



MANAGEMENT OF AI SMART MONITORING IN RAILWAY SYSTEMS: A REVIEW OF PREDICTIVE MAINTENANCE, RISK-INFORMED DECISION SUPPORT, AND OPERATIONAL RESILIENCE

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Abstract – Artificial intelligence, data-driven condition monitoring and digital twins are increasingly used to anticipate railway degradation, yet their managerial value depends on whether predictions are converted into defensible maintenance actions. This paper provides a structured narrative review of recent peer-reviewed evidence on railway predictive maintenance, focusing on maintenance management rather than algorithmic performance alone. The synthesis examines condition assessment, failure anticipation, maintenance prioritization, scheduling and resource allocation, and closed-loop performance feedback across infrastructure and rolling-stock applications. Recent studies show that machine-learning models can identify high-risk track sections, provide explainable real-time fault warnings, and optimize tamping schedules under operational constraints. However, a persistent translation gap remains between accurate diagnosis and network-level management because of limited field validation, weak interoperability, uncertainty, black-box models, and fragmented system integration. A monitoring-to-management framework is therefore proposed, linking sensing, diagnosis, prognosis, criticality assessment, prioritization, scheduling, intervention and feedback, supported by explainability, data governance and lifecycle costing. The review positions AI monitoring as a decision-support capability embedded within railway asset-management processes.

Keywords – railway maintenance; maintenance management; predictive maintenance; artificial intelligence; decision support.

1. INTRODUCTION

Railway maintenance management is fundamentally a decision problem: managers must determine where, when and how to intervene across heterogeneous assets while balancing safety, service availability, possession time, workforce, machinery and lifecycle cost. Predictive maintenance is supported by sensors, machine learning and digital twins, and recent reviews document rapid growth of these technologies across railway subsystems [1,2]. Yet the practical value of prediction is not determined by diagnostic accuracy alone. A model becomes useful to maintenance management only when its output changes priority, schedule, resource allocation,

renewal choice or operational restriction. This distinction exposes a recurring gap in literature. Technical studies commonly optimize detection, classification or remaining-life estimation, whereas railway managers require decisions under uncertainty and operational constraints. Predictions may arrive without sufficient lead time, without explicit criticality, without transparent reasoning, or without integration with maintenance planning systems. Conversely, studies now connect condition data to prioritization, scheduling and prescriptive analytics, creating a basis for a more management-oriented synthesis. The objective of this paper is to review how recent AI railway monitoring progresses from

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condition information to actionable maintenance management. The contribution is a structured narrative synthesis organized by decision function and a monitoring-to-management framework that identifies the stages and enabling conditions required to translate predictive outputs into operational action.

2. REVIEW APPROACH

A structured narrative review was adopted to fit the conference format while retaining a transparent analytical logic. The evidence base comprises recent peer-reviewed studies published in 2025-2026 and selected because they explicitly connect monitoring or prediction with at least one management function: condition assessment, failure anticipation, prioritization, scheduling, resource allocation, decision explainability, or lifecycle asset management. Candidate studies were identified through targeted Scopus searches using combinations of railway, predictive maintenance, artificial intelligence, machine learning, digital twin, maintenance management, decision support, scheduling and asset management. Final selection was purposive, retaining studies that demonstrated an explicit link between a monitoring or predictive output and a maintenance-management decision, operational outcome or implementation barrier. Review papers were used to identify field-level gaps, while empirical studies were used to examine how technical outputs are converted into decisions. The synthesis is organized by decision function rather than by algorithm family; it is interpretive and comparative, not a pooled-effect meta-analysis.

3. FROM PREDICTION TO MAINTENANCE DECISIONS

Recent evidence shows that prediction is becoming more directly linked to intervention needs. Morais et al. proposed a framework in which heterogeneous performance indicators are processed and forecast to support railway-track maintenance management over time [3]. In a Western Balkans case study, Trajkova et al. used inspection, infrastructure, operational and maintenance variables to predict Track Quality Index on the Kolashin-Podgorica line [4]. Random Forest outperformed multiple linear regression ($R^2 = 0.69$ versus 0.57), and the model achieved 86.4% sensitivity for high-risk segments. Importantly, the output was interpreted as a basis for prioritizing tamping, renewal and targeted interventions rather than merely as a prediction score. The choice of management variable can be as important as the predictive algorithm. For freight-wagon wheelsets, Bhadouria et al. compared time, mileage and gross-ton mileage through regression, survival analysis and reinforcement learning, identifying gross-ton mileage

as the most reliable lifetime variable for maintenance decisions [5]. Toribio et al. addressed another management requirement: lead time. Their two-stage framework combined forecasting and anomaly detection for metro trains and maintained effective detection at one- and three-hour horizons, giving maintenance teams time to prepare interventions rather than react only after deviations become visible [6].

Decision support in safety-critical maintenance requires not only a warning but also a credible basis for action. Using real data streams from the Porto metro operator, García-Méndez et al. developed an online predictive-maintenance pipeline with visual and natural-language explanations, reporting more than 98% F-measure and 99% accuracy [7]. The contribution is managerial as well as technical: explanations allow decision-makers to relate an alert to the underlying sensor behavior and respond more rapidly. Sayed et al. reached a complementary conclusion for track-geometry defects [8]. Their SMOTE-SHAP workflow improved minority-defect recall for several classifiers and exposed the influence of physically meaningful variables, but precision trade-offs and moderate overall discrimination led the authors to position the models as screening and prioritization aids rather than stand-alone operational decision systems. Together, these studies show why explainability should be treated as part of decision quality, especially when false alarms consume scarce maintenance capacity.

The strongest transition from prediction to management occurs when models optimize a maintenance action. MajidiParast et al. presented a prescriptive analytics framework using graph convolutional networks and historical maintenance data to support optimal railway-track maintenance scheduling while representing spatial interdependencies [9]. Ge et al. moved further toward operational planning by integrating stochastic track deterioration, maintenance-window constraints and cost into a deep-reinforcement-learning model for tamping [10]. Validation on a real 50 km ballasted-track section produced feasible schedules and reduced labor, material and machinery-use costs by 27.8%, 8.3% and 16.9%, respectively. These results illustrate a central management principle: predictive accuracy becomes operational value when the objective function also represents possession, timeliness, cost, resource use and expected maintenance benefit.

Digital twins provide a potential architecture for connecting monitoring, simulation and maintenance decisions. Bianchi et al. combined a digital twin of bonded insulated rail joints with AI classifiers to support predictive structural-health monitoring [11], and a subsequent physics-informed DT-AI framework

extended this logic to coupled joint and sleeper degradation, creating a decision-oriented workflow for automated condition assessment and future prioritization [12]. At a broader level, Kazemi et al. found that DT applications can improve monitoring and decision support, but most implementations remain conceptual or pilot-scale and face interoperability, scalability, data-governance and validation barriers [13]. Mutlu and Kaewunruen similarly identified a 'Digital Twin Gap': many railway systems remain unidirectional digital representations rather than fully synchronized decision environments [2]. Rolling-stock work integrating BIM, PdM and continuously updated digital representations further demonstrates the potential for lifecycle-oriented asset management, while also underscoring the need for robust interoperability [14].

4. MONITORING-TO-MANAGEMENT FRAMEWORK

The reviewed evidence supports a decision-maturity sequence in which each technical output must answer a progressively more managerial question. Condition data establish what is happening; diagnosis identifies the health state; prognosis estimates what is likely to happen and when; criticality assessment adds consequence and uncertainty; prioritization determines where intervention is most valuable; scheduling determines when the work can be executed; resource allocation determines with what crew, machinery and budget; and feedback verifies whether the intervention restored the expected condition. Fig. 1 summarizes this monitoring-to-management logic.

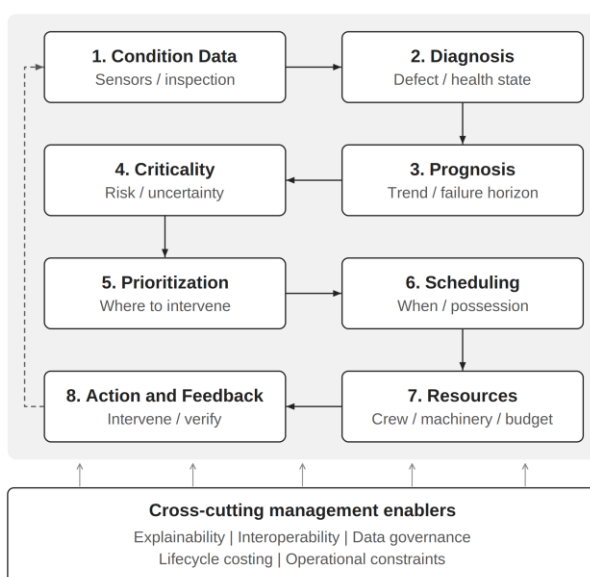


Fig. 1. Monitoring-to-management framework for AI-enabled railway maintenance

Three cross-cutting requirements determine

whether this chain is reliable. First, decision traceability requires interpretable indicators, confidence information and a documented link between a prediction and the proposed intervention. Second, constraint-aware optimization requires technical conditions to be evaluated together with maintenance windows, costs, resources and service effects. Third, closed-loop validation requires post-intervention data to be returned to the asset record and used to test whether predicted benefits were achieved. This shifts performance assessment away from model accuracy alone toward management outcomes such as avoided failures, intervention lead time, possession hours, resource utilization, cost per maintained asset, false-alarm burden and post-maintenance condition recovery.

5. DISCUSSION

A consistent pattern is seen across the literature: railway research is strongest at detection and prognosis, while evidence becomes thinner as the decision moves toward network-level prioritization, integrated scheduling and closed-loop management. Systematic reviews report concentration on selected assets and limited practical validation [1], while DT reviews show that many implementations remain subsystem-specific prototypes [2,13]. The implication is not that more complex algorithms are always needed; rather, railway maintenance systems require stronger integration between analytics and the management processes that convert evidence into executable work. Viewed through the proposed framework, the literature can be interpreted in four decision-maturity levels: condition visibility, prediction of degradation or failure, prescriptive support for prioritization or scheduling, and closed-loop management in which intervention results update subsequent decisions. For deployment, this means that technical validation should be accompanied by decision validation. A high-performing model that cannot express uncertainty, explain an alert, accommodate possession constraints or exchange data with asset-management systems may add little operational value. By contrast, the most management-relevant studies in the reviewed set explicitly linked prediction to prioritization [4,8], actionable lead time [6,7], prescriptive scheduling [9,10], or lifecycle integration [11-14]. Future work should test integrated solutions across multiple asset classes and operating conditions, report lifecycle cost and service outcomes, and evaluate whether recommendations remain stable when data quality, traffic, weather and resource constraints change.

6. CONCLUSION

AI monitoring is expanding the technical basis of

railway predictive maintenance, but its management value is realized only when diagnostic and prognostic outputs are translated into decisions that can be prioritized, scheduled, resourced and verified. Recent studies demonstrate credible progress: high-risk track segments can be identified, warnings can be produced with useful lead time and explanations, and maintenance schedules can be optimized under practical constraints. At the same time, field validation, interoperability, uncertainty treatment and system-level integration remain major barriers. The proposed monitoring-to-management framework places predictive models inside an asset-management cycle that links condition data to criticality, prioritization, scheduling, intervention and feedback. This management perspective provides a practical basis for evaluating railway AI not only by what it predicts, but by the quality and measurability of the maintenance decisions it enables.

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