From Prediction to Prescription: A Systematic Survey of Maintenance Techniques and Sector-Specific Applications in Industry 4.0

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Abstract

The evolution of Industry 4.0 and the emerging Industry 5.0 have transformed maintenance from a support activity into a critical factor for economic competitiveness and operational resilience. As industrial assets ranging from offshore wind turbines to mobile networks become increasingly complex, traditional reactive and preventive strategies are proving inefficient. While predictive maintenance (PdM) has made significant strides in using artificial intelligence to estimate remaining useful life (RUL), the field is now advancing toward prescriptive maintenance (RxM), which goes beyond prediction to optimize decision-making and automate corrective actions. To map this transition, this study conducts a systematic literature review, analyzing 26 key studies published between 2019 and 2025 across the automotive, energy, manufacturing, and infrastructure sectors.

The findings reveal that while deep learning techniques like LSTM remain the standard for fault detection, high-value sectors are increasingly adopting prescriptive frameworks supported by digital twins and federated learning. The paper concludes by presenting a practical case study using the NASA C-MAPSS dataset to demonstrate the implementation of a prescriptive workflow.

Keywords: Predictive Maintenance (PdM), Prescriptive Maintenance (RxM), Remaining Useful Life (RUL), Industry 5.0, Systematic Literature Review, Digital Twin.

1 Introduction

In the last decade, the industrial landscape has undergone a profound transformation driven by the fourth industrial revolution (Industry 4.0) and the emerging Industry 5.0 paradigms. As industrial systems ranging from offshore wind farms to complex telecommunication networks grow in scale and complexity, the reliability of assets has become a critical determinant of economic competitiveness. In industry, any outages and unplanned downtime of machines or systems would degrade or interrupt a company's core business, potentially resulting in significant penalties and immeasurable reputation and economic loss.

Historically, organizations have relied on traditional maintenance strategies. The most basic approach, reactive maintenance (RM) or "run-to-failure," often leads to catastrophic breakdowns and excessive downtime. To mitigate this, preventive maintenance (PM) was introduced, relying on scheduled interventions based on time or usage cycles. However, PM strategies suffer from high prevention costs and the waste of components that still possess a significant remaining useful life (RUL).

To address these inefficiencies, predictive maintenance (PdM) has emerged as a transformative approach to optimize the reliability and availability of industrial systems. By leveraging artificial intelligence (AI) and deep learning, PdM enables precise forecasts of equipment failure, allowing operators to intervene only when necessary. Recent advancements in machine learning, such as long short-term memory (LSTM) networks, are now widely explored for their applicability in early fault detection and condition-based monitoring. [18]

However, while PdM successfully answers the question "when will it break?", it often lacks the capability to advise on the optimal corrective strategy. This has led to a movement towards prescriptive maintenance (RxM), which is an evolution of the predictive paradigm. Unlike simple prediction, prescriptive strategies provide optimized maintenance actions, incorporating predictions into a wider plan to address failure modes under uncertainty.[8] Despite the clear benefits, the current body of literature is highly fragmented and lacks a thorough review that bridges the gap between predictive diagnostics and prescriptive decision-making across diverse sectors.

1.1 Running example: the aero-propulsion maintenance scenario

To ground the theoretical analysis of this systematic literature review, we introduce a running example based

on a high-value industrial asset: an aircraft turbofan engine. This scenario, derived from the NASA C-MAPSS data repository (Saxena et al., 2008), illustrates the critical transition from predictive to prescriptive process management.
Consider a fleet of commercial jet engines monitored by a network of embedded sensors. In a traditional predictive maintenance workflow, the system analyzes these sensor streams to estimate the remaining useful life (RUL) predicting, for instance, that "engine #10 will fail in 50 cycles." While valuable, this insight is passive; it alerts the operator to a problem but offers no solution other than scheduling downtime.
The scenario evolves when we apply prescriptive maintenance. Here, the system not only predicts the failure trajectory but also identifies actionable interventions to alter that outcome. For example, the system might simulate that "reducing the throttle load by 5% will extend the RUL by 20 cycles," effectively allowing the aircraft to complete its mission safely before requiring overhaul.

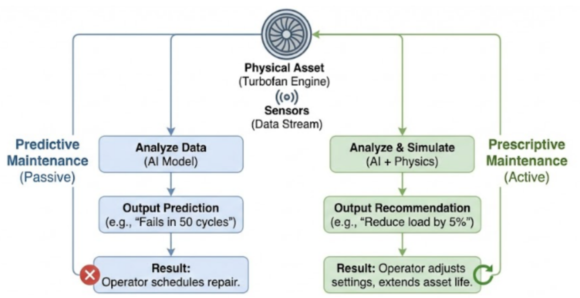

Figure 1: The diagram illustrates the operational difference between traditional predictive approaches (left path), which stop at forecasting failure, and prescriptive approaches (right path), which close the loop by recommending actions to alter the outcome.

1.2 Problem statement

The scenario described in the running example (Section 1.1) showcases the shortcomings of current maintenance modeling approaches. While modern sensors provide vast amounts of operational data, process participants often lack an integrated view that connects this predictive data directly to actionable business decisions. [18] In many standard predictive maintenance (PdM) workflows, an operator is alerted to a declining remaining useful life (RUL), but the process model does not explicitly show how to manipulate operational parameters such as load factors or pressure settings to alter that outcome. Note that without such an integrated view, the relevant context required to move from diagnosis to prescription is missing during process execution. Moreover, when deciding on a maintenance action, the operator often lacks access to the projected consequences of different intervention strategies. [8]

In contrast to sophisticated AI data pipelines, the process management systems used to manage maintenance workflows are often limited by a common activity-centric paradigm. This paradigm is effective for highly structured, repetitive tasks, such as standard preventive maintenance. However, it enforces a rigid work practice and predefined activity sequences, which leads to a lack of flexibility during process execution when dealing with dynamic machine degradation. As highlighted in the running example, merely following a static "repair checklist" is insufficient when the goal is to actively extend the asset's life through parameter tuning.
However, the maintenance processes found in Industry 4.0 scenarios are often characterized as unstructured or semi-structured. In addition, they are considered to be knowledge-intensive and driven by complex user decisions. This means that the response to a fault alert may vary depending on the asset's current health and business needs. Thus, different intervention sequences need to be supported. For example, while one operator might choose to schedule an immediate replacement for an engine, another might choose to apply a "load-shedding" prescription to safely extend operations until the next scheduled stop.[8] This requires increased flexibility during process execution, which is usually not provided by the rigid, activity-centric predictive maintenance tools currently in use.

1.3 Contribution

It has been acknowledged by various authors that many of the limitations of contemporary maintenance strategies can be traced back to the missing integration of predictive analytics and process execution [1, 3, 18]. While advanced algorithms such as those utilizing deep learning and LSTM networks [4, 9, 12] can successfully predict failure, current process management systems often fail to effectively operationalize these insights into actionable maintenance workflows. To tackle this issue, prescriptive maintenance (RxM) approaches have emerged[8]. They adopt a fundamentally different view on asset management, where data predictions are not just passive alerts but are considered as main drivers for automated decision-making and process optimization.
Until now, however, a general understanding of the inherent relationships that exist between predictive data models and prescriptive process execution is still missing. Whereas many studies solely focus on the algorithmic accuracy [9, 12], only a few approaches take the entire maintenance lifecycle comprising monitoring, analysis, decision-making, and execution into account. In a nutshell, there is a lack of profound methods and comprehensive frameworks for systematically assessing, analyzing, and comparing existing data-centric maintenance approaches.
The remainder of the paper is organized as follows. Section 2 explains the research methodology applied during the literature review. The results of the SLR are

presented in Sect. 4, while Sect. 3 highlights possible limitations and discusses threats to validity. To demonstrate the practical utility of our findings, Sect. 5 shows the application of the framework SpaceVis, developed to simulate the scenarios identified in the SLR. Section 6 examines similar literature reviews in the field. Finally, to conclude our paper Sect. 7 contains a summary and an outlook.

2 Methodology

A systematic literature review (SLR) was conducted with the goal of analyzing the state-of-the-art techniques in predictive and prescriptive maintenance. An SLR is a rigorous method used to identify, evaluate, and interpret relevant scientific works regarding a specific research topic. We designed a protocol for conducting the SLR that strictly follows the guidelines and policies presented by Kitchenham and Charters in [27] in order to ensure that the results are replicable and the means of knowledge acquisition are both scientific and transparent. Additionally, the probability of any bias occurring during the review process is significantly reduced by adhering to this structured protocol [27].
The necessary steps taken to guarantee compliance with the SLR guidelines include the formulation of the specific research questions (cf. Sect. 2.1), the composition of the search string (cf. Sect. 2.2), the selection of the data sources on which the search is performed (cf. Sect. 2.3), the identification of inclusion and exclusion criteria (cf. Sect. 2.4), the study selection process (cf. Sect. 2.5).

2.1 Research questions

One goal of the SLR is to identify approaches that define predictive strategies or extend existing maintenance paradigms with prescriptive capabilities. The first step when conducting an SLR is the formulation of research questions [27], which poses a particular challenge. The predictive approaches known to us before conducting the SLR use a wide variety of methods, ranging from physics-based degradation models to black-box deep learning architectures. As opposed to purely predictive models, there are emerging prescriptive approaches where the estimation of remaining useful life (RUL) is integrated with decision-support logic to optimize operational parameters. However, the maintenance approaches unknown to us prior to conducting the SLR might utilize entirely different sensing modalities or apply known techniques in novel industrial sectors.
In regard to the formulation of the research questions, this heterogeneity must be accounted for. It is therefore mandatory to find terms for different concepts that do not exclude potential maintenance approaches based on the phrasing of the research questions. In order to account for the diversity of techniques and data sources, we define the terms maintenance technique and asset representation.

Definition 1 (maintenance technique) a maintenance technique is a general term for any computational method used to estimate the future state of an asset (predictive) or to recommend optimized actions to alter that state (prescriptive).

Common established examples of maintenance techniques are long short-term memory (LSTM) networks in data-driven approaches and physics-based approaches. Another relevant concept for data-centric maintenance is how the physical asset is observed.

Definition 2 (asset representation) asset representation describes the means by which an approach acquires physical data values (sensors) and the datasets used to validate these observations.

For example, asset representation refers to the specific sensor typology used to monitor a component. For approaches focusing on algorithmic benchmarking, it refers to the specific dataset used to train the model.

As the terms maintenance technique and asset representation are intentionally designed to cover a wide variety of different concepts, a certain level of uncertainty remains with respect to the formulation of research questions. However, this uncertainty cannot be eliminated entirely. Approaches may have several concepts that fit the definition of either a technique or a representation.
Based on these considerations, we formulated the following research questions, which will be discussed in the following:

- RQ1: What are the main categories of techniques in predictive and prescriptive maintenance?
- RQ2: What are the most commonly used sensor types in this field?
- RQ3: What is the availability of open datasets?
- RQ4: What are the most frequent areas of use?

As research literature refers to various approaches for industrial maintenance, where the algorithmic perspective is as important as the operational outcome, we are interested in identifying what kind of techniques have been used to predict or extend the life of assets of any complexity (RQ1).
In addition, the SLR shall provide an overview of the way physical assets are monitored, namely what sensor types are utilized to construct the data representation of the equipment (RQ2).
A common challenge in data-centric research is reproducibility. Therefore, the SLR shall investigate the availability of open datasets versus proprietary data, providing an understanding of the resources available

to the research community (RQ3).
Finally, in order to assess the practical applicability of existing maintenance strategies, the SLR shall further identify the areas of use, mapping the techniques to specific industrial sectors to understand where these approaches are most effectively applied (RQ4).

2.1.1 RQ1: What are the main categories of techniques in predictive and prescriptive maintenance?

RQ1 focuses on the analysis of the different algorithmic strategies employed to estimate asset health and recommend interventions. Taking existing knowledge on maintenance engineering into account, we may assume that the majority of modern approaches rely on statistical learning. However, a clear distinction must be made between purely predictive techniques (estimating RUL) and prescriptive techniques (optimizing outcomes).
To account for this heterogeneity, we introduce the classification of maintenance techniques into three primary categories: data-driven, knowledge-based, and hybrid.

Definition 3 (data-driven approach) an approach is considered data-driven if the predictive model is learned exclusively from historical operational data without explicit physical equations describing the failure mode. Common examples include random forests, LSTMs, and CNNs.

The literature confirms that data-driven methods, particularly deep learning architectures like long short-term memory (LSTM) networks, are becoming dominant for early fault detection. Furthermore, comparative studies have begun to analyze the specific strengths of regression-based approaches (for RUL estimation) versus classification-based approaches (for failure probability). [1, 11, 17]
However, the most significant evolution addressed by RQ1 is the shift towards prescriptive maintenance.

Definition 4 (prescriptive capability) In order to be classified as prescriptive, a maintenance approach must fulfill two criteria:

- It must provide a quantitative estimate of future asset health (RUL).
- It must explicitly suggest an operational action that alters the predicted trajectory.

This evolution is clearly observed in sectors such as offshore wind, where strategies are moving from reactive to proactive, incorporating predictions into wider optimization plans. Similarly, in renewable energy, AI is used not just for prediction but for energy optimization and grid integration. [8, 25]

2.1.2 RQ2: What are the most commonly used sensor types in this field?

The quality of any data-centric approach is strictly dependent on the "asset representation," which is derived from sensor data. RQ2 investigates the physical inputs used to train these models. In general, sensor data is the bridge between the physical degradation process and the digital model.
We distinguish between two types of sensing strategies that RQ2 aims to identify:

- Physical sensors: Direct measurements of physical quantities. For instance, vibration analysis remains a gold standard for rotating machinery like electric motors. In the nuclear sector, critical parameters include temperature, water flow, and pressure. Recent innovations also include the integration of IoT sensors directly into natural fiber composites for real-time structural health monitoring.[13, 11, 4, 2]
- Visual and virtual sensors: The rise of augmented reality (AR) and mixed reality (MR) has introduced new forms of data consumption, where visual indicators overlay physical assets to assist operators. [11, 5]

2.1.3 RQ3: What is the availability of open datasets?

One of the major challenges in the field of prognostics and health management (PHM) is the reproducibility of results. RQ3 focuses on the "data availability" aspect. While many studies claim high accuracy, they are often validated on proprietary datasets that are not accessible to the scientific community. This creates a barrier to benchmarking and validation.
RQ3 aims to identify the prevalence of standard open datasets. Reviews in the automotive and maritime sectors explicitly highlight the need to map available public datasets to support model development. Furthermore, the lack of standardized data often leads to fragmentation in research results, making it difficult to synergize findings across different studies.[3, 19, 17, 4]
Our review reveals a significant paradox in the field of industrial AI: while algorithms are open-source and widely available, high-quality industrial data remains a scarce, proprietary asset. Companies are generally reluctant to release operational data due to privacy concerns and the risk of revealing trade secrets regarding asset reliability.
Consequently, the literature is heavily biased towards a small set of standardized, open-source benchmark datasets. As illustrated in the primary studies, researchers overwhelmingly rely on three specific repositories to validate their frameworks:

1. NASA C-MAPSS (turbofan engines) the commercial modular aero-propulsion system simulation (C-MAPSS) dataset is the de facto standard for

prognostics and health management (PHM) research. It appears in the majority of studies focusing on remaining useful life (RUL) prediction.

2. CWRU bearing dataset (rotating machinery) for the manufacturing and energy sectors, the case western reserve university (CWRU) bearing dataset remains the primary benchmark. It consists of vibration signals collected from ball bearings with seeded faults (inner race, outer race, and ball defects). It is crucial for validating classification algorithms (diagnosis) used in studies focusing on CNC machines and pumps.

3. IMS bearing dataset the intelligent maintenance systems (IMS) dataset, generated by the University of Cincinnati, is frequently cited alongside CWRU. Unlike CWRU, which deals with seeded faults, IMS represents a natural degradation process (run-to-failure), making it more suitable for developing RUL estimation models.

The ”synthetic gap” The analysis of RQ3 highlights a critical barrier to the deployment of prescriptive maintenance. Because real-world assets rarely fail catastrophically, there is a lack of labeled failure data for these critical infrastructures. This forces researchers to rely on:

- Synthetic data: Generated by digital twins.
- Hybrid models: Using physics-informed layers to compensate for data scarcity.

2.1.4 RQ4: What are the most frequent areas of use?

Maintenance solutions are rarely ”one-size-fits-all.” The applicability of a technique (RQ1) or a sensor type (RQ2) often depends on the specific industrial context. RQ4 investigates the domain specificity of the selected studies.
We categorize the ”areas of use” based on the complexity and criticality of the assets involved:

- Energy sector: This is a dominant field, with extensive research on photovoltaic (PV) systems , offshore wind farms , and oil and gas assets like electrical submersible pumps (ESPs). [1, 6, 8]
- Transportation: Significant contributions are found in the automotive industry , maritime shipping , and defense aircraft sustainment.[3, 19, 20]
- Infrastructure: Research extends to civil structures, such as bridges, where predictive capabilities are critical to managing aging road networks. [15]

RQ4 serves to map the theoretical contributions to their practical application domains. We specifically look for ”cross-domain” approaches techniques developed in one sector that are successfully applied in another as this indicates a high level of generalizability in the proposed method.

2.2 Search string

To perform a comprehensive search over the selected data sources, we designed specific boolean search strings. Given the choice of Google Scholar as the primary database, the queries were optimized to manage high result volumes by targeting titles and specific keywords.
Two distinct queries were executed to cover both the general state of the art and the specific prescriptive focus:

- Query 1: This query was designed to capture broad surveys across multiple sectors.

  allintitle:(”predictive maintenance” OR ”prescriptive maintenance”) AND (review OR survey OR ”state of the art”)

- Query 2: This query was designed to specifically identify the emerging transition from prediction to decision support, explicitly excluding purely preventive approaches.

  ”prescriptive maintenance” AND (”optimization” OR ”decision support”) -preventive

The search string resulted from iteratively refining an initial set of search terms. The refinement was performed by conducting pilot searches to find a suitable set of terms that maximized the yield of relevant studies while minimizing noise from unrelated domains. Finally, the filters were applied to restrict results to the 2019–2025 timeframe, ensuring the review captured only modern Industry 4.0 methodologies.

2.3 Data sources

When we started testing our search strings, we noticed a significant issue with the standard scientific databases (such as IEEE Xplore, SpringerLink, and Scopus). Because ”predictive maintenance” sits right between computer science (AI algorithms) and mechanical engineering (physical hardware), specialized databases often focused on just one side of the topic. For example, IEEE is excellent for algorithms but might miss important mechanical case studies.
Using different search queries for every database to fix this would make our review inconsistent and hard to reproduce. Therefore, we needed a strategy to capture both sides of the field in one go.
We decided to use Google Scholar as our main data source. Unlike specialized libraries, Google Scholar indexes the entire academic spectrum. This allowed us to retrieve papers on both algorithms and physics subject using a single, uniform query. While Google can sometimes personalize results, our specific keywords (see Sect. 2.2) were precise enough to filter out irrelevant noise. [28]

Finally, to prove that this strategy worked, we performed a validation check on IEEE Xplore and Scopus. We searched for our selected papers in these databases and confirmed that the high-quality studies identified via Google Scholar were indeed present in these rigorous academic libraries. This confirmed that our approach was valid and successfully captured the ”top-tier” research.

2.4 Inclusion and exclusion criteria

In order to identify the relevant studies for the SLR, we defined the following inclusion and exclusion criteria. These criteria were designed to filter out irrelevant domains and ensure the selected papers provide a broad overview of the field.
Inclusion criteria:

1. Topic relevance: The study explicitly addresses predictive maintenance (PdM), prescriptive maintenance (RxM)
2. Industrial domain: The approach focuses on physical assets rather than IT or software systems.
3. Document type: The study is a review, survey, meta-analysis, or a comprehensive framework proposal that includes a state-of-the-art analysis.
4. Timeframe: The study was published within the Industry 4.0/5.0 era (2019–2025).

Exclusion criteria:

1. Language: The study is not entirely written in english.
2. Out of scope: The study focuses solely on ”preventive” (time-based) or ”reactive” (fix-when-broken) maintenance.
3. Wrong domain
4. Redundancy: All relevant aspects of the study are described in another, more complete (superset) study, or the paper is a duplicate.

A study was included in the SLR if it satisfied at least one of the inclusion criteria (specifically #1 and #2 are mandatory), but none of the exclusion criteria. If a study matched any exclusion criterion, the study was discarded from the SLR.

2.5 Selecting the studies

The search string defined in Sect. 2.2 was used to conduct a search on Google Scholar. The search query yielded a total of 120 potentially relevant studies. For a better analysis, the relevant metadata was exported to Zotero for bibliographic management. Metadata included the title, author, source, abstract, and publication year. Based on the metadata, each study was reviewed for investigating its relevance to the SLR, using the inclusion and exclusion criteria defined in Sect. 2.4.
The review started with examining the titles and abstracts of the studies. Studies having titles that clearly did not deal with physical assets or lacked a specific predictive/prescriptive focus were immediately discarded as they did not match the inclusion criteria. This filtering resulted in the removal of 77 records. The remaining 43 high-potential studies were provisionally included in the SLR. Each of the 43 provisional studies was read thoroughly and assessed systematically through the inclusion and exclusion criteria. This in-depth analysis resulted in the identification of 26 primary studies (cf. Table 1) that were included in the final SLR, while 17 studies were discarded due to insufficient technical depth or lack usefull notice.

Table 1: List of primary studies

Study ID	Authors and bibliography reference
S01	Khalili et al. [1]
S02	Arockiasamy et al. [2]
S03	Mahale et al. [3]
S04	Gupta et al. [4]
S05	Matthias et al. [5]
S06	Hamza et al. [6]
S07	Dagroum Ali and Elaswad [7]
S08	Fox et al. [8]
S09	Imran Mohd Ali et al. [9]
S10	Grubišić et al. [10]
S11	Mohamad Nor et al. [11]
S12	Almazrouei et al. [12]
S13	Manjare and Patil [13]
S14	Guaresea et al. [14]
S15	Lydon et al. [15]
S16	Darwish [16]
S17	Jamshidi et al. [17]
S18	Zhu et al. [18]
S19	Kalafatelis et al. [19]
S20	Scott et al. [20]
S21	Ismail et al. [21]
S22	Syed et al. [22]
S23	Yedurkar et al. [23]
S24	Ohalete et al. [24]
S25	Hamdan et al. [25]
S26	Schmidt and Wang [26]

3 Threats to validity

This section discusses factors that may call the results of the SLR conducted in this paper into question or diminish the meaningfulness of the results. These factors are denoted as threats to validity.
As we consider selection bias to be the primary threat to validity for the SLR conducted in this article, the review carefully adheres to the guidelines outlined by Kitchenham [27] in order to minimize this risk. Con-

cretely, I prioritized high-quality sources by filtering for peer-reviewed journals and major conference proceedings on the topic of Industrial AI and reliability engineering. This way, I ensured that the study selection was as complete as possible.
Another threat to validity is the fragmentation of information within the primary studies. Of the 26 primary studies included in the SLR, some focus heavily on the algorithmic mathematics while omitting details about the physical data acquisition or the industrial deployment context. This might endanger the overall accuracy of the representation of certain approaches in the SLR. Additionally, there might be an information gap between the academic proposal and real-world applicability; many approaches validated on "clean" benchmark datasets may face unreported challenges when applied to noisy, proprietary industrial data. This information gap adds a layer of uncertainty when assessing the true maturity of prescriptive maintenance in the field.
Finally, the SLR may be threatened by insufficient reliability. To address this threat, I ensured that the search process can be replicated by other researchers by documenting the exact boolean search strings (cf. Sect. 2.2) and the specific databases used. Of course, the search may produce different results in the future, as search algorithms of engines like Google Scholar change and new papers are published daily. Additionally, as the process of creating an SLR involves subjective judgment particularly when deciding if a paper is "truly prescriptive" or merely "advanced predictive" other researchers might come to slightly different conclusions regarding the classification of specific papers. However, by strictly adhering to the definitions provided in Section 2.1, we have strived to minimize this subjectivity.

4 Results: sector-specific analysis

The systematic selection process resulted in 26 primary studies covering the period from 2019 to 2025, with a significant concentration of papers published in the last two years (2023–2025). This recency underscores the rapid evolution of Industry 4.0 technologies into the Industry 5.0 paradigm.
The analysis of these studies reveals that while predictive maintenance (PdM) has reached a level of maturity in fault detection, the transition to prescriptive maintenance (RxM) where the system explicitly optimizes decision-making is unevenly distributed across industrial domains. The literature is heavily weighted towards high-value, critical assets where downtime results in immediate financial loss or safety risks.

Energy and power systems: This is the most dominant sector in our review. It encompasses diverse assets ranging from electrical submersible pumps (ESPs) in the oil and gas industry to renewable energy systems like offshore wind farms and photovoltaic arrays.

Manufacturing: The second largest cluster focuses on production efficiency, specifically highlighting computer numerical control (CNC) tools and the integration of IoT sensors into smart composite materials.

Transportation: Research in this domain is split between automotive advancements , maritime fleet management , and defense aircraft sustainment.

Infrastructure and networks: A niche but critical area of research applies maintenance theories to static civil infrastructure like bridges and dynamic telecommunication networks.

Across all sectors, the "technological engine" driving these strategies is shifting. However, the most recent literature (2024–2025) highlights a dependency on deep learning (specifically LSTM and Transformers) and digital twins to handle the complexity of modern data. Furthermore, to bridge the gap between "black box" AI predictions and human decision-making, technologies like augmented reality (AR) and explainable AI (XAI) are increasingly cited as necessary components of a prescriptive workflow.
The following subsections analyze these findings in depth, categorized by their specific industrial application areas.

4.1 Energy and power systems

The energy sector represents the most mature application of maintenance technologies in our survey. This dominance is driven by the extreme cost of downtime: in oil production, a single pump failure can cost millions in lost revenue, while in offshore wind, a failure requires expensive maritime logistics to repair. Consequently, the literature in this domain has evolved from simple condition monitoring to complex, prescriptive decision-support systems.

4.1.1 Oil and gas: the criticality of pumping systems

In the hydrocarbon sector, the literature is heavily concentrated on electrical submersible pumps (ESPs) and water injection pumps, which are the heart of artificial lift systems.
As highlighted by Khalili et al. [S01], recent advancements rely on high-precision algorithms like XGBoost and long short-term memory (LSTM) networks. These models are not just used for binary failure prediction but are integrated with principal component analysis (PCA) to perform root cause analysis (RCA).
The primary objective here is to extend the "run life" of the equipment under difficult environment. Almazrouei et al. [S12] further emphasize that the barrier in this

sector is often data quality; reliable prediction requires cleaning noisy sensor data from deep-sea environments before it can be fed into predictive models.

4.1.2 Renewable energy: from diagnosis to optimization

The transition to green energy has shifted the maintenance focus from "preventing breakage" to "optimizing."

This sector presents unique logistical challenges. Fox et al. [S08] argue that predictive maintenance alone is insufficient for offshore farms. Instead, a prescriptive (RxM) approach is required, where maintenance schedules are optimized based on weather windows and vessel availability. The system doesn't just say "the turbine will break"; it says "the turbine will break in 4 days, but the weather is calm tomorrow, so send the boat now."

For solar energy, Hamza et al. [S06] discuss the use of AI for diagnosing non-critical faults that reduce efficiency, such as soiling or partial shading. Here, the maintenance strategy is driven by cost-benefit analysis: is the energy loss from the dust greater than the cost of cleaning the panel?

Hamdan et al. [S25] broaden the scope to the grid level, noting that AI is crucial for balancing the intermittent nature of renewables, effectively treating the entire power grid as a maintained asset.

4.1.3 Nuclear energy: safety and human interaction

In the nuclear domain, the tolerance for "black box" AI is zero. Safety is paramount.

Nor et al. [S11] describe a distinct approach where technology is used to assist, not replace, the human operator. Their work explores augmented reality (AR) to visualize critical parameters directly onto the physical infrastructure. This ensures that while data is processed digitally, the final verification remains in human hands, bridging the gap between Industry 4.0 automation and Industry 5.0 human-centricity.

4.2 Transportation and mobility

Unlike static industrial plants, the transportation sector involves mobile assets operating in highly variable and dynamic environments. This mobility introduces unique challenges regarding data transmission (edge vs. cloud) and the operational context of the maintenance "prescription."

4.2.1 Automotive

The automotive industry is currently undergoing a paradigm shift from "on-board diagnostics" (simple rule-based alerts) to "vehicle health management" (VHM).

A critical barrier to adoption in this sector is trust. Arockiasamy et al. [S03] highlight that for a predictive system to be effective, the driver or mechanic must understand why a maintenance action is recommended. Their work explores the integration of Generative AI and explainable AI (XAI) to translate complex "black-box" fault codes into human-readable diagnostic reports.

The goal is to move beyond the traditional "check engine" light which often appears after degradation has occurred to a proactive system that schedules service during planned stops, minimizing inconvenience.

4.2.2 Maritime

The maritime sector faces a "data silo" problem. While thousands of ships use the same engines, they belong to competing companies who are unwilling to share operational data.

Kalafatelis et al. [S19] propose a solution using federated learning (FL). In this architecture, a global predictive model is trained collaboratively across the fleet without the raw data ever leaving the individual ship. Each vessel trains a local model on its own data and sends only the weight updates to a central server. This allows the industry to build robust, fleet-level predictive models while strictly preserving data privacy and commercial secrets.

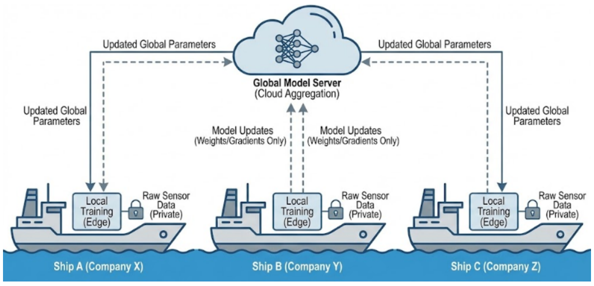

Figure 2: Federated learning architecture applied to maritime fleets, allowing collaborative training without sharing proprietary data

4.2.3 Fleet management challenges

Across both domains, a recurring theme is the balance between edge computing and cloud computing. Since continuous 5G/satellite connectivity cannot be guaranteed for vehicles or ships in remote areas, modern maintenance architectures are increasingly deploying edge AI lightweight algorithms capable of running directly on the vehicle's ECU to detect faults in real-time without internet access.

4.3 Smart manufacturing and materials

Manufacturing is the sector where the concept of Industry 4.0 originated, and it remains the primary testing ground for maintenance innovations. The literature in this domain focuses heavily on "zero downtime"

(ZDT) and "zero defect" manufacturing. Unlike the energy sector, where the goal is preventing catastrophic explosions, the goal in manufacturing is precision and efficiency reducing scrap rates and maximizing overall equipment effectiveness (OEE).

4.3.1 Machine tool health

The most frequent application of predictive maintenance in manufacturing is on computer numerical control (CNC) machines. The critical failure mode here is tool wear. If a cutting tool becomes blunt, it does not immediately break the machine, but it ruins the surface finish of the product, leading to waste.
Yedurkar et al. [S23] and Schmidt et al. [S26] highlight that vibration sensors remain the gold standard for this task. By analyzing the frequency spectrum of the spindle, algorithms can predict the remaining useful life of a drill bit to the minute.
Similarly, Manjare et al. [S13] discuss the monitoring of industrial electric motors. The shift here is towards non-invasive monitoring, using "motor current signature analysis" (MCSA) to detect faults inside the motor without attaching external accelerometers, thereby reducing the cost of the sensing setup.

4.3.2 Smart materials

A distinct and innovative trend identified in this survey is the move from external sensors to embedded sensing. Arockiasamy et al. [S02] present a review on "smart natural fiber composites." Instead of sticking a sensor on a component, the sensor is embedded inside the composite material during the manufacturing process.

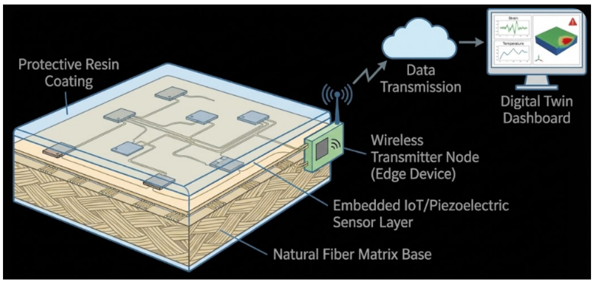

Figure 3: Architecture of a smart composite material with embedded IoT sensors for real-time structural health monitoring

This allows the material to become "self-aware," transmitting data about internal delamination, humidity absorption, or stress fatigue. This approach is particularly relevant for high-performance sectors like aerospace manufacturing, where the material integrity is as critical as the machine producing it.

In manufacturing, the line between maintenance and quality control is blurring. Prescriptive maintenance strategies are being used to close the loop:

- Predict: The system detects that the spindle vibration has increased by 5
- Prescribe: Instead of stopping the machine, the system automatically adjusts the feed rate or cutting speed to compensate for the vibration, maintaining product quality while allowing the shift to finish before replacing the tool.

4.4 Civil infrastructure

Civil infrastructure represents a unique domain within the maintenance landscape. Unlike rotating machinery (which might fail in months) or electronics (which fail in years), assets like bridges, tunnels, and pipelines are designed to last for decades or even centuries. This extreme longevity creates a "data scarcity" problem: since total structural collapse is rare, there is almost no historical labeled data for "failure" conditions. Consequently, the literature in this sector heavily favors hybrid approaches over pure black-box AI.

4.4.1 Bridge maintenance

Bridges are the critical nodes of transportation networks. Lydon et al. [S15] review the state of "smart bridge" monitoring. They argue that pure deep learning is often unsuitable because training a model requires thousands of "failure examples," which simply do not exist for critical infrastructure.
The dominant technique is therefore the physics-informed approach. Sensor data (strain gauges, accelerometers) is not used to predict "end of life" directly, but is fed into a finite element model (FEM). The digital model calculates the structural stress, and if the simulation exceeds safety thresholds, a maintenance alert is triggered. This combines the real-time nature of IoT with the reliability of civil engineering physics.

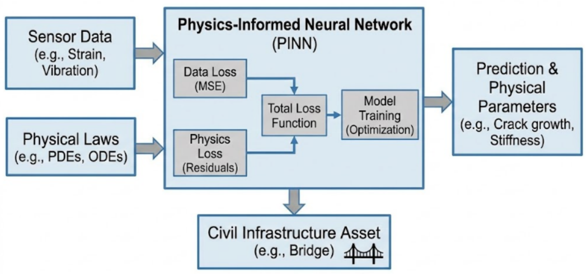

Figure 4: A physics-informed machine learning workflow, typical in civil infrastructure where data is scarce but physical laws are well-understood

4.4.2 Corrosion prediction

For pipelines and marine structures, the primary failure mode is corrosion, which is a slow, non-linear chemical process.

Ali et al. [S09] provide a comprehensive review of corrosion prediction models. They highlight a shift from simple linear extrapolation (e.g. "0.1mm loss per year") to stochastic processes. Modern approaches use historical environmental data (humidity, salinity, temperature) to model corrosion as a probabilistic curve.
The prescriptive element enters when deciding when to apply protective coatings. instead of a fixed 5-year schedule, the model prescribes the optimal recoating interval based on the specific micro-climate exposure of that specific pipe section, potentially saving millions in unnecessary maintenance.

4.5 Key enablers: digital twins and advanced AI

While the application domains differ significantly in their operational constraints, the systematic review reveals that they share a common set of technological "enablers." These technologies act as the catalysts that allow organizations to transition from simple condition monitoring (predictive) to autonomous optimization (prescriptive).

4.5.1 The digital twin

The digital twin (DT) is identified in multiple studies as the foundational architecture for prescriptive maintenance. It is no longer defined merely as a static 3D model, but as a dynamic, physics-based simulation that evolves in real-time.
Hamdan et al. [S25] and Guarese et al. [S14] emphasize that the true value of a digital twin lies in its ability to simulate future scenarios. Before a prescriptive system recommends "Increase pump speed by 10%," the digital twin simulates the impact of this action on the virtual asset to ensure it won't cause immediate failure. This "sandbox" environment is critical for safety-critical sectors like nuclear and aerospace.

4.5.2 Generative AI

A recurring barrier identified in Section 4.5 (infrastructure) is the lack of "run-to-failure" data. Deep learning models require thousands of failure examples to learn, but industry rarely lets assets break.
Arockiasamy et al. [S03] highlight the emergence of generative AI in the automotive sector. These algorithms can create realistic "synthetic failure data" mathematically generating thousands of examples of engine faults that have never actually happened. This allows predictive models to be trained for rare "black swan" events.

4.5.3 Explainable AI (XAI)

As models evolve from simple regression to complex deep learning, human operators struggle to trust the output.
Gupta et al. [S04] and Syed et al. [S22] argue that Explainable AI (XAI) is the key enabler for Industry 5.0, which places the human back in the center of the loop. XAI techniques do not just output a probability; they explain the cause.
Example: Instead of simply displaying "Alert: 90% failure risk," an XAI-enabled system displays: "Risk: 90% because vibration >5Hz AND oil pressure <2 Bar." This transparency allows the human operator to validate the prescription before authorizing the repair.

4.5.4 Federated learning

Finally, Kalafatelis et al. [S19] introduce Federated learning as the enabler for collaborative maintenance. This technology allows predictive models to be trained across organizational boundaries without sharing raw data. This "data mesh" approach is expected to become the standard for sectors where data privacy is a competitive advantage.

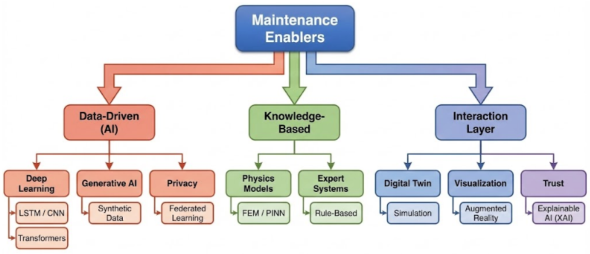

Figure 5: Taxonomy of maintenance enablers identified in the literature, classifying approaches into Data-Driven, Knowledge-Based, and Interaction categories.

5 The SpaceVis framework

In this chapter, we present the design and implementation of SpaceVis, a python-based decision support framework developed to operationalize the concept of prescriptive maintenance. While the literature review established the theoretical necessity of moving from Industry 4.0 (prediction) to Industry 5.0 (prescription), practical implementations remain scarce.

SpaceVis addresses this implementation challenge by integrating a random forest prognostic engine with a streamlit-based interactive frontend. The system serves two primary engineering objectives: first, to provide a transparent visualization of multivariate sensor degradation; and second, to enable active parameter optimization. By allowing the user to manipulate operational variables, the framework demonstrates how algorithmic predictions can be converted into actionable maintenance prescriptions that maximize asset utility under stress.

5.1 Design and architecture

The SpaceVis framework is engineered as a modular decision-support system, adhering to the model-view-controller (MVC) architectural pattern. It is implemented using python, leveraging streamlit for the frontend interface and scikit-learn for the inference engine. The application design is divided into four distinct functional zones, each addressing a specific layer of the prescriptive maintenance workflow.

Data ingestion and configuration The entry point of the architecture is the configuration module (located in the application sidebar). This component handles the data retrieval from the NASA C-MAPSS repository.The system enables the user to select specific engine units from the fleet. A cycle-selector slider allows the operator to travel back in time to any point in the asset's history. This is critical for "post-mortem" analysis validating how a prescriptive decision could have altered the outcome of a failed engine.

The prescriptive control module The core innovation of SpaceVis is located in the top-left panel, designated as "control parameters." Unlike static dashboards that only display read-only data, this module acts as the "Write" interface for the digital twin. The interface features a dynamic slider that controls the theoretical load applied to the engine. This parameter α represents the prescriptive action.When the user adjusts α, the backend immediately intercepts the incoming sensor vector X_t. It applies a scalar transformation defined as $X_t' = X_t \times \alpha$. This modified vector simulates the physical state of the engine under relaxed operational conditions without requiring physical testing.

The prognostic inference engine The "prognostic results" panel serves as the quantitative feedback loop. It runs two parallel inference tasks using the pre-trained random forest regressor:

- Baseline inference (P_{base}): The model predicts the remaining useful life (RUL) based on the unaltered, real-time sensor data.
- Prescribed inference (P_{new}): The model simultaneously predicts RUL based on the modified vector from the control module.

The system calculates the Delta (Δ) between these two predictions. This metric represents the "value of action," offering the operator a clear, numerical justification for the maintenance decision.

Multivariate state analysis To ensure the mathematical modification of data corresponds to a realistic physical state, the "multivariate sensor analysis" panel utilizes a radar chart. This visualization overlays two datasets: the Baseline State (gray) and the Prescribed State (blue). It plots the top five most sensitive features (s_2, s_3, s_4, s_7, s_8) on radial axes. This allows the engineer to visually verify that the load reduction is distributed correctly across all thermodynamic parameters, ensuring that the prescriptive model is not hallucinating an impossible physical state.

Temporal degradation tracking The final section, "asset degradation history," provides the necessary historical context. Using a time-series line graph, this module plots the degradation curve of the most critical sensor from the beginning of the engine's life up to the current cycle. A specific visual marker indicates the "current simulation point," helping the operator understand if the asset is in the healthy, degrading, or critical phase of its lifecycle. This context is essential, as prescriptive actions are often more effective in the early degradation phase than in the terminal phase.

5.2 Implementation of prescriptive logic and model validation

The core functionality of the SpaceVis framework lies in its ability to dynamically modify input vectors to simulate future operational states.
To transition from passive prediction to active prescription, the framework introduces a user-controlled variable, the load reduction factor (α). This parameter represents the operator's decision to "derate" the engine running it at a lower capacity to extend its useful life. The mathematical transformation applied to the sensor vector is defined as:

$$S_{modified} = S_{original} \times \alpha$$

Where:

- $S_{original}$ is the current vector of thermodynamic sensor readings.
- α is the scalar control parameter (ranging from 0.9 to 1.1).

When the operator adjusts α, the system scales the input features X before feeding them into the regressor. The model then outputs a new remaining useful life (RUL_{new}), allowing the system to calculate the "value of action" ($\Delta = RUL_{new} - RUL_{baseline}$).
The root mean squared error (RMSE) serves as the standard reliability benchmark and is calculated as:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_{test} - \hat{y}_{pred})^2}$$

As shown in the dashboard sidebar, the model possesses a fixed validation RMSE of 17.21.

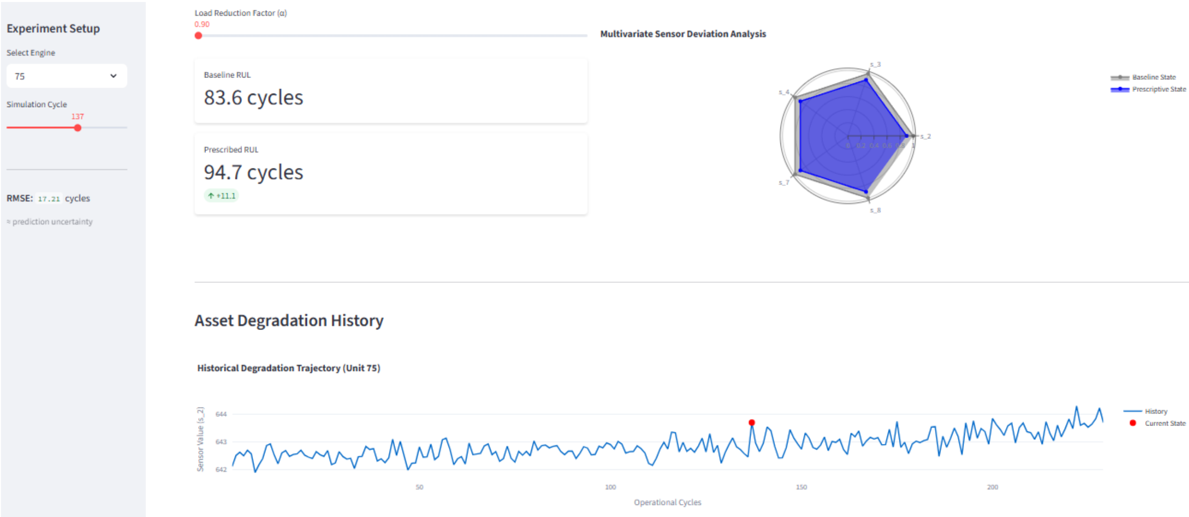

Figure 6: The SpaceVis interface displaying a prescriptive scenario for engine unit 75.

5.3 Execution and results (case study)

To validate the framework's operational utility, a controlled experiment was conducted using engine unit #75 from the C-MAPSS FD001 dataset. The simulation was initialized at cycle 137, a critical juncture where the asset exhibits signs of intermediate degradation but has not yet reached functional failure.

The engine has been running for 137 cycles. The thermodynamic indicators show elevated values compared to a new engine, indicating internal wear. The random forest model processes this raw sensor vector and predicts a baseline RUL of 83.6 cycles. This indicates that, under current stress levels, the engine is expected to fail at approximately cycle 221.

To simulate a life-extension strategy, the "load reduction factor" (α) in the control module was adjusted from 1.0 to 0.90 (90% load). This action represents a strategic decision to "derate" the engine reducing its maximum power output to lower internal stress and temperature.The system mathematically transformed the input vector X in real-time:

$$X_{prescribed} = X_{baseline} \times 0.90$$

The modified sensor vector was fed back into the inference engine, yielding immediate results. The model predicted a new prescribed RUL of 94.7 cycles.. This result suggests that a modest 10% sacrifice in immediate power output yields around 10% increase in remaining useful life. This quantifies the "performance-for-longevity" trade-off, providing the operator with the data needed to make an informed economic decision.

To ensure the trustworthiness of this prescription, the radar chart (multivariate analysis) panel was analyzed, the chart displays two distinct polygons. The gray area represents the high-stress baseline state, while the blue area represents the prescribed state. The visualization confirms that the reduction is uniform across all five critical sensors (s_2, s_3, s_4, s_7, s_8). The blue polygon is strictly contained within the gray polygon, verifying that the simulated state represents a physically valid, lower-energy thermodynamic equilibrium, rather than an erratic or impossible sensor combination.

The experiment on Unit 75 demonstrates that SpaceVis successfully bridges the gap between prediction and action. By converting the abstract concept of "derating" into a specific numerical forecast, the framework empowers the operator to move from reacting to a failure alert to actively managing the asset's degradation trajectory.

6 Related work

The contribution of this paper consists of a comprehensive framework that bridges the theoretical transition from predictive to prescriptive maintenance with a practical, human-centric implementation. To achieve this, a systematic literature review was conducted to map the current state of the art, followed by the development of the SpaceVis decision-support system. To the best of my knowledge, there is no published work that combines a systematic review of prescriptive maintenance enablers with a reproducible, open-source implementation framework for life-extension strategies. There are, however, several literature reviews on related research fields, of which three categories are presented here.

A dominant body of work in the field of industrial artificial intelligence focuses on the algorithmic performance of failure detection. A comprehensive survey by Carvalho et al. provides an overview of machine learning techniques applied to Industry 4.0. The authors perform a systematic review to classify algorithms into supervised and unsupervised categories, evaluating their accuracy in fault diagnosis. Furthermore, this work provides a framework for selecting algorithms based on data availability. However, while these surveys offer deep insights into prediction accuracy, they often stop at the "alert" stage. They do not systematically address the decision-making process (prescription) or the optimization strategies required to mitigate the detected faults, which is a central focus of our study.

In the specific domain of maintenance strategy optimization, Matyas et al. aims at defining the procedural differences between predictive and prescriptive approaches. The authors apply a theoretical approach to categorize maintenance maturity levels, distinguishing between "prognostics" (estimating RUL) and "management" (scheduling repairs). They present a taxonomy of decision support systems used in manufacturing. However, this work is largely conceptual. Unlike our paper, which analyzes the specific technological enablers (like federated learning and generative AI) across multiple sectors, their work focuses on high-level management definitions and lacks a focus on the emerging "human-in-the-loop" technologies required for Industry 5.0.

Regarding sector-specific reviews, several studies define maintenance architectures for single domains. For instance, reviews in the wind energy sector focus heavily on the physical modeling of turbine drive-trains.While valuable for their specific niche, these reviews lack cross-domain generalizability. They do not explore how techniques developed in one sector could be transferred to another. Our systematic review addresses this by explicitly analyzing cross-sector applications and identifying common technological denominators.

The general conclusion of the existing surveys is that while the prediction of failure is a well-researched topic, the prescription of action remains fragmented. Furthermore, most existing works evaluate approaches based on computational metrics alone, neglecting the usability and understandability of the system for human operators. This paper addresses this gap by not only reviewing the literature but also proposing SpaceVis, a framework that explicitly targets the "information gap" by visualizing the trade-off between asset performance and longevity.

7 Summary and outlook

This paper initially presented the results of a systematic literature review on the transition from predictive to prescriptive maintenance. The main insight gained from the SLR is that while the algorithmic foundations for failure prediction (Industry 4.0) have reached a high level of maturity particularly in the energy and manufacturing sectors the capability to systematically optimize decision-making (Industry 5.0) remains fragmented. The interest in prescriptive approaches has surged significantly in the last three years (2023–2025), yet the field is characterized by a "technological gap" between advanced black-box models and the human operators who must trust and act upon them.

The paper further presented the SpaceVis framework, a decision-support system designed to operationalize the findings of the review. We applied this framework to the NASA C-MAPSS benchmark dataset, demonstrating how a "human-in-the-loop" architecture can bridge the gap between raw probability scores and actionable maintenance strategies. By enabling real-time sensitivity analysis (specifically through the load reduction factor α), SpaceVis reinforces our finding that the true value of AI lies not just in predicting the time of failure, but in calculating the value of intervention.As discussed in section 4, the results obtained by the SLR show that prescriptive maintenance is still at an early development stage regarding cross-domain application. Indicative of this fact are the data silos in the maritime sector, the scarcity of failure data in civil infrastructure, and the general lack of "explainable AI" (XAI) interfaces in commercial tools. To make prescriptive maintenance applicable to real-world projects, tool implementations must evolve beyond simple dashboards to become true "digital twins" that simulate the physical and economic consequences of a maintenance action before it is executed.

As a possible future topic, it would be interesting to evaluate how the integration of generative AI could further lower the barrier to entry for maintenance operators. Empirically, this could be evaluated by extending the SpaceVis framework to include a large language model (LLM) agent that automatically generates natural language reports explaining why a specific prescription was made. Furthermore, future iterations of the framework should integrate an economic cost module. By assigning monetary values to "remaining useful life" versus "production output," the system could be tested in a business simulation to compare the financial ROI of prescriptive strategies against traditional preventive schedules.

We would like to finally encourage the research community to shift the focus from merely improving the accuracy of prediction algorithms to improving the interpretability and actionability of those predictions. We believe that frameworks like SpaceVis will help researchers and practitioners move towards "Industry 5.0" paradigm, where algorithms do not replace human judgment, but rather augment the human capacity to manage complex physical assets for maximum longevity and sustainability.

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