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Framework for Asset Digitalization: IoT Platforms and Asset Health Index in Maintenance Applications

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Abstract: This study proposes a comprehensive framework for digitalizing and managing assets with low initial digital maturity, focusing on their operation and maintenance (O&M) lifecycle. The framework integrates Internet of Things (IoT) networks with Asset Health Index (AHI) models through four interconnected components. The Asset Definition Model ensures standardized data representation based on IEC 81346-1:2022 and ISO 14224:2016, while the Asset Criticality Model prioritizes maintenance actions using risk-informed analysis. The Asset Monitoring Model enables real-time data acquisition through IoT sensors, facilitating condition-based monitoring and dynamic decision-making. Finally, the Intelligent Asset Management Models support long-term planning by simplifying data complexity and aligning with advanced maintenance strategies. A case study on bridge maintenance demonstrates the practical value of the framework, showcasing its ability to integrate real-time monitoring with predictive decision-making tools. By bridging asset monitoring and lifecycle planning, the framework enhances operational efficiency, reduces maintenance costs, and addresses the challenges posed by limited digital maturity in critical infrastructure. This approach represents a significant advancement in the digital transformation of maintenance management.

Keywords: asset digitalization; digital maintenance; IoT; AHI; civil infrastructure digitalization; bridge maintenance

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1. Introduction

The challenge posed by digital transformation necessitates fundamental shifts in the conceptualization of assets. The current Industry 5.0 paradigm introduces a landscape where the fusion of digital and physical features of assets with human elements reaches an unprecedented level of interaction, resulting in increasingly complex systems of systems (SoSs) [1–3]. Achieving interoperability among all entities involved in this context becomes a global challenge, requiring not only technological advancements but also a mature vision for defining key entities such as assets, processes, and human involvement.

A noteworthy concern in addressing interoperability lies in the efficient integration of comprehensive data and information within each asset [4–6]. Frequently, asset data are scattered across diverse locations, including information systems, applications, edge devices, and cloud platforms. This dispersion limits direct accessibility, coherence, and seamless interaction with human stakeholders, exacerbating the issue of information silos.

Digital assets encompass more than raw data; they integrate critical components such as data, models, and services, forming the foundation of digital twins [7]. As digitalization advances from its early focus on data collection and standalone models, the emphasis has shifted towards managing these models effectively. This evolution is critical, as models act as enablers of innovative services that enhance asset value and improve decision-making processes.

The feasibility of overseeing and coordinating all models representing an asset as a management entity is now achievable [8]. This aligns with the broader adoption of model-based systems engineering (MBSE) in systems engineering [5]. MBSE supports technologies such as digital twins, Building Information Modeling (BIM), and the Asset Administration Shell (AAS), facilitating a structured approach to digitalization.

While technology and platform design are vital to digitalization, there is a growing need to prioritize assets as the central focus [8]. The rapid development of IoT technology offers a practical entry point by bridging the physical and digital worlds. IoT networks enable processes like asset digitization and the digitalization of asset management, as illustrated by frameworks such as the Industrial Internet Reference Architecture (IIRA) and RAMI 4.0 [4,9,10]. IoT sensor networks, as key components of the physical asset layer, allow for real-time data acquisition and processing.

Designing IoT networks typically begins with identifying and describing the assets to be monitored. However, this initial representation often falls short of addressing the complexities required for advanced digitalization, particularly in supporting predictive processes and strategic decision-making. Maintenance digitalization, a vital subset of asset digitalization, leverages IoT platforms and Prognostics and Health Management (PHM) methods to gather real-time data on asset conditions. This continuous influx of data supports proactive maintenance strategies, reducing unplanned downtime and extending asset lifespans [1,11–14].

This shift from reactive to dynamic Intelligent Asset Management underscores the importance of aligning IoT technology with the specific needs of assets. Holistic solutions that improve decision-making and operational outcomes unlock greater value, reduce costs, and accelerate digital transformation initiatives. As digitalization strategies evolve, IoT remains a foundational technology for modern asset management systems.

Technologies like Building Information Modeling (BIM) [15–17] or Augmented Reality (AR) [18–20] play key roles in maintenance, offering practical benefits such as enhanced reliability and reduced costs. Despite advancements in data accessibility and processing, the maturity of leveraging digitalization outputs in decision-making remains low. Many organizations continue to rely on traditional practices, limiting the potential of emerging capabilities.

A critical observation is that digitalization in asset management and maintenance extends beyond technological challenges. Practical management and decision-making aspects must guide the design and implementation of advanced solutions like IoT platforms and digital twins. Effective integration of system architecture and data models is essential for addressing the operational demands of maintenance and asset management. Established frameworks for maintenance and IT systems under Industry 4.0 provide a foundation, but highly integrated solutions merging these domains are still rare [21].

This paper answers the following questions:

- How can a model-based approach for asset digitalization be effectively introduced to serve maintenance and asset management purposes?
- How can this approach be incorporated into digital maintenance decision-making workflows?

- How can the integration of an IoT monitoring platform with short-term models (e.g., Condition-Based Maintenance) and long-term models (e.g., Asset Health Index) improve asset digitalization and management practices?

This work's content is structured as follows: Section 2 discusses the key issues and approaches related to asset digitalization, including its definition, relevant frameworks, and architectures for advanced digitalization strategies. Section 3 outlines the proposed methodology, which is applied in Section 4 to a bridge maintenance case study using an IoT platform and AHI model. Finally, Section 5 summarizes conclusions and future applications.

2. Background

2.1. Asset Digitalization

This work explores the concept of asset digitalization, addressing the nuanced differences between terms such as digitization, digitalization, and digital transformation [22]. For clarity, the term "asset digitalization" is used here as a broad framework that encompasses both the creation of asset data and the transformative processes that unlock new value [21]. Within this context, in this paper, we define three critical dimensions that serve as the foundation for our proposed framework:

- Asset Digitization: This foundational step involves defining an asset's data and information model, and creating a structured digital representation. Unlike existing works, which often stop at isolated models, this step establishes the basis for integrating IoT-enabled real-time data streams.
- Asset Digitalization: Building on digitization, this dimension introduces workflows and dynamic updates that enhance the asset's value proposition. For instance, our framework goes beyond static representations by integrating advanced models like the Asset Health Index (AHI) to enable predictive insights and decision-making.
- Digital Transformation: This broader perspective captures the societal and organizational impact of digital technologies. Unlike prior studies, this paper emphasizes how IoT integration within the asset lifecycle directly contributes to digital transformation by bridging real-time data with strategic maintenance decisions.

Within the scope of asset digitalization, this paper addresses the contemporary concept of the digital twin (DT) [3,11,23–26]. The evolving nature of digital twins poses a challenge in precisely defining the concept, with the inherent technological nature contributing to their dynamic essence. The examination of the relationship and role of digital twins in maintenance is discussed in reference [6]. This paper positions itself as a "digital shadow" falling between a digital model and a digital twin proposal [10]. Infrastructure assets inherently exhibit passivity, setting them apart from industrial assets capable of actively closing the control loop and adjusting operational variables based on intelligent maintenance insights fed back to the asset. In infrastructure maintenance, intelligent decision-making is reintegrated into the asset through meticulous maintenance planning and scheduling. Consequently, the outcomes presented in this paper occupy a position between a digital model and a digital twin proposal. While the work does not explicitly align itself with the broader 'umbrella' of a digital twin, as it is not the primary focus of this research, the central emphasis remains on advancing asset digitalization. Despite not explicitly categorizing the work as a DT, the foundational principles outlined are deemed valuable in complementing the broader DT concept, emphasizing a focus on asset digitalization.

Moving beyond digital twins, the Asset Administration Shell (AAS) emerges as a key concept in Industry 4.0 [9,27,28]. The AAS serves as the embodiment of the "digital twin" concept, facilitating cross-vendor interoperability and interaction. It encompasses essential information and functionalities for digital representation, contributing to novel digital business models and use cases. Sub-models within the AAS encapsulate varied information, aligning with the vision of seamless and interoperable interactions in the industrial landscape.

The ISO 23247 series [29] introduces the term OME (Observe Manufacturing Element) and defines the digital twin for manufacturing. This definition emphasizes a fit-for-purpose digital representation with synchronization between the OME and its digital counterpart. The standard defines various types of OMEs and delineates essential fundamental attributes for their management [30]. Like AAS, the importance of precisely defining the element to be modeled, establishing digital entities, and segregating functions and models is underscored.

The concept of the Cognitive Digital Twin (CDT) [3,31] is proposed to address the complexities arising from interconnected systems of systems (SoSs). CDT leverages cognitive capabilities to manage and comprehend the multitude of data and models generated by these interactions. CDT design and management are interconnected with the discipline of model-based system engineering (MBSE), incorporating physical entities, cognitive entities formed by digital models, ontologies describing model relations, and communication channels.

2.2. Digital Maintenance

While digital capabilities are often initially associated with predictive maintenance, the reality is that the maintenance function, and by extension asset management (AM), encompasses more than just failure prediction. It involves complex tasks integrating different types of analysis and decisions that impact asset and system performance [13,30]. Digital maintenance goes beyond predictive maintenance alone; it entails integrating strategic and operational perspectives into maintenance management processes through effective data and model management.

Asset digitalization necessitates a good technical architecture that can include various systems and platforms. While digitalization solutions often originate from a technological perspective, incorporating a maintenance-focused approach is vital. This ensures that digitalized assets remain reliable and aligned with broader business goals by addressing maintenance requirements without delving deeply into architectural specifics.

A maintenance-oriented approach prioritizes understanding and managing the digital functionalities of IT solutions. It focuses on overseeing end-to-end processes for data and model handling, tailored to maintenance needs. This perspective complements the technology-driven approach, emphasizing long-term asset performance and operational reliability.

Information system providers design their technical and commercial offerings with the needs of end users in mind, often revolving around platforms and apps. Platforms integrate core digital services to support end-to-end processes, functioning similarly to IoT and cloud platforms. Apps, on the other hand, are tied to specific functionalities desired by users and rely on platforms for seamless integration in complex industrial environments.

Intelligent Asset Management Platforms (IAMPs) play a central role in industrial systems by collecting and analyzing data from assets. These platforms are commonly categorized into Enterprise Asset Management (EAM), Asset Performance Management (APM), and Asset Investment Planning (AIP), offering comprehensive support for asset management strategies across different operational contexts.

Crespo [13] proposes a visual tool (Figure 1) that integrates the Input–Process–Output (I-P-O) framework with the requirement to use multiple models and applications across different stages of the maintenance process. This tool highlights how raw data from various business systems are converted into specialized models, which are crucial for different facets of asset digitalization. The Input–Process–Output framework is structured in alignment with ISO 14224:2016, where each component represents a specific function ensuring a cohesive strategy for managing digital maintenance. These functions leverage models to produce outputs that interface with Intelligent Asset Management (IAM) applications, supporting activities across all stages of the maintenance and asset management lifecycle.

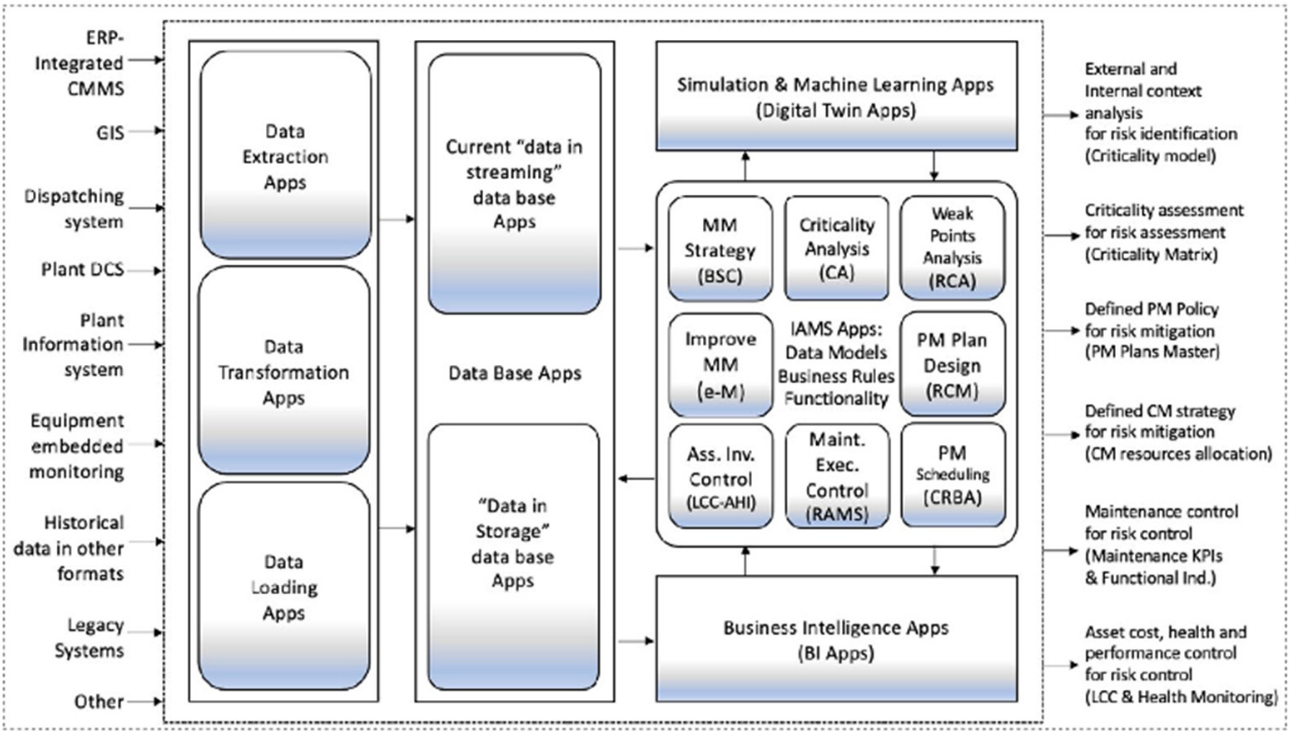

Figure 1. Input–Process–Output diagram of a digital maintenance framework as in [13].

The concept of digital maintenance operates on the premise that models and apps collaborate rather than operate in isolation. The results of one model serve as inputs for higher-level models, fostering interconnectedness. This interconnectedness is evident when the outcomes of models and apps from condition-based monitoring (CBM) contribute inputs to models focused on dynamic maintenance scheduling and investment optimization [13,32,33]. Similarly, the outputs of monitoring or CBM apps can be utilized as inputs for models such as the Asset Health Index (AHI) and Life Cycle Cost (LCC) models, as exemplified in this document.

Figure 1 illustrates a concept that maps relevant applications across the full spectrum of management, from strategic to operational levels, while distinctly separating applications from IT functional blocks. This approach builds upon the asset and maintenance management framework originally outlined in references [34–36]. Widely utilized in the management of network utilities enabled by IT systems [37], this framework has since evolved to support both the implementation of digital maintenance solutions and the development of digital twins [38].

2.3. Reference Architecture for Digitalization

ISO/IEC/IEEE 42010:2022 [39], titled "*Software, systems and enterprise—Architecture description*", defines architecture as "the fundamental structure of a system, or more specifically, the structure of system components, their relationships, and the principles and guidelines that govern their design and evolution over time". Architecture provides a framework for the interactions of system components to reach specific goals.

Reference architectures, as common bases for multiple applications, play an important role in generalizing the application of concepts and elements. They provide a foundation that can be adapted and interpreted into concrete architectures for specific system designs. In the context of asset digitization, establishing clear methods for usage and definition in relation to new technologies is crucial. Standardization becomes a key component to ensure the recognizability, interchangeability, and efficient operability of digital assets within digital environments, encompassing various platforms like IoT infrastructures and edge-cloud computational paradigms.

A comprehensive review of reference architectures, as presented in [10], emphasizes the comparison of layered architectures, particularly RAMI 4.0 and IIRA (Figure 2), against classical pyramid-style architectures like ANSI/ISA-95 or 5C. Layered architectures, gaining dominance in many applications, foster interoperability, communication between layers, and flexibility. This approach aligns with the advancements in digital twin technology.

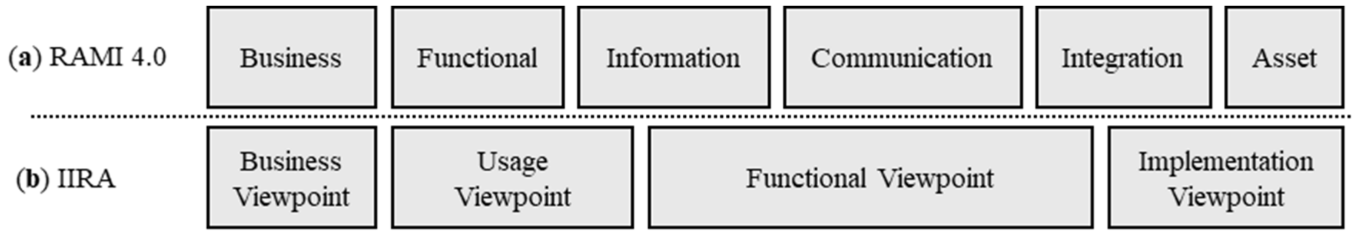

Figure 2. Architectures: (**a**) RAMI 4.0 [9]; (**b**) IIRA [4].

RAMI 4.0 and IIRA are now taken as foundational references, given their broad acceptance and influence in both academic and industrial contexts. Both frameworks employ a layered approach to structure systems, promoting modularity, adaptability, and incremental upgrades. Each architecture offers a distinct perspective, but they share fundamental principles and methodologies to address the challenges of industrial digitization.

RAMI 4.0 uses a dual-axis framework that integrates lifecycle considerations with hierarchical system structures, offering a comprehensive view. In contrast, IIRA adopts a more streamlined approach, emphasizing simplicity. A significant feature of RAMI 4.0 is the introduction of the Asset Administration Shell (AAS), which serves as a cornerstone for driving digital transformation, as detailed in the section on digital twins. Additionally, RAMI 4.0 explicitly highlights the importance of managing the lifecycle of assets and systems, a critical factor in the digitization process.

2.4. Asset Health Index

The Asset Health Index (AHI) is defined as a quantitative measure that characterizes the condition of an asset and its proximity to the end of its useful life, according to standard EN 13306:2017 [40]. This index allows for the evaluation of the state of assets at a specific moment and usually relies on historical values to parameterize metrics that define intervention thresholds. Since its inception, the AHI has evolved to include multiple indicators and modifiers reflecting operational, maintenance, and reliability conditions, offering a more comprehensive framework for decision-making in asset management [41].

The concept of AHI originates in the British telecommunications sector, where it was used to assess risk based on the condition of electrical assets. Initially, its methodology incorporated modifiers such as geographic location, load, and historical conditions observed [42]. This approach has been expanded to include aspects related to reliability, such as operations and preventive and corrective maintenance, to provide more realistic representations of asset health [41]. These improvements have been fundamental in enabling comparisons between assets and prioritizing investments in maintenance and renovation.

Regarding its application, AHIs have proven useful in various industrial and infrastructural sectors. For example, as has been developed in [43], they have been used in the management of bridges [44,45], roads [46,47], power transmission lines [48], and transformers [49]. However, many of these applications have primarily depended on sporadic inspections or qualitative evaluations by experts, limiting their ability to dynamically capture the real-time conditions of assets. This reliance on historical and qualitative data restricts the potential of AHIs to predict failures or anticipate maintenance needs in complex systems [48,50].

One of the main current limitations of AHIs is their inability to integrate real-time data from IoT sensors, which could provide a more accurate and timely perspective on asset degradation [51,52]. Furthermore, traditional approaches tend to focus on individual components or simple systems, failing to fully capture interactions among multiple dimensions affecting more complex systems. This challenge is exacerbated when a lifecycle perspective is not adopted, reducing the utility of AHIs as predictive tools for long-term planning [53,54].

Recently, methodologies have been developed to address these limitations through the incorporation of real-time data and the use of IoT technologies. These innovations include dynamic factors, such as real-time operational load, which allow for a more accurate reflection of operational conditions' impact on asset health. Additionally, integrating sensor data with maintenance records and information systems has enabled the creation of more comprehensive and adaptive models [43]. These improvements not only enhance the AHI's ability to predict failures but also facilitate the optimization of maintenance strategies and the efficient allocation of resources in complex systems.

Structural Health Monitoring (SHM) in bridges highlights the need to overcome the limitations of traditional methods, such as visual inspections, which are ineffective at detecting early-stage damage in aging infrastructure [45]. Recent advances in SHM techniques, including Operational Modal Analysis (OMA) and automation through advanced algorithms, have improved damage identification. However, the significant influence of environmental and operational factors (EOCs) on structural responses requires statistical normalization to isolate damage indicators. Despite these advances, industrial implementation of SHM remains limited due to the lack of standardized solutions integrating heterogeneous sensors and processing large volumes of data.

While SHM technologies have achieved significant progress, such as process automation and data filtering to mitigate environmental effects, a fundamental disconnect persists. This disconnect arises from the focus on monitoring and damage detection rather than adopting a broader perspective that treats infrastructure as integrated digital assets. This approach entails not only data collection and analysis but also the inclusion of digital models to enable comprehensive maintenance management within a digitized environment. Integrating SHM-generated data with tools such as digital twins facilitates not only real-time structural monitoring but also predictive maintenance strategies, resource optimization, and data-driven decision-making.

In this context, SHM advancements bridge the gap between existing monitoring technologies and the need for holistic, digitized management. This work aims to serve as a bridge, addressing the challenges of digital transformation in infrastructure maintenance by proposing an approach rooted in a holistic and structured vision of assets to optimize SHM integration into sustainable infrastructure management.

To enhance clarity and facilitate understanding, we have categorized the references discussed in this section into four main groups: conceptual foundations of digitization and digitalization, reference architectures, advanced models integrating IoT and AHI, and practical applications through case studies. This classification highlights the contributions of the existing literature in relation to the proposed framework. Table 1 summarizes these categories and their key characteristics.

Table 1. References discussed in this section.

Classification	Description	Main References
1. Conceptualization and Definitions	Foundational concepts of "digitization", "digitalization", and "digital transformation", exploring their implications for asset management.	[1,4,34,35,45]
2. Reference Architectures	Standardized frameworks offering high-level guidance for modularity, interoperability, and lifecycle management.	[4,9]
3. Advanced Models for Digitalization and Predictive Management	Integration of IoT, digital twins, and models like the Asset Health Index (AHI) to enable predictive management and lifecycle optimization.	[39–53]
4. Practical Applications and Case Studies	Case studies demonstrating how the discussed architectures and models can be implemented in specific scenarios, such as critical infrastructure (bridges) and industrial systems.	[29,36,55,56]

3. Suggested Framework for Asset Digitalization and Management

3.1. The Context of the Asset at the Beginning of This Research

This research focuses on assets characterized by a low initial level of digitization during their operational and maintenance (O&M) phase, occurring in the central period of their lifecycle. The assumption here is the existence of an Internet of Things (IoT) network, designed concurrently with the asset's digitization and maintenance processes, and the absence of any prior monitoring or historical data. The paper emerges from collaborative research, bringing together diverse expertise from multidisciplinary groups encompassing maintenance management specialists and experts in the hardware/software design of monitoring networks.

3.2. Asset Models for Digitalization and Management

This section proposes a set of four asset models, each tailored to address distinct facets of the asset digitalization and management process:

- The Asset Definition Model, which captures the intricacies of asset data and information within diverse systems, aligning with standards such as IEC 81346-1:2022 [35] and ISO 14224:2016 [34].
- The Asset Criticality Model, to prioritize the asset using risk analysis.
- The Asset Monitoring Model, for leveraging IoT networks and intricate signal integration processes.
- The Intelligent Asset Management Models, which cater to specific decision-making processes, ensuring management sustainability with minimal data handling efforts.

3.2.1. The Asset Basic Definition Model

This model follows the guidelines outlined in the IEC 81346-1:2022 [35] and ISO 14224:2016 [34] standards and defines the complete set of asset data and information inherently available across various information systems and applications used in asset management (Figure 3):

- Physical Asset Registration Code. Each physical asset is assigned an individual and non-transferable code. This code serves as a unique identifier for that specific asset. The assigned code is solely for identification purposes and has no inherent connection to other characteristics or attributes of the asset.

- Asset Class. Class determines the technical aspects of asset maintenance tasks. Subclasses (or types as per the IEC 81346 standard) can be used to establish distinctions within the same class. This aspect aligns with the type-oriented forming structure following the IEC 81346 standard and the taxonomy generation introduced in standard ISO 14224:2016 [34].
- Asset Functional Location. The physical or logical location where an asset is installed or used. This could be a specific room, building, piece of equipment, or any other defined area where an asset performs its intended function. A complex system can be represented by a tree of functional locations, also known as a functional structure. This aspect aligns with the function-oriented structure defined by the standard IEC 81346. A physical asset may occupy different functional locations at different times throughout its useful life.
- Asset Reference System. Different systems, from global satellite navigation to local cartography and specialized environments, may utilize specific coordinate reference systems to accurately represent and manage assets. The reference system becomes an integral part of asset definition, especially in distributed networks, and is essential for effective analysis, visualization, and maintenance purposes.

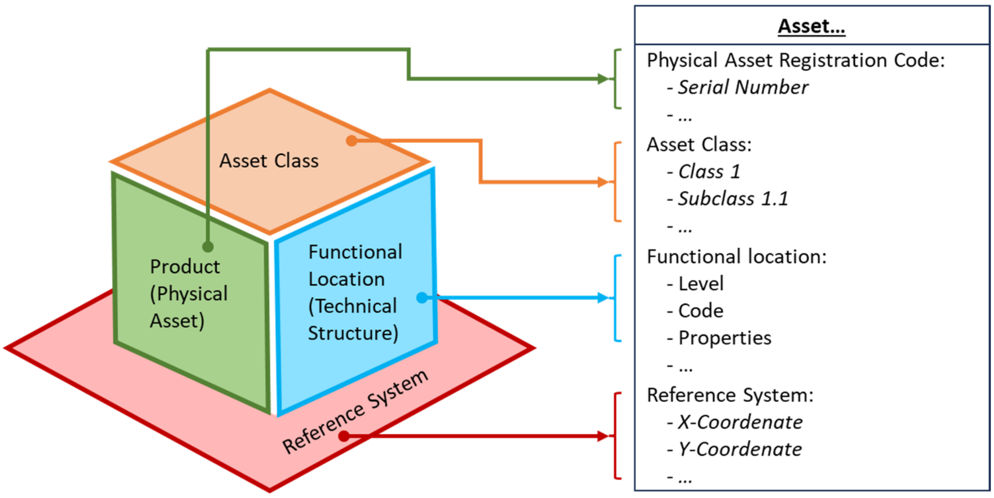

Figure 3. Asset basic definition model as maintenance object following IEC81346 [35].

This basic definition of the asset is independent of the interfaces required to manage the asset, which are shown in Figure 1 as BI Apps. The basic model will be limited and stable, while the number of interfaces will be as many as deemed necessary, adapting to the needs of the different roles and users involved in the management.

3.2.2. The Asset Criticality Model

An Asset Criticality Model is a key aspect of infrastructure management. This model enables the prioritization of assets, organizing them from highest to lowest criticality. Despite gaining popularity, some authors note [8] that many of these models lack uncertainty and sensitivity analysis. Also, these tools are frequently utilized in isolated applications tailored for specific management areas, lacking integration with other decisions that influence maintenance and, more broadly, the lifecycle management of assets. These deficiencies may lead to misleading results, potentially resulting in non-essential maintenance efforts in less critical areas. To address this, asset criticality risk analysis should be carefully conducted to reduce or eliminate significant sources of risk [31]. The criticality model and analysis should consider the following process design requirements [see for instance the paper CA for MP]:

- Applicability to a large scale of in-service systems within a plant or infrastructure.
- Consistency with the scope (indenture level) of the current asset preventive maintenance program's development and implementation.
- Supportability for regular changes in the scale of severity effects of functional losses of assets to align with dynamic business environments.
- Easy identification of new asset criticality, and therefore maintenance needs, for assets facing new operating conditions.
- Compatibility with the company's Enterprise Asset Management system for automated periodic analysis reproduction.
- Practical effectiveness of the process demonstration in an industrial setting.

Once the criticality of assets has been determined, the framework facilitates integration with other maintenance management models as per Figure 1.

3.2.3. The Asset Monitoring Model

An Asset Monitoring Model incorporates signal integration and a robust Extract, Transform, Load (ETL) process to transform raw signals into meaningful asset-related information. This process is carried out by advanced systems that utilize sensors distributed throughout an Internet of Things (IoT) network. The network consists of sensors, nodes, and cloud computing infrastructure. Nodes aggregate sensor data, facilitate efficient communication within the network, and transmit the collected information to cloud platforms and applications for further analysis and processing. The following aspects are crucial in designing an efficient and meaningful IoT network for asset management and monitoring (Figure 4):

- The network topological design. Physical aspects of node placement and connectivity. Nodes capture signals using sensors with different sampling frequencies, and it is essential to identify variables related to the asset to manage. Each node will have a number of sensors, each with a distinct sampling frequency.
- The logical grouping. The conceptual organization of sensors to ensure effective data analysis and interpretation. The identification of variables related to the asset to manage.
- The server hosting essential services. For the processing, utilization, and delivery of information to end users.

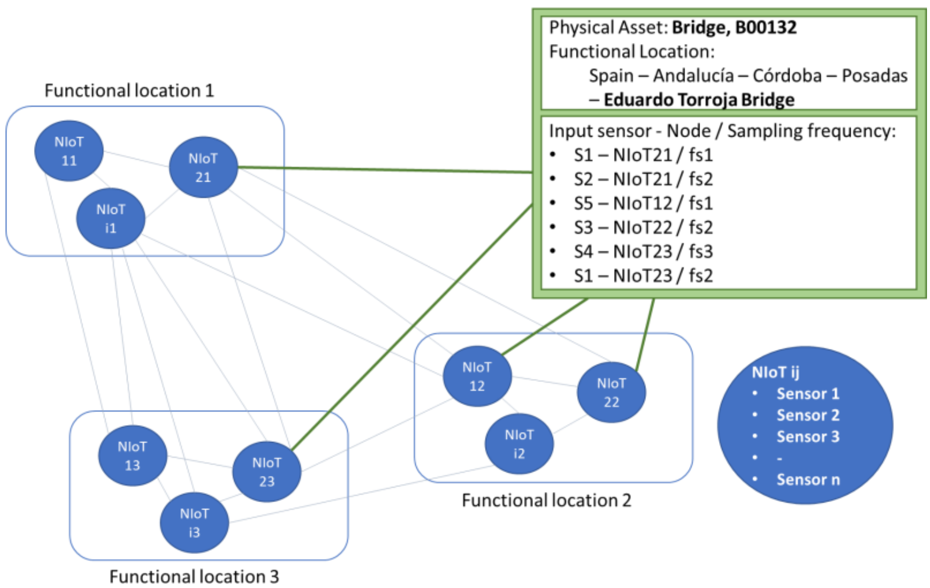

Figure 4. Scheme for defining indicators of the digitized asset based on sensors and nodes from the IoT network.

3.2.4. The Intelligent Asset Management Models

These modes are selected for the specific management of a given asset, while ensuring sustainability with minimal effort in data handling. This is addressed by a framework that connects different data models, structurally correlating data tables akin to human reasoning. This supports decision-making processes with specific asset data models. Asset management models are embedded into the Intelligent Asset Management Platform App (IAMP App), catering to decision-making processes such as [13] Reliability-Centered Maintenance (RCM), Condition-Based Maintenance (CBM), Life Cycle Costing (LCC), etc.

These apps configure data models based on their analysis scope and can interact with simulation and AI tools, supplementing database records with results. These tools also interact with or provide Business Intelligence Apps (BI Apps) to generate tailored information presentations.

3.3. Comparison with Existing Frameworks

The existing frameworks in Section 2.3 serve as high-level guides for designing interoperable and scalable digital systems. However, they lack the specificity needed for practical application in asset maintenance and management. The proposed framework in this section addresses this gap by providing detailed models and workflows tailored to the challenges of low-digital-maturity assets, leveraging IoT platforms, and integrating predictive maintenance strategies. Together, these approaches form a comprehensive view of asset digitalization, from conceptual design to practical implementation.

This approach complements the theoretical guidance of existing frameworks by demonstrating how their principles can be applied to real-world challenges, bridging the gap between abstract architectures and actionable asset management solutions. Together, these frameworks form a cohesive pathway from conceptual design to practical implementation, enhancing the overall impact of digital transformation efforts.

4. Asset Digitalization Use Case: IoT and AHI App for a Bridge Maintenance

4.1. Introduction to the Use Case

Bridges, as critical assets in transport infrastructures, bear significant management implications in terms of Total Expenditure (TOTEX) and associated risks. The need to control the condition of bridges is essential for proper physical, operational, and economic management, not just for individual bridges but for the entire asset portfolio managed by infrastructure asset managers. However, tools for effectively managing this type of infrastructure are currently limited. The real threat of climate change adds urgency to the demand for control, increasing uncertainty about infrastructure performance under evolving operating conditions.

Presently, most bridges lack a real-time online monitoring system that applies comprehensively to the entire asset. The advancement of IoT networks with affordable costs opens possibilities for massive monitoring of distributed passive systems like [57] or [58], which use local SHM algorithms that are not sufficiently accurate, such as peak picking detection, or [59], which proposes a solution similar to the nodes presented here but with the need for a solar panel for power supply and unsecured communications (UDP), which justifies the development proposed here. In addition, the increased monitoring of bridges through IoT technology generates vast amounts of data, necessitating the application of advanced data analytics and machine learning for meaningful insights. A comprehensive interpretation of the data allows for a better understanding of bridge behavior and the identification of potential issues. Integrating data from multiple bridges provides a global perspective and aids in the development of predictive models.

The research questions encapsulating the essence of this use case are outlined as follows:

- What is the best way to implement a model-based approach for bridge digitalization to support maintenance and management objectives effectively?
- How can the integration of an IoT platform with short-term monitoring models and long-term frameworks like the Asset Health Index (AHI) be utilized to improve the digitalization and management of bridges?

In the rest of this section, we will delineate the use case that serves as an illustration for the asset digitization process. This involves the introduction of key models tailored to assess various aspects of the bridge's lifecycle and performance. Firstly, the Asset Definition Model will be unveiled, providing a holistic framework that captures the intricacies of bridge data and information across diverse systems. Following this, we will delve into the Asset Criticality Model, designed to prioritize bridge assets based on their criticality and importance. Subsequently, we will introduce the bridge monitoring model. Lastly, we will explore the Intelligent Asset Management Models, specifically adapted to estimate the health index of the bridge.

4.2. Bridge Definition and Criticality Models

In the examined scenario, an in-depth analysis is performed on the infrastructure of a bridge, categorizing it into five primary components, each characterized by a distinct lifecycle and degradation process. These components encompass the roadway surface, superstructure (load-bearing structure), piers and/or abutments, foundation, and coatings. Given the inherent critical nature of this type of asset, namely a bridge, its failure could lead to severe consequences, particularly in terms of safety and the overall quality of service extended to infrastructure users.

The focus of this analysis centers on the Eduardo Torroja Bridge, situated south of Posadas, Córdoba, spanning the Guadalquivir River. With its inauguration dating back to 1951, the bridge boasts specific dimensions, including a length of 235 m, a width of 11 m, seven cement pillars, and a distinctive appearance featuring eight eyes or inverted bristles supporting the deck.

In the context of this analysis, the methodology will be exclusively employed for the components of the roadway surface and superstructure. The pertinent data related to the functional location and O&M cost of these specific components are documented and outlined in Table 2.

Table 2. Platform and superstructure functional location data.

Data Type	Description	Platform	Superstructure
Functional Location Data	Distant to the coast Altitude	160 km, 86 m	160 km
	Average outdoor temperature	22.5 °C	86 m
	Corrosive atmosphere	No	22.5 °C
	Dust in suspension	No	No
O&M Cost Data	Corrective maintenance cost	EUR 10,000	EUR 20,000
	Preventive maintenance cost	EUR 3000	EUR 2000
	Other operational costs	EUR 1000	EUR 1000
	Major maintenance cost	EUR 60,000	EUR 100,000

4.3. Bridge Monitoring Model

The functional block diagram of the proposed architecture is shown in Figure 5. On the one hand, at the sensor node level, we can distinguish the acquisition layer (in orange), the local processing and storage layer (in red), and the wireless communication layer (in purple). On the other hand, at the cloud processing server level, dockerized microservices are included for role management, data reception, management and processing of the models of each asset, and the presentation of the Graphical User Interface (GUI).

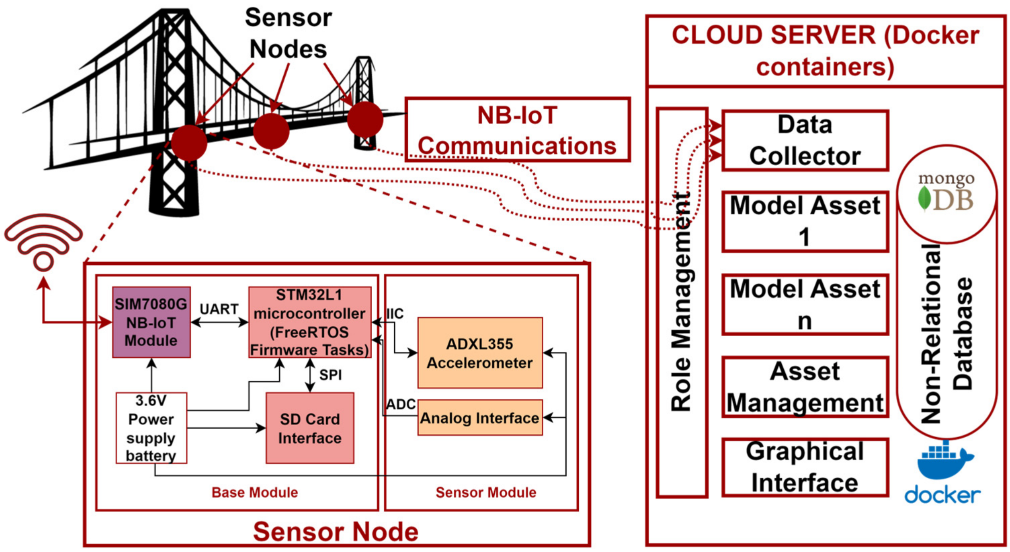

Figure 5. The IoT network.

To digitize the asset's condition monitoring, it is imperative to establish integration with information sourced from the IoT/cloud network strategically positioned at various points across the bridge. For instance, Figure 6 illustrates the selected mesh for data acquisition at each point, highlighting specific locations in a roadway section measuring 42 m in length and 10.5 m in width. These nodes serve the dual purpose of capturing information from the bridge and offering data not only exclusive to the roadway due to their location but also insights into the condition of other bridge components, as delineated in Figure 6. According to the structural modal analysis community [60], the interval of measurements must be greater than 1000 times the fundamental period of the structure, so a periodic monitoring duration of 8 min with an accuracy of 3.8 µg in a range of ± 2 g is chosen. The dynamics of change and degradation of the structures are slow enough to select a monitoring periodicity of 24 h, which guarantees the autonomy of the nodes for up to 10 years.

From a perceptual standpoint, the solution integrates hardware and firmware design in order to face the challenges presented by the application framework. On the one hand, since these structures are usually located in rural environments that are difficult to access, a low-energy-consumption design is created in order to maximize their useful lifetime and reduce battery replacement actions on the devices. To this end, the hardware design adopts a modular structure consisting of a base module and a sensor module. The base module manages local processing, device control, NB-IoT wireless communications, data storage, and power supply, housing crucial components like the microcontroller (STM32L1), the NB-IoT communications transceiver (SIM7080G), and the SD memory interface. The sensor module, connected to the base module, includes sensors for real-time structure monitoring, such as accelerometers (ADXL355) and analog interfaces for strain gauges, which are not used in this application case, but allow the solution to be scaled to other frameworks. The firmware design, structured modularly, involves real-time operating system tasks like FreeRTOS with tasks for sensor monitoring, local information processing, and wireless transceiver control. This allows simple events such as collapses or high-intensity impacts to be detected in real time and transmitted wirelessly to the central server. The modularity allows flexibility in adapting the sensor node to various structures, ensuring efficient and customized monitoring. In addition, time synchronization between nodes is carried out via the A2235H GPS module.

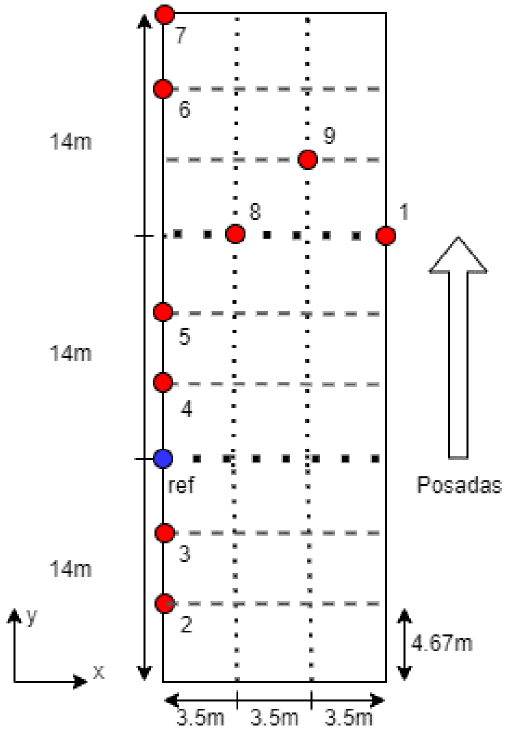

Figure 6. Node distribution along the platform.

While some structures benefit from existing mobile or local networks, others, particularly civil structures like bridges, may be situated in areas with limited connectivity. Narrow-Band IoT (NBIoT) technology, offering a cost-effective and long-range connection service, proves advantageous for such scenarios. NBIoT's low energy requirements make it suitable for low-power devices, aligning perfectly with the presented application. Despite its low speed and high latency, the technology's capacity and security mechanisms (SSL/TCP/IP communication stack), which have been applied to this use case, prevent intrusion into the transmitted information and ensure that the information reaches its intended destination. This selection therefore makes it the right solution for the application described, facilitating immediate and cost-effective deployment.

The server centralizes the processing and management of monitored structures. To accommodate scalability, a microservice-based development on Docker technology containers is adopted, which allows the migration of these microservices with minimum effort, thus avoiding dependencies on static architectures or specific service providers. These microservices communicate through REST API connections and handle tasks such as collecting information from deployed nodes, storing it in a non-relational database (MongoDB), and processing data according to different asset digitalization models. These models allow versatile management of structures as complete assets or compositions of different assets, enhancing asset management efficacy. Additionally, this microservice-based architecture allows the scaling of the system and the future updating of the algorithms applied by predictive applications based on artificial intelligence, thus preventing the obsolescence of the entire system. The server also implements a role management system to ensure secure and controlled access to system information (Figure 7).

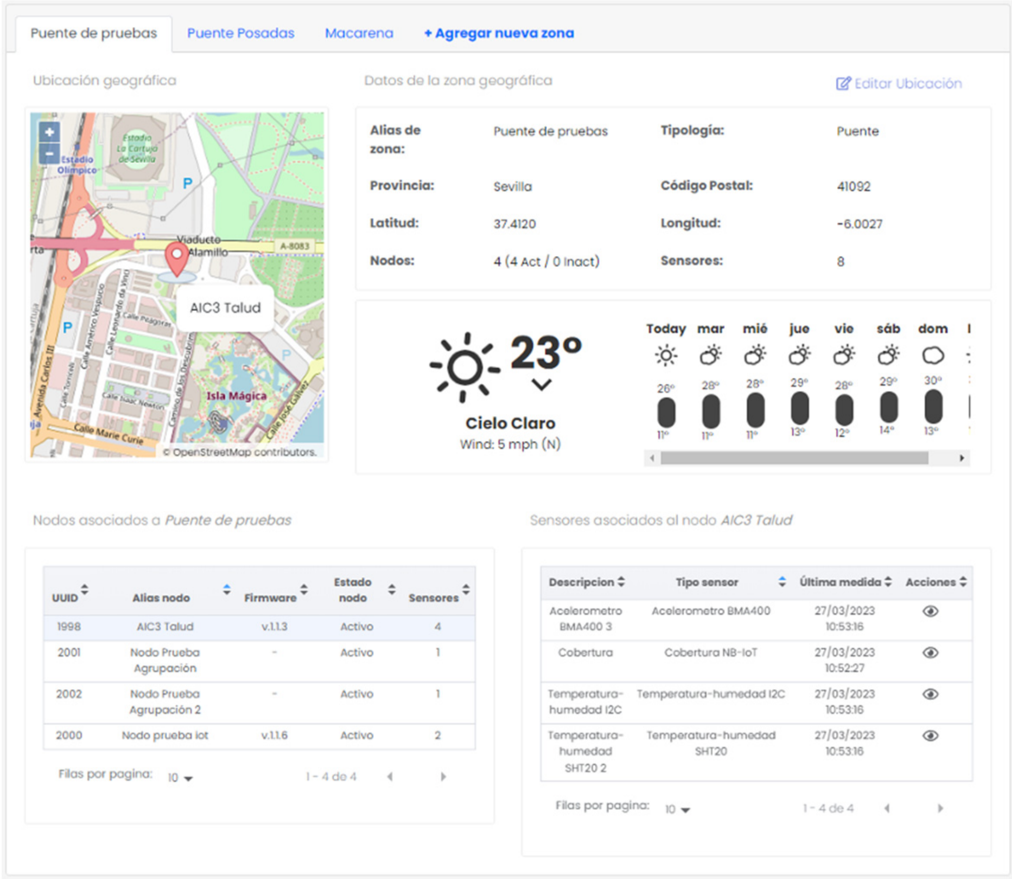

Figure 7. IoT platform with information about bridge location, nodes, and sensors.

4.4. The Bridge Health Index Model

The initiation of the health model hinges on the information gathered through the monitoring and digitization solution outlined in the preceding section, constituting an integral component of the entire process. However, it is crucial to view the management of the health model as an ongoing, open-ended procedure, as illustrated in Figure 8.

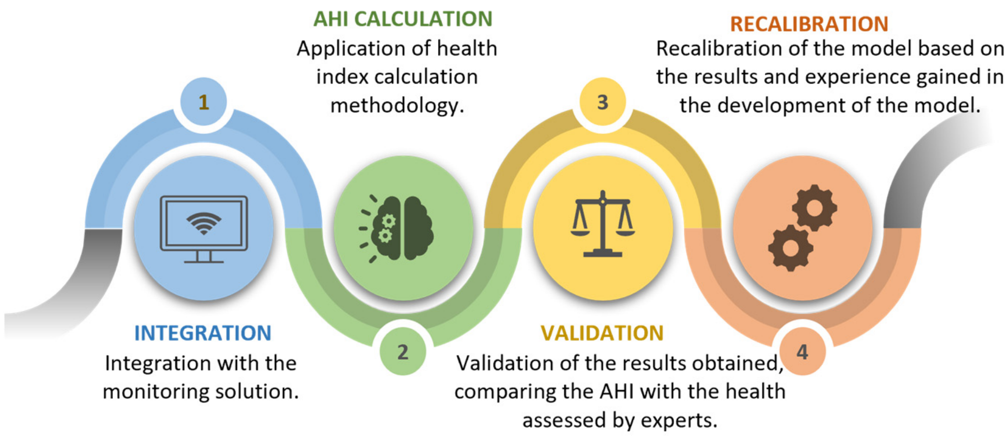

Figure 8. AHI model evolution process.

Integrating the proposed IoT network is essential for processing monitoring data on the platform, allowing for the computation of indicators that represent the asset's health condition. The application of a novel methodology involves calculating the health index based on indicators, input variables, and interpretation of health and reliability modifiers.

Validation of the results, comparing calculated health status with expert estimates, is crucial for refining the model.

In Figure 9, the reader can also appreciate the steps of the process where the different factors acting as health (temperature, radiation, humidity, etc.) or reliability modifiers (maintenance fulfillment level, etc.) are introduced. Formal equations can be found in [37].

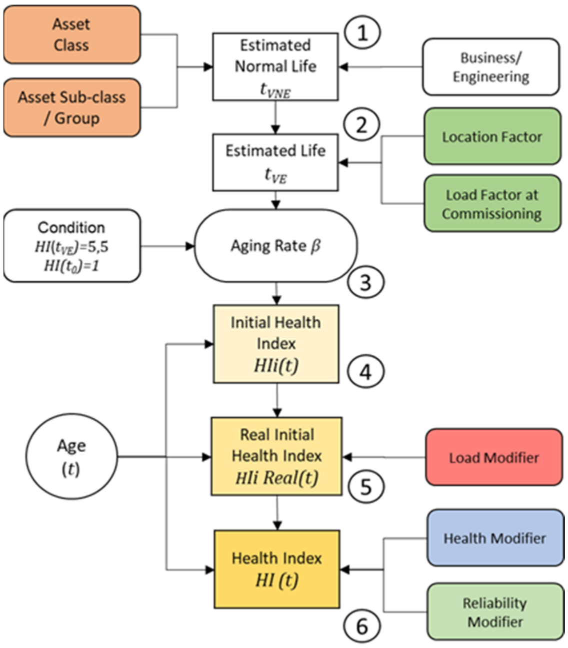

Figure 9. The six-step methodology presented in [37] to obtain the health index.

Figure 10 outlines the comprehensive framework for the architecture of the Asset Health Index (as presented in Figure 1 [13]) proposed using the six-step methodology (process) elaborated upon in [37] (see Figure 9).

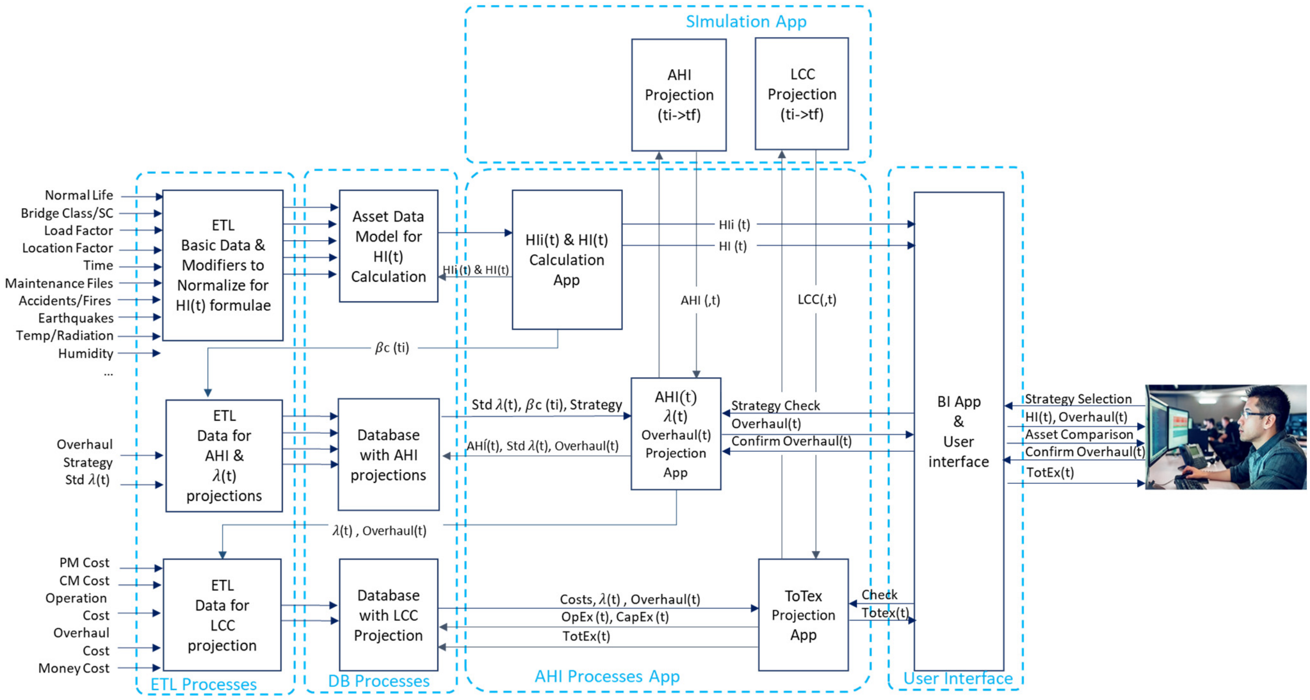

Figure 10. The AHI model description through the DMM framework.

The complete model integration with the platform involves data extraction, processing, and loading (ETL Processes), providing necessary inputs for databases (DB Processes) needed for the following:

- Calculating the Asset Health Index to interpret the impact on the asset's health through normalized and pondered modifiers (asset class, normal life, location and load factors, age, maintenance and other incidents files, sensors, etc.).
- Updating and correcting aging rate ($\beta c(ti)$) at a given time ti to project the health index and failure frequency over the asset lifecycle according to a given strategy for overhauls (for instance, conduct overhauls based on the AHI or the asset's age) and considering a standard failure rate when the asset is in good condition ($Std\ \lambda(t)$).
- Estimating the lifecycle cost profiles assuming the cost of different maintenance operations (PM, CM, and overhaul or major maintenance).

The Intelligent Asset Management systems (in AHI Processes Apps), supported by mathematical modeling, simulation modeling (Simulation App), and interpretation rules, establish thresholds for modifier calculation and formulate the health index, facilitating result representation in Business Intelligence tools (BI App/User Interface)). They also project health and cost metrics over the asset lifecycle, if needed, according to selected overhaul/replacement strategies (see Figure 8).

Interpreting the Asset Health Index (AHI) directly for an individual asset facilitates decision-making at the specific asset level. This involves defining and managing thresholds established on the index to delineate states and state changes that guide the maintenance strategy, as illustrated in Table 3. When the AHI is determined at the component level or "child asset" level, understanding the health of the "parent asset" involves applying interpretation rules. These rules enable the combination of AHI interpretations for all children, providing a comprehensive overview of the parent asset's health.

Table 3. Strategies according to the AHI calculation.

AHI	Condition	Requirements
1–4	Very Good	Normal maintenance
4–5.5	Good	Normal maintenance
5.5–7	Fair	Increase diagnostic testing, replacement depending on criticality
7–8	Poor	Start planning process to replace
8–10	Very poor	Immediately assess risk; replace or rebuild based on assessment

AHI handling complements economic calculation models like ToTex or Life Cycle Cost (LCC) models in designing data-driven decision-making processes for medium- and long-term decisions, such as planning major maintenance, replacements, and reinvestments.

Moreover, this AHI interpretation can be performed on an individual basis for decision-making on a specific asset or comparatively for decisions affecting a group of similar assets managed by the same organization or responsible entity under the same budgetary constraints. The comparative management of AHI values for similar assets holds particular significance in global management decisions for a network of infrastructure assets. In the interpretation process, multivariable analysis is conducted, including factors such as remaining useful life, and expected degradation. When comparing assets, the combined management of these variables facilitates the generation of overall network control and knowledge management.

In the given example of the bridge case study, the simulation explored the behavior of four bridges under varying operational and maintenance conditions. Table 4 presents the initial/estimated health index, the actual achieved health index, and the deviation at the current time since the last overhaul.

Table 4. Sample results obtained for different bridges in the use case.

Variable	Bridge 1	Bridge 2	Bridge 4	Bridge 4
IHi	2.573	1.912	2.458	1.919
IH	3.015	2.668	3.485	2.478
Relative deterioration	0.442	0.455	1.027	0.560
Months of operation since last OH	300	320	410	480

According to the framework proposed in Figure 1 and its interpretation in Figure 10, in order to use the results obtained, it is possible to propose and design the necessary interfaces in the BI App. For instance, Figure 11 is an example of an interface designed to support decision-making for a group of bridges. It represents the comparative evolution status of different bridges that are managed jointly, as they share maintenance and investment resources. In Figure 11, each bridge is represented by a ball, and each bridge ball is placed at its operating time and its IHIi, while the value of IHs sets the ball diameter. The greater the relative deterioration, the greater the diameter. We would be very concerned with bridges having a very low operating time with large-diameter balls, since that is a symptom of unexpected early deterioration that could be a consequence of specific O&M conditions. In the obtained results in Table 4, it is noticeable that Bridge 1, despite accumulating the least operating time, is predicted to have the highest estimated health index due to its initial operating conditions. Bridge 1, compared to Bridge 3, has a lower real health index, indicating a faster aging rate. Figure 11 illustrates this projection, showing health index trends against the age of Bridge 1 and Bridge 4. The varying ball sizes in the figure represent relative deterioration, with larger balls indicating greater deterioration. For instance, Bridges 1 and 2, constructed within a short time difference, show differences in health index and relative deterioration, warranting further investigation. Bridge 3, despite having the highest health index, exhibits significant relative deterioration, emphasizing the need for focused attention and resource allocation to preventive maintenance activities. In contrast, Bridge 4, despite being the oldest, has a lower health index, but the deviation from the predicted health index is not alarming, suggesting a manageable health status relative to its age.

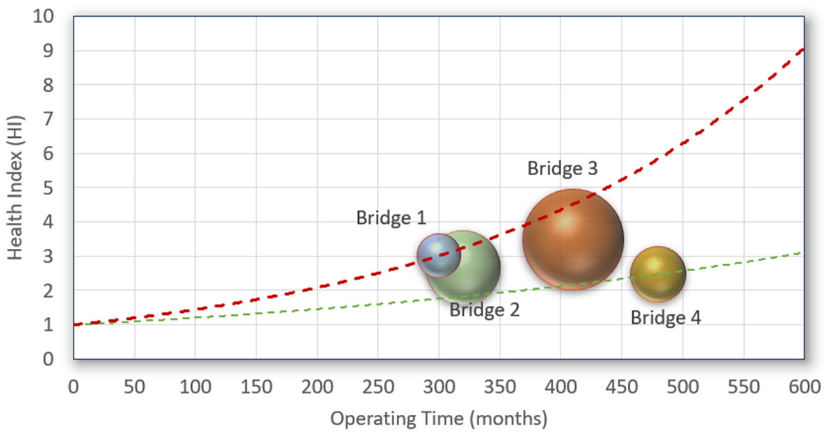

Figure 11. AHI versus age projection. Representation of the current health index versus the initially estimated bridge age. Comparison among assets in the same asset class.

Note that all these conclusions and potential "calls for action" are revisited every few months, whenever this information is updated. This is a mid/long-term management tool for the control of asset O&M programs, the scheduling of major overhauls, and better planning of future reinvestments.

A summary of the valuable insights offered by the results presented in Figure 11 is as follows:

- Objective Measurement of Degradation: The framework enables the precise identification of the asset's degradation percentage relative to expected deterioration over a given period. This is achieved using real-time monitoring data from IoT platforms.
- Strategic Maintenance Planning: By analyzing trends in asset health, the framework helps optimize the timing of major maintenance activities, preventing excessive corrective interventions and minimizing operational risks.
- Risk Mitigation: Early identification of critical conditions allows managers to proactively address potential failures, enhancing asset reliability and safety.
- TOTEX Optimization: The approach facilitates a balance between operational expense (OPEX) and capital expenditure (CAPEX), providing a comprehensive view of total ownership costs (TOTEX). This balance is achieved by assessing and adjusting preventive maintenance policies based on their impact on degradation.

4.5. Validation and Reproducibility

In the study, the alignment of modeling results with expert assessments is achieved through a structured validation process:

- Validation Against Expert Judgments: The calculated results must be systematically compared with evaluations provided by domain experts, leveraging their extensive experience in asset health assessment and management. This comparative process involves identifying and addressing discrepancies to refine the model.
- Accuracy Confirmation: The framework integrates real-time IoT monitoring data with advanced decision-making tools like the Asset Health Index (AHI). This integration will ensure that the predictions are continuously updated based on objective, real-world data, which enhances the reliability of the outputs.
- Reproducibility: The proposed framework is designed with modularity and transparency, enabling other researchers and practitioners to replicate the methodology. We have expanded the manuscript to include detailed descriptions of the following:
    - The data sources and their preprocessing steps.
    - The bibliographic sources including algorithms used to calculate the AHI.
    - Suggesting specific steps in comparing model results with expert assessments.

4.6. Conclusions of the Use Case

This use case demonstrates the potential of a model-based approach for bridge digitalization to significantly enhance bridge maintenance and management. It shows how by leveraging IoT technologies and advanced analytics, infrastructure asset managers can gain real-time insights into bridge performance, prioritize maintenance efforts, and optimize resource allocation. The integration of short-term monitoring models with long-term predictive models such as AHI enables proactive maintenance strategies, ensuring the resilience and sustainability of bridge infrastructure in the face of evolving operational conditions and challenges.

5. Discussion of Results, Practical Implications, and Future Research

This section discusses the results of this paper, focusing on the contributions of the model-based approach to asset digitalization and management. It emphasizes the integration with digital maintenance decision-making processes, the application of IoT monitoring and model integration, and the broader implications for the advancement of digitization practices.

- Introduction of Model-Based Approach for Asset Digitalization: Our research addresses the pressing need for a comprehensive model-based framework to facilitate the digitalization and management of assets, particularly those with low initial levels of digitization during their operational and maintenance (O&M) phase. A structured approach encompassing four tailored asset models is provided, offering practical guidance on how organizations can effectively digitize their assets to serve maintenance and asset management purposes.
- Integration with Digital Maintenance Decision-Making Processes: One of the primary contributions of our work lies in the seamless integration of the proposed model-based approach with digital maintenance decision-making processes. The paper delineates how organizations can incorporate digital asset management practices into their existing workflows. This integration enhances the efficiency and effectiveness of maintenance operations, leading to improved asset performance and reduced operational costs.
- Application of IoT Monitoring and Model Integration: Our research explores the combined use of an IoT monitoring platform with short-term monitoring models, such as Condition-Based Maintenance (CBM), and long-term models, such as the Asset Health Index (AHI), to enhance asset digitalization and management. Leveraging IoT technologies and integrating diverse data sources are important for organizations to gain real-time insights into asset health and performance. This integrated approach enables proactive maintenance strategies, optimizing resource allocation and minimizing downtime.
- The incorporation of standards such as IEC 81346-1:2022 and ISO 14224:2016 ensures compatibility and interoperability with existing systems, setting our framework apart from previous studies.
- Scalability and Adaptability: The scalability and adaptability of the framework enable its application across diverse industries and organizational settings. Future research could explore strategies for further enhancing the scalability and adaptability of the framework to accommodate evolving technological and operational requirements.
- Bridging the Gap between Theory and Practice: We provide practical guidance for implementing digital asset management strategies. Continued collaboration with multidisciplinary groups and industry partners could further enhance the relevance and applicability of our findings in real-world settings.
- Overcoming Implementation Challenges: The framework addresses data integration using a microservice-based design that efficiently handles large volumes of heterogeneous data from distributed sensors. However, its application in complex environments requires enhanced cybersecurity measures, such as end-to-end encryption and intrusion detection mechanisms. Additionally, processing algorithms can be further optimized to manage real-time constraints in critical systems.
- Framework Generalization: The modular and scalable structure of the framework allows its adaptation to assets with diverse lifecycles and operational complexities. While the case study focuses on infrastructure such as bridges, the framework's design can be extended to industrial and energy assets by tailoring the models to the specific requirements of each sector. This adaptability ensures broad applicability and maximizes the framework's impact across varied contexts.
- Algorithm and Model Generalization: In this example, the AHI model is very similar to the ones proposed in the CNAIM [42]. However, we acknowledge that machine learning (ML) algorithms and advanced analytical techniques, when data are available, can play a significant role in enhancing the predictive accuracy and adaptability of the framework. Although specific ML algorithms are not applied in this study, the

modular design of the framework allows for the future integration of approaches such as Supervised Learning (e.g., regression models, decision trees) to model asset degradation; Unsupervised Learning (e.g., clustering) for identifying patterns in degradation data; or Reinforcement Learning for optimizing major maintenance scheduling based on feedback.

6. Conclusions and Areas for Further Research

This study focuses on maintenance digitization, highlighting the gap between technological advancements like IoT platforms and digital twins and their practical implementation. The proposed framework creates a unique digital representation of the asset, akin to concepts like the Asset Administration Shell (AAS), while promoting a model-based approach for asset and maintenance management.

The practical aspects of maintenance management take center stage in the framework, highlighting the need to integrate advanced digitization solutions with a focus on IoT platforms and digital twins. By prioritizing the development of asset-related models and advocating for their integration within a comprehensive digitalization architecture, this study provides a structured approach that prevents the isolation of models, reduces extra costs, shortens implementation times, and mitigates interoperability issues.

As a use case, a notable contribution of this study is the consideration of an AHI model, addressing the limitation of many IoT/cloud networks that primarily focus on short-term decisions. This model connects real-time monitoring with medium- and long-term planning, including End-of-Life (EOL) management. The integration of the AHI model emerges as an interesting component in digitization, facilitating knowledge management within advanced asset digitization models.

This study addresses challenges with infrastructure assets lacking historical data by integrating monitoring variables with factors influencing asset degradation. The adaptable model enables refinement through real degradation processes and emphasizes detailed data recording and analysis.

The results of this study demonstrate the effectiveness of integrating IoT-based monitoring with the AHI model for asset management. However, incorporating uncertainty and sensitivity analyses could further enhance the framework's robustness. Uncertainty analysis would evaluate how variations in input data, such as sensor inaccuracies and environmental changes, affect AHI outputs, while sensitivity analysis would identify key parameters influencing decisions. These additions would improve predictive reliability and provide greater confidence in recommendations. Future work could employ advanced computational methods, such as Monte Carlo simulations, to address these aspects and optimize maintenance strategies.

In summary, this study provides a framework for effective maintenance digitization, emphasizing practical implementation, model-based perspectives, and the strategic integration of an Asset Health Index model, ultimately contributing to the advancement of digitization practices in the field of maintenance management.

While our research represents a step forward in the field of asset digitalization and management, there are several avenues for future exploration. These include further refinement of model integration techniques, empirical validation of the proposed framework in diverse industrial contexts, and strategies for scaling the framework across different organizational settings and industry sectors. In order to do so, a positive factor is that the proposed framework is designed with modularity and flexibility to ensure its applicability to a broad range of asset types and operational contexts. For instance, for assets with shorter lifecycles, such as equipment in manufacturing plants, the framework could incorporate dynamic monitoring parameters and more frequent updates to the Asset Health Index

(AHI). Similarly, for highly complex systems, such as chemical plants or power grids, the IoT network design could integrate redundant monitoring systems to ensure continuous data flow and robustness under critical conditions. Also, although this study focuses on bridges, the underlying methodology is inherently scalable. For instance, the criticality model can be recalibrated to reflect the specific risk profiles of other asset types, while the monitoring model's IoT architecture can be tailored to different physical and operational environments. These potential adaptations are part of ongoing research and will be validated in future studies across diverse industries and asset categories.

A limitation of this work is the absence of immediate quantitative metrics demonstrating the framework's impact on key performance indicators such as unplanned downtime reduction, maintenance cost optimization, or overall TOTEX or efficiency improvements. This is due to the study's focus on establishing the feasibility of integrating IoT networks with the AHI model in the context of bridge maintenance. In future research, longitudinal studies will capture these metrics over extended periods, enabling a robust comparison with traditional maintenance methods and further validating the framework's applicability to diverse asset types and industries.

The authors also acknowledge that a detailed evaluation of the accuracy, uncertainty, and sensitivity of the models is essential for further validating their reliability. For instance, the Asset Health Index (AHI) model could benefit from an uncertainty analysis that examines the effects of sensor accuracy, data completeness, or environmental variability on the calculated health scores. Sensitivity analysis could also be used to identify critical parameters—such as degradation rates, risk factors, or maintenance thresholds—that have the most significant impact on the model's outputs.

Additionally, exploring advanced algorithms and machine learning approaches to optimize model performance and accuracy presents exciting opportunities for future research and development.

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the authors utilized ChatGPT 4.0 to enhance clarity and readability. Following its use, the authors thoroughly reviewed and adjusted the content as necessary, taking full responsibility for the final publication.

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