Advanced MRO Processes in Industry 4.0 with proactive Asset Administration Shell and Digital Product Passport

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Abstract

As industries enhance efficiency, reliability, and sustainability in Maintenance, Repair, and Overhaul (MRO) operations, digitalization plays a pivotal role. In this context, Industry 4.0 technologies are transforming maintenance into autonomous, data-driven systems, improving performance and reducing costs. Within this shift, Prognostics and Health Management (PHM) provides a structured approach to organizing condition monitoring, event diagnosis, prediction and instruction. However, its implementation remains complex due to the heterogeneous nature of the assets, the large number of potential events (e.g. anomalies), the quality and incompleteness of the data, and the missing standardized data exchange. In this regard, the paper explores how PHM can be effectively implemented using proactive Asset Administration Shells (AAS) and Digital Product Passports (DPPs), enabling smart, self-managed maintenance ecosystems on a common ground. Thus, the integration of AAS and DPPs facilitates PHM by enabling autonomous event detection, prediction, and service negotiation while translating predictive insights into actionable maintenance workflows. They also consolidate lifecycle data, ensuring regulatory compliance, traceability, and circular economy integration.

An experimental setup utilizing an Unmanned Aircraft System (UAS) and a robotic MRO station verifies this approach. The system integrates Z-factor statistical analysis, multi-tiered predictive modeling, and structured event-task mapping to automate maintenance actions and optimize decision-making. Results demonstrate improved failure detection, extended asset lifetimes, and reduced material waste and operational downtime.

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1. Introduction

Industry 4.0 (I4.0) has introduced a new era of connected, smart systems, presenting opportunities to enhance how industries manage assets and maintenance operations. Current maintenance practices often involve heterogeneous systems, manual interventions, and reliance on analog documentation, which can limit scalability and responsiveness in increasingly complex industrial environments (Timjerdine, Taibi , & Moubachir, 2024). Emerging approaches aim to complement these practices with self-managing, data-driven solutions that leverage technologies such as Internet of Things (IoT) devices, digital twins, and artificial intelligence to streamline workflows, optimize resource use, and support sustainability goals (Zonta, da Costa, & da Rosa, 2020). For instance, predictive maintenance enabled by I4.0 technologies can reduce machine downtime by 30-50 % and extend machine lifespans by 20-40 %, leading to significant cost savings and improved operational reliability (Shaheen & Németh, 2022).

In the recent years, research and development in academia and industry in the field of Prognostics and Health Management (PHM) has increased. By leveraging physical knowledge and analyzing information and data of structures, systems, and components from design, production, operation and maintenance, PHM helps to identify potential issues before they occur, such as detecting and diagnosing faults and forecasting their progression towards failure. This enables the estimation of Remaining Useful Life (RUL). The outcomes support condition-based and predictive maintenance decisions that can improve system performance, reliability, and safety. By implementing these strategies, organizations can adopt tailored, timely, and efficient maintenance practices. However, the application of PHM methods in real practice faces challenges. Some challenges originate from anomalies in real data collected in the field such as missing data due to malfunctioning sensors or transmission errors. Furthermore, the scarcity and incompleteness of available data related to the state of degradation of a component or system makes it hard to provide suitable training data sets for PHM method development and calibration and their usage in real applications. In order to establish PHM methods, more requirements have to be met, especially when they are used in safety-critical applications. Sufficient levels of model security, interpretability and uncertainty estimation must be provided to decision makers (Zio, 2021).

Supporting these transformations are Asset Administration Shells (AAS) and Digital Product Passports (DPP), which offer promising pathways for advancing Maintenance, Repair, and Overhaul (MRO) operations (Rahal, Schwarz, Sahelices, Weis, & Antón, 2023) (Winkler, Gill, & Fay, 2022) (Weiss, Pakala, Wicke, Gill, & Wende, 2023). In this context, it is envisioned that these tools will enable real-time monitoring, autonomous decision-making, and seamless communication within interconnected systems, thereby promising highly efficient PHM (Donghan, Wei, Xiangyu, & Yan, 2021). This vision can be effectively realized through proactive AAS (Grunau, Redeker, Göllner, & Wisniewski, 2022).

Complementary to the AAS, DPPs serve as structured digital repositories that consolidate and standardize critical lifecycle data, including technical specifications, regulatory compliance, and environmental impact metrics (Jensen, Kristensen, Adamsen, Christensen, & Waehrens, 2023). By fostering transparency, traceability, and circularity across value chains, DPPs address both operational and sustainability challenges. Under the European Union's Ecodesign for Sustainable Products Regulation (EU 2024/1781, 2024), DPPs are becoming mandatory for certain product categories, starting with batteries, and will play a critical role in ensuring compliance with sustainability and circular economy goals (CIRPASS-2, n.d.). By integrating into a proactive AAS, the DPP not only adopts a standardized metamodel but also extends its functionality through the advanced features of the proactive AAS, enabling seamless data exchange and improved maintenance workflows among stakeholders in the MRO domain (Weiss, Raddatz, & Wende, 2024).

However, a systematic literature review by (Rahal, Schwarz, Sahelices, Weis, & Antón, 2023) unveiled a research gap in integrating AAS with Predictive Maintenance (PdM) and broader PHM solutions. While existing studies have explored the potential of digital twins and data-driven methods for fault diagnosis and RUL estimation, few have considered the role of AAS in these contexts. For instance, (Cavalieri & Salafia, 2020) presented an AAS-based model for predictive maintenance, but this remained conceptual and focused on standardized data access rather than realizing a proactive AAS with autonomous decision-making. (Winkler, Gill, & Fay, 2022) discussed AAS as an enabler for interoperable digital twins of aircraft components in MRO, yet did not extend it toward closed-loop PHM execution. Similarly, (Sakurada, Prieta, & Leitao, 2023) outlined AAS–Multi-Agent System integration for collaborative decision-making, but without experimental verification in a physical testbed. In contrast, our work differentiates itself by combining a proactive AAS with PHM algorithms and a DPP, and demonstrating this integration in an experimental MRO station setup. This operational example goes beyond prior studies by showing how lifecycle data, predictive insights, and service negotiation can be directly translated into execution and feedback, thereby closing the loop between anomaly detection and maintenance action. To address this question, the paper first examines the complementary roles of proactive AAS and DPP. Next, a standard PHM framework is mapped onto the functional capabilities of the proactive AAS to illustrate its alignment with predictive maintenance methodologies. Finally, an experimental verification using a UAS and a robotic MRO service station, serving as stakeholder surrogates, demonstrates the practical implementation of this integration and its impact on transforming industrial MRO ecosystems. Given this challenge, the subsequent research question is formulated:

How can a proactive AAS with DPP be used to leverage PHM methodologies in order to improve the efficiency, interoperability, and sustainability of MRO operations in accordance with Industry 4.0 paradigms?

2. DEVELOPMENT OF PROACTIVE AAS AND DPP

As key technologies of I4.0, AAS and DPP redefine how assets are represented, managed, and integrated into cyber-physical systems and, in a broader scope, into data spaces. AAS provides a digital framework for embedding technical and lifecycle data, operational behaviors, and interaction capabilities into assets, transforming them into I4.0 components (I4.0C). Meanwhile, the DPP complements AAS by consolidating and sharing lifecycle information, aligning with sustainability objectives. Together, these technologies enable seamless interoperation, autonomous decision-making, and enhanced scalability in IoT-driven MRO ecosystems.

2.1. Proactive Asset Administration Shell

Briefly, the AAS consists of three distinct types, each tailored to specific levels of interaction and complexity (IDTA, 2023a):

- Type 1 (File-Based AAS): This form stores asset information as a static digital file, suitable for offline scenarios and basic data sharing.
- Type 2 (Reactive AAS): A more advanced form that incorporates Application Programming Interfaces (APIs) like REST, enabling real-time data exchange between assets and external systems upon request.
- Type 3 (Proactive AAS): The most sophisticated form, capable of autonomous interaction, decision-making, and dynamic task execution within IoT ecosystems. Proactive AAS utilizes embedded algorithms and semantic communication to initiate actions without further intervention.

Common to all types of AAS is their already standardized meta-information model (DIN EN IEC 63278) and their complementary role in jointly transforming the associated asset into an I4.0C, with the AAS serving as its digital counterpart. This is initially achieved through submodels that describe in a standardized way all the information and functionality required to support specific use cases, such as

- features,
- properties,
- parameters,
- capabilities.
- characteristics,
- status,
- measurement data and

These submodels include:

1. **Operational Data**: Metrics such as efficiency, energy consumption, and performance indicators, enabling real-time monitoring and decision-making.
2. **Behavioral Specifications**: Functional descriptions detailing expected interactions, including bidding for services or negotiating schedules, to facilitate smooth integration with other components.
3. **Lifecycle Parameters**: Dynamic updates reflecting usage history, maintenance events, and end-of-life conditions, ensuring comprehensive asset management.

The modelling of proactive AAS is not (yet) specified and realized only in few applications (Sakurada, Prieta, & Leitao, 2023), but it is "*one key factor for interdisciplinary information exchange*" (Sapel & Hopmann, 2023). We focus on its research and development as the most advanced approach, also including type 1 and type 2 AAS, to the digital representation of assets and their smart interactions within an MRO 4.0 ecosystem. Going beyond the passive digital twins most commonly used "*to study and predict the working of a physical object under particular conditions*" (Crespi, Drobot, & Minerva, 2023), the proactive AAS incorporates capabilities for real-time monitoring, autonomous decision-making, and dynamic communication. These features make proactive AAS a valuable component of predictive maintenance and lifecycle management of the related assets, introducing new paradigms in asset management within the MRO 4.0 data spaces:

The continuous monitoring of Key Condition Indicators (KCI) by the assets with their administering AAS themselves ensures the consistent capture and analysis of real-time data. This data, which includes metrics such as vibration levels, temperature, energy consumption or just time limits, is processed using advanced syntheses and algorithms to detect anomalies, predict potential failures and facilitate effective decision-making. To illustrate this, consider a UAS equipped with a proactive AAS. In such an instance, the UAS can autonomously identify an inefficiency in its system and negotiate a maintenance service order before a critical failure occurs (see Chapter 3 for further details).

In accordance with the (DIN EN IEC 63278) and guided by the IDTA specifications (IDTA, 2023a), (IDTA, 2023b), (IDTA, 2023c) and (IDTA, 2023d), the proactive AAS framework in our research is mainly developed in Python: Originated at the University of Magdeburg – Chair of Integrated Automation – and further developed by the German Aerospace Center (DLR), the core provides a modular architecture (Figure 1 top) for structured and autonomous operation, managing I4.0-uniform data structures to encapsulate asset properties, capabilities, and behaviors within standardized submodels. Communication adapters enable data exchange through different protocols (e.g. OPC UA, COAP, REST, MQTT), ensuring seamless interoperability of real assets in Cyber-Physical-Social Systems (CPSS). These adapters are implemented for both directions, connecting the AAS northbound to the network (IoT) and southbound to the asset (Figure 1 below). A detailed description is published in (Weiss, Wicke, & Wende, 2022), (Weiss, Pakala, Wicke, Gill, & Wende, 2023).

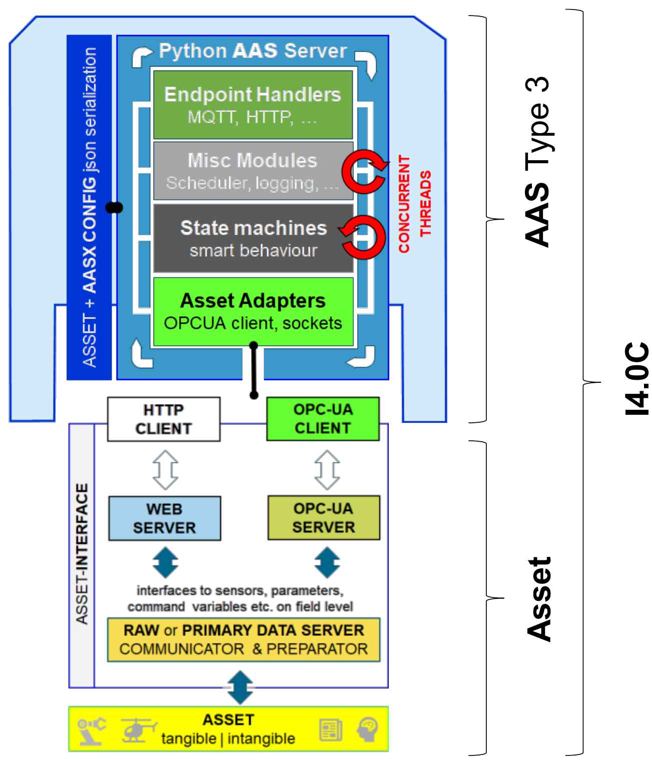

Figure 1. Industry 4.0 Component = AAS + Asset

Operational logic is implemented through finite state machines (FSM) defined by discrete states, transitions and event-driven actions. These state machines primarily enable interaction workflows, decision making and asset operations. An internal message bus synchronizes data flows and manages communication between modules, ensuring consistent processing of receiving and sending Industry 4.0 messages. Further enhancements introduced by DLR include specialized modules for autonomous task execution, with a focus on MRO activities:

1. **Event Manager** FSM: Monitors condition indicators and triggers threshold dependent event codes (EC) mapped to tasks (Step 1). Single tasks are ordered directly via the Service Requester (Step 2a), while task sequences are forwarded to the AAS Production Manager (Step 2b). For this, the FSM uses specific "*Indicator-Threshold-Event-Task"* profiles of the asset, which are provided and administered by the Event Manager.
2. **Service Requester** (SR) and **Service Provider** (SP) FSM: Handle Call for Proposals (CfPs) by matching requested MRO capabilities with available MRO skills. The SP FSM validates skills and submits a proposal if requirements are met, while the SR FSM evaluates proposals using algorithms (e.g., TOPSIS) to select the best match.
3. **Production Manager** FSM: Oversees Bills of Processes (BoPs) and orchestrates task execution. When a task arises, it generates a capability request with task-specific parameters and forwards it to the Service Requester FSM.

The asset-integrated decision-making enabled by the encapsulating AAS represents a significant advance through the use of robust FSM and multi-criteria decision analysis (MCDA). These mechanisms enable the AAS to evaluate complex scenarios, considering variables such as cost, urgency, and operational constraints. In experimental studies from (Weiss, Pakala, Wicke, Gill, & Wende, 2023), these decision-making algorithms proved to be critical in enabling the UAS to manage maintenance schedules autonomously, reducing downtime and enhancing operational efficiency.

2.2. Interacting Stakeholders in an MRO 4.0 ecosystem

In an MRO 4.0 ecosystem, the treated asset itself can become an active individual, enabled by its extension with a proactive AAS. This transformation aligns with the methodology proposed by (Sakurada, Prieta, & Leitao, 2023) for integrating AASs and Multi-Agent Systems (MAS), which underscores the potential of assets to achieve autonomy, intelligence, and collaborative capabilities. In this context, the asset, in conjunction with asset owners, maintenance service providers, technology suppliers, regulatory bodies, and supply chain partners, the asset contributes to an interconnected, autonomous maintenance environment as we discussed in (Weiss, Wicke, & Wende, 2022).

The interaction between these stakeholders, and the level of autonomy afforded to the system, is profoundly influenced by the paradigms of orchestrated and choreographed processes (Diedrich, Schroeder, & Belyaev, 2022):

1. **Orchestration**: This approach uses centralized control mechanisms to manage workflows. For instance, a kind of MRO Supervision System (MSS) might aggregate data from AASs to plan and delegate maintenance tasks (Weiss, Wicke, & Wende, 2022). The MSS ensures compliance, optimizes scheduling, and monitors execution, providing a clear chain of command.
2. **Choreography**: In contrast, choreography relies on decentralized interactions, where each AAS autonomously determines its actions based on predefined rules and real-time data. This configuration fosters scalability and adaptability, as processes evolve in response to immediate conditions without requiring central oversight. In (Leitão, Queiroz, & Sakurada, 2022) such decentralized approach is described, driven by collective intelligence in MAS-based CPS, enable self-organization and emergent behaviors that are critical for real-time decision-making and adaptation

Thus, the asset – such as an aircraft, a component, or a part – no longer plays a passive role. Through the Event Manager, introduced in Chapter 2.1, the proactive AAS continuously monitors key metrics such as vibration, energy consumption, deformation, degradation, usage cycles, or aggregated health indicators (Figure 2). The embedded algorithms detect anomalies, predict failures, and generate service requests. Broadcasted as CfP via the Industrial Internet of Things (IIoT), these requests prompt relevant assets (stakeholders) to respond. The requesting asset evaluates, negotiates, and orders maintenance actions based on the optimal proposal, achieving autonomous decision-making.

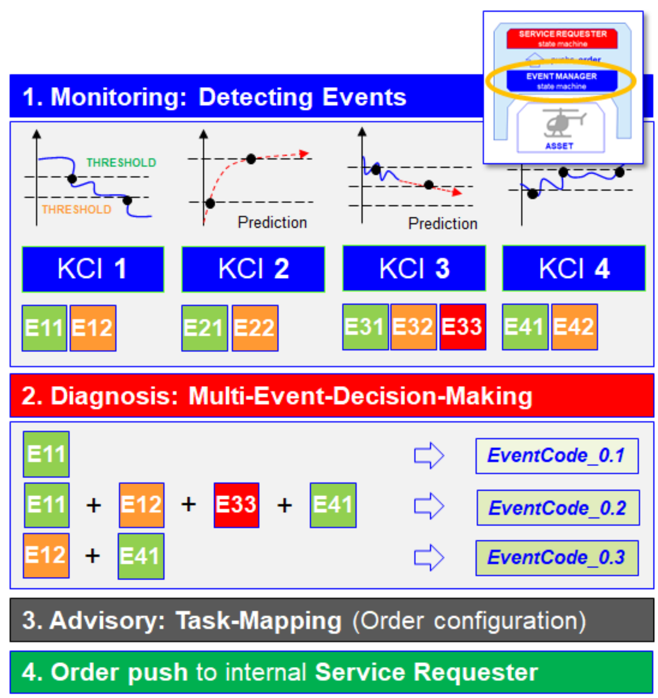

Figure 2. AAS Event Manager workflow (reduced)

To enable such seamless stakeholder interactions, the MRO 4.0 system is underpinned by a layered interoperability model. Based on the findings on the general descriptions of interoperability in (Zeid, Sundaram, Moghaddam, Kamarthi,

& Marion, 2019), four levels can be defined as in (Diedrich, Schroeder, & Belyaev, 2022):

1. **Technical** Interoperability: Reliable data exchange requires standardized communication protocols as supported by the AAS as described in Chapter 2.1.
2. **Syntactic** Interoperability: Uniform data formats and schemas, as defined by the AAS Metamodel (DIN EN IEC 63278), the I4.0 language (VDI2193-1, 2020) (VDI2193-2, 2022), IEC 61360, or AutomationML, ensure consistent representation and processing of asset data across systems.
3. **Semantic** Interoperability: Accurate interpretation of asset data relies on embedding metadata and ontologies within the AAS to ensure consistency and shared understanding. For example, the data standard from (ECLASS, 2025) focuses on ensuring clear semantics for product and service specifications.
4. **Organizational** Interoperability aligns workflows and interaction patterns across stakeholders through clearly defined roles. Business process models such as Business Process Model and Notation (BPMN) and Product-Process-Resource (PPR) models define workflows with capability-specific process steps and decision points. The proactive AAS framework provides the modules and logic to operationalize workflows by translating these high-level processes into individual or sequential tasks and tendering them within the IoT ecosystem.

2.3. Digital Product Passport in the MRO 4.0 context

In terms of common syntactic and semantic interoperability between stakeholders, as highlighted in Chapter 2.2, the DPP is a promising and transformative enabler in digitized value chains, addressing the need for transparency, integrity, traceability, and sustainability in asset lifecycle management. Emerging as a mandatory requirement under evolving legislation – starting 2026 with batteries as outlined in the EU Ecodesign for Sustainable Products Regulation (EU 2024/1781, 2024) – the DPP consolidates lifecycle data into a structured digital repository. To ensure consistency and maximize benefits, the use of standards and guidelines is critical to avoid that "*the implementation of DPPs might become fragmented, leading to inconsistency and limiting their potential benefits*" (Kebede, Moscati, Tan, & Johansson, 2024). In return, we utilized it in (Weiss, Raddatz, & Wende, 2024) with the help of the AAS metamodel (DIN EN IEC 63278) to support the standardization of a semantic and syntactic interoperability.

The DPP includes elements such as nameplate (*minimum*), material composition (BoM), current and historic operational performance data, functional settings, events, manuals, compliance records, or even environmental impact numbers, fostering resource efficiency and supporting circular economy principles. As (Watson, Patzer, Schöppenthau, & Schnebel, 2023) emphasize, "*A DPP is a fundamental enabler to achieve…* [a circular economy] *as it holds all essential product information needed to inform product purchasers, as well as facilitating repairs and recycling*". In combination with the proactive AAS, the DPP supports a data curation system that helps reduce downtime, optimize costs, and extend asset lifecycles, because, as described in general, such systems "*utilize IoT sensors that are distributed to the infrastructure, collect the generated data, and proceed with thorough preprocessing for appropriate ML* [machine learning] *models for the prediction and avoidance of potential production errors before they occur*" (Voulgaridis, et al., 2024). In this context, a key feature of the DPP is its ability to facilitate the seamless exchange of datasets, ensuring both syntactic and semantic interoperability across stakeholders, including manufacturers, service providers, regulators, and end-users. As (Jensen, Kristensen, Adamsen, Christensen, & Waehrens, 2023) highlight, "*Digital product passports are expected to serve as vessels for data sharing, as supply-chain actors… may both utilize and insert data to support each other in transitioning towards a circular supply chain*". For detailed insights into the development of DPP's anatomy, system-level frameworks, and its alignment with global initiatives, refer to (CIRPASS-2, n.d.), (Weiss, Raddatz, & Wende, 2024).

2.3.1. DPP implemented into the AAS Framework

The implementation of the DPP into the AAS, interoperating within a dedicated data space, addresses the DPP system requirements outlined by (Wiesner, Moreira, Guizzardi, & Scholz, 2024): They recommend a flexible granularity, use of standards, commonality with existing systems, the capability of dynamic data management, a micro-service event-driven architecture. The proactive AAS contributes to all of these demands by embedding the DPP as a dynamic, interoperable component, able to interact as a micro-service on events, through the subsequent features:

1. **Integration in the AAS Metamodel**: The general AAS metamodel is "*...providing a structured framework for modeling lifecycle data, supporting submodels that capture…*" (Pourjafarian, et al., 2023) regulatory compliance, lifecycle metrics, material composition, and operational data. Equally to (Plociennik, et al., 2022) and as described in (Weiss, Raddatz, & Wende, 2024), we organized the DPP as a set of submodels, which are containerized in an submodel element list (SML) with their semanticIds. Thus, compatibility and adaptability across diverse systems are ensured.
2. **Dynamic Data-** and **Event-Management**: Embedded within the AAS, the DPP is dynamically updated with operational data and validated against lifecycle records. The AAS leverages event-managing mechanism to monitor condition indicators and trigger PHM tasks based on DPP data. By utilizing event-sourcing logics inspired by (Ajdinović, Strljic, Lechler, & Riedel, 2024), the proactive AAS aggregates real-time events, aligning DPP lifecycle data with operational conditions. This

continuous data synchronization and interpretation supports autonomous anomaly prediction, maintenance scheduling, and workflow adaptation, driving efficient, sustainable, and predictive maintenance actions.

3. **Semantic and Syntactic Interoperability**: The AAS enables a seamless unitization of DPP data through uniform syntax and semantics, which "*plays a critical role in enabling organizations to effectively manage and analyze their data and make informed decisions based on accurate and reliable information*" (Pourjafarian, et al., 2023). Combined with standardized communication protocols, this ensures that all PHM processes can consistently exchange, interpret, and utilize data across stakeholders and systems.
4. **Intelligent Decision Support**: By incorporating PHM logics with DPP data, the proactive AAS facilitates multi-criteria decision-making. Lifecycle data provides a foundation to optimize maintenance schedules while addressing operational constraints and sustainability goals. Event triggers activate decision-tree frameworks that assess maintenance options. These frameworks prioritize tasks, balancing factors like urgency, cost-effectiveness, and long-term asset health.

2.4. Mapping to a PHM System

A PHM system, as defined in (ISO 13374-1, 2003), can be abstracted into four key stages: Monitoring, Diagnosis, Prognosis, and Advisory. This structure aligns with the work of (Bhat, Muench, & Roellig, 2023), as well as (Zhao, et al., 2021), who further explored these stages in their studies. Mapping these stages onto the proactive AAS framework presented earlier, Figure 3 illustrates how this system is utilized mainly through the AAS components Event Manager and DPP. The Event Manager ensures real-time monitoring, control, and coordination, while the DPP provides contextual and historical data, enabling a dynamic, scalable, and interoperable maintenance solution. The exchange of data between these components occurs within the upper layer of the proactive AAS (e.g., via a data or message bus), as illustrated by the flow arrows in Figure 3, thereby linking the stages into a cohesive and adaptive PHM process. The subsequent sections detail each of the stages in the PHM process, beginning with Monitoring, followed by Diagnosis, Prognosis, and Advisory:

1. **Monitoring** (Events detection): It aims to detect anomalies in the operational data. The implemented state machine of the AAS Event Manager (Chapters 2.1, 2.2, Figure 2) monitors Key Condition Indicators (KCIs) that originate from data-based sources (e.g., IoT sensors), model-based simulations (e.g., physics-based models), or hybrid approaches. These KCIs are checked against thresholds that are dynamically adjusted if necessary, using the data stored in the DPP (Chapter 2.3), including technical specifications and historical performance. Additionally, predicted values enhance event detection by identifying potential failures and enabling the optimization of operations before anomalies occur. As (Zio, 2021) outlines, these values can also be summarized under a set of aggregated *Prognostic Performance Indicators* (PPI).

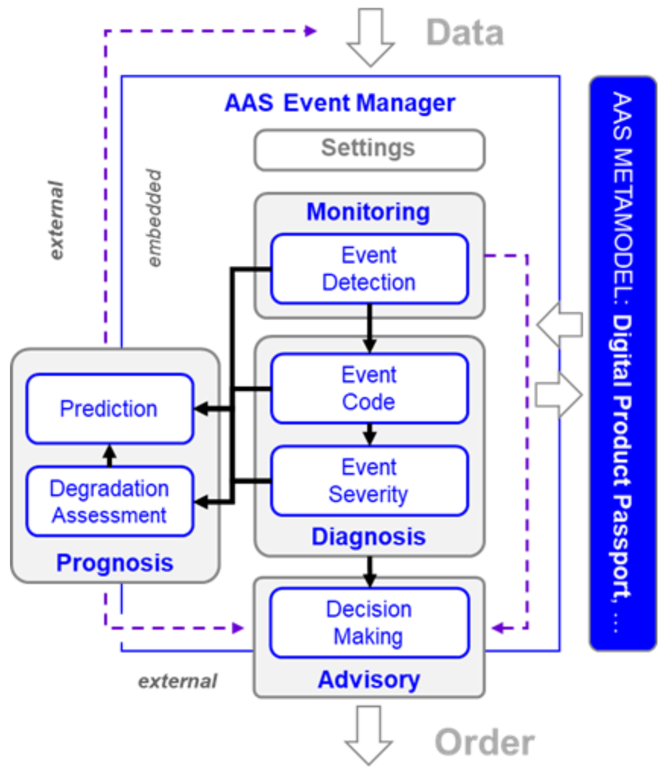

Figure 3. General PHM scheme mapped to AAS + DPP

2. **Diagnosis** (Event code and severity): Based on the monitored KCIs, diagnosis aims to unveil the fault state, mode, location and further attributes. Any detected faults or other anomalies are primarily processed by assigning them to event codes (e.g., fault types) (see Chapter 2.1). The severity of each event is quantified based on the magnitude of the associated indicators in combination with their historic values, either retrieved from the DPP (long-term assessment) or a ring buffer (shot-term). A multi-event prioritization mechanism evaluates overlapping events, factoring in their severity and operational impact to guide decision-making.
3. **Prognosis** (Predicting RUL and degradation trends): This stage uses assessment logics to determine Remaining Useful Life (RUL), degradation trends, and future conditions by integrating real-time data with historical data from the DPP. It provides predictive values to the monitoring stage, which can be sourced from three distinct mechanisms:
   - **Onboard** algorithms: Complex predictions are made by asset's embedded applications and retrieved from the AAS as KCIs. This approach offers

the fastest response time and is ideal for high-priority scenarios requiring immediate action.

- **AAS-embedded** algorithms: Prediction models integrated into the AAS enable real-time actions based on current and historical data from the DPP or integrated ring buffer, using the pre-processed KCIs.
- **Remote Prediction Services**: External IoT-based services use DPP data and advanced algorithms to generate predictions in terms of KCIs. While highly robust, this approach incurs the highest reaction time, making it less suitable for urgent decisions.

In addition, the knowledge gained is stored in the DPP and used to recalibrate models by comparing the predictions with the actual realized states (e.g. degradation curves, parameters), ensuring more accurate and adaptive predictions.

4. **Advisory** (Decision Support and Task Prioritization): Diagnosed event codes are mapped to advisory actions, such as specific maintenance services, through a continuously updated matrix that incorporates learned experiences. Among other things, depending on the number of tasks but also of potential service providers, the AAS evaluates maintenance priorities based on urgency, cost, and sustainability goals. Metrics from the DPP, such as carbon footprints and recyclability rates, guide decisions, while task execution workflows generate feedback to enrich Monitoring and Prognosis stages.

3. VERIFICATION BY APPLICATION

This chapter demonstrates the application and verification of the framework developed in the previous chapter. This is achieved through an experimental setup involving assets such as a UAS (Holybro X500) and a maintenance robot system (UR10e), which serve as representatives in an experimental MRO data space. These assets act as surrogates to verify the broader applicability of the proactive AAS framework

First, the practical operation of the different stages of the AAS-implemented PHM framework is described based on simulated failure scenarios leading to advisories and tasks. Then, the procedure of how the AAS requests and negotiates the required MRO services with MRO service providers is introduced. Finally, after the MRO executions, the return of the learnings into the DPP is sketched.

3.1. Autonomous MRO Task Identification

An enabler of the operational setup is the proAAS BOX, a DLR-engineered edge device (microcomputer) that hosts the Python-based proactive AAS and its supporting feeder application (Weiss, Pakala, Wicke, Gill, & Wende, 2023): Physically connected to the assets (here: UAS and robot), the proAAS BOXs provide the necessary processing capabilities and connectivity to run the proactive AAS, creating an operational Industry 4.0 Component (I4.0C). While the proAAS BOX manages the asset's primary data and provides connectivity to the data space (via LTE, Ethernet), its software uses this data to manage the asset by contextualizing, storing, preparing, distributing, and evaluating it, and ultimately making autonomous decisions.

The UAS I4.0C continuously measures properties such as vibration, acceleration, strain, temperature, power consumption, attitude or RPM. All values are accessible within the proactive AAS and are used by the Event Manager as KCIs, either raw or pre-processed, e.g. as a synthesized health indicator. When a KCI, whether real-time or predicted, exceeds a threshold, the Event Manager flags the issue and maps it to a maintenance task. Task templates stored in the AAS, which can be predefined or dynamically updated, specify procedural steps, required components, and compliance criteria. For example, the detection of a potential motor failure triggers a motor replacement task, informed by DPP data and technical specifications. In the experimental use case, we focus on vibration and battery voltage as KCIs to investigate advanced health management of the UAS propulsion system:

1. **Normal** Operation Phase (0 s – 100 s): The system operates normally, and the normalized battery voltage gradient and the vibration signals remain steady within the acceptable range (Figure 4: lower and upper curves). The proactive AAS evaluates the data in real-time, storing it in the DPP and ring buffer for ongoing analysis:
   - Event Detection: No anomaly is detected since the observation values stay well within the predefined thresholds, and no event codes are triggered.
   - Event Severity: The system continues evaluating the health of the asset, with no issues identified.
2. **Fault Insertion** and **Degradation Phase** (100 s – 300 s): At 100 seconds, an unbalance in the form of an asymmetrical propeller (with a tip cut off by 5 mm) is attached to one of the four idling motors of the UAS, causing a sudden increase in vibrations. To notify anomalies and assess theirs causes and severity, the Z-Factor is continuously checked for both KCIs:
   - Event Classification based on Z-Factor:

$$Z_{KCI} = \frac{x_{KCI} - \mu_{KCI}}{\sigma_{KCI}} \tag{1}$$

where x_{KCI} is the observed indicator, μ is the mean, and σ is the standard deviation of the past phase.

The results of the intercorrelation between Z-Factors are primarily assigned to initial event codes (EC) as shown in Table 1 with considering Z-Factor thresholds only. The implemented logic uses this statistical anomaly detection with a dynamically updated Z-factor (see Appendix a.) and thus operates in two modes:

- **Non-adaptive** mode (standard mode) → Uses a fixed historical reference to detect anomalies based on deviations from a predefined statistical baseline (e.g. from the DPP). This is particularly useful for applications requiring strict fault detection against known conditions.

- **Adaptive** mode → Continuously learns from real-time data, dynamically updating its reference set (ring-buffer + DPP data) to detect evolving trends and gradual shifts. This mode is beneficial in self-learning systems and environments with changing operational baselines. If no historical data is available, the logic automatically switches to adaptive modes.

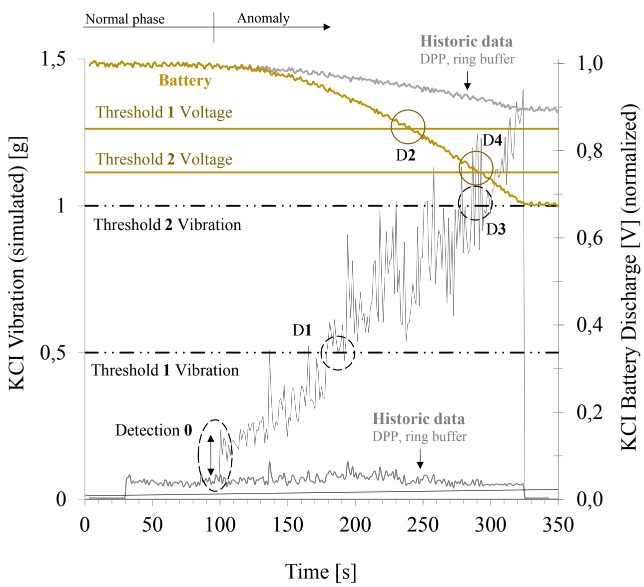

Figure 4. Detection of events (anomaly, threshold crossing)

Z-Factor Vibration	Z-Factor Power	Possible Root Causes	EC
☑ Normal	☑ Normal	---	---
☒ High	☑ Normal	Mechanical unbalance, structural issue only	#1
☑ Normal	☒ High	Battery degradation, electrical issue only	#2
☒ High	☒ High	Electromechanical fault (e.g., failing motor)	#3

Table 1. General intercorrelation cases using Z-Factor interpretation (Z > 1: Abnormal) assigned to initial Event Codes

In the use case (Figure 5), anomalies are detected when the Z-Factor exceeds 1 (first dotted horizontal line):

- Detection 0 (D0): The proactive AAS detects the first anomaly in the vibration signal at 100 s based on the deviation from its Z-Factor baseline (Figure 5: bottom left).

To simulate degradation, the throttle is then raised, causing vibration to increase and battery voltage to decline. Both parameters deviate from normal ranges, indicated by their gradients of change, and approaching the thresholds of their direct value (Figure 4 → D1 – D4). The non-adaptive Z-Factor increases continuously as it references fixed historical data, while the adaptive Z-Factor stabilizes as it learns from new inputs. In addition, fixed thresholds (T1, T2) define critical limits, while the statistical Z-Factor thresholds (Z > 1, 2, 3) also classify the anomaly's severity.

By combining fixed (T) and statistical (Z) threshold violations, this method differentiates short-term fluctuations from persistent failures and aligns with an Event Classification Table (Table 2). This table covers over 36 classification scenarios, considering single and combined failures across multiple systems (here vibration and power anomalies). For example, a high vibration Z-Factor (> 2.0) with stable power may indicate an isolated mechanical issue, whereas a simultaneous increase in vibration and power deviations suggests electromechanical intercorrelation. Event code 0 to 3 Normal degradations are classified too, where an indicator breaches the fixed threshold, but its related Z-Factor remains below 1 (using historic data).

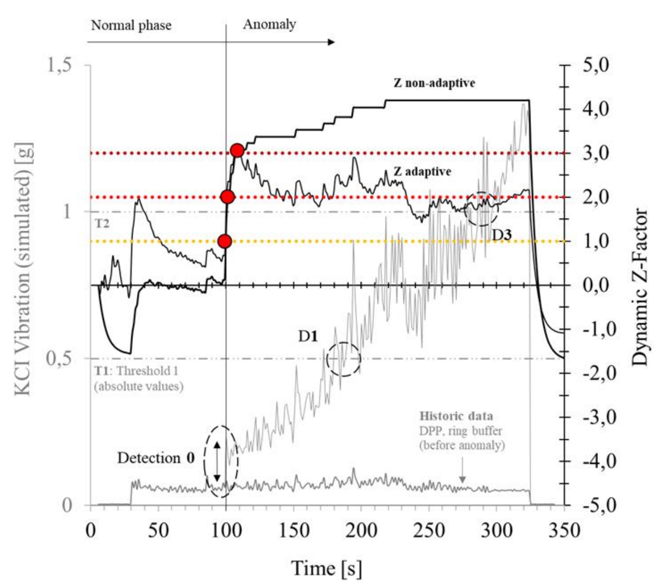

Figure 5. Vibration Z-Factor (non-adaptive: related to historic reference data; adaptive: reference data learned)

Thus, the system enables a complex context-aware decision-making, allowing predictive maintenance models to prioritize failures based on severity and interdependency.

3. **Prognosis**: In a parallel running stage, future events and their severity are estimated continuously in both the normal and the anomaly phases. This prediction is AAS-internally based on ring buffer (short-term) and/or DPP (long-term) indicator data, allowing the dynamic

generation of preliminary prediction functions (linear, quadratic, exponential), that improve as more data becomes available. For more complex predictions, external services can be involved (see before). Prediction curves for both vibration and battery are depicted in Figure 6:

- **Early** prediction curves (e.g., P1a, P1b, P2a, P2b)
- **Late** prediction curves (e.g., P1c, P1d, P2c, P2d)

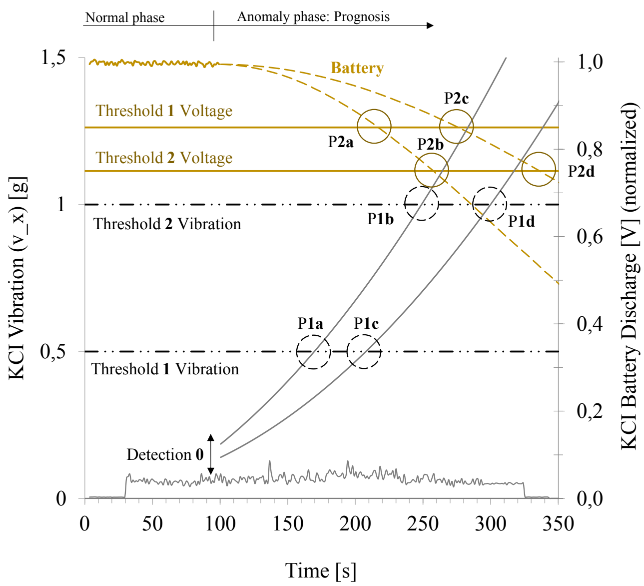

Figure 6. Prediction of early and late events

Fixed **Threshold**	Z-Factor **Affected System**	Z-Factor **Other System**	**EC**
below	abnormal	abnormal	**#0–3**
D1 (T1)	normal	Power normal	**#4**
	medium 1.0 - 2.0	Power normal	**#5**
	high (> 2.0)	Power normal	**#6**
Vibration	**…**	**…**	…
> 0.5 g	medium (1.0 - 2.0)	Power (-1.0 to -2.0)	**#8**
	high (> 2.0)	Power (-1.0 to -2.0)	**#9**
	…	**…**	**…**
	high (> 2.0)	Power (< -2.0)	**#12**
D2 (T1)	normal	Vibration normal	**#13**
Battery	medium (-1.0 to -2.0)	Vibration normal	
< 0.9 V	**…**	**…**	…
	high (< -2.0)	Vibration (> 2.0)	**#21**
D3 (Vibr.)	**…**	**…**	…
> 1.0 g (T2)	high (> 2.0)	Power (< -2.0)	**#30**
D4 (Batt.)	**…**	**…**	…
< 0.8 V (T2)	high (< -2.0)	Vibration (> 2.0)	**#39**

Table 2. Event Classification Matrix (reduced)

Each prediction curve has a corresponding probability of occurrence. The predicted value is finally the result of weighting the two prediction curves according to their probabilities. The predicted values are treated equally compared to the real-time value as described above. In this way, predicted Z-Factors and threshold violations help to assign to an event code (Table 2) with its time of occurrence. Thus, measurements to handle normal and irregular events are detected early by the asset, announcing it to service providers and enabling them for proper preparations to avoid downtimes.

4. **Advisory**: The diagnosed event codes (Table 2) are assigned by the UAS-AAS Event Manager to specific advice or tasks related to maintenance services. It uses a map (Table 3) where a task is described as a more or less comprehensive combination of required capabilities (bold) expressed in single or multiple service requests (Bill of Process). For initialization, maintenance manuals for UAS, such as (DJI, 2024), were used to identify and assign applicable treatments to event codes, with this assignment being made with respect to the expected conditions. In cases where multiple event codes are triggered, a prioritized task list is configured and sent as request to potential service providers (see next Chapter).

EC	**Condition**	**Prescriptive Tasks** (Capabilities)
…	…	…
#5	Moderate mechanical unbalance	1. **Inspect, repair** fasteners. 2. **Calibrate** rotors. 3. **Check** for deformations. 4. **Adjust** vibration damping.
#6	Severe mechanical unbalance	1. **Inspect**, **replace** damaged propellers. 2. **Check** motor alignment and bearings. 3. **Calibrate** motor RPM.
…	…	…
#9	Severe vibration with electrical effects	1. **Inspect** full structure. 2. **Check** all power connections. 3. **Reset** power connections. 4. **Run diagnosis** motor and ESC.
…	…	…
#30	Severe mechanical issue with major electrical impact	1. **Analyze** motor failure deeply. 2. **Inspect** motor, damaged propellers. 3. **Replace** motor, damaged propellers. 4. **Recalibrate** propulsion system and power regulation.
…	…	**…**

Table 3. Example of Event-Task mapping matrix (reduced)

3.2. Autonomous MRO Task Negotiation and Execution

Once the maintenance task list has been configured by the Event Manager, following the advice given in the previous chapter, they are attached to a standardized Service Request Notification template like (IDTA, 2023e). This is sent into the experimental data space as a Call for Proposals (CfP) in I4.0-compliant language (VDI2193-1, 2020) (VDI2193-2, 2022), ensuring syntactic and semantic consistency, and includes:

- **Frame** (Metadata): Sender/receiver ID, Message ID, Conversation ID, …
- **Interaction Element** (Content): List of tasks, tasks related diagnostic details (e.g., predicted vibration exceeding safe thresholds), relevant DPP submodels (e.g., bill of materials, component specifications, maintenance history), and task-specific requirements such as urgency and environmental constraints, …

The UAS AAS broadcasts this CfPs to all IoT registered Service Providers (SPs) via a registry as presented in (Weiss, Pakala, Wicke, Gill, & Wende, 2023). This overall sequence of broadcast, proposal exchange, and decision is depicted in Figure 7. Upon receiving the CfP, SPs evaluate the outlined SR's requirements from the notification and submit proposals that specify their skill characteristics, resource requirements, and associated costs to process the tasks. The UAS AAS evaluates the received proposals using MCDA algorithms, weighing factors like cost-effectiveness, compliance with technical standards, and task urgency. The optimal proposal is accepted, with confirmation sent to the selected SP and rejections are issued to others.

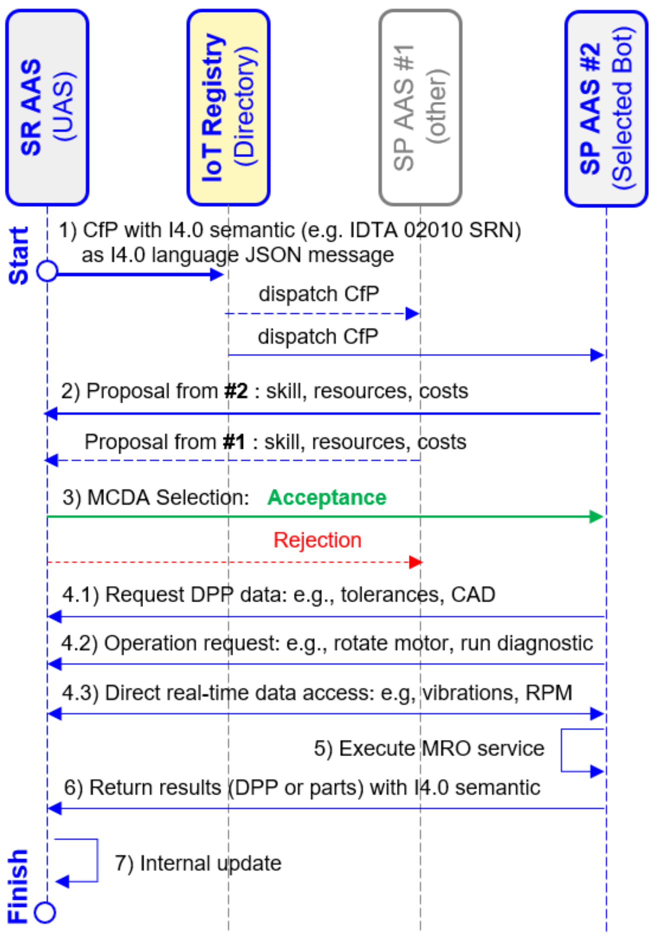

Figure 7. Interaction sequence of UAS AAS, registry AAS and MRO stations' AAS in the data space

In the experimental setup, the robotic MRO station, part of the institute, is selected for practical reasons (in Figure 7 the SP AAS #2). After selection, the robotic MRO station takes on a bilateral role as both service provider (executing maintenance tasks) and service requester (retrieving specific data or requesting actions from the UAS AAS).

After acceptance of the proposal, the propeller exchange follows (steps 4 – 5 in Figure 7), supported by bilateral interactions between the UAS AAS and the robotic MRO station:

1. **Requesting** Data: The MRO robot station's AAS requests the UAS AAS to access specific submodels of its DPP. This allows the MRO provider to tailor its maintenance actions to the UAS precise requirements. For example:
    - Component Tolerances: Ensures that replacement parts meet the required operational specifications, reducing the risk of improper installation.
    - Historical Recalibration Settings: Guides recalibration steps by referencing prior adjustments, ensuring consistency and minimizing deviations from expected performance.
2. **Updating** Data → chapter 3.3
3. **Operation** Requests: The MRO station's AAS may issue real-time requests to the UAS AAS to facilitate specific tasks during maintenance. For instance:
    - Rotating the motor to a predefined position to enable access to a component.
    - Activating diagnostic functions to verify post-maintenance performance.
4. **Direct** Data Access: The robotic station's AAS may request live data streams directly from the UAS AAS during critical maintenance operations. These real-time parameters provide the context necessary for dynamic adaptation of workflows. For example:
    - During a recalibration step, if live data indicates deviations from predicted operational thresholds, the station dynamically adjusts its maintenance actions to restore alignment with system tolerances.
    - Real-time vibration or temperature readings can inform precise adjustments to ensure component stability.

3.3. Post-Maintenance Execution Updates

At the end of the maintenance process, the MRO station (service provider) updates the DPP of the UAS with comprehensive records to provide a complete and up-to-date overview of the life cycle. These updates are made either directly, if the robot has access to the UAS DPP, or indirectly by transmitting the modified data to the UAS AAS, which processes and integrates it into two key domains (steps 6 – 7 in Figure 7):

1. **MRO Documentation** and Compliance Records:
    - Details of Maintenance Actions: Replaced components, recalibration results, tools used, and procedural notes.
    - Compliance Records: Documentation to ensure adherence to regulatory and procedural standards.
    - Sustainability Metrics:
        - CO_2-Equivalent Emissions: Recorded to assess environmental impact.
        - Material and Energy Consumption: Logged for lifecycle analysis and circular economy tracking.

2. **System**-Internal Refinement and Diagnostics:
    - Process Parameters: Updated calibration thresholds, adjustment protocols, or control logic learned during operations.
    - Post-Maintenance KCIs: Revised key condition indicators like vibration levels and energy efficiency, used to recalibrate monitoring baselines.
    - Component Lifespan Updates: New estimates of remaining useful life (RUL) for critical components, enabling predictive maintenance.

These updates not only enrich the DPP but also significantly enhance the UAS PHM capabilities. By integrating Lifecycle, real-time and predicted data, the AAS supports:

- Improved Anomaly Detection: Updated metrics and historical trends enable the system to detect subtle deviations earlier, reducing the risk of undetected failures.
- Enhanced Predictive Maintenance: Refined RUL models optimize maintenance schedules, minimizing both premature interventions and unexpected breakdowns.
- Sustainability: Maintenance actions align with circular economy goals by tracking metrics such as recyclability and environmental impact.

Furthermore, the updated DPP facilitates transparency and traceability, ensuring stakeholders have access to the latest lifecycle data. This data supports compliance verification, asset management, and informed decision-making, driving more efficient and sustainable operations.

4. CONCLUSION

The findings demonstrate that proactive AAS and DPPs enhance PHM frameworks by supporting real-time event detection, predictive maintenance, and automated service negotiation. AAS facilitates dynamic decision-making and process execution, while DPPs ensure structured lifecycle data management, traceability, and compliance. Their integration strengthens data availability and interoperability, improving information flow within MRO processes. An experimental verification using an Unmanned Aircraft System (UAS) and a robotic MRO station has demonstrated how an AAS-integrated PHM system improves real-time monitoring, anomaly detection, and predictive maintenance. The implementation of Z-factor statistical analysis, multi-tiered predictive modeling, and structured event-task mapping has shown measurable benefits, including more effective fault detection, extended asset lifetimes, and optimized maintenance scheduling.

Taken together, these results confirm that a proactive AAS, extended by a DPP, can effectively leverage PHM methodologies to increase efficiency, interoperability, and sustainability of MRO operations within Industry 4.0 ecosystems.

Despite these advancements, challenges remain in standardization, event-task mapping (prescriptions), and modeling precise prediction functions. Future research should focus on refining PHM methodologies within AAS, improving system interoperability, and developing adaptive learning mechanisms to enhance predictive accuracy. Additionally, the progressive integration of AI-driven analytics will be essential for advancing automation, optimizing maintenance workflows, and enhancing decision adaptability.

This research contributes to the development of scalable and sustainable PHM-driven MRO ecosystems, supporting the long-term evolution of Industry 4.0 maintenance strategies while enabling more effective, data-driven, and interoperable maintenance solutions.

APPENDIX

a. Dynamic Z-Factor calculation based on formula (1)

$$Z_t = \max\left(\frac{x_t - \mu_{\text{mode},t}}{\sigma_{\text{mode},t}}\left(1 - e^{\frac{x_{t-1}-x_t}{x_t+\epsilon}}\right), C_t\right)$$

With adaptive correction to prevent false positives and smooth results:

$$C_t = \begin{cases} \max\left(Z_{t-1}, \dfrac{x_t - \mu_{\text{mode},t}}{\sigma_{\text{mode},t}}\right) \cdot 1.2,\ x_t > \mu_{\text{mode},t} + 3\sigma_{\text{mode},t} \\ Z_{t-1} \cdot 0.5 + \dfrac{x_t - \mu_{\text{mode},t}}{\sigma_{\text{mode},t}},\ x_t < \mu_{\text{mode},t} + 2\sigma_{\text{mode},t} \\ max\left(Z_{t-1}, \dfrac{x_t - \mu_{\text{mode},t}}{\sigma_{\text{mode},t}}\right), otherwise \end{cases}$$

- Case 1: The correction factor is scaled up by 1,2, meaning a higher weight is assigned to large deviations.
- Case 2: The correction factor is reduced using 0,5 smoothing and adjusted based on the fixed historical reference mean and standard deviation.
- Case 3: The correction factor is simply the maximum between the previous Z-score and the current computed Z-score.

With adaptive (real-time) or non-adaptive (historic) mode:

$$\mu_{\text{mode},t}, \sigma_{\text{mode},t} = \begin{cases} (\mu_{\text{dyn,t}}, \sigma_{\text{dyn,t}}), \text{adaptive} \\ (\mu_{\text{fixed}}, \sigma_{\text{fixed}}), \text{non-adaptive} \end{cases}$$

To prevent sudden jumps in the Z-factor due to anomalies, smoothing is applied:

$$Z_t = 0.2 \cdot Z_t + 0.8 \cdot Z_{t-1}$$

with

Z_t, Z_{t-1}	Current, previous Z-factor
x_t, x_{t-1}	Current, previous indicator
$\mu_{\mathrm{mode},t}, \sigma_{\mathrm{mode},t}$	Mean and standard deviation
$\mu_{fixed}, \sigma_{fixed}$	Mean and std of fixed dataset (historic)
$\mu_{dyn,t}, \sigma_{dyn,t}$	Mean and std of dynamic dataset (adaptive)
C_t	Intermediate outlier adjustment term
ϵ	Small constant to prevent division by zero
mode	adaptive (dynamic) or non-adaptive (fixed)

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NOMENCLATURE

AAS	Asset Administration Shell
BoP	Bill of Process
BPMN	Business Process Model and Notation
CfP	Call for Proposals
COAP	Constrained Application Protocol
CPS	Cyber-Physical System
CPSS	Cyber-Physical-Social Systems
DPP	Digital Product Passport
EC	Event Code
IIoT	Industrial Internet of Things
IoT	Internet of Things
KCI	Key Condition Indicator
MCDA	Multi-Criteria Decision Analysis
MQTT	Message Queuing Telemetry Transport
MRO	Maintenance, Repair, and Overhaul
OPC UA	Open Platform Communications Unified Architecture
PHM	Prognostics and Health Management
PPI	Prognostic Performance Indicator
PPR	Product-Process-Resource Model
REST	Representational State Transfer
RUL	Remaining Useful Life
FSM	Finite State Machine
SP	Service Provider
SR	Service Requester
UAS	Unmanned Aircraft System
Z-Factor	Statistical Anomaly Detection Factor

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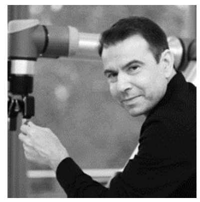
BIOGRAPHIES



Marco Weiss studied aeronautics and astronautics at the Technical University of Berlin, earning a Dr.-Ing. in 2007 on noise-reduced aircraft designs. He then spent six years with DLR and Airbus FPO, developing a framework for sustainable aviation technology assessment, which led to a second doctorate (Dr. rer. pol.) in economics from TU Hamburg in 2020. Since 2016, he has led the Technology Assessment Group at DLR’s Air Transportation System Unit. In 2017, he joined the DLR Institute of Maintenance, Repair and Overhaul, focusing on digital transformation, system architecture, and I4.0 in aviation.

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