characteristics mentioned in Section 4.1.3 were kept unchanged. For the repair capabilities scattered through all 150 plus hubs' network, repair capabilities per ATA Chapter were randomically distributed to test the scenario described in Section 3.2.3. The full list of distribution per ATA Chapter and Hub is available in Appendix D.

Building on the discussion of maintenance capabilities across various hangar locations, it is essential to highlight the role of Ground Support Equipment (GSE). Table 4.28 details the consolidation of GSE into specialized kits according to maintenance technicians' areas of expertise: airframe, powerplant, and avionics. This consolidation ensures that each hangar is equipped with the necessary tools and equipment tailored to the specific maintenance tasks performed at that location.

Table 4.28 – Consolidation of GSE according to the airframe, powerplant, and avionics ATA Chapter.

Airframe maintenance kit ATA Chapters	**Powerplant maintenance kit ATA Chapters**	**Avionics maintenance Kit ATA Chapters**
21: air conditioning	49: auxiliary power unit	22: auto flight
25: equipment	70: standard practices - engine	23: communications
28: fuel	71: power plant	24: electrical power
30: ice & rain protection	72: engine	31: instruments
32: landing gear	73: engine fuel and control	34: navigation
33: lights	74: ignition	44: cabin systems
35: oxygen	75: air	45: central maintenance computer
36: pneumatic	76: engine controls	46: information system
38: water/waste	77: engine indicating	
52: doors	78: exhaust	

Airframe maintenance kit ATA Chapters	Powerplant maintenance kit ATA Chapters	Avionics maintenance Kit ATA Chapters
53: fuselage	79: oil	
54: nacelle/pylons	80: starting	
55: stabilizers		
56: windows		
57: wings		

To ensure that maintenance operations are conducted efficiently, it is crucial to consider the availability and allocation of maintenance personnel. The effectiveness of the GSE and the maintenance capabilities of each hangar is inherently dependent on the skilled technicians and supervisors who perform the maintenance tasks. Table 4.29 provides an overview of the estimated team sizes and skill availability at depot hangars to perform C-check maintenance for each aircraft model. The Table assumes three shifts of 8 hours each, operating 7 days a week. It categorizes the team members into four key roles: supervisor, powerplant technician, airframe technician, and avionics technician in alignment with FAA certifications[150].

For instance, for the Airbus A320neo, each shift requires 0.67 supervisors, 5 powerplant technicians, 6 airframe technicians, and 5 avionics technicians. The Embraer E195-E2 has similar requirements, reflecting the standardized approach to staffing across different aircraft models. Larger aircraft, such as the Airbus A330-900 and A350-900, require more extensive teams, with each shift needing 1 supervisor, 14 powerplant technicians, 15 airframe technicians, and 14 avionics technicians.

Table 4.29 – Daily estimated technicians and skills needed to perform C-check.

Aircraft	C-check maintenance team members' skills and quantities per day per shift			
	Supervisor	Powerplant	Airframe	Avionics
A320neo	0,67	5	6	5
E-195	0,67	5	6	5
ATR-72-600	0,67	5	6	5
Cessna 208B	0,5	2	2	2
E195-E2	0,67	5	6	5
A321neo	0,67	5	6	5
A330-900	1	14	15	14
A330-200	1	14	15	14
A350-900	1	14	15	14

Table 4.30 outlines the required personnel for conducting intermediate checks, which are also assumed to be performed in three shifts of 8 hours each, operating 7 days a week. For all aircraft models, each shift requires 1 supervisor, 2 powerplant technicians, 2 airframe technicians, and 2 avionics technicians. This standardized staffing ensures that intermediate maintenance tasks are consistently executed with the necessary expertise, allowing for timely and effective upkeep of the fleet.

Table 4.30 – Daily team members and skills needed to perform A-checks.

Aircraft	A-check team members' skills and quantities per day per shift			
	Supervisor	Powerplant	Airframe	Avionics
All models	1	2	2	2

Table 4.31 specifies the team compositions needed for organizational and corrective maintenance activities. Assuming to be carried out in two shifts of 8 hours each, operating 7 days a week. Similar to intermediate checks, each shift requires 1 supervisor, 2 powerplant technicians, 2 airframe technicians, and 2 avionics technicians for all aircraft models. This configuration ensures that the routine and corrective maintenance tasks are adequately staffed, providing the flexibility and capability to address both scheduled and unscheduled maintenance needs.

By clearly defining the required team compositions for different maintenance activities, these tables facilitate effective resource modeling and optimization by the prescriptive algorithm.

Table 4.31 – Daily team members and skills needed to perform unscheduled maintenance.

Aircraft	Organizational and corrective maintenance team members' skills and quantities per day per shift			
	Supervisor	Powerplant	Airframe	Avionics
All models	1	2	2	2

4.3.3 Aircraft Maintenance Requirement

Table 4.32 presents the estimated required maintenance FTE needed to provide C-check and A-check maintenance for each aircraft model. Values were validated with industry expert as data is not publicly shared by OEMs.

Table 4.32 – Aircraft maintenance check duration and estimated FTE needed.

Aircraft	Check			
	A		C	
	Duration (days)	Labor (FTE/day)	Duration (days)	Labor (FTE/day)
A320neo	7	100	30	400
E-195	7	100	30	400
ATR-72-600	7	100	30	400
Cessna 208B	5	30	20	156
E195-E2	7	100	30	400
A321neo	7	100	30	400
A330-900	7	250	30	1056
A330-200	7	250	30	1056
A350-900	7	250	30	1056

Additionally, a set of maintenance tasks per each model and ATA chapter were created to serve as input for the maintenance prescription. As presented in Table 4.33 to each task were assigned an ID, execution time in hours, and FTE – powerplant, airframe or avionics - to be deployed. Tasks' descriptions and attributes were validated by industry experts, since related publicly available data is very limited.

Table 4.33 – Aircraft maintenance C-check tasks estimated FTE needed.

Model	ATA	Task	Task ID	Execution Time (hs)	Powerplant FTE	Airframe FTE	Avionics FTE
A330-900	21	Operational Check	21.12	1	0	32	0
A330-900	21	Component Testing and Replacement	21.13	1	0	32	0
A330-900	21	Calibration and Adjustment	21.14	1	0	32	0
A330-900	21	Filling out Documentation	21.15	1	0	1	0
A330-900	21	Component Testing and Replacement	22.12	1	0	0	128
A330-900	21	Software Update	22.14	1	0	0	128
A330-900	21	Cable and Connection Checks	22.15	1	0	0	128

Full task list is available in Appendix D.

The following Section presents the mathematical model underpinning the optimization algorithm used in the Smart Optimization Framework for PsM. This model is designed to optimize the allocation of maintenance resources, scheduling of maintenance activities, and overall operational efficiency. By incorporating the constraints identified in this Section, parameters, and objective functions, the model aims to provide a robust and scalable solution for managing maintenance operations across diverse asset types, including aircraft and human health systems.

4.3.4 Mathematical Model and Optimization

The mathematical model integrates multiple elements, such as the availability of maintenance personnel, ground support equipment (GSE), and maintenance facilities. It accounts for different maintenance levels—organizational, intermediate, and depot—and their respective resource requirements. Additionally, the model considers predictive maintenance capabilities to enhance decision-making and minimize downtime.

The specifics of the optimization algorithm are detailed in terms of the parameters, constraints, and objective functions adopted that form the core of the model. The algorithm was implemented on 3 phases:

- Phase 1: C-check tasks were assigned and scheduled to each day at each Depot station according to slot, FTE and GSE availability.
- Phase 2: A-check tasks were assigned and scheduled according to FTE availability at each Intermediate or Depot base.

- Phase 3: For unscheduled maintenance, flights were diverted (or not) to specific stations according to the type of failure and FTE availability at the destiny station. Unscheduled maintenance task and FTE were also assigned.

Constants & parameters

- F: fleet size;
- $Acft_{payload}$ = number of seats;
- $\boldsymbol{Revenue_{per\_seat}}$= average ticket price;
- $\boldsymbol{Occupation_{ratio}}$= average fleet aircraft occupation ratio;
- $Flight_{day}$ = number of flights per day;
- H_d: set of available hangar slots at each day d;
- h: hangar slot;
- D: number of operational days;
- i: aircraft of the fleet F;
- d: day of the period D;
- d_A: day in which A-check should be scheduled according to the interval $\boldsymbol{I_A}$;
- d_B: day in which unscheduled maintenance should be executed according to operation simulation results;
- d_C: day in which C-check should be scheduled according to the interval $\boldsymbol{I_C}$;
- I_A: A-check interval;
- I_C: C-check interval;
- $C_{baseline_A}$: daily maintenance cost when A-check maintenance occurs in the baseline interval;
- C_{early_A}: daily maintenance cost when A-check maintenance occurs before the baseline;
- C_{late_A}: daily maintenance cost when A-check maintenance occurs after the baseline;
- $C_{baseline_B}$: daily unscheduled maintenance cost when maintenance is executed on the day of the event;
- C_{late_B}: daily unscheduled maintenance cost when maintenance is executed later than 1 day after the event;
- $C_{baseline_C}$: daily maintenance cost when C-check maintenance occurs in the baseline interval;
- C_{early_C}: daily maintenance cost when C-check maintenance occurs before the baseline;
- C_{late_C}: daily maintenance cost when C-check maintenance occurs after the baseline;
- K_A: number of A-check intervals in the period D considered;
- K_C: number of C-check intervals in the period D considered;
- d_{late_A}: day after d_A in which A-check is scheduled;
- d_{late_B}: day after d_B in which unscheduled maintenance is scheduled;
- d_{late_C}: day after d_C in which C-check is scheduled;
- d_{early_A}: day in which A-check is scheduled, before d_A;
- d_{early_C}: day in which C-check is scheduled, before d_C;
- E_A: quantity of days before d_A in which A-check is scheduled;
- E_C: quantity of days before d_C in which C-check is scheduled;

- F_A: quantity of days after d_A in which A-check is scheduled;
- F_B: quantity of days after d_B in which unscheduled maintenance occurs;
- F_C: quantity of days after d_C in which C-check is scheduled;
- S: set of stations (or hangars) S;
- s: station or hangar of the set of stations S;
- $FTE_{air,S}$: airframe FTE available at station s;
- $FTE_{pow,S}$: powerplant FTE available at station s;
- $FTE_{avi,S}$: avionics FTE available at station s;
- $FTE_{air,Needed\_ata,i}$: airframe FTE needed for each system Ata Chapter and aircraft i;
- $FTE_{air,Needed\_ata,i}$: powerplant FTE needed for each system Ata Chapter and aircraft i;
- $FTE_{air,Needed\_ata,i}$: avionics FTE needed for each system Ata Chapter and aircraft i;
- $GTE_{air,S}$: airframe GTE available at station s;
- $GTE_{pow,S}$: powerplant GTE available at station s;
- $GTE_{avi,S}$: avionics GTE available at station s;
- $GTE_{air,Needed\_ata,i}$: airframe GTE needed for each system Ata Chapter and aircraft i;
- $GTE_{air,Needed\_ata,i}$: powerplant GTE needed for each system Ata Chapter and aircraft i;
- $GTE_{air,Needed\_ata,i}$: avionics GTE needed for each system Ata Chapter and aircraft i;

<u>*Decision variables*</u>

Table 4.34 – Decision variables.

Variable	State	Type
X_{idh}	• Equal to 1 if A-check is scheduled for aircraft *i* on day *d* and hangar slot *h* • 0 otherwise	Binary
Y_{idh}	• Equal to 1 if unscheduled maintenance is executed for aircraft *i* on day *d* and hangar slot *h* • *0* otherwise	Binary
Z_{idh}	• Equal to 1 if C-check is scheduled for aircraft *i* on day *d* and hangar slot *h* • 0 otherwise	Binary
O_{idh}	• Equal to 1 if flight is assigned for aircraft *i* on day *d* and hangar slot *h* • 0 otherwise	Binary

<u>*Objective Function*</u>

$$Cost = \sum X_{idh} * C_{early_A} * days\_before_A + \sum X_{idh} * C_{late_A} * days\_after_A + \sum X_{idh} * C_{baseline_A} + \sum Z_{idh} * C_{early_C} * days\_before_C + \sum Z_{idh} * C_{late_C} * days\_after_C + \sum Z_{idh} * C_{baseline_C} + \sum Y_{idh} * C_{baseline_B} + \sum Y_{idh} * C_{late_B} * days\_after_B \quad (4.46)$$

$$Revenue = \sum O_{idh} * \left(Revenue_{per\_seat} * Flight_{day} * Acft_{payload} * Occupation_{ratio} \right)_{i_d} \quad (4.47)$$

$$ObjectiveFunction = Max(Revenue - Cost) \tag{4.48}$$

Calculations

Equations 4.49 and 4.50 define that d_A and d_C are multiples of the respective A-check and C-check intervals. Equations 4.51 and 4.52 determine the number of intervals, which is given by the division between D and the interval I_A for A-check and I_C for C-check. Equations 4.53, 4.54, and 4.55 define d_{late} while equations 4.56 and 4.57 present the calculation for d_{early} since, if no slots are available, maintenance may be pushed back or pulled forward. Equations 4.58 and 4.59 calculate the number of days in which A-check is scheduled before or after d_A. Similarly, equations 4.60 and 4.61 calculate the number of days in which the C-check is scheduled before or after d_C. Equation 4.62 calculates delay in the unscheduled maintenance.

$$d_A = n \times I_A \mid n: 1 \rightarrow K_A, n \in Integer \tag{4.49}$$

$$d_C = n \times I_C \mid n: 1 \rightarrow K_C, n \in Integer \tag{4.50}$$

$$K_A \geq \frac{D}{I_A}, \ K_A \in Integer, K_A > 0 \tag{4.51}$$

$$K_C \geq \frac{D}{I_C}, \ K_C \in Integer, K_C > 0 \tag{4.52}$$

$$d_A < d_{late_A} \leq d_A + I_A - A \tag{4.53}$$

$$d_A - I_A + A \leq d_{early_A} < d_A \tag{4.54}$$

$$d_B < d_{late_B} \leq d_B + I_B - B \tag{4.55}$$

$$d_C < d_{late_C} \leq d_C + I_C - C \tag{4.56}$$

$$d_C - I_C + C \leq d_{early_C} < d_C \tag{4.57}$$

$$E_A = d_A - d_{early_A} \qquad \text{for } d_A > d_{early_A} \tag{4.58}$$

$$F_A = d_{late_A} - d_A \qquad \text{for } d_{late_A} > d_A \tag{4.59}$$

$$E_C = d_C - d_{early_C} \qquad \text{for } d_C > d_{early_C} \tag{4.60}$$

$$F_C = d_{late_C} - d_C \qquad \text{for } d_{late_C} > d_C \tag{4.61}$$

$$F_B = d_{late_B} - d_B \qquad \text{for } d_{late_B} > d_B \tag{4.62}$$

Constraints

A key logistical consideration is the limitation imposed by the number of available maintenance slots described in Equation 4.63. For any given day *d*, the number of aircraft slated to receive maintenance — be it an A-check, C-check, or unscheduled — must not exceed the number of hangar slots available, denoted by *H*. This stipulation enforces a cap on the maximum number of aircraft undergoing maintenance at any time, ensuring that the physical space available is not exceeded. Equations 4.64 and 4.65 enforce that for each aircraft *i* on each day *d*, the cumulative number of A-checks and C-checks conducted is bound by a non-negotiable OEM requirement. These requirements, denoted as K_A, K_C, serve as the minimum thresholds for A-checks and C-checks that must be performed to uphold the safety and performance standards. This constraint not only ensures the airworthiness of the fleet but also reinforces the commitment to operational excellence and regulatory compliance. Constraints 4.66, 4.67 and 4.68 enforce that for each maintenance event the available FTE are not exceeded while constraints 4.69, 4.70 and 4.71 enforce that available GSE are not exceeded. Pseudocodes 4.11 and 4.12 presents the algorithm implementation.

$$\sum_{h\in H}\sum_{i\in F}\sum_{d\in D}(X_{idh} + Y_{idh} + Z_{idh}) \leq H_d \qquad \text{for each day } d, \text{ aircraft } i \text{ and slot } h \tag{4.63}$$

$$\sum_{h\in H}\sum_{i\in F}\sum_{d\in D} X_{idh} \geq K_A$$ for each day *d,* aircraft *i* and slot *h* (4.64)

$$\sum_{h\in H}\sum_{i\in F}\sum_{d\in D} Z_{idh} \geq K_C$$ for each day *d,* aircraft *i* and slot (4.65)

$$\sum_{h\in H}\sum_{i\in F}\sum_{d\in D} (Y_{idh} + X_{idh} + Z_{idh}) * FTE_{air,Needed\_ata,i} \leq FTE_{air,S}$$ for each day *d,* aircraft *i* and slot *h* (4.66)

$$\sum_{h\in H}\sum_{i\in F}\sum_{d\in D} (Y_{idh} + X_{idh} + Z_{idh}) * FTE_{pow,Needed\_ata,i} \leq FTE_{pow,S}$$ for each day *d,* aircraft *i* and slot *h* (4.67)

$$\sum_{h\in H}\sum_{i\in F}\sum_{d\in D} (Y_{idh} + X_{idh} + Z_{idh}) * FTE_{avi,Needed\_ata,i} \leq FTE_{avi,S}$$ for each *d* and *i* (4.68)

$$\sum_{h\in H}\sum_{i\in F}\sum_{d\in D} (Y_{idh} + X_{idh} + Z_{idh}) * GSE_{air,Needed\_ata,i} \leq GSE_{air,S}$$ for each *d* and *i* (4.69)

$$\sum_{h\in H}\sum_{i\in F}\sum_{d\in D} (Y_{idh} + X_{idh} + Z_{idh}) * GSE_{pow,Needed\_ata,i} \leq GSE_{pow,S}$$ for each *d* and *i* (4.70)

$$\sum_{h\in H}\sum_{i\in F}\sum_{d\in D} (Y_{idh} + X_{idh} + Z_{idh}) * GSE_{avi,Needed\_ata,i} \leq GSE_{avi,S}$$ for each *d* and *i* (4.71)

Pseudocode 4.11 is summarized below:

1. **Model Initialization (Step 5)**: an optimization model (gp.model) is created to structure the constraints and objectives.
2. **Define Decision Variables (Steps 6–8)**:
   - X_{idh}: binary variable representing whether an A-check is scheduled for an asset *i* on a specific day *d* and slot *h.*
   - Y_{idh}: binary variable for unscheduled maintenance on asset *i* for day *d* and slot *h.*
   - Z_{idh}: binary variable for a C-check on asset *i* for day *d* and slot *h.*

3. **Iterate Through Assets and Days (Steps 9–11)**

4. **Constraints**:

   i. **Station Slot Constraint (Step 12)**: The total number of maintenance tasks (X, Y, Z) across all assets and days must not exceed the total available station slots (H).

   ii. **Minimum Events Constraint (Steps 13–14)**: Ensure a minimum number of C-checks (KC) and A-checks (KA) are performed as required.

5. **Ground Support Equipment (GSE) Constraints (Steps 15–17)**: Ensure GSE resources (airframe, powerplant, and avionics) are not exceeded at any maintenance station (S).

6. **Technician (FTE) Constraints (Steps 18-20)**: ensure the FTE personnel (airframe, powerplant, and avionics) are not exceeded. This constraint accounts for all tasks across days and assets.

7. **Cost Function Definition (Step 24-30)**: The cost function is a summation of maintenance costs associated with early, baseline, and late actions for A-checks and C-checks and unscheduled maintenance occurrence.

8. **Objective Definition (Steps 31)**: the optimization model defines the objective function as the minimization of total maintenance cost (min(Cost)),

9. **Solver Invocation (Steps 32)**: The model is passed to the Gurobi optimizer (gurobi(model)), which processes the defined constraints and objectives to find the optimal solution.

10. Post-Optimization Calculations (Steps 33): the results from the solver are used to compute metrics such as dispatch reliability (Availability) to measure fleet readiness after the optimization.

11. Output Results Printing (Steps 34–37).

Pseudocode 4.11 – Case study 3: non-prescriptive objective function.

Input: operational data, maintenance data, hangars/stations data, fleet data

Output: fleet availability, operational revenue, maintenance cost and revenue for the non-prescriptive objective function

1: **operational_data**← operational data ▻ *Load operational data*

2: **fleet_data**← fleet data ▻ *Load fleet data*

3: **maintenance_data**← maintenance_data ▻ *Load maintenance data*

4: **stations_data**← stations_data ▻ *Load hangar data*

5: model←gp.model ▻ *Optimization start*

6: X_{idh} ←a_check(days, serial, slot binary) ▻ *A-check variable definition*

7: Y_{idh} ←unscheduled(days, serial, slot binary) ▻ *Unscheduled maint. variable definition*

8: Z_{idh} ←c_check(days, serial, slot binary) ▻ *C-check variable definition*

9: **for each** $i \in I$ ▻ *Iterate through assets*

10: **for each** $d \in D$ ▻ *Iterate through days*

11: **for each** $h \in H$ ▻ *Iterate through slots*

12: $\sum_{h\in H}\sum_{i\in F}\sum_{d\in D}(X+Y+Z) \leq H$ ▻ *Station slot constraint*

13: $\sum_{h\in H}\sum_{i\in F}\sum_{d\in D} Z_{idh} \geq K_C$ ▻ *C_check minimum events constraint*

14: $\sum_{h\in H}\sum_{i\in F}\sum_{d\in D} X_{idh} \geq K_A$ ▻ *A_check minimum events constraint*

15: $\sum_{h\in H}\sum_{i\in F}\sum_{d\in D}(Y_{idh}+X_{idh}+Z_{idh}) * GSE \quad \leq GSE_{air,S}$ ▻ *Airframe GSE cannot be surpassed*

16: $\sum_{h\in H}\sum_{i\in F}\sum_{d\in D}(Y_{idh}+X_{idh}+Z_{idh}) * GSE \quad \leq GSE_{pow,S}$ ▻ *Powerplant GSE cannot be surpassed*

17: $\sum_{h\in H}\sum_{i\in F}\sum_{d\in D}(Y_{idh}+X_{idh}+Z_{idh}) * GSE \quad \leq GSE_{avi,S}$ ▻ *Avionics GSE cannot be surpassed*

18: $\sum_{h\in H}\sum_{i\in F}\sum_{d\in D}(Y_{idh}+X_{idh}+Z_{idh}) FTE \quad \leq FTE_{air,S}$ ▻ *Airframe FTE cannot be surpassed*

19: $\sum_{h \in H} \sum_{i \in F} \sum_{d \in D} (Y_{idh} + X_{idh} + Z_{idh}) FTE \quad \leq FTE_{powr,S}$ ▻ *Powerplant FTE cannot be surpassed*

20: $\sum_{h \in H} \sum_{i \in F} \sum_{d \in D} (Y_{idh} + X_{idh} + Z_{idh}) FTE \quad \leq FTE_{avion,S}$ ▻ *Avionics FTE cannot be surpassed*

21: **end for** ▻ *End iteration through slots*

22: **end for** ▻ *End iteration through assets*

23: **end for** ▻ *End iteration through days*

24: **for each** $i \in I$ ▻ *Iterate through assets*

25: **for each** $d \in D$ ▻ *Iterate through days*

26: **for each** $h \in H$ ▻ *Iterate through slots*

27: $Cost = \sum X_{idh} * C_{early_A} * days\_before_A + \sum X_{idh} * C_{late_A} * days\_after_A + \sum X_{idh} * C_{baseline_A} + \sum Z_{idh} * C_{early_C} * days\_before_C + \sum Z_{idh} * C_{late_C} * days\_after_C + \sum Z_{idh} * C_{baseline_C} + \sum Y_{idh} * C_{baseline_B} + \sum Y_{idh} * C_{late_B} * days\_after_B$ ▻ *Objective function definition*

28: **end for** ▻ *End iteration through slots*

29: **end for** ▻ *End iteration through assets*

30: **end for** ▻ *End iteration through days*

31: *ObjectiveFunction* ← *min(Cost)* ▻ *Objective definition*

32: gurobi(model) ▻ *Solver definition*

33: Availability ← *Dispatch_reliability* ▻ *Post-optimization availab. calculation*

34: Print results ← *Print_availability* ▻ *Availability ouput*

35: Print results ← *Print_maintenance_cost* ▻ *Maintenance cost output*

36: Print results ← *Print_revenue* ▻ *Revenue output*

37: Print results ← *Print_maintenance_schedule* ▻ *Maintenance schedule output*

Pseudocode 4.12 is similar to pseudocode 4.11. The difference is in the objective function (step 29) which is prescriptive trying to maximize the difference between revenue and cost. The step 25 defines the equation revenue as being dependent on the operation variable O_{id} and the revenue per flight.

Pseudo-code 4.12 – Case study 3: prescriptive objective function.

Input: operational data, maintenance requirements, hangars data, fleet data

Output: fleet availability, operational revenue, maintenance cost and profit for the prescriptive objective function

operational_data← operational data ⊳ *Load operational data*

fleet_data← fleet data ⊳ *Load fleet data*

maintenance_data← maintenance_data ⊳ *Load maintenance data*

stations_data← stations_data ⊳ *Load hangar data*

model←gp.model ⊳ *Optimization start*

X_{idh} ←a_check(days, serial, slot, binary) ⊳ *A-check variable definition*

Y_{idh} ←unscheduled(days, serial, slot, binary) ⊳ *Unscheduled maint. variable definition*

Z_{idh} ←c_check(days, serial, slot, binary) ⊳ *C-check variable definition*

O_{idh} ←*Flight_assigned*(days, serial, slot, binary) ⊳ *Flight variable definition*

$\sum_{h\in H}\sum_{i\in F}\sum_{d\in D}(Y_{id}+X_{id}+Z_{id})FTE \quad \leq FTE_{air,S}$ ⊳ *Airframe FTE cannot be surpassed*

$\sum_{h\in H}\sum_{i\in F}\sum_{d\in D}(Y_{idh}+X_{idh}+Z_{idh})FTE \quad \leq FTE_{powr,S}$ ⊳ *Powerplant FTE cannot be surpassed*

$\sum_{h\in H}\sum_{i\in F}\sum_{d\in D}(Y_{idh}+X_{idh}+Z_{idh})FTE \quad \leq FTE_{avion,S}$ ⊳ *Avionics FTE cannot be surpassed*

for each $i \in I$ ⊳ *Iterate through assets*

  for each $d \in D$ ⊳ *Iterate through days*

    for each $h \in H$ ⊳ *Iterate through slots*

$\sum_{h\in H}\sum_{i\in F}\sum_{d\in D}(X+Y+Z) \leq H$ ⊳ *Station slot constraint*

$\sum_{h\in H}\sum_{i\in F}\sum_{d\in D} Z_{idh} \geq K_C$ ⊳ *C_check minimum events constraint*

$\sum_{h\in H}\sum_{i\in F}\sum_{d\in D} X_{idh} \geq K_A$ ⊳ *A_check minimum events constraint*

$\sum_{h\in H}\sum_{i\in F}\sum_{d\in D}(X_{idh} + O_{idh}) = 1$ ⊳ *No flight if a_check happens*

$\sum_{h\in H}\sum_{i\in F}\sum_{d\in D}(Y_{idh} + O_{idh}) = 1$ ⊳ *No flight if unscheduled maint. happens*

$\sum_{h\in H}\sum_{i\in F}\sum_{d\in D}(Z_{idh} + O_{idh}) = 1$ ⊳ *No flight if c_check happens*

$\sum_{h\in H}\sum_{i\in F}\sum_{d\in D}(Y_{idh}+X_{idh}+Z_{idh}) * GSE \quad \leq GSE_{air,S}$ ⊳ *Airframe GSE cannot be surpassed*

$\sum_{h\in H}\sum_{i\in F}\sum_{d\in D}(Y_{idh}+X_{idh}+Z_{id}h) * GSE \quad \leq GSE_{pow,S}$ ⊳ *Powerplant GSE cannot be surpassed*

$\sum_{h \in H} \sum_{i \in F} \sum_{d \in D} (Y_{id} + X_{id} + Z_{id}) * GSE \quad \leq GSE_{avi,S}$	▻ *Avionics GSE cannot be surpassed*
end for	▻ *End slots iteration*
end for	▻ *End day iteration*
end for	▻ *End assets iteration*
for each $i \in I$	▻ *Iterate through assets*
for each $d \in D$	▻ *Iterate through days*
for each $h \in H$	▻ *Iterate through slots*
$Revenue = \sum O_{idh} * \left(Revenue_{per\_seat} * Flight_{day} * Acft_{payload} * Occupation_{ratio} \right)_{i_d}$	▻ *Revenue definition*
$Cost = \sum X_{idh} * C_{early_A} * days\_before_A + \sum X_{idh} * C_{late_A} * days\_after_A + \sum X_{idh} * C_{baseline_A} + \sum Z_{idh} * C_{early_C} * days\_before_C + \sum Z_{idh} * C_{late_C} * days\_after_C + \sum Z_{idh} * C_{baseline_C} + \sum Y_{idh} * C_{baseline_B} + \sum Y_{idh} * C_{late_B} * days\_after_B$	▻ *Cost definition*
end for	▻ *End iteration through slots*
end for	▻ *End iteration through assets*
end for	▻ *End iteration through days*
ObjectiveFunction ← *max(Rev-Cost)*	▻ *Objective definition*
gurobi(model)	▻ *Solver definition*
Availability ← *Dispatch_reliability*	▻ *Post-optimization availab. calculation*
Print results ← *Print_availability*	▻ *Availability ouput*
Print results ← *Print_maintenance_cost*	▻ *Maintenance cost output*
Print results ← *Print_revenue*	▻ *Revenue output*
Print results ← *Print_maintenance_schedule*	▻ *Maintenance schedule output*

The next section discusses the results of the third case study, focusing on performance metrics in both prescriptive and non-prescriptive scenarios.

4.3.5 Results

This section presents the results of the experiment. Figure 4.13 depicts an extract of the prescription provided by the algorithm. The outputs highlight the maintenance recommendations for an ATR-72-600 aircraft with serial number 1093, specifically for C-Check. It advises executing two tasks on day 193 at the Pampulha maintenance facility. Task 21.12, an Operational Check, requires the use of a 21.2ATR air conditioning service cart, with 12 Airframe FTEs allocated, while no Avionics or Powerplant FTEs are needed. Similarly, Task 21.13, which involves Component Testing and Replacement, also requires 12 Airframe FTEs and no Avionics or Powerplant FTEs, using 21.3ATR Environmental Control System (ECS) testers. These recommendations ensure optimal resource allocation and adherence to maintenance requirements, leveraging specific Ground Support Equipment (GSE) for efficient task execution. Full list of recommendation for C-check, A-check and unscheduled maintenance are available on Appendix D.

```
Serial: 1093
Model: ATR-72-600
Maintenance: Check C
Recommendation:
  Execute Task 21.12 (Operational Check) on day 193 in Pampulha -
    Avionics FTE expended: 0
    Airframe FTE expended: 12
    Powerplant FTE expended: 0
    GSE: 21.2ATR Air conditioning service cart
  Execute Task 21.13 (Component Testing and Replacement ) on day 193 in Pampulha -
    Avionics FTE expended: 0
    Airframe FTE expended: 12
    Powerplant FTE expended: 0
    GSE: 21.3ATR Environmental control system (ECS) testers
```

Figure 4.13 – Maintenance task prescriptive recommendation for C-check. (Source: this author)

Focused on performance metrics across both prescriptive and non-prescriptive scenarios, for each simulation, it is presented solver execution time, availability, revenue gains, and maintenance costs. Table 4.35 presents the results.

The prescriptive strategy demonstrates an improvement in operational outcomes at the cost of increased execution time. While the execution time for the prescriptive approach is 780 seconds, compared to just 6 seconds for the non-prescriptive approach, this trade-off yields substantial benefits. Dispatch reliability improves from 73.12% to 99.53%, reflecting a 26.41% increase, indicating more consistent and dependable operations and the achievement of a dispatch reliability which is comparable to the best industry practices[162,163]. Profitability under the prescriptive approach rises dramatically, with an additional $297.132.592 in profit, driven by a revenue boost of $290.651.904 and a cost reduction of $6,480,688.

Table 4.35 – Case Study 3 results.

Metric	Non-prescriptive	Prescriptive	Difference
Execution time	6 seconds	780 seconds	774 seconds
Dispatch reliability	73,12%	99,53%	26,41%
Profitability	$ 97.206.888,00	$ 394.339.480,00	$ 297.132.592,00
Revenue	$ 119.810.304,00	$ 410.462.208,00	$ 290.651.904,00
Cost	$ 22.603.416,00	$ 16.122.728,00	$ 6.480.688,00

4.4 Results Summary

The Framework proved to be effective in both commercial aviation and healthcare case studies. Table 4.36 provides a summary of how each experiment addressed the key research questions, demonstrating the versatility and effectiveness of the Holistic Optimization Framework for PsM. Each experiment was designed to evaluate specific aspects of the framework's capabilities across different operational contexts, providing comprehensive insights into its potential applications.

Experiment 1 focused on evaluating maintenance operations within the aviation sector, demonstrating how the framework optimizes maintenance resources. It also addressed maintenance imperfections by considering the wiener equation. The results showed an improvement in aircraft availability (+35.16%) and profitability (+0.81%), validating the framework's ability to provide an optimized maintenance recommendation.

Experiment 2 extended the framework to the healthcare sector during a pandemic. By modeling hospital operations and patient admissions, the experiment illustrated the method's ability to optimize resources and support decisions in critical situations. The framework improved potential survivorship by 65%, emphasizing its value in life-critical scenarios and highlighting its scalability.

Experiment 3 revisited the aviation sector with a focus on short-term (14 days) operations and variability of support across hubs. The results revealed an increase in profitability (+406%) and dispatch reliability (+26.41%), reaffirming the value of prescriptive maintenance in improving both operational and financial outcomes.

Together, these experiments illustrate how the PsM framework addresses the study's core research questions, from optimizing maintenance resources to adapting across industries, and delivering data-driven, actionable insights to improve efficiency and outcomes.

Table 4.36 –Results summary.

Research questions		**Experiment 1**	**Experiment 2**	**Experiment 3**
Are maintenance resources considered?	Infrastructure	✓	✓	✓
	Labor			✓
	Tools			✓

Research questions		Experiment 1	Experiment 2	Experiment 3
Are maintenance imperfections considered?		✓		
Is the method extensible to different assets?		✓	✓	✓
Is the method adaptable to different industries (health/aerospace)?		✓	✓	✓
Does it provide optimized maintenance course of action?		✓	✓	✓
Are maintenance and operations efficiency improved?	Potential Survivorship	Not applicable	707 (+65%)	Not applicable
	Availability	99,84% (+35,16%)	Not applicable	99,53% (+ 26,41%)
	Profitability	$ 15.223.935,12 (+0,81%)	Not applicable	$ 297.132.592,00 (+406%)

The results presented in this Chapter show the practical impact and adaptability of the framework. By addressing research questions through experimental scenarios, this study has demonstrated the framework's potential to enhance operations, resource allocation, and adapt to diverse industries and assets. However, while these findings highlight the framework's potentials, they also reveal key challenges and limitations that must be addressed. Next Chapter is a reflection about the broader implications of this research, its constraints, and the future directions that could further extend the reach and impact of PsM.

5 Conclusion

This research establishes the Holistic Optimization Framework for Prescriptive Maintenance as a pivotal solution for addressing the challenges faced by industries operating in dynamic environments. By combining predictive analytics, optimization algorithms, and resource allocation concepts, this framework goes beyond traditional maintenance approaches to prescribe actionable recommendations tailored to real-world constraints.

Through the validation in three scenarios— two scenarios addressing regional airline operations and one adressing public health pandemic response—this thesis demonstrates the versatility and scalability of the PsM framework. In the aviation context, the experiments demonstrated that the framework is adaptable to assets of different technological maturities, provides optimized maintenance and operational course of actions considering available resources. Implementing this framework industry-wide could enable airlines to enhance operational efficiency by optimizing maintenance schedules, reducing downtimes, and improving asset availability, fostering effective resources deployment, delays, minimization and increase profitability, even amidst workforce shortages and stringent sustainability goals.

In public health, the framework's application in a pandemic case study highlights its ability to allocate critical resources effectively, prioritize patient admissions, and optimize hospital operations while demonstrating its scalability to different industries. Municipal health departments could adopt this framework to improve responsiveness during crises, ensure equitable distribution of care resources, and potentially increasing patients' survival rates. Beyond emergencies, this adaptability suggests long-term improvements in health system efficiency, resource planning, and resilience against future challenges are achievable with the framework.

The Holistic Optimization Framework for Prescriptive Maintenance developed in this research demonstrates its potential as a paradigm towards holistic decision-making in complex and dynamic environments. However, as with any new paradigm, this work is not without its limitations, nor is it the final word in prescriptive maintenance methodology, and, as presented in Figure 5.1, more experiments are needed to test material constraints and explore other prescriptive methods to manage more parameters. Thus, the insights gained from this research reveal both the vast potential of the framework and the areas where future exploration is necessary to address current constraints and expand its applicability, as can be seen in the following Sections 5.1 and 5.2.

Figure 5.1 – Hospital network location considered in the experiment. (Source: this author)

5.1 Limitations

This research faced limitations that impacted the ability to fully validate the proposed algorithm under more realistic conditions. A significant constraint was the lack of reliable data regarding health personnel availability and equipment, such as ventilators, at the peak of the epidemic. Additionally, while the MILP approach demonstrated its effectiveness in the case studies addressed, it may be inadequate for addressing more complex scenarios such as multiple failure modes per equipment, if hundred equipment are considered in a large fleet. The following limitations highlight these challenges:

- The lack of reliable data related the to the health personnel as well as the data related to the equipment (ventilators) available at each hospital at the time of the epidemic did not allow to fully test the algorithm. Real data would be needed to obtain feasible results.
- The lack of data was also noticed for the airliner experiment. No public, up to date data regarding asset’s RUL, MTBUR and MTBUF could be accessed. Similarly, no exact numbers about available resources at each hangar could be found, although values could be estimated indirectly through public sources and industry experts.
- MILP may not be suitable for more complex real-case scenarios that consider failure (such as several failure modes per equipment), or considerations of more detailed support systems such as shop repair personnel, logistic turn-around time, and material stock availability.
- Recommendations based on optimization are not feasible for AI since not a lot of data is available to train AI algorithms.
- Health experiment assumes that optimal admission duration is directly related to survivorship. This is a simplification, as other factors such as human genetics, existing pre-conditions and order of arrival play an important role in survivability chances. The presented result then is just a potential number of survivors, indicating that more people could be assisted for longer than the historical data showed.
- If for physical assets, such as machines and vehicles, operation can be reorganized, stopped or increased, and their degradation estimated through PHM systems that continuously monitor them, that is not the case for humans. Although wearables are opening possibilities to do that, PHM for humans is still not available so the possibility to provide a course of action related to human operation is still very limited.

The findings of this research provide valuable insights into optimization strategies for critical scenarios. However, the simplifications and assumptions, particularly in the health-related experiment, mean that the results are indicative rather than definitive. The challenges in integrating human-related factors and the absence of PHM systems for humans illustrate the need for future work to address these gaps, as presented in the next Section.

5.2 Future Work

Leveraging the limitations and insights of this research, there are promising directions for future work that can refine and expand the proposed framework. As operational contexts become increasingly complex and interconnected, addressing challenges such as equipment failures, material logistics, and computational constraints will be crucial. Furthermore, the growing integration of advanced technologies and prescriptive analytics methods, such as AI, heuristics, and digital twins, offers exciting opportunities to enhance the framework. Looking ahead, the future work could address the following themes:

- The refinement of the optimization model with the adoptions of heuristics to address a wider array of maintenance complexities, down to the hundreds of equipment failures, and deal with more complexity related to material logistic uncertainties.
- In the health experiment became clear that as the number of assets and support characteristics grew, the processing time could be a strong limitation. Future work could explore other methods such as genetics algorithms to get solutions faster.
- Although this author does not see potential in AI to provide optimized recommendations based on real-time asset state, inputs based on artificial intelligence analysis providing failure prognostics or troubleshooting diagnostics to improve prescription represent an opportunity for future development.
- Integration with AR/VR systems and integrated electronic technical publications (IETP) to provide maintenance recommendations to technicians should also be explored.

- If this study has focused somewhere in the middle between support environment and operations, future work could focus on the MRO “one-day problem”: in this context, the MRO represents the operational universe with resources that must be optimally deployed to provide maintenance to the aircraft that is arriving to undergoes maintenance. Similarly, for the health industry, the hospital can be seen as a support organization with various resources that need to be continuously optimized to provide the best health care possible (“the emergency room problem”).
- As healthcare is shifting towards more proactive approaches with the advent of wearables that monitor vital signs, the research could focus on the inclusion of a model simulating “PHM for humans”, to evaluate how this prognostic technology, coupled with a prescriptive framework, could provide better care and potentially save more lives by recommending the best course of action to patients and health practitioners, leveraging real-time data.

Future research in this domain holds significant potential to revolutionize industry 4.0 operations, including the healthcare systems. By leveraging advancements in AI and wearables, the proposed framework can evolve into a powerful tool for addressing complex, real-time challenges in the health industry.

Through continuous exploration and refinement, this framework has the potential to serve as pillar for advancing prescriptive strategies across industries. By embracing PsM, organizations can shift from reactive and scheduled maintenance approaches to proactive, data-driven decision-making that holistically integrates maintenance and operations. This paradigm not only drives operational excellence but also promotes long-term sustainability, positioning industries to meet the challenges of an increasingly dynamic and interconnected world.

6 References

[1] NEMETH, T. *et al*. PriMa-X: A reference model for realizing prescriptive maintenance and assessing its maturity enhanced by machine learning. *Procedia CIRP*, v.72, p.1039–1044, 2018. DOI: https://doi.org/10.1016/j.procir.2018.03.280

[2] JONES, D. *et al*. Characterizing the digital twin: A systematic literature review. *CIRP Journal of Manufacturing Science and Technology*, v. 29, p. 36–52, 2020. DOI: https://doi.org/10.1016/j.cirpj.2020.02.002

[3] YEUNG, A. W. K. Identification of seminal works that built the foundation for functional magnetic resonance imaging studies of taste and food. *Current Science*, v.113, n.7, p. 3, 2017.

[4] MAGUIRE, M.; DELAHUNT, B. Doing a thematic analysis: a practical, step-by-step guide for learning and teaching scholars. *AISHE-J*, v.9, n.3, 3351, 2017. DOI: http://ojs.aishe.org/index.php/aishe-j/article/view/335

[5] ANSARI, F.; GLAWAR, R.; NEMETH, T. PriMa: A prescriptive maintenance model for cyber-physical production systems. *International Journal of Computer Integrated Manufacturing*, v.32, n.4-5, p. 482–503, 2019. DOI: https://doi.org/10.1080/0951192X.2019.1571236

[6] ERRANDONEA, I.; BELTRÁN, S.; ARRIZABALAGA, S. Digital Twin for maintenance: A literature review. *Computers in Industry*, v.123, 103316, 2020. DOI: https://doi.org/10.1016/j.compind.2020.103316

[7] CHOUBEY, S.; BENTON, R. G.; JOHNSTEN, T. A Holistic end-to-end prescriptive maintenance framework. *Data-Enabled Discovery and Applications*, v.4, n.1, 11, 2020. DOI: https://doi.org/10.1007/s41688-020-00045-z

[8] MATTIOLI, J.; PERICO, P.; ROBIC, P.-O. Artificial Intelligence based asset management. *In*: IEEE INTERNATIONAL CONFERENCE OF SYSTEM OF SYSTEMS ENGINEERING, 15th., 2020. *Proceedings* […]. Piscataway: IEEE, 2020.p. 151–156. DOI: https://doi.org/10.1109/SoSE50414.2020.9130505

[9] GLAWAR, R. *et al*. Conceptual design of an integrated autonomous production control model in association with a Prescriptive Maintenance Model (PriMa). *Procedia CIRP*, v.80, p. 482–487, 2019. DOI: https://doi.org/10.1016/j.procir.2019.01.047

[10] ORR, D. A. *New concepts for provisioning parameter estimates*: maintenance factors and replacement rates part I. Alexandria, VA: Army Logistic Management Center, U.S., 1976. (IRQ-TR-77-3).

[11] SILVA, G. Pump failure mode forecasting through the use of an integrated diagnostic methodology. *SAE Technical Paper*, 861307, 1986. DOI: https://doi.org/10.4271/861307

[12] WILLIAMS, P. B.; SWANSSON, M. L.A new approach to flood protection design and riparian management. *In:* ABELL, Dana L. (Coord). *Proceedings of the California Riparian Systems Conference:* protection, management, and restoration for the 1990s; 1988 Sept. 22-24;Davis, CA. Berkeley, CA: Pacific Southwest Forest and Range Experiment Station, Forest Service, U.S. Department of Agriculture, 1989. p. 40-46 (Gen. Tech Rep. PSW-110).

[13] HARRIS, S. E.; SLATE, E. V. Lamp Ray: Ship hull assessment for value, safety and readiness. *In*: OCEANS, MTS/IEEE. RIDING THE CREST INTO THE 21TH CENTURY.

CONFERENCE AND EXHIBITION, 1999, Seatlle. *Proceedings* […]. Piscataway: IEEE, 1999. p. 493–500. DOI: https://doi.org/10.1109/OCEANS.1999.799792

[14] SAUER, O. Developments and trends in shopfloor-related ICT systems. *In*: IEEE INTERNATIONAL CONFERENCE ON INDUSTRIAL ENGINEERING AND ENGINEERING MANAGEMENT, 2014. *Proceedings* […]. Piscataway: IEEE, 2014. p. 1352-1356. DOI: https://doi.org/10.1109/IEEM.2014.7058859

[15] LINDEN, A. *Big Data:* alles hype! Oder nicht? Gartner45 Webinar, of 28 november 2013.

[16] KHOSHAFIAN, D. S.; ROSTETTER, C. *Digital prescriptive maintenance:* Disrupting manufacturing value streams through Internet of Things, big data, and dynamic case management. U.S.: PEGA, 2015. 20 p. whitepaper

[17] ANSARI, F.; GLAWAR, R.; SIHN, W. Prescriptive Maintenance of CPPS by integrating multimodal data with dynamic Bayesian networks. *Machine Learning for Cyber Physical Systems*, v.11, p.1–8, 2017. DOI: https://doi.org/10.1007/978-3-662-59084-3_1

[18] KOHL, L. *Design and development of Automatic Recommendation Generation Module of Prescriptive Maintenance Model (AutoPriMa)*. 2019. 121 p. Thesis (PhD in Engineering) - Vienna University of Technology, Vienna, 2019

[19] LEMOINE, D.; CASTANIER, B. How to use prescriptive maintenance to construct robust master production schedules. *In*: EUROPEAN SAFETY AND RELIABILITY CONFERENCE, 31st., 2021. *Proceedings* […]. [*S. l.*]: ESREL, 2021. p. 3280–3286. DOI: https://doi.org/10.3850/978-981-18-2016-8_693-cd

[20] GAO, G. *et al*. An Intelligent Health diagnosis and Maintenance Decision-making approach in Smart Manufacturing. *Reliability Engineering*: System Safety, v.216, 107965, Dec. 2021. DOI: https://doi.org/10.1016/j.ress.2021.107965

[21] SCHENKELBERG, K.; SEIDENBERG, U.; ANSARI, F. Analyzing the impact of maintenance on profitability using dynamic Bayesian networks. *Procedia CIRP*, v. 88, p. 42–47, 2020. DOI: https://doi.org/10.1016/j.procir.2020.05.008

[22] CHOUBEY, S.; BENTON, R.; JOHNSTEN, T. Dynamic thresholding leading to optimal inventory maintenance. *In:* IEEE INTERNATIONAL CONFERENCE ON BIG DATA, 2020, Atlanta. *Proceedings* […]. Piscataway: IEEE, 2020.p. 4112–4121. DOI: https://doi.org/10.1109/BigData50022.2020.9378469

[23] KOVACS, K. *et al*. A multi-level model for realizing data-driven maintenance in manufacturing enterprises: Use case of Jewelry Production. *Procedia CIRP*, v. 104, 1553–1558, 2021. DOI: https://doi.org/10.1016/j.procir.2021.11.262

[24] ERRANDONEA, I. *et al*. A Maturity model proposal for industrial maintenance and its application to the railway sector. *Applied Sciences*, v.12, n.16, 8229, 2022. DOI: https://doi.org/10.3390/app12168229.

[25] JOVANOVIC, A.; AUERKARI, P.; BAREISS, J. M. Practical determination of probability of failure in risk-based inspection and life management of coal power plants. *In*: SHIBLI, A. (ed.). *Coal power plant materials and life assessment*. Amsterdam: Elsevier, 2014. p. 288-317. DOI: https://doi.org/10.1533/9780857097323.2.288

[26] SINGH, R.; VRANA, J. NDE 4.0 -What Happens on This Bus? *Canadian Institute for* Non-Destructive Evaluation, v.42, n. 3, p. 15-22, 2021. Available at: https://www.researchgate.net/publication/354005848_NDE_40_-What_Happens_on_This_Bus. Accessed on: Jan 30, 2024.

[27] ELLIS, S.; SANTAGATE, J.; MORRIS, H. D. *IoT-enabled analytic applications revolutionize supply chain planning and execution.* Framingham, MA: IDC, 2015. p. 1-13. IDC 259697. White paper

[28] VYAS, D. A.; BHATT, D.; JHA, D. IoT Trends, challenges and future scope. *International Journal of Computer Science and Communications*, v.*7*, n.1, p. 186-197, 2016.

[29] NIKOLAEV, S. *et al*. data-driven and physics-based modelling for prescriptive maintenance of gas-turbine power plant. *In*: FORTIN, C.*et al*. (ed). *Product lifecycle management in the Digital Twin Era*. Cham, 2019. p. 379-388 DOI: https://doi.org/10.1007/978-3-030-42250-9_36

[30] STRACK, B. *et al*. Prescriptive maintenance for onshore wind turbines. *In*: CONFERENCE ON PRODUCTION SYSTEMS AND LOGISTICS, 2nd., 2021, Hannover. *Proceedings* […]. Hannover: Leibniz University Hannover, 2021. DOI: https://doi.org/10.15488/11282

[31] DUTTA, A.; KARIMI, I. A.; FAROOQ, S. PROAD (Process Advisor): A health monitoring framework for centrifugal pumps. *Computers Chemical Engineering*, v.163, 107825. 2022. DOI: https://doi.org/10.1016/j.compchemeng.2022.107825

[32] FOX, H. *et al*. A Review of predictive and prescriptive offshore wind farm operation and maintenance. *Energies*, v. 15, n.2, 504, 2022. DOI: https://doi.org/10.3390/en15020504

[33] VANDERSCHUEREN, T.; BOUTE, R.; VERDONCK, T.; BAESENS, B.; VERBEKE, W. *Prescriptive maintenance with causal machine learning.* Ithaca: arXiv Operational Status, Cornell University´s, 2022. DOI: https://doi.org/10.48550/arXiv.2206.01562

[34] GORDON, C. A. K. *et al*. Data-Driven prescriptive maintenance: failure prediction using ensemble support vector classification for optimal process and maintenance scheduling. *Industrial Engineering Chemistry Research*, v.59, n. 44, p. 19607–19622, 2020. DOI: https://doi.org/10.1021/acs.iecr.0c03241

[35] GORDON, C. A. K.; PISTIKOPOULOS, E. N. DATA-DRIVEN prescriptive maintenance toward FAULT-TOLERANT MULTIPARAMETRIC control. *AIChE Journal*, v.68, n.6, p.1-12, 2022. DOI: https://doi.org/10.1002/aic.17489

[36] MOMBER, A. W. *et al*. A Digital Twin concept for the prescriptive maintenance of protective coating systems on wind turbine structures. *Wind Engineering*, v.46, n.3, p. 949–971, Dec. 2021. DOI: https://doi.org/10.1177/0309524X211060550

[37] PETROUTSATOU, K.; LADOPOULOS, I. Integrated Prescriptive Maintenance System (PREMSYS) for construction equipment based on productivity. *IOP Conference Series: Materials Science and Engineering*, v. 1218, n.1, 012006, 2022. DOI: https://doi.org/10.1088/1757-899X/1218/1/012006

[38] LORENTE, Q. *et al*. Development of a digital twin for collaborative decision-making, based on a multi-agent system: Application to prescriptive maintenance. *INCOSE International Symposium*, v.32, p. 109-117, 2022. DOI: https://doi.org/10.1002/iis2.12875

[39] STRACK, B. *et al*. Sociotechnical implementation of prescriptive maintenance for onshore wind turbines. *In*: HAWAII INTERNATIONAL CONFERENCE ON SYSTEM SCIENCES, 55th.,2022. *Proceedings* […]. [*S. l.*]: HICSS, 2022. p. 1288-1297. DOI: https://doi.org/10.24251/HICSS.2022.158

[40] BÜSSOW, R.; HAIN, B.; AL NUAIMI, I. Innovative approach to build a scalable hybrid model for prescriptive maintenance. *In*: INTERNATIONAL PETROLEUM EXHIBITION;

CONFERENCE, 2021, Abu Dhabi. *Proceedings* […]. Texas: ADIPEC, 2021. DOI: https://doi.org/10.2118/208031-MS

41 GOETZ, W. The path to prescriptive maintenance: Three steps to drive reliability while preparing for IIoT. *Plant Engineering*, v. 71, n. 4, 26, 2017.

42 HOSKE, Mark T. IIoT avoids downtime: Remote monitoring, sensors, analytics and real-time intelligence is helping in the manufacture, use, and repair motors and attached critical assets to avoid downtime with prescriptive maintenance. *Control Engineering*, v. 66, n. 8, p. 22, Aug. 2019, Available at: https://www.link.gale.com/apps/doc/A597810239/AONE?u=googlescholar;sid=googleScholar;xid=21f4430a. Accessed on: Mar 5, 2023.

43 KOOPS, L. Optimized maintenance decision-making – a simulation-supported prescriptive analytics approach based on probabilistic cost-benefit analysis. *European Conference of the Prognostics and Health Management Society*, v.5, n.1, p. 1-14, 2020. DOI: https://doi.org/10.36001/phme.2020.v5i1.1269

44 KARIM, R.; WESTERBERG, J.; GALAR, D., ; KUMAR, U. Maintenance analytic: the new know in maintenance. *IFAC-PapersOnLine*, v.49, n. 28, p. 214–219, 2016. DOI: https://doi.org/10.1016/j.ifacol.2016.11.037

45 BOKRANTZ, J. *et al*. Maintenance in digitalised manufacturing: Delphi-based scenarios for 2030. *International Journal of Production Economics*. 191, p. 154-169, Jun 2017. https://linkinghub.elsevier.com/retrieve/pii/S092552731730172X. Acessed on: Nov 06, 2022.

46 SIEMENS. *MindSphere for prescriptive maintenance*. *S. l.*: Siemens, 2019. Available at: https://www.plm.automation.siemens.com/media/global/pt/Siemens%20MindSphere%20for%20Prescriptive%20Maintenance_tcm70-65551.pdf Acessed on: Nov 06, 2022.

47 SITSCAPE. *Prescriptive-Maintenance.* [*S. l.*]: SitScape, 2018. Available at: https://www.sitscape.com/wp-content/uploads/2018/01/SitScape-Prescriptive-Maintenance-Whitepaper.pdf Acessed on: Nov 2022.

48 MATYAS, K. *et al*. A procedural approach for realizing prescriptive maintenance planning in manufacturing industries. *CIRP Annals*, v. 66, n.1, p.461–464, 2017. DOI: https://doi.org/10.1016/j.cirp.2017.04.007

49 CONSILVIO, A. *et al*. Prescriptive maintenance of railway infrastructure: from data analytics to decision support *In*: INTERNATIONAL CONFERENCE ON MODELS AND TECHNOLOGIES FOR INTELLIGENT TRANSPORTATION SYSTEMS, 6th., 2019, Cracow. *Proceedings* […]. Piscataway: IEEE, 2019. p. 1–10. *(MT-ITS)* DOI: https://doi.org/10.1109/MTITS.2019.8883331

50 LIU, B. *et al*. A dynamic prescriptive maintenance model considering system aging and degradation. *IEEE Access*, v.7, p. 94931–94943, 2019. DOI: https://doi.org/10.1109/access.2019.2928587

51 MARQUES, H.; GIACOTTO, A. *Prescriptive maintenance*: building alternative plans for smart operations. *In*: AEROSPACE TECHNOLOGY CONGRESS, 10th., 2019. Stockholm. *Proceedings* […]. Linköpings: Linköpings Universited, 2019.p.231–236. DOI: https://doi.org/10.3384/ecp19162027

52 LEPENIOTI, K. *et al*. Prescriptive analytics: Literature review and research challenges. *International Journal of Information Management*, v.50, p. 57–70, 2020. DOI: https://doi.org/10.1016/j.ijinfomgt.2019.04.003

[53] GRIJALVO MARTÍN, M. *et al*. New business models from prescriptive maintenance strategies aligned with sustainable development goals. *Sustainability*, v.13, n.1, 216, 2020. DOI: https://doi.org/10.3390/su13010216

[54] MEISSNER, R.; MEYER, H.; WICKE, K. Concept and economic evaluation of prescriptive maintenance strategies for an automated condition monitoring system. *International Journal of Prognostics and Health Management*, v. 12, n.3, p. 1-17, 2021. DOI: https://doi.org/10.36001/ijphm.2021.v12i3.2911

[55] GIACOTTO, A. *et al*. The Need for Ecosystem 4.0 to support maintenance 4.0: an aviation assembly line case. *Applied Sciences*, v.11, n.8, 3333, 2021. DOI: https://doi.org/10.3390/app11083333

56 MEISSNER, R.; RAHN, A.; WICKE, K. Developing prescriptive maintenance strategies in the aviation industry based on a discrete-event simulation framework for post-prognostics decision making. *Reliability Engineering; System Safety*, v.214, 107812, 2021. DOI: https://doi.org/10.1016/j.ress.2021.107812

[57] CHO, A. D.; CARRASCO, R. A.; RUZ, G. A. Improving prescriptive maintenance by incorporating post-prognostic information through chance constraints. *IEEE Access*, v.10, p. 55924–55932, 2022. DOI: https://doi.org/10.1109/ACCESS.2022.3177537

[58] WESENDRUP, K.; HELLINGRATH, B. A prescriptive maintenance aligned production planning and control reference process. *ECIS 2022 Research Papers*. 51. Available at: https://aisel.aisnet.org/ecis2022_rp/51 Acessed on: Nov 06, 2022.

[59] BIEBL, F. *et al*. A conceptual model to enable prescriptive maintenance for etching equipment in semiconductor manufacturing. *Procedia CIRP*, v.*88*, p.64–69, 2020. DOI: https://doi.org/10.1016/j.procir.2020.05.012

[60] PADOVANO, A. *et al*. A prescriptive maintenance system for intelligent production planning and control in a smart cyber-physical production line. *Procedia CIRP*, v.104, p. 1819–1824, 2021. https://doi.org/10.1016/j.procir.2021.11.307

[61] CHOUBEY, S.K.; BENTON, R.G.; JOHNSTEN, T. Prescriptive equipment maintenance: a framework. *In*: IEEE INTERNATIONAL CONFERENCE ON BIG DATA, 2019. *Proceedings* […]. Piscataway: IEEE, 2019. p. 4366-4374.

[62] DIAS LONGHITANO, P. *et al*.. Proposition of a generic decision framework for prescriptive maintenance. *In*: PINTO, J. O. P. *et al*. (ed.). *15th WCEAM Proceeding*. WCEAM 2021. Cham: Springer, 2022. p. 263–273. DOI: https://doi.org/10.1007/978-3-030-96794-9_24

[63] THAM, C.-K.; SHARMA, N. Prescriptive maintenance using Markov decision process and GPU-accelerated edge computing. *In:* MUKHERJEE, A. *et al*. (ed.). *Mobile edge computing* Cham: Springer, 2021. p. 167-181. DOI: https://doi.org/10.1007/978-3-030-69893-5_8

[6]4 VANDERSCHUEREN, T. *et al*. Failure prediction vs. Maintenance prescription: Optimizing maintenance interventions by learning individual treatment effects. *In*: INTERNATIONALWORKINGSEMINAR ON PRODUCTION ECONOMICS,22nd., 2022, Innsbruck. *Proceedings* […]. [*S. l.*: *s. n.*], 2022. p. 1-16 DOI: https://doi.org/pre-print

[65] KOUKARAS, P. *et al*. Proactive buildings: a prescriptive maintenance approach. *In*: MAGLOGIANNIS, I. *et al*. (ed.). *Artificial Intelligence Applications and Innovations. AIAI 2022 IFIP WG 12.5* Cham: Springer, 2022. p. 289-300. DOI: https://doi.org/10.1007/978-3-031-08341-9_24

[66] KOHESTANI NEJAD, V. *Evaluation of prescriptive maintenance strategies for a tire pressure indication System (TPIS) assuming imperfect maintenance*. 2020. Thesis (M.Sc. Mechanical Engineering) - Technical University of Munich, Munich, 2020.(DLR-IB-MO-HF-2020-208).

[67] van de LOO, A. F. L. *A decision making framework to achieve pre- scriptive maintenance in the FMCG production industry. 2019.* Thesis (M.Sc. Mechanical Engineering) - Delft University of Technology, Delft, 2019

[68] PARASCHOS, S. *et al*. VisioRed: a visualisation tool for interpretable predictive maintenance. *In*: INTERNATIONAL JOINT CONFERENCE ON ARTIFICIAL INTELLIGENCE, 30th., 2021. *Proceedings* […]. [*S. l.*: *s. n.*], 2021. p. 5004–5007. DOI: https://doi.org/10.24963/ijcai.2021/713

[69] GULLO, L. J. Design for machine learning. *In*: GULLO, L. J.; J. DIXON, J. (ed). *Design for maintainability.* Hoboken*:* Wiley*,* 2021. p. 141–156. DOI: https://doi.org/10.1002/9781119578536.ch8

[70] JASIULEWICZ-KACZMAREK, M.; LEGUTKO, S.; KLUK, P. Maintenance 4.0 technologies – new opportunities for sustainability driven maintenance. *Polska Akademia Nauk*, v. 11, n.2, p.74-87, 2020. https://doi.org/10.24425/MPER.2020.133730

[71] BALTAZAR, C. I. M. *Prescriptive system for reconfigurable manufacturing systems considering variable demand and production rates.* 2020. 68 p. Dissertation (Mestrado Integrado em Engenharia Elétrica e de Computadores) – Faculdade de Engenharia da Universidade do Porto, Porto, 2020. https://hdl.handle.net/10216/132786

[72] SANG, G. M. *Predictive maintenance for industry 4.0*. Thesis (PhD) – Faculty of Science and Technology, Bournemouth University, Bournemouth 2021. Available at: http://eprints.bournemouth.ac.uk/36855/. Accessed on: Mar 05, 2023.

[73] LEE, J.; NI, J. *et al*. Intelligent maintenance systems and predictive manufacturing. *Journal of Manufacturing Science and Engineering*, v.142, n.11, 110805, 2020. DOI: https://doi.org/10.1115/1.4047856

[74] ALCAYAGA, A.; WIENER, M.; HANSEN, E. G. Towards a framework of smart-circular systems: An integrative literature review. *Journal of Cleaner Production*, v. 221, p. 622–634, 2019. DOI: https://doi.org/10.1016/j.jclepro.2019.02.085

[75] FILO, G. Analysis of neural network structure for implementation of the prescriptive maintenance strategy. *Material Research Proceedings*, v.24, p. 273–280, 2022. DOI: https://doi.org/10.21741/9781644902059-40

[76] CHILAMI, B. D. *et al*. Optimization of uses, production and overall cost of a plant through dynamic prescriptive maintenance. *International Journal of Research in Engineering and Science*, v.10, n.7, p. 7-12, 2022.

[77] DENG, H.; KHAN, S.; ERKOYUNCU, J. A. A framework for constructing a common knowledge base for human-machine system to perform maintenance tasks. *In*: INTERNATIONAL CONFERENCE ON THROUGH-LIFE ENGINEERING SERVICES, 11th., 2022, Cranfield. *Proceedings* […]. Cranfield: Cranfield University, 2022.

[78] JAIN, A. *et al*. Integrating the maintenance process: A framework to bridge design for maintenance to prescriptive maintenance. *In*: *SITRAER* AIR TRANSPORTATION SYMPOSIUM, 2022, São José dos Campos. *Proceedings* […]. São José dos Campos: SITRAER, 2022.

79 GARCIA FIGUEIREDO PINTO, D. *A military aircraft fleet support management model based on the optimal integration of predictive and scheduled maintenance*. 2022. Thesis (PhD in Field Technology of Management) - Instituto Tecnológico de Aeronáutica, São José dos Campos, 2022.

80 ANGLOU, F.-Z.; PONIS, S.; SPANOS, A. A machine learning approach to enable bulk orders of critical spare-parts in the shipping industry. *Journal of Industrial Engineering and Management*, v. 14, n.3, p. 604-621, 2021. DOI: https://doi.org/10.3926/jiem.3446

81 VENKATACHALAM, S. *et al*. Prescriptive analytics for swapping aircraft assignments at all Nippon Airways. Interfaces, *INFORMS*, v.50, n.2, p. 99–111, 2020. DOI: https://doi.org/10.1287/inte.2019.1016

82 NAKOUSI, C. *et al*. An asset-management oriented methodology for mine haul-fleet usage scheduling. *Reliability Engineering: System Safety,* v.180, p.336–344, 2018. DOI: https://doi.org/10.1016/j.ress.2018.07.034

83 LETURIONDO, U. *et al.* Architecture for hybrid modelling and its application to diagnosis and prognosis with missing data. *Measurement*, 108, 152–162, 2017. DOI: https://doi.org/10.1016/j.measurement.2017.02.003

84 ABRAMOVICI, M. *et al*. Predicting the behavior of solution alternatives within product improvement process. *Proceedings of the International Conference on Engineering Design*, v. 9 DS75-09, p. 397–406, 2013.

85 FLETCHER, J. D.; JOHNSTON, R. Effectiveness and cost benefits of computer-based decision aids for equipment maintenance. *Computers in Human Behavior*, v.18, n.6, p.717–728, 2002. DOI: https://doi.org/10.1016/S0747-5632(02)00026-2

86 LABIB, A.; WILLIAMS, G.; O'CONNOR, R. An intelligent maintenance model (system): An application of the analytic hierarchy process and a fuzzy logic rule-based controller. *Journal of the Operational Research Society*, v.49, n.7, p. 745–757, 1998. DOI: https://doi.org/10.1038/sj.jors.2600542

87 BEAUDOUIN, F. ; MUNIER, B.; SERQUIN, Y. Multi-attribute decision making and generalized expected utility in nuclear power plant maintenance. *In*: MACHINA, M. J.; MUNIER, B. (ed.). *Beliefs, interactions and preferences in decision making*. New York: Springer, 1999. p. 341–357. DOI: https://doi.org/10.1007/978-1-4757-4592-4_22

88 BROWN, D. Transforming unstructured data into useful information *In*: KUDIBA, S. (ed). *Big Data, mining, and analytics.* New York: Auerbach Publications, 2014. Chapter 10, p. 227–246. DOI:10.1201/B16666-14.

89 ANSARI, F.; KHOBREH, M.; SEIDENBERG, U.; SIHN, W. A problem-solving ontology for human-centered cyber physical production systems. *CIRP Journal of Manufacturing Science and Technology*, v. 22, p. 91–106, 2018. DOI: https://doi.org/10.1016/j.cirpj.2018.06.002

90 GALAR, Diego; KUMAR, Uday. Maintenance decision support systems. *In*: GALAR, Diego; KUMAR, Uday. *eMaintenance*: essential electronics tools for efficiency. London: Elsevier, 2017. Chapter 7, p. 371-474.

91 ARAMON BAJESTANI, M.; BECK, J. C. Scheduling a dynamic aircraft repair shop with limited repair resources. *Journal of Artificial Intelligence Research*, v.47, p. 35–70, 2013. DOI: https://doi.org/10.1613/jair.3902

[92] CONSILVIO, A. *et al*. On applying machine learning and simulative approaches to railway asset management: the earthworks and track circuits case studies. *Sustainability*, v.12, n.6, 2544, 2020. DOI: https://doi.org/10.3390/su12062544

[93] FILO, G. Analysis of neural network structure for implementation of the prescriptive maintenance strategy. *Material Research Proceedings*, v.24, p.273–280, 2022. DOI: https://doi.org/10.21741/9781644902059-40

[94] GAVRANIS, A.; KOZANIDIS, G. An exact solution algorithm for maximizing the fleet availability of a unit of aircraft subject to flight and maintenance requirements. *European Journal of Operational Research*, v.242, n.2, p. 631–643, 2015. DOI: https://doi.org/10.1016/j.ejor.2014.10.016

[95] KOZANIDIS, G.; GAVRANIS, A.; LIBEROPOULOS, G. Heuristics for maximizing fleet availability subject to flight; maintenance requirements. *In:* INTERNATIONAL CONFERENCE ON APPLICATIONS OF ADVANCED TECHNOLOGIES INTRANSPORTATION, 10th.,2008, Athens. Proceedings […]. Athens: National Technical University of Athens, 2008. v.5, p. 4040-4054.

[96] ROBERT, E. *et al*. Joint dynamic scheduling of missions and maintenance for a commercial heavy vehicle: Value of on-line information. *IFAC-PapersOnLine*, v.51, n.24, p. 837–842, 2018. DOI: https://doi.org/10.1016/j.ifacol.2018.09.672

[97] SCHROTENBOER, A. H.; URSAVAS, E. ; VIS, I. F. A. Mixed Integer Programming models for planning maintenance at offshore wind farms under uncertainty. *Transportation Research Part C: Emerging Technologies*, v.112, p.180–202, 2020. DOI: https://doi.org/10.1016/j.trc.2019.12.014

[98] SAFAEI, N.; BANJEVIC, D.; JARDINE, A. K. S. Workforce-constrained maintenance scheduling for military aircraft fleet: A case study. *Annals of Operations Research*, v.186, n.1, p. 295–316, 2011. DOI: https://doi.org/10.1007/s10479-011-0885-4

[99] ANSARI, F.; HOLD, P.; KHOBREH, M. A knowledge-based approach for representing jobholder profile toward optimal human–machine collaboration in cyber physical production systems. *CIRP Journal of Manufacturing Science and Technology*, v. 28, p. 87–106, 2020. DOI: https://doi.org/10.1016/j.cirpj.2019.11.005

[100] SILVESTRI, L. *et al.* Maintenance transformation through Industry 4.0 technologies: A systematic literature review. *Computers in Industry*, v. 123, 103335, 2020. DOI: https://doi.org/10.1016/j.compind.2020.103335

[101] CISTERNA, A. R. *Digital Twin for the management of wind power plants*. *In*: EUROPEAN CONFERENCE ON RENEWABLE ENERGY SYSTEMS, 10th., 2022, Istanbul. *Proceedings* […]. [*S. l.*: *s. n.*], 2022.

[102] AMERI, F. *et al.* (ed.). *Advances in production management systems. Production Management for the Factory of the Future:* IFIP WG 5.7 International Conference, APMS 2019, Austin, TX, USA, September 1–5, 2019, Proceedings, Part I. Cham: Springer, 2019. DOI: https://doi.org/10.1007/978-3-030-30000-5

[103] ARRIETA, A. B. *et al*. *Explainable Artificial Intelligence (XAI*): concepts, taxonomies, opportunities and challenges toward responsible AI. Ithaca: arXiv Operational Status, Cornell University, 2019. DOI: http://arxiv.org/abs/1910.10045

[104] PINCIROLI, L.; BARALDI, P.; ZIO, E. Maintenance optimization in industry 4.0. *Reliability Engineering and System Safety*, v.*234,* 109204, 2023. DOI: https://doi.org/10.1016/j.ress.2023.109204

[105] LEMES, L. C.; HVAM, L. Maintenance costs in the process industry: a literature review. *In:* IEEE INTERNATIONAL CONFERENCE ON INDUSTRIAL ENGINEERING AND ENGINEERING MANAGEMENT, 2019. *Proceedings* […]. Piscataway: IEEE, 2019. p.1481–1485. DOI: https://doi.org/10.1109/IEEM44572.2019.8978559

[106] ALBAKKOUSH, S.; PAGONE, E.; SALONITIS, K. Scheduling challenges within maintenance repair and overhaul operations in the Civil Aviation Sector. *In:* INTERNATIONAL CONFERENCE ON THROUG- LIFE ENGINEERING SERVICE, 9th., 2019, Crenfield. *Proceedings* […]. Amsterdam: Elsevier, 2020. DOI: https://doi.org/10.2139/ssrn.3718006

[107] COMPARE, M.; BARALDI, P.; ZIO, E. Challenges to IoT-Enabled predictive maintenance for industry 4.0. *IEEE Internet of Things Journal*, v.7, n. 5, p. 4585–4597, 2019. DOI: https://doi.org/10.1109/JIOT.2019.2957029

[108] ACHOUCH, M. *et al*. On predictive maintenance in industry 4.0: overview, models, and challenges. *Applied Sciences*, v.12, n. 16, 8081, 2022. DOI: https://doi.org/10.3390/app12168081

[109] COANDĂ, P.; AVRAM, M.; CONSTANTIN, V.A state of the art of predictive maintenance techniques. *IOP Conference Series: Materials Science and Engineering*, v. 997, n.1, 012039, 2020. DOI: https://doi.org/10.1088/1757-899X/997/1/012039

[110] ZHAO, J.; GAO, C.; TANG, T. A Review of sustainable maintenance strategies for single component and multicomponent equipment. *Sustainability*, v. 14, n.5, 2992, 2022. DOI: https://doi.org/10.3390/su14052992

[111] WAZLAWICK, R. S. *Metodologia de pesquisa para ciência da computação* 3ª ed. Rio de Janeiro: LTC, 2022.

[112] CANADAY, H. Japanese carriers make predictive maintenance progress. New York: Aviation Week, 2023 Available at: https://aviationweek.com/mro/emerging-technologies/japanese-carriers-make-predictive-maintenance-progress. Accessed on: May 08, 2023.

[113] BJERREGAARD, L. *ADE Launches new digital aftermarket product.* New York: Aviation Week, 2023. Available at: https://aviationweek.com/mro/emerging-technologies/ade-launches-new-digital-aftermarket-products . Accessed on: June 15, 2023.

[114] KHATAB, A. *et al*. Optimization of the joint selective maintenance and repairperson assignment problem under imperfect maintenance. *Comput. Ind. Eng.*, v. 125, p.413–422, 2018.

[115] INTERNATIONAL LABOUR ORGANIZATION. *Benchmarking of qualifications frameworks*: a report on potential comparability between the Bangladesh technical and vocational qualifications framework and qualifications frameworks of other countries of origin and destination of migrant workers. Bangladesh: ILO Country Office for Bangladesh, 2015. Available at: http://apskills.ilo.org/resources/benchmarking-of-qualifications-frameworks-a-report-on-potential-comparability-between-the-bangladesh-technical-and-vocational-qualifications-framework-and-qualifications-frameworks-of-other-countries-of-origin-and-destination-of-migrant-workers Accessed on: March 11, 2021.

[116] GUROBI OPTIMIZATION. *Run Gurobi across a broad range of computing platforms.* Gurobi Optimization, 2021. Available at: https://www.gurobi.com/downloads/. Accessed on: March 11, 2021.

[117] MATHWORKS. *MATLAB. Simulink.* U.S.: Mathworks, 2021. Available online: https://www.mathworks.com/products/matlab.html. Accessed on: March 11, 2021.

[118] MADEIRA, A.; MOUTINHO, V.; FUINHAS, J. A. Does waiting times decrease or increase operational costs in short and long-term? Evidence from Portuguese public hospitals. *European Journal of Health Economics*, v.22, n. 8, p. 1195–1216, 2021. DOI: https://doi.org/10.1007/s10198-021-01331-y

[11]9 SICILIANI, L.; STANCIOLE, A.; JACOBS, R. Do waiting times reduce hospital costs? *Journal of Health Economics*, v. 28, n.4, p. 771–780, 2009. DOI: https://doi.org/10.1016/j.jhealeco.2009.04.002

[120] MOSCELLI, G.; GRAVELLE, H.; SICILIANI, L. The effect of hospital choice and competition on inequalities in waiting times. *Journal of Economic Behavior Organization*, v. 205, p. 169–201, 2023. DOI: https://doi.org/10.1016/j.jebo.2022.10.040.

[121] WELTCHECK, MALLHAN AND WELTCHECK. *How to calculate lost wages from medical malpractices*. Lutherville: Medical Malpractice Law Firm, 2016. https://wmwlawfirm.com/blog/how-calculate-lost-wages-medical-malpractice/ Accessed on :June 20, 2023**.**

[122] BEN CRUMP. *How is death compensation calculated?* Tallahassee: Ben Crump Law, 2023. Available at: https://bencrump.com/faqs/how-is-death-compensation-calculated/ Accessed on: June 12, 2023.

[123] LEWBEL, A. Calculating compensation in cases of wrongful death. *Journal of Econometrics*, v.113, n.1, p. 115–128, 2003. DOI: https://doi.org/10.1016/S0304-4076(02)00169-0

[124] ALAGOZ, O. *et al*. Markov Decision Processes: a tool for sequential decision making under uncertainty. *Medical Decision Making*, v. 30, n.4, p. 474–483, 2010. DOI: https://doi.org/10.1177/0272989X09353194

[125] WHITE, D. J. Real applications of Markov decision processes. *Interfaces*, v. 15, n. 6, p. 73–83, 1985. http://www.jstor.org/stable/25060766

[126] MAZZUCHI, T. A.; van NOORTWIJK, J. M.; KALLEN, M.- J. Maintenance optimization. *In*: FALTIN, F.W.; RUGGERI, F.; KENETT, R. (ed*). Encyclopedia of statistics in quality and reliability*. Chichester: John Wiley and Sons, c2007.

[127] URBANUCCI, L. Limits and potentials of Mixed Integer Linear Programming methods for optimization of polygeneration energy systems. *Energy Procedia*, v.148, p.1199–1205, 2018. DOI: https://doi.org/10.1016/j.egypro.2018.08.021

[128] WOLSEY, L. A. *Integer programming.* New York: John Wiley& Sons, c1998. Chapter 1, p. 1-16

[129] HOFFMAN, K. L.; RALPHS, T. K. Integer and combinatorial optimization. *In*: GASS, S. I.; FU, M. C. (ed).. *Encyclopedia of Operations Research and Management Stability*. Boston: Springer, 2013. p.771-783.

[130] BRASIL. Ministério da Saúde. *Data SUS.Tabnet*. Brasília, DF: MS, 2023. Available at: https://datasus.saude.gov.br/informacoes-de-saude-tabnet/ Accessed on: June 15, 2023.

[131] SILAPARASETTY, V. *Quais são os principaisdesafios e limitações dos processosde decisão Markov em aplicações de ciencias e dados. Linkedin, 2023.*Available at: https://www.linkedin.com/advice/1/what-main-challenges-limitations-markov-decision-processes Accessed on: June 15, 2023.

[132] CONSTANZA, D. *et al*. *Not enough mechanics*: how the industry can address decade`s shortage in aircraft maintenance workers. [*S. l.*]: Oliver Wyman ,2022. Available at: https://arsa.org/wp-content/uploads/2023/03/OW-2023WorkforceAnalysis-Technicians.pdf Accessed on: June 15, 2023.

[133] PIPELINE Report and AMTS Directory 2024. Aviation Technician Education Council, Oliver Wyman, 2024. Available on: https://assets.noviams.com/novi-file-uploads/atec/atec_pipereport24_042624_v3w-9da8fa0e.pdf. Accessed on: Dec 2024.

[134] INTERNATIONAL AIR TRANPORT ASSOCIATION. *Airlines set to earn 2.7% Net profit margin on record revenues in 2024*. Geneve: IATA, 2023. (Press Realease, n. 68).

[135] SUN, Y. *et al*. AI-based prescriptive maintenance for sustainable operation. *In*: CONFERENCE ON LEARNING FACTORIES, 13th, 2023. *Proceedings* […]. Amsterdam: Elsevier, 2023. DOI: https://doi.org/10.2139/ssrn.4457075

[136] PINCIROLI, L.; BARALDI, P.; ZIO, E. Maintenance optimization in industry 4.0. *Reliability Engineering and System Safety*, v. 234, 109204, 2023. https://doi.org/10.1016/j.ress.2023.109204

[137] ZONTA, T. *et al*. Predictive maintenance in the Industry 4.0: A systematic literature review. *Computers and Industrial Engineering*, v.150, 106889, 2020. DOI: https://doi.org/10.1016/j.cie.2020.106889.

[138] ZHAO, Y.; WANG, W. *TranDRL*: a transformer-driven deep reinforcement learning enabled prescriptive maintenance framework. Ithaca: arXiv Operational Status, Cornell University, 2023. https://doi.org/10.48550/arXiv.2309.16935.

[139] PINCIROLI, L. *et al*. Optimal operation and maintenance of energy storage systems in grid-connected microgrids by deep reinforcement learning. *Applied Energy*, v.352, 121947, 2023. DOI: https://doi.org/10.1016/j.apenergy.2023.121947

[140] TEUBERT, C.; POHYA, A. A.; GOROSPE, G.*An analysis of barriers preventing the widespread adoption of predictive and prescriptive maintenance in aviation*. Moffett Field, CA: NASA, 2023. (NASA/TM-20230000841)

[141] GOBY, N.; BRANDT, T.; NEUMANN, D. Deep reinforcement learning with combinatorial actions spaces: An application to prescriptive maintenance. *Computers and Industrial Engineering,* v.179, 109165, 2023. DOI: https://doi.org/10.1016/j.cie.2023.109165

[142] ONETO, L. *et al*. DAYDREAMS: development of prescriptive analytics based on artificial intelligence for railways intelligent asset management systems. *Transportation Research Procedia,* v.72, p. 478–485, 2023. DOI: https://doi.org/10.1016/j.trpro.2023.11.927

[143] MOLĘDA, M. *et al*. From corrective to predictive maintenance—a review of maintenance approaches for the power industry. *Sensors*, v.23, n.13, 5970, 2023. DOI: https://doi.org/10.3390/s23135970

[144] MAO, H. *et al*. Prescriptive maintenance for complex products with digital twin considering production planning and resource constraints. *Measurement Science and Technology*, v.34, n.12, 125903, 2023. DOI: https://doi.org/10.1088/1361-6501/aced5f

[145] KHATRI, M. R. Integration of natural language processing, self- service platforms, predictive maintenance, and prescriptive analytics for cost reduction, personalization, and real-time insights customer service and operational efficiency. *International Journal of Information and Cybersecurity*, p. 1-20, 2023.

[146] BOYD, S.; VANDENBERGHE, L. *Convex optimization*. Cambridge: Cambridge University Press, 2004

[147] GRÖNKVIST, M. *The tail assignment problem*. Thesis (PhD) – Department of Computer Science Engineering, Chalmers University and Technology and Götenborg University, Götenborg, 2005.

[148] BRASIL. Ministério da Saúde. CNES-Cadastro Nacional de Estabelecimentos da Saúde. *Consulta Estabelecimento: identificação*. Brasília, DF: M.S., 2024. Available at: https://cnes.datasus.gov.br/pages/estabelecimentos/consulta.jsp Accessed on: Sep 05, 2024.

[149] BAKAKOS A. *et al*. The real impact of age on mortality in critically ill Covid-19 Patients. *J Pers Med*., v.13, n.6, 908, 2023. DOI: 10.3390/jpm13060908.

[150] UNITED STATES. Federal Administration Aviation. *Become an aviation mechanics*. Washington, DC: FAA, 2024. https://www.faa.gov/mechanics/become

[151] HERLITZ, J. Factors associated with survival to hospital discharge among patients hospitalised alive after out of hospital cardiac arrest: Change in outcome over 20 years in the community of Goteborg, Sweden. *Heart*, v.89, n.1, p. 25–30, 2003. DOI: https://doi.org/10.1136/heart.89.1.25

[152] COLLUCCI, C.; AMÂNCIO, T. ICU Hospitalizations Will Cost Brazil's public healthcare more than USD 232 million. *Folha de São Paulo*, São Paulo, Mar 20, 2020. Available on: https://www1.folha.uol.com.br/internacional/en/scienceandhealth/2020/03/icu-hospitalizations-will-cost-brazils-public-healthcare-more-than-us-232-million.shtml Accessed in: June, 2024.

[153] AGÊNCIA IBGE NOTÍCIAS. *Em 2022, expectativa de vida era de 75,5 anos. IBGE*. Rio de Janeiro: IBGE, 2023. Available on: https://agenciadenoticias.ibge.gov.br/agencia-sala-de-imprensa/2013-agencia-de-noticias/releases/38455-em-2022-expectativa-de-vida-era-de-75-5-anos#:~:text=Uma%20pessoa%20nascida%20no%20Brasil,%2C%20de%2079%2C0%20anos. Accessed in: June, 2024

[154] INTERNATIONAL MONETARY FUND. *Brazil Datasets*. Washington, DC: IMF, 2024. Available on: https://www.imf.org/external/datamapper/profile/BRA Accessed in: June 2024.

[155] PELINOVSKY, E. *et al*. Logistic equation and COVID-19. *Chaos, Solitons and Fractals*, v. 140, 110241, 2020. DOI: https://doi.org/10.1016/j.chaos.2020.110241

[156] GOLDMAN, A. I. Survivorship analysis when cure is a possibility: A Monte Carlo study. *Statistics in Medicine*, v.3, n.2, p. 153–163, 1984. DOI: https://doi.org/10.1002/sim.4780030208

[157] AUSTIN, P. C. *et al*. Quantifying the impact of survivor treatment bias in observational studies. *Journal of Evaluation in Clinical Practice,* v.12, n.6, p. 601–612, 2006. DOI: https://doi.org/10.1111/j.1365-2753.2005.00624.x

[158] RODRIGUES, L. R. et al. Use of PHM Information and system architecture for optimized aircraft maintenance planning. *IEEE Systems Journal*, v. 9, n. 4, p. 1197–1207, Dec. 2015. DOI: https://doi.org/10.1109/JSYST.2014.2343752

[159] RODRIGUES, L. R.; YONEYAMA, T.; NASCIMENTO, C. L. How aircraft operators can benefit from PHM techniques. *In*: IEEE AEROSPACE CONFERENCE, 2012, Big Sky. *Proceedings* [...]. Piscataway: IEEE, 2012. DOI: https://doi.org/10.1109/AERO.2012.6187376

[160] FU, S.; AVDELIDIS, N. P. Prognostic and Health Management of Critical Aircraft Systems and Components: An Overview. *Sensors,* v. 23, n. 19, 8124, Sep. 2023. DOI: https://doi.org/10.3390/s23198124

[161] JET PARTS ENGINEERING. *ATA Chapters refer to the standardized system of categorizing technical information in the aviation industry, particularly for aircraft maintenance and repair documentation*. Brisbane City, Australia: JET PARTS. Available on: https://www.jetpartsengineering.com/ata-chapters#:~:text=ATA%20Chapters%20refer%20to%20the,which%20initially%20developed%20this%20system. Accessed in: June 2024.

[162] FERM, B.; *ISTAT Asia 2017: The fight for the lead*. Saint-Paul-de-Vance, France: LEEHAM NEWS AND ANALYSIS, 2017. Available on: https://leehamnews.com/2017/05/11/istat-asia-2017-fight-lead/. Accessed in: June 2024.

[163] RAJ, T. V.; *Is your aircraft reliable?* Madrid, Spain: RAMCO, 2013. Available on: https://www.ramco.com/blog/aircraft-reliable#:~:text=Major%20and%20large%20airlines%20achieve,of%20an%20Approved%20Maintenance%20Program. Accessed in: December 2024.

[164] FILIP, R. *et al*. Global Challenges to Public Health Care Systems during the COVID-19 Pandemic: A Review of Pandemic Measures and Problems. *Journal of Personalized Medicine*, v. 12, n. 8, p. 1295, 7 ago. 2022. DOI: 10.3390/jpm12081295

[165] KAPUR, N. *et al.* Aviation and healthcare: a comparative review with implications for patient safety. *JRSM Open*, v. 7, n. 1, p. 2054270415616548, 1 jan. 2016. DOI: 10.1177/2054270415616548

[166] BONDI-KELLY, E. *et al.* Taking Off with AI: Lessons from Aviation for Healthcare. Equity and Access in Algorithms, Mechanisms, and Optimization. *In:* EAAMO ’23: EQUITY AND ACCESS IN ALGORITHMS, MECHANISMS, AND OPTIMIZATION. Boston MA USA: ACM, 30 out. 2023. *Proceedings*[...]: Available on: https://dl.acm.org/doi/10.1145/3617694.3623224. Accessed in: January 2025. DOI: 10.1145/3617694.3623224

Appendix A – Experiments Results

A.1 Experiment 1: Non-Prescriptive Schedule Results

Full data is available on file "Appendix A.docx" shared through the link: https://www.aerologlab.ita.br/static/datafiles/alessandro_giacotto.zip

A.2 Experiment 1: Prescriptive Schedule Results

Full data is available on file "Schedule_results_pampulha.xlsx" and "Schedule_results_campinas.xlsx" shared through the link: https://www.aerologlab.ita.br/static/datafiles/alessandro_giacotto.zip

A.3 Experiment 1: New MTBURs Evaluated Considering Maintenance Imperfections

Full data is available on file "Maint_Imperfections.docx" shared through the link: https://www.aerologlab.ita.br/static/datafiles/alessandro_giacotto.zip

A.4 Experiment 2: Optimal Patients Admissions

Full data is available on file "Opt_Patients_Adm.docx" shared through the link: https://www.aerologlab.ita.br/static/datafiles/alessandro_giacotto.zip

A.5 Experiment 3: Maintenance Task Prescription C-check

Full data is available on file "Maintenance Task Presciption C-check.docx", shared through the link: https://www.aerologlab.ita.br/static/datafiles/alessandro_giacotto.zip

A.6 Experiment 3: Maintenance Task Prescription A-check

Full data is available on file "Maintenance Task Presciption A-check.docx", shared through the link: https://www.aerologlab.ita.br/static/datafiles/alessandro_giacotto.zip

A.7 Experiment 3: Unscheduled Maintenance Task Prescription

Full data is available on file "Unscheduled Maintenance Task Presciption.docx", shared through the link: https://www.aerologlab.ita.br/static/datafiles/alessandro_giacotto.zip

Appendix B – Case Study 1 Inputs

B.1 Experiment 1: Full Airliner Operation Description

Full data is available on file "Airliner_Operation_rev4.xlsx" shared through the link: https://www.aerologlab.ita.br/static/datafiles/alessandro_giacotto.zip

B.2 Experiment 1: MTBUR List

Full data is available on file "MTBUR List.xlsx" shared through the link: https://www.aerologlab.ita.br/static/datafiles/alessandro_giacotto.zip

B.3 Experiment 1: Flight Hours & Maintenance Events

Full data is available on file "Flight_Hours_and_Maintenance_Events.xlsx" shared through the link: https://www.aerologlab.ita.br/static/datafiles/alessandro_giacotto.zip

B.4 Experiment 1: C-check Events

Full data is available on file "Flight_Hours_and_Maintenance_Events.xlsx" shared through the link: https://www.aerologlab.ita.br/static/datafiles/alessandro_giacotto.zip

B.5 Experiment 1: A-check Events

Full data is available on file "Flight_Hours_and_Maintenance_Events.xlsx" shared through the link: https://www.aerologlab.ita.br/static/datafiles/alessandro_giacotto.zip

B.6 Experiment 1: Unscheduled Events PHM Adjusted

Full data is available on file "Flight_Hours_and_Maintenance_Events.xlsx" shared through the link: https://www.aerologlab.ita.br/static/datafiles/alessandro_giacotto.zip

Appendix C – Case Study 2 Inputs

C.1 Experiment 2: Patients Data Extraction

Patient	Age	Gender	City	Admission day	Discharge day	Patient deceased?	Hospital
316102723855	37	F	JACAREI	09/01/21	09/01/21	Y	P A UNIMED ESTACAO JACAREI
316103926076	55	F	SAO PAULO	08/01/21	08/01/21	Y	HOSPITAL ADVENTISTA DE SAO PAULO
316153503977	64	F	JACAREI	09/03/21	14/03/21	Y	SANTA CASA DE MISERICORDIA DE JACAREI
316154657780	74	M	JACAREI	10/03/21	30/03/21	Y	SANTA CASA DE MISERICORDIA DE JACAREI
316159047888	52	F	JACAREI	08/03/21	10/05/21	Y	HOSPITAL SAO FRANCISCO DE ASSIS
316165310935	40	M	JACAREI	23/03/21	25/03/21	Y	HOSPITAL ALVORADA JACAREI
316175982613	76	M	JACAREI	04/04/21	04/04/21	Y	SANTA CASA DE MISERICORDIA DE JACAREI
316188341754	69	F	JACAREI	17/04/21	17/04/21	Y	SANTA CASA DE MISERICORDIA DE JACAREI
316188353747	30	M	JACAREI	18/04/21	18/04/21	Y	SANTA CASA DE MISERICORDIA DE JACAREI
316201358091	63	M	JACAREI	03/05/21	03/05/21	Y	HOSPITAL SAO FRANCISCO DE ASSIS
316214254852	58	M	SAO JOSE DOS CAMPOS	18/05/21	29/05/21	Y	HOSPITAL SAO JOSE
316222257918	83	F	JACAREI	28/05/21	30/05/21	N	HOSPITAL SAO FRANCISCO DE ASSIS
316250475696	84	M	JACAREI	22/05/21	22/05/21	Y	SANTA CASA DE MISERICORDIA DE JACAREI
316257521356	66	M	JACAREI	05/07/21	07/07/21	Y	SANTA CASA DE MISERICORDIA DE JACAREI
316279233884	86	M	JACAREI	05/08/21	05/08/21	Y	SANTA CASA DE

Patient	Age	Gender	City	Admission day	Discharge day	Patient deceased?	Hospital
							MISERICORDIA DE JACAREI
316281696025	36	F	JACAREI	11/09/21	11/09/21	N	SANTA CASA DE MISERICORDIA DE JACAREI
316315397794	47	M	JACAREI	09/11/21	09/11/21	N	HOSPITAL VIVALLE
316365418431	33	M	SAO JOSE DOS CAMPOS	13/11/21	29/11/21	N	HOSPITAL SAO FRANCISCO DE ASSIS
316383654914	2	M	JACAREI	20/01/21	21/01/21	Y	SANTA CASA DE MISERICORDIA DE JACAREI
316109751326	41	F	SAO JOSE DOS CAMPOS	25/01/21	26/01/21	N	HOSPITAL SAO JOSE
316111526925	83	M	JACAREI	22/01/21	23/01/21	Y	HOSPITAL SAO JOSE
316116792893	31	M	SAO JOSE DOS CAMPOS	11/02/21	13/02/21	Y	HOSPITAL SAO FRANCISCO DE ASSIS
316117557721	50	M	SAO JOSE DOS CAMPOS	18/02/21	19/02/21	N	HOSPITAL SAO FRANCISCO DE ASSIS
316133899607	60	F	JACAREI	09/03/21	10/03/21	Y	SANTA CASA DE MISERICORDIA DE JACAREI
316139953293	54	F	JACAREI	23/03/21	24/03/21	Y	SANTA CASA DE MISERICORDIA DE JACAREI
316153862233	74	F	JACAREI	25/03/21	26/03/21	N	HOSPITAL SAO FRANCISCO DE ASSIS
316165896255	85	F	JACAREI	26/04/21	27/04/21	Y	HOSPITAL SAO FRANCISCO DE ASSIS
316167712390	42	F	JACAREI	02/05/21	03/05/21	Y	HOSPITAL SAO FRANCISCO DE ASSIS
316195488364	62	F	JACAREI	09/05/21	10/05/21	Y	HOSPITAL DE CLINICAS ANTONIO AFONSO
316200620196	63	M	JACAREI	06/05/21	11/05/21	Y	SANTA CASA DE MISERICORDIA DE JACAREI

Patient	Age	Gender	City	Admission day	Discharge day	Patient deceased?	Hospital
316206705923	82	M	JACAREI	11/05/21	12/05/21	Y	SANTA CASA DE MISERICORDIA DE JACAREI
316208361422	56	F	JACAREI	18/05/21	19/05/21	Y	SANTA CASA DE MISERICORDIA DE JACAREI
316208376525	52	F	JACAREI	01/06/21	02/06/21	N	HOSPITAL VIVALLE
316215108843	19	M	JACAREI	08/06/21	09/06/21	Y	SANTA CASA DE MISERICORDIA DE JACAREI
316225450163	39	F	SAO JOSE DOS CAMPOS	17/06/21	18/06/21	Y	SANTA CASA DE MISERICORDIA DE JACAREI
316232399415	55	M	JACAREI	21/06/21	22/06/21	N	HOSPITAL VIVALLE
316240206051	72	M	JACAREI	21/06/21	22/06/21	Y	SANTA CASA DE MISERICORDIA DE JACAREI
316243716458	48	M	SAO JOSE DOS CAMPOS	27/06/21	04/07/21	Y	HOSPITAL POLICLIN
316243799860	77	F	JACAREI	27/06/21	28/06/21	N	HOSPITAL VIVALLE
316248711904	85	F	SAO JOSE DOS CAMPOS	07/07/21	08/07/21	N	HOSPITAL VIVALLE
316248847482	42	M	SAO JOSE DOS CAMPOS	10/07/21	17/07/21	Y	HOSPITAL SAO JOSE
316257602059	43	F	SAO JOSE DOS CAMPOS	11/07/21	28/07/21	Y	HOSPITAL SAO FRANCISCO DE ASSIS
316260975874	58	M	SAO JOSE DOS CAMPOS	08/08/21	09/08/21	Y	HOSPITAL SAO FRANCISCO DE ASSIS
316260998826	40	M	JACAREI	30/08/21	31/08/21	N	HOSPITAL SAO FRANCISCO DE ASSIS
316285175852	86	F	JACAREI	25/09/21	26/09/21	N	HOSPITAL VIVALLE
316302704791	82	F	JACAREI	24/09/21	25/09/21	N	HOSPITAL SAO FRANCISCO DE ASSIS

Patient	Age	Gender	City	Admission day	Discharge day	Patient deceased?	Hospital
316304125554	72	M	JACAREI	02/10/21	03/10/21	Y	SANTA CASA DE MISERICORDIA DE JACAREI
316326526003	66	M	SAO JOSE DOS CAMPOS	30/12/21	31/12/21	N	HOSPITAL VIVALLE
316327505120	42	M	JACAREI	08/01/21	10/01/21	N	HOSPITAL SAO FRANCISCO DE ASSIS
316333664459	76	M	JACAREI	23/01/21	25/01/21	Y	DR RUBENS SAVASTANO HOSPITAL REGIONAL DE SAO JOSE DOS CAMPOS

C.2 Experiment 2: Hospitals’ ICU Capability

Hospital	ICU
Hospital 1	15
Hospital 2	30
Hospital 3	41
Hospital 4	24
Hospital 5	59
Hospital 6	15
Hospital 7	15
Hospital 8	22
Hospital 9	15
Hospital 10	16

Hospital	ICU
Hospital 11	12
Hospital 12	106
Hospital 13	15
Hospital 14	21
Hospital 15	23
Hospital 16	10
Hospital 17	49
Hospital 18	15
Hospital 19	46
Hospital 20	30
Hospital 21	113
Hospital 22	106
Hospital 23	82
Hospital 24	80
Hospital 25	411
Hospital 26	64
Hospital 27	108
Hospital 28	26
Hospital 29	15
Hospital 30	15
Hospital 31	104
Hospital 32	15

Hospital	ICU
Hospital 33	15
Hospital 34	16
Hospital 35	11
Hospital 36	15
Hospital 37	83
Hospital 38	15
Hospital 39	20
Hospital 40	19
Hospital 41	54
Hospital 42	49
Hospital 43	72
Hospital 44	20
Hospital 45	33
Hospital 46	200
Hospital 47	44
Hospital 48	26
Hospital 49	100
Hospital 50	52
Hospital 51	15
Hospital 52	26
Hospital 53	15
Hospital 54	22

Hospital	ICU
Hospital 55	100
Hospital 56	1

Appendix D – Case Study 3 Inputs

D.1 Experiment 3: Hangars' Support Capability

Full data is available on file "Airliner station data_rev4.xlsx" shared through the link: https://www.aerologlab.ita.br/static/datafiles/alessandro_giacotto.zip

D.2 Experiment 3: C-check Maintenance Tasks

Full data is available on file "CheckC Maint_Plan_rev2_A330_A350.xlsx", "CheckC Maint_Plan_rev2_Cessna.xlsx", "CheckC Maint_Plan_rev2_E1_ATR.xlsx" and "CheckC Maint_Plan_rev2_E2_A320_A321.xlsx" shared through the link: https://www.aerologlab.ita.br/static/datafiles/alessandro_giacotto.zip

D.3 Experiment 3: A-check Maintenance Tasks

Full data is available on file "CheckA Maint_Plan_rev2_A330_A350.xlsx", "CheckA Maint_Plan_rev2_Cessna.xlsx", "CheckA Maint_Plan_rev2_E1_ATR.xlsx" and "CheckA Maint_Plan_rev2_E2_A320_A321.xlsx" shared through the link: https://www.aerologlab.ita.br/static/datafiles/alessandro_giacotto.zip

D.4 Experiment 3: Unscheduled Maintenance Tasks

Full data is available on file "unscheduled_maintenance_tasks.xlsx", shared through the link: https://www.aerologlab.ita.br/static/datafiles/alessandro_giacotto.zip

Appendix E – ATA Chapters List

ATA Chapter	ATA Chapter Description
ATA 00	GENERAL
ATA 01	MAINTENANCE POLICY
ATA 02	OPERATIONS
ATA 03	SUPPORT
ATA 04	AIRWORTHINESS LIMITATIONS
ATA 05	TIME LIMITS/MAINTENANCE CHECKS
ATA 06	DIMENSIONS AND AREAS
ATA 07	LIFTING AND SHORING
ATA 08	LEVELING AND WEIGHING
ATA 09	TOWING AND TAXIING
ATA 10	PARKING, MOORING, STORAGE AND RETURN TO SERVICE
ATA 11	PLACARDS AND MARKINGS
ATA 12	SERVICING
ATA 13	HARDWARE AND GENERAL TOOLS
ATA 15	AIRCREW INFORMATION
ATA 16	CHANGE OF ROLE
ATA 18	VIBRATION AND NOISE ANALYSIS (HELICOPTER ONLY)
ATA 20	STANDARD PRACTICES- AIRFRAME
ATA 21	AIR CONDITIONING AND PRESSURIZATION

ATA 22	AUTO FLIGHT
ATA 23	COMMUNICATIONS
ATA 24	ELECTRICAL POWER
ATA 25	EQUIPMENT / FURNISHINGS
ATA 26	FIRE PROTECTION
ATA 27	FLIGHT CONTROLS
ATA 28	FUEL
ATA 29	HYDRAULIC POWER
ATA 30	ICE AND RAIN PROTECTION
ATA 31	INDICATING / RECORDING SYSTEM
ATA 32	LANDING GEAR
ATA 33	LIGHTS
ATA 34	NAVIGATION
ATA 35	OXYGEN
ATA 36	PNEUMATIC
ATA 37	VACUUM
ATA 38	WATER / WASTE
ATA 39	ELECTRICAL - ELECTRONIC PANELS AND MULTIPURPOSE COMPONENTS
ATA 40	MULTISYSTEM
ATA 41	WATER BALLAST
ATA 42	INTEGRATED MODULAR AVIONICS
ATA 43	EMERGENCY SOLAR PANEL SYSTEM (ESPS)
ATA 44	CABIN SYSTEMS

ATA 45	ONBOARD MAINTENANCE SYSTEMS (OMS)
ATA 46	INFORMATION SYSTEMS
ATA 47	INERT GAS SYSTEM
ATA 48	IN FLIGHT FUEL DISPENSING
ATA 49	(AIRBORNE) AUXILIARY POWER UNIT
ATA 50	CARGO AND ACCESSORY COMPARTMENTS
ATA 51	STANDARD PRACTICES AND STRUCTURES - GENERAL
ATA 52	DOORS
ATA 53	FUSELAGE
ATA 54	NACELLES / PYLONS
ATA 55	STABILIZERS
ATA 56	WINDOWS
ATA 57	WINGS
ATA 60	STANDARD PRACTICES - PROP./ROTOR
ATA 61	PROPELLER / PROPULSORS
ATA 62	MAIN ROTOR(S)
ATA 63	MAIN ROTOR DRIVE(S)
ATA 64	TAIL ROTOR
ATA 65	TAIL ROTOR DRIVE
ATA 66	FOLDING BLADES/PYLON
ATA 67	ROTORS AND FLIGHT CONTROLS
ATA 70	STANDARD PRACTICES - ENGINE
ATA 71	POWER PLANT

ATA 72	ENGINE
ATA 72	ENGINE - TURBINE/TURBOPROP, DUCTED FAN/UNDUCTED FAN
ATA 72	ENGINE - RECIPROCATING
ATA 73	ENGINE - FUEL AND CONTROL
ATA 74	IGNITION
ATA 75	BLEED AIR
ATA 76	ENGINE CONTROLS
ATA 77	ENGINE INDICATING
ATA 77	ENGINE INDICATING
ATA 78	EXHAUST
ATA 79	OIL
ATA 80	STARTING
ATA 81	TURBINES (RECIPROCATING ENGINES)
ATA 82	WATER INJECTION
ATA 83	ACCESSORY GEAR BOX (ENGINE DRIVEN)
ATA 84	PROPULSION AUGMENTATION
ATA 85	FUEL CELL SYSTEMS

DOCUMENT RECORD SHEET

[1.] CLASSIFICAÇÃO/TIPO	[2.] DATA	[3.] REGISTRO N°	[4.] N° DE PÁGINAS
TD	31 de janeiro de 2025	DCTA/ITA/TD-079/2024	169

[5.] TÍTULO E SUBTÍTULO:

Holistic optimization framework for prescriptive maintenance

[6.] AUTOR(ES):

Alessandro Giacotto

7. INSTITUIÇÃO(ÕES)/ÓRGÃO(S) INTERNO(S)/DIVISÃO(ÕES):

Instituto Tecnológico de Aeronáutica – ITA

[8.] PALAVRAS-CHAVE SUGERIDAS PELO AUTOR:

1. Prescriptive Maintenance 2. Optimization 3. Aeronautics

9.PALAVRAS-CHAVE RESULTANTES DE INDEXAÇÃO:

Programas de aplicação (computadores); Manutenção; Otimização; Aeronaves; Análise computacional; Simulação computadorizada; Computação.

[10.] APRESENTAÇÃO: **(X) Nacional** **( ) Internacional**

ITA, São José dos Campos. Curso de Doutorado. Programa de Pós-Graduação em Ciências e Tecnologias Espaciais. Área de Gestão Tecnológica. Orientador: Prof. Dr. Henrique Costa Marques. Defesa em 10/12/2024. Publicada em 2024.

[11.] RESUMO:

Prescriptive maintenance (PsM) is a proactive approach enabled by the Internet of Things (IoT), asset health prognostics, and prescriptive analytics that aims to optimize maintenance by prescribing a course of action. In a challenging context, in which industries face shortage of workforce and fierce competition, complex systems operating in dynamic operations are supported by traditional maintenance practices, that based on reactive or preventive approaches, often result in inefficiencies, high costs, and unexpected equipment failures. To address these challenges, a new PsM-based optimization framework is required to process the information available and recommend possible maintenance actions holistically, considering both operation and support. Therefore, the purpose of this research is to demonstrate that maintenance efficiency and effectiveness can be improved through the implementation of a PsM framework that provides optimal course of action, is adaptable across different industries and extensible to assets with different technological maturities. To achieve these objectives and highlight the novelty of this work, a comprehensive review of existing literature on prescriptive maintenance is presented, followed by the design and verification of a PsM Mixed-Integer Linear Programming (MILP) based optimization framework. The framework is tested in real-world case scenarios, through three experiments, that include a Brazilian regional airline operation and the São Paulo state health system's pandemic response. The two experiments with the airline demonstrated the framework's efficacy, achieving increases of 36.16% and 26.41% in fleet availability, along with profitability improvements of 0.81% and 406%, respectively. The health system experiment further highlighted the framework's adaptability, showing a potential 65% increase in patients' survivorship. These results provide valuable insights and guidance for researchers and practitioners, emphasizing the viability and potential of the prescriptive maintenance paradigm.

[12.] GRAU DE SIGILO:

(X) OSTENSIVO **( ) RESERVADO** **( ) SECRETO**