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"Asset MAnagement in the new Digital Twins environment" (AMADIT)

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1. Introduction

The digital transformation of railway maintenance represents not merely a technological evolution but a profound paradigm shift encompassing organizational, cultural, and methodological dimensions. Modern railway systems constitute highly complex socio-technical infrastructures that integrate thousands of distributed assets—each contributing to the overall safety, reliability, and availability of services. Traditional maintenance strategies, often based on corrective interventions or rigid time-based schedules, have increasingly revealed their limitations in addressing such complexity. These approaches tend to result in suboptimal resource allocation, excessive downtime, and limited responsiveness to evolving operational and environmental conditions.

In this context, Asset Performance Management (APM) has emerged as a comprehensive framework that integrates data, analytics, and human decision-making to optimize asset lifecycle performance. By leveraging digital technologies—including IoT, sensor networks, cloud computing, and advanced data analytics—APM models enable a systematic transition from reactive to predictive and prescriptive maintenance paradigms. This transition ensures that performance, cost-efficiency, and safety objectives are jointly achieved in alignment with sustainability and reliability requirements.

The application of APM models within Digital Twin (DT) environments constitutes a particularly promising direction for the railway sector. Digital Twins provide a bidirectional connection between the physical and digital domains, facilitating the continuous integration of data streams, health assessment, and decision support. When combined with APM methodologies, they allow maintenance activities to be optimized dynamically according to asset condition, operational context, and risk exposure.

This deliverable presents and analyses four representative use cases that illustrate the practical implementation of APM models in digitalized railway maintenance. Each case focuses on a specific aspect of the digital transformation process—from the predictive analytics of critical components to the systemic optimization of maintenance strategies—demonstrating the maturity and scalability of APM frameworks in real industrial contexts.

- *Use Case 1 – Predictive maintenance of train bearings (TALGO):* This case demonstrates the application of Digital Twin architectures to predict axle bearing degradation in high-speed trains. Temperature-based analytics and machine learning techniques were used to detect and classify anomalies, while interactive human–system diagrams enhanced transparency and user trust. The results evidenced improvements in diagnostic precision, data efficiency, and technician engagement, validating the scalability of data-driven predictive models.

- *Use Case 2 – Structured data model for Asset Health Index (AHI) integration in energy converters*: This case addresses the integration of Asset Health Index methodologies into real-time Digital Twin environments. A standards-aligned data model (based on ISO 14224, RAMI 4.0, and IIRA) was implemented on Microsoft Azure, enabling continuous health assessment and dynamic updating of asset condition scores. The approach demonstrated significant reductions in unexpected failures, improvements in maintenance planning accuracy, and scalability across asset categories.

- *Use Case 3 – Dynamic criticality analysis for railway asset management*: This use case illustrates how digitalization enables the transformation of static criticality assessments into dynamic, data-driven decision tools. Through an ontological data model and automated business rules, criticality indices were computed and visualized for over 4,000 railway assets, integrating technical, operational, and economic dimensions. The approach enhanced transparency in prioritization, reduced unplanned stops, and generated measurable cost savings, evidencing the strategic value of digitalized decision support systems.

- *Use Case 4 – APM model for preventive maintenance interval optimization (DFMAS Project)*: The final case introduces an analytical semi-Markov APM model integrated within the Digital Twin of the Matisa B66 maintenance machine. The model determines the optimal preventive maintenance interval by balancing corrective and preventive costs under reliability constraints derived from Weibull distributions. Implemented in PowerBIM, the system dynamically updates the optimal interval as new operational data become available. The results demonstrated substantial improvements in economic efficiency and adaptability, extending to condition-based configurations through four-state models.

Taken together, these four use cases illustrate the progressive integration of APM principles within digital maintenance ecosystems. They collectively demonstrate how diverse layers of digitalization—from predictive analytics at component level to systemic frameworks for risk and cost optimization—can converge into coherent, data-centric asset management strategies.

Beyond their technical contributions, the studies highlight several critical enablers of success: the engagement and training of maintenance personnel, the transparency of analytical models, and the establishment of robust data governance practices. These factors confirm that digital maintenance maturity depends as much on organizational alignment and human interaction as on the adoption of advanced technologies.

Ultimately, the implementation of APM-based digital maintenance models contributes to the realization of safe, reliable, and economically sustainable railway operations, while also enabling the transition toward advanced business paradigms such as servitization and performance-based contracting. The railway sector thus provides an exemplary testbed for the deployment of integrated digital asset management solutions, offering valuable lessons transferable to other infrastructure-intensive industries.

2. Use Case 1: Digital Twin for Predictive Maintenance of Train Bearings (TALGO)

2.1. Context and Need

Predictive Maintenance (PdM) in the railway sector faces the challenge of ensuring reliability in critical components, such as axle bearings in high-speed trains. Traditional approaches based on physical models are complex and difficult to apply in real operating conditions. Moreover, large volumes of raw data often provide limited value for operational decision-making. TALGO set the objective of anticipating bearing failures, optimizing maintenance planning, and reducing costs. To achieve this, a Digital Twin (DT) focused on temperature data analytics was developed to support PdM.

2.2. APM Model Architecture Applied

The Asset Performance Management (APM) model implemented in this case was structured around three main elements:

- Data: axle bearing temperatures and ambient temperature.
- Analytics: anomaly detection using machine learning, fault classification with Deep Learning algorithms, and prognosis through statistical estimation of Remaining Useful Life (RUL).
- Human interaction: maintenance technicians were actively integrated using Digital Twin Interaction Diagrams (DIO-GD), which clearly represented the relationships between events, actions, and states, thus avoiding the perception of a 'black box' system.

Figure 1. Simplified architecture of the APM model applied to the TALGO Digital Twin use case.

2.3. Implementation and Results

The implementation of the Digital Twin followed a progressive approach:

- Detection: A simple anomaly detection rule was defined (Absolute Error ≥ 10 °C, train speed ≥ 90 km/h, lasting > 1 min), achieving 100% accuracy in identifying damaged bearings.
- Classification: Physical models were replaced with data-driven ones, transforming temperature values into cycles. This reduced the volume of stored data and enabled training of a Deep Learning model capable of distinguishing between internal bearing degradation and external overtemperature due to guidance issues.
- Prognosis: A statistical approach was applied to estimate the Remaining Useful Life (RUL) of the bearing after the first anomaly, thus supporting proactive replacement decisions without the need for additional inspections.

The impact achieved can be summarized as follows:

- Improved diagnostic accuracy.
- Significant reduction in required data volume.
- More reliable and proactive maintenance planning.
- Enhanced confidence and engagement of maintenance technicians.

2.4. Lessons Learned and Replicability

The case demonstrated the importance of involving technicians in the design of the Digital Twin to overcome cultural barriers and build trust in advanced analytics. Data-driven models proved simpler and more scalable than purely physical models, allowing for broader deployment across railway fleets. The use of the DMM framework combined with DIO-GD diagrams provided a standardized way of documenting and managing the interaction between analytics, systems, and users, reinforcing the practical value of digital solutions in predictive maintenance.

3. Use Case 2: Structured Data Model for Asset Health Index Integration in Digital Twins of Energy Converters

3.1. Context and Need

Energy converters are vital components in modern energy systems, enabling the transformation of direct current (DC) into alternating current (AC) and ensuring grid compatibility in applications such as renewable energy plants and battery energy storage systems (BESS). Their performance directly impacts energy efficiency, operational costs, and reliability. Failures in power devices or capacitors often lead to costly downtime and safety concerns, making predictive maintenance a strategic necessity.

Traditional approaches to monitoring converters tend to be fragmented: condition data are often managed in spreadsheets, SCADA logic, or proprietary solutions, without integration into a standardized framework. Asset Health Index (AHI) methodologies exist but are usually implemented offline and periodically, limiting their potential for real-time decision support. This creates gaps in transparency, scalability, and replicability.

The need addressed in this case study was clear: to design and validate a structured and standards-aligned data model that integrates AHI methodologies into Digital Twin architectures, enabling continuous monitoring, automated health assessment, and risk-informed decision-making. The target was to provide a scalable and cost-efficient solution that could be applied not only in large utilities but also in smaller organizations, bridging the gap between academic models and industrial practice.

3.2. APM Model Architecture Applied

The Asset Performance Management (APM) model in this case is based on five interconnected domains, aligned with international standards such as ISO 14224, RAMI 4.0, and IIRA:

- Physical Domain: Defines assets in a hierarchical tree (system, subsystem, maintainable item). For converters, this includes stacks, cooling systems, and individual components.
- Logical Domain: Links assets to functional locations and organizational structures, ensuring traceability across the company.
- Property Domain: Captures operational and maintenance variables (e.g., voltages, temperatures, harmonics, vibration), which are transformed into measurable properties for health assessment.
- Data Domain: Stores historical information such as maintenance records, manufacturer specifications, environmental conditions, and estimated life data.
- AHI Domain: Integrates all inputs to compute the health score dynamically, using modifiers (load, health, reliability) and producing a Final Health Index (HI(t)).

A Decision-Making Domain overlays these layers, where strategy plans, proactive tasks, and risk models connect health indicators to real maintenance workflows. This ensures that digital analytics translate directly into operational and strategic decisions.

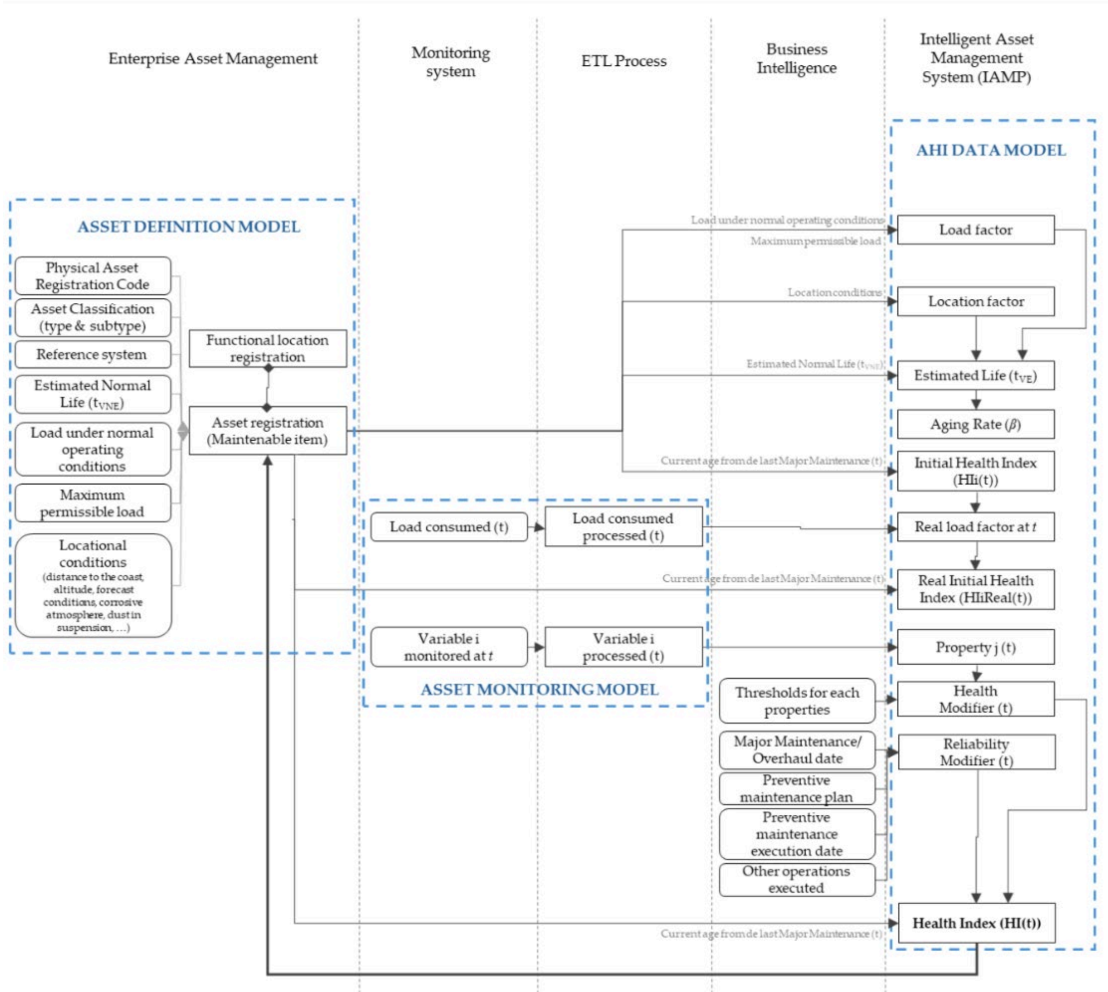


Figure 2. Pipeline of the asset data model implementation

The UML class diagram formalized relationships among these domains, offering an interoperable and extensible blueprint for industrial digitalization. This model was implemented using a cloud-native approach, specifically Microsoft Azure, to support scalability, automation, and economic deployment.

3.3. Implementation and Results

The implementation followed a four-phase methodology inspired by Agile and DevOps principles:

- Application Context and Problem Definition: Requirements were compiled from standards and best practices, highlighting the need for structured models compatible with fragmented industrial environments.
- Data Model Design: Domains were defined and connected through UML diagrams, ensuring alignment with RAMI 4.0 and supporting integration of diverse telemetry sources.
- Cloud Implementation: Microsoft Azure services were deployed to realize the model. IoT Hub ingested data, Azure Functions processed it, Cosmos DB stored historical data, Data Explorer calculated the AHI, and Azure Digital Twins synchronized virtual assets with physical telemetry. Visualization was achieved via Power BI dashboards, ensuring user-friendly interpretation of health indicators.
- Validation: A case study with three high-capacity DC/AC converters (1.5 MW, 1525 V DC input, 690 V AC output) operating under different conditions was performed. Sensors streamed electrical, thermal, and mechanical data into the cloud-based model. AHI was computed in real time and displayed in dashboards for decision support.

Results obtained:

- Converter 1 (moderate conditions) showed gradual degradation, with AHI rising above 7 before its first overhaul. The digital twin highlighted reduced lifespan despite stable operation.
- Converter 2 (harsh thermal cycling, load peaks) degraded early, requiring an overhaul at 12,000 h—earlier than planned. The system showed how dynamic AHI-based monitoring prevents excessive deterioration.
- Converter 3 (variable environment) maintained stable AHI values near initial levels, confirming resilience. Preventive overhauls were planned proactively, validating the model's predictive accuracy.

Quantitatively, the system achieved:

- 43% reduction in unexpected failures, by enabling early detection of degradation. - >30% improvement in maintenance planning accuracy, by aligning overhaul schedules with actual health conditions.
- Operational savings through prevention of unnecessary interventions and optimized spare parts management.
- High scalability, as the architecture proved viable for replication to other asset types (transformers, pumps, turbines).

3.4. Lessons Learned and Replicability

The case highlighted several key insights:

- Structured models enable scalability: By aligning with standards (ISO 14224, RAMI 4.0), the solution avoids ad hoc logic and can be replicated across assets and organizations.
- Integration with IoT and cloud platforms is critical: Real-time ingestion and automated computation allowed the AHI to evolve from a periodic, offline indicator to a continuous decision-support mechanism.
- User-centric dashboards build trust: Maintenance teams and managers engaged more actively when AHI scores were visualized transparently, avoiding the "black box" perception often associated with advanced analytics.
- Context matters: Even identical converters showed different health trajectories, reinforcing the need for condition-based strategies rather than fixed schedules.
- Cost-effectiveness is possible: The Azure-based serverless architecture provided a balance between advanced functionality and affordability, making the approach suitable even for smaller companies.

Impact achieved:

- Predictive maintenance accuracy was significantly improved.
- Overhaul planning became adaptive and risk-informed.
- Asset availability increased, while lifecycle costs were optimized.
- The methodology proved replicable for other industries, supporting digital transformation agendas and servitization strategies.

4. Use Case 3: Digitalization and Dynamic Criticality Analysis for Railway Asset Management

4.1. Context and Need

Railway infrastructures are highly complex systems that involve thousands of assets distributed across large geographical areas. Their reliability directly impacts passenger safety, punctuality, and operational costs. Traditional criticality analyses in railways have often been static, relying on expert judgment and limited datasets. While these approaches provided a first-level prioritization, they lacked scalability, adaptability, and the capacity to integrate real-time information.
Several challenges were identified:

- *Safety and reliability risks:* Failures in signaling systems, track devices, or power substations can trigger large-scale disruptions and safety incidents.
- *Fragmented data:* Asset information is dispersed across inventories, maintenance records, GIS, and operational databases, with little integration.
- *Static assessment methods:* Criticality evaluations are usually performed periodically, based on average data, without considering dynamic variations such as operational context, load, or network configuration.
- *Decision-making gap:* Managers lack a unified tool that combines technical, operational, and economic perspectives to prioritize interventions and allocate resources efficiently.

To address these gaps, a *digitalized and dynamic criticality analysis model* was developed. This model integrates heterogeneous data sources, applies systematic rules for asset evaluation, and generates a dynamic criticality matrix that supports prescriptive decision-making in railway asset management.

4.2. APM Model Architecture Applied

The Asset Performance Management (APM) model applied in this case was structured around four key pillars:

- *Data Integration (ETL Process):* An Extract, Transform, Load (ETL) pipeline was created to gather data from multiple sources, including asset inventories, failure databases, sensor systems, and GIS platforms. This ensured that both static attributes (e.g., asset type, location, age) and dynamic variables (e.g., failure rates, load conditions) were integrated into a centralized framework.
- *Asset Attribute Characterization (AAC):* Each asset was described with a set of operational and contextual attributes. Examples include its location in a tunnel or open track, speed limits, passenger density, or type of surrounding infrastructure. This enriched characterization allowed a more accurate calculation of failure consequences.
- *Ontological Data Model and Asset Administration Shell (AAS):* Assets were digitally represented using an ontological model aligned with Industry 4.0 standards. The AAS served as the digital twin container, enabling interoperability across systems and standardizing the way information was exchanged and managed.
- *Analytics and Rules Engine:* Criticality rules were codified in Python scripts and linked to the data model. The algorithm calculated criticality indexes based on multi-criteria dimensions such as safety, environmental risk, service quality, and economic impact. The results were visualized in a digital dashboard, providing managers with a dynamic and transparent criticality matrix.

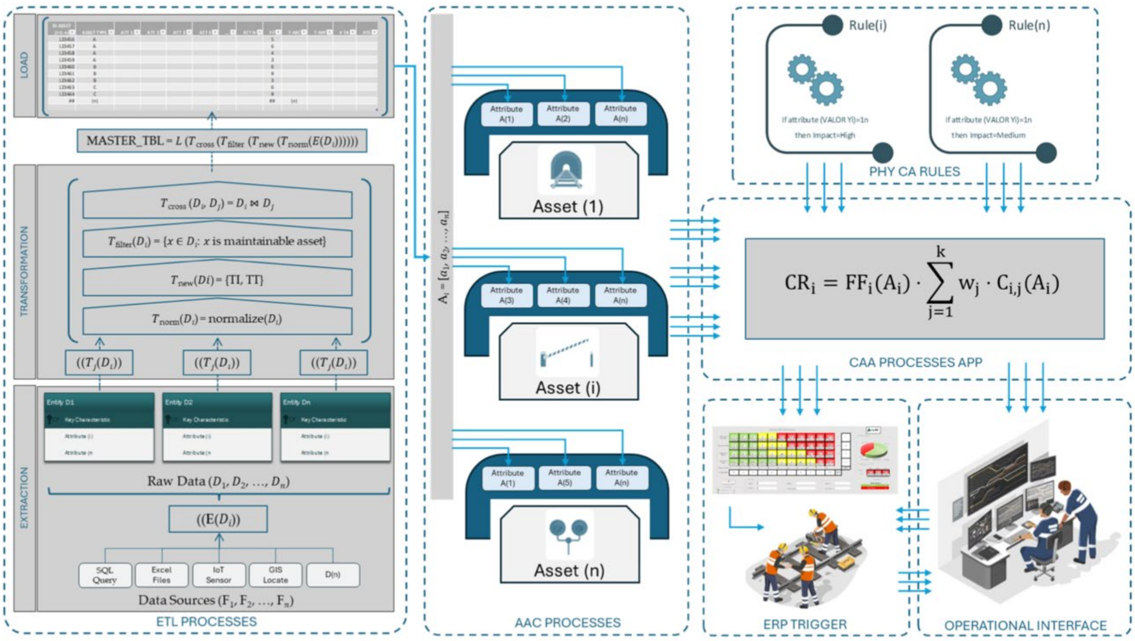


Figure 3. Simplified architecture of the APM model applied to the railway dynamic criticality analysis use case

4.3. Implementation and Results

The methodology was implemented in a large metropolitan railway network comprising over 700,000 assets. A representative sample of 4,018 critical assets was evaluated, drawing from more than 200,000 historical failure records.
Implementation steps included:

- Building a *Master Table* that consolidated attributes, failure records, and contextual data.
- Developing a set of criticality rules (safety, environment, cost, quality of service, operational penalties).
- Running the dynamic criticality engine to produce indexes for each asset class.
- Visualizing results through a dashboard, enabling both global overviews and asset-level drill-down.

Key results obtained:

- *Signaling systems:* Over 500 signaling subsystems were analyzed. Failures were found to generate delays averaging 45 minutes, affecting more than 60,000 passengers per day.
- *Track devices:* Around 700 critical devices (switches, crossings) were assessed, with an average failure frequency of 0.4 per year and an estimated cost of €50,000 per disruption.
- *Electrical substations:* 320 substations were evaluated. Failures in these systems were identified as highly critical, with potential impacts exceeding €100,000 per hour of downtime.

Impact achieved:

- A 25% reduction in unplanned stops, as maintenance strategies were adjusted based on criticality scores.
- A 15% reduction in operational costs, through optimized scheduling and resource allocation.
- Estimated savings of €2 million per year, by prioritizing high-criticality assets for proactive interventions.
- Significant improvements in asset availability and decision-making transparency, enabling better alignment between technical teams and management.

4.4. Lessons Learned and Replicability

Several important lessons emerged from this case study:

- *From static to dynamic criticality:* Moving from periodic, spreadsheet-based assessments to a dynamic, digitalized process improved responsiveness and accuracy.
- *Objective prioritization:* By integrating safety, cost, and service quality, criticality scores provided a transparent and defensible basis for decision-making.
- *Data-driven culture:* Adoption required cultural change, with engineers and managers engaging with digital dashboards instead of manual reports.
- *Challenges:* Data quality and interoperability across legacy systems remain key challenges, requiring continuous improvement in ETL pipelines and governance.

Replicability:
The methodology, while demonstrated in a railway network, is adaptable to other critical infrastructures such as *water utilities, power distribution networks, or airports.* By adjusting the attributes and criticality rules, the framework can provide dynamic asset prioritization in diverse industrial contexts.
Strategic value:
The case showed that digitalization of criticality analysis is not only a technical improvement but also a strategic enabler. It supports servitization models, risk-informed investment planning, and continuous alignment of maintenance strategies with organizational goals.

5. Use Case 4: APM Model for Preventive Maintenance Interval Optimization in Digitalized Railway Machines (DFMAS Project)

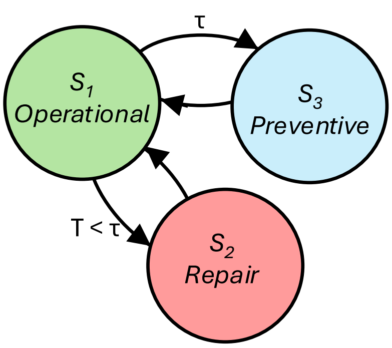
5.1. Context and Need

The digital transformation of railway maintenance has reached a new level of maturity through the integration of analytical Asset Performance Management (APM) models into Digital Twin environments. Within the DFMAS project, the ballast tamper Matisa B66 serves as a representative asset for the digitalization of complex maintenance processes in railway infrastructure machinery. These high-value assets are subject to both scheduled (preventive) and corrective maintenance actions, whose optimization has a direct economic and operational impact on fleet availability and the certification process known as *"Certificado de Aptitud para el Servicio"* (CAS).

Traditional preventive maintenance policies in railway maintenance fleets have been mainly time-based, defined by conservative inspection intervals. However, this approach often leads to non-optimal decisions: excessive preventive interventions that increase downtime and cost, or delayed interventions that increase the likelihood of failures. To overcome these limitations, the DFMAS project introduced an analytical semi-Markov APM model to determine the optimal preventive maintenance interval dynamically, based on operational data, failure statistics, and maintenance cost structures.

The approach distinguishes between two maintenance strategies:

1. A three-state model for assets managed under time-based preventive maintenance (predetermined interval), and
2. A four-state model for assets where degradation can be monitored in real time (condition-based maintenance).



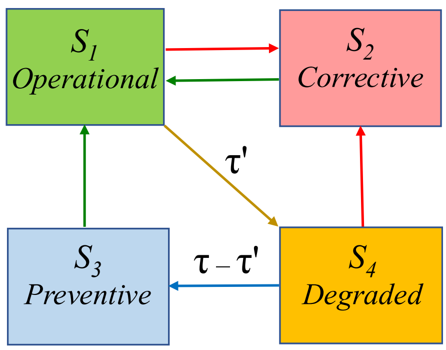


Figure 4. Analytical semi-Markov APM models (three and four states)

Both are integrated digitally within the Matisa B66 Digital Twin to enable continuous optimization of preventive intervals and maintenance planning across the fleet.

5.2. APM Model Architecture Applied

The analytical semi-Markov APM model builds upon the method originally formalized and adapted to the DFMAS digital architecture. The model represents the asset's lifecycle as a stochastic process evolving through discrete states, where each state corresponds to an operational condition and has associated costs, revenues, and transition probabilities.

For the three-state model, the system transitions among:

- E1: Operational state – the asset is functional and generating income per operating hour (R_1),
- E2: Corrective state – the asset has failed and is under repair, incurring costs per hour (R_2) and transition costs (R_{21}),

- E3: Preventive state – the asset undergoes scheduled maintenance, incurring costs (R_3) and transition costs (R_{31}).

The model assumes that after a preventive or corrective action, the asset returns to the operational state. The evolution between states follows a semi-Markov process, in which the probability of transition depends not only on the state but also on the elapsed time since entering it. The failure distribution of the asset is modelled using the Weibull probability density function, whose shape (α), scale (β), and location (γ) parameters are derived from historical maintenance data obtained through the company's CMMS (Computerized Maintenance Management System).
The objective is to maximize the average accumulated return over a finite operating horizon. An analytical solution is obtained by applying the z-transform to the system of difference equations governing state transitions, yielding a closed-form expression for the optimal preventive interval τ_o. This interval represents the operating time that maximizes economic return, balancing the costs of corrective actions with the cost and frequency of preventive ones.

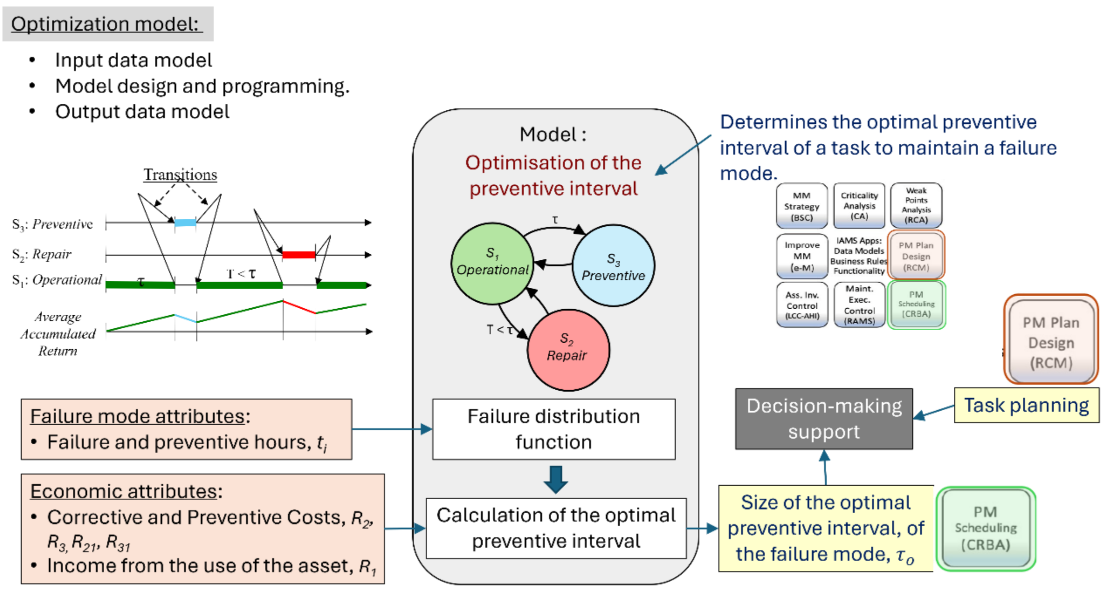


Figura 5. Digital integration of APM model (DFMAS Project)

For assets with measurable degradation, such as bearings or hydraulic systems equipped with vibration or temperature sensors, the model extends to a four-state configuration. The additional state, E4 (Degraded state), captures the intermediate condition between fully operational and failure, allowing the APM model to incorporate real-time degradation indicators into the decision logic. The digital system updates the preventive interval dynamically as new operational or failure data become available, ensuring continuous alignment between physical asset performance and maintenance policy.

5.3. Implementation and Results

The model was implemented within the Digital Twin of the Matisa B66 as part of the DFMAS project's *Intelligent Maintenance Model* layer, using PowerBIM as the visualization and integration platform. The model interacts with the asset database (structured according to ISO 14224 and RAMI 4.0 standards), IoT telemetry, and the maintenance management system (CMMS). Historical data from field operations and CAS inspections were used to calibrate the Weibull parameters and the economic coefficients for each state transition.

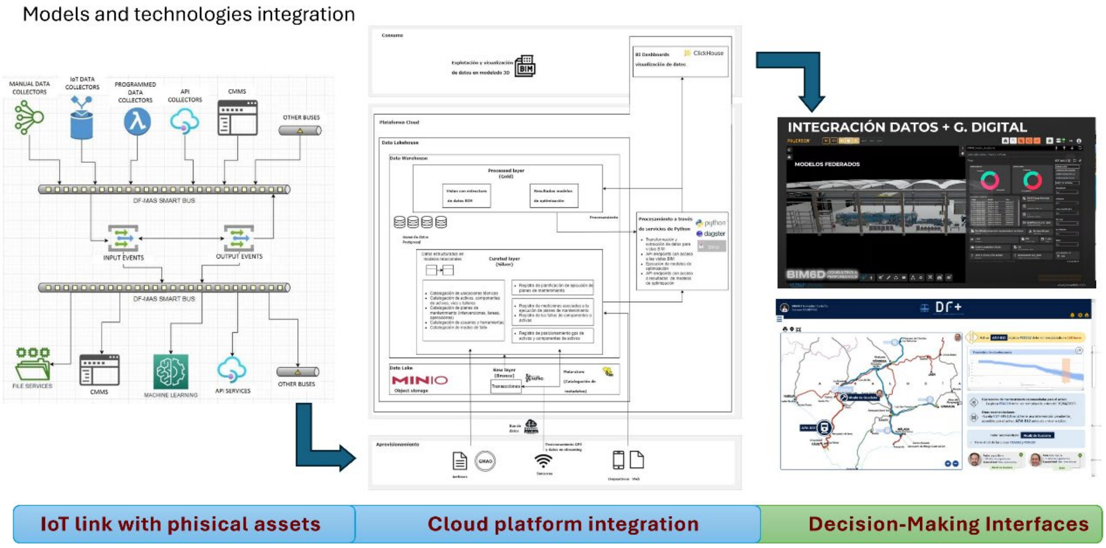


Figura 6. Digital integration of APM model (DFMAS Project)

A case study was performed on the belt tensioner of the Matisa B66 engine system — a component subject to annual preventive replacement as part of the CAS certification. The baseline preventive interval established by regulation was 3,500 operating hours per year. By applying the analytical semi-Markov APM model with historical and synthetic data, the optimal preventive interval τ_o was determined to be 2,375 hours, meaning that performing the preventive action earlier would maximize the average accumulated return over the asset's lifecycle.
The digital implementation also demonstrated key advantages:

- Dynamic recalculation of the preventive interval each time new operational or failure data were entered, enabling adaptive maintenance planning.
- Reduction of maintenance cost variability, as optimal intervals balanced repair and downtime costs.
- Improved decision transparency, since the digital model displayed both economic inputs (R-values) and probabilistic transitions within the PowerBIM interface.

A parallel study was carried out for rolling system bearings, applying the four-state version of the semi-Markov model. In this configuration, sensorized vibration data allowed the inclusion of the degraded state (E4), where the asset still operates but with reduced economic performance. The Digital Twin continuously adjusted the preventive interval according to updated degradation and reliability data, improving alignment between technical and economic criteria in condition-based maintenance.

5.4. Lessons Learned and Replicability

The implementation of the analytical semi-Markov APM model in the DFMAS Digital Twin yielded several technical and organizational insights:

- Analytical modeling enhances automation: The semi-Markov analytical formulation allows for the direct computation of optimal maintenance intervals without requiring complex simulations or heuristic optimization. This enables full automation of preventive scheduling in the Digital Twin.
- Integration of cost, reliability, and operational data: The use of standardized data models (ISO 14224, RAMI 4.0) ensured interoperability between the APM layer, the IoT data streams, and maintenance records, facilitating transparent decision-making.
- Scalability and adaptation: The model can be replicated for other subsystems of the Matisa B66 or across different types of maintenance vehicles (e.g., profiling machines, inspection units) by adjusting only the Weibull parameters and cost coefficients.
- Continuous optimization through digitalization: The integration of the model in PowerBIM enabled continuous updates of the preventive interval as new data entered the system, closing the loop between physical performance and digital decision-making.

- Human–system interaction and trust: Maintenance engineers were able to validate and interpret the model outputs easily, avoiding the perception of a "black box" system and fostering confidence in data-driven maintenance decisions.

Overall, the DFMAS implementation of the analytical semi-Markov APM model demonstrates how digitalization, reliability engineering, and economic optimization converge in the context of railway maintenance. The approach offers a robust and replicable methodology for achieving cost-effective, data-driven preventive maintenance scheduling within the framework of digital twin–based asset management.