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AI-DRIVEN PREDICTIVE OPTIMIZATION FRAMEWORK FOR RAILWAY INFRASTRUCTURE MAINTENANCE

Daniela Henríquez Flores, Zacarias Grande Andrade
Universitat Politècnica de Catalunya, Spain

Abstract

The railway system is a critical component of the transport sector, offering seamless connectivity between city centers, regional hubs, and distant rural areas. Its long-distance reachage and high-volume capacity enable the efficient movement of passengers and goods, while its energy efficiency and strong multimodal integration help alleviate urban road congestion and enhance overall network performance. Maintaining safety, efficiency, and operational capacity is essential to preserve these advantages and sustain the railway system's competitiveness over time. Traditionally, maintenance strategies have been based on preventive inspections focused on scheduled reviews and manual record keeping, along with the predefined replacement of components and parts without integrity or predictive-based analysis. Moreover, prediction lackage usually leads to repair and replacement interventions executed after fault detection, consequently generating high costs and operational congestion and unavailability. Hence, these maintenance strategies with marginal predictive approach generate unforeseen events, significant labor costs, planning difficulties, operational impacts, and higher safety risks due to the lack of early detection. Artificial Intelligence (AI) has demonstrated substantial effectiveness in processing and interpreting large-scale datasets, positioning it as a highly suitable technology for integration into railway maintenance systems. Driven by accurate analysis and prediction of real-time data with high parameter variability, enabling the early detection of anomalies, reducing the manual inspections dependency, and improving the infrastructure resilience. This study presents an optimization maintenance model based on a machine learning failure prediction, real-time AI data analysis, correlated with operational scenario and maintenance cost shared between corrective and predictive action, providing a maintenance plan action based on sensor, auscultation and predictive action, for the sake of minimizing the reactive/correctives interventions.

Keywords: predictive maintenance, railway maintenance, maintenance optimization, artificial intelligence

1 Introduction

The railway system is a critical component of transport due to its capacity, efficiency, and contribution to territorial connectivity [1], and its maintenance is essential to sustain adequate levels of safety, reliability, and availability in networks that operate continuously under constrained intervention windows [2]. In recent years, the use of condition data from inspections and non-destructive testing has gained relevance for improving decision-making [3]; however, a significant share of maintenance practice remains grounded in manual strategies and predefined preventive/corrective schemes, limiting the anticipation of degradation and the joint prioritization of interventions by risk and cost [4].

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Although advances exist in data analytics, artificial intelligence, and risk-based approaches, the challenge to integrate these elements into an operational and reliable framework persists [5]. Hence, this work addresses the aim to transform inspection information into prioritized decisions with a cost–resilience-risk criteria. The objective of this communication is to propose and structure a predictive optimization framework that connects condition data, AI-driven analytics, and a procedural knowledge base, under the hypothesis that such integration improves the consistency and traceability of prioritization and supports a progressive transition towards predictive strategies.

2 Research methodology

This research follows the Design Science Research (DSR) methodology and is structured into five main stages, with the aim of proposing and specifying an AI-based predictive optimization framework for railway infrastructure maintenance, oriented to cost and risk criteria [6]. Stage 1 characterizes the problems in operational terms, as well as establishing the maintenance requirement framework through scientific literature and technical documentation review, including railway standards, maintenance protocols, and cost databases. In addition, the RAMS approach is adopted, as a reference to structure reliability, availability, maintainability, and safety [7]. Based on this evidence, a knowledge foundation is built and organized by element and subcomponent, compiling damage, failure modes, associated interventions, and their descriptive parameters (occurrence probability, hazardous probability repair cost, infrastructure occupancy cost and failure/consequence cost). stage 2 proposes a maintenance management solution. Its purpose is to state succinctly the proposed solution and its scope: a predictive optimization framework that connects data-driven inspection, AI-based analysis, and cost–risk decision-making to prioritize and plan maintenance interventions [2]. Stage 3, methodology design, it consists of maintenance predictive optimization method development, thus building on the damage database defined in stage 1, a workflow is configured in which a "detected damage" provokes a systematic linkage among the affected asset, damage type, associated maintenance interventions (RAMS-oriented) [7] and the relevant probability and cost parameters. With this aim, the method applies prioritization rules and criteria to estimate risk and lifecycle impact, proposing, as output, a structured set of interventions ranked by urgency or suitability to the forecasted or occurred incident in a particular infrastructure and operative situation. Finally, stage 4, final validation, this section exposes the methodology validation in a simple pilot to verify consistency and full traceability, and in the last stage 5, to finish an impact assessment is developed in a wider scenario with the aim to evaluate the performance evidence of this methodology in the railway maintenance protocol and LCC.

3 Results

3.1 Challenges in the current railway maintenance management

After reviewing the state of the art, it becomes evident that current railway maintenance practices largely rely on manually predefined strategies, mainly based on preventive maintenance, complemented by corrective actions once failures occur [2]. This approach leads to significant operational limitations. In particular, there is a strong dependence on human-based inspections, which are not always systematically formalized [5]. Maintenance decisions are often static, being based on fixed intervals or generic thresholds, and therefore fail to adequately adapt to the dynamic variability of railway systems in operation [5]. Such variability includes weather and climatic conditions, changes in the operational context, and evolving usage patterns.

Consequently, these limitations can have a substantial impact on both operational costs and overall system performance. The current strategy driven by both unplanned urgent interventions as well as premature replacements or actions that fail to maximize the asset's service life [2]. In many main lines, the deployment of diagnostic trains and instrumented monitoring has already reduced reliance on purely manual inspections; however, human-led inspections and validation remain essential for a wide range of assets and contexts, particularly outside heavily monitored corridors.

3.2 Knowledge base developed from the review

In response to the problem characterization stage, the documentary outputs supporting the subsequent development of the proposed framework were produced and organized. The maintenance procedure for each asset element is formalized, based on the applicable technical standards. As a result of the review of technical standards and reference documentation, the knowledge base was aligned with the RAMS approach [7], representing damage as hazards that can be characterized in terms of frequency and consequence. To support prioritization, a simplified probabilistic–economic scheme was adopted based on the annual probability of occurrence and the annual conditional probability of a severe consequence. These probabilities were discretized using an ordinal five-level scale (1–5), associated with representative orders of magnitude in the approximate range of 10^{-5}–10^{-1} per year, as shown in table 1 [7]. Each damage type was assigned to a corresponding level through engineering judgement, supported by cross-checking against typical frequencies reported in railway reference sources, and distinguishing between relatively frequent defects and rarer but potentially critical events. Since occurrence classes and thresholds are not fully standardized across Infrastructure Managers (IMs), organizations responsible for managing and maintaining railway infrastructure, the boundaries adopted here are presented as a methodological construct aligned with RAMS-oriented risk assessment practice and supported by evidence gathered from the literature (and, where available, historical records).

Table 1 Ordinal probability scale for annual occurrence (levels 1–5)

Level	Qualitative range	Annual probability
1	Very rare	10^{-5}
2	Rare	10^{-4}
3	Occasional	10^{-3}
4	Frequent	10^{-2}
5	Very frequent/common	10^{-1}

Table 2 presents a snapshoot of the element- and subcomponent-level tables, detailing damage and failure modes and their corresponding maintenance interventions. In this paper, the exemplified entries are primarily grounded in Spanish railway documentation (ADIF), while other parts of the knowledge base also draw on the broader research literature and additional technical sources. Table 3 presents an excerpt of the probabilistic parameter table, detailing damage-type-specific probabilities of occurrence and severe consequences, along with repair costs and the impacts associated with each consequence scenario. Repair cost values reported in table 3 were compiled from the official ADIF unit-cost database.
These inputs form the structured basis for the design of the prioritization process and predictive optimization in subsequent stages.

Table 2 Knowledge base snapshot: damage/failure modes and interventions

Nº	Element	Subdivision	Damage type	Actions	Ref.
1	Track	Rail head	Rail corrugation	Rail grinding	[8, 9]
2	Track	Sleepers	Breakage	Replace defective sleepers	[8, 10]
3	Track	Track geometry	Longitudinal level defect	Tamping and lining to re-level and realign the track	[8-12]
4	Signaling	Lineside sign installation	Sign incorrectly positioned	Relocate the sign	[13]
5	Control system	Electronic interlocking	Configuration error	Correct parameter configuration	[14]
6	Catenary	Contact wire	Excessive contact wire wear	Replace contact wire	[15]
7	Telecommunications	Optical fibre	Cable cut/break	Replace the affected section	[16]
8	Earthworks	Cut slope	Shallow/surface slides	Remove slipped material and reprofile the slope	[17-20]

Table 3 Probabilistic parameters and repair costs by damage type

Nº	Occurrence probability	Fatality probability	Repair cost	Unit
1	$3 \dashrightarrow 10^{-3}$	$3 \dashrightarrow 10^{-4}$	29, 21	€/m
2	$2 \dashrightarrow 10^{-4}$	$3 \dashrightarrow 10^{-4}$	194, 15	€/ud
3	$3 \dashrightarrow 10^{-3}$	$3 \dashrightarrow 10^{-4}$	3, 88	€/m
4	$2 \dashrightarrow 10^{-4}$	$2 \dashrightarrow 10^{-5}$	461, 53	€/ud
5	$2 \dashrightarrow 10^{-4}$	$4 \dashrightarrow 10^{-3}$	5408, 28	€/ud
6	$3 \dashrightarrow 10^{-3}$	$3 \dashrightarrow 10^{-4}$	18797, 02	€/km
7	$3 \dashrightarrow 10^{-3}$	$2 \dashrightarrow 10^{-5}$	3, 42	€/m
8	$3 \dashrightarrow 10^{-3}$	$3 \dashrightarrow 10^{-4}$	14, 54	€/m^3

3.3 Operational workflow of the proposed framework

An operational workflow was defined to describe how the proposed framework functions, from information capture to the generation of a maintenance plan. This result is presented as a five-stage diagram (figure 1) synthesizing the key transformations that convert inspection data into cost–risk decisions. In stage 1, condition data are acquired through different inspection techniques, together with variables describing the operational and environmental context. In stage 2, these data are consolidated and referenced to the asset and its location so that they can be consistently compared and integrated. In stage 3, AI-based analytics are applied to identify anomalies or damage and to generate a detected event with minimum set attributes (type, location, severity, and confidence). In stage 4, the detected event is transformed into a time-dependent risk profile through AI-supported probabilistic updating, combining condition evidence with baseline parameters and cost information retrieved from the knowledge base.

Finally, in stage 5, maintenance interventions are prioritized and selected in accordance with the defined procedural logic and a cost–risk criterion, resulting in an optimized intervention plan. Within this workflow, stage 3 links detected events to the damage/failure classification and candidate interventions (table 2); stage 4 updates risk using the occurrence discretization (table 1) together with the probabilistic and cost parameters (table 3); and stage 5 prioritizes interventions by combining the intervention logic (table 2) with cost inputs (table 3) under a cost–risk perspective.

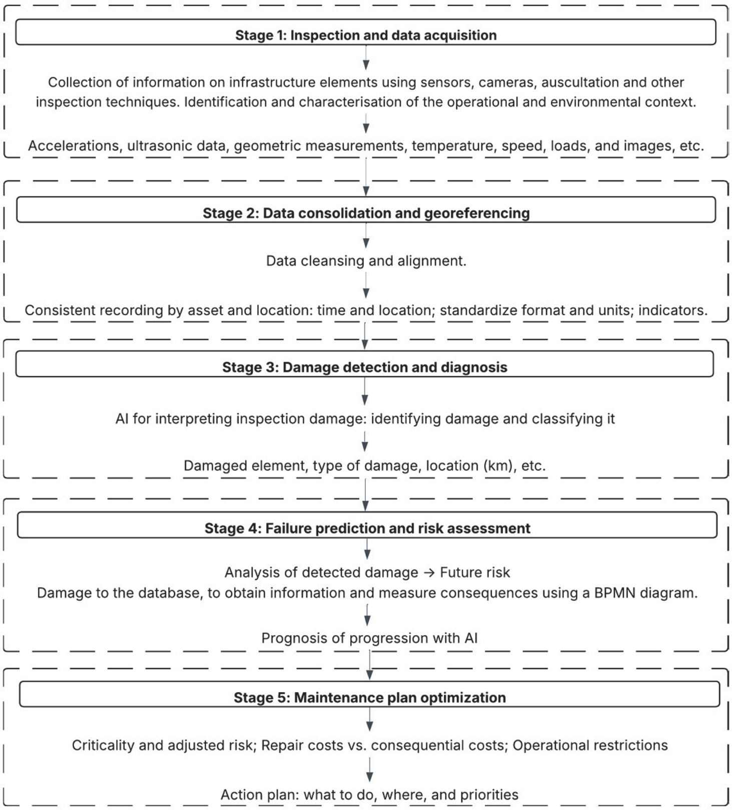

Figure 1 Operational workflow of the proposed framework (five stages)

4 Discussions

4.1 Current operational limitations in railway maintenance

In practice, railway maintenance systems and protocols largely rely on predefined preventive schemes and reactive corrective interventions, with limited implementation of predictive maintenance approaches aimed at anticipating degradation and preventing the occurrence of infrastructure failures [21]. This gap gives rise to a range of recurring operational constraints. From a cost perspective, defects can lead to unforeseen expenditure due to urgent repairs and unplanned procurement of spare parts, in addition to labor costs associated with periodic inspections that do not always reflect the asset's actual condition. In parallel, interval-based approaches may induce premature component replacement before an optimal service life has been reached, generating economic inefficiencies [2].

From a planning standpoint, uncertainty in the availability and replenishment of spare parts can extend intervention durations and complicate resource scheduling. In terms of operational impact, unexpected failures cause service disruptions and delays, while even scheduled overhauls, although less disruptive than corrective maintenance, still require downtime windows and impose operational restrictions [21]. Finally, from a safety perspective, the absence of systematic early-detection mechanisms and risk-based prioritization increases exposure to critical events and potential accidents.

4.2 Potential benefits of the proposed optimization

Under the proposed workflow, the potential benefits of this methodology can be articulated across three complementary dimensions-time, operations, and economics- and stem from its ability to integrate, within a single framework, data-driven inspection, AI-supported analytics (intended to complement rather than replace codified maintenance logic), and cost–risk decision-making [2, 5]. From a time perspective the primary contribution lies in enhanced scheduling and prioritization of maintenance interventions, achieved by transforming condition measurements into structured events and, subsequently, into actionable recommendations. This enables resources to be directed towards more timely and necessary interventions, thereby reducing re-planning associated with poorly informed decisions [21].
From an operational perspective, the tool supports more proactive maintenance strategy by enabling early detection and characterization of anomalies or damage, and by incorporating a probabilistic updating logic that translates observed condition evidence into decision-relevant information [3]. This facilitates criticality-based prioritization and improves consistency between asset conditions and the recommended maintenance action. Finally, economically, cost–risk an improved balance between corrective and predictive actions can contribute to reducing the expected total cost of maintenance. This is achieved in particular by explicitly accounting for consequence-related costs alongside repair costs, while promoting more efficient resource allocation and extending component service life through condition-aligned interventions.

4.3 Limitations of the study in its current state

This work is presented as a methodological proposal in a design phase, with some components already structured and others yet to be implemented and empirically validated. First, the robustness of the approach depends on the quality, completeness, and traceability of inspection data, as inconsistencies in data capture or metadata directly affect detection performance and risk estimation [5]. Second, the cost–risk parameterization is constrained by the limited availability of probabilistic information in open sources, which complicates and slows calibration, particularly in the absence of a validated historical record [2]. Third, some relevant procedures and technical specifications are contained in restricted-access documentation, limiting coverage and requiring initial assumptions. Finally, because the framework spans multiple railway asset types, consistent normalization criteria, scales, and shared decision rules are required to compare priorities across assets and to progressively incorporate operational constraints, which may vary by network and operator.

5 Conclusion

This work presented a proposal to progress from predominantly preventive and corrective maintenance approaches towards a more predictive, cost- and risk-oriented logic for railway infrastructure management. The study addresses the challenge of converting inspection information into prioritized intervention decisions, while remaining consistent with technical procedures and the operational constraints inherent to railway systems.

The main contributions include the structuring of a knowledge base to organize damage and failure modes, associated maintenance interventions, and relevant parameters; the formalization of procedural maintenance logic through diagrams, and the definition of an operational workflow that links data acquisition, AI-supported detection, risk updating, and intervention prioritization. Taken together, these elements establish a traceable methodological foundation for the development and subsequent implementation of the proposed framework.
Although the proposal still requires empirical validation and parameter calibration, conditioned by data availability, access to technical documentation, and context-specific operational constraints, the approach provides a clear pathway for integrating condition evidence with cost–risk criteria in maintenance planning. Future work will focus on implementing a prototype and evaluating its performance in bounded cases studies, with the aim of quantifying its impact and progressively refining the framework towards operational applications.

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