Study on:

Digitalization of Assets, Facilities and Maintenance Management

By the DAFMM IMA Research Committee

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CONTENT

1. LIST OF ACRONYMS

- AHI: Asset Health Index
- AI/ML: Artificial Intelligence / Machine Learning
- AIP: Asset Investment Planning
- APM: Asset Performance Management
- AR: Augmented Reality
- BI: Business Intelligence
- CAPEX: Capital Expenditure
- CBM: Condition-Based Maintenance
- CMMS: Computerized Maintenance Management System
- CPS: Cyber-Physical Systems
- DT: Digital Twin
- DMM: Digital Maintenance Management
- EAM: Enterprise Asset Management
- ETL: Extract, Transform, Load
- GIS: Geographic Information System
- IAMM: Intelligent Asset Management Model
- IAMP: Intelligent Asset Management Platform
- IaaS: Infrastructure as a Service
- IoT: Internet of Things
- LCC: Life Cycle Cost
- OEM: Original Equipment Manufacturer
- OPEX: Operational Expenditure
- PaaS: Platform as a Service
- PdM: Predictive Maintenance
- RAMS: Reliability, Availability, Maintainability, and Safety
- RCBO: Risk-Based Optimization
- RCFA: Root Cause Failure Analysis
- RCM: Reliability-Centered Maintenance
- RUL: Remaining Useful Life
- SaaS: Software as a Service
- TCMS: Train Control Monitoring System

2. LIST OF DEFINITIONS

- **Artificial Intelligence / Machine Learning (AI/ML)**: Technologies that enable predictive analytics and decision-making through data analysis, pattern recognition, and self-learning algorithms.
- **Asset Data Model:** A model that defines the structure and organization of asset-related data, used to improve problem analysis and decision making.
- **Asset Health Index (AHI):** A metric used to assess the condition of an asset in real-time and predict its future performance based on monitored data.
- **Asset Investment Planning (AIP):** A system used to optimize long-term financial planning related to asset maintenance, including CAPEX and OPEX considerations.
- **Asset Performance Management (APM):** A system focused on improving asset reliability, availability, and safety through real-time performance monitoring and predictive analytics.
- **Attribute:** A characteristic or feature of an asset that can be used to evaluate its importance or performance.
- **Business Intelligence (BI):** Tools and processes used to transform raw data into actionable insights to support decision-making.
- **Condition-Based Maintenance (CBM):** A maintenance strategy that monitors the real-time condition of assets to determine when maintenance is needed.
- **Cyber-Physical Systems (CPS):** Integrations of computation, networking, and physical processes, often used in smart manufacturing and asset management.
- **Digital Asset:** A digital representation of a physical asset, including all relevant data and information that can be used for management and analysis.
- **Digital Maintenance Management (DMM):** The integration of digital tools and processes to manage maintenance tasks, planning, and decision-making.
- **Digital Servitization:** The transformation of traditional product-based businesses into service-oriented ones through the use of digital technologies.
- **Digital Twin (DT):** A virtual replica of a physical asset, system, or process, used to simulate and monitor real-time performance.
- **Digitalization:** The process of using digital technologies to change a business model and provide new revenue and value-producing opportunities.
- **Digitization:** The process of converting information into a digital format.
- **E-maintenance:** The use of digital technologies to enhance maintenance management, reducing unnecessary activities and improving decision-making.
- **Enterprise Asset Management (EAM):** A system used to manage and optimize the lifecycle of physical assets, including maintenance, inventory, and asset tracking.
- **Extract, Transform, Load (ETL):** A process that gathers data from multiple sources, processes it, and stores it in a structured format for analysis.
- **Framework:** A structured approach or supporting structure used to guide the implementation and management of processes, often used to improve decision-making and problem analysis.
- **GIS (Geographic Information System):** A system that captures, stores, analyzes, and presents spatial or geographic data, often used in asset management.
- **Internet of Things (IoT):** A network of connected devices that communicate with each other and collect data to monitor asset performance in real-time.
- **Life Cycle Cost (LCC):** The total cost associated with an asset over its entire lifespan, including acquisition, operation, maintenance, and disposal costs.

- **Predictive Maintenance (PdM):** A maintenance strategy that uses data analytics to predict when an asset will require maintenance, reducing downtime and optimizing efficiency.
- **Reliability-Centered Maintenance (RCM):** A process used to determine the most effective maintenance strategies based on reliability and safety considerations.
- **Root Cause Failure Analysis (RCFA):** A method used to identify the underlying causes of equipment failures, aiming to prevent their recurrence by addressing the root causes.

3. EXECUTIVE SUMMARY

The digitalization of maintenance management is a key transformation that organizations must undertake to remain competitive, efficient, and sustainable in today's fast-evolving industrial landscape. This document provides a comprehensive strategy and framework for guiding organizations through the digitalization of their assets and maintenance management processes. It presents a roadmap aligned with both *Maintenance and Asset Management (MAM) maturity and Digital Maturity*, allowing organizations to not only assess where they currently stand but also define clear objectives for their future digital growth.

The Need for Digitalizing Maintenance Management

Digital maintenance management provides significant benefits, including:

- *Enhanced Decision-Making:* The integration of real-time data from connected assets allows for smarter, data-driven decision-making.
- *Cost Efficiency*: Predictive maintenance reduces unplanned failures, optimizing resource allocation and extending asset lifespans.
- *Improved Compliance and Reporting:* Advanced digital solutions facilitate compliance with regulatory requirements by providing greater data granularity and transparency in reporting.
- *Sustainability:* Digitalization contributes to sustainability goals by improving energy efficiency, reducing waste, and optimizing resource usage.

Organizations that fail to embrace digitalization risk falling behind competitors, encountering higher operational costs, and being unable to meet the growing demands for compliance, traceability, and efficiency.

The Strategic Roadmap for Digitalization

This document outlines a structured *roadmap* that organizations can follow to guide their digital transformation efforts in maintenance management. It emphasizes the importance of understanding the starting point—evaluating both the organization's current *MAM maturity* and *digital maturity*—and setting a clear vision of where the organization intends to be within a specified timeframe.

The *IMA Dual Maturity Matrix* is introduced as a central tool for assessing both MAM and digital capabilities. This matrix helps organizations determine the level of digital maturity required to support their asset management processes effectively, providing a clear alignment between strategic maintenance management goals and the digital tools needed to achieve them.

The *dual maturity matrix* categorizes digital maturity into five levels, ranging from *Low Digital Maturity (Basic Tools, Isolated Systems) to Leading-Edge Digital Maturity (Industry Leadership, Continuous Innovation):* Organizations achieve continuous innovation through fully integrated digital ecosystems.

Parallel to digital maturity, *MAM maturity* is categorized into six levels, ranging from *Innocent/Pathological (Level 0) to Excellent/Leadership (Level 5).* The roadmap links these two dimensions, allowing organizations to understand the technologies, systems, and data models they need to introduce as they evolve from basic to advanced levels of both MAM and digital maturity.

The Four Core Asset Data Models

A key component of this document is the introduction of *four core asset data models*, which are essential for the digitalization of asset for their management:

1. *Asset Identification Model:* Focuses on fundamental asset data, including asset function, class, reference, and product information. This model is critical for asset tracking and evolves as maturity increases.
2. *Asset Criticality Model:* Enables the prioritization of assets based on their importance to operations. This model becomes increasingly sophisticated with predictive analytics and risk management tools as organizations advance in maturity.
3. *Asset Monitoring Model:* Leverages IoT technologies to monitor real-time asset conditions, supporting predictive maintenance and the integration of Digital Twins.
4. *Asset Intelligent Management Model:* Incorporates, in different submodules, data for advanced decision-making methodologies, such as *RCFA, RCM,* and *RAMS*, to optimize asset performance, costs, and risks. This data model is essential at higher levels of digital and MAM maturity.

These models form the foundation of a comprehensive digital strategy, enabling organizations to systematically manage and optimize their assets as they progress along the maturity spectrum.

Digital Technologies, IT Systems, Architectures and Platforms

The roadmap also outlines the integration of various *digital technologies and IT systems* into the maintenance management process. Key technologies, such as *IoT, Big Data, AI/ML, Digital Twins, and Blockchain,* are introduced at different stages of maturity to enhance the organization's capabilities in asset monitoring, data analytics, and intelligent decision-making. For example:

- *IoT* is initially introduced for basic asset tracking but expands to fully integrate real-time data across all asset classes.
- *Big Data* plays a fundamental role in predictive and real-time analytics, becoming more crucial as organizations integrate more complex data streams.
- *AI/ML* starts with predictive analytics and evolves into advanced decision-making tools that optimize the entire asset lifecycle.
- *Digital Twins* evolve from simple models of individual assets to fully integrated ecosystems that connect real-time data and simulations, allowing for predictive maintenance and real-time decision-making.

The document also explores the gradual introduction of IT systems such as *Enterprise Asset Management (EAM), Asset Performance Management (APM),* and *Asset Investment Planning (AIP)*, explaining how these systems mature and integrate into the organization's operations over time.

Similarly, the document presents *various architectures and platform* options for supporting digital maintenance, providing practical examples to illustrate their application. It highlights scalable architectures that integrate *edge, fog*, and *cloud* computing to enable real-time data processing, optimized latency, and effective asset monitoring. Additionally, platform examples—such as the integration of IoT for real-time asset tracking and AI-based systems for predictive maintenance—demonstrate how different technologies can be layered to meet specific organizational needs. These architectures and platforms are presented in a way that allows organizations to select and adapt solutions that align with their operational and digital maturity levels.

Workforce Training and Upskilling

A successful digital transformation requires not only the right technology and systems but also a skilled workforce that is prepared to adapt to new ways of working. Resistance to change is a common challenge during digitalization, as employees may feel uncertain about how new technologies will affect their roles or may be reluctant to shift away from familiar processes. Effective *change management* is essential to overcome these hurdles. The *workforce training and upskilling matrix* presented in the document outlines the training required at each level of maturity, but it also emphasizes the importance of addressing potential resistance. Clear communication about the benefits of digital tools, alongside practical training and support, can help alleviate fears and increase buy-in. As organizations progress, the workforce needs to be equipped not only with technical skills to leverage new technologies, systems, and data models effectively but also with an understanding of how these changes will improve their daily work. Training programs are recommended for IoT, predictive analytics, AI/ML, Digital Twins, and other advanced technologies as the organization advances through the digital maturity levels. Equally important are initiatives that foster a culture of openness to change, ensuring that employees feel supported and engaged throughout the transformation process.

Conclusion and Long-Term Vision

The digitalization of maintenance management is an ongoing journey that requires continuous innovation, leadership, and strategic foresight. This document provides organizations with the tools and frameworks necessary to assess their current maturity, define their digitalization goals, and implement a step-by-step guide to achieving them. To that end, a roadmap is also provided.

Ultimately, the aim is to foster a culture of continuous improvement, enabling organizations to stay at the forefront of digital innovation in maintenance management and asset management. Through the successful implementation of digital technologies, systems, and data models, organizations can drive long-term value, remain competitive, and lead their industries into the future.

4. INTRODUCTION

4.1. The IMA Research Committee Study

The primary objective of this study is to explore and recommend a comprehensive structure for the digitalization of Assets, Facilities and maintenance management. This includes developing guidelines and procedures, identifying challenges and solutions, and creating a roadmap for excellence. Our aim is to highlight future trends and innovations in the field, providing practical steps and tips for successful implementation.

The committee will delve into the following key areas of exploration:

- *Maintenance Digitalization Structure:* Propose a robust framework for the digital transformation of maintenance management.
- *Guidance and Procedures:* Develop comprehensive guidelines and procedures to support digitalization efforts.
- *Challenges and Solutions*: Identify potential obstacles and provide practical solutions to overcome them.
- *Excellence Roadmap:* Outline a roadmap to achieve excellence in digitalized maintenance management.
- *Future Trends and Innovations:* Explore emerging trends and innovative technologies that will shape the future of maintenance management.
- *Steps and Tips:* Offer actionable steps and valuable tips for organizations embarking on their digitalization journey.

Additional Areas of Interest that the committee will also explore and make recommendations on, are:

- *Data Integration and Management:* Strategies for integrating and managing data from various sources.
- *Predictive Maintenance:* Leveraging AI and machine learning for predictive maintenance.
- *Sustainability Practices:* Incorporating sustainable practices into maintenance management.
- *Cost-Benefit Analysis:* Evaluating the financial implications and benefits of digitalization.
- *Case Studies:* Analyzing successful case studies of digitalization in maintenance management.

Committee Members:

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4.2. Background

With the advent of digital technologies, maintenance management is transforming into a predictive and data-driven process that enhances decision-making and resource allocation at all three levels of maintenance activities: strategic, process, and operational. While much of the focus has been on operational improvements, such as real-time monitoring and predictive maintenance, the impact of digitalization extends to higher-level strategic decisions as well.

- *Operational Level:* Digitalization directly addresses operational issues by integrating technologies like IoT, AI, and Digital Twins to monitor asset conditions in real time. This allows for predictive maintenance, minimizing unplanned downtime and improving overall asset reliability. IoT sensors collect vast amounts of operational data, which is analyzed to identify patterns that indicate potential failures. Maintenance tasks can then be scheduled based on actual asset conditions, reducing unnecessary maintenance activities and optimizing resource use.
- *Process Level:* At the process level, digitalization enhances workflow optimization by integrating maintenance management software (e.g., EAM systems) with real-time data. It supports the automation of maintenance schedules, resource allocation, and inventory management, streamlining processes and improving efficiency. Additionally, data analytics provide insights into process performance, helping organizations identify bottlenecks, reduce inefficiencies, and improve coordination across teams and departments.
- *Strategic Level:* Digitalization offers substantial benefits at the strategic level, where higher-level decisions regarding asset management, reinvestment planning, and long-term maintenance strategies are made. For instance, digital tools can support criticality analysis by providing comprehensive data on asset performance, failure rates, and operational importance. This allows organizations to prioritize assets for reinvestment or targeted maintenance efforts. Additionally, maintenance and reinvestment planning can be enhanced through predictive analytics, which use historical and real-time data to forecast future maintenance needs, optimize budgets, and ensure the long-term sustainability of assets. This strategic alignment helps decision-makers plan for asset upgrades, resource allocation, and risk mitigation over extended periods.

By integrating digital tools at all levels of maintenance activities, organizations can reach a proactive management, ensuring that both short-term operational issues and long-term strategic objectives are addressed efficiently.

4.3. Objectives and Scope of the Document

The objective of this document is to provide a comprehensive guide on how to digitalize assets and maintenance management processes and to identify the frameworks that support these digital transformations. Digitalization is not only about enhancing existing processes but also about enabling new and innovative ways of managing maintenance through advanced technologies. The key goals include:

- Offering actionable steps for implementing digital maintenance processes.
- Identifying relevant frameworks and standards that facilitate digital integration in maintenance.

- Addressing common challenges and providing strategies for overcoming them.
- Highlighting the role of sustainability in digital maintenance practices.
- Exploring emerging processes that digitalization may bring to maintenance management. For instance, AI-powered systems, smart scheduling and resource allocation, the integration of collaborative platforms and augmented reality, etc.

The scope of this document focuses on:

- How digital technologies such as IoT, AI/ML, and digital twins can be used to enhance maintenance management processes.
- The critical importance of integrating advanced digital frameworks into the maintenance process.
- Practical recommendations for aligning digitalization with organizational objectives and improving maintenance outcomes.

4.4. Importance of Frameworks in Supporting Digitalization

Frameworks play an essential role in streamlining digital maintenance processes by ensuring consistent data flows, enabling effective decision-making, and providing organizations with a clear roadmap for scaling their digitalization efforts. They act as the backbone for aligning maintenance practices with broader organizational goals, including regulatory compliance, sustainability targets, and long-term asset management strategies. Without the support of well-defined frameworks, the integration of advanced technologies can become fragmented, leading to inefficiencies such as data silos, limited interoperability between systems, and missed opportunities for leveraging insights across the organization. Moreover, frameworks provide a standardized approach to digital maintenance that is necessary for ensuring that processes are scalable and adaptable. They allow for the seamless integration of real-time data from multiple sources, which is crucial for making informed, data-driven decisions in maintenance management. As organizations move through their digital transformation journey, having a structured approach becomes even more critical, as it helps maintain clarity and continuity in the deployment and management of digital systems.

In this context, understanding the structure and rationale behind these frameworks is vital. They not only ensure that digital maintenance processes are consistent and reliable, but also enable organizations to respond proactively to challenges, optimize operational performance, and create a future-proof system.

As we explored how to digitalize assets and improve maintenance processes, we have identified practical, well-supported recommendations that are both innovative and rooted in industry best practices.

Table 1 outlines a range of key frameworks and standards that support asset digitalization across various industries. While not exhaustive, this selection highlights widely recognized methodologies that provide structured approaches for managing the lifecycle, data integration, and operational performance of assets. These frameworks act as foundational tools, enabling organizations to navigate the complexities of digital transformation while maintaining alignment with their strategic objectives and ensuring sustainability in the long run.

Category	Framework/Standard	Sector	Description
General Enterprise/Architecture Frameworks	The Open Group Architecture Framework (TOGAF)	IT, Enterprise Architecture	The Open Group Architecture Framework (TOGAF) is a framework for enterprise architecture, helping organizations align IT strategies with business goals.
	ISO 55000: Asset Management – Management Systems	Cross-industry	ISO 55000 focuses on asset management systems, offering a framework for managing physical assets over their life cycles.
	ISO/IEC/IEEE 42010: Systems and Software Eng. - Architecture Description	IT, Systems Engineering	ISO/IEC/IEEE 42010 provides guidelines for the architecture description of systems, ensuring consistency in system design and management.
Industry-Specific Frameworks	ISO 15926-13:2018: Industrial automation systems and integration	Cross-industry	Integration of life-cycle data for process plants including oil and gas production facilities.
	Building Information Modeling (BIM). ISO 19650	Construction, Architecture, AEC	Building Information Modeling (BIM) integrates 3D modeling with digital databases to support all phases of construction and facility management.
	Common Information Model (CIM). IEC 61970-301:2020	Energy, Utilities	Common Information Model (CIM) standardizes the representation of network data for utilities, especially in the energy sector.
	Product Lifecycle Management (PLM). ISO 10303 (STEP)	Manufacturing, Aerospace	Product Lifecycle Management (PLM) manages a product's lifecycle from inception through engineering design and manufacturing to service and disposal.
	UIC Reference Framework	Railway infrastructure	Utilized in the railway industry to guide digitalization efforts in maintenance and AM, promoting sustainable and resilient practices.
	ISO 14224: Collection and Exchange of Reliability and Maintenance Data	Oil & Gas, Utilities	ISO 14224 provides a standard for collecting and exchanging reliability and maintenance data for equipment, especially in high-reliability industries.
Digital and IIoT-Driven Frameworks	Reference Architecture Model for Industrie 4.0 (RAMI 4.0)	Manufacturing, Industry 4.0	RAMI 4.0 is a reference architecture that connects industrial assets to Industry 4.0, emphasizing interoperability and asset lifecycle management.
	Industrial Internet Reference Architecture (IIRA)	IIoT, Industrial Automation	Industrial Internet Reference Architecture (IIRA) provides a framework for integrating physical assets into the digital ecosystem of the Industrial Internet of Things (IIoT).
	Asset Administration Shell (AAS)	Industry 4.0, Digital Twins	Asset Administration Shell (AAS) is the digital twin standard for Industry 4.0, facilitating interoperability and data exchange across systems.
	IEC 81346-1: Industrial Systems, Installations, and Equipment – Structuring Rules	Manufacturing, Energy, Utilities	IEC 81346-1 offers structuring principles and reference designations for industrial systems, helping organize and classify complex assets.
	IEC 62264/ISA-95: Enterprise-Control System Integration	Manufacturing	IEC 62264/ISA-95 bridges the gap between business planning and control systems, facilitating integration in manufacturing operations.
Governance and Data Management	OECD Framework for the Classification of AI Systems	OECD Countries	Emphasizes the importance of specificity in AI applications, the role of data types and quality, and the adaptability of AI models.
	Control Objectives for Information and Related Technologies (COBIT)	IT, Governance, Data Management	Control Objectives for Information and Related Technologies (COBIT) is a framework for IT governance and management, ensuring alignment with business goals.
	Industry Foundation Classes (IFC). ISO 16739-1:2024	Construction, Building Management	Industry Foundation Classes (IFC) is an open standard for data sharing in the construction and facility management industries, used in BIM.

Table 1. Overview of some key frameworks and standards supporting asset digitalization

5. THE NEED FOR DIGITALIZING MAINTENANCE MANAGEMENT

5.1. Why is crucial. Key Challenges.

In today's competitive and regulated environment, digitalizing maintenance management is essential. Failing to do so can lead to the following key challenges:

1. *Missed Opportunities with Modern Technologies:* Digital tools like IoT, AI, and predictive maintenance enable better decision-making, early fault detection, and automated workflows. Without these, companies face more downtime, inefficient repairs, and shorter asset lifespans.
2. *Falling Behind in Competitive Markets:* Digital maintenance improves operational efficiency, which is critical for staying competitive. Companies that don't adopt digital tools risk losing market share as competitors optimize their maintenance processes and reduce costs.
3. *Non-Compliance with Regulations:* As regulations require more detailed reporting, digitalization ensures compliance through automated data collection and reporting. Without it, companies face potential fines or operational restrictions due to non-compliance.
4. *Higher Operational Costs:* Traditional, reactive maintenance leads to unnecessary repairs and unplanned downtime. Digital tools allow for condition-based maintenance, reducing costs and optimizing resource use.
5. *Inability to Scale*: As organizations grow, manual or outdated systems struggle to keep up. Digital platforms scale seamlessly, supporting growing asset bases and complex operations. Without it, companies may become overwhelmed by operational complexity.
6. *Missed Sustainability Goals:* Digital maintenance supports sustainability by optimizing energy use, reducing waste, and extending asset life. Failing to digitalize means businesses miss out on sustainability benefits, risking regulatory and reputational issues.
7. *Reduced Agility in Responding to Disruptions:* Market disruptions demand quick responses. Digital tools enable real-time insights and remote operations, giving companies the agility to adapt. Without these, businesses face bottlenecks and slower reaction times.
8. *Decreased Asset Value and Shorter Lifecycles:* Without digital maintenance, assets deteriorate faster, leading to increased failure rates and shorter lifecycles. This drives up capital expenditure and reduces overall return on investment.

5.2. The benefit of digital processes

The benefits of digitalizing maintenance processes are numerous and transformative, providing organizations with tangible improvements in several areas:

- *Increased Efficiency:* One of the primary benefits of digital maintenance is the ability to improve the efficiency of maintenance activities. For example, automated diagnostics, smart scheduling, or remote monitoring reduce the time required to identify and address issues. This streamlining of processes leads to faster issue resolution and better resource management.

- *Cost Savings:* Digitalized maintenance can significantly reduce costs by optimizing maintenance schedules and minimizing unplanned downtime. Predictive maintenance models enable organizations to perform maintenance only when necessary, based on actual asset conditions, rather than following rigid, time-based schedules. This approach reduces unnecessary repairs and extends the lifespan of assets, ultimately lowering total maintenance costs.
- *Predictive Capabilities:* Predictive maintenance relies on real-time data from IoT sensors, AI algorithms, and machine learning models to predict when and where failures are likely to happen. This not only prevents costly breakdowns but also ensures that assets operate at optimal performance levels.
- *Improved Asset Reliability:* With digital tools in place, organizations can monitor the health and performance of assets continuously. Real-time data allows for more accurate decision-making, reducing the likelihood of unexpected failures and increasing overall system dependability.
- *Data-Driven Decision Making:* This approach allows maintenance teams to make more informed decisions, optimize maintenance activities, and align maintenance strategies with broader organizational goals.
- *Enhanced Sustainability:* Digital processes enable more sustainable maintenance practices by reducing waste, improving energy efficiency, and optimizing resource use. For example, by preventing unnecessary repairs and replacements, digital tools can help organizations reduce their carbon footprint and contribute to long-term environmental sustainability.

6. KEY CONSIDERATIONS FOR ASSET DIGITALIZATION

6.1. The Asset Digitalization Concept

This document recognizes the subtle differences between terms such as digitization, digitalization, and digital transformation (Raza et al., 2023). For the purposes of this work, "asset digitalization" is used as a comprehensive term that includes both the creation of asset data models and the transformative processes that generate new value (Gong and Ribiere, 2020). In line with this approach, the document focuses on three key dimensions:

- **Asset Digitization**: Refers to the creation of a foundational data and information model for an asset, effectively generating a digital twin with the necessary level of detail.
- **Asset Digitalization**: Expands beyond digitization to encompass the development of new processes, starting with the creation and ongoing updates of the digital twin. The emphasis is on enhancing the asset's value and management through emerging processes, which may not yet fully leverage digital technologies.
- **Digital Transformation**: The broader impact of this work contributes to digital transformation, aligning with the wider goals of enterprise transformation and the role of digitalization in shaping business and societal outcomes.

While digitalization solutions often originate from a technological perspective, it is essential according to the scope of this work to adopt a maintenance-focused approach to complement this. Such an approach ensures the longevity and reliability of digitalized assets, aligning with overall business objectives. This involves understanding and managing the digital capabilities of the IT solutions and overseeing the complete data and model management process, specifically tailored to maintenance needs, without delving deeply into the architecture design itself.

6.2. Background on Asset Data Models.

The question of how to digitalize an asset has been addressed by several key standards, one of which is ISO/IEC/IEEE 42010:2011, titled *"Systems and software engineering - Architecture description."* This standard broadly defines architecture as "the fundamental structure of a system, including the structure of its components, their relationships, and the principles and guidelines that govern their design and evolution over time" (ISO/IEC/IEEE 42010:2022 - Software, systems, and enterprise — Architecture description).

In systems engineering, architecture is essential because it provides a framework for describing the organization and interaction of system components, ensuring they work together to achieve defined objectives (Figure 1).

Another important standard is EN IEC 81346:2022, titled *"Industrial systems, installations, and equipment and industrial products - Structuring principles and reference designations - Part 1: Basic rules."* This standard offers principles for the classification and designation of objects within industrial systems, equipment, and plants. It plays a crucial role in organizing and structuring complex systems by offering a common language to identify system components based on their function, location, and product type (Figure 2).

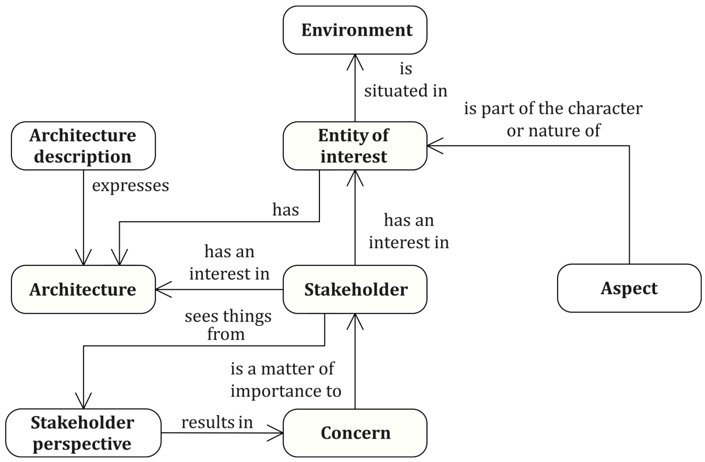


Figure 1. Relationships between concerns, aspects, and stakeholder perspectives as utilized in an architecture description according to ISO/IEC/41010:2022

In asset digitalization, EN IEC 81346:2022 systematically classifies and manages digital representations of assets, ensuring consistency and interoperability across different platforms and technologies such as IoT, digital twins, and asset management systems.

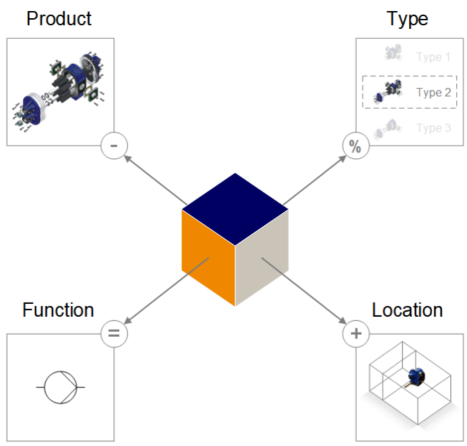


Figure 2. A technical view of the system of interest in relevant aspect EN IEC 81346.

In addition to these, ISO 14224:2016 provides valuable guidelines for the collection and exchange of reliability and maintenance data for equipment. This standard is crucial for digitalizing assets in industries where equipment reliability and maintenance are vital. It ensures that critical data on asset failure, performance, and maintenance history is consistently gathered and applied to improve operational efficiency.

ISO 14224:2016 complements asset digitalization by ensuring that all relevant operational and maintenance information is digitized and structured for better decision-making and performance analysis (Figure 3).

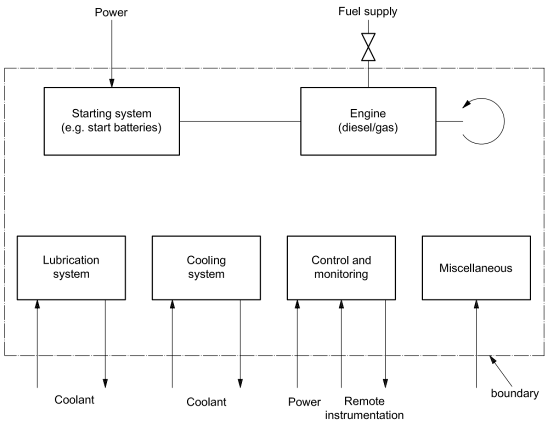


Figure A.2 — Boundary definition — Combustion engines

Table A.6 — Equipment subdivision — Combustion engines

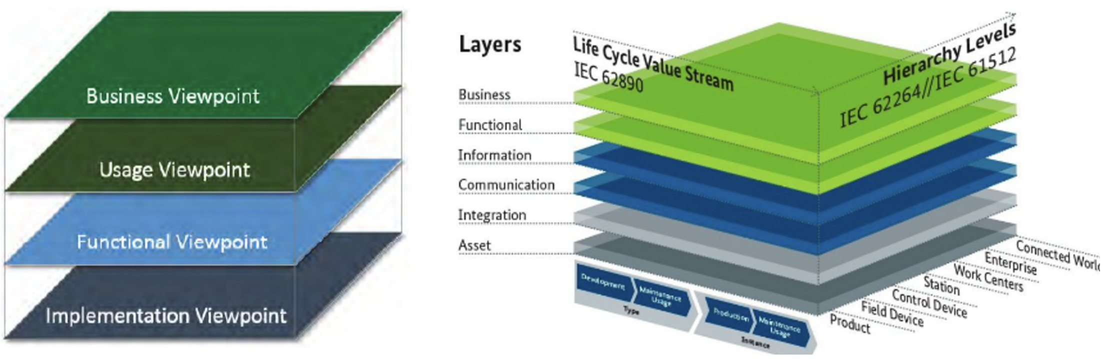
Equipment unit	Combustion engines					
Subunit	Start system	Combustion engine unit	Control and monitoring	Lubrication system	Cooling system [a]	Miscellaneous
Maintainable items	Start energy (battery, air) Starting unit Start control	Air inlet Ignition system Turbocharger Fuel pumps Injectors Fuel filters Exhaust Cylinders Pistons Shaft Thrust bearing Radial bearing Seals Piping Valves	Actuating device Control unit Internal power supply Monitoring Sensors [b] Valves Wiring Piping Seals	Reservoir Pump Motor Filter Cooler Valves Piping Oil Temperature-control sensor	Heat exchanger Fan Motor Filter Valves Piping Pump Temperature-control sensor	Hood Flange joints

Table A.7 — Equipment-specific data — Combustion engines

Name	Description	Unit or code list	Priority
Driven unit	Driven unit (equipment class, type and identification code)	Specify	High
Power - design	Maximum rated output (design)	Kilowatt	High
Power - operating	Specify the approximate power at which the unit has been operated for most of the surveillance time	Kilowatt	High
Speed	Design speed	Revolutions per minute	High
Number of cylinders	Specify number of cylinders	Integer	Low
Cylinder configuration	Type	Inline, vee, flat	Low
Starting system	Type	Electric, hydraulic, pneumatic	Medium
Ignition system	Otto, diesel	Compression ignition (diesel), spark plugs	Medium
Fuel	Type	Gas, light oil, medium oil, heavy oil, dual	Low
Air-inlet filtration type	Type	Free text	Low
Engine-aspiration type	Type of engine aspiration	Turbo, natural	Medium

Figure 3. Sample Equipment boundary definition, subdivision and specific data requirements for reliability & maintenance data exchange as in ISO 14224:2016,

Together, these standards—ISO/IEC/IEEE 42010:2011, EN IEC 81346:2022, and ISO 14224:2016—form a comprehensive framework for asset digitalization. They provide essential guidelines for structuring, classifying, and managing assets, ensuring that the complexities of digital assets are handled in a consistent and scalable manner. These standards are critical references for this study, enabling effective integration, interoperability, and long-term management of digitalized assets.



a) IIRA

b) RAMI 4.0

Figure 4. Layered reference architectures: a) IIRA; b) RAMI 4.0

In addition to the standards previously mentioned, two other critical frameworks that nowadays must be considered in asset digitalization are RAMI 4.0 (*Reference*

Architectural Model for Industrie 4.0) and the IIRA (*Industrial Internet Reference Architecture*) presented in Figure 4. These frameworks provide essential guidelines for structuring and integrating digital assets within the broader context of Industry 4.0 and the Industrial Internet of Things (IIoT).

RAMI 4.0 introduces two axes—lifecycle and hierarchy in system integration— and introduces the *Asset Administration Shell* (AAS) as a notable contribution, playing a fundamental role in the digital transformation of the industry. The AAS serves as the "digital representation" or "digital twin" of a physical asset. In order to do so, defines several key data models that form the foundation of a Digital Twin. These models include the *Identification Model*, which provides unique identifiers for the asset; the *Structural Model*, organizing the asset's components and subcomponents; and the *Functional and Technical Data Model*, which captures performance specifications and technical attributes. The *Operational Data Model* includes real-time data from sensors, supporting monitoring and predictive maintenance, while the *Lifecycle Data Model* tracks the asset's entire lifecycle, including maintenance history and upgrades. Additionally, the *Behavioral and Simulation Data Model* simulates the asset's behavior in various conditions, and the *Asset Health and Status Model* monitors real-time asset health. The Security and Compliance Model ensures regulatory compliance and data integrity, and the Communication and Interaction Model governs how the asset interacts with other systems, ensuring interoperability in a digital ecosystem. These models collectively enable comprehensive asset management through the Digital Twin, supporting real-time monitoring, predictive analytics, and seamless system integration.

The *Industrial Internet Reference Architecture* (IIRA) is another key framework, designed specifically for the Industrial Internet of Things (IIoT). IIRA provides a reference architecture that enables the connection, management, and optimization of industrial assets within a digital ecosystem. It emphasizes scalability, interoperability, and security, ensuring that assets can be integrated into a larger, interconnected industrial network.

6.3. Dimensions to consider when digitalizing an asset.

The digitalization of assets is a multifaceted process that requires comprehensive frameworks to manage and optimize assets across their lifecycle. To fully harness the potential of digitalization, a structured approach is essential—one that incorporates different aspects of asset management. Drawing from established standards such as ISO/IEC/IEEE 42010:2011, EN IEC 81346:2022, ISO 14224:2016 and architectures like RAMI 4.0 and IIRA, we propose four key models that address the various dimensions of asset digitalization and management. These models not only align with existing systems engineering principles but also enhance the integration, monitoring, and decision-making capabilities of digitalized assets.

Based on this, a suitable recommendation would be to collect data to populate the following asset models:

1. *Asset Definition Model (ADM).* The *Asset Definition Model* provides a comprehensive framework for defining the structure, properties, and relationships of an asset within a digital system. This model aligns with the standards of ISO/IEC/IEEE 42010:2011, which emphasizes the need for a well-structured architecture description that defines the fundamental components and relationships of a system. The ADM is essential for creating a digital twin of the

asset, ensuring that the digital representation is complete and can serve as the foundation for further processes, such as monitoring and maintenance. Additionally, the EN IEC 81346:2022 standard on object classification further supports this model by offering a systematic way to categorize and manage asset data within complex systems, ensuring consistency and interoperability across platforms.

2. *Asset Criticality Model (ACM)***.** The Asset Criticality Model addresses the prioritization of assets based on their impact on operations and their associated risks. This model is critical in ensuring that digitalization efforts focus on the most essential assets, maximizing value and minimizing downtime. RAMI 4.0, with its emphasis on asset lifecycle and hierarchical structures, supports this model by integrating the importance of criticality within the broader context of Industry 4.0. The ACM helps organizations focus on the assets that are most likely to influence operational efficiency and safety, ensuring that resources are allocated effectively in both short-term and long-term management.
3. *Asset Monitoring Model (AMM).* The Asset Monitoring Model facilitates real-time condition monitoring of assets using IoT networks and other digital technologies. This model draws from both RAMI 4.0 and IIRA, which emphasize the need for interconnected systems and continuous data flow between physical assets and digital systems. By integrating IoT sensors and signal processing, the AMM enables real-time visibility into asset conditions, supporting predictive maintenance and minimizing unplanned downtime. This model also resonates with the Asset Administration Shell (AAS) in RAMI 4.0, which acts as the digital representation of the physical asset, ensuring seamless data exchange and analysis.
4. Intelligent Asset Management Models (IAMMs). The Intelligent Asset Management Models provide a higher-level view of asset health and performance, utilizing advanced analytics to deliver actionable insights. These models are closely tied to Asset Performance Management (APM) and Asset Investment Planning (AIP) systems and supports the goals of ISO 55000 on asset management, which emphasizes the need for integrating asset management practices into broader organizational goals. The IAMMs enable organizations to predict future asset conditions, optimize maintenance schedules, and align asset management with business objectives. Asset's health index model provides critical insights for long-term asset management planning, ensuring that digitalization efforts lead to sustainable value creation.

7. STRUCTURING DATA FOR DIGITAL ASSETS

In this document we recommend a structure of four data models for the digitalization of the asset:

7.1. The Asset Definition Model.

The *Asset Definition Model* serves as the foundational framework for describing and managing the comprehensive asset data that exists across various information systems and applications used for asset management. It leverages established standards like *IEC 81346-1:2022* and *ISO 14224:2016* to ensure that asset data is structured and represented consistently and effectively. These standards provide guidance on how assets are classified, organized, and maintained, promoting interoperability across platforms and systems.

The proposed Asset Definition Model includes four key dimensions that provide a holistic view of the asset. These dimensions ensure that the asset is properly registered, classified, located, and referenced in a way that supports digitalization and integration into management systems (Figure 5):

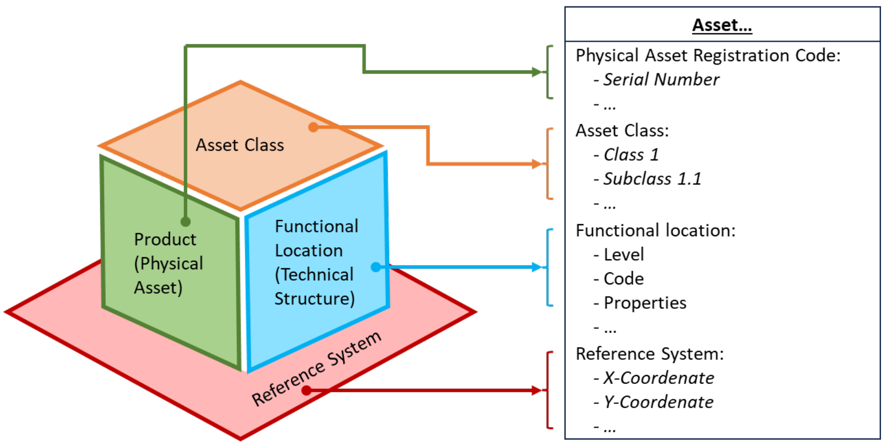


Figure 5: The Asset Definition Model

1. *The Physical Asset Registration Data.* The Physical Asset Registration refers to a code that can be the unique identifier assigned to a tangible object or entity within the asset management system. This code enables tracking and management of the asset throughout its lifecycle, from procurement and installation to operation and maintenance and consistent identification of assets across different platforms, ensuring accurate data exchange between systems. The physical registration code not only tracks the asset itself but also serves as the link between the physical and digital worlds, enabling the development of digital twins. These digital representations, which mirror the physical asset in real time, are essential for optimizing maintenance and management activities.
2. *The Asset Functional Location Data.* The Asset Functional Location refers to the physical or logical location where the asset is installed or used within the broader system or network. This concept is essential for assets that are part of larger

systems, such as infrastructure networks, where their location plays a critical role in their operation and maintenance. For example, in a transportation system, the functional location of a bridge or tunnel must be precisely recorded to ensure it can be properly maintained and monitored. Additionally, functional location data supports the integration of Geographic Information Systems (GIS), enabling advanced spatial analysis and real-time monitoring of asset conditions.

3. *The Asset Class Data.* The Asset Class describes the technology and technical specifications of the asset, independent of its functional location. This classification system allows for the grouping of assets based on shared characteristics, such as their function, technology, or construction. Within IEC 81346, asset classes are further divided into subclasses (or types), which offer more granular categorization of assets within the same class. For example, a bridge may be classified under the "Infrastructure" asset class, with subclasses detailing specific types of bridges (e.g., suspension bridge, arch bridge). This classification is crucial for defining the asset’s failure catalog or maintenance requirements. A structured asset class system allows organizations to manage large portfolios of assets better, ensuring consistency in the application of maintenance practices and technologies.
4. *Asset Reference System Data.* The Asset Reference System defines the coordinate system used to geolocate the asset within an infrastructure system or network. This is particularly important for assets that are spread over large geographical areas, such as power grids, transportation systems, or water networks. The choice of a reference system depends on factors like the location, precision requirements, and the specific needs of the infrastructure. By establishing a clear and consistent reference system, organizations can ensure that all stakeholders have access to accurate location data, which is critical for planning maintenance activities and responding to emergencies. The IEC 81346 standard supports the use of a reference system by providing guidelines for the classification and documentation of assets within spatial contexts. Integrating this system with IoT platforms further enhances the ability to track and monitor assets in real time

7.2. The Asset Criticality Model.

The *Asset Criticality Model* is an indispensable tool in maintenance and asset management, providing the foundation for risk-based decision-making and resource allocation. By prioritizing assets based on their criticality, organizations can focus their efforts on those assets that have the greatest impact on safety, performance, and operational continuity. Furthermore, by integrating with other asset management models—such as preventive maintenance, asset monitoring, and life cycle cost models—the ACM enables a holistic, data-driven approach to digitalization that supports long-term sustainability and resilience in infrastructure systems.

The primary function of the *Asset Criticality Model* is to rank assets according to their criticality. As suggested by Jinzhi et al. (2022), this analysis must allow the large-scale applicability of the model, its consistency with the organization's asset management strategy, and its ability to adapt to changes over time.

This ranking is crucial for decision-making, ensuring that the most critical assets receive the necessary attention and resources. Critical assets are those whose failure would have a significant impact on the system's overall performance, safety, or compliance with regulations. For instance, in the context of transportation infrastructure, the failure of a bridge could have severe consequences for public safety, traffic flow, and economic activity. The criticality ranking helps to identify where risks are highest, allowing organizations to prioritize maintenance activities, resource allocation, and monitoring efforts. This process not only reduces the likelihood of unexpected failures but also enhances the resilience and efficiency of the infrastructure system.

The *ACM* operates as a central component that connects to various other asset management models, facilitating an integrated approach to digitalization. These connections include preventive maintenance planning, real-time monitoring, and life cycle cost analysis, among others. A description of the importance of these model's connections is the following:

- *Integration with Preventive Maintenance Models*: Once the criticality of assets is determined, the ACM integrates seamlessly with preventive maintenance models, such as Reliability-Centered Maintenance (RCM), Maintenance Task Analysis (MTA), and Risk-Based Maintenance (RCBM). These models define specific maintenance tasks, and their required frequency based on the criticality ranking of each asset. For example, highly critical assets may require more frequent inspections and preventive maintenance actions to mitigate the risk of failure and ensure continued operation. This integration is vital for aligning maintenance activities with the organization's asset management objectives. By connecting criticality analysis with preventive maintenance planning, organizations can develop maintenance strategies that focus on high-risk assets, reducing downtime and improving operational efficiency.
- *Connection with Asset Monitoring Models:* The Asset Monitoring Model plays a crucial role in managing critical assets by providing real-time insights into their condition and performance. By integrating with the ACM, asset monitoring becomes more focused on the most critical assets, enabling organizations to deploy IoT networks and advanced monitoring technologies where they are needed most. For instance, critical infrastructure assets, such as bridges, often lack continuous monitoring systems. However, by incorporating IoT sensors and signal processing capabilities, real-time monitoring of these assets becomes feasible. This real-time data feeds into predictive models, helping organizations detect early signs of deterioration or failure and take preventive action. The integration of monitoring models with the ACM is especially important for assets whose failure would have significant repercussions, such as public safety or operational disruption.
- *Connection with Life Cycle Cost Models:* The Asset Criticality Model also links to Life Cycle Cost (LCC) Models, which analyze the total cost of owning and operating an asset over its entire lifecycle. By understanding the criticality of each asset, organizations can make informed decisions about long-term investments and cost optimization. Criticality analysis helps in determining how much to invest in maintaining or upgrading an asset, based on its expected performance and the risk associated with its failure. For example, for highly critical assets, organizations might justify higher upfront costs in exchange for reduced long-term risk and lower maintenance costs. This connection between the ACM and LCC Models ensures that decisions about asset replacement, refurbishment, or disposal are made in a way that balances risk, performance, and cost over the asset's lifespan.

- *Adaptability to Organizational and Environmental Changes:* As infrastructure systems evolve, asset criticality may shift due to changes in technology, environmental conditions, or operational priorities. The ACM must be flexible enough to adapt to these changes, allowing organizations to re-evaluate asset priorities over time. For instance, as climate change continues to impact the performance of infrastructure assets, the criticality of certain assets may increase, necessitating a more proactive approach to their management.

7.3. The Asset Monitoring Model.

The *Asset Monitoring Model* is a critical part of asset digitalization, providing the necessary infrastructure for real-time monitoring and decision-making. By utilizing IoT networks and cloud computing, organizations can gain continuous insights into asset conditions, enabling predictive maintenance and optimizing asset performance. When integrated with other asset digitization models, the monitoring model supports a comprehensive and proactive approach to asset management, ensuring long-term sustainability and operational efficiency.

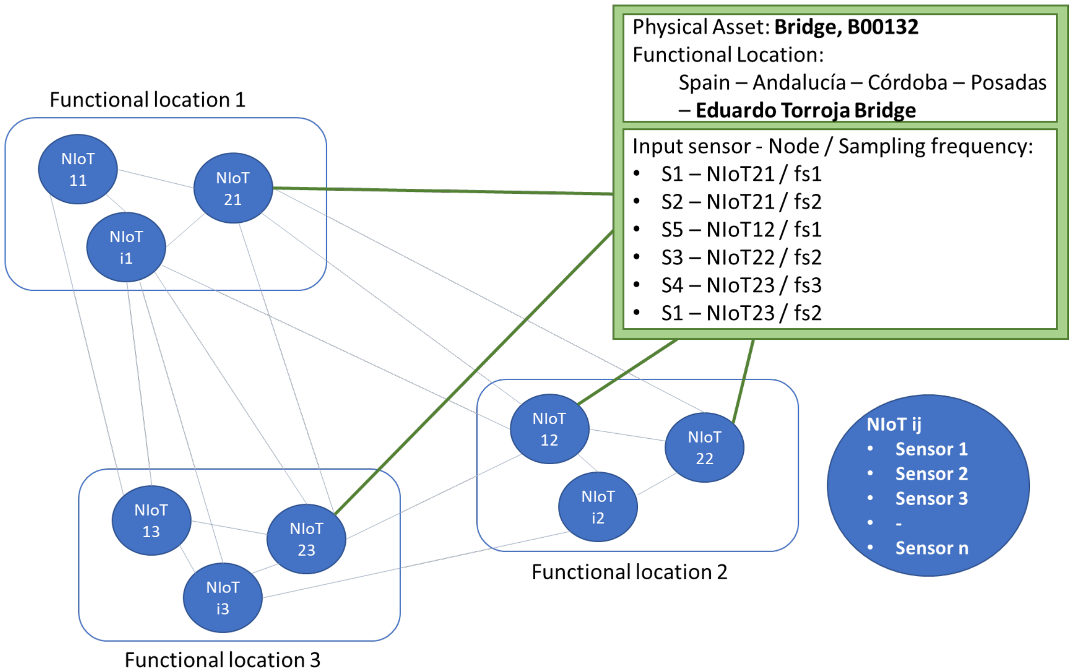


Figure 6. The Asset Monitoring Model

The asset monitoring process begins with the development of a comprehensive monitoring solution tailored to each specific asset. This involves signal integration, which is the process of collecting, converting, and interpreting signals from sensors placed on or around the asset (Figure 6). The collected data is then processed using an Extract, Transform, Load (ETL) system, where the signals are transformed into meaningful, actionable information related to the asset's health and performance.

Elements to identify in this asset monitoring model are the following:

- *IoT Networks and Signal Processing:* At the core of the Asset Monitoring Model is the use of IoT networks. An IoT network consists of three main components: sensors, nodes, and cloud computing systems. Sensors are deployed on the asset

to measure various physical parameters such as temperature, vibration, strain, or pressure. These sensors collect real-time data that is crucial for monitoring the asset's condition.
Nodes play a critical role in the system by aggregating data from multiple sensors. Each node acts as a central point for a group of sensors, ensuring efficient communication and data transfer. These nodes are responsible for local data processing and transmitting the information to the cloud. Cloud computing platforms then store, analyze, and present the data, offering end-users a detailed and comprehensive view of the asset's status.

- *Design of the Asset Monitoring System.* The design of an asset monitoring system typically follows an IoT-based framework, which includes the following key layers:
    - Acquisition and Local Processing: Data is acquired from sensors located on the asset, and local processing is performed at the sensor nodes. This allows for the immediate interpretation of data before it is transmitted, enabling faster response times.
    - Information Transport Network: The data collected by sensor nodes is transmitted through a secure communication network, typically via wireless protocols. This network ensures that data flows seamlessly from the sensors to the cloud.
    - Processing Server: At the heart of the system is the processing server, which hosts essential services for data transformation, analysis, and presentation. This server is responsible for executing the ETL process and ensuring that the data is structured and analyzed in alignment with asset-specific digitization models.

  To ensure scalability, the system can adopt a microservices-based architecture. This approach allows the system to handle large-scale data from multiple assets, ensuring that each component—whether it is data gathering, storage, or analysis—can be managed independently and scaled as needed.
- *Integration with other Asset Digitalization Models.* The Asset Monitoring Model is not a standalone process. It works in conjunction with other asset management models, such as the Asset Definition Model and the Intelligent Asset Management Model. By integrating real-time data with asset-specific models, organizations can gain a comprehensive view of asset performance, health, and criticality. For example, in infrastructure management, such as monitoring a bridge, real-time data from sensors strategically placed on the structure can be used to detect stress, wear, and potential points of failure. This data can then be fed into an intelligent asset management system to predict when maintenance should be scheduled and what specific actions are required to prolong the asset's life.
- *Hardware and Software Integration.* The Asset Monitoring Model relies on the integration of both hardware and software components. Hardware includes the physical sensors and nodes installed on the asset, while software involves the local and cloud-based systems that process and analyze the data. The system requires:
    - Real-time Operating Systems (RTOS) to manage sensor data and ensure timely responses to changing asset conditions.
    - Wireless communication protocols to transmit data from sensors to nodes and from nodes to the cloud.

- Data storage and data processing solutions, capable of handling large volumes of information, typically housed on cloud platforms.

- *Server and Centralized Processing.* At the heart of the monitoring system is the server responsible for centralized data processing and management. This server collects information from the various nodes and executes tasks such as data storage, real-time data processing, and presenting insights to end-users through dashboards or other visualization tools. As assets and their monitoring systems grow in complexity, the server's architecture must be scalable and capable of handling increasingly large datasets, which is why a microservices-based development is commonly adopted. This approach allows for individual tasks, such as data collection or processing, to be scaled independently based on demand.

7.4. The Asset Intelligent Maintenance Model.

The Intelligent Asset Management Models (IAMM) represents the final layer in asset digitalization, focusing on integrating real-time and historical asset data for advanced decision-making processes. Once an asset's data has been captured, processed, and structured (via the Asset Definition and Monitoring Models), and its criticality is addressed (via the Asset Criticality Model), the need arises to connect this data with human reasoning and decision-making tools.

Intelligent asset management relies heavily on the development and integration of robust data models that allow for the digital execution of key methodologies, such as RCFA, RCM, CBM), RAMS, LCC, AHI, etc. These data models provide the essential framework to capture, organize, and analyze the wealth of information generated by industrial assets, supporting decision-making processes that drive asset optimization.

By structuring asset data into models for identification, criticality, monitoring, and intelligent management, it becomes possible to effectively apply advanced maintenance techniques in a digital context.

The integration of these data models ensures that decision-making processes are streamlined, and that predictive analytics and simulation tools are leveraged to generate actionable insights. This approach enables organizations to move beyond manual methods, optimizing maintenance strategies and aligning them with broader business goals through data-driven insights.

8. CASE STUDIES IN ASSETS DIGITALIZATION

The following case studies— Axle Bearing Data Model for CBM Program Management and a Data Model for A Bridge Health Management —demonstrate how well-structured data models can provide the foundation for advanced digital management systems. By utilizing these models, organizations can not only monitor asset conditions in real-time but also apply predictive and intelligent maintenance strategies, ultimately improving performance, safety, and cost-efficiency.

These case studies introduce four key data models for each asset: the Identification Model, the Criticality Model, the Monitoring Model, and the Intelligent Management Model (CBM for axle bearings and AHI for Bridges). Together, these models form the basis for integrating advanced technologies like IoT, AI/ML, and predictive analytics into the asset's lifecycle management. This structured approach enables more accurate decision-making and resource allocation, ensuring optimal performance and reduced downtime. In Section 13, these assets—axle bearings and bridges—will be digitally managed by leveraging the data gathered through these models, allowing for proactive and predictive maintenance actions. The transition from traditional maintenance to digital asset management showcases the strategic value of integrating comprehensive data models into maintenance processes, helping organizations move towards a fully digitalized maintenance ecosystem.

8.1. An Axle Bearing Data Model for CBM program Management.

- *Asset Identification Model:* serves as the foundational layer, ensuring the correct tracking of the axle bearing throughout its lifecycle. It includes detailed metadata that is essential for managing the bearing in maintenance operations and digital systems (e.g., CMMS or EAM).

Data Field	**Description**	**Example**	**Additional Notes**
Bearing ID	Unique identifier for the bearing	BRG-12345	Alphanumeric identifier for global tracking.
Manufacturer	Manufacturer of the bearing	SKF	Could include manufacturing details like country.
Model Number	Bearing model number	SKF6215-Tapered	Manufacturer-specific model number.
Serial Number	Serial number of the bearing	9876543210	Useful for traceability and warranty claims.
Date of Manufacture	Date the bearing was manufactured	2022-12-01	Important for lifecycle tracking.
Date of Installation	Date the bearing was installed	2023-03-15	Installation date helps with maintenance scheduling.
Installation Technician	Name/ID of technician who installed bearing	John Doe/Tech-098	Allows for tracking human factors in installation.
Maintenance Contract ID	Contract ID linked to bearing maintenance	MC-2023-45	Links to maintenance agreements, if applicable.
Warranty Expiration Date	Warranty expiration date	2025-12-01	For warranty claim management.

Data Field	Description	Example	Additional Notes
Asset Functional Location	Physical location within a train	Left Front Axle, Train-045	GPS/location data for better asset management.
Position on Axle	Position of the bearing on the axle	Outer left	Specifies inner/outer or front/rear bearing position.
Train ID	Unique identifier for the train	TR-5678	Used for linking bearing to the specific train.
Axle ID	ID of the axle where bearing is installed	AX-5678-LF	Location-specific axle ID (e.g., Left Front).
Service Class	Bearing's service category (e.g., heavy-duty)	Heavy-duty	Reflects load/operational environment.
Bearing Type	Type of bearing	Tapered Roller Bearing	Defined by bearing manufacturer.

Table 2. Asset identification data model

- *Asset Criticality Model:* The Asset Criticality Model assesses the criticality of the bearing based on its importance to the operational system and helps prioritize maintenance actions. This model is data-driven and integrates with risk management and decision-support systems.

Data Field	Description	Data/ Weighting	Notes
Asset Criticality	Calculated value		Result of the Algorithm used in the organization
Failure History	Frequency of failures (historical)	3 incidents per 1000,000 km	Past failure rate helps estimate future risks.
Operational Impact	Bearing's failure impact on train operations	90/100 (High)	Direct correlation to operational downtime.
Safety Risk	Risk posed by bearing failure to safety	85/100 (High)	Safety-critical components receive higher weighting.
Environmental Risk	Bearing's failure impact on environment	90/100 (High)	Safety-critical components receive higher weighting.
Passenger Comfort	Bearing's failure impact on comfort	90/100 (High)	Safety-critical components receive higher weighting.
Mean Time to Repair (MTTR)	Average time to repair or replace bearing	5 hours	Extended MTTR increases criticality.
Cost of Replacement	Cost of corrective activity to replace the bearing	80/100 (High)	Calculated based on experience.
Impact on Connected Systems	Impact on other components (axle, wheels)	High	Reflects cascading effects of failure.

Table 3. Asset criticality data model

- *Asset Monitoring Model:* The monitoring model include key parameters providing a comprehensive view of the bearing's behavior in its operating environment and help detect anomalies more efficiently.

Data field	Description	Threshold/ Range	Sensor Type	Data Frequency
Temperature	Measures all bearings temperature	Max: 100°C	Thermocouple sensor	Continuous, every 10s
External Temperature	Measures external ambient temperature	Temp: -40 to +50°C	Ambient temperature sensor	Every 30 minutes
Kilometers Traveled by the Bearing	Measures kilometers traveled by the bearing	Up to 30,000 km	Distance tracking system (GPS-based)	Every 10 km
Train Speed	Measures speed of the train	Max: 0-250 Km/h	Speed sensor	Continuous, every 10s

Table 4. Asset monitoring data model

- *Condition-Based Maintenance (CBM) Model.* The CBM model facilitates the detection of anomalies, diagnosis of failure modes, and prediction of the remaining useful life (RUL) of the axle bearing. The new monitoring parameters such as kilometers traveled, and external temperature are integrated into predictive models.

CBM Parameter	Description	Data/Source	Analytical Method
Anomaly Detection (Yes/No)	Identifies deviations from normal behavior (kms)	Real-time data from temperature, km	Anomaly Detection Algorithm (ML)
Failure Mode Diagnosis (%FM1, % FM2, etc.)	Identifies the failure mode (e.g., wear, fracture)	Real-time transformed data of temperature cycles, km since anomaly, km traveled	Classification /Diagnosis Algorithm (ML)
Remaining Useful Life (RUL per FM)	Predicts the time before bearing failure (kms)	Historical failure data, kilometers traveled since anomaly	Statistical RUL Model (Weibull Analysis)
Failure Thresholds: Error in prediction, % Failure mode probability, % bearing reliability.	Sets predefined limits to trigger action: For Anomaly detection, classification and RUL.	Operating data	Rules analysis /Confusion matrix
PM Action Schedule	Scheduling PM interventions based on RUL	Derived from RUL and real-time data	Company Rule or Optimization Algorithm in Scheduling App
Maintenance Action Triggered	Type of action triggered according to CBM App Output	Derived from RUL and real-time data	Company Rules for Supervision/Action

Table 5. Asset CBM data model

8.2. A Bridge Data Model for the Bridge Health Management.

In this case study, we explore the process of obtaining and structuring the data models required for the digital management of a bridge asset. Digitalization allows for enhanced monitoring, maintenance, and management of infrastructure assets like bridges, where the complexity of operations, safety risks, and environmental conditions demand accurate and timely information.

The goal of this study is to illustrate how different data models—ranging from asset identification to health monitoring—are created and utilized to support decision-making processes throughout the bridge's lifecycle. The integration of these data models enables predictive maintenance, risk management, and optimization of resources, ultimately enhancing the bridge's reliability, performance, and lifespan.

- *Asset Identification Model:* This table outlines the key attributes that should be collected to define the identification of an asset, in this case, a bridge. This includes the basic information needed to register and manage the asset in various systems and track its lifecycle.

Attribute	Description
Asset ID	Unique identifier for the bridge, automatically generated or assigned by the EAM system.
Asset Class	Type of bridge (e.g., suspension, beam, arch, etc.).
Functional Location	GPS coordinates of the bridge, geospatial reference system (e.g., WGS84).
Product Code	Standard code for the bridge design, if applicable.
Manufacturer	Company or entity responsible for constructing the bridge.
Year of Construction	Year the bridge was built.
Construction Material	Primary material used (e.g., steel, concrete, etc.).
Bridge Dimensions	Length, width, and height of the bridge.
Load Capacity	Maximum load capacity in tons.
Owner/Operator	Organization responsible for the bridge's maintenance and operation.
Last Inspection Date	Date of the last physical inspection performed.
Normal life	Estimated years of service without major repairs.
Legal Registration Number	Legal identification number in regulatory records.
Regulatory References	Standards and regulations governing the design (e.g., Eurocode, AASHTO, etc.).

Table 6. Asset criticality data model

- *Asset Criticality Model:* This table provides attributes that help prioritize the asset based on its criticality to operations and risk. The criticality model allows organizations to rank assets based on importance and urgency for maintenance interventions.

Attribute	Description
Criticality Score	Numerical value based on the importance of the bridge and associated failure risks.
Impact on Traffic Flow	High, medium, or low depending on the traffic volume the bridge handles.
Redundancy Availability	Availability of alternative routes in case of bridge failure.
Critical Load Capacity	Load level at which failure becomes critical.
Usage Frequency	Daily frequency of vehicles and/or pedestrians using the bridge.
Proximity to Urban Centers	Population density near the bridge (urban, rural).
Environmental Conditions	Factors such as weather, corrosion exposure, flooding, etc.
Incident History	Previous incidents or maintenance events (failures, repairs, etc.).
Maintenance Priority Level	Priority level for maintenance interventions (high, med., low).
Risk of Failure	Probability of failure based on current condition and years in service.
Socioeconomic Importance	Impact on local or regional economy in case of failure.
Availability of Critical Spares	Availability of critical spare parts or lead time for supply.
Urgency of Intervention	Assessment of how urgent a preventive intervention is required.

Table 7. Asset criticality data model

- *Asset Monitoring Model:* The asset monitoring model focuses on real-time data collected through IoT sensors and other monitoring systems, providing essential information for predictive maintenance and condition-based decision-making.

Attribute	Description
Vibration Sensors	Real-time vibration monitoring to detect structural stress.
Load Sensors	Real-time measurement of the load on the bridge.
Temperature Sensors	Monitoring the material temperature of the bridge, used to detect deformations.
Corrosion Detection	Sensors measuring corrosion levels in metallic components.
Crack Detection	Sensors that detect and monitor structural cracks.
Displacement Measurement	Sensors measuring lateral or vertical displacement of the bridge.
Humidity Monitoring	Sensors detecting moisture in critical areas susceptible to corrosion.
Water Flow Monitoring	Data on water flow beneath the bridge (for bridges over rivers) to assess scouring.
Security Cameras	Cameras capturing visual data on the bridge's condition and traffic flow.
Traffic Data	Information on traffic volume and type (e.g., heavy, light vehicles).
External Weather Conditions	Temperature, humidity, wind data from nearby weather stations.

Table 8. Asset monitoring data model

- *Asset Health Index (AHI) Calculation Model:* This table outlines the key data needed to calculate the Asset Health Index (AHI) and estimate the asset's remaining life. It includes both historical and real-time data for calculating future maintenance needs.

Attribute	Description
Current Condition Score	Health index calculated from real-time monitoring data.
Predicted vs. Actual Health Differences	Differences between originally predicted health and actual observed health, due to changing conditions.
Aging Rate	Speed at which the structure should be degrading based on experience.
Corrected Aging Rate	Speed at which the structure is degrading based on continuous monitoring.
Probability of Failure	Calculated probability of failure over a set period (e.g., the next year).
Remaining Useful Life (RUL)	Estimated years or months left before major maintenance or repairs are needed.
Health Modifiers (structural integrity index, etc.)	Value of significant indicators selected for asset health
Maintenance History & Reliability Modifiers	Details of past maintenance over the last few years.
Future Condition Projection	Projection based on simulations and predictive models of how the bridge's health will evolve.
Recommended Major Intervention Interval	Time suggested for the next major preventive maintenance intervention.
Projected Maintenance Costs	Future maintenance costs based on current condition and degradation projections.
Life Cycle Cost (LCC/TotEx) Estimate	Total maintenance, operation, and repair costs estimated over the bridge's remaining lifespan.

Table 9. Asset health Index data model

9. DIGITAL MAINTENANCE PROCESSES. KEY CHALLENGES.

A very relevant information concerning these challenges can be found in the GFMAM 2024 report on digital transformation in Maintenance and Asset Management. This report is based on the results a survey with 505 respondents worldwide and offers a synthesis main challenges identified (Figure 7) and potential solutions to overcome them. A summary would be as follows:

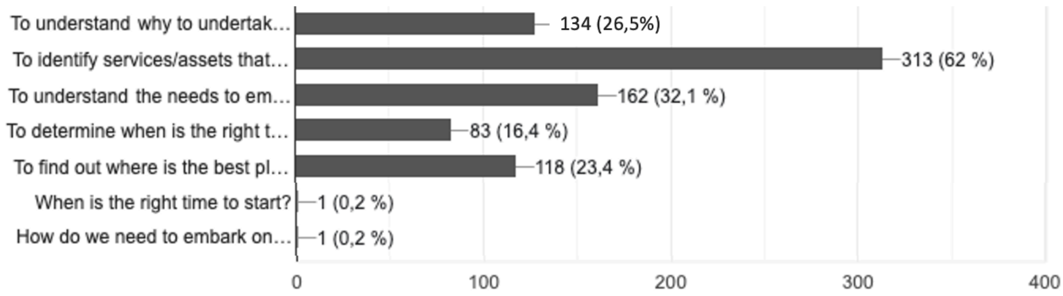


Figure 7. Challenges selected by respondents.

- *Identifying Services and Assets that Benefit Most from Digital Transformation:*
  - *Challenge:* A key challenge, as noted by 62% of respondents in the GFMAM 2024 survey, is identifying the services and assets that will benefit the most from digital transformation.
  - *Solution:* Conduct a comprehensive assessment of all assets, evaluating their criticality, operational impact, and potential for improvement through digital technologies. Prioritize high-impact assets for transformation efforts to maximize return on investment.

- *Understanding Organizational Needs for Digital Transformation:*
  - *Challenge:* According to 32.1% of respondents, understanding the specific needs of the organization before embarking on digital transformation is crucial.
  - *Solution:* Perform a thorough analysis of existing processes, systems, and stakeholder expectations. Ensure alignment between the digitalization strategy and the organization's overall goals by engaging key stakeholders early in the process to define clear objectives and expectations.

- *Building Awareness of the Benefits of Digital Transformation*
  - *Challenge:* With 26.5% of respondents identifying the need to understand why digital transformation should be undertaken, it is critical to raise awareness about its long-term benefits.
  - *Solution:* Develop communication strategies and educational programs that highlight the advantages of digitalization, such as improved operational efficiency, cost savings, and enhanced sustainability. Involve leadership and create case studies to demonstrate successful outcomes.

- *Determining the Optimal Starting Point for Digitalization*
  - *Challenge:* Knowing where to start was cited as a challenge by 23.4% of respondents, reflecting the complexity of prioritizing areas for transformation.
  - *Solution:* Adopt a systematic approach to evaluate factors such as feasibility, resource availability, and the potential impact of digital transformation. Pilot

programs for high-criticality assets or processes can help create a roadmap for broader implementation.

- *Timing the Digital Transformation*
  - *Challenge:* Timing was less of a concern for respondents (16.4%), but it still plays a role in the success of digitalization efforts.
  - *Solution:* Assess organizational readiness, technological advancements, and market conditions to determine the best time to initiate digital transformation. Ensure that the workforce is prepared and that the necessary technology and infrastructure are in place to support the change.

As a result of the observation of the above mentioned GFMAM report, besides experiences and discussions inside our group, for the purpose of this study, we identify the following challenges as the broader obstacles that organizations face during the digital transformation of asset management.

- *Data integration*. As organizations often rely on multiple legacy systems, integrating these with new digital platforms and ensuring seamless data flow can be complex. Disparate systems, inconsistent data formats, and data silos can hinder the ability to generate actionable insights from asset data, limiting the effectiveness of digitalization efforts. For example, many enterprises use legacy Enterprise Asset Management (EAM) systems that were not initially designed to handle real-time IoT data. Integrating these with new predictive maintenance tools or digital twins may require custom solutions, complex middleware, or significant system upgrades, which can slow down the digitalization process.
- *Technology adoption*. Introducing new technologies such as IoT, AI, and Digital Twins requires not only a significant investment but also ensuring that these technologies are aligned with the organization's goals and infrastructure. In many cases, organizations struggle with determining which technologies best suit their needs and how to integrate them into their existing maintenance processes effectively. For instance, while predictive maintenance powered by AI and machine learning can drastically reduce downtime, implementing these systems requires both high-quality data and substantial computing power, which may not be readily available in all organizations. Additionally, scaling these technologies across all assets may present cost and infrastructure challenges.
- *Workforce adaptation* remains a critical barrier. As digital technologies reshape maintenance operations, employees must develop new skills and adapt to more data-driven and technology-dependent workflows. Resistance to change, lack of training, and a skills gap can slow down the adoption of digital tools, preventing organizations from realizing the full potential of digitalized maintenance. For instance, employees may face difficulty transitioning from traditional maintenance approaches to digital methods. Technicians who are accustomed to hands-on inspections and routine maintenance schedules may struggle with the shift to predictive analytics and remote monitoring. Furthermore, the training required to use advanced digital tools, such as augmented reality (AR) systems for remote maintenance or AI-driven predictive maintenance platforms, can be extensive and time-consuming.

10. DIGITALIZATION OF MAINTENANCE MANAGEMENT PROCESSES

10.1. Key managerial areas digitally supported.

Most of the data that is collected through new digital technologies can be used to increase the effectiveness of asset management decision-making. Consequently, the types of asset management decisions and their importance in meeting the organization's AM objectives need to be identified. The importance of each reporting requirement associated to a given decision-making process can be estimated by identifying the benefits of better a reporting and decision making and the risks associated with poor (non-data-driven) decision making or reporting. To this end, the process to follow could be (Dunn, 2019):

1. Identify the requirements of all key stakeholders with respect to the provision of information.
2. Identify the most critical assets and then select the information that must be considered that will lead to effective decision making. Finally, it is necessary to determine what data is needed to obtain this information. The necessary data could take many different forms, including:
    - Data about the assets (themselves, current condition, current level of performance).
    - Data relating to the activities that have been performed on the assets (operational activities, maintenance activities and modifications, upgrades or replacements);
    - Data about the financial or other impacts if the assets underperform or fail to perform at all.
    - Data relating to safety, environmental or other incidents.
    - Data relating to expected future asset performance, costs, and risks.
    - Etc.
3. Identifying the types of decisions which will have the greatest potential impact on the achievement of asset management (and organizational) objectives. The decisions can be made at many different organizational levels, including:
    - *Strategic Decisions* – potentially those with the greatest potential business impact, capital investment and allocation of operating expenditure decisions. Also, those decisions for which objective data is most likely to be difficult to obtain and analyze.
    - *Management Decisions* – such as to replace or upgrade an asset to meet specific business needs, about the timing of these major events, also those related to the allocation of working capital (such as for spare parts holdings), decisions relating to whether to insource or outsource activities.
    - *Operational Decisions* – involved with short term control of maintenance and operational activities, these are technical decisions relating to day-to-day Operations.

Some experts agree that there has been unequal attention paid to the *management* and *operational* areas over the last decades where many business resources were spent on activities to get the jobs done more efficiently (Crespo Márquez, 22). For instance, master asset registers were created, work management systems and procurement systems were developed, and communication with craftsmen was improved. However, it seems that a better balanced and more *strategic* view is needed, understanding business priorities in work and investments.

10.2. Starting from the Maintenance Management Processes and Framework

Effective maintenance management requires a structured approach—a systematic process that organizes management activities into a series of "management building blocks". These blocks serve as key areas of focus, and a "framework" is then established, grouping the techniques and methods used to support decision-making in each of these areas. A generic maintenance management model for both built and in-use assets, consisting of eight sequential management building blocks is presented by Crespo (2007), as illustrated in Figure 8.

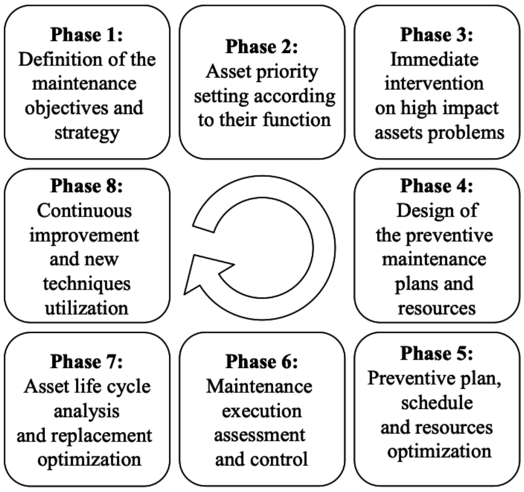


Figure 8. Maintenance Management Model

Each of these building blocks represents a critical decision-making area for asset maintenance and lifecycle management. Techniques, methods, and models within each decision area are used to guide and streamline decision-making, some of which are shown in Figure 9.

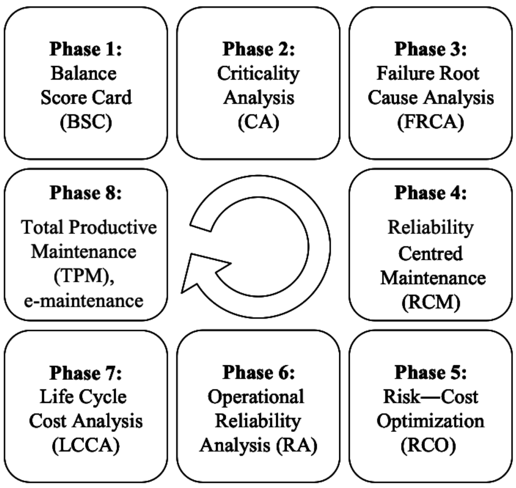


Figure 9. Sample methods and models (Crespo Márquez A, 2007)

10.3. The DMM Processes & Framework

In digital maintenance management (DMM) data plays a central role, enabling asset managers to access diverse information that can significantly improve decision-making.

DMM is possible thanks to the inclusion of new data-related processes and a digital framework. The framework provides a comprehensive approach to managing and optimizing maintenance activities in the processes by leveraging advanced digital tools and data-driven decision-making. This framework integrates multiple models, each serving a critical function in the digitalization of maintenance processes.

To have a better visualization of the overall DMM process we can use an *Input—Process—Output* diagram, as shown in Figure 10 (taken from Crespo Márquez A, 2022).

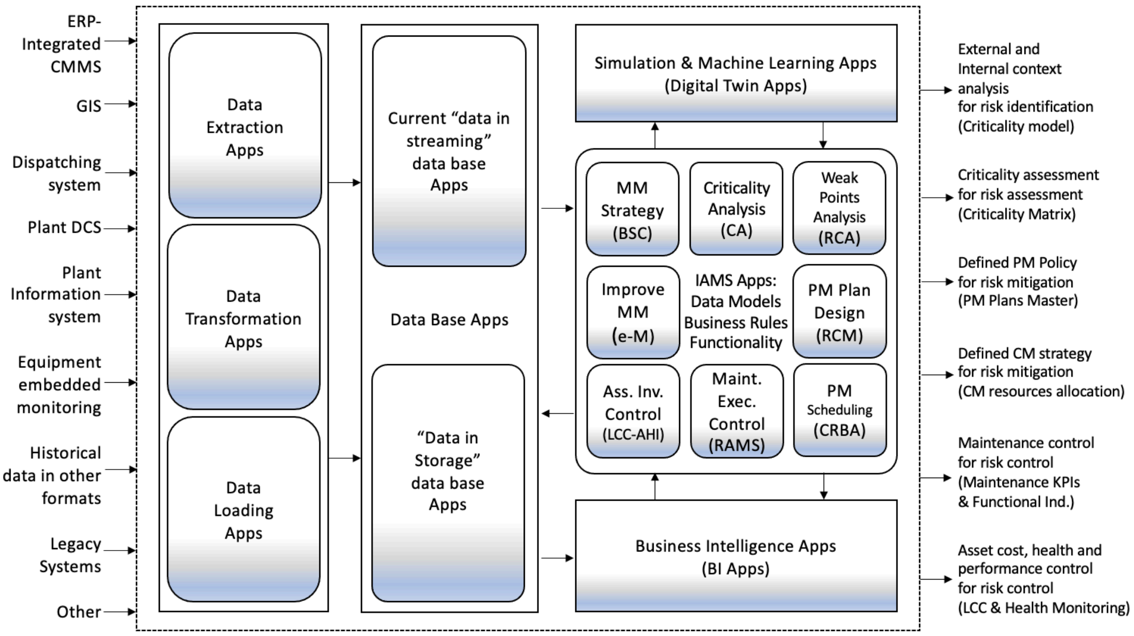


Figure 10. Input—Process—Output Diagram of the DMM Framework

The difference with previous section maintenance management processes can be explained as follows: Although the core processes of MM remain the same (in figure 10 now named as IAMS Apps), four new data related processes are incorporated to:

1. Extrac, transform, and load data from various sources into structured, accessible formats, to flow into decision-making systems. Process accomplished by the ETL Apps in Figure 10.
2. Organize and maintain the amounts of data collected, to serve as the foundation for decision-making in each management area IAMS Apps, whether for strategic planning, operational control, predictive maintenance or whatever. Process accomplished by the Data Base Apps in Figure 10.
3. Generate Digital Twin models to serve as a virtual replica of the physical assets, integrating real-time operational data, historical performance, and predictive analytics. To simulate asset behavior under various conditions and scenarios, enabling to account on these results for proactive decision-making. Process accomplished by the DT Apps in Figure 10.

4. Provide the interface to extract actionable insights from the data repositories. According to specific business needs, to align with organizational goals. Process accomplished by the BI Apps in Figure 10.

Let’s now explain a bit the new supporting structure, the framework of the comprehensive DMM. It can be presented as consisting in different models: ETL, Database, IAM, AI, and BI models:

1. *ETL Model (Extract, Transform, Load):* The ETL process is the backbone of digital maintenance management, facilitating the extraction, transformation, and loading of data from various sources into structured, accessible formats. The ETL model automates this process, allowing real-time and historical data to flow efficiently into decision-making systems. This includes:
   - *Historical data* on asset management, planning, and costs, providing insights into past maintenance activities and expenditures.
   - *Geographic and operational data* on assets, which considers environmental conditions and location changes, critical for understanding asset behavior under different contexts.
   - *Real-time equipment status*, including alarms, degradation patterns, and thresholds, to monitor current conditions and anticipate potential failures.
   - *Predictive data*, derived from reliability studies and AI-based models, forecasting future maintenance needs based on trends and degradation rates.
   - *Etc.*

   The ETL model ensures that data is transformed to meet specific information and format requirements before being loaded into cloud-based databases using Infrastructure as a Service (IaaS) and Platform as a Service (PaaS) tools, making it readily accessible for further analysis. ETL can be designed and supported by big-data tools having these capabilities.

2. *Database Management Model (DB).* The Database Management Model is responsible for organizing and maintaining the vast amounts of data that are collected, transformed, and stored. In this model, the cloud databases allow for scalable storage, enabling organizations to store and retrieve large volumes of data in real time. Data can be queried and retrieved on-demand, and with advanced data structuring, it becomes easy to integrate with other digital tools within the framework. This model ensures that relevant data is always accessible, secure, and properly organized, allowing for seamless integration into decision-making processes.

3. *Intelligent Asset Management System (IAMS) Models.* The Intelligent Asset Management System (IAMS) models are the core part, are possible thanks to the proper digital definition of the asset and sustain decision-making. These models analyze and organize data from different repositories to support specific maintenance and asset management decisions. IAMS models may include:
   - *RCM* Models. To design maintenance of very crucial systems.
   - *Predictive maintenance* models that use real-time and historical data to forecast equipment failure and optimize maintenance schedules.
   - *Risk and reliability* models that assess the likelihood of failure based on various factors such as operational stresses, maintenance history, and environmental conditions.

- *Asset health indexing*, which evaluates the condition of each asset in relation to its operational parameters and environment, helping to prioritize maintenance activities.
- *Life cycle costing* models. To determine the cost of ownership and better reinvestments decisions.

IAMS apps work alongside ETL tools to create custom data repositories tailored to each decision-making block. They ensure the selection of the right data for each decision, applying appropriate business rules for optimal asset management. Additionally, IAMS apps interact with DT Apps (machine learning and simulation models) to generate additional data providing further analytical capabilities.

4. *Machine learning and Simulation Models (DT).* To generate the Digital Twin models to serve as a virtual replica of the physical assets, integrating real-time operational data, historical performance, and predictive analytics. This allows maintenance teams to simulate asset behavior under various conditions and scenarios, enabling proactive decision-making. The Digital Twin is not just a static representation but a dynamic, evolving model that continuously updates with live data from sensors and IoT networks. It enables:
   - Simulations of how assets will perform under different stress conditions, allowing organizations to test maintenance strategies before implementing them.
   - Predictive analytics, providing forecasts of equipment failure, performance degradation, and operational inefficiencies.
   - Real-time monitoring, which ensures that maintenance teams are alerted to any deviations in asset performance, enabling swift corrective action.

   These models are vital for developing deeper insights into asset behavior, supporting both immediate operational decisions and long-term planning.

5. *Business Intelligence (BI) Models for User Interaction.* The Business Intelligence (BI) models provide the critical interface between the data and the end users, making it easy to extract actionable insights from the data repositories. BI models are tailored to specific business needs, allowing maintenance managers to generate reports, dashboards, and analytics that align with organizational goals. The BI apps within the DMM framework enable:
   - Real-time reporting on asset performance, maintenance schedules, and operational efficiency.
   - Interactive dashboards that allow users to explore data through customizable visualizations, facilitating decision-making at all levels.
   - Advanced analytics, helping users interpret data trends, forecast future performance, and assess the impact of maintenance interventions.

   BI models also support collaboration by enabling multiple stakeholders to access the same data and insights, ensuring that maintenance decisions are aligned with broader business objectives.

11. TECHNOLOGIES INTEGRATION IN THE DMM FRAMEWORK

11.1. Technologies for ETL and DB Apps.

10.1.1. The Internet of Things (IoT) Technologies

The adoption and development of advanced Internet of Things (IoT) technologies have significantly impacted maintenance management. This progress has been driven by open membership organizations like the Industrial Internet Consortium (IIC), which have promoted the development, implementation, and widespread use of interconnected devices and intelligent analytics. Thanks to these initiatives, many companies are now planning to support the expanding Industrial Internet of Things (IIoT) by utilizing cloud servers and app stores, allowing application components to be accessed in cloud environments and integrated with systems managed in private clouds or data centers.

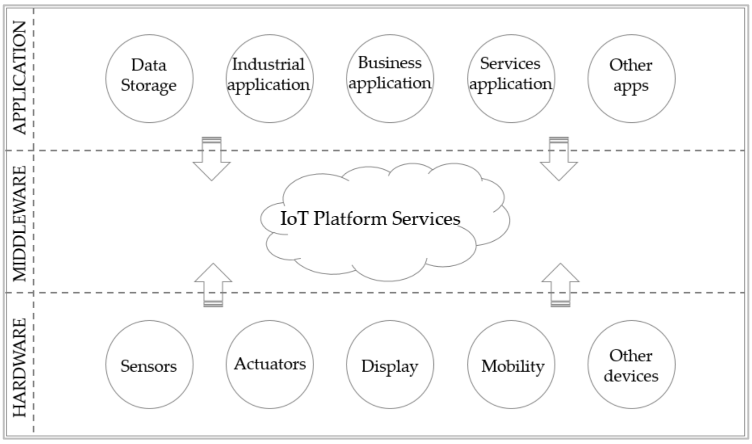


Figure 11. IoT Platform layer

Originally, IIoT platforms emerged as IoT middleware, serving as a bridge between the hardware and application layers. Major IT vendors like SAP HANA, GE Predix, and RFID4U have adopted this structure, as illustrated in Figure 11. One of the key advantages of IIoT platforms is their ability to integrate with almost any connected device and seamlessly interact with third-party applications. This flexibility between hardware and software allows a single platform to manage diverse devices uniformly. These modern IoT platforms offer a range of advanced features, including front-end analytics, on-device data processing, and cloud-based deployment. Studies by Mineraud et al. (2016), Borgia (2014), and Perry (2016) highlight several critical characteristics to consider when selecting an IoT platform:

- *Device management:* The platform must handle thousands or even millions of connected devices, maintaining operational status with low power consumption and efficient communication protocols.
- *Data collection and storage:* The platform should manage large volumes, variety, and velocity of data stored in the cloud.
- *Creation of virtual machines:* The platform enables real-time, batch, predictive, or interactive analysis of sensor data, providing valuable insights.
- *Remote device configuration and control:* Managing device configuration is essential for optimizing performance.

- *Reliability and data security:* The platform must be highly reliable, especially in mission-critical environments, where data security and system reliability are paramount.

The best IoT platforms also offer flexibility, allowing the addition of industry-specific components and third-party applications without incurring significant additional costs or delays.

10.1.2. Big Data

In modern Asset Performance Management (APM) systems, high-quality data is essential for effective decision-making in managing critical assets. To ensure good results, organizations must:

- Identify the necessary data for analyzing and managing critical assets.
- Establish quality standards for data, such as:
  - *Completeness:* Ensuring all required data is collected.
  - *Accuracy:* Verifying that the data accurately represents reality, especially when human input is involved.
  - *Timeliness:* Ensuring data is available when needed.
  - *Availability:* Ensuring data is accessible to users.
  - *Consistency:* Applying uniform definitions and standards across the organization.

Data scientists typically spend nearly 80% of their time on data processing and preparation, including collection, cleaning, and organization (Figure 12). This task is often the most time-consuming part of data analysis.

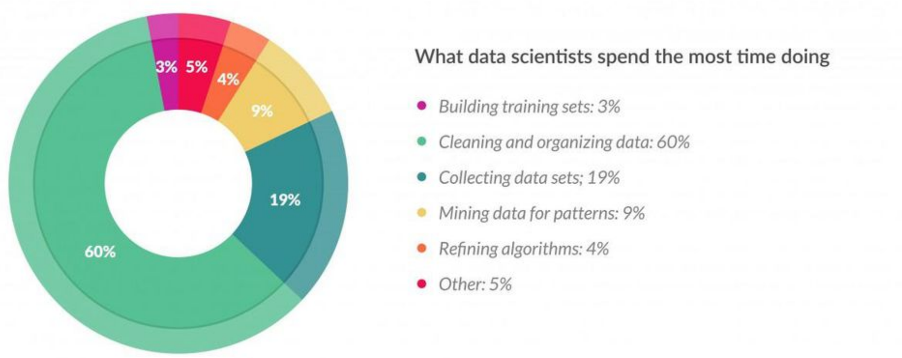


Figure 12. Percentage of time consumed by data scientists (Wilder-James, 2016)

In IoT platforms that handle health monitoring and predictive analytics, data is managed differently due to its large volume, high velocity, variability, and noise. The diversity of data also presents unique challenges. Big data analytics can facilitate the collection and processing of this data through:

- *Complex aggregation analysis:* Processing data collected at different times and locations.
- *Multi-dimensional query and analysis:* Extracting asset data from various perspectives.
- *Log data analysis:* Monitoring asset health during operation.
- *Time-window-based stream data analysis:* Identifying operational trends.

- *Complex event processing:* Detecting failures before they occur.

These advanced functions enable organizations to manage and analyze data more effectively, improving asset performance and maintenance strategies

11.2. Technologies for DT Apps.

10.2.1. Predictive Analytics

Although predictive analytics has been around for years, the development of new technologies has significantly enhanced these techniques. Business leaders are increasingly recognizing the importance of predictive analytics and machine learning, as they directly contribute to increased profitability. A survey conducted in 2016 revealed that 69% of business managers and data scientists believed data analysis was essential for the future of their business, and 79% considered predictive or prescriptive maintenance as extremely or very important. This trend has only grown in importance over recent years. Depending on the desired outcomes and the available data, different types of analytics can be applied (Figure 13):

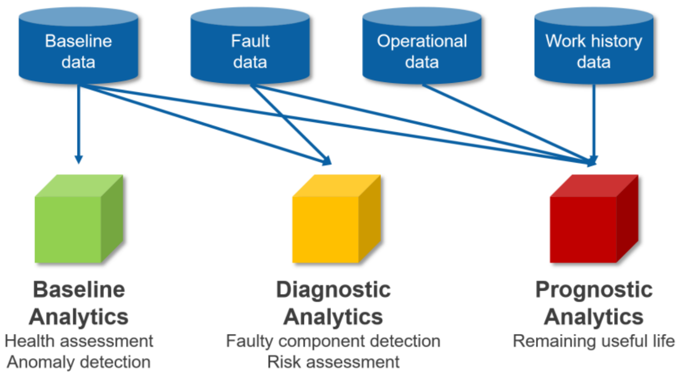


Figure 13. Types of analytics based on their applications (IIC, 2015)

- *Baseline analytics:* Used to detect anomalies, relying on data from the asset under normal operating conditions.
- *Diagnostic analytics:* Provides rapid results, identifying the root cause of failures by studying the different failure states.
- *Prognostic analytics:* Estimates the remaining useful life (RUL) of components, requiring more input data and longer processing times than diagnostic analytics.

The deployment of analytics typically follows three steps:

- Training the predictive model.
- Testing and validating the model with diverse data.
- Implementing the model in real-world scenarios.

Developing effective analytic models requires considerable effort to improve asset performance. In complex systems, while physical models may exist for individual components, the interaction between elements and varying environmental conditions makes it impractical to model an entire system using simple mathematical expressions. Stochastic models are often employed to address this complexity.

The integration of Artificial Intelligence (AI) and Machine Learning (ML) enhances the intelligence and adaptability of predictive models, helping uncover behavioral patterns amid randomness. This flexibility is why these technologies are becoming increasingly valuable. In diagnostic analytics, data is examined to answer, "Why did it happen?" using techniques like drill-down, data discovery, data mining, and correlations to understand causes of failures and behaviors. In prognostic analytics, data-based approaches are gaining traction, especially when modeling a complex system is too costly or impractical. While these approaches often have broader confidence intervals and require substantial data to train the models, they can be useful for estimating remaining useful life (RUL) through fleet-based statistics and sensor-based conditioning.

10.2.2. Digital Twin Simulations

Digital Twins (DTs) are virtual replicas of physical assets or processes, used to simulate real-world conditions to enhance understanding, predict outcomes, and inform decision-making throughout an asset's lifecycle. By creating digital twins of physical assets, industries can reduce fault detection times, uncover potential hazards, and improve overall efficiency, safety, and flexibility. One particularly valuable use case of DTs is predicting how long an asset will remain operational. A DT can track its own failures and degradation in real time.

Moving from the physical to the digital realm enables companies to experiment with different scenarios and anticipate potential problems. When combined with Artificial Intelligence, digital twins can further support decision-making. The effectiveness of DTs depends on three key factors:

- *Model quality:* Models must accurately reflect the relevant physical processes of the real system, ranging from basic linear models to complex nonlinear ones. While more detailed models can provide precise predictions, they are often harder to calibrate and solve quickly enough to aid real-time decision-making.
- *Data quality and availability:* The Internet of Things (IoT) has revolutionized data collection by using sensors to monitor machines and processes, continuously feeding digital twins with valuable information. This data is crucial for calibrating and refining the models, as well as for limiting drift during real-time operation. Integrating data-driven and analytical models—often referred to as black- or grey-box modeling—provides a more comprehensive approach to asset management.
- *Computational power:* As digital twins grow in complexity, new CPU and GPU architectures are required to ensure real-time performance, especially when exploring potential or unexpected behaviors in virtual systems.

These capabilities must be leveraged for digital twins to offer a powerful tool for improving asset management and predictive maintenance, driving better decision-making and operational efficiency.

11.3. Technologies for BI Apps.

Business intelligence (BI) refers to a set of technologies and processes designed to provide business metrics and insights to users. These processes are often essential because many transactional systems lack robust reporting capabilities, making it challenging to generate the specific reports needed by the business.

To implement BI processes, a data warehouse is typically created. This warehouse consolidates relevant transactional data and other dimensions that may be of interest to users (organized as fact tables and dimension tables), offering a more comprehensive view of business activities. Data warehouses require integration with source systems or transactional systems, as reports often need to aggregate data from multiple systems to present a more complete picture than any one system can provide.

However, introducing BI processes can be complex and may require substantial effort to address issues like data cleansing and harmonization, particularly for geographically dispersed companies with multiple transactional systems serving different business lines. BI also separates transactional from analytical databases, enabling faster calculations and broader functionality across multiple systems.

In addition to BI processes, data visualization (DV) plays a crucial role in presenting information quickly, clearly, and intuitively. DV transforms raw data into accessible information through various formats:

- *Dashboards:* A single page summarizing key metrics in tables, graphs, charts, and numbers, allowing users to quickly identify areas needing attention.
- *Reports:* Lists of transactions that occurred over a specific period, in a particular location, or other relevant parameters.
- *Alerts:* Notifications that warn users when an event exceeds a predefined threshold, prompting immediate action.

Beyond existing BI and DV tools, additional data analytics may be required to uncover insights from data that may not be in the current data warehouse or reports. Data analysts use specialized tools to explore the data, produce new views, and identify patterns. It's important to recognize that BI is not a single type of software but rather a suite of applications that transform data into valuable information, helping organizations better monitor performance and execute their functions.

11.4. Other complementary Technologies.

Augmented Reality (AR) is a form of human-machine interaction that superimposes computer-generated information (virtual data) onto the physical world (real objects) (Zhu et al., 2013) AR prototypes have shown great potential in improving the execution of maintenance tasks, particularly when users need access to additional information (Martinez et al., 2013). The visualization capabilities offered by AR can revolutionize various maintenance processes. However, AR research in this field is still in the prototype phase, and full integration of AR into maintenance systems has not yet been achieved (Nee et al., 2012).

Emerging frameworks are now being developed to enhance the performance and knowledge of maintenance processes by leveraging AR capabilities. These frameworks aim to properly manage, acquire, and display data to optimize maintenance workflows (Fernández et al, 2018).

The integration of mobility systems remains a crucial element in enhancing asset management strategies and optimizing fieldwork. Many organizations require robust mobile capabilities for Asset Performance Management (APM) and complementary technologies, especially for offline functionality. Some companies seek industry-specific solutions, such as mobile workforce management (see Gartner's "Market Guide for Mobile Workforce Management Systems for Utilities" in Foust, 2019), while others prefer more generalized mobile solutions like field service management systems (see "Magic Quadrant for Field Service Management" in Robinson et al., 2020).

In addition to data collected through IoT, mobile technologies enable the capture of inspection data in the field, which can be easily converted into statistics and condition-related information. These capabilities significantly enhance data collection and improve work efficiency. Workers are empowered with real-time access to relevant data, providing insight into asset status, its associated location, context, and even the underlying reasons for its condition.

GIS systems can also be integrated as graphical interfaces to aid in planning and routing. Examples of this technology include field mapping for asset maintenance and procurement, which can significantly improve field decision-making.

Today, location- and context-aware apps are becoming essential for boosting productivity. These apps go beyond standard GPS-enabled tools found in smartphones. While GPS allows for features such as dynamic rerouting using public map sources (e.g., Google, Bing, or Here), GIS systems offer more advanced capabilities by providing infrastructure layers sourced from more specialized, non-public data, enabling more effective field operations.

12. ARQUITECTURE, PLATFORMS AND SYSTEMS FOR DMM.

12.1. Architectures and Platforms.

Central to the design and implementation of DMM solutions are two key concepts: architecture and platform. These terms are often used interchangeably but represent distinct stages and aspects of a digital solution. Understanding the distinction between architecture as a conceptual design and platform as the technological foundation is essential for the successful development and deployment of maintenance solutions.

Architecture refers to the high-level design that defines the structure, components, and interactions within a system. In the context of digital maintenance solutions, architecture outlines the flow of data, the layers of technology (e.g., sensing, storage, and analytics), and the principles governing the solution's scalability, security, and efficiency. RAMI 4.0, IRA or ISO 23247 "Automation systems and integration — Digital Twin framework for manufacturing".

The role of architecture is to provide a blueprint for how the system should function. It involves decisions about data collection methods, processing techniques, and analysis workflows that ensure optimal asset management. For example, a predictive maintenance architecture might include the use of IoT sensors for real-time data collection, ontologies for defining entities and semantic data models, cloud-based databases for data storage, and the integration of machine learning, AI, or simulation capabilities within the data processing architecture for failure prediction and to inform decision-making processes at the business level. While the architecture defines what needs to be done and how, the platform provides the tools and services to make it happen. For example, a digital maintenance platform may include services for IoT device management, data storage, real-time analytics, and machine learning execution.

The platform, on the other hand, refers to the technological environment where the solution is deployed and operates. Platforms such as Microsoft Azure, Amazon Web Services (AWS), and Google Cloud provide a range of services, from Infrastructure as a Service (IaaS) and Platform as a Service (PaaS) to Software as a Service (SaaS). These platforms enable developers to build, deploy, and manage digital solutions while also offering SaaS-based services like data management, machine learning, and business analytics. Additionally, specialized SaaS platforms such as SAP Intelligent Asset Management (IAM), IBM Maximo, and Oracle Cloud Maintenance focus on asset management, predictive maintenance, and business process optimization. Furthermore, open-source solutions like FIWARE, Kaa IoT, ThingsBoard, and Mainflux provide flexible, cost-effective options for organizations seeking open-source alternatives to proprietary SaaS platforms, allowing high levels of customization, integration with IoT infrastructures, and full control over asset and maintenance management processes. Moreover, organizations can also develop ad hoc solutions tailored to their specific project needs, ensuring complete alignment with their operational requirements.

Platforms can be either cloud-based or on-premise, depending on whether the solution is hosted in the cloud or within the organization's own physical infrastructure. While cloud platforms offer scalability and flexibility, they also present significant challenges, particularly in terms of cost (due to ongoing subscription fees and variable costs) and security risks, as sensitive data is stored in external servers, making it more vulnerable to cyberattacks or data breaches.

Table 10 summarizes the key differences between architecture and platform, providing an example of how these concepts interact in the context of digital maintenance.

Aspect	Architecture	Platform
Definition	High-level design defining how the system's components are structured and interact.	Technological environment providing the tools and services to implement and operate the solution.
Purpose	To plan and structure the system to meet functional, performance, and security requirements.	To provide the necessary infrastructure and tools for building, deploying, and managing the system.
Key Components	- Data flow and processing layers - Security and scalability principles - System interactions	- Cloud services (storage, analytics) - IoT device management - Machine learning and data processing tools
Example in Digital Maintenance	- Sensors collect real-time data - Cloud database stores historical data - Machine learning models predict asset failures	- Azure IoT Hub connects and manages devices - Azure Data Explorer analyzes data in real-time - Azure Machine Learning trains prediction models
Output	A blueprint for how the system should function.	The infrastructure where the solution is deployed and executed.

Table 10. Platforms and Architectures. Key differences.

Designing the architecture and selecting the appropriate platform is critical for successful digital transformation. To that end several aspects must be taken into consideration:

- Maintenance management strategy definition, *identifying the functionalities required for real-time monitoring, predictive maintenance, and long-term asset performance optimization*.
- *Platform scalability* must be evaluated to ensure it can accommodate increasing data volumes and complexity as the organization matures digitally.
- *Interoperability* is crucial choosing a platform that integrates seamlessly with existing systems, such as EAM, APM, and AIP, ensures cohesive data flow and prevents silos.
- *Security and regulatory compliance* also play an essential role. The platform should offer robust data security and align with industry regulations, particularly for sensitive operational data.
- *Flexibility*, the platform must be capable of adopting emerging technologies like IoT, AI/ML, and blockchain as the digital transformation advances.
- *Customization* is vital to ensure that the platform can be tailored to specific workflows and business needs. Platforms that allow modular feature deployment as the organization evolves offer long-term value.
- Finally, evaluating the *Total Cost of Ownership (TCO)*, including setup, maintenance, and future scalability costs, ensures the platform aligns with the organization's long-term digitalization strategy.

In summary, architecture and platform involves analyzing functional requirements, scalability, security, flexibility, and costs, ensuring the platform can support both current operations and future growth aligned with strategic digitalization goals.

12.1.1. A Platform Architecture Case Study. Axle Bearing CBM

In the case of a Condition-Based Maintenance (CBM) application, which is a SaaS (Software as a Service) solution, its interaction with the Platform happens during the entire process of data collection, processing, analysis, and decision-making. Here's a clear explanation of how this interaction works, particularly when diagnosing asset health and generating maintenance recommendations:

1. *Data Collection and Preprocessing Layer*
   - Sensors installed on assets (such as vibration sensors, temperature sensors, or speed sensors) collect real-time data. This layer plays a foundational role providing the necessary infrastructure for the higher layers to operate efficiently. Many IaaS are available to manage this layer.
   - This raw sensor data is transferred to undergoes ETL (Extract, Transform, Load) processes at a higher level of the architecture. During ETL, data is cleaned, aggregated, and transformed into a format that the CBM app can use for analysis. These services can be classified as PaaS.
   - The PaaS tools offer often includes fog/cloud-based data storage services (like Google BigQuery or Amazon S3), where this cleaned and processed data is stored for easy access by the CBM App.
2. *Data Processing and Machine Learning Layer*
   - This layer provides the AI/ML tools required to analyze the incoming data. For CBM, these tools might include:
     - Anomaly detection algorithms that identify unusual patterns in the data (e.g., unusual temperature spikes in a bearing).
     - Predictive maintenance models, which use historical and real-time data to forecast potential failures (e.g., determining Remaining Useful Life (RUL) of a component).

   These ML models are trained, normally with services offered as PaaS, using historical data from the assets. Once trained, they are hosted in the fog/cloud and are made accessible through APIs that the CBM app (often found as SaaS) can call to generate predictions.
3. *Decision-Making and Diagnosis Layer*
   - The CBM (SaaS App) interacts with the platform services by making API requests to the trained ML/AI models. For example, the CBM App sends real-time data from the sensors (via the PaaS) to the prediction fog/cloud hosted model and requests a diagnosis.
   - The model runs the diagnosis, performing advanced analytics and processing through ML models to determine the asset's condition (e.g., "Bearing temperature is 15% above normal, indicating early-stage failure") and use the same service PaaS to deliver the results.

- The results are sent back to the SaaS CBM App in the decision-making layer, where the CBM app presents the analysis in a user-friendly dashboard. The CBM app could generate alerts, maintenance recommendations, and detailed reports based on the received results.

4. *Visualization and Alerts Layer*

- The display of the CBM SaaS app can be done through specific services offering intuitive interfaces for the end-user (e.g., maintenance engineers or asset managers).
- This SaaS visualization apps might visualize the asset's health in dashboards, provide diagnostic reports, and send alerts (such as warnings about potential failures or suggestions for maintenance actions) based on the analysis performed.
- Users can schedule maintenance actions or adjust operational parameters directly through the CBM app, which integrates with the organization's Enterprise Asset Management (EAM) system.

An example of Interaction for the *CBM app* dealing with the axle bearing will be now presented. Here's how the interaction works for a diagnosis:

1. The sensors detect bearing temperature.
2. The raw data is sent (IaaS) to undergo preprocessing (ETL PaaS) and it is analyzed by the ML models designed to predict and classify bearing failure (These models were obtained by a different App – offered as PaaS). This interaction is guided by the cloud based CBM App (SaaS).
3. Another ML model calculates that the bearing's RUL for a given failure mode is now only 20.000 kms and sends this diagnosis back to the CBM app.
4. The CBM app interacts with a visualization App (SaaS) to display this information in a dashboard, sends an alert to maintenance personnel, and suggests a maintenance intervention to avoid failure.

In this example:

- The PaaS layer handles data ingestion, storage, processing, and running AI/ML models.
- The SaaS CBM app handles the user interaction through a SaaS visualization App, presenting the diagnosis results to users and facilitating decision-making.
- This interaction allows the CBM app to provide real-time, data-driven maintenance recommendations without requiring the user to understand or manage the complex processes occurring in the different layers of the architecture.

12.1.2. A Platform Architecture Case Study. Axle Bearing CBM

The architecture configuration proposed for this digital maintenance solution was designed to meet the specific needs of managing bridge health through a modern, efficient, and scalable system (see Table 10). Below is a detailed rationale for each architectural component and why it was selected:

Layers in Reference Architectures		Bridge Project Correspondence
RAMI 4.0	**IIRA**	**A Bridge Health Indexing App**
Business	Business vision	- Long-term behavior determination for maintenance. - Control of defects and short-term degradation based on monitoring. - Support for controlling the effects of climate change on infrastructure.
Functions	Usage vision	- Cloud platform and services (information functions). - Data analysis and processing models. - User Interface and representation models.
Information Communication Integration	Functional vision & Implementation vision	- Design and construction of IoT platform and Integration of monitoring technologies. - Design the cloud AHI and user interface Apps
Asset	Implementation vision	Digitalization of various entities: - Infrastructure assets - Monitoring and degradation control process - Major bridge maintenance scheduling process

Table 10. The reference architectures layers and their mirror in the bridge platform project

1. Sensors & Data Collection (Edge Computing)

- *Real-time Monitoring:* The wireless IoT sensors selected for vibration, strain, temperature, humidity, and corrosion detection are essential for continuous, real-time monitoring of the bridge's structural integrity. Bridges are critical infrastructure, and the ability to detect issues like stress or corrosion in real-time can prevent catastrophic failures.
- *Low Power, Wide Area Coverage:* The choice of NB-IoT (Narrowband IoT) is strategic due to its excellent coverage, even in remote areas, and low power consumption. This ensures long battery life for the sensors and reliable data transmission, even from difficult-to-reach locations like rural bridges.
- *Edge Computing for Pre-Processing:* By placing computing power close to the sensors, data can be aggregated and processed locally before being transmitted. This reduces the amount of data sent to the cloud and ensures faster response times. For example, edge computing can filter out irrelevant data or identify critical events (such as a spike in stress) for immediate action.

2. Data Integration (Fog Computing)

- *Enhanced Data Processing Near the Source:* Fog computing nodes are positioned between the edge devices and the cloud. This layer performs more sophisticated computations, such as aggregating data from multiple sensors and applying algorithms to detect patterns.
- *Reduced Latency:* Fog computing reduces latency by ensuring that most critical computations happen closer to the data source. In cases where real-time actions might be needed (e.g., alerting maintenance teams about structural issues), fog computing allows for faster decision-making compared to relying solely on cloud-based analysis.

3. Cloud Platform (AHI SaaS Solution)

- *Data Fusion:* Aggregated & transformed sensor data can be now integrated with EAM historical maintenance records, central operational data, and lifecycle information.

This is crucial for generating an accurate bridge health index (AHI), which considers both real-time data and long-term performance trends.

- *Cost-Effective Scalability:* Cloud infrastructure provides a scalable and flexible platform for periodic, large-scale computations, such as the monthly aggregation of data from multiple bridges and calculation of the AHI. A SaaS model allows the company to avoid large upfront capital expenditures on hardware and focus on paying for what they use (scalable cloud services).
- *Centralized Analytics and Reporting:* The cloud acts as a centralized hub where the aggregated data from fog nodes is processed once a month. The health index for each bridge is calculated and stored in the cloud, enabling users to compare the health of different bridges, track changes over time, and make maintenance decisions.
- *Data Security and Redundancy:* Cloud platforms (such as AWS or Azure) offer robust security features and ensure data redundancy, protecting critical infrastructure data from loss or breaches.

4. User Interface (Visualization SaaS App)

- *User-Friendly Access to Data:* A mobile/web-based app offers ease of access to critical data for maintenance teams, engineers, and decision-makers. By centralizing bridge health data, the app provides a simple interface for users to visualize bridge conditions, receive alerts, and compare health indices across different assets.
- *AI-Driven Insights:* The app can integrate AI and simulation-driven insights for future degradation and cost estimations, allowing users to not only view current conditions but also receive predictions on when maintenance should be scheduled based on the health index and historical data.

The combination of edge, fog, and cloud computing ensures that data is processed efficiently at different levels, avoiding cloud overload with raw data, thus optimizing costs and minimizing latency. With edge computing handling local pre-processing and fog computing integrating data from multiple sources, only the most relevant and actionable data is sent to the cloud. This minimizes network bandwidth usage and ensures that cloud processing remains focused on high-level tasks like AHI calculation and long-term trend analysis. The architecture is therefore designed to be scalable. As more bridges are added, additional sensors can be deployed, and fog computing nodes can handle increasing data loads without significantly raising operational costs. Cloud computing ensures that AHI calculations can scale without requiring large infrastructure investments. This architecture is also modular, meaning that components can be upgraded or replaced without disrupting the whole system. For example, if better sensors or more advanced AI models for AHI prediction become available, they can be integrated into the existing infrastructure without significant changes to the system.

The cost structure for this digital maintenance process solution is presented in Table 11, that shows how the initial setup of the system can be around €38,400 (sensors, edge/fog devices, app development, integration), while the annual recurring costs of the solution is calculated in €10,800/year (network, cloud, maintenance). Figures 14 and 15, show initial setup and yearly costs structures representations.

Component	Description	Estimated Cost (€/Unit)	Qty	Total Cost (€)
Sensors	Vibration, strain, temperature, humidity, corrosion detection IoT sensors.	300	20	6,000
Wireless Network (NB-IoT)	Monthly cost for wireless communication via NB-IoT (subscription).	10/month/sensor	20	2,400/year
Edge Computing Devices	Local data aggregation and processing units near the bridge site.	2,000	2	4,000
Fog Computing Nodes	Pre-processing and integration with EAM.	3,000	1	3,000
EAM Integration	Integration with EAM system (for ETL and synchronization with hist. data).	5,000 (one-time setup)	1	5,000
Cloud Hosting (SaaS App)	Cloud services for AHI calculation and storage (e.g., AWS, Azure).	200/month	12	2,400/year
App Development (AHI App)	Development of the custom AHI SaaS application for mobile/web platforms.	20,000 (one-time)	1	20,000
Maintenance & Support	Ongoing maintenance and technical support.	500/month	12	6,000/year

Table 11. An approximative cost structure for the AHI Digital Process

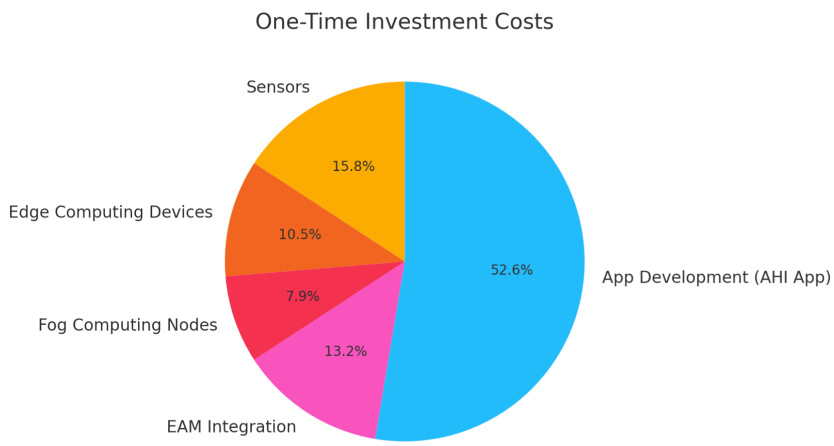


Figure 14. Initial setup cost structure representation

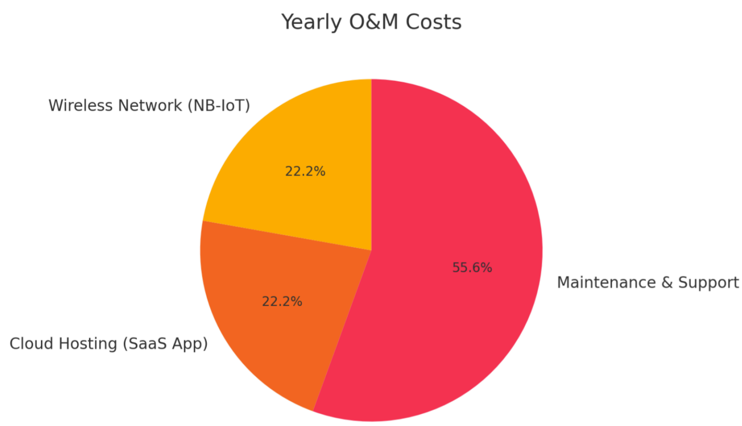


Figure 15. Yearly platform cost structure representation

12.2. Applications (Apps).

From the end-user perspective, they will observe how providers of information systems design their technical and commercial offerings for asset management around platforms and applications (Crespo et al., 2020). Applications (Apps) are closely linked to the specific functionalities users need, are often delivered as SaaS, and rely on the platform for seamless integration and operation within complex industrial systems.

The Software as a Service (SaaS) model has become a dominant delivery method for asset management apps due to its accessibility, flexibility, and cost-effectiveness. Unlike traditional software that requires complex, on-site installations, SaaS apps are hosted in the cloud and accessed via the internet, enabling real-time updates and reducing the need for local IT maintenance. SaaS offerings also allow users to scale resources up or down according to their needs, optimizing operational efficiency and cost management for asset-intensive organizations. SaaS applications often incorporate additional services, including analytics, machine learning, and digital twins, which are accessible through APIs and microservices. This service-oriented architecture allows apps to draw upon various data sources and analytical models, extending the app's functionality beyond basic asset management. For example, an APM SaaS solution might integrate with an IoT analytics service on the platform, enabling predictive maintenance by processing data from connected sensors and delivering insights directly to users. The flexibility of APIs also allows SaaS apps to interoperate with third-party applications, providing a tailored user experience and fostering collaboration across different departments and systems.

Concerning current market situation in asset management Apps, Gartner's distinguishes since 2019 among three different types of asset management systems in the market: EAM, APM and AIP Solutions (Figure 16). Traditional Enterprise Asset Management (EAM) systems or Computerized Maintenance Management Systems (CMMS) are increasingly being supplemented with various solutions and apps to enhance managerial capabilities. Asset Performance Management (APM) and Asset Investment Planning (AIP) tools, both benefiting from connectivity and digital technologies, often share the same data and utilize similar predictive analytics, but each serves distinct purposes:

- *EAM investments* focus on managing asset inventory, configuration, and the execution of maintenance tasks.
- *APM tools* are adopted by organizations to reduce corrective maintenance, improve asset availability, and minimize failure risks, especially for critical assets. Additionally, APM solutions can help organizations meet regulatory requirements related to asset inspections and maintenance. Through data capture, analytics, and visualization, APM tools enhance operations, optimize maintenance scheduling, and guide inspection activities for industrial assets. While the APM market has existed for over a decade, recent R&D investments from vendors have accelerated growth in this sector.
- *AIP software* is used to support complex, longer-term tactical and strategic decisions related to CAPEX/OPEX budgeting and overall asset management planning (Voulgaropoulos, 2021). AIP tools forecast an asset's current and future performance, linking this expected performance to various investment options over mid- and long-term periods.

SaaS enables providers to regularly update applications with new features, patches, and enhancements without requiring significant input from the user. This model is especially beneficial for industries with rapidly evolving needs, as users can take advantage of continuous innovation in areas like predictive analytics and machine learning. Vendors frequently invest in R&D to enhance SaaS offerings, particularly for APM solutions, which benefit from advancements in predictive analytics and risk modeling, and for AIP systems, which support increasingly sophisticated financial forecasting and decision-making.

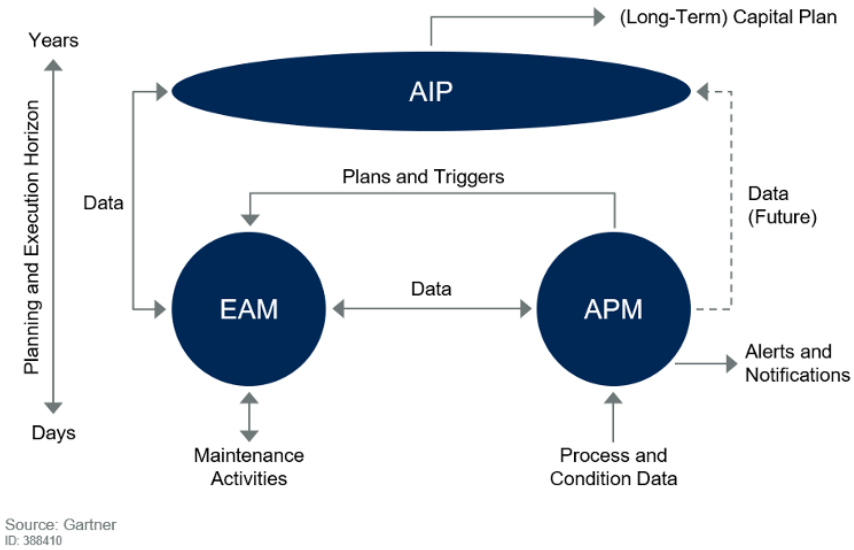


Figure 16. The flow of data in advanced asset management systems.

In summary, the shift to SaaS applications has revolutionized asset management by providing scalable, continuously updated tools that can easily integrate with platforms and external services. This model offers companies greater flexibility, cost savings, and enhanced functionality, positioning SaaS as an indispensable element in modern asset management strategies."

13. CASE STUDIES IN DIGITAL MAINTENANCE PROCESSES

13.1. A CBM case study using Predictive Analytics in Axle Bearings

The introduction of new Condition-Based Maintenance (CBM) and Predictive Maintenance (PdM) strategies in the short to medium term often involves a combination of manual and automated processes. In the context of train maintenance, manual interventions remain necessary due to regulatory requirements for legacy equipment that lacks sensor technology and for components not covered by new CBM/PdM plans. However, new plans that leverage big data and advanced analytics for PdM offer significant opportunities for organizations to improve maintenance efficiency and ensure sufficient reserve asset capacity for rail operators.

In a recent study by Crespo Márquez et al. (2020), a CBM/PdM strategy was applied to train axle bearings to extend preventive maintenance (PM) intervals while enhancing the reliability and availability of the trains (see Figure 18).

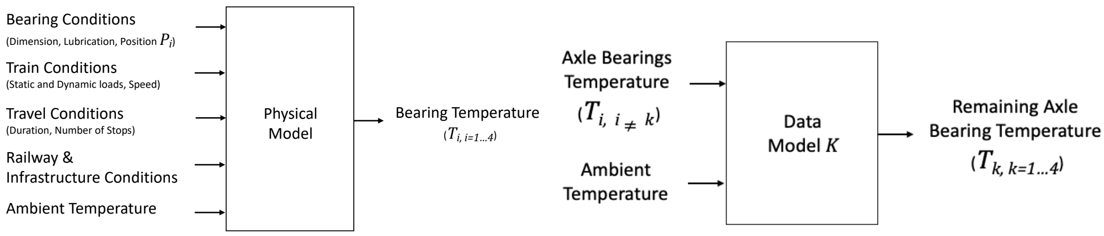


Figure 18. Physical model vs. data Model to predict axle bearing temperatures (Crespo et al., 2020&23).

The paper explains the selection of the machine learning predictive model and details how the model was trained with various datasets. Big data processes allowed the development and validation of a universal model for each bearing position, regardless of the axle or train within the fleet. This overcame the complexity typically introduced by the non-ergodicity of these assets. Early failure detection rules, based on advanced predictive analytics, were compared to existing rules within the train's on-board control monitoring system (TCMS), ensuring that train safety was not compromised. The performance of the CBM plan was evaluated before its implementation to facilitate ongoing control during train operations, and the plan was approved by the OEM, initiating the implementation process.

The benefits of this new CBM strategy were significant. The plan achieved 100% precision in identifying damaged bearings at any train speed, using a 10ºC Absolute Error threshold for the predicted bearing temperature. Although a speed threshold was added to reduce the size of the scoring datasets, the resulting accuracy improvement was not found to be substantial in all cases. Probabilistic estimates of the P-F interval (the time between potential failure and functional failure) enabled the extension of PM intervals for these bearings—up to 30,000 km in some instances—resulting in a substantial increase in maintenance efficiency.

Figure 19 presents the comprehensive functional description of the new CBM digital processes as included in the CBM App, as per the original design in collaboration with the Smart Maintenance Department of the company TALGO. In this figure all algorithms, and models to simulate and classify bearings behavior are placed within the DT area, while business rules are implemented in the Apps located within the CBM processes apps area.

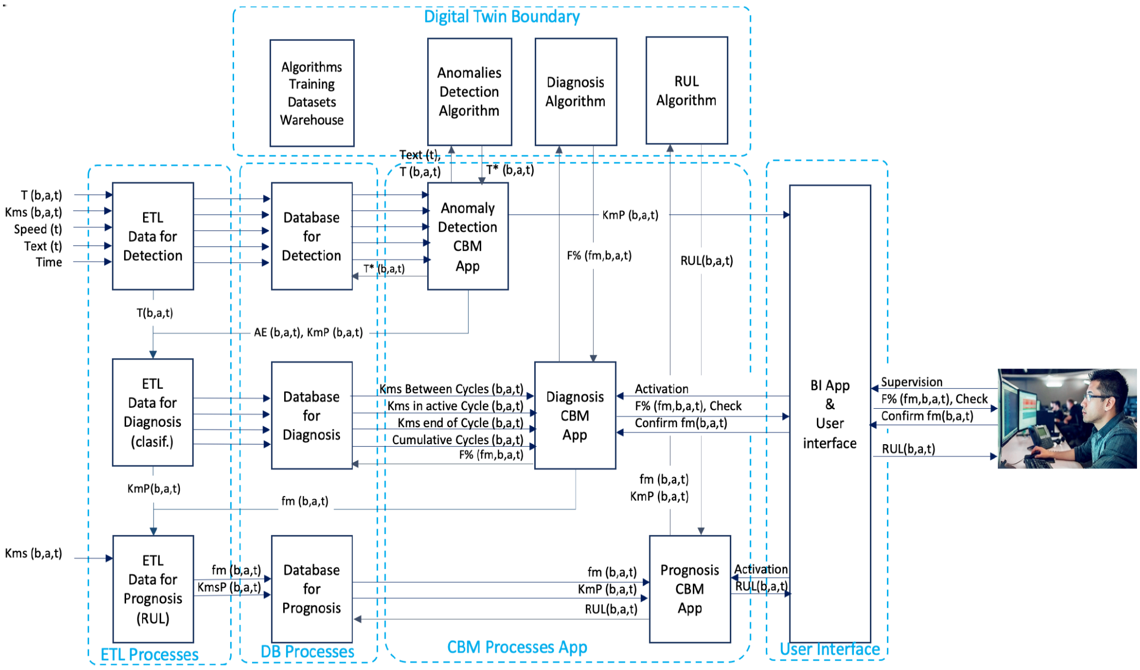


Figure 19. Details of the DT CBM App structure using the diagram in Figure 10

Notice that some new digital processes of the CBM App, for instance the ones included in the Diagnosis CBM App, required further ETL processes (than those for the Anomaly Detection App) and different modeling tools. The most significant challenge was the decision (of the Smart Maintenance Department together with the Maintenance Engineering Department of the company), to approach this problem modeling temperature cycles instead of temperature points. This is a popular method (Healey et al., 2021) to study fatigue data analysis of mechanical components. This required to set up an ETL process for diagnosis, together with a new database for the same purpose. At the same time, a different algorithm is used in the DT App area providing additional inputs to this diagnosis database. The ML algorithm selected is receiving the data of the bearing temperature cycles over time and classifies the probability of different bearing failure modes. The selection of the algorithm was done taking into consideration performance metrics like classification error, gain, execution time, training time, etc. For this case, the selected algorithm was a Deep Learning one.

13.2. An AHI case study in Bridges

This case study examines the integration of Internet of Things (IoT)-based monitoring models with the Asset Health Index (AHI) and Life Cycle Cost (LCC) models. This combination provides a comprehensive approach to asset digitization, addressing a more strategic level of complex asset management processes. It facilitates a stronger link between real-time monitoring and a more in-depth, long-term assessment of asset condition and performance. The synergy created by this integration significantly improves the effectiveness of asset digitization strategies, particularly in critical areas like infrastructure management.

The design of the bridge monitoring model is based on an IoT framework that incorporates the layer of acquisition and local processing at the measurement points (sensor nodes), the information transport network, and the processing server responsible for hosting essential services for the processing, exploitation, and presentation of information to end-users (Figure 20). To digitize the monitoring, an integration with the information coming from the IoT/Cloud network strategically located at various points of the bridge is established. The use case solution integrates both hardware and firmware design to fulfill local processing, device control, wireless communication, data storage, power supply, sensors for real-time structure monitoring, real-time operating system tasks, along with sensor monitoring tasks, local information processing, and wireless control. The server plays a crucial role by centralizing the processing and management of monitored structures. To adapt to scalability, a microservices-based development is adopted, performing tasks such as gathering information from deployed nodes, storing it in a database, and processing data according to different asset digitization models.

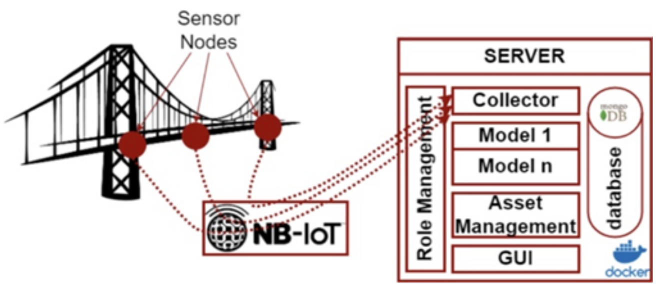


Figure 20. The IoT Network to monitor bridges

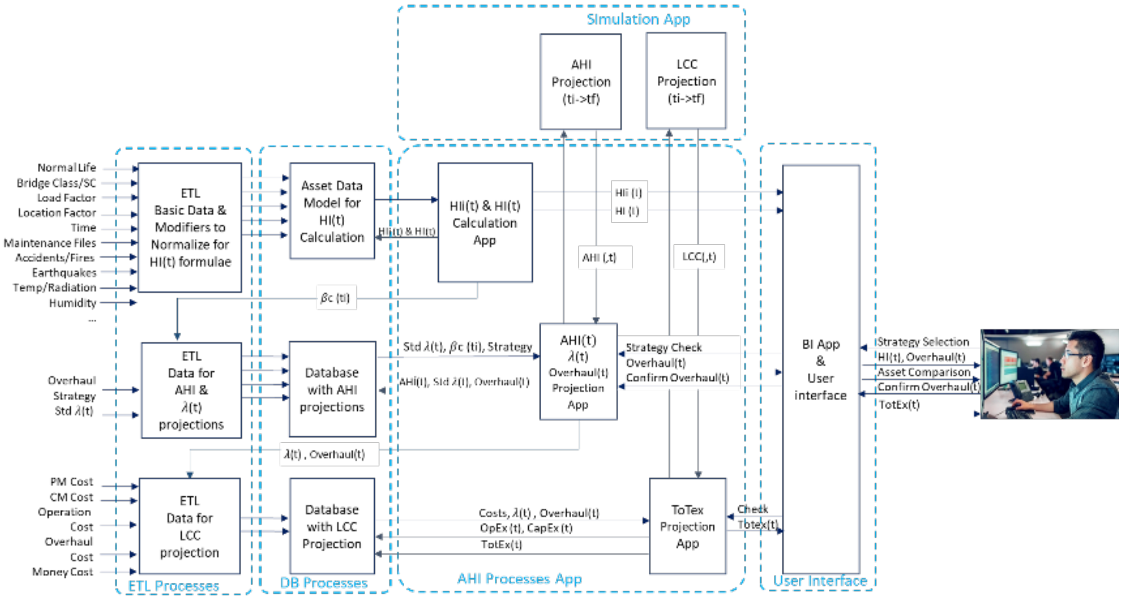
In this case study, using the framework described above, there is a comprehensive integration of ETL processes, database management processes, and Intelligent Asset Management processes (IAMs: AHI & LCC) that in this case are supported by mathematical and simulation modeling (Simulation Apps), with results presented through business intelligence tools (BI App/User Interface).

This comprehensive integration, illustrated in Figure 21, enables the following:

- Determining the health status of the bridge by calculating the Asset Health Index (AHI), which facilitates short- and medium-term decision-making on which operational or maintenance activities should be prioritized based on the bridge's current condition.
- Projecting the AHI using simulation tools, which supports medium- and long-term planning by comparing different scenarios and strategies for major maintenance or overhauls of the asset.
- Estimating the Asset's Life Cycle Cost (LCC) by considering historical and projected operations and maintenance activities throughout the asset's lifecycle.

By integrating with an IoT network, real-time monitoring data is processed through the platform, allowing for the calculation of input indicators for the health index model. In this case study, the health index was calculated for four bridges, each with different characteristics in terms of class, technical location, and operating and maintenance conditions.

Figure 21. The AHI/LCC model presentation using the DMM framework.



The results, represented in Figure 22 show the relationship between the bridge's operating age (x-axis), the obtained maintenance index (y-axis), and deviations from predicted deterioration (indicated by ball diameter).

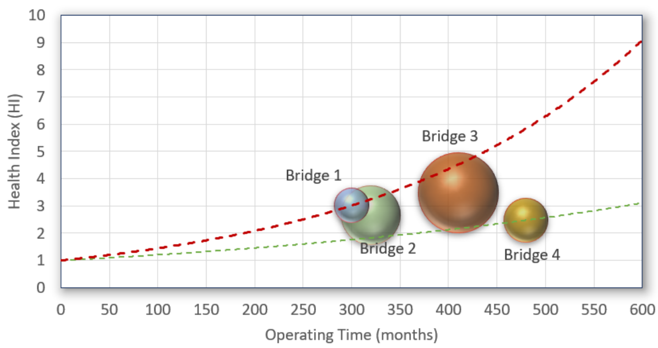


Figure 22. AHI versus age projection. Current health index versus the initially estimated for bridge age.

For example, Bridge 1 exhibits the most unfavorable health index, despite having fewer operating hours. However, the rate of aging is aligned with expectations, unlike Bridge 3, which, despite a higher age, was expected to have a better health status.

This deviation in Bridge 3 could be attributed to factors such as:

- Worse operating or maintenance conditions than initially planned, such as increased heavy vehicle traffic or exposure to more adverse weather conditions than anticipated during the design phase.
- A mismatch between the calculated health index and the actual bridge condition, necessitating recalibration of the model based on insights from expert personnel.

14. ROADMAP FOR DIGITAL MAINTENANCE MANAGEMENT

Digitalizing maintenance management is a transformative journey that enables organizations to enhance asset reliability, reduce operational costs, and improve decision-making.

When developing a strategy and roadmap for the digitalization of maintenance management, it is crucial to start by understanding the current situation. Knowing where we stand provides clarity and helps in setting realistic goals. Equally important is having a clear vision of where we want to be within a specific timeframe.

The starting point can be determined by evaluating the maturity levels in both asset management and maintenance as well as the company's digital maturity. This dual evaluation allows for a thorough assessment of existing processes, technologies, and systems, highlighting strengths and areas that need improvement. By identifying these maturity levels, organizations can tailor their digitalization efforts more effectively and create a roadmap that aligns with their long-term objectives, ensuring that each step of the journey is grounded in reality while aiming for significant advancements in efficiency and technology adoption.

Although we will later provide a Step-by-Step Guide for Digitalizing Maintenance Management, this directive should only be followed once the starting and endpoint of the strategic change plan are clearly defined. Understanding the current maturity in asset management and digitalization, along with a clear vision of the desired future state, are essential prerequisites for successfully implementing the step-by-step approach. This ensures that the guide is applied in the right context, fully aligned with the company's strategic goals and digital transformation objectives.

14.1. Maintenance and AM Maturity vs. Digital Maturity Matrix

The degree to which digital technologies and asset management practices are implemented varies significantly across organizations, largely depending on two key factors: The Maintenance and Asset Management Maturity and The Digital Maturity of the organization (Figure 23). The IMA committee would propose these two dimensions, that interact and influence the implementation of advanced digital technologies and management systems, to be represented in a matrix which helps in identifying suitable strategies for digital transformation of maintenance. The matrix is elaborated considering the work from the Global Forum on Maintenance and Asset Management (2021). *Guidelines for Assessing Asset Management Maturity*; and the widely recognized reference for digital maturity models is provided by Gill, M., & Van Boskirk, S. (2016) in their report *"The Digital Maturity Model 4.0"* published by Forrester Research.

This matrix helps organizations to visualize their current (as is) and desired (to be) digital maintenance management position and determine the next steps for both asset management and digitalization, thereby fostering a more strategic and holistic approach to managing assets in the digital age.

The matrix provides an overview of the interaction between different levels of maturity. As organizations progress along both axes, they are able to have more accessible and effective digital technologies (IoT, Big Data, AI/ML, cloud computing, Digital Twins, VR, etc.) supporting more complex and integrated maintenance processes embedded in advanced solutions within their Enterprise Asset Management (EAM) systems, Asset Performance Management (APM) tools, and Asset Investment Planning (AIP) Apps.

GFMAM Asset Management Maturity Levels vs. Forrester R's Digital Maturity Levels.	**Low Digital Maturity (Basic Tools, Isolated Systems)**	**Developing Digital Maturity (Partial Integration, Early IoT)**	**Integrated Digital Maturity (Predictive, IoT Integration)**	**Advanced Digital Maturity (AI, Digital Twins, Full Integration)**	**Leading-Edge Digital Maturity (Industry Leadership, Continuous Innovation)**
Level 0: Innocent/Pathological (No recognition of asset management needs)	Basic spreadsheets or manual methods for asset management.	Minimal digital systems, mostly isolated without integration.	Early-stage CMMS with little or no real-time monitoring.	Limited use of digital monitoring, few integrations with existing platforms.	Basic AI experimentation but with little strategic focus.
Level 1: Aware/Reactive (Basic recognition but reactive management)	Initial efforts to implement digital solutions, possibly basic CMMS or EAM.	Partial IoT integration for asset monitoring; focus remains reactive.	CMMS linked to preventive maintenance; minimal analytics.	Predictive analytics starting to be adopted in select areas.	More advanced AI-driven processes in key areas, limited strategic alignment.
Level 2: Developing/Bureaucratic (Formal systems in place but bureaucratic)	Basic digital record-keeping and reporting tools.	Standardized tools like CMMS/EAMS but no optimization or real-time monitoring.	IoT and sensors deployed in critical assets, early analytics in APM.	Data-driven decision-making using AI and advanced analytics for key assets.	Fully integrated digital ecosystem leveraging AI for proactive decision-making.
Level 3: Competent/Proactive (Aligned with ISO standards, proactive)	Basic dashboards with manual data integration for asset tracking.	Partial integration of data through APM for PdM and condition monitoring.	Comprehensive IoT and predictive tools in APM connected to major assets in EAM.	Advanced AI and predictive analytics used for strategic decisions with basic AIP.	Continuous AI-driven optimization across the asset lifecycle with digital twins in APM/AIP.
Level 4: Optimizing/Generative (Optimized asset management aligned with full value)	Isolated advanced tools, limited by non-integrated systems.	Widespread adoption of IoT and basic AI but lacking real-time optimization.	Predictive models optimized with IoT, but not yet full digital twin integration.	Full digital twin implementation, AI-supported real-time optimization. Advanced APM-AIP.	Industry-leading proactive asset management based on real-time optimization and digital twins.
Level 5: Excellent/Leadership (Industry-leading practices, continuous improvement)	Minimal digital strategies beyond basic asset tracking.	Advanced analytics for monitoring asset health but lacking a full digital strategy.	Integrated AI systems for predictive and proactive asset management.	Comprehensive digital twin ecosystems; AI-driven asset management strategies.	Fully optimized, AI-powered AM framework EAM-APM-AIP driving continuous innovation and business value.

Figure 23. IMA Dual Maturity Matrix with the description of possible existing scenarios in the organization.

After presenting examples of current scenarios using the IMA Dual Maturity Matrix, we will further analyze the matrix through three key perspectives that are crucial to our focus: data models, technologies, and information systems. Each of these components plays an essential role in the digitalization of asset management and maintenance processes. The data models define how assets are identified, monitored, and intelligently managed, shaping the foundation for decision-making. The technologies, such as IoT, AI/ML, and Digital Twins, enable these processes by providing real-time data, predictive capabilities, and simulations that optimize asset performance. Finally, the information systems (EAM, APM, and AIP) serve as the operational frameworks that organize and integrate both data and technology into the broader maintenance management system, ensuring that digital strategies align with asset management goals.

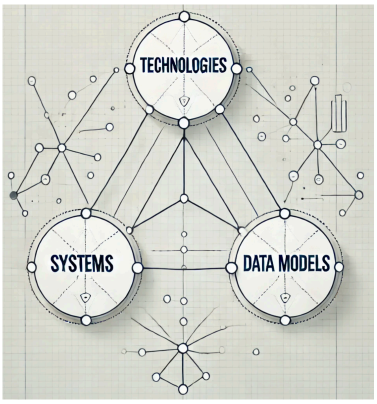


Figure 24. Digitalization multi-dimensional analysis

This multi-dimensional analysis allows us to understand how data models, technologies, and information systems interact within the digital and asset maturity framework, supporting the evolution from basic operational processes to advanced, *fully integrated digital maintenance frameworks* (Figure 24). It ensures that digitalization strategies are both comprehensive and aligned with organizational objectives, enabling a more efficient and proactive approach to asset management.

14.2. The data model perspectives and the maturity levels

We can place the introduction of each data model in the sequence according to the organization's maturity in both Digital and Asset Management Maturity levels (see Figure 25). For instance, the Asset Identification Model will be introduced first, establishing the basic structure for tracking and managing assets through essential data like asset function, class, and product information. Once identification is in place, the Asset Criticality Model is applied to prioritize assets based on their importance to the organization. Next, the Asset Monitoring Data Model is implemented to enable real-time condition monitoring through technologies like IoT and Digital Twins, allowing for predictive maintenance. Finally, at higher maturity levels, the Asset Intelligent Management Model incorporates advanced decision-making methodologies data models (e.g., RCFA, RCM, RAMS) allowing the use of AI/ML, optimizing asset performance and minimizing risks. This matrix guides in the implementation of asset data models aligned with the organization's digital and asset management maturity levels. It highlights the progressive introduction and enhancement of data models as an organization's maturity increases.

GFMAM Asset Management Maturity Levels vs. Forrester R's Digital Maturity Levels.	**Low Digital Maturity (Basic Tools, Isolated Systems)**	**Developing Digital Maturity (Partial Integration, Early IoT)**	**Integrated Digital Maturity (Predictive, IoT Integration)**	**Advanced Digital Maturity (AI, Digital Twins, Full Integration)**	**Leading-Edge Digital Maturity (Industry Leadership, Continuous Innovation)**
Level 0: Innocent/Pathological	**Asset Identification Model**: Basic asset data (function, class, reference) stored in isolated systems like spreadsheets.	**Asset Identification Model**: Early use of structured databases for asset data, some cloud integration.	**Asset Identification Model**: Fully digital records integrated into EAM/CMMS with limited IoT connectivity.	**Asset Criticality Model**: Introduction of asset criticality for prioritizing assets, integrated with predictive analytics.	**Asset Monitoring Model**: Early-stage monitoring, basic IoT for critical assets, leading to asset condition monitoring.
Level 1: Aware/Reactive	**Asset Identification Model**: Basic asset structure (function, class), with manual updates.	**Asset Criticality Model**: Initial classification of critical assets for basic prioritization, still mostly manual.	**Asset Criticality Model**: Integrated with EAM/CMMS, real-time updates of critical asset conditions based on performance data.	**Asset Monitoring Model**: IoT sensors start real-time monitoring of critical assets, improving response times for maintenance needs.	**Asset Intelligent Management Model**: Early adoption of RCFA/RCM methodologies for high-criticality assets, data-driven insights for maintenance actions.
Level 2: Developing/Bureaucratic	**Asset Identification Model**: Digitally stored asset functions and classes, basic use of asset reference codes.	**Asset Criticality Model**: Early predictive analytics used for critical asset management.	**Asset Monitoring Model**: Predictive monitoring starts, using Big Data to analyze asset health and generate insights.	**Asset Intelligent Management Model**: RCM and RCBA applied to asset data to optimize maintenance decisions, introducing AI.	**Asset Intelligent Management Model**: Further integration of RAMS and AHI for high-criticality assets, driving cost-efficient decisions.
Level 3: Competent/Proactive	**Asset Identification Model**: Expanded with asset product data, integrated across systems like ERP and EAM.	**Asset Criticality Model**: Advanced criticality analysis using IoT and analytics to prioritize assets based on risk and impact.	**Asset Monitoring Model**: Full IoT integration, real-time monitoring of critical assets with predictive capabilities.	**Asset Intelligent Management Model**: LCC, RCFA, RCM, and RAMS models embedded into intelligent systems, allowing proactive maintenance strategies.	**Asset Intelligent Management Model**: AI-driven AHI and LCC projections for high-criticality assets, allowing advanced predictive maintenance.
Level 4: Optimizing/Generative	**Asset Identification Model**: Fully integrated, comprehensive asset data model linked to monitoring systems.	**Asset Criticality Model**: Advanced AI tools prioritize assets based on operational impact, aligned with business strategy.	**Asset Monitoring Model**: Digital Twins simulate asset performance based on monitoring data, enhancing predictive analytics.	**Asset Intelligent Management Model**: AI and ML optimize decision-making in real-time for critical assets, based on all available data models.	**Asset Intelligent Management Model**: Continuous optimization of asset management through advanced simulation models and real-time analytics.
Level 5: Excellent/Leadership	**Asset Identification Model**: Real-time asset identification updates integrated with cloud systems.	**Asset Criticality Model**: Industry-leading prioritization models using real-time data and AI-driven analytics.	**Asset Monitoring Model**: Full Digital Twin integration for real-time monitoring and optimization.	**Asset Intelligent Management Model**: AI-enhanced predictive maintenance across all assets, fully integrated with LCC and AHI models for real-time optimization.	**Asset Intelligent Management Model**: Continuous innovation using AI, real-time optimization, Digital Twins, and predictive analytics for asset performance.

Figure 25. IMA Dual Maturity Matrix with the description of common asset data models implementation

14.3. The technologies perspectives and the maturity levels

This approach allows organizations to clearly see the progression of digital technologies as they enhance both their asset management practices and digital capabilities (see Figure 26).

For instance, the reader can see the following:

- IoT: Initially deployed for basic asset tracking, such as monitoring location or operational status, IoT gradually evolves to provide full integration of real-time data across all asset classes. Over time, IoT connects with more complex systems, enabling predictive maintenance, automated alerts, and deep insights into asset performance through continuous data collection from sensors and devices.
- Big Data: At first, Big Data is used to support basic analysis, such as reviewing historical performance trends or maintenance logs. As digital maturity increases, Big Data becomes a core element for real-time and predictive analytics, driving insights across vast datasets. This allows companies to forecast failures, optimize maintenance schedules, and improve asset utilization in a dynamic, data-driven environment.
- AI/ML: AI and machine learning start by enhancing predictive analytics, identifying patterns in maintenance and asset performance data. Over time, these technologies become central to decision-making, automating processes, and optimizing asset management. AI/ML algorithms learn from operational data, enabling advanced scenarios such as failure prediction, resource allocation, and lifecycle cost optimization.
- Digital Twin: The implementation begins with simple, static models of individual assets, used for visualization and simulation of specific scenarios. As the digital maturity increases, Digital Twins evolve into fully integrated ecosystems, where real-time data from IoT sensors feeds into the digital replica of assets, providing a comprehensive view of asset condition, performance simulations, and predictive insights for long-term planning.
- Blockchain: Introduced at higher maturity levels, Blockchain ensures secure and decentralized data storage, offering traceability in asset management. It provides a reliable method for verifying asset histories, maintenance logs, and transactions across different parties, enhancing transparency and reducing the risk of data tampering, especially in supply chain management and regulatory compliance.
- AR/VR: Initially employed for remote diagnostics and troubleshooting, Augmented Reality (AR) and Virtual Reality (VR) gradually expand into more immersive training and complex field applications. As organizations mature digitally, AR/VR enhances on-site maintenance by overlaying real-time data on physical assets and enabling remote experts to guide field technicians through repairs or inspections, improving efficiency and reducing errors.

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GFMAM Asset Management Maturity Levels vs. Forrester R's Digital Maturity Levels.	**Low Digital Maturity (Basic Tools, Isolated Systems)**	**Developing Digital Maturity (Partial Integration, Early IoT)**	**Integrated Digital Maturity (Predictive, IoT Integration)**	**Advanced Digital Maturity (AI, Digital Twins, Full Integration)**	**Leading-Edge Digital Maturity (Industry Leadership, Continuous Innovation)**
Level 0: Innocent/Pathological	No digital technologies in use, relying on manual processes and spreadsheets.	Basic digitalization with minimal IoT and cloud storage for record-keeping.	Limited use of IoT for data capture, early Big Data analytics for basic insights.	AI/ML models start to automate simple decision-making, predictive analytics are being tested.	Testing advanced tools like blockchain for secure data management, minimal Digital Twin adoption.
Level 1: Aware/Reactive	Initial use of IoT sensors for asset tracking, cloud-based storage for maintenance data.	Expanded IoT deployment, basic dashboards for real-time monitoring, some use of Big Data.	Predictive analytics using AI/ML, initial implementation of IoT for monitoring critical assets.	Full IoT network across assets, AI/ML models for predictive maintenance, early Digital Twin models for critical assets.	Blockchain tested for asset history and traceability, advanced Digital Twin for major assets, AR/VR for remote diagnostics.
Level 2: Developing/Bureaucratic	CMMS with IoT integration for limited asset categories, cloud for maintenance management.	Big Data analytics introduced to analyze trends, early predictive models implemented, IoT sensors expanded.	AI/ML used for optimizing asset operations, real-time data analytics in place, more sophisticated IoT networks.	Digital Twins begin to model more complex asset systems, advanced predictive maintenance using AI, AR/VR for field technicians.	Blockchain incorporated for secure, decentralized data storage, full-scale Digital Twin ecosystems across operations.
Level 3: Competent/Proactive	Partial IoT deployment, cloud data storage for asset monitoring and basic analysis.	IoT fully implemented for critical assets, real-time monitoring and data analytics integrated.	AI/ML used for predictive maintenance and decision support, Digital Twins beginning to be adopted.	Full Digital Twin models simulating asset performance, AI/ML driving decision-making and maintenance strategies.	AR/VR heavily used for training and remote maintenance, Blockchain ensuring data integrity, Digital Twin connected to all operational systems.
Level 4: Optimizing/Generative	Basic digital systems for tracking, some IoT sensors deployed.	Full IoT across asset classes, integrated Big Data analytics for monitoring and predictive tasks.	AI/ML optimized for predictive maintenance; Digital Twins deployed for critical infrastructure.	Digital Twins connected to real-time data streams, AI optimizing asset performance across the lifecycle.	Blockchain for secure asset transactions, industry-leading Digital Twin implementations across assets, AI optimizing resource allocation.
Level 5: Excellent/Leadership	Basic digital logging, limited data integration from isolated systems.	Expanding IoT infrastructure, advanced Big Data for decision-making, early AI tools for operational insights.	AI/ML fully integrated, Digital Twins driving strategic asset decisions, IoT widespread.	Real-time optimization through Digital Twins, AI/ML continuously improving asset performance and resource allocation.	Blockchain-enabled asset management, AR/VR for immersive maintenance, industry-leading Digital Twin ecosystems, continuous AI-driven improvements.

Figure 26. IMA Dual Maturity Matrix with the description of technologies implementation

14.4. The IT systems perspectives and the maturity levels

This matrix perspective offers a comprehensive approach to aligning digital technologies and system implementation (such as EAM, APM, and AIP) with the evolving levels of both asset and digital maturity (see Figure 27). It provides organizations with a structured map, helping them to understand not only which technologies to adopt at each stage, but also how these systems can integrate seamlessly into their operations over time. The reader can progressively advance through the maturity spectrum, and can make informed decisions about when and how to implement these systems, ensuring that they extract maximum value from their digital investments, improve operational efficiency, and strategically align technology with business objectives. This alignment fosters smoother transitions between maturity levels and ensures that technology adoption is both scalable and sustainable in the long term.

- *Enterprise Asset Management (EAM):* At the basic level of maturity, EAM systems are primarily used for tracking assets, managing inventories, and maintaining records of asset lifecycles. As maturity increases, EAM evolves into a more comprehensive platform, automating a wide range of asset management tasks such as preventive maintenance scheduling, work order management, and resource allocation. At higher maturity levels, EAM integrates with other digital platforms like IoT and Big Data analytics, facilitating seamless data flow between systems and enabling a more holistic view of asset health and performance across the entire organization.
- *Asset Performance Management (APM):* APM systems typically appear at mid-maturity levels, where the focus shifts from basic asset tracking to real-time monitoring and predictive maintenance. Initially, APM is used to gather data from IoT sensors, providing insights into asset performance, identifying trends, and predicting potential failures. As digital maturity advances, APM becomes more sophisticated, incorporating AI/ML algorithms to enable automated decision-making, risk analysis, and optimization of maintenance strategies. In highly mature organizations, APM systems play a crucial role in ensuring asset reliability, extending asset lifecycles, and reducing unplanned downtime.
- *Asset Investment Planning (AIP):* AIP systems are introduced at higher levels of maturity, where organizations start aligning their financial strategies with asset performance. Early stages of AIP focus on optimizing CAPEX (capital expenditure) and OPEX (operational expenditure) decisions based on historical data and asset criticality. As digital maturity grows, AIP systems become more dynamic, incorporating real-time asset data and predictive analytics to provide more accurate forecasts and financial planning. At advanced maturity levels, AIP becomes a central component of strategic asset management, allowing organizations to make informed investment decisions that balance cost, performance, and risk, while maximizing asset value over the long term

GFMAM Asset Management Maturity Levels vs. Forrester R's Digital Maturity Levels.	**Low Digital Maturity (Basic Tools, Isolated Systems)**	**Developing Digital Maturity (Partial Integration, Early IoT)**	**Integrated Digital Maturity(Predictive, IoT Integration)**	**Advanced Digital Maturity (AI, Digital Twins, Full Integration)**	**Leading-Edge Digital Maturity (Industry Leadership, Continuous Innovation)**
Level 0: Innocent/Pathological	**EAM**: Basic, manual asset tracking with spreadsheets or isolated systems. No formal system in place.	**EAM**: Initial implementation of basic EAM with limited asset data and no real-time updates.	**EAM**: EAM system integrated with IoT for real-time asset data. Simple automated processes.	**APM**: Early-stage APM introduced, focused on monitoring asset performance and automating maintenance schedules.	**AIP**: Initial AIP system for managing CAPEX/OPEX, limited scope; early planning of asset lifecycle investments.
Level 1: Aware/Reactive	**EAM**: Manual processes still dominate, but some digital tools (CMMS) for basic asset management.	**EAM**: EAM system linked to key assets; early integration with maintenance planning, still reactive.	**APM**: Predictive analytics beginning to emerge in maintenance scheduling and asset health tracking.	**APM**: Full predictive maintenance based on APM system; connected to real-time data from IoT sensors.	**AIP**: Asset investment planning begins to incorporate risk and criticality into budgeting processes.
Level 2: Developing/Bureaucratic	**EAM**: Full implementation of EAM for asset inventory, still mostly manual decision-making.	**EAM**: EAM connected to critical assets; some automation in maintenance scheduling.	**APM**: Early-stage APM optimizing preventive maintenance, predictive analytics improving efficiency.	**APM**: APM driving performance improvements and cost reductions; predictive analytics fully operational.	**AIP**: Full AIP system in place; investments aligned with asset performance and lifecycle predictions.
Level 3: Competent/Proactive	**EAM**: EAM automates inventory, asset tracking, and reporting, but limited integration.	**EAM**: EAM integrated with CMMS and IoT for real-time tracking; some predictive features.	**APM**: APM system integrated with AI for predictive insights, improving asset reliability.	**APM**: Advanced APM fully connected to IoT and AI; asset health monitored in real-time, enabling proactive interventions.	**AIP**: AIP optimizes long-term investment strategies based on predictive analytics and asset health data.
Level 4: Optimizing/Generative	**EAM**: Basic EAM system expanded to include lifecycle management but lacks advanced integration.	**EAM**: EAM and APM systems integrated, supporting early predictive maintenance strategies.	**APM**: APM enhances predictive maintenance and starts to optimize operations.	**APM**: Full lifecycle management through APM, integrated with Digital Twins for enhanced simulation and prediction.	**AIP**: AIP system provides real-time financial insights based on the performance of asset portfolios, enabling dynamic CAPEX/OPEX adjustments.
Level 5: Excellent/Leadership	**EAM**: Basic asset management system providing limited operational insights.	**EAM**: EAM with enhanced data capture, but lacking full integration across business processes.	**APM**: APM system driving asset optimization, predictive capabilities in place.	**APM**: Full APM system working alongside Digital Twins and AI to continually improve asset health and performance.	**AIP**: AIP used for real-time investment decisions, connected to strategic objectives and asset lifecycle predictions via advanced analytics.

Figure 27. IMA Dual Maturity Matrix with the description of systems implementation

14.5. The workforce perspectives and the maturity levels

As organizations increasingly embrace digital technologies to enhance their maintenance and asset management processes, aligning workforce training and upskilling initiatives with both digital maturity and Maintenance and Asset Management (MAM) maturity becomes essential. The IMA Dual Maturity Matrix is a strategic framework designed to outline the competencies required at different stages of this journey, helping organizations ensure that their teams are well-equipped to implement and sustain digital transformation (see Figure 28).

At the lower levels of digital maturity, training focuses on building foundational skills such as the use of CMMS/EAM systems for asset tracking and basic maintenance processes. Early exposure to IoT technologies and digital monitoring tools introduces the workforce to connected devices and basic data management. As maturity progresses, organizations need to invest in training employees on real-time monitoring and predictive maintenance, using Big Data and analytics to optimize asset performance.

Similarly, maintenance and asset management maturity progresses from reactive to proactive and ultimately leadership-driven approaches. In the early stages, organizations focus on preventive maintenance and ensuring that basic asset management systems are in place. As maturity advances, comprehensive training is required on APM systems, which enable real-time condition monitoring and proactive decision-making. Employees also need to be skilled in advanced AI/ML techniques, which drive predictive and prescriptive maintenance.

At higher maturity levels, both digital and MAM systems converge to deliver sophisticated decision-making tools. Advanced Digital Twins allow real-time simulations and predictive modeling, while AI/ML drives autonomous maintenance processes. At this stage, workforce training shifts towards leadership development, focusing on strategic foresight, innovation, and maintaining continuous improvement in digital practices. Executives and managers must be equipped to not only understand the technologies but to lead the organization through ongoing digital transformation.

By following this matrix, organizations can align their training programs with their overall strategic goals, ensuring that they are building the right skills for the future. As companies mature, their workforce will be capable of implementing advanced digital solutions, such as Digital Twins, blockchain, and augmented reality (AR/VR), helping to drive both operational efficiency and innovation. This structured approach enables organizations to stay competitive and lead the industry in digital maintenance management.

GFMAM Asset Management Maturity Levels vs. Forrester R's Digital Maturity Levels.	**Low Digital Maturity (Basic Tools, Isolated Systems)**	**Developing Digital Maturity (Partial Integration, Early IoT)**	**Integrated Digital Maturity(Predictive, IoT Integration)**	**Advanced Digital Maturity (AI, Digital Twins, Full Integration)**	**Leading-Edge Digital Maturity (Industry Leadership, Continuous Innovation)**
Level 0: Innocent/Pathological	Introductory workshops on basic asset management principles and digital literacy.	Training on CMMS/EAM fundamentals with IoT awareness for monitoring.	Upskilling on early-stage predictive maintenance and monitoring integration.	Basic AI/ML awareness workshops to introduce data-driven maintenance.	Exposure to case studies of leading-edge digital transformation and best practices.
Level 1: Aware/Reactive	Basic CMMS/EAM training, focusing on asset tracking and manual data entry.	Workshops on IoT setup, basic digital monitoring, and sensor data collection.	Training on integrating predictive maintenance algorithms with real-time monitoring.	Upskilling on AI/ML applications for asset failure prediction and optimization.	Advanced learning on blockchain for secure asset tracking and AR/VR applications.
Level 2: Developing/Bureaucratic	Advanced EAM training for preventive maintenance planning and resource management.	IoT integration training for assets with enhanced analytics and reporting.	Predictive maintenance model workshops, including Big Data and analytics basics.	Comprehensive Digital Twin training for real-time asset monitoring and optimization.	Leadership workshops on industry innovation and advanced AI/ML-driven maintenance.
Level 3: Competent/Proactive	Comprehensive APM training, focusing on real-time condition monitoring and reporting.	Advanced IoT and predictive analytics integration with asset management systems.	Advanced training on AI/ML for predictive maintenance and risk management.	Full-scale implementation of Digital Twins, AI, and machine learning for maintenance.	Continuous upskilling on emerging digital technologies and innovation frameworks.
Level 4: Optimizing/Generative	Mastery of APM systems and optimization of asset lifecycle using CAPEX/OPEX planning.	Training on IoT-based simulations, real-time analytics, and proactive strategies.	Expert-level AI/ML implementation in predictive and prescriptive maintenance.	Mastery of Digital Twin ecosystems, integrating AI/ML and blockchain solutions.	Executive training on digital leadership and continuous technological innovation.
Level 5: Excellent/Leadership	Leadership in asset management innovation, with optimized APM and strategic foresight.	Full-scale integration of IoT, predictive analytics, and AI-driven decision-making.	Expert in AI/ML for maximizing asset performance, integrating into strategic operations.	Pioneering digital ecosystems with advanced Digital Twins, AI, and blockchain.	Continuous industry-leading innovation training, preparing for future digital trends.

Figure 28. IMA Dual Maturity Matrix with the description of workforce training and up-skilling needs

14.6. Step-by-Step Guide for Digitalizing MM

The following roadmap provides a structured, step-by-step guide for organizations to follow, key milestones to track progress, and a long-term vision for sustaining digitalization efforts. Here is the course of action we can follow, aided by the tools we have presented above:

Step 1: *Assess the Current State of Maintenance Management.* Evaluate existing maintenance strategies, tools, and processes. Actions to accomplish would be:

- Conduct an audit of current maintenance practices (e.g., reactive, preventive, predictive).
- Identify gaps in technology, data, and workforce skills.
- Assess the readiness of the organization for digital transformation.

The Outcome will be a comprehensive report outlining the current state, strengths, and areas for improvement.

Step 2: *Define Digitalization Goals and Objectives.* Set clear, measurable goals for digitalizing maintenance management. Actions to accomplish would be:

- Engage key stakeholders to define strategic goals (e.g., increase asset reliability, reduce downtime, optimize maintenance costs).
- Prioritize assets and processes for digitalization based on criticality.

The outcome will be a well-defined digitalization strategy aligned with organizational goals.

Step 3: *Select and Implement Digital Technologies.* Identify and deploy the necessary architecture using digital tools and platforms. If the organization is simultaneously integrating technologies like IoT sensors or Digital Twins, data models may need to be constructed earlier to ensure these technologies have a standardized framework for data input and output. Actions to accomplish would be:

- Choose relevant technologies such as IoT sensors, predictive analytics, AI/ML models, and Digital Twins.
- Integrate these tools with existing systems like Enterprise Asset Management (EAM) and Computerized Maintenance Management Systems (CMMS).
- Establish robust data pipelines using ETL (Extract, Transform, Load) models for seamless data integration using specific platforms.

The outcome will be the implementation of digital technologies capable of real-time monitoring and predictive maintenance. Notice that the development of data models ensures the infrastructure is not only scalable but also optimized for interoperability and effective analytics, such as real-time condition monitoring and predictive maintenance

Step 4: *Build the Data Infrastructure.* Ensure data is collected, stored, and analyzed efficiently. Actions to accomplish would be:

- Establish platform-based databases (fog, cloud) or data warehouses to store and manage maintenance data. Here data models serve as the foundational structure for organizing and categorizing data within these platforms. For instance, models like the Asset Definition Model and Asset Criticality Model define how data about assets and their conditions is stored and accessed.

- Implement Business Intelligence (BI) tools for data visualization and reporting.
- Ensure data governance practices, including data quality (accuracy, consistency, timeliness) and security. Data models play a critical role in maintaining data quality, consistency, and lineage by defining standards and relationships between data points

The outcome will be a scalable, centralized data infrastructure capable of supporting analytics and decision-making.

Step 5: *Train and Upskill the Workforce.* Prepare the workforce for digitalized maintenance processes. Actions to accomplish would be:

- Provide training on the use of new digital tools, such as IoT systems, AR interfaces, and analytics platforms.
- Upskill employees in data interpretation, predictive maintenance techniques, and AI-driven decision-making.
- Encourage a culture of innovation and continuous improvement.

The outcome will be a skilled workforce capable of using advanced tools to optimize maintenance operations.

Step 6: *Pilot and Test Digital Solutions.* Validate the digital tools and processes in a controlled environment. Actions to accomplish would be:

- Implement a pilot program focusing on a high-priority asset or process.
- Monitor performance using KPIs such as asset uptime, failure reduction, and cost savings.
- Gather feedback to refine and optimize the solutions.

The outcome will be the successful validation of digital solutions, ready for broader deployment.

Step 7: *Scale and Optimize Digital Maintenance.* Expand digital maintenance strategies across the organization. Actions to accomplish would be:

- Roll out digital solutions to additional assets and departments.
- Continuously monitor and refine processes using predictive analytics, AI models, and data-driven insights.
- Ensure interoperability between systems, such as GIS and mobile technologies.

The outcome will be the Full-scale deployment of digital maintenance solutions, delivering increased efficiency and reduced costs.

14.7. Key Milestones and Metrics for Tracking Progress

To ensure successful digitalization, it's important to establish key milestones and metrics (see example in Table 12). The following table clearly outlines only possible milestones, metrics, and target dates for tracking progress in the digitalization process.

Milestone	Metrics	Target Date
Milestone 1: Completion of Digitalization Strategy	Documentation of goals, asset priorities, and expected outcomes.	Within 3 months
Milestone 2: Technology Implementation	Percentage of IoT sensors deployed, number of digital tools integrated, and data pipeline setup.	Within 6 months

Milestone	Metrics	Target Date
Milestone 3: Workforce Training Completion	Percentage of employees trained on digital tools, feedback from training sessions, and improvements in digital proficiency.	Within 9 months
Milestone 4: Pilot Program Results	Reduction in asset downtime, improvements in maintenance efficiency, and overall cost savings during the pilot phase.	Within 12 months
Milestone 5: Full Deployment and Optimization	Percentage of assets and processes using digital tools, ROI from digital maintenance, and long-term reliability improvements.	Within 18 months

Table 12. Sample Milestones Table

14.8. Long-Term Vision for Sustaining Digitalization Efforts

Digitalizing maintenance management is an ongoing process rather than a one-time effort. Sustaining these efforts over the long term requires continuous actions, which are outlined in Table 12:

Area	Objective	Suggested Actions
Continuous Innovation and Improvement	Foster a culture of continuous innovation by regularly reviewing and enhancing digital solutions.	• Invest in emerging technologies such as Augmented Reality (AR) for remote maintenance and enhanced visualization. • Experiment with new analytics models, AI/ML algorithms, and predictive maintenance techniques. • Regularly update systems to align with business and technological needs.
Data-Driven Decision-Making	Maintain a data-centric approach to asset management and maintenance.	• Use real-time data and predictive models for asset repair, replacement, and upgrade decisions. • Continuously improve data quality and governance practices. • Implement advanced BI tools for better reporting and decision-making.
Sustainability and Efficiency	Align digital maintenance efforts with long-term sustainability goals.	• Optimize maintenance practices to reduce energy consumption, extend asset lifecycles, and minimize waste. • Monitor carbon footprints and environmental impact using digital tools. • Promote sustainable practices within the workforce through data-driven decision-making.
Adaptability to New Technologies and Trends	Ensure the organization remains agile and adaptable to new digital trends.	• Regularly assess and adopt technologies such as Digital Twins, AI-driven simulations, and mobile workforce management systems. • Stay updated on industry trends to remain competitive and future-ready.

Table 13. Sample long term vision table

This table provides a structured overview of the objectives and actions for each key area, ensuring a clear path for sustaining and improving digitalization efforts.¡

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