CETRA2026 27-30 May 2026, Bol, Island Brač, Croatia
9th International Conference on Road and Rail Infrastructure

AI-ENHANCED CONDITION-BASED MAINTENANCE FRAMEWORK FOR NRPCES - NEW REPLACEMENT POLICY CONSIDERING ENVIRONMENTAL SUSTAINABILITY PROJECT

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Abstract

This paper presents an integrated framework for condition-based railway track maintenance combining monitoring data, vehicle–track dynamic simulation, predictive modelling, and life-cycle assessment. Applied to a freight line upgraded to passenger service, track geometry measurements are used to predict degradation and support maintenance planning. A numerical modelling approach is performed, including vehicle–track dynamic simulations to evaluate wheel–rail interaction forces under representative operating conditions to serve as inputs for modelling the estimation of track degradation. Climate-related factors are included in the analysis, and maintenance/repair alternatives are evaluated through Life Cycle Assessment (LCA), with focus on the carbon footprint, and Life Cycle Cost (LCC) analyses. In the present study, the maintenance analysis focuses on tamping interventions. The current results mainly address the dynamic modelling for rigid and flexible track representations. The prediction of track degradation and the development of an AI-based condition-based maintenance decision model is part of the ongoing work, where degradation indicators will be used to support future maintenance scheduling within the proposed framework. Overall, the proposed approach will contribute to more sustainable, cost-effective, and resilient railway infrastructure management, aligning with the objectives of modern railway systems and environmental sustainability priorities. This work is part of the ongoing NRPCES (New Replacement Policy Considering Environmental Sustainability) project, funded by the EUREKA program, which aims to develop innovative, sustainability-oriented approaches to asset management and maintenance planning.

Keywords: railway infrastructure, AI-based condition-maintenance approach, track geometrical degradation

1 Introduction

Railway infrastructure maintenance is essential to ensure safety, availability, ride comfort, and cost-efficient operation under increasing traffic demands [1]. Current studies have focused on track degradation and maintenance planning through integrated analyses of local track per-

DOI: https://doi.org/10.5592/CO/CETRA.2026.1871

formance, data-driven prediction methods, and condition-based maintenance models based on deterministic and probabilistic/stochastic deterioration assumptions [2-5], while persistent challenges related to data quality, inspection irregularity, and model implementation in practice are indicated [6]. These limitations have driven the adoption of predictive maintenance approaches based on measured condition indicators and track quality data [7-9]. The increasing availability of monitoring data and advances in artificial intelligence (AI) have enabled condition-based moving forward to predictive maintenance scheduling. Machine learning and deep learning models can learn degradation patterns from historical measurements and improve the prediction of track geometry evolution, supporting maintenance planning and prioritization [8-10]. In parallel, vehicle–track dynamic modelling remains essential, providing physically meaningful quantities such as wheel–rail contact forces to support degradation assessment and maintenance analysis [11]. Climate and environmental conditions represent an important external driver of railway infrastructure degradation and operational performance. Temperature extremes influence rail thermal expansion and track-level thermal loading, while precipitation and runoff govern drainage loading, moisture conditions, and the occurrence of localized flooding or erosion, which can adversely affect track stability and performance [12, 13]. Previous studies [12-14] have shown that long-term warming trends and short-duration hydrological extremes can significantly affect railway reliability, maintenance demand, and life-cycle costs, particularly in coastal and urban corridors. Consequently, the integration of consistent weather and climate information is essential for linking observed track condition, numerical simulation, and sustainability-oriented maintenance planning.

Integrating LCA, carbon footprint evaluation, and cost analysis into railway maintenance planning is increasingly relevant as infrastructure managers seek to enhance the sustainability of their operations. Traditional maintenance strategies often lead to inefficient use of resources, either by intervening too early on assets that remain in good condition or by reacting too late to accelerate degradation, thereby increasing material consumption, energy use, and associated emissions. The shift toward predictive, data-driven maintenance frameworks supported by monitoring technologies, AI-based degradation modelling, and vehicle–track dynamic simulations provides a more accurate understanding of when and where interventions are truly needed. When combined with climate-informed degradation indicators, these approaches allow maintenance actions to be optimized not only for performance and safety but also for environmental impact. Embedding LCA and carbon footprint metrics into this decision-making process enables the quantification of emissions and resource use across the full maintenance cycle, while LCC analysis ensures economic viability [15]. This paper presents the railway component of an AI-enhanced condition-based maintenance framework that combines monitoring data, dynamic simulation, and climate-informed degradation indicators. The framework supports maintenance and renewal decisions through LCC, LCA) promoting more sustainable infrastructure management.

2 Project description

NRPCES is an international project funded under the EUREKA program, involving academic and industrial partners from a consortium spanning Sweden, Belgium, and Portugal. The Portuguese consortium includes the Faculty of Engineering of the University of Porto (FEUP), Instituto Superior de Engenharia do Porto (ISEP), and the company Dosta Tec. To fulfil these objectives, the project is structured into seven work packages: WP1 – Project Management and Coordination; WP2 – Requirements, Specifications, and Data Collection; WP3 – Environmental Impacts and Circular Economy; WP4 – Monitoring, Inspection, and Predictive Maintenance Modelling; WP5 – Economic Replacement Time Modelling; WP6 – Platform Integration, Validation, and Demonstration; and WP7 – Dissemination and Exploitation. In the Portuguese use case, the contribution of the FEUP focuses on the upgrading of a freight railway line to urban passenger service, with emphasis on condition-based maintenance, environmental performance, and life-cycle efficiency.

3 Case study and model description

The study focuses on the Leixões Line, a 20.9 km railway corridor in the Porto Metropolitan Area connecting Porto-Campanhã to the Port of Leixões (figure 1). After passenger services ceased in 1966, the line was mainly used for freight transport, with limited passenger operations reintroduced between 2009 and 2011. A recent modernization initiative led by Infraestruturas de Portugal (IP), Comboios de Portugal (CP), and the Matosinhos municipality aims to upgrade the line and reinstate regular passenger services. This railway line carries 60 passenger trains on weekdays, 30 in each direction, with a frequency of two trains per hour per direction during peak hours in the morning and evening, while on weekends and public holidays, 34 trains are scheduled, 17 per direction [16].

Figure 1 Track routes in Portugal: Leixões Line

4 Data collection and monitoring sources

Track geometry and condition-state monitoring include key parameters affecting vehicle dynamics and track deterioration: longitudinal level, alignment, gauge, twist, and cross level. Measurements on the Leixões Line are collected through periodic inspections using the EM120 track-geometry measurement vehicle at 0.25 m intervals. Six campaigns (2020–2025) cover 17 km of the 20.9 km corridor. The dataset supports defect identification, vehicle–track dynamic simulations, and degradation modelling within the NRPCES framework. Figure 2 illustrates the spatial variability of longitudinal level and alignment along the track, highlighting both localized defects and distributed irregularities. These characteristics motivate the use of segment-level statistical indicators, which are later used as inputs for the prediction model and maintenance optimization.

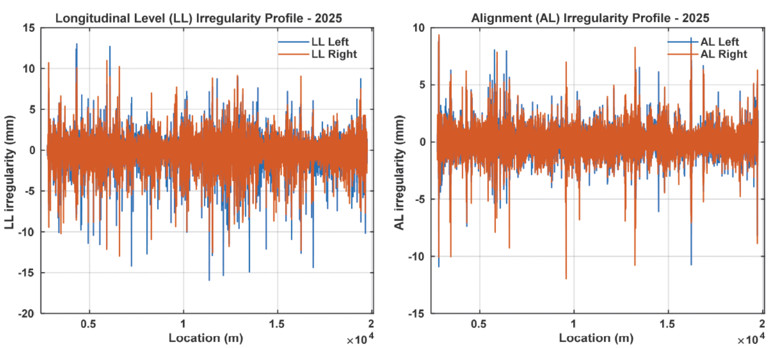

Figure 2 Example LL and AL irregularity profiles obtained from one inspection campaign (left and right rails)

Weather and climate data are used to characterize environmental forcing affecting railway track behavior. Meteorological and land-surface variables were obtained from the ERA5-Land reanalysis dataset, which provides hourly data at ~9 km spatial resolution and ensures temporal consistency through the integration of observations and physically based models [17]. Climatic conditions along the railway corridor were represented using a Thiessen polygon–based aggregation, where ERA5-Land grid points were weighted according to the proportion of track length within each polygon, yielding a representative time series for the alignment. The extracted variables include precipitation, runoff, evaporation, soil moisture at multiple depths, air and surface temperatures, soil temperature, solar radiation, wind speed, and surface pressure. These data were processed at hourly resolution and aggregated to monthly, seasonal, and annual scales as required. The resulting dataset provides consistent environmental input for numerical simulations, degradation analysis, and condition-based maintenance modelling. These variables provide the environmental context for interpreting degradation behavior and support the future climate-informed expansion of the framework. Real and specific literature environmental data from several maintenance operations will be used to express the current practices ongoing in the railways. Environmental data will comprehend the amounts of energy (electricity or fuels) used in machinery, the quantity and type of materials used, and the cost associated with the maintenance operations. The data will identify the critical spots in terms of the number and frequency of the operations and will feed the numerical simulations aiming for the appropriate improvements in the maintenance planning.

5 Overall framework and methodology

The proposed framework integrates multi-source monitoring, mechanical modelling, and predictive maintenance analysis to support condition-based management of railway infrastructure. As illustrated in figure 3 the workflow combines track geometry measurements, infrastructure records, LCA and cost data, and maintenance information to derive degradation indicators and support maintenance decision-making. The figure summarizes the overall workflow of the proposed framework. The process starts with monitoring data (track geometry and environmental variables), which are pre-processed to derive condition indicators. These indicators are then used in two parallel branches: a physics-based simulation to estimate wheel–rail interaction forces, and a data-driven model to predict future track condition. The outputs of these two branches are subsequently integrated into the maintenance optimization model, which determines the required interventions and supports sustainability assessment. Initially, track geometry and condition-state measurements are pre-processed to synchronize in space inspection campaigns. From these data, EN-based segment-level standard deviation indicators are computed over 200 m length segments for each rail. In parallel, reanalysis-based climatic and hydrological datasets (ERA5-Land) are processed to characterize corridor-scale thermal and precipitation-related forcing through trend and extreme-event analysis. These environmental metrics provide contextual information for interpreting observed track condition and support future integration within predictive maintenance modelling.

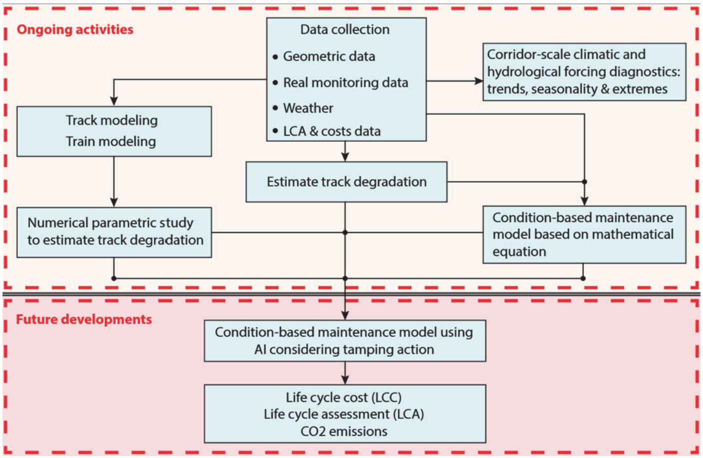

Figure 3 Overall workflow of the proposed framework, from data collection and condition indicator derivation to simulation, prediction, maintenance optimization, and sustainability assessment

Two complementary modelling branches are then developed. In the physics-based branch, a detailed vehicle–track interaction model is implemented in the multibody simulation software. Freight train configurations are simulated under varying speeds, friction coefficients, and track geometry states. The track is represented by using both rigid and flexible configurations to evaluate sensitivity to track flexibility. The resulting wheel–rail contact forces are subsequently transferred to a finite-element model to estimate degradation rates of ballast and other track components. These wheel–rail contact forces also constitute the main output of the physics-based branch reported in section 6.1, where the differences between rigid and flexible track representations are analyzed. In the data-driven branch, historical multi-year geometry indicators are used to train a Long Short-Term Memory (LSTM) model to predict the condition state at the next inspection cycle. By combining predicted and measured values, segment-level degradation rates are derived, enabling early identification of deterioration hotspots and providing inputs for maintenance planning. Accordingly, the outputs of this branch are presented in the Results section through the comparison between predicted and measured values for the unseen campaign and through the forecasted condition state for the following year. These results provide the basis for identifying future degradation patterns and prioritizing maintenance actions. The estimated deterioration behaviour from the physics-based and data-driven models is then incorporated into a condition-based maintenance optimization model, formulated as a Mixed-Integer Linear Programming (MILP) problem extending the previous works of Vale et el. [4, 5]. The resulting optimized maintenance scheduling will then be used to quantify LCC, LCA, and associated CO_2 emissions. This final step quantifies economic and environmental impacts, enabling the selection of maintenance policies that balance performance, cost efficiency, and sustainability within the NRPCES framework. Accordingly, the proposed framework is organized into four interconnected stages: (i) monitoring and pre-processing of track and environmental data, (ii) physics-based simulation of wheel–rail interaction, (iii) data-driven prediction of future condition states, and (iv) condition-based maintenance optimization. The results presented in the following section are structured in line with these stages, in order to make the progression from methodology to findings and conclusions more explicit.

6 Results

This section presents the main outputs of the proposed framework following the methodology described in section 5, including the physics-based simulation results, the data-driven condition predictions, and the maintenance optimization results.

6.1 Dynamic simulation results

Figure 4 presents the vertical contact forces from a freight wagon (first right wheel) along a 10 km section of the Leixões Line, comparing rigid and flexible track representations. Simulations were performed at 50 km/h with a load consistent with a maximum axle load of 22.5 tons with vertical track unevenness. In the rigid configuration, the track infrastructure (sleepers, ballast, sub-ballast, and subgrade) is represented as a single equivalent body, providing a simplified structural response. In contrast, the flexible configuration models these components as separate layers with individual stiffness and damping properties. The interaction between layers allows dynamic effects, such as resonance and energy transfer, leading to higher wheel–rail contact forces compared to the rigid model.

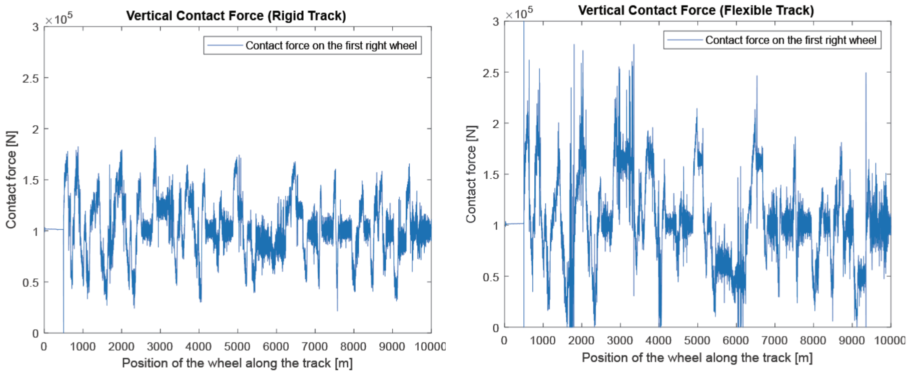

Figure 4 Vertical contact forces along 10 km on rigid and flex track

6.2 Condition prediction results

In the data-driven branch of the proposed framework (shown in figure 3), the LSTM model forecasts the EN-based segment-level standard deviation (SD) of the longitudinal level (vertical profile) computed over 200 m segments. Figure 5 presents the predicted versus measured SD values for the unseen 2025 campaign to evaluate model performance, together with the forecasted 2026 condition. The results show that the model captures the spatial variability of the longitudinal level along the corridor, including higher-variability segments. The model achieved an accuracy of 87%, indicating that it can reproduce the main degradation patterns observed along the line. These forecasts provide a forward-looking condition map that supports preventive maintenance through segment prioritization and early identification of emerging degradation trends.

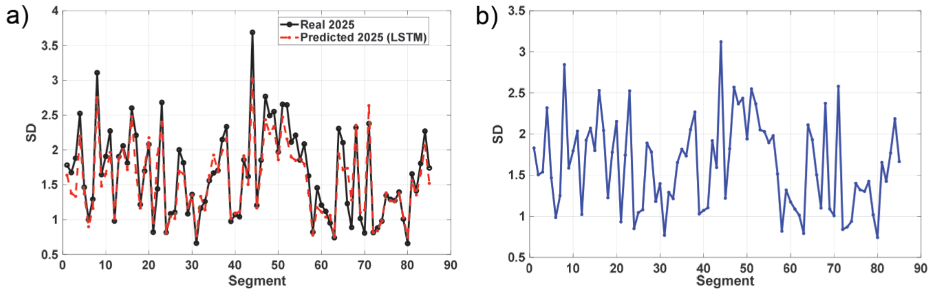

Figure 5 Segment-level SD of longitudinal level: a) 2025 predicted vs. measured, b) 2026 forecast

6.3 Maintenance optimization results

The condition-based maintenance optimization model is applied to the Leixões Line, considering 85 fixed-length track segments over planning horizons of 5, 7, and 10 years, corresponding to 20, 28, and 40 quarterly periods. Track condition evolution is evaluated using predicted degradation rates and recovery after tamping, while maintaining geometry quality below the intervention thresholds of 3.0 mm for longitudinal level and 1.8 mm for alignment [18]. The optimization determines the minimum number of tamping interventions required to maintain acceptable track quality. Results show that alignment governs the maintenance need along the corridor. Corrective actions triggered by alignment simultaneously restore the longitudinal level; therefore, independent scheduling of LL and AL leads to redundant interventions, while combined optimization eliminates unnecessary maintenance actions. Table 1 compares tamping demand considering individual and combined indicators. Joint optimization produces the same number of interventions as the alignment-only case, demonstrating that alignment acts as the controlling degradation parameter. When LL and AL are planned separately, duplicate interventions occur at the same locations; the joint optimization removes these redundancies, reducing tamping actions by 113, 152, and 205 for planning horizons of 20, 28, and 40 quarters, respectively. This reduction translates into fewer track possessions, lower machinery usage, and reduced ballast disturbance, improving both operational availability and infrastructure durability. These results provide the basis for the conclusion that combining geometry indicators within a condition-based optimization framework can reduce unnecessary maintenance actions while preserving track quality. Overall, the results demonstrate that combining geometry indicators within a condition-based optimization framework avoids unnecessary maintenance actions while preserving track quality, supporting more efficient and sustainable infrastructure management.

Table 1 Comparison of tamping interventions for LL, AL and joint optimization across different planning horizons

Horizon (months)	LL only	AL only	Joint (LL & AL)	Separate LL+AL	Saved actions
20	113	265	265	113+265=378	113
28	152	347	347	152+347=499	152
40	205	517	517	205+517=722	205

6.4 Discussion

The results demonstrate that the conclusions of the study are derived from three connected outputs of the proposed framework. First, the physics-based simulations show that the flexible track representation produces higher and more variable wheel–rail contact forces than the rigid model, highlighting the importance of structural representation in degradation-related analyses. Second, the LSTM model captures the spatial variability of the longitudinal level and provides a reliable forecast of future conditions, supporting the identification of segments with greater degradation potential. Third, the optimization results show that alignment governs tamping demand and that joint consideration of geometry indicators avoids redundant interventions. Taken together, these findings indicate that integrating simulation, prediction, and optimization can support more efficient and sustainable maintenance planning.

7 Conclusion

Although the present study demonstrates the applicability of the proposed condition-based maintenance framework, several developments are ongoing within the NRPCES project. First, further refinement of the track degradation analysis is underway. The integration of physics-based contact force results with data-driven degradation indicators will be completed to improve the accuracy of segment-level deterioration estimates. Additional sensitivity analyses are being conducted to evaluate the influence of external factors, including wind direction and intensity, on vehicle–track interaction simulations and their potential impact on degradation mechanisms. Second, the alignment-governed optimization strategy will be further developed and fully integrated with LCA, LCC) and CO_2 emission analyses. The optimized maintenance schedules generated by the MILP model will serve as inputs for quantifying environmental and economic impacts, enabling a comprehensive sustainability-based comparison of maintenance policies. From an environmental performance perspective, ongoing work focuses on collecting annually environmental data specific for the overall maintenance operations occurring in the railways line. The activity-based data (energy and materials) data will be used together with specific emissions factors to estimate the greenhouse emissions and the overall environmental impacts. The collected materials data sheets assist in the estimation of materials type used. Future developments include the identification of adequate emission factors to be used to estimate the carbon emissions associated to the energy used (electricity and fuels). A later step is the gather of the associated costs data.
Regarding environmental forcing, the long-term climatic and hydrological characterization provides a consistent basis for interpreting degradation behavior at corridor scale. The analysis focuses on identifying trends and extreme-event indicators relevant to railway exposure, including heat waves and intense rainfall episodes. These metrics establish a structured climatic baseline that can support future coupling with track condition indicators, numerical simulations, and AI-based maintenance modelling. Overall, future work will focus on consolidating the multi-physics, data-driven, and sustainability components into a unified decision-support platform capable of guiding resilient and environmentally optimized railway maintenance strategies.

Acknowledgements

The authors want to acknowledge UIDB/04708/2020 with DOI 10.54499/UIDB/04708/2020 (https://doi.org/10.54499/UIDB/04708/2020) and the Programmatic Funding—UIDP/04708/2020 with DOI 10.54499/UIDP/04708/2020 (https://doi.org/10.54499/UIDP/04708/2020) of the CONSTRUCT— Instituto de I&D em Estruturas e Construções—funded by national funds through the FCT/MCTES (PIDDAC). The first author acknowledges Grant No. 2021.04272.CEECIND from the Stimulus of Scientific Employment, Individual Support (CEECIND)—4th Edition provided by ‘‘FCT – Fundação para a Ciência e Tecnologia’’. This work is a result of the project “NRPCES—New replacement policy considering environment sustainability”, with No. 19217 and operation code at the Funds Platform (Balcão dos Fundos) NORTE2030-FEDER-01671200, co-financed by the European Union, through the NORTE 2030 Regional Program, of Portugal 2030. The authors also thank Infraestruturas de Portugal (IP) for providing the track-geometry inspection data used in this study.

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