HOLISTIC AND SCALABLE SMART OPTIMIZATION FRAMEWORK FOR PRESCRIPTIVE MAINTENANCE

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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. For complex systems operating in dynamic operations, traditional maintenance practices based on reactive or preventive approaches often result in inefficiencies, high costs, and unexpected equipment failures. In this context, a new PsM-based optimization framework is required to process all sources of information available with the associated uncertainties, manage a large number of system states, and recommend possible maintenance actions. Therefore, the purpose of this paper is to demonstrate that maintenance efficiency and effectiveness can be improved by implementing a prescriptive maintenance framework that provides an optimal course of action and is extensible across industries and assets of different technological maturities. To achieve these objectives and demonstrate the novelty of this work, a thorough review of the existing literature on prescriptive maintenance is presented. The work involves the design of a smart optimization framework for prescriptive maintenance and its verification on Brazilian regional airline operations and São Paulo state health system real-life scenarios. The framework will offer practical guidance and insights for practitioners, enabling them to make informed decisions related to maintenance management, reducing costs, and improving equipment performance with implications for various industries, paving the way for more proactive and efficient maintenance practices in digitalization and prescriptive analytics.

Keywords: Prescriptive Maintenance, Maintenance Optimization, Aeronautics, Health Systems.

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 [104][108][109][110]. 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 the dynamic operations of complex systems [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 operate 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 and costs [5][6][17][19][22][23][29][32][33][34][50][51][52][54][55][59][58][63][64][68][73][75][77][79][80], operating parameters, maintenance activities, and maintenance resources [5][9][17][54][56][58][79] . And, finally, developers are struggling to propose extensible or scalable frameworks, undermining large industrial adoption in several fields [5][7][22][24][30][32][33][35][48][49][51][52][54][58][60][62][64][65][81].

The primary objective of this research is to develop a comprehensive framework for prescriptive maintenance that addresses some of the challenges mentioned above, namely the holistic decision-making optimization algorithm and the scalability problems. The specific research objectives are the obtention of maintenance cost decrease and increase or maintenance of asset availability as a result of PsM implementation in aeronautical operations and framework scalability to the health industry.

The successful implementation of PsM has the potential to revolutionize the field of maintenance management. By adopting a data-driven and proactive approach, organizations can optimize maintenance activities, reduce costs, increase equipment availability, and improve overall operational efficiency. This research contributes to the existing body of knowledge by developing a comprehensive framework for prescriptive maintenance that addresses the challenges faced by industrial organizations. The proposed work will provide practical guidance and insights for practitioners, enabling them to make informed decisions regarding maintenance strategies and resource allocation.

1.1 Context and Research Problem

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] and pressure to lower emissions to boost sustainability [1][2][3].

Despite the competition, operational costs, the workforce crisis, and the new sustainability 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 [7], 19 in 2022 [133] and 11 in 2023 [134]. In this context, a new maintenance strategy is needed to overcome these challenges by augmenting current workforce capability and skills, lowering asset life cycle costs, optimizing maintenance resources while increasing asset availability. Prescriptive Maintenance is this strategy.

Although what PsM entails might not be clear, as several definitions have been presented over the years as researchers have not agreed on a unified concept, for the sake of setting the groundwork, these authors defines PsM as *a proactive maintenance strategy that, 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.* The aforementioned challenging context is these authors' initial motivation of implementing the PsM philosophy; however, it is the following research problem that 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 many system states, and recommend possible maintenance actions [104][107].

As it will be shown in Section 2 Literature Review, an optimization framework capable of processing all information related to maintenance, such as labor, special equipment, tooling, infrastructure, material repair, material stock, logistics, operational requirements as well as maintenance uncertainties, imperfections, and tasks related to different product states has not been proposed so far. This is a problem worth solving since, as described at the beginning of this section, the increasing scarcity of labor accompanied by dynamic operations and 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's operations costs [105], finding a way to reduce maintenance expenditures is paramount.

1.2 General and Specific Objectives

The general objective of this paper is to demonstrate that maintenance efficiency and effectiveness can be improved by implementing a smart optimization framework for Prescriptive Maintenance, which:

1. Provides an optimal course of action.
2. Is extensible across industries.
3. Is adaptable to assets of different technological maturities.
4. Considers all maintenance resources and imperfections.

As stated in Section 1, in the competitive landscape of the aviation industry, organizations are compelled to reduce operating costs, with maintenance—a significant cost driver—emerging as a focal point for efficiency improvements [56][24]. Traditional maintenance approaches, however, are misaligned with the demands of contemporary, complex Industry 4.0 systems.

Corrective maintenance restores the functionality of the asset after failure and while apt for non-critical assets [104] can lead to expensive operational disruptions [108][109] and poorly optimized maintenance resources [109].

Preventive maintenance, based on fixed schedules determined by cycles or calendar intervals [10][110], often results in either neglect [110] or excessive servicing due to unknown actual wear [24][58][64], leaving the risk of failure due to an increase in the rate of degradation unavoidable [110][58][64].

Predictive maintenance, which forecasts the need for service by estimating the Remaining Useful Life (RUL) of components, falls short in prescribing actions to avert downtime [137][138] and is limited by data availability and quality [72][110], failing to consider system-wide implications and varying levels of technology adoption [23][26][64][137][138].

Despite these challenges, traditional maintenance methods may still be the most viable for certain assets, depending on their complexity and operational context. However, these gaps underscore the need for a more advanced approach, paving the way for PsM which is poised to overcome these shortcomings by providing holistically optimized maintenance schedules recommendations and enhance asset availability.

The specific objectives must be non-trivial, verifiable, and constitute the general objective subproducts [111]. Thus, these authors have selected specific objectives that will support the demonstration of maintenance efficiency improvement as a result of the adoption of the PsM framework described in Section 1.2:

1. Specific objective 1: verify the maximization of the difference between revenue and total maintenance cost a result of PsM implementation in aeronautical operation.
2. Specific objective 2: verify, for aeronautical operations, if fleet availability is greater or equal to the availability obtained using legacy maintenance strategies.
3. Specific objective 3: verify if results obtained in specific objectives 1 and 2 are scalable to other dynamic operations, namely, the health industry.

1.3 Paper Organization

This draft manuscript has the objective of presenting the prescriptive maintenance research developed by the authors, related results obtained so far, the research questions addressed, the next steps, and a comprehensive literature review; Section 2 presents the literature review; Section 3 discusses the research developed so far and related methods; Section 4 describes next steps plan; Section 5 depicts the partial conclusion, and Section 6 lists the references.

2. Theoretical Background

The origin of the term PsM is attributed to Donald A. Orr who, in a report commissioned by the U.S. Army Logistic Management Center published in December 1976, writes that PsM provides information about "how things should occur" in maintenance [10]. In the following four decades PsM has been associated with scheduled maintenance and often as a synonym of preventive maintenance [11][12][13], with very few or no publications at all until the last decade, during which an increasing of interest has been observed, with 85 papers published between 2013 and 2023. Within the last decade, and more recently in past five years, the interest in the PsM has increased even more across both the academia and the industry, accompanied by a growth in the number of related publications, as shown in table 2.1.

Table 2.1 – PsM publications in the last 5 years.

Year	Number of publications
2019	13
2020	14
2021	15
2022	18
2023	12

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 further action proposition through decision support systems and decision automation systems enabled by sensing capabilities, machine condition monitoring and diagnostic analysis, thus drastically differentiating PsM from scheduled maintenance [14][15]. One year later, Setrag Khoshafian and Carolyn Rostetter reaffirmed and 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 with the Internet of Things (IoT) sensors and Dynamic Case Management (DCM)". Also 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 main enabler is the so-called Dynamic Case Management (DCM) which is used to "automatically create a maintenance case with tasks that can be assigned to things or people”. The machines (or things) that are covered by the DCM system 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. Additionally, case tracking and resolution data will point managers and operators to additional opportunities able to eliminate bottlenecks, streamline and simplify. 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 boost 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 2.1 summarizes the PsM core concepts discussed in this section.

Table 2.2 – 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 and DCM with machines predicting potential failures and autonomously triggering maintenance	[15][16][17]
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]

A thematic analysis was performed to identify the definitions, enablers and expected outputs that characterize PsM. Sections 2.1, 2.2 and 2.3 list and describe these identified characteristics.

2.1 PsM Definition

As discussed in Section 1, pinning down a precise definition of Prescriptive Maintenance (PsM) is challenging due to the variety of interpretations over the years. Despite the absence of consensus among scholars, a careful review of the literature allows us to distill several core characteristics that define PsM. At its essence, PsM emerges as a proactive strategy, adept at assimilating the information—and the inherent uncertainties—within the Industry 4.0 ecosystem to inform optimal maintenance decisions [65][104][107]. It is both a knowledge-based [1][5][9][18] and data-centric approach [39][43][64][65][21][22], leveraging predictive analytics to anticipate failures, which is pivotal in crafting effective maintenance recommendations and scheduling [1][6][7][16][17][22][23][29][39][48][49][50][51][135].

Moreover, PsM's holistic nature is evident as it extends beyond mere maintenance tasks to integrate with production [9][135] and inventory systems [22], as well as the overall operation of the asset [1][7][9][17][19][22][35][38][41][48][56][61][66][138][139] and its interconnected ecosystem [136]. It is a self-evolving, cognitive methodology [9][24][29][39][53][73][135][139], a testament to its intelligent approach to maintenance [61][20]. While some studies emphasize its context-aware capabilities [51], others underscore its ability to autonomously recommend maintenance actions [60][65]. Crucially, PsM is characterized by its adaptability across various industrial domains

[7][51][55], with a capacity for adaptations tailored to individual assets, whether they are aircraft, machinery, or equipment [1][5][16][17][39][62][63][65][68][138].

In conclusion, these perspectives coalesce to define PsM as a maintenance strategy that, propelled by the Internet of Things (IoT), asset health prognostics, and prescriptive analytics, delivers action plans designed to refine maintenance operations and enhance asset uptime.

Progressing to the subsequent section, the enablers of PsM will be presented to analyze the technological and methodological foundations of this maintenance paradigm.

2.2 PsM Enablers

The heart of an Ecosystem 4.0, pivotal for enabling PsM, lies in the devices and digital infrastructure that facilitate real-time data collection and sharing, as described by [1][17][39]. In this ecosystem, sensors play a crucial role in detecting early signs of potential asset failure, like temperature spikes or unusual vibrations [1][5][6][9][14][16][17][21][23][27][30][31][36][37][38][49][50][54][57][60][63][65][137]. This data collection is amplified by digitization and the Cyber-Physical-Production-System (CPPS) environment [1][5][9][17][18][20][22][26][59][60][67][83], which together with augmented reality (AR) [60] and GPU computing [63], enhances maintenance technicians' efficiency and learning curve by overlaying actionable insights onto the real-world view of assets.

Crucial for PsM, the capability for failure prognosis—predicting asset failure and estimating remaining useful life (RUL)—is underscored as a fundamental requirement [5][6][7][9][20][22][23][24][29][31][32][34][39][41][43][52][54][55][56][57][58][59][60][61][62][67][68][71][76][78][83][136][137]. Enabled by Prognostic and Health Management (PHM) systems [20][31][32][43][56][57][61], RUL predictions are derived using advanced analytical models like the Wiener process, Weibull distributions, Markov chains, machine learning, and Bayesian networks [27][43][50][57][62][70]. This predictive prowess is applied across sectors, from shop floors to aerospace, demonstrating PsM's versatility [7][14][20][29][30][31][32][34][36][37][38][39][40][41][48][49][51][52][54][55][58][70][83].

The integration and analysis of real-time and historical data are facilitated by IoT, which provides the backbone for effective data analysis [1][5][6][20][27][28][29][31][32][37][38][43][45][48][49][50][51][54][60][63][67][70][76][78][83]. This data, after pre-processing, supports various analytical methodologies, including descriptive, diagnostic, predictive, and anomaly detection analytics [5][8][18][22][24][26][30][33][39][43][48][49][59][65][67][69][138].

Finally, the extracted insights empower Decision Support Systems (DSS), which translate prescriptive analytics into actionable maintenance recommendations [52][57][83][84][85][86]. These systems are adaptable across industries, from civil construction to aerospace and railways, showcasing the extensibility of PsM [7][22][23][24][27][38][60][65][66][67][78][80][81][82][87]. Knowledge classification and semantic reasoning, often through ontologies, further enhance the DSS, providing a structured approach to asset management [1][3][5][8][9][18][19][30][60].

The table 2.3 presented here summarizes the consideration of this section outlining the enablers of PsM. Each enabler listed is a critical component, ranging from the analytical foresight of prescriptive analytics to the connectivity of the IoT. They form an integrated platform that not only anticipates maintenance needs but also crafts a strategic response.

Table 2.3 – PsM enablers.

Enabler	**Description**
Prescriptive Analytics	These analytics typologies guide actions, paving the way for proactive business decisions that enhance overall performance
Failure prognosis systems	These systems provide the data that enable the estimation of the potential failures timing - a predictive window into an asset's future failures

Enabler	Description
Data analysis	A process that involves refining and remodeling data to unearth insights, which are crucial for informed decision-making
Internet of things	A network where physical devices are endowed with the ability to collect and exchange data, creating a more responsive and interconnected ecosystem
Decision support system	An integrated toolset that leverages data analytics to facilitate informed decisions, acting as a navigator in the sea of business choices
Ontology	A framework that structures domain knowledge in a format computers can understand, defining entities and the relationships between them

The next section's focus is shifted from the enablers to the outputs, as it is presented how these enablers lead to real-world outcomes—how the ideas of analytics, prognosis, and connectivity become concrete maintenance actions that are potentially prone to lower costs and improve asset performance.

2.3 PsM Outputs

PsM delivers an advanced course of action prescription, advising on schedules, tasks, resources use, and execution strategies to optimize maintenance operations [5][6][9][10][16][17][22][26][41][44][46][47][58][60][67][70][71][73][75][76][78][135][138][139]. It extends beyond predictive measures by utilizing recommendations to actively enhance and mitigate future risks [24][73], considering a broad temporal scope [65], and dynamically customizing maintenance plans in real-time through Decision Support Systems (DSS) [18][20][45][50][51][59][68].

PsM's proactive nature not only lists tasks but also manages and schedules the necessary resources, from personnel to ground support equipment [6][7][8][16][17][22][58], taking into account the operational mode of the asset [62]. Enabled by IoT and CBM, PsM actively monitors operational systems to predict and prevent potential failures, optimizing asset management and implementing timely maintenance, potentially remotely [73][68][49][65][37].

Methodologically, PsM automates maintenance workflows, with self-diagnostic assets initiating maintenance actions with minimal human oversight, leading to the automated creation of work orders and enhancing the efficiency of maintenance management [14][24][47][70][74][5][53][59][73][69][65]. This optimization is reflected in the references to optimized maintenance and plans [5][43][64][136], promoting life cycle cost minimization and asset availability maximization [1][5][6][7][16][17][20][22][23][35][43][56][63][64][65][73][78][137].

The cost-effectiveness of PsM is noted, with savings achieved through less frequent use of spare parts [32][41][43][57], reduced overall system exploitation costs [43][62][82], and optimal costs as part of frameworks that include cost minimization as an objective function [7][33][56][61]. PsM's contribution to ESG goals includes decreased energy waste and ecological impact assessments [32][53][56][137]. Moreover, it results in significantly higher asset availability [6][7][14][17][24][30][32][39][41][43][45][46][54][55][59][61][64][65][66][67][72][78], which enhances customer service and corporate reputation [6][32].

As a self-learning system, PsM evolves through feedback loops that incorporate lessons learned for future recommendations [1][5][7][14][16][63], sharing insights with OEMs for product or service design improvements and facilitating knowledge management [7][43][78][84]. Finally, PsM frameworks also aim to optimize operations and productivity [66][37][46][135][138][139], offering real-time data for production control and supply chain integration [46][47][58][35][7][58].

The following table 2.4 summarizes these outputs and the considerations made in this section. These outputs not only guide maintenance decisions but also integrate closely with operational practices to enhance the overall efficacy and cost-efficiency of asset management. Each row in the table briefly describes one of the key parts of PsM, from actionable prescriptions to the seamless integration of operations and maintenance. This shows a methodical effort to lower life cycle costs and increase asset availability. This table serves as a concise reference for understanding the multifaceted benefits and functionalities that PsM provides to modern maintenance practices.

Table 2.4 – PsM outputs descriptions

Outputs	Description
The course of action prescription	Provides a strategic set of tasks designed to answer "What should be done?" in order to proactively enhance business performance through targeted maintenance actions
Life cycle cost minimization and asset availability maximization	Focuses on minimizing total life cycle cost, including operational and ESG-related expenses while maximizing asset availability to ensure readiness
Optimized maintenance	A maintenance approach that leverages resources efficiently, reduces lifec-cycle cycle expenses and bolsters both asset availability
Automated maintenance workflow	A self-regulating maintenance system that continuously monitors the health and performance of assets, autonomously initiating maintenance actions, minimizing the need for human input
Maintenance recommendation continuous improvement	A self-improving feedback mechanism that assesses the effectiveness of maintenance predictions and refines the recommendations for enhanced precision and reliability
Integration between operation and maintenance	Synchronizes operational and maintenance activities to enhance the cost-effectiveness and reliability of assets

With the PsM outputs clearly delineated, the benefits they impart to maintenance management are grasped.
Pivoting to the next section, the attention turns to the research gaps that this work bridges. Challenges within the current PsM paradigms will be explored, setting the stage for how this research contributes to the evolution of maintenance strategy and execution in the Industry 4.0 ecosystem.

2.4 Research Gaps Addressed by this Work

This section highlights the research gaps and questions to tackle, as if the research on PsM has the potential to revolutionize complex system management, it's crucial to focus on the untapped frontiers. Meissner et al. [54][56] developed an agent-based simulation optimizing maintenance based on an asset's real-time condition, yet it currently only factors in human maintenance resources, with plans to expand the algorithm to address prognostics' inaccuracies and scheduling robustness [56]. Subsequent expansions have considered maintenance and prognostics uncertainties, but still, overlook resources beyond labor [56]. Koops [43], van de Loo [67], and Nejad [66] offer methodologies for addressing maintenance imperfections in scheduling but do not integrate resource constraints or varying asset maturities.
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][142], Markov Decision Process [20][63][67][135], machine learning [8][23][92][22][67][64][65][137][139][145], Monte-Carlo simulation [43][92][62][50], Heuristics [60][79][91][92][95][50][96][30][135][145], discrete-event simulation [54][56][79], agent-based simulation [54][56][79][66][67] and ontology [5][8][9][17][30][60][79] to provide maintenance optimization through action prescription however, no work has considered resource constraints other than human labor, or maintenance and prognostics imperfection altogether [19][43][54][56] [135][142].
The potential for human-cobot collaboration in PsM is acknowledged as a future direction [5][17][22][100][101][102], with limited research like that of Deng et al. [77] and Ansari [89][99] exploring the dynamics of knowledge sharing between humans and cobots. However, there's no comprehensive model that integrates this collaboration with all maintenance resources and accounts for maintenance imperfections.
Cross-industry extensibility is frequently mentioned as a prospective feature or future work [5][7][22][24][30][35][48][49][51][52][54][58][60][62][64][65][81][137][139], yet it remains untested in

optimization algorithms. While methodologies by Strack et al. [30] and Koukaras et al. [65] suggest simulation [30] and machine learning [65] approaches, there's a lack of experimental validation for these methods.
These gaps originated the research question addressed by this work and presented in table 2.6.

Table 2.6 - Research questions addressed by this work.

How maintenance efficiency can be improved through a prescriptive maintenance framework which:		
Considers	1.	All maintenance resources involved namely labor, material, tools, equipment and infrastructure [5][9][17][54][56][58][79]?
	2.	Maintenance uncertainties and imperfections [19][43][54][56] [135][142]?
Is	3.	Adaptable to different assets with different technological maturities [5][7][22][24][30][32][33][35][48][49][51][52][54][58][60][62][64][65][81] [137][138]?
	4.	Scalable to different industries, namely Aerospace and Health [51][22][52][138][139]
Provides	5.	Optimized maintenance course of action? [5][7][54][56][135][138][139]

Table 2.7 summarizes the authors approaches with regard the research question showing what has been done to improve maintenance efficiency. It can be noted that although the focused has been maintenance optimization, no work considers maintenance imperfection, resources beyond line maintenance labor all together. 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, as seen in the last line of the table table 2.7.

Table 2.7 – PsM works related to the research gaps address.

Approached by	Resources constraint	Asset maturity	Maintenance imperfections	Maintenance optimization	Prognostics uncertainties	Humans-cobot collaboration	Scalability to different industries	Main Goal
Meissner et al. [54]	◐	○	○	●	○	○	○	Cost
Meissner et al. [56]	◐	◐	◐	●	○	○	○	Cost
Ansari et al. [5]	◐	○	○	●	○	○	○	Framework
Choubey et al. [7]	◐	○	○	●	○	○	○	Framework
Mattioli et al. [8]	○	○	○	◐	○	○	○	Framework
Glawar et al. [9]	◐	○	○	◐	○	○	○	Framework
Ansari et al. [17]	◐	○	○	◐	○	○	○	Framework
Silvestri et al. [100]	○	○	○	○	○	◐	○	Concept
Cisterna [101]	○	○	○	○	○	◐	○	Concept
Ameri et al. [102]	○	○	○	○	○	◐	○	Concept
Gao et al. [20]	○	○	○	●	○	○	○	Cost
Kovacs et al. [23]	○	○	○	●	○	○	○	Cost
Strack et al. [30]	○	○	○	◐	○	○	○	Framework
Strack et al. [39]	◐	○	○	◐	○	○	○	Framework
Koops [43]	○	○	●	●	○	○	○	Cost
Padovano et al. [60]	◐	○	○	●	○	○	○	Framework
Deng et al. [77]	○	○	○	●	○	●	○	Framework
Garcia et al. [79]	◐	○	○	●	○	○	○	Cost & availability
Ansari et al. [89]	○	○	○	◐	○	●	○	Framework
Ansari et al. [99]	○	○	○	●	○	●	○	Framework
Aramon et al. [91]	◐	○	○	●	○	○	○	Cost & availability
Cho et al. [57]	◐	○	○	●	○	○	○	Cost
Consilvio et al. [49]	◐	○	○	●	○	○	○	Cost
Consilvio et al. [92]	◐	○	○	●	●	○	○	Concept
Dias et al. [62]	○	○	○	●	○	○	○	Concept
Filo et al. [22]	○	○	○	●	○	○	○	Concept
Gavranis et al. [94]	◐	○	○	●	○	○	○	Cost & availability
Kozanidis et al. [95]	◐	○	○	●	○	○	○	Cost & availability
Liu et al. [50]	○	○	○	●	○	○	○	Cost
Nakousi et al. [82]	○	○	○	●	○	○	○	Cost
Nejad [66]	◐	○	●	●	○	○	○	Cost
Robert et al. [96]	○	○	○	●	○	○	○	Cost
Schrotenboer et al. [97]	●	○	○	●	○	○	○	Cost
Safei et al. [98]	◐	○	○	●	○	○	○	Availability
Tham et al. [63]	○	○	○	●	○	○	○	Cost
van de Loo [67]	○	○	●	●	○	○	○	Cost
Vanderschueren et al. [64]	○	○	○	●	○	○	○	Cost
Venkatachalam et al. [81]	○	○	○	●	○	○	○	Cost

Approached by	Resources constraint	Asset maturity	Maintenance imperfections	Maintenance optimization	Prognostics uncertainties	Humans-cobot collaboration	Scalability to different industries	Main Goal
Mao et al. [142]	◐	○	○	●	◐	○	○	Cost & availability
Pinciroli et al. [139]	○	○	○	●	○	○	○	Cost & availability
Sun et al. [137]	○	○	○	●	○	○	○	Cost
Goby et al. [145]	◐	○	○	●	○	○	◐	Cost
Zhao et al. [135]	○	○	○	●	○	○	○	Cost
Esposito et al. [145]	○	○	○	●	○	○	○	Cost
This work approach	●	●	●	●	○	○	●	Cost & availability

Legend: ● regarded ◐ rudimentary regarded ○ not regarded

As the journey through the landscape of prescriptive maintenance literature until January 2024 is concluded, it is evident that this field has witnessed remarkable growth and innovation in the last 5 years. The tapestry of research presented in this section underscores the multifaceted nature of PsM, where prescriptive analytics, the IoT and predictive modeling converge to shape the future of maintenance practices in complex operations. In drawing from the collective teachings and future directions of these works, the research question and corresponding gaps that guide the development of this research have been identified. Building upon the foundation laid by these studies, Section 3 will delve into the methods and results of this research, ultimately contributing to the ongoing evolution of PsM practices and future works.

3. Development, Methods & Results

This section delves into the heart of this research, exploring the development, methods, and results that underpin the Holistic and Scalable Smart Prescriptive (HSSP) Optimization Framework. The work is intricately linked with the Smart Prescriptive Maintenance Framework (SPMF), an innovative Information Technology and Communication approach for prescriptive maintenance [51] first introduced by Marques et al. in 2019 and later reproposed [55] by Giacotto et. al in 2021. This framework places a strong emphasis on holistic optimization, seamlessly integrating operation, maintenance, and maintenance resources into a unified strategy. Similarly, as the venture goes forward, it will be possible to witness how this work extends its reach beyond the aerospace industry, associating diverse assets such as aircraft and human health, laying the foundation for a cross-industry prescriptive maintenance paradigm shift. See table 3.1 for a glimpse of this association.

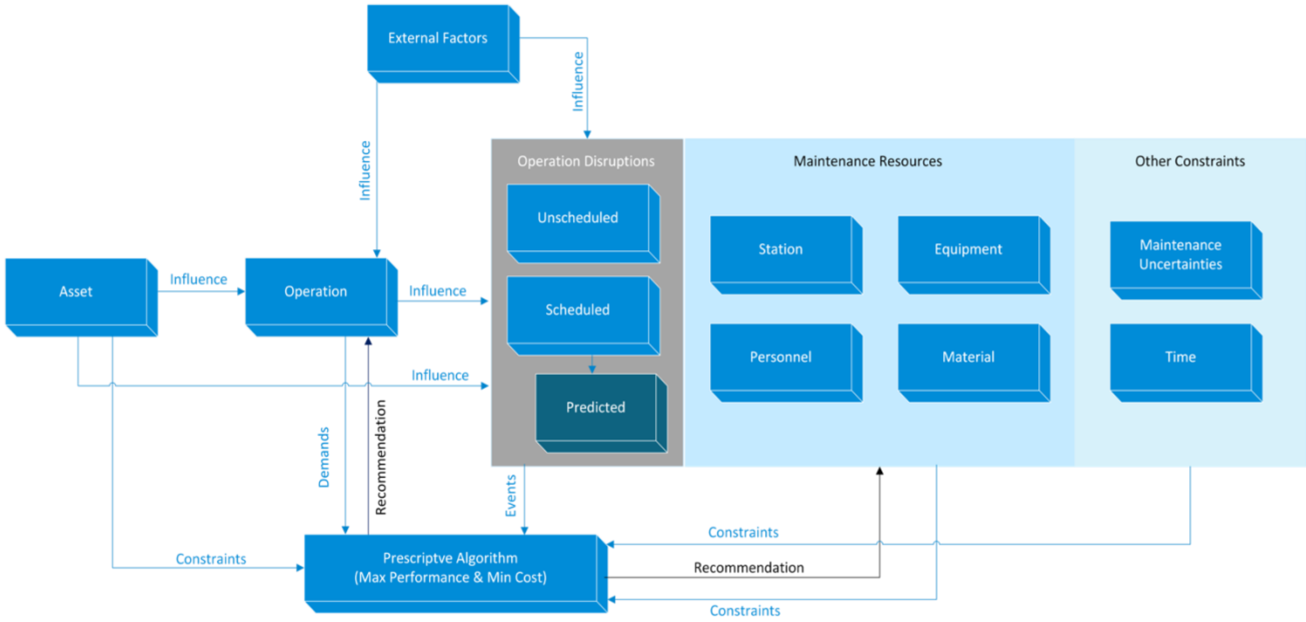
3.1 Development & Methods

Building on the previous works [51][55], current research proposes a new framework, tests it using mixed-integer linear programming (MILP) on the operation of a Brazilian regional airline and São Paulo's public health system COVID-19 response. The airline's fleet and patients' community are treated as assets in their respective scenarios, with airliner data covering operations, aircraft models, estimated fleet sizes, hangars capabilities, maintenance costs and operational revenue, and the public health system data covering the 2020 Covid crisis patients' admissions, hospitals' network and their estimated resources at the time of the epidemic in terms of medical teams, intensive care units (ICUs) and ventilators.

3.1.1 Holistic and Scalable Smart Optimization Framework for PsM

The Holistic and Scalable Smart Optimization Framework for PsM, shown in figure 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 1 – Holistic and scalable smart optimization framework for PsM.



The asset can encompass an aircraft 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. The asset directly influences how the operation occurs, that is, how the activities and actions performed by these assets, such as transporting goods or people, extracting and processing raw materials, producing consumer packaged goods, or conducting human activities happen. Operation, however, can be disrupted for various reasons, including the wear and tear of machines and equipment 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 necessary resources 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 activites. 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 predictive maintenance. For continuously monitored assets, it is possible not only to assess the current health state but also to predict future states and potential failures using artificial intelligence, data analytics, and mathematical models. 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 or if they have it, the prediction assertiveness is still a work in progress. 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, although not all ethic issues about data privacy have not been addressed yet.

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 (e.g., wars, strikes, labor shortages) or natural (e.g., 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, robustness, performance indices, and design characteristics. For human assets, this includes genetic information, innate resistance to infections, and responsiveness to specific treatments. The operation provides demands, indicating what is expected from the asset in terms of quality of the product, service or activity and related costs. 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. Through this data, constraints and demand, 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 and Scalable Smart Optimization Framework for PsM, table 2.8 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 2.8 – 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

Element	Action	Element	Description
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 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

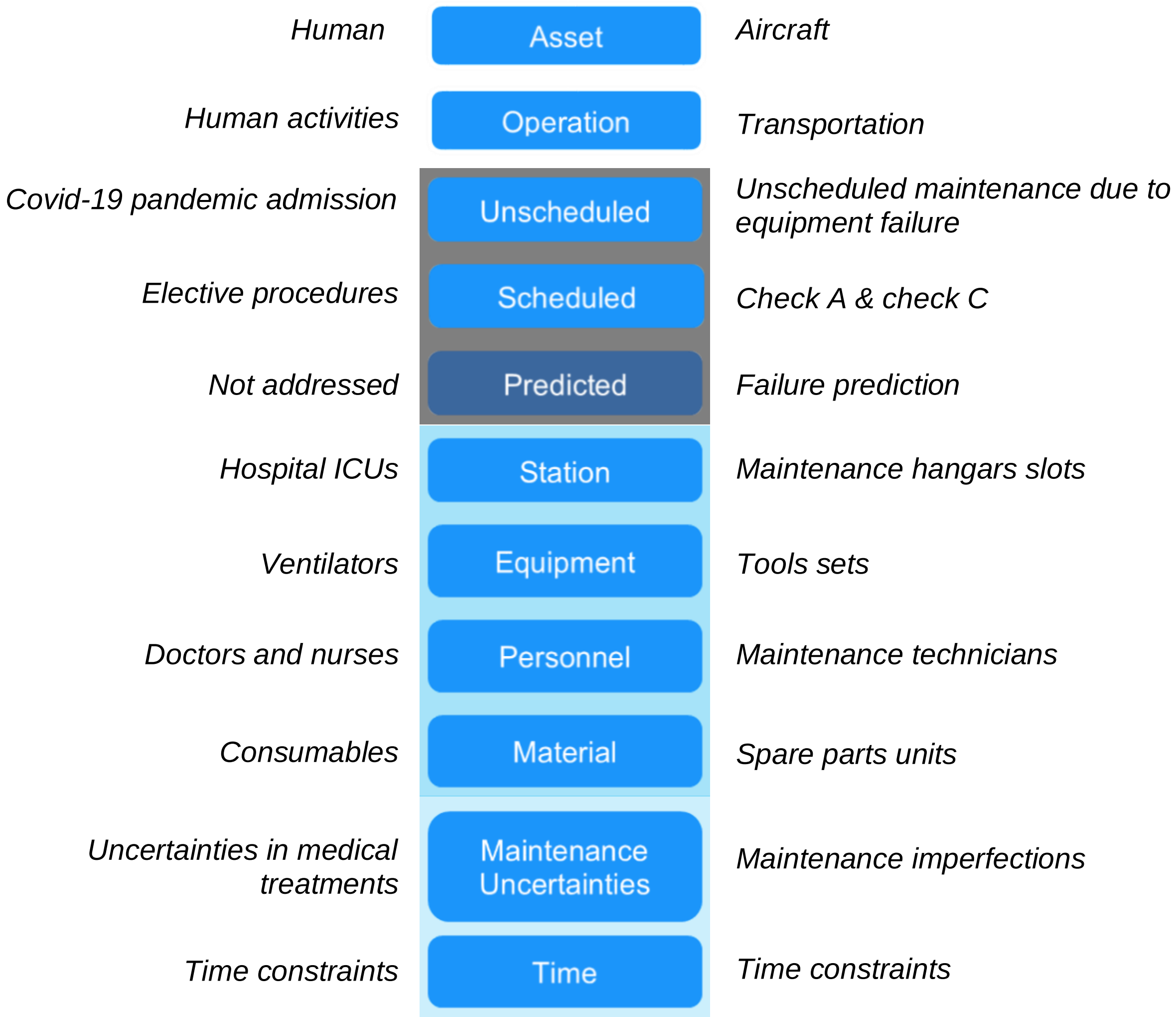
By considering the intricate relationships between the elements, this framework enables informed decision-making that enhances maintenance and operation seamlessly. As we delve deeper into the holistic aspect of the algorithm, the following sections will illustrate its application to diverse assets, such humans and aircraft. By this comparison, it will be uncovered how the framework's can be implemented across various industries.

3.1.2 Holistic Aspect and Mathematical Framework

Within the 2019 paper, the PsM definition and scope emphasizing the holistic optimization integrating operation, maintenance, and maintenance resources beyond labor as the main characteristic were introduced. In the same publication, it was proposed the concept of extensibility across different industries associating different assets, namely aircraft and humans in need of health assistance. The chart in figure 2 refines that idea presenting the main characteristics of these two diverse assets based on the framework presented in section 3.1.1 and on the case-studies further explained in next sections. 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 Check A and Check C. Predicted maintenance, a future work area for humans, involves anticipating human health issues or aircraft failures through predictive analytics.

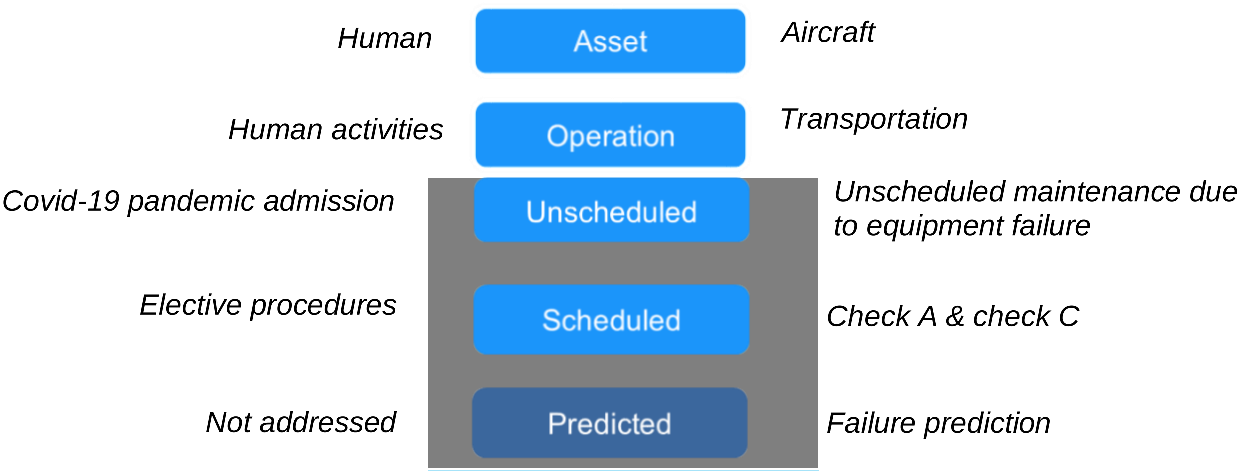
Maintenance resources for humans involve hospital ICUs (stations), ventilators (equipment), doctors and nurses (personnel), and hospital consumables (material). Similarly, aircraft maintenance resources include hangar slots (stations), tool sets (equipment), maintenance technicians (personnel), and spare 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 2 – Humans and aircraft characteristics association.



To further elucidate the Smart Optimization Framework for PsM, the next illustration, figure 3, introduces the mathematical structure underpinning main elements of the framework. This includes defining parameters, constraints, and objective functions for both human and aircraft assets. By providing a detailed mathematical perspective, the i strate how the framework quantitatively integrates various factors to optimize ma

Figure 3 – Mathematical structure of the model.



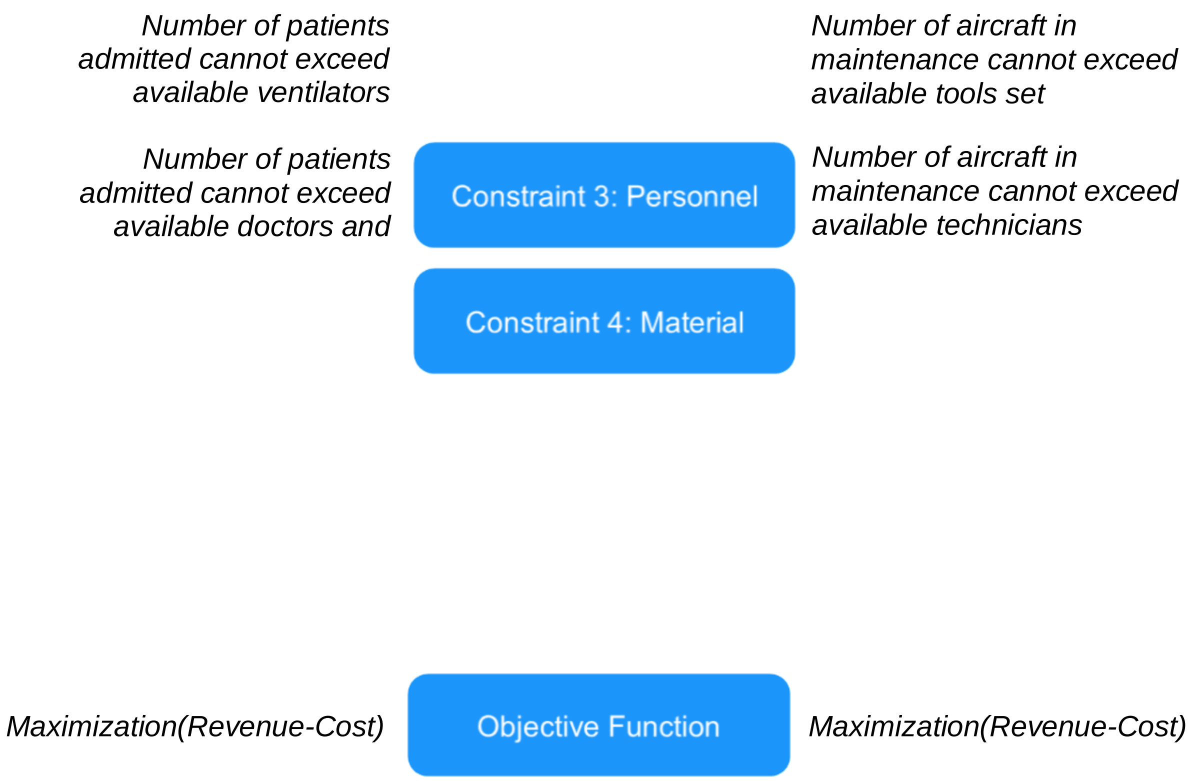


Figure 3 delineates the mathematical structure of the Smart Optimization Framework by mapping the elements of human and aircraft assets into parameters, constraints, and objective functions. For both humans and aircraft, the assets (individuals and aircraft) engage in operations (human activities and 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 check-A, check-C 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 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 by providing the required treatment to patients while costs are correlated to the daily ICUs cost. 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 sections.

As this section concludes, the framework's adaptability has been exemplified transcending industry boundaries and discussing the universality of its core principles by drawing parallels between the maintenance of complex systems like aircraft and the care of human health. Moving forward, the insights gleaned here serve as a platform to next sections that present the two case study in details.

3.2 Case Study 1: Smart Optimization Framework for PsM Applied to a Commercial Aviation Regional Fleet

This simulation model is 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. The model integrates multiple factors, including flight schedules, maintenance durations, hangar capacities, and resource availability.
Simulation was run locally on MacOS Sonoma 14.0 operational system with 16GB of memory and implemented on Python 3.12.4 environment using the Pandas and Numpy libraries, while optimization utilized them MILP method through Gurobi 11.0.2.
Next sections present operation simulation assumption and optimization mathematical model.

3.2.1 Operation Simulation

The simulation model was based on a Brazilian regional airliner operation with the fleet summarized in table 2.9 [148][152][153]. This airliner operates in more than 150 cities scattered in all Brazilian territory and in 7 cities internationally.

Table 2.9 – Operational simulation assumptions.

OEM	Aircraft	Quantity	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
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

OEM	Aircraft	Quantity	PHM enabled	Average age (years)	Seats	Wingspan x length (m^2)	Slot occupation (m^2)
Airbus	A350-900	2	✓	6	334	4325	3028
	Total	205	-	5	-		

The fleet characteristics encompass several key parameters for each aircraft model, including the original equipment manufacturer (OEM), the number of aircraft in the fleet, whether Prognostics and Health Management (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 multiplying the aircraft wing span and lengths.
For instance, 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 necessitates an adaptable approach to maintenance as required by the research question presented in table 2.6.
Regarding flight paths (origin-destination) and flight hours flown per day by each aircraft were collected directly from the airliner website for all the 150 destinations [151]. Table 3.0 presents an example of the data collected in terms of flight hours per trip, flight path and flight frequency over a period of 365 days.

Table 3.0 – Example of operational assumptions in terms of flight hours and flight paths [151].

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 check-A and check-C were identified as presented in table 3.1.

Table 3.1 – Aircraft maintenance check intervals [160][161].

Aircraft	Maintenance check interval					
	Check-A			Check-C		
	Flight hours (hours)	Calendar (months)	Duration (days)	Flight hours (hours)	Calendar (months)	Duration (days)
A320neo	750	4	7	7500	24	30

Aircraft	Maintenance check interval					
	Check-A			Check-C		
	Flight hours (hours)	Calendar (months)	Duration (days)	Flight hours (hours)	Calendar (months)	Duration (days)
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 function of time *t* corresponding at the accumulated sum of flight hours while the probability distribution utilized is the exponential distribution [155] as shown in equations (1)-(2). Specialists were consulted to validate estimated MTBUR for each ATA chapter for each model. Table 3.2 list the MTBUR values. The unscheduled maintenance duration was estimated as 1 day if the maintenance is performed in hangar with corrective maintenance capability, and 2 days if the aircraft was located in an 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.

- *F(t)*: probability of failure
- λ: failure ratio
- t: accumulated flight hours

$$F(t) = 1 - e^{-\lambda t} \quad (1)$$

$$\lambda = 1/MTBUR \quad (2)$$

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 were estimated using the MTBUR as baseline and reference values mapped in the literature [157][158].
The simulation provided for each aircraft the number and dates 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 and PHM forecasts estimation. Table 3.2 present an extract of the operational simulation results.

3.2 – Extract of operational simulation results in terms of maintenance occurrences.

Aircraft	Serial	Check-A dates	Check-C dates	Unscheduled maintenance estimated dates
E195-E2	1158	15 40 80 122 160	215	2 22 32 44 56 58 85 95 130 200 220 243 280 300 345

In conclusion, the operational simulation effectively provided maintenance schedules and estimated unscheduled events dates for each aircraft in the fleet, representing the events that must be managed by the optimization algorithm.
As we transition to the next section, we will delve into the maintenance capability model that addresses the maintenance resources used to perform maintenance—such as hangar slots, tooling, personnel, and materials. It is by considering these constraints, that the algorithm must ensure schedules are optimized.

3.2.2 Maintenance Capability Model

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 ariliner locations. The maintenance capability model considers three primary levels of maintenance: depot, intermediate, and organizational as flows:

- 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 Check-C in the 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 Check-A in the 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].

Table 3.3 illustrates the main maintenance hangar locations and their capabilities across these three levels. 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. 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 3-5 the largest narrowbody and widebody were used to estimate the slot area.

$$Largest\ narrow\ body\ area = 1028m^2 \tag{3}$$

$$Largest\ wide\ body\ area = 3028m^2 \tag{4}$$

$$Estimated\ Campinas\ hub\ slot\ area \geq MAX \begin{cases} 1028\ x\ 8 = \ 8224m^2 \\ 3028\ x\ 2 = \ 6056m^2 \end{cases} \tag{5}$$

Similarly, for Pampulha hub it is estimated that its capability is at least 5 narrow bodies [166][167]. Equations 6 and 7 presents the estimating calculations for Pampulha's hub slot area.

$$Largest\ narrow\ body\ area = 778m^2 \tag{6}$$

$$Estimated\ Pampulha\ hub\ slot\ area \geq 778\ x\ 5 = 3885m^2 \tag{7}$$

Table 3.3 – Main maintenance hangars locations and their maintenance capability [152][154][162][163][166][167][168].

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

Location	IATA code	Slots area (m^2)	Maintenance level capability		
			Organizational	Intermediate	Depot
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 3.4 provides a comprehensive overview of the maintenance locations available for each aircraft in the fleet, detailing where basic and intermediate checks (Check-A and Check-C) as well as unscheduled maintenance can be performed. The table highlights specific bases where the Check-C 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 Check-C maintenance at the Campinas facility, with additional 30 locations available for Check-A maintenance and over 120 locations for unscheduled maintenance. Similarly, the ATR 72-600 is serviced for Check-C at Pampulha, with a similar spread of additional locations for Check-A and unscheduled maintenance.

Table 3.4 – Fleet Check-C and intermediate checks locations.

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

Aircraft	Locations and Maintenance Levels		
	Depot	Intermediate	Organizational
	Check-C Check-A Unscheduled	Check-A Unscheduled	Unscheduled
A350-900	Campinas	+30 locations	+120 locations

Building on the discussion of maintenance capabilities across various hangar locations, it is essential to highlight the role of Ground Support Equipment (GSE). Table 4.4 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 3.5 – Consolidation on GSE in kits according to airframe, powerplant and avionics ATA chapters.

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	
53: fuselage	79: oil	

Airframe maintenance kit ATA chapters	Powerplant maintenance kit ATA chapters	Avionics maintenance Kit ATA chapters
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 are inherently dependent on the skilled technicians and supervisors who perform the maintenance tasks. Table 3.6 provides a detailed overview of the estimated team sizes and skill availability at depot hangars to perform Check-C 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 technicians, airframe technicians, and avionics technicians in alignment with FAA certifications [164].
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 3.6 – Estimated technicians teams size and skills daily availability for each aircraft model to perform check-C.

Aircraft	Basic 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

Aircraft	Basic maintenance team members skills and quantities per day per shift			
	Supervisor	Powerplant	Airframe	Avionics
A330-900	1	14	15	14
A330-200	1	14	15	14
A350-900	1	14	15	14

Table 3.7 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 3.7 – Team members numbers and skill needed daily to perform intermediate checks.

Aircraft	Intermidiate checks team members skills and quantities per day per shift			
	Supervisor	Powerplant	Airframe	Avionics
All models	1	2	2	2

Table 3.8 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 resources modelling and optimization by the prescriptive algorithm.

Table 3.8 – Team members numbers and skill needed daily to perform organizational and corrective 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

In conclusion, table 3.9 presents the estimeted required maintenance FTE needed to ptovide check-C and check-A maintenance for each aircraft model.

Table 3.9 – 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

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 the 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.

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.

In the following section, the specifics of the optimization algorithm will be detailed in terms of the parameters, constraints, and objective functions adopted and that form the core of the model.

3.2.3 Optimization Algorithm Mathematical Model

The evolution from the framework presented in section 3.1.2 to the one described in this section, reflects a paradigm in PsM that recognizes the interdependence of maintenance and operations within a complex system context. In the initial model, the focus was primarily on the maintenance aspect, following a structured flow based on maintenance capability data, technical data and asset

health, which then influenced the maintenance recommendation providing decision support for maintenance actions.
The evolved framework integrates operations management as a critical component that interacts directly with the maintenance decision-making process. By acknowledging the influence of operations on maintenance and vice versa, the new model positions operations management as a feedback loop that can affect all levels of the maintenance planning and execution process.
This holistic approach underscores that for PsM to be fully effective, it must not only optimize maintenance activities but also shape operational decisions. The change indicates a more dynamic and interconnected system where the optimization of maintenance activities is carried out in tandem with operational adjustments, facilitating a more agile maintenance strategy. This strategy ensures that both maintenance and operations are aligned, leading to enhanced efficiency, reduced downtime, and improved overall performance of complex systems.
The enhanced framework paves the way for a robust and comprehensive mathematical model. Initially derived from the wing production line algorithms, this model is being refined to accommodate the needs of a Brazilian regional airline and the public health operations of São Paulo state. This section presents the updated mathematical model and pseudocode, currently in development, focusing on the scheduling of fixed interval maintenance checks. The forthcoming stages of this model's evolution will be detailed in Section 4.

Constants & parameters

- F: fleet size;
- $Acft_{payload}$ = number of seats;
- $Revenue_{per\_seat}$= average ticket price;
- $Occupation_{ratio}$= 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: hangar slots;
- D: number of operational days;
- i: aircraft of the fleet F;
- d: day of the period D;
- d_A: day in which check-A should be scheduled according to the interval I_A;
- d_B: day in which unscheduled maintenance should be executed according to operation simulation results
- d_C: day in which check-C should be scheduled according to the interval 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 check-C maintenance occurs in the baseline interval;
- ${C_{early}}_C$: daily maintenance cost when check-C maintenance occurs before the baseline;

- C_{late_C}: daily maintenance cost when check-C maintenance occurs after the baseline;
- K_A: number of check-A intervals in the period *D* considered;
- K_C: number of check-C intervals in the period *D* considered;
- d_{late_A}: day after d_A in which check-A is scheduled;
- d_{late_B}: day after d_B in which unscheduled maintenance is scheduled;
- d_{late_C}: day after d_C in which check-C is scheduled;
- d_{early_A}: day in which check-A is scheduled, before d_A;
- d_{early_C}: day in which check-C is scheduled, before d_C;
- E_A: quantity of days before d_A in which check-A is scheduled;
- E_C: quantity of days before d_C in which check-C is scheduled;
- F_A: quantity of days after d_A in which check-A 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 check-C is scheduled;
- *m:* maintenance type
- *GSE:* equipment set availability per day, hangar slot and maintenance;
- *FTE:* full time equivalent personnel available per day, hangar slot and maintenance;
- *MAT:* spare parts available per day, hangar slot and maintenance

Decision variables

Table 3.3 – Decision variables.

Variable	State	Type
X_{id}	• Equal to 1 if check-A is scheduled for aircraft *i* on day *d* • 0 otherwise	Binary
Y_{id}	• Equal to 1 if if unscheduled maintenance is executed for aircraft *i* on day *d* • *0* otherwise	Binary
Z_{id}	• Equal to 1 if check-C is scheduled for aircraft *i* on day *d* 0 otherwise	Binary

Objective Function

$$Cost = \sum X_{id} * C_{early_A} * days\_before_A + \sum X_{id} * C_{late_A} * days\_after_A + \sum X_{id} * C_{baseline_C} + \sum Z_{id} * C_{early_C} * days\_before_C + \sum Z_{id} * C_{late_C} * days\_after_C + \sum Z_{id} * C_{baseline_A} + \sum Y_{id} * C_{baseline_B} + \sum Y_{id} * C_{late_B} * days\_after_B \quad (8)$$

$$Revenue = \sum\left(Revenue_{per\_seat} * Flight_{day} * Acft_{payload} * Occupation_{ratio}\right)_{i_d} \quad (9)$$

$$ObjectiveFunction = Max(Revenue - Cost) \quad (10)$$

Calculations

Equations 11 and 12 define that d_A and d_C are multiples of the respective check-A and check-C intervals. Equations 13 and 14 determine the number of intervals, which is given by the division between *D* and the interval I_A for check-A and I_C for check-C. Equations 15, 17 and 18 define d_{late} while equations 16 and 19 present the calculation for d_{early} since, if no slots are available, maintenance may be push back or pull forward. Equations 20 and 21 calculate the number of days in which A-check is scheduled before or after d_A. Similarly, equations 22 and 23 calculate the number of days in which check-C is scheduled before or after d_C.

$$d_A = n \times I_A \mid n: 1 \rightarrow K_A,\ n \in Integer \quad (11)$$

$$d_C = n \times I_C \mid n\!: 1 \rightarrow K_C,\ n \in Integer \tag{12}$$

$$K_A \geq \frac{D}{I_A},\ K_A \in Integer,\ K_A > 0 \tag{13}$$

$$K_C \geq \frac{D}{I_C},\ K_C \in Integer,\ K_C > 0 \tag{14}$$

$$d_A < d_{late_A} \leq d_A + I_A - A \tag{15}$$

$$d_A - I_A + A \leq d_{early_A} < d_A \tag{16}$$

$$d_B < d_{late_B} \leq d_B + I_B - B \tag{17}$$

$$d_C < d_{late_C} \leq d_C + I_C - C \tag{18}$$

$$d_C - I_C + C \leq d_{early_C} < d_C \tag{19}$$

$$E_A = d_A - d_{early_A} \qquad \text{for } d_A > d_{early_A} \tag{20}$$

$$F_A = d_{late_A} - d_A \qquad \text{for } d_{late_A} > d_A \tag{21}$$

$$E_C = d_C - d_{early_C} \qquad \text{for } d_C > d_{early_C} \tag{22}$$

$$F_C = d_{late_C} - d_C \qquad \text{for } d_{late_C} > d_C \tag{23}$$

Constraints

A key logistical consideration is the limitation imposed by the number of available maintenance slots described in equation 24. For any given day *d*, the number of aircraft slated to receive maintenance — be it an check-A, check-C 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 one time, ensuring that the physical space available is not exceeded. Equation 25 and 26 enforce that for each aircraft *i* on each day *d*, the cumulative number of checks-A 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 checks-A and checks-C 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.

Similarly, equations 27 and 28 enforce the intervals between maintenance checks. For A-checks, the left hand of the equation 33, $X_{(id)n} - X_{(id)\,n-1}$, 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 $Z_{(id)n} - Z_{(id)\,n-1}$,adhering to the OEM-specified limits I_C.
Constraints 29, 30 and 31 enforce that for each maintenance event the available FTE, GSE and spare parts quantities are not exceeded.

$$\sum_{i\in F}\sum_{d\in D}(X_{id} + Y_{id} + Z_{id}) \leq H \quad \text{for each day } d \text{ and aircraft } i \tag{24}$$

$$\sum_{i\in F}\sum_{d\in D} X_{id} \geq K_A \quad \text{for each day } d \text{ and aircraft } i \tag{25}$$

$$\sum_{i\in F}\sum_{d\in D} Z_{id} \geq K_C \quad \text{for each day } d \text{ and aircraft } i \tag{26}$$

$$X_{(id)n} - X_{(id)\,n-1} \leq I_A \quad \text{for each } d, i \text{ and } n \tag{27}$$

$$Z_{(id)n} - Z_{(id)\,n-1} \leq I_C \quad \text{for each } d, i \text{ and } n \tag{28}$$

$$\sum_{i\in F}\sum_{d\in D}(X_{id} + Y_{id} + Z_{id}) * GSE_{idm} \leq GSE_{Hd} \quad \text{for each day } d, \text{ aircraft } i \text{ and maintenance } m \tag{29}$$

$$\sum_{i\in F}\sum_{d\in D}(X_{id} + Y_{id} + Z_{id}) * FTE_{idm} \leq FTE_{Hd} \quad \text{for each day } d, \text{ aircraft } i \text{ and maintenance } m \tag{30}$$

$$\sum_{i\in F}\sum_{d\in D}(X_{id} + Y_{id} + Z_{id}) * MAT_{idm} \leq MAT_{Hd} \quad \text{for each day } d, \text{ aircraft } i \text{ and maintenance } m \tag{31}$$

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 process model known as the Wiener process, which can be 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 (32).

$$X(t) = \eta\Lambda(t) + \sigma B(\Lambda(t)) \tag{32}$$

Being $X(t)$ the degradation at time *t*, $\Lambda(t)$ =*t* assuming a linear degradation model, $\eta > 0$ is the drift coefficient, σ denotes the diffusion coefficient, and *B(t)* is the standard Brownian motion [43]. In the context of imperfect repairs, Koops (2020) utilizes an improvement factor α_k to describe the

(33)

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 (33):

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

where 0 ≤α_k ≤ 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], specifically α_k~TN(u,v,0,1), where υ and ν are parameters of the normal distribution. The assumption is that for a almost perfect maintenance procedure based on replace and removal, as the ones addressed by this simulation, $\alpha_k = 0{,}9, \eta = 1, \sigma = 0{,}3,\ B = 1$ which is the maximum degradation allowed. 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 was observed a decrease of MTBUR values of around 10% by the end of one year.

3.3 Case Study 2: Smart Optimization Framework for PsM Applied to COVID-19 response

For this case was not necessary to simulate the asset operation to estimate maintenance event since the historical data of 3000 patients admitted in public hospitals of São Paulo state during the pandemic of 2020 was considered. The data based contained, age, gender, day of admission, hospital, duration of admission, if intensive care units (ICUs) and ventilators were used, and if the patients deceased. In the following section the result of statistical study that identifies optimal admissions durations and the mathematical model utilized to optimize patients admissions are presented. Optimization was run locally on MacOS Sonoma 14.0 operational system with 16GB of memory and implemented on Python 3.12.4 through MILP on Gurobi 11.0.2.

3.3.1 Survivability Statistical Study Result

Analyzing the historical data related to 1085 patients that had severe COVID and had to be admitted at ICU, the admission duration that should ensure best chances of survival were identified for each age group. Table 4.0 categorizes patients by age range and gender, listing the number of patients in each category, the optimal admission duration in days, and the corresponding probability of survival. For example, male patients aged 0-4 have 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 have an optimal duration of 12 days with a probability of survival of 1. This data is critical for optimization algorithm to tailor the admissions schedules towards patient survival maximization.

Table 4.0 – Survival statistical analysis to identify optimal duration.

Age range	Gender	Patients	Optimal admission duration (days)	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

Age range	Gender	Patients	Optimal admission duration (days)	Probability of survival
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
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

Age range	Gender	Patients	Optimal admission duration (days)	Probability of survival
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 4.0 offers valuable insights into the optimal admission durations required to enhance patient survival rates. By leveraging this data, healthcare providers can make informed decisions to optimize patient care and resource allocation. The next section will address the health care infrastructure capability while successively we will build upon these findings by introducing the optimization algorithm to schedule patient admissions and allocate healthcare resources effectively.

3.3.2 Health Care Infrastructure Capability

Table 4.1 presents the healthcare infrastructure capabilities of four hospitals, detailing the availability of critical resources such as ICU beds, ventilators, doctors, and nurses. This information is essential for understanding the capacity of each hospital to handle patient admissions and provide adequate care, especially in scenarios involving high demand or emergencies such as a pandemic.
For instance, Hospital 1 has 15 ICU beds, 15 ventilators, 23 doctors, and 40 nurses, while Hospital 3 has the highest capacity with 41 ICU beds, 41 ventilators, 50 doctors, and 104 nurses.
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 4.1 – Health care infrastructure capability [173].

Hospital	ICU	Ventilators	Doctors	Nurses
Hospital 1	15	15	23	40
Hospital 2	30	30	35	68
Hospital 3	41	41	50	104
Hospital 4	24	24	30	51

Hospital	ICU	Ventilators	Doctors	Nurses
Hospital 5	59	59	50	87
Hospital 6	15	15	10	20
Hospital 7	15	15	10	20
Hospital 8	22	22	40	90
Hospital 9	15	15	12	40
Hospital 10	16	16	15	35
Hospital 11	12	12	14	19
Hospital 12	106	106	80	104
Hospital 13	15	15	11	15
Hospital 14	21	21	15	20
Hospital 15	23	23	20	27
Hospital 16	10	10	4	5
Hospital 17	49	49	20	26
Hospital 18	15	15	4	7
Hospital 19	46	46	35	46
Hospital 20	30	30	25	33
Hospital 21	113	113	60	78
Hospital 22	106	106	67	89
Hospital 23	82	82	73	100
Hospital 24	80	80	68	100
Hospital 25	411	411	356	467
Hospital 26	64	64	43	55
Hospital 27	108	108	91	120
Hospital 28	26	26	31	41
Hospital 29	15	15	9	12

Hospital	ICU	Ventilators	Doctors	Nurses
Hospital 30	15	15	3	4
Hospital 31	104	104	88	115
Hospital 32	15	15	12	17
Hospital 33	15	15	9	12
Hospital 34	16	16	21	28
Hospital 35	11	11	17	23
Hospital 36	15	15	8	15
Hospital 37	83	83	85	112
Hospital 38	15	15	4	10
Hospital 39	20	20	22	32
Hospital 40	19	19	21	29
Hospital 41	54	54	57	81
Hospital 42	49	49	51	76
Hospital 43	72	72	75	100
Hospital 44	20	20	27	37
Hospital 45	33	33	37	50
Hospital 46	200	200	187	276
Hospital 47	44	44	47	70
Hospital 48	26	26	31	60
Hospital 49	100	100	91	131
Hospital 50	52	52	43	75
Hospital 51	15	15	17	30
Hospital 52	26	26	16	30
Hospital 53	15	15	7	18
Hospital 54	22	22	18	30

Hospital	ICU	Ventilators	Doctors	Nurses
Hospital 55	100	100	80	120
Hospital 56	1	1	4	12

3.3.3 Optimization Algorithm Mathematical Model - Health

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 and the allocation of healthcare resources. 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 among Revenue and Cost. These parameters include sets of patients and hospitals, admission periods, optimal treatment durations, and the availability of critical resources such as ICU beds, doctors, and nurses. 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. The

Constants & parameters

- I: patients set;
- H = hospitals set;
- i: patient;
- d: day of the of admission period;
- d_f: final day of treatment;
- d_i: day of admission according to historical data;
- d_a: day of admission;
- d_{oi}: optimal duration per patient;
- ICU_{Hd}: available ICU beds in hospital h;
- Doc_{id}: required quantity of doctors per patient per day;
- Doc_{hd}: available quantity of doctors per patient per day;
- Nur_{id}: required quantity of nurses per patient per day;
- Nur_{hd}: available quantity of doctors per patient per day;
- $C_{admission_{day}}$: daily cost of ICU and ventilators use, including health personnel;
- $Yearly_{salary}$: yearly average salary;
- $Life\_expectancy_i$: average life expectancy per patient I;

Decision variables

Table 4.2 – Decision variables.

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

Objective Function

$$Cost = \sum X_{id} * C_{admission_{day}} * d_{o_i} \tag{34}$$

$$Revenue = \sum X_{id} * \left(Life\_expectancy_i * Yearly_{salary}\right) \tag{35}$$

$$ObjectiveFunction = Max(Revenue - Cost) \tag{36}$$

Calculations

Equations 37 equals parameter $d_a$with the informed actual data of admission d_i.

$$d_a = d_i \tag{37}$$

Constraints

Equation 38 enforces that admission must happen while constraint 39 ensures that the duration of admission is equal to optimal duration.
Constraints 40, 41, 42 and 43 enforce that for each admission event the available ICUs, ventilators and hospital personnel are not exceeded.

$$\sum_{i \in F} \sum_{d \in D} (X_{id}) \geq 1 \qquad \text{for each day } d \text{ and patient } i \tag{38}$$

$$d_f - d_a = d_o \qquad \text{for each patient } i \tag{39}$$

$$\sum_{i \in F} \sum_{d \in D} (X_{id}) \leq ICU_{hd} \qquad \text{for each day } d \text{ and patient } i \tag{40}$$

$$\sum_{i \in F} \sum_{d \in D} (X_{id}) \leq Ven_{hd} \qquad \text{for each day } d \text{ and patient } i \tag{41}$$

$$\sum_{i \in F} \sum_{d \in D} (X_{id}) * Doc_{id} \leq Doc_{hd} \qquad \text{for each day } d \text{ and patient } i \tag{42}$$

$$\sum_{i \in F} \sum_{d \in D} (X_{id}) * Nur_{id} \leq Nur_{hd} \qquad \text{for each day } d \text{ and patient } i \tag{43}$$

4. Results and Future Work

The Holistic Smart Optimization Framework for Prescriptive Maintenance proved to be highly effective in both the commercial aviation and healthcare case studies. In aviation, the holistic approach not only increased revenue by 0.79%, amounting to an additional USD 15,424,687.20MM annually, but also significantly improved dispatch reliability from 72.61% to 99.79%. In the healthcare context, the framework, evaluated through Monte Carlo simulation, demonstrated a substantial increase in patient survivability, with an estimated 782 patients surviving compared to 429 in historical data. These results underscore the framework's potential to enhance operational efficiency, financial performance, and reliability across diverse domains.
Moreover, the method opens up exciting opportunities for healthcare as the field shifts towards more proactive strategies. With the advent of wearables that continuously monitor vital signs, the framework can leverage real-time data to further optimize patient care and resource allocation. This integration of continuous monitoring technology aligns with the broader trend towards predictive and preventive medicine, promising even greater improvements in patient outcomes and healthcare efficiency. Future work will focus on further refining the model, expanding its applicability, and

exploring additional optimization opportunities to continue driving improvements in both commercial and healthcare settings.

5. Conclusion

This manuscript underscores the transformative potential of the smart optimization framework for PsM in redefining maintenance operations. By bridging critical research gaps, such as the inclusion of maintenance resources, the consideration of maintenance imperfections and asset of different technological maturities and the model's adaptability to different context – health and commercial aviation. This research extends the scope of PsM beyond traditional boundaries.
The framework's potential presents promising results in maintenance efficiency and availability.
The research's trajectory from theoretical foundations to practical applications in aviation and healthcare showcases its scalability and adaptability across industries. Looking ahead, the research signals continuous development, with a focus on refining the model to address a wider array of operational complexities and real-life study cases, fully leveraging the capabilities of ecosystem 4.0. This work lays the groundwork for future advancements, positioning the smart optimization framework for PsM as a catalyst for innovation in maintenance strategies.

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8. Copyright Statement

9. References

[1] Nemeth, T., Ansari, F., Sihn, W., Haslhofer, B., & Schindler, A. (2018). PriMa-X: A reference model for realizing prescriptive maintenance and assessing its maturity enhanced by machine learning. Procedia CIRP, 72, 1039–1044. https://doi.org/10.1016/j.procir.2018.03.280

[2] Jones, D., Snider, C., Nassehi, A., Yon, J., & Hicks, B. (2020). Characterizing the Digital Twin: A systematic literature review. CIRP Journal of Manufacturing Science and Technology, 29, 36–52. https://doi.org/10.1016/j.cirpj.2020.02.002

[3] Yeung, A. W. K. (2017). Identification of seminal works that built the foundation for functional magnetic resonance imaging studies of taste and food. CURRENT SCIENCE, 113(7), 3.

[4] Maguire, M., & Delahunt, B. (2017). Doing a Thematic Analysis: A Practical, Step-by-Step Guide for Learning and Teaching Scholars. AISHE-J, 8(3). http://ojs.aishe.org/index.php/aishe-j/article/view/335

[5] Ansari, F., Glawar, R., & Nemeth, T. (2019). PriMa: A prescriptive maintenance model for cyber-physical production systems. International Journal of Computer Integrated Manufacturing, 32(4–5), 482–503. https://doi.org/10.1080/0951192X.2019.1571236

[6] Errandonea, I., Beltrán, S., & Arrizabalaga, S. (2020). Digital Twin for maintenance: A literature review. Computers in Industry, 123, 103316. https://doi.org/10.1016/j.compind.2020.103316

[7] Choubey, S., Benton, R. G., & Johnsten, T. (2020). A Holistic End-to-End Prescriptive Maintenance Framework. Data-Enabled Discovery and Applications, 4(1), 11. https://doi.org/10.1007/s41688-020-00045-z

[8] Mattioli, J., Perico, P., & Robic, P.-O. (2020). Artificial Intelligence based Asset Management. 2020 IEEE 15th International Conference of System of Systems Engineering (SoSE), 151–156. https://doi.org/10.1109/SoSE50414.2020.9130505

[9] Glawar, R., Ansari, F., Kardos, C., Matyas, K., & Sihn, W. (2019). Conceptual Design of an Integrated Autonomous Production Control Model in association with a Prescriptive Maintenance Model (PriMa). Procedia CIRP, 80, 482–487. https://doi.org/10.1016/j.procir.2019.01.047

[10] Orr, D. A. (1976). New concepts for provisioning parameter estimates: Maintenance factors and replacement rates (IRQ-TR-77-3). U.S. Army Logistic Management Center.

[11] Silva, G. (1986). Pump Failure Mode Forecasting Through the Use of an Integrated Diagnostic Methodology. 861307. https://doi.org/10.4271/861307

[12] Williams, P., & Mitchell, S. (1988). A new approach to flood protection design and riparian management. Protection, Management, and Restoration for the 1990's, 110 of General technical report PSW, 544.

[13] Harris, S. E., & Slate, E. V. (1999). Lamp Ray: Ship hull assessment for value, safety and readiness. Oceans '99. MTS/IEEE. Riding the Crest into the 21st Century. Conference and Exhibition. Conference Proceedings (IEEE Cat. No.99CH37008), 1, 493–500. https://doi.org/10.1109/OCEANS.1999.799792

[14] Sauer, O. (2014). Developments and trends in shopfloor-related ICT systems. 2014 IEEE International Conference on Industrial Engineering and Engineering Management, 1352–1356. https://doi.org/10.1109/IEEM.2014.7058859

[15] Linden, A. (2013). Big Data: Alles Hype! Oder Nicht? Gartner45 Webinar.

[16] Khoshafian, D. S., & Rostetter, C. (2015). Disrupting Manufacturing Value Streams through Internet of Things, Big Data, and Dynamic Case Management. PEGA, 20.

[17] Ansari, F., Glawar, R., & Sihn, W. (2017). Prescriptive Maintenance of CPPS by Integrating Multimodal Data with Dynamic Bayesian Networks. Machine Learning for Cyber Physical Systems, 11, 1–8. https://doi.org/10.1007/978-3-662-59084-3_1

[18] Kohl, L. (2019). Design and Development of Automatic Recommendation Generation Module of Prescriptive Maintenance Model (AutoPriMa). Vienna University of Technology.

[19] Lemoine, D., & Castanier, B. (2021). How to Use Prescriptive Maintenance to Construct Robust Master Production Schedules. Proceedings of the 31st European Safety and Reliability Conference (ESREL 2021), 3280–3286. https://doi.org/10.3850/978-981-18-2016-8_693-cd

[20] Gao, G., Zhou, D., Tang, H., & Hu, X. (2021). An Intelligent Health diagnosis and Maintenance Decision-making approach in Smart Manufacturing. Reliability Engineering & System Safety, 216, 107965. https://doi.org/10.1016/j.ress.2021.107965

[21] Schenkelberg, K., Seidenberg, U., & Ansari, F. (2020). Analyzing the impact of maintenance on profitability using dynamic bayesian networks. Procedia CIRP, 88, 42–47. https://doi.org/10.1016/j.procir.2020.05.008

[22] Choubey, S., Benton, R., & Johnsten, T. (2020). Dynamic Thresholding Leading to Optimal Inventory Maintenance. 2020 IEEE International Conference on Big Data (Big Data), 4112–4121. https://doi.org/10.1109/BigData50022.2020.9378469

[23] Kovacs, K., Heistracher, C., Giner, J., Sihn, W., & Schneeweiss, J. (2021). A multi-level model for realizing data-driven maintenance in manufacturing enterprises: Use case of jewelry production. Procedia CIRP, 104, 1553–1558. https://doi.org/10.1016/j.procir.2021.11.262

[24] Errandonea, I., Alvarado, U., Beltrán, S., & Arrizabalaga, S. (2022). A Maturity Model Proposal for Industrial Maintenance and Its Application to the Railway Sector. Applied Sciences, 12(16), 8229. https://doi.org/10.3390/app12168229

[25] Jovanovic, A., Auerkari, P., & Bareiss, J. M. (2014). Practical determination of probability of failure in risk-based inspection and life management of coal power plants. In Coal Power Plant Materials and Life Assessment (pp. 288–317). Elsevier. https://doi.org/10.1533/9780857097323.2.288

[26] R., & Vrana, J. (2021). NDE 4.0—What Happens on This Bus? Canadian Institute for Non-Destructive Evaluation, 42, 8.

[27] Ellis, S., Santagate, J., & Morris, H. D. (2015). IoT-Enabled Analytic Applications Revolutionize Supply Chain Planning and Execution. IDC.

[28] Vyas, D. A., Bhatt, D., & Jha, D. (2016). IoT: Trends, Challenges and Future Scope. International Journal of Computer Science and Communications, 7, 12. https://doi.org/10.090592/IJCSC.2016.08

[29] Nikolaev, S., Belov, S., Gusev, M., & Uzhinsky, I. (2019). Hybrid Data-Driven and Physics-Based Modelling for Prescriptive Maintenance of Gas-Turbine Power Plant. In C. Fortin, L. Rivest, A. Bernard, & A. Bouras (Eds.), Product Lifecycle Management in the Digital Twin Era (Vol. 565, pp. 379–388). Springer International Publishing. https://doi.org/10.1007/978-3-030-42250-9_36

[30]Strack, B., Frank, J., Stich, V., & Pfau, F. (2021). Prescriptive Maintenance for Onshore Wind Turbines. 2nd Conference on Production Systems and Logistics, Hannover, Germany. https://doi.org/10.15488/11282

[31]Dutta, A., Karimi, I. A., & Farooq, S. (2022). PROAD (Process Advisor): A health monitoring framework for centrifugal pumps. Computers & Chemical Engineering, 163, 107825. https://doi.org/10.1016/j.compchemeng.2022.107825

[32]Fox, H., Pillai, A. C., Friedrich, D., Collu, M., Dawood, T., & Johanning, L. (2022). A Review of Predictive and Prescriptive Offshore Wind Farm Operation and Maintenance. Energies, 15(2), 504. https://doi.org/10.3390/en15020504

[33]Vanderschueren, T., Boute, R., Verdonck, T., Baesens, B., & Verbeke, W. (2022). Prescriptive maintenance with causal machine learning (arXiv:2206.01562). arXiv. http://arxiv.org/abs/2206.01562

[34]Gordon, C. A. K., Burnak, B., Onel, M., & Pistikopoulos, E. N. (2020). Data-Driven Prescriptive Maintenance: Failure Prediction Using Ensemble Support Vector Classification for Optimal Process and Maintenance Scheduling. Industrial & Engineering Chemistry Research, 59(44), 19607–19622. https://doi.org/10.1021/acs.iecr.0c03241

[35]Gordon, C. A. K., & Pistikopoulos, E. N. (2022). Data-driven prescriptive maintenance toward fault-tolerant multiparametric control. AIChE Journal, 68(6). https://doi.org/10.1002/aic.17489

[36]Momber, A. W., Möller, T., Langenkämper, D., Nattkemper, T. W., & Brün, D. (2022). A Digital Twin concept for the prescriptive maintenance of protective coating systems on wind turbine structures. Wind Engineering, 46(3), 949–971. https://doi.org/10.1177/0309524X211060550

[37]Petroutsatou, K., & Ladopoulos, I. (2022). Integrated Prescriptive Maintenance System (PREMSYS) for Construction Equipment Based on Productivity. IOP Conference Series: Materials Science and Engineering, 1218(1), 012006. https://doi.org/10.1088/1757-899X/1218/1/012006

[38]Lorente, Q., Villeneuve, E., Merlo, C., Boy, G. A., & Thermy, F. (2022). Development of a digital twin for collaborative decision-making, based on a multi-agent system: Application to prescriptive maintenance. INCOSE International Symposium, 32, 10. https://doi.org/10.1002/iis2.12875

[39]Strack, B., Frank, J., Stich, V., Lenart, M., & Pfau, F. (2022). Sociotechnical Implementation of Prescriptive Maintenance for Onshore Wind Turbines. Hawaii International Conference on System Sciences. https://doi.org/10.24251/HICSS.2022.158

[40]Büssow, Richard, Hain, Bruno, and Ismael Al Nuaimi. "Innovative Approach to Build a Scalable Hybrid Model for Prescriptive Maintenance." Paper presented at the Abu Dhabi International Petroleum Exhibition & Conference, Abu Dhabi, UAE, November 2021. doi: https://doi.org/10.2118/208031-MS

[41]Goetz, W. (2017). The path to prescriptive maintenance: Three steps to drive reliability while preparing for IIoT. Plant Engineering, 71(4), 26.

[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, vol. 66, no. 8, Aug. 2019, p. 22. Gale Academic OneFile, link.gale.com/apps/doc/A597810239/AONE?u=googlescholar&sid=googleScholar&xid=21f4430a. Accessed 5 Mar. 2023.

[43]Koops, L. (2020). Optimized Maintenance Decision-Making – A Simulation-supported Prescriptive Analytics Approach based on Probabilistic Cost-Benefit Analysis. Proceedings of the Virtual European Conference of the Prognostics and Health Management Society, 15.

[44]Karim, R., Westerberg, J., Galar, D., & Kumar, U. (2016). Maintenance Analytics – The New Know in Maintenance. IFAC-PapersOnLine, 49(28), 214–219. https://doi.org/10.1016/j.ifacol.2016.11.037

[45]Bokrantz, J., Skoogh, A., Berlin, C., & Stahre, J. (2017). Maintenance in digitalised manufacturing: Delphi-based scenarios for 2030. International Journal of Production Economics. https://linkinghub.elsevier.com/retrieve/pii/S092552731730172X

[46]Siemens (2019). Siemens MindSphere for Prescriptive Maintenance. https://www.plm.automation.siemens.com/media/global/pt/Siemens%20MindSphere%20for%20Prescriptive%20Maintenance_tcm70-65551.pdf Acessed on November 2022.

[47] Sitscape https://www.sitscape.com/wp-content/uploads/2018/01/SitScape-Prescriptive-Maintenance-Whitepaper.pdf Acessed on November 2022.

[48]Matyas, K., Nemeth, T., Kovacs, K., & Glawar, R. (2017). A procedural approach for realizing prescriptive maintenance planning in manufacturing industries. CIRP Annals, 66(1), 461–464. https://doi.org/10.1016/j.cirp.2017.04.007

[49]Consilvio, A., Sanetti, P., Anguita, D., Crovetto, C., Dambra, C., Oneto, L., Papa, F., & Sacco, N. (2019). Prescriptive Maintenance of Railway Infrastructure: From Data Analytics to Decision Support.

2019 6th International Conference on Models and Technologies for Intelligent Transportation Systems (MT-ITS), 1–10. https://doi.org/10.1109/MTITS.2019.8883331

[50]Liu, B., Lin, J., Zhang, L., & Kumar, U. (2019). A Dynamic Prescriptive Maintenance Model Considering System Aging and Degradation. IEEE Access, 7, 94931–94943. https://doi.org/10.1109/ACCESS.2019.2928587

[51]Marques, H., & Giacotto, A. (2019). Prescriptive Maintenance: Building Alternative Plans for Smart Operations. 231–236. https://doi.org/10.3384/ecp19162027

[52]Lepenioti, K., Bousdekis, A., Apostolou, D., & Mentzas, G. (2020). Prescriptive analytics: Literature review and research challenges. International Journal of Information Management, 50, 57–70. https://doi.org/10.1016/j.ijinfomgt.2019.04.003

[53]Grijalvo Martín, M., Pacios Álvarez, A., Ordieres-Meré, J., Villalba-Díez, J., & Morales-Alonso, G. (2020). New Business Models from Prescriptive Maintenance Strategies Aligned with Sustainable Development Goals. Sustainability, 13(1), 216. https://doi.org/10.3390/su13010216

[54]Meissner, R., Meyer, H., & Wicke, K. (2021). Concept and Economic Evaluation of Prescriptive Maintenance Strategies for an Automated Condition Monitoring System. International Journal of Prognostics and Health Management, 12(3). https://doi.org/10.36001/ijphm.2021.v12i3.2911

[55]Giacotto, A., Costa Marques, H., Pereira Barreto, E. A., & Martinetti, A. (2021). The Need for Ecosystem 4.0 to Support Maintenance 4.0: An Aviation Assembly Line Case. Applied Sciences, 11(8), 3333. https://doi.org/10.3390/app11083333

[56]Meissner, R., Rahn, A., & Wicke, K. (2021). Developing prescriptive maintenance strategies in the aviation industry based on a discrete-event simulation framework for post-prognostics decision making. Reliability Engineering & System Safety, 214, 107812. https://doi.org/10.1016/j.ress.2021.107812

[57]Cho, A. D., Carrasco, R. A., & Ruz, G. A. (2022). Improving Prescriptive Maintenance by Incorporating Post-Prognostic Information Through Chance Constraints. IEEE Access, 10, 55924–55932. https://doi.org/10.1109/ACCESS.2022.3177537

[58]Wesendrup, K., & Hellingrath, B. (2022). A Prescriptive Maintenance Aligned Production Planning and Control Reference Process. ECIS 2022, 20.

[59]Biebl, F., Glawar, R., Jalali, A., Ansari, F., Haslhofer, B., Boer, P. de, & Sihn, W. (2020). A conceptual model to enable prescriptive maintenance for etching equipment in semiconductor manufacturing. Procedia CIRP, 88, 64–69. https://doi.org/10.1016/j.procir.2020.05.012

[60]Padovano, A., Longo, F., Nicoletti, L., Gazzaneo, L., Chiurco, A., & Talarico, S. (2021). A prescriptive maintenance system for intelligent production planning and control in a smart cyber-physical production line. Procedia CIRP, 104, 1819–1824. https://doi.org/10.1016/j.procir.2021.11.307

[61]Choubey, S.K., Benton, R.G., & Johnsten, T. (2019). Prescriptive Equipment Maintenance: A Framework. 2019 IEEE International Conference on Big Data (Big Data), 4366-4374.

[62]Dias Longhitano, P., Tidriri, K., Bérenguer, C., & Echard, B. (2022). Proposition of a Generic Decision Framework for Prescriptive Maintenance. In J. O. P. Pinto, M. L. M. Kimpara, R. R. Reis, T. Seecharan, B. R. Upadhyaya, & J. Amadi-Echendu (Eds.), 15th WCEAM Proceedings (pp. 263–273). Springer International Publishing. https://doi.org/10.1007/978-3-030-96794-9_24

[63]Tham, C.-K., & Sharma, N. (2021). Prescriptive Maintenance Using Markov Decision Process and GPU-Accelerated Edge Computing. In A. Mukherjee, D. De, S. K. Ghosh, & R. Buyya (Eds.), Mobile Edge Computing (pp. 167–181). Springer International Publishing. https://doi.org/10.1007/978-3-030-69893-5_8

[64]Vanderschueren, T., Boute, R., Verdonck, T., Baesens, B., & Verbeke, W. (2022). Failure prediction vs. Maintenance prescription: Optimizing maintenance interventions by learning individual treatment effects. 16. https://doi.org/pre-print

[65]Koukaras, P., Dimara, A., Herrera, S., Zangrando, N., Krinidis, S., Ioannidis, D., Fraternali, P., Tjortjis, C., Anagnostopoulos, C.-N., & Tzovaras, D. (2022). Proactive Buildings: A Prescriptive Maintenance Approach. In I. Maglogiannis, L. Iliadis, J. Macintyre, & P. Cortez (Eds.), Artificial Intelligence Applications and Innovations. AIAI 2022 IFIP WG 12.5 International Workshops (Vol. 652, pp. 289–300). Springer International Publishing. https://doi.org/10.1007/978-3-031-08341-9_24

[66]Nejad, V. K. (2020). Evaluation of Prescriptive Maintenance Strategies for a Tire Pressure Indication Sys- tem (TPIS) assuming Imperfect Maintenance. Technical University of Munich.

[67]van de Loo, A. F. L. (2019). A decision making framework to achieve pre- scriptive maintenance in the FMCG production industry.pdf. Delft University of Technology.

[68]Paraschos, S., Mollas, I., Bassiliades, N., & Tsoumakas, G. (2021). VisioRed: A Visualisation Tool for Interpretable Predictive Maintenance. Proceedings of the Thirtieth International Joint Conference on Artificial Intelligence, 5004–5007. https://doi.org/10.24963/ijcai.2021/713

[69]Gullo, L. J. (2021). Design for Machine Learning. In L. J. Gullo & J. Dixon (Eds.), Design for Maintainability (1st ed., pp. 141–156). Wiley. https://doi.org/10.1002/9781119578536.ch8

[70]Jasiulewicz-Kaczmarek, M., Legutko, S., & Kluk, P. (2020). Maintenance 4.0 Technologies – New Opportunities for Sustainability Driven Maintenance. Polska Akademia Nauk, 11(2). https://doi.org/10.24425/MPER.2020.133730

[71]Baltazar, C. I. M. (2020). Prescriptive System for Reconfigurable Manufacturing Systems considering Variable Demand and Production Rates [University of Porto]. https://hdl.handle.net/10216/132786

[72]Sang, G. M. (2021). Predictive Maintenance for Industry 4.0 [Bournemouth University]. http://eprints.bournemouth.ac.uk/36855/

[73]Lee, J., Ni, J., Singh, J., Jiang, B., Azamfar, M., & Feng, J. (2020). Intelligent Maintenance Systems and Predictive Manufacturing. Journal of Manufacturing Science and Engineering, 142(11), 110805. https://doi.org/10.1115/1.4047856

[74]Alcayaga, A., Wiener, M., & Hansen, E. G. (2019). Towards a framework of smart-circular systems: An integrative literature review. Journal of Cleaner Production, 221, 622–634. https://doi.org/10.1016/j.jclepro.2019.02.085

[75]Filo, G. (2022). Analysis of Neural Network Structure for Implementation of the Prescriptive Maintenance Strategy. Material Research Proceedings, 24, 273–280. https://doi.org/10.21741/9781644902059-40

[76] Chilami, B. D., Karate, R. V., Kakate, O. S., Shintre, S. R., & Shinde, S. M. (2022). Optimization of uses, Production and Overall cost of a plant through Dynamic Prescriptive maintenance. International Journal of Research in Engineering and Science, 10(7), 6.

[77]Deng, H., Khan, S., & Erkoyuncu, J. A. (2022). A Framework for Constructing a Common Knowledge Base for Human-Machine System to Perform Maintenance Tasks. International Conference on Through-Life Engineering Services, 7.

[78][78] Jain, A., Giacotto, A., Marques, H. C., & Martinetti, A. (2022). Integrating the maintenance process: A framework to bridge design for maintenance to prescriptive maintenance. SITRAER 2022. Air Transportation Symposium, SITRAER 2022.

[79]Garcia Figueiredo Pinto, D. (2022). A MILITARY AIRCRAFT FLEET SUPPORT MANAGEMENT MODEL BASED ON THE OPTIMAL INTEGRATION OF PREDICTIVE AND SCHEDULED MAINTENANCE. Instituto Tecnológico de Aeronáutica.

[80]Anglou, F.-Z., Ponis, S., & Spanos, A. (2021). A machine learning approach to enable bulk orders of critical spare-parts in the shipping industry. Journal of Industrial Engineering and Management, 14(3), 604. https://doi.org/10.3926/jiem.3446

[81]Venkatachalam, S., Acharya, S., Oba, K., & Nakayama, Y. (2020). Prescriptive Analytics for Swapping Aircraft Assignments at All Nippon Airways. INFORMS Journal on Applied Analytics, 50(2), 99–111. https://doi.org/10.1287/inte.2019.1016

[82]Nakousi, C., Pascual, R., Anani, A., Kristjanpoller, F., & Lillo, P. (2018). An asset-management oriented methodology for mine haul-fleet usage scheduling. Reliability Engineering & System Safety, 180, 336–344. https://doi.org/10.1016/j.ress.2018.07.034

[83]Leturiondo, U., Salgado, O., Ciani, L., Galar, D., & Catelani, M. (2017). Architecture for hybrid modelling and its application to diagnosis and prognosis with missing data. Measurement, 108, 152–162. https://doi.org/10.1016/j.measurement.2017.02.003

[84]Abramovici, M., Lindner, A., Dienst, S., & Fathi, M. (2013). Predicting the behavior of solution alternatives within product improvement process. DS 75-9: Proceedings of the 19th International Conference on Engineering Design (ICED13), Design for Harmonies, 9, 397–406.

[85]Fletcher, J. D., & Johnston, R. (2002). Effectiveness and cost benefits of computer-based decision aids for equipment maintenance. Computers in Human Behavior, 18(6), 717–728. https://doi.org/10.1016/S0747-5632(02)00026-2

[86]Labib, A., Williams, G., & O'Connor, R. (1998). 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, 49(7), 745–757. https://doi.org/10.1038/sj.jors.2600542

[87]Beaudouin, F., Munier, B., & Serquin, Y. (1999). Multi-Attribute Decision Making and Generalized Expected Utility in Nuclear Power Plant Maintenance. In M. J. Machina & B. Munier (Eds.), Beliefs, Interactions and Preferences in Decision Making (pp. 341–357). Springer US. https://doi.org/10.1007/978-1-4757-4592-4_22

[88] "Transforming Unstructured Data into Useful Information", Big Data, Mining, and Analytics, Auerbach Publications, pp. 227–246, 2014-03-12, doi:10.1201/b16666-14, ISBN 978-0-429-09529-0, retrieved 2021-05-29

[89] Ansari, F., Khobreh, M., Seidenberg, U., & Sihn, W. (2018). A problem-solving ontology for human-centered cyber physical production systems. CIRP Journal of Manufacturing Science and Technology, 22, 91–106. https://doi.org/10.1016/j.cirpj.2018.06.002

[90] Diego Galar, and Uday Kumar. "Chapter 7 - Maintenance Decision Support Systems." EMaintenance. Elsevier, 2017. 371-474. Web.

[91] Aramon Bajestani, M., & Beck, J. C. (2013). Scheduling a Dynamic Aircraft Repair Shop with Limited Repair Resources. Journal of Artificial Intelligence Research, 47, 35–70. https://doi.org/10.1613/jair.3902

[92] Consilvio, A., Solís-Hernández, J., Jiménez-Redondo, N., Sanetti, P., Papa, F., & Mingolarra-Garaizar, I. (2020). On Applying Machine Learning and Simulative Approaches to Railway Asset Management: The Earthworks and Track Circuits Case Studies. Sustainability, 12(6), 2544. https://doi.org/10.3390/su12062544

[93] Filo, G. (2022). Analysis of Neural Network Structure for Implementation of the Prescriptive Maintenance Strategy. Material Research Proceedings, 24, 273–280. https://doi.org/10.21741/9781644902059-40

[94] Gavranis, A., & Kozanidis, G. (2015). 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, 242(2), 631–643. https://doi.org/10.1016/j.ejor.2014.10.016

[95] Kozanidis, G., Gavranis, A., & Liberopoulos, G. (2018). HEURISTICS FOR MAXIMIZING FLEET AVAILABILITY SUBJECT TO FLIGHT & MAINTENANCE REQUIREMENTS. 16.

[96] Robert, E., Berenguer, C., Bouvard, K., Tedie, H., & Lesobre, R. (2018). Joint dynamic scheduling of missions and maintenance for a commercial heavy vehicle: Value of on-line information. IFAC-PapersOnLine, 51(24), 837–842. https://doi.org/10.1016/j.ifacol.2018.09.672

[97] Schrotenboer, A. H., Ursavas, E., & Vis, I. F. A. (2020). Mixed Integer Programming models for planning maintenance at offshore wind farms under uncertainty. Transportation Research Part C: Emerging Technologies, 112, 180–202. https://doi.org/10.1016/j.trc.2019.12.014

[98] Safaei, N., Banjevic, D., & Jardine, A. K. S. (2011). Workforce-constrained maintenance scheduling for military aircraft fleet: A case study. Annals of Operations Research, 186(1), 295–316. https://doi.org/10.1007/s10479-011-0885-4

[99] Ansari, F., Hold, P., & Khobreh, M. (2020). 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, 28, 87–106. https://doi.org/10.1016/j.cirpj.2019.11.005

[100] Silvestri, L., Forcina, A., Introna, V., Santolamazza, A., & Cesarotti, V. (2020). Maintenance transformation through Industry 4.0 technologies: A systematic literature review. Computers in Industry, 123, 103335. https://doi.org/10.1016/j.compind.2020.103335

[101] Cisterna, A. R. (2022). Digital Twin for the management of wind power plants.

[102] Ameri, F., Stecke, K. E., von Cieminski, G., & Kiritsis, D. (Eds.). (2019). 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 (Vol. 566). Springer International Publishing. https://doi.org/10.1007/978-3-030-30000-5

[103] Arrieta, A. B., Díaz-Rodríguez, N., Del Ser, J., Bennetot, A., Tabik, S., Barbado, A., García, S., Gil-López, S., Molina, D., Benjamins, R., Chatila, R., & Herrera, F. (2019). Explainable Artificial Intelligence (XAI): Concepts, Taxonomies, Opportunities and Challenges toward Responsible AI (arXiv:1910.10045). arXiv. http://arxiv.org/abs/1910.10045

[104] Pinciroli, L., Baraldi, P., & Zio, E. (2023). Maintenance optimization in industry 4.0. Reliability Engineering & System Safety, 234, 109204. https://doi.org/10.1016/j.ress.2023.109204

[105] Lemes, L. C., & Hvam, L. (2019). Maintenance Costs in the Process Industry: A Literature Review. 2019 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM), 1481–1485. https://doi.org/10.1109/IEEM44572.2019.8978559

[106] Albakkoush, S., Pagone, E., & Salonitis, K. (2020). Scheduling Challenges within Maintenance Repair and Overhaul Operations in the Civil Aviation Sector. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.3718006

[107] Compare, M., Baraldi, P., & Zio, E. (2020). Challenges to IoT-Enabled Predictive Maintenance for Industry 4.0. IEEE Internet of Things Journal, 7(5), 4585–4597. https://doi.org/10.1109/JIOT.2019.2957029

[108] Achouch, M., Dimitrova, M., Ziane, K., Sattarpanah Karganroudi, S., Dhouib, R., Ibrahim, H., & Adda, M. (2022). On Predictive Maintenance in Industry 4.0: Overview, Models, and Challenges. Applied Sciences, 12(16), 8081. https://doi.org/10.3390/app12168081

[109] Coandă, P., Avram, M., & Constantin, V. (2020). A state of the art of predictive maintenance techniques. IOP Conference Series: Materials Science and Engineering, 997(1), 012039. https://doi.org/10.1088/1757-899X/997/1/012039

[110] Zhao, J., Gao, C., & Tang, T. (2022). A Review of Sustainable Maintenance Strategies for Single Component and Multicomponent Equipment. Sustainability, 14(5), 2992. https://doi.org/10.3390/su14052992

[111] Wazlawick, R. S. (2022). Metodologia de Pesquisa para Ciência da Computação, 3ª Edição. Rio de Janeiro: LTC. ISBN: 978-85-951-5109-3

[112] Aviation Week (2023). Japanes Carriers Make Predicitve Maintenance Progress. https://aviationweek.com/mro/emerging-technologies/japanese-carriers-make-predictive-maintenance-progress. Visited on May 2023.

[113] Aviation Week (2023). ADE Launches new digital aftermarket product. https://aviationweek.com/mro/emerging-technologies/ade-launches-new-digital-aftermarket-products . Visited on June 2023.

[114] Khatab, A.; Diallo, C.; Venkatadri, U.; Liu, Z.; Aghezzaf, E.-H. Optimization of the Joint Selective Maintenance and Repairperson Assignment Problem under Imperfect Maintenance. Comput. Ind. Eng. 2018, 125, 413–422.

[115] ILO 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—Skills and Employability Network. Available online: http://apskills.ilo.org/resources/benchmarking-of-qualificatio ns-frameworks-a-report-on-potential-comparability-between-the-bangladesh-technical-and-vocational-qualifications-frame work-and-qualifications-frameworks-of-other-countries-of-origin-and-destination-of-migrant-workers (accessed on 11 March 2021).

[116] Gurobi Software Downloads and License Center. Available online: https://www.gurobi.com/downloads/ (accessed on 11 March 2021).

[117] Mathworks MATLAB & Simulink. Available online: https://www.mathworks.com/products/matlab.html (accessed on 11 March 2021).

[118] Madeira, A., Moutinho, V., & Fuinhas, J. A. (2021). Does waiting times decrease or increase operational costs in short and long-term? Evidence from Portuguese public hospitals. The European Journal of Health Economics, 22(8), 1195–1216. https://doi.org/10.1007/s10198-021-01331-y

[119] Siciliani, L., Stanciole, A., & Jacobs, R. (2009). Do waiting times reduce hospital costs? Journal of Health Economics, 28(4), 771–780. https://doi.org/10.1016/j.jhealeco.2009.04.002

[120] Moscelli, G., Gravelle, H., & Siciliani, L. (2023). The effect of hospital choice and competition on inequalities in waiting times. Journal of Economic Behavior & Organization, 205, 169–201. https://doi.org/10.1016/j.jebo.2022.10.040

[121] Weltcheck, Mallhan Attorneys. How to calculate lost wages from medical malpractices. https://wmwlawfirm.com/blog/how-calculate-lost-wages-medical-malpractice/ (accessed on June 2023).

[122] Crump, B. How is death compensation calculated? https://bencrump.com/faqs/how-is-death-compensation-calculated/ (accessed on June 2023).

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

[124] Alagoz, O., Hsu, H., Schaefer, A. J., & Roberts, M. S. (2010). Markov Decision Processes: A Tool for Sequential Decision Making under Uncertainty. Medical Decision Making, 30(4), 474–483. https://doi.org/10.1177/0272989X09353194

[125] White, D. J. (1985). Real Applications of Markov Decision Processes. Interfaces, 15(6), 73–83. http://www.jstor.org/stable/25060766

[126] Mazzuchi, T. A., van Noortwijk, J. M., & Kallen, M. J. (2007). Maintenance Optimization. The Institute for Integrating Statistics in Decision Sciences

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

[128] Wolsey, L. A. (1998). Integer programming. John Wiley & Sons. (Chapter 1, pages 1-16)

[129] Hoffman, K. L., & Ralphs, T. K. (n.d.). Integer and Combinatorial Optimization.

[130] Brazilian Health Ministry. Data SUS. https://datasus.saude.gov.br/informacoes-de-saude-tabnet/ (accessed on June 2023).

[131] Silaparesetty, V. https://www.linkedin.com/advice/1/what-main-challenges-limitations-markov-decision-processes (accessed on June 2023).

[132] Bjerregaard L. MROs Deploy New Workforce Strategies As Labor Gap Worsens. Aviationweek,

[133] Aviationweek. https://aviationweek.com/mro/workforce-training/mros-deploy-new-workforce-strategies-labor-gap-worsens, 2003

[134] Bailey J. Losers: The Airlines That Failed During 2022. Simple Flying. https://simpleflying.com/airline-failures-2022/. 2022

[135] All Plane TV. https://allplane.tv/blog/2023/1/14/the-2023-airline-bankruptcy-list-is-now-open-as-of-14123. 2023.

[136] Zhao, Y., & Wang, W. (2023). TranDRL: A Transformer-Driven Deep Reinforcement Learning Enabled Prescriptive Maintenance Framework (arXiv:2309.16935). arXiv. http://arxiv.org/abs/2309.16935

[137] Teubert, C., Pohya, A. A., & Gorospe, G. (2023). An Analysis of Barriers Preventing the Widespread Adoption of Predictive and Prescriptive Maintenance in Aviation.

[138] Sun, Y., Chan, R., Yang, Z., & Zhiquana, Y. (2023). AI-based Prescriptive Maintenance for Sustainable Operation. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.4457075

[139] Pinciroli, L., Baraldi, P., & Zio, E. (2023). Maintenance optimization in industry 4.0. Reliability Engineering & System Safety, 234, 109204. https://doi.org/10.1016/j.ress.2023.109204

[140] Pinciroli, L., Baraldi, P., Compare, M., & Zio, E. (2023). Optimal operation and maintenance of energy storage systems in grid-connected microgrids by deep reinforcement learning. Applied Energy, 352, 121947. https://doi.org/10.1016/j.apenergy.2023.121947

[141] Oneto, L., Anastasopoulos, M., Anguita, D., Baroni, I., Canepa, R., Dambra, C., Gogos, S., Jentner, W., & Petralli, S. (2023). DAYDREAMS - Development of Prescriptive Analytics based on Artificial Intelligence for Railways Intelligent Asset Management Systems. Transportation Research Procedia, *72*, 478–485. https://doi.org/10.1016/j.trpro.2023.11.927

[142] Molęda, M., Małysiak-Mrozek, B., Ding, W., Sunderam, V., & Mrozek, D. (2023). From Corrective to Predictive Maintenance—A Review of Maintenance Approaches for the Power Industry. Sensors, 23(13), 5970. https://doi.org/10.3390/s23135970

[143] Mao, H., Liu, Z., Qiu, C., Huang, Y., & Tan, J. (2023). Prescriptive maintenance for complex products with digital twin considering production planning and resource constraints. Measurement Science and Technology, 34(12), 125903. https://doi.org/10.1088/1361-6501/aced5f

[144] Khatri, M. R. (2023). 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.

[145] Hoffmann, M. A., & Lasch, R. (2023). Tackling Industrial Downtimes with Artificial Intelligence in Data-Driven Maintenance. ACM Computing Surveys, 56(4), 1–33. https://doi.org/10.1145/3623378

[146] Goby, N., Brandt, T., & Neumann, D. (2023). Deep reinforcement learning with combinatorial actions spaces: An application to prescriptive maintenance. Computers & Industrial Engineering, 179, 109165. https://doi.org/10.1016/j.cie.2023.109165

[147] Esposito, N., Castanier, B., & Giorgio, M. (2023). An Adaptive Prescriptive Maintenance Policy for a Gamma Deteriorating Unit. Proceeding of the 33rd European Safety and Reliability Conference, 960–967. https://doi.org/10.3850/978-981-18-8071-1_P311-cd

[148] Azul linhas aereas investors presentation 1Q24. (2024). https://api.mziq.com/mzfilemanager/v2/d/ed78542a-4e01-429a-8926-03d69ccfa307/1fbbab00-b91d-3173-7375-f252bd5a320f?origin=1

[149] Gurobi Optimization. https://www.gurobi.com. Gurobi (2023)

[150] Python. https://www.python.org. (2023).

[151] Azul linhas aéreas (2024). https://www.voeazul.com.br/br/pt/sobreazul/mapa-de-rotas

[152] Azul Linhas Aereas, “Sustainability Report.pdf,” 2022. Accessed: Sep. 08, 2023. [Online]. Available: https://ri.voeazul.com.br/en/investor-information/esg/

[153] Aviacaocomercial.net, “Frota – Azul”, 2023. Accessed: Jan. 07, 2024. [Online]. Avaliable: https://www.aviacaocomercial.net/frotaazul.htm
[154] IATA, “Airline and Airport Code Search”. 2023. Accessed: Jan. 07, 2024. [Online]. Avaliable: https://www.iata.org/en/publications/directories/code-search/?airport
[155] S. Albakkoush, E. Pagone, and K. Salonitis, “Scheduling Challenges within Maintenance Repair and Overhaul Operations in the Civil Aviation Sector,” SSRN Journal, 2020, doi: 10.2139/ssrn.3718006.
[156] H. Qiu, B. Wang, and J. Yu, “Aircraft Maintenance Process Knowledge Modeling Method,” in 2020 IEEE 2nd International Conference on Civil Aviation Safety and Information Technology (ICCASIT, Weihai, China: IEEE, Oct. 2020, pp. 717–723. doi: 10.1109/ICCASIT50869.2020.9368785.
[157] M. Kordestani, M. E. Orchard, K. Khorasani, and M. Saif, “An Overview of the State of the Art in Aircraft Prognostic and Health Management Strategies,” IEEE Trans. Instrum. Meas., vol. 72, pp. 1–15, 2023, doi: 10.1109/TIM.2023.3236342.
[158] S. Fu and N. P. Avdelidis, “Prognostic and Health Management of Critical Aircraft Systems and Components: An Overview,” Sensors, vol. 23, no. 19, p. 8124, Sep. 2023, doi: 10.3390/s23198124.
[159] A. Bashir Babeker Abdulgader, O. M. Abdulraheem Ebishi, S. Y. Abdulazeez Mohammed, and T. S. Elzaky Ibrahim, “Factors Affecting Civil Aircraft Availability,” Sudan University of Science and Technology, 2015.
[160] “A320 base check maintenance inputs” Aircraft Commerce, 2017. [Online]. Available: https://www.aircraft-commerce.com/wp-content/uploads/aircraft-commerce-docs1/Maintenance/2017/111_MTCE_A.pdf
[161]“Maintenance Review Board Report.” AIRBUS SAS, 2014. [Online]. Available: https://sassofia.com/wp-content/uploads/2022/02/253296850-A320Fam-MRBR-Rev19.pdf
[162] Google Maps (2024). Available from: https://www.google.com/maps/ [Accessed 31 March 2024]
[163] On time aviation (2023). https://ontimeaviation.net/noticias-brasil/maior-hangar-da-america-latina-completa-tres-anos-de-operacao/#
[164] FAA (2024). https://www.faa.gov/mechanics/become
[165] Chron (2021). https://work.chron.com/can-specialize-aircraft-mechanic-22519.html
[166] https://www.melhoresdestinos.com.br/centro-manutencao-azul-pampulha.html
[167] https://www.aeroflap.com.br/en/conheca-todos-os-detalhes-do-centro-de-manutencao-da-azul-em-pampulha/
[168] https://aeroin.net/centro-de-manutencao-da-azul-na-pampulha-1808/
[169] https://www1.folha.uol.com.br/internacional/en/scienceandhealth/2020/03/icu-hospitalizations-will-cost-brazils-public-healthcare-more-than-us-232-million.shtml
[170] https://www.ncbi.nlm.nih.gov/pmc/articles/PMC137273/
[171] Bakakos A, Koukaki E, Ampelioti S, Ioannidou I, Papaioannou AI, Loverdos K, Koutsoukou A, Rovina N. The Real Impact of Age on Mortality in Critically Ill COVID-19 Patients. J Pers Med. 2023 May 29;13(6):908. doi: 10.3390/jpm13060908. PMID: 37373897; PMCID: PMC10303099.
[172] Jones J. V. (2010),”Integrated Logistic Support Handbook”. McGraw Hill.
[173] https://cnes.datasus.gov.br/pages/estabelecimentos/consulta.jsp
[174] Attia P. (2023),”Outlive – the science & art of longevity”. Harmony