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ARTIFICIAL INTELLIGENCE TECHNIQUES FOR FORECASTING RAILWAY TRACK PROFILE: LEIXÕES LINE CASE STUDY

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Abstract

Accurate forecasting of railway track profiles is essential for maintenance planning, safety, and cost-effective operation of rail networks. Predicting changes in track geometry allows railway operators to anticipate maintenance needs, optimize resource allocation, and improve overall operational reliability. This study explores the potential of artificial intelligence techniques, including sequence-based models such as Long Short-Term Memory networks, to forecast the standard deviation of longitudinal level and alignment of railway tracks using historical measurement data for preventive maintenance purposes. As a use case, the 17-km Leixões Line in Portugal is considered. Track geometry indicators, including longitudinal level and alignment, are processed and used as inputs to the forecasting models. The proposed Long Short-Term Memory framework predicts the segment-level standard deviation of longitudinal level and alignment with good accuracy, achieving R^2 values of approximately 0.87 for longitudinal level and 0.71 for alignment. Integrating AI-driven forecasts into maintenance planning can support safer operations, more effective intervention prioritization, and lower lifecycle costs.

Keywords: artificial intelligence, railway track profile forecasting, predictive maintenance, long short-term memory (LSTM), railway track degradation

1 Introduction

Presently, railways face increasing demand for both passenger and freight transport, which puts pressure on the network capacity and raises expectations for service quality. As a result, infrastructure managers are required to keep the infrastructure available and reduce life-cycle costs. A key approach to reach these goals is to apply predictive maintenance programs that are effective, efficient, and sustainable. Track geometry monitoring plays an important role in this process. Traditionally, track geometry is monitored using dedicated inspection (track-recording) vehicles; however, recent advances have enabled onboard monitoring on in-service trains, allowing more frequent and less disruptive assessment by recording the vehicle's dynamic response and inferring geometry-related irregularities. Geometry indicators such as longitudinal level (LL), alignment (AL), gauge, twist, and cross level are then compared with predefined limits to identify segments needing preventive/corrective maintenance or, in extreme cases, immediate actions [1].
Despite regular monitoring, deciding when and where to intervene optimally remains challenging. Mathematical modelling approaches have been proposed to derive optimal tamping schedules under track deterioration, recovery effects, and operational constraints [2, 3]. However, track degradation is neither uniform along the line nor constant over time, as it is influenced by local conditions such as traffic loading, track structure, ballast condition, maintenance history, and environmental effects [4, 5].

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This also reflects the physical complexity of railway-track behavior, as mechanistic studies have shown that the dynamic response of the track under moving loads is inherently complex [6]. This complexity is particularly relevant for AL, whose evolution may be further affected by curvature-related effects, temperature-dependent stresses, and the accumulation of lateral irregularities, making it more difficult to predict accurately [7]. Recent studies have also highlighted that the adopted segmentation strategy can influence track-quality assessment and the interpretation of maintenance needs, particularly in heterogeneous track sections [8]. Traditional probabilistic methods have often relied on simplified assumptions, such as constant inspection intervals and limited dependence on degradation history, which may not fully reflect real monitoring conditions. To mitigate these limitations, previous studies [9, 10] have proposed stochastic and data-driven prediction models calibrated with inspection records, including a Dagum-based deterioration model for LL and a logistic-binary framework that accounts for non-constant time gaps between inspections. This paper presents an AI-based framework for forecasting track-geometry condition using historical inspection data, applied to a Portuguese railway line. Six years of measurements are segmented into 200 m sections, following the European Standard [11], and the standard deviation (SD) of LL and AL is used as a track-condition indicator for preventive maintenance. In this study, Long Short-Term Memory (LSTM) networks are adopted to predict the evolution of these two indicators, as they can learn temporal dependencies from past sequences and capture the non-linear evolution of track condition. The proposed workflow is illustrated in figure 1.

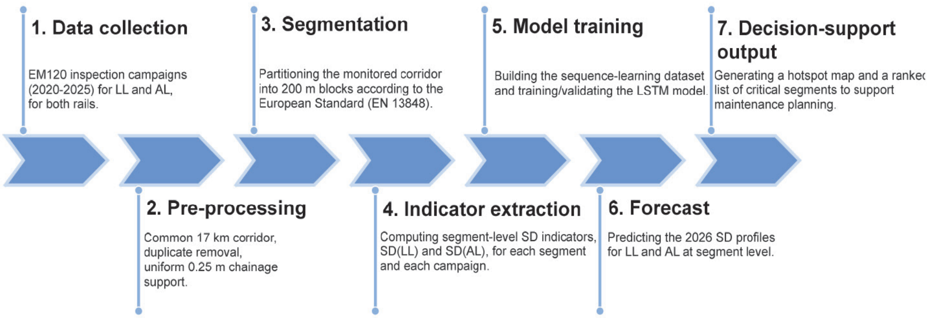

Figure 1 Workflow for forecasting of track profile (LL and AL)

2 Case study: Leixões line

2.1 Leixões line context and operational relevance

The Leixões Line is a historic railway corridor in the Porto Metropolitan Area, opened in 1938 to connect the Port of Leixões to the national rail network and initially used mainly for freight traffic. The line is 20.9 km long, crossing dense urban areas and serving key centers such as Porto, Matosinhos, and Gondomar (figure 2). Passenger services were discontinued in 1966, briefly reintroduced between 2009 and 2011, and recently reinstated through modernization led by Infraestruturas de Portugal, Comboios de Portugal, and the Matosinhos municipality. The line currently supports mixed traffic, with 60 passenger trains operating on weekdays and reduced but regular service on weekends and public holidays. The alignment of the selected corridor includes 35 curves, with a total curved length of about 11.5 km and a minimum circular curve radius of approximately 274 m. In this study, a 17 km common corridor was selected as the section consistently covered across all measurement campaigns.

Figure 2 Key stations and representative passenger service on the Leixões Line

2.2 Data collection for analysis

The track geometry of the Leixões Line is regularly monitored using the EM120 inspection vehicle, which measures the main track-geometry parameters, including LL, AL, cross level, gauge, and twist, for both rails along the corridor at 0.25 m intervals. Six inspection campaigns are available between 2020 and 2025, with non-constant intervals ranging from 134 to 585 days between consecutive inspections. Following the EN criteria for distributed-defect assessment, track condition is quantified using the SD of LL and AL computed over 200 m segments for each rail [11]. Along the 17 km common corridor, this segmentation results in 85 segments.

3 Methodology

3.1 LSTM background and forecasting concept

LSTM networks are a gated variant of recurrent neural networks (RNNs) designed to model sequential data. In standard RNNs, learning long-term dependencies is often difficult due to vanishing/exploding gradients during backpropagation through time. LSTMs address this limitation by introducing a memory cell (cell state) and gating mechanisms that control what information is stored, forgotten, and exposed at each time step [12]. Specifically, the input, forget, and output gates regulate the update of the cell state, enabling the network to retain relevant information over longer horizons and capture non-linear temporal dynamics [13].
The LSTM is suitable for this application because track degradation is influenced by the accumulated effect of traffic loads, local track characteristics, and maintenance history. As a result, the SD values along the years can follow trends or gradual changes that a sequential model can capture. After training, the model can generate predictions for all 200 m segments, producing a segment-level forecast map for the corridor. These forecasts can then be used to highlight segments that are expected to show higher variability and potentially higher degradation risk in the next inspection campaign.

3.2 LSTM implementation and prediction setup

The forecasting objective is to predict the next year's evolution of segment-level track geometry condition from yearly inspection records. For each 200 m segment, a supervised sequence-to-one regression problem is formulated, where a short historical sequence of SD indicators for LL and AL (computed separately for the left and right rails) is used as input, and the target is the SD value in the subsequent campaign (one-year-ahead forecast). Using a four-year input window, the model learns the mapping from [t – 3, t – 2, t – 1, t] to [t + 1], and it is finally used to generate the 2026 forecast using 2022–2025 as input.

Because the inspection campaigns are not equally spaced in time, the time gaps (Δt) between consecutive years were included as an additional input feature. The Δt values were normalized by the maximum observed time gap to keep them on a comparable scale. Therefore, each input sample contains both the historical indicator values and the corresponding normalized Δt sequence.
To assess generalization, the 2025 campaign was first defined as a fully unseen true test. The LSTM+Δt network was trained on the 2020–2023 sequences to predict the next campaign (2024), using an internal train/validation split within the 2024 training set to tune the model settings. The trained model was then evaluated on the true-test task by forecasting 2025 using only the 2021–2024 input window (i.e. without using any 2025 information during training). After confirming generalization on this unseen campaign, the same trained network was applied to generate the 2026 forecast from the 2022–2025 inputs. The network follows a compact regression design with one LSTM layer, followed by dropout and a regression output. Model performance is evaluated using the statistical error metrics RMSE (Root Mean Square Error) and MAE (Mean Absolute Error) and the goodness-of-fit measure, R^2.

4 Results and discussion

4.1 Model performance

Figure 3 compares the measured and predicted segment-level SD profiles for the unseen 2025 campaign for LL and AL on both the left and right rails. Overall, the predicted profiles reproduce the main spatial patterns along the corridor and consistently highlight the same high-variability segments. The remaining discrepancies are concentrated in a limited number of localized extreme peaks, where the predictions tend to be smoother than the measurements, which is expected in one-year-ahead forecasting based on short historical sequences.

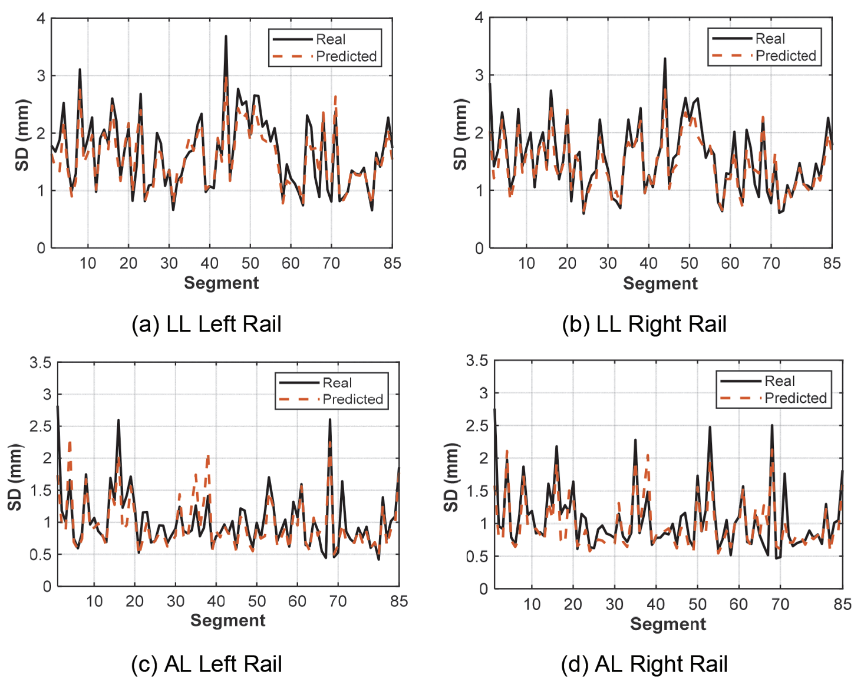

Figure 3 Measured vs. predicted 2025 segment-level SD

Following this qualitative assessment, table 1 summarizes the prediction accuracy of the proposed LSTM+Δt model for LL and AL (left and right rails). The 2024 validation results are close to the 2025 true-test results, suggesting stable generalization to an unseen campaign. Overall, the true-test performance remains high, indicating that the model captures most of the segment-level spatial variability along the corridor. LL is predicted more accurately than AL, which is consistent with AL exhibiting stronger short-scale variability and localized fluctuations.

Table 1 LSTM+Δt prediction performance for segment-level SD of LL and AL

Parameter (SD)		Val RMSE (2024)	Val MAE (2024)	Val R^2 (2024)	Test RMSE (2025)	Test MAE (2025)	Test R^2 (2025)
LL	Left Rail	0.27	0.18	0.78	0.22	0.16	0.87
	Right Rail	0.22	0.16	0.84	0.21	0.15	0.86
AL	Left Rail	0.14	0.08	0.77	0.25	0.16	0.70
	Right Rail	0.18	0.12	0.62	0.25	0.17	0.71

4.2 Forecasted segment-level profiles

After confirming generalization on the unseen 2025 campaign, the trained LSTM+Δt model was used to generate the 2026 forecasts for both LL and AL using the 2022–2025 input window. Since the inspection date of the next campaign was not available at the time of this study, the time gap between 2025 and 2026 was assumed to be one year. Figure 4a–b present the 2026 segment-level SD forecasts for LL on the left and right rails, generated by the trained LSTM+Δt model using the 2022–2025 input window. The predicted profiles describe the expected spatial distribution of LL variability in the next campaign and support predictive tamping scheduling by highlighting segments with relatively higher forecasted SD values. Overall, higher SD values are concentrated in a limited number of segments.

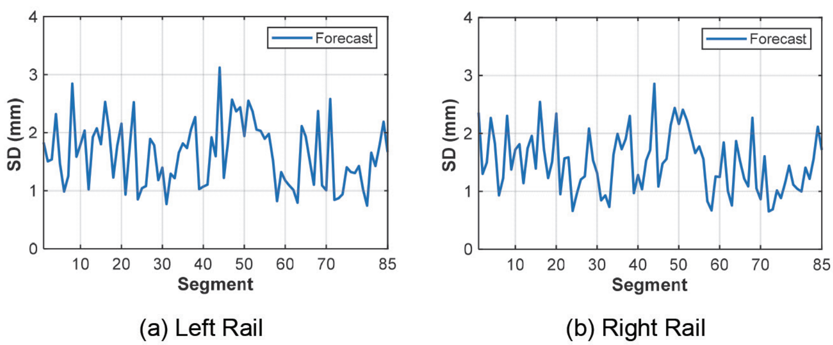

Figure 4 Forecasted 2026 segment-level SD of LL

Figures 5a and 5b present the 2026 segment-level SD forecasts for AL on the left and right rails, generated by the trained LSTM+Δt model. Compared with LL, the AL profiles show more short-scale variability and sharper localized changes, which is consistent with the lower true-test accuracy observed for AL. Overall, segments with relatively higher predicted SD values of AL across both rails can be considered higher-priority inputs for predictive tamping scheduling in the next campaign.

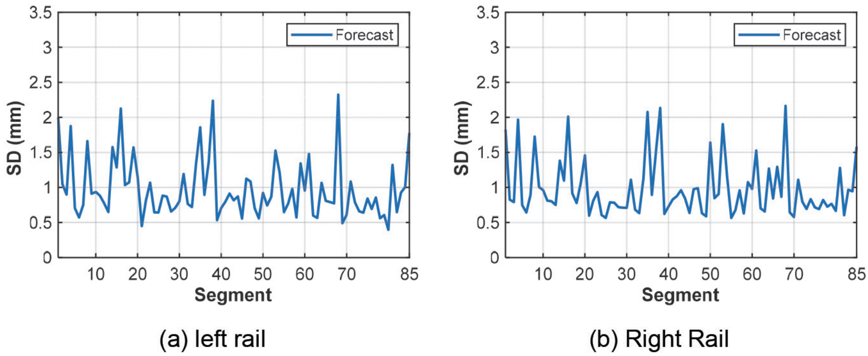

Figure 5 Forecasted 2026 segment-level SD of AL

In particular, segments 4, 8, 16, and 38 repeatedly appear among the highest predicted SD values for both LL and AL, reflecting their consistently higher SD history within the input window used by the LSTM+Δt model. Moreover, a small set of segments shows consistently high predicted SD on both the left and right rails, including LL peaks around segments 44 and 49–51 and AL peaks around segments 35 and 68. The left and right rail forecasts highlight largely the same high-SD locations, which supports the robustness of the predicted spatial patterns and helps define consistent candidate segments for predictive tamping scheduling in the next campaign.

5 Conclusion

An AI-based forecasting framework for predicting the segment-level SD of LL and AL on a ballasted track is presented in this paper. Using multi-campaign EM120 inspection data and an EN-based 200 m segmentation, the approach produces corridor-wide SD profiles for both rails, which can be directly used as decision-support outputs for maintenance planning. The results show that the proposed approach can reproduce the main spatial patterns of LL/AL variability along the corridor and generalize well to an unseen inspection campaign. The forecasts indicate that higher SD values are concentrated in a limited number of segments rather than being uniformly distributed along the line. Compared with LL, the AL forecasts show sharper short-scale variability, which is consistent with the greater difficulty of predicting AL from a short inspection history. In asset management, these forecasts can support (i) risk-based inspection planning, (ii) preventive maintenance prioritization, such as tamping, by highlighting sections where irregularities are likely to increase, and (iii) resource allocation by focusing on a limited set of critical locations rather than treating the corridor uniformly. In this context, the predicted LL/AL SD profiles are intended to support predictive tamping scheduling by providing quantitative inputs to optimization-based planning models for the next inspection campaign. In line with the project vision, this forecasting layer can be integrated into digital asset-management platforms and coupled with tamping scheduling models to improve planning under practical operational constraints. Key limitations include the short inspection history, the use of SD as the sole target, and the absence of explanatory covariates governing track geometry evolution, such as curvature information, operational/loading proxies, environmental effects, and maintenance history. Future work will extend the dataset and incorporate additional indicators and uncertainty information to support more robust maintenance decisions.

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