

Tiltmeter-Based Forecasting and Anomaly Detection for Proactive Structural Monitoring of Railway Infrastructure

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Summary:

Railway operators increasingly require predictive tools that transform continuous tiltmeter sensing into actionable structural health indicators. This work presents a physics-informed data-driven framework for rail and sleeper monitoring and validates it on a dataset collected from several tiltmeters with hourly sampling deployed in Spain over more than two years. The pipeline combines robust preprocessing, feature engineering, multi horizon forecasting and temperature aware anomaly detection. Results show accurate one week forecasting and effective separation of temperature-driven behaviour from structural deviations, supporting earlier maintenance decisions. The framework is designed for real-world deployment and scalability across large railway networks.

Keywords: tiltmeter sensors, time-series forecasting, anomaly detection, structural health monitoring, railway infrastructure monitoring.

Background, Motivation and Objective

Continuous sensing is gaining importance in railway asset management because conventional inspections are episodic while structural degradation can evolve between interventions. Structural health monitoring provides a route toward earlier detection and condition-based maintenance [1]. In railway infrastructure, distributed sensing and smart track instrumentation are increasingly regarded as enablers of safer and more sustainable operation [2].

Tiltmeter signals capture slow structural rotations and thermal responses. However, they are noisy, non-stationary, and strongly temperature-dependent. This work addresses that gap by developing an operator-oriented forecasting and anomaly-detection framework for long-term railway tiltmeter data, aimed at detecting faults and operational risks in infrastructure, thereby supporting operational decision-making. This enables earlier detection of structural issues, reduces inspection costs, and facilitates the transition toward predictive maintenance strategies.

Description of the New Method

Standard unsupervised methods and general-purpose forecasting models are unable to separate normal thermal variability from structural deviations in this dataset [3], motivating the physics-informed approach adopted here. The proposed system processes hourly measurements from 42 rail and sleeper tiltmeters installed in a

rail facility in Spain, from November 2023 to December 2025, including temperature and tilt angles (x, y, and z axis, in degrees). A robust preprocessing pipeline integrates outlier filtering, gap filling, changepoint detection, and signal smoothing. A set of 226 engineered features captures temporal, lag, rolling, trend, and temperature-correlation behavior. Multi-horizon forecasting is performed with a stacked Long Short-Term Memory (LSTM) neural network, a deep learning model designed to capture patterns in sequential data [4]. The anomaly detection step finally models how the track normally responds to temperature. Deviations from the expected temperature-driven response are flagged as potential structural anomalies. Changepoints identified by PELT algorithm (Pruned Exact Linear Time) [5] are retained rather than removed, as they may indicate structural shifts or emerging instabilities.



Fig. 1. Wireless tiltmeter installed on a railway sleeper for real-time track monitoring.

Results

A representative output obtained with the proposed pipeline is shown in Fig. 2 for a rail tiltmeter. One-week forecasts achieved R^2 (coefficient of determination) values between 0.81 and 0.998 across the three tilt axes and temperature, with consistently low prediction errors and the best performance for z axis and temperature due to their regular thermal cycles.

These high R^2 values indicate that the proposed model explains between 81% and 99.8% of the variance in the observed data, demonstrating a strong predictive capability and a close agreement between forecasts and measurements.

In comparison, generic statistical (SARIMAX, Prophet) and machine-learning (XGBoost, CatBoost, N-HITS) baselines produced negative R^2 at the same horizon, meaning that their predictions perform worse and fail to capture the underlying temporal dynamics.

This stark contrast highlights the superiority of the proposed approach, which is specifically tailored to the characteristics of tilt-meter data and significantly outperforms standard off-the-shelf methods for long-term forecasting in railway infrastructure monitoring.

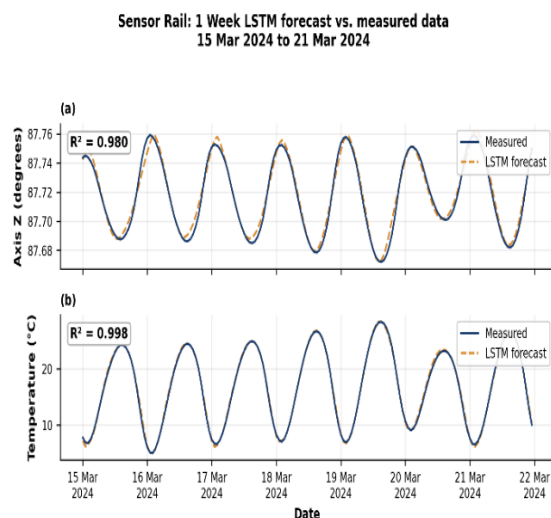


Fig. 2. Zoomed forecast versus measured data for rail sensor 75288 (z axis and temperature, one-week window). Blue: actual; orange dashed: LSTM forecast

For anomaly detection, synthetic validation showed that the pipeline recovered 84.6 percent of injected events, with full (100%) event-level recall for sustained level shifts and gradual drifts. These results are promising, as they demonstrate the capability of the approach to reliably identify relevant structural changes, and provide

a solid foundation for its application to real-world event analysis in operational railway infrastructure. This demonstrates the importance of incorporating physical context into data-driven models for infrastructure monitoring.

This work introduces a novel framework that combines temperature-aware anomaly detection with multi-horizon forecasting in a unified pipeline for railway tiltmeter data. The results demonstrate that integrating physics-informed modeling with data-driven approaches provides a robust decision-support tool for proactive infrastructure monitoring. This capability directly addresses the growing demand for advanced monitoring solutions that enhance operational safety, improve risk mitigation, and enable predictive maintenance in railway systems.

References

- [1] C. R. Farrar, K. Worden, An introduction to structural health monitoring, *Philosophical Transactions of the Royal Society A* 365, 303-315 (2007); doi: 10.1098/rsta.2006.1928
- [2] J. M. Castillo-Mingorance, M. Sol-Sanchez, F. Moreno-Navarro, M. C. Rubio-Gamez, A critical review of sensors for the continuous monitoring of smart and sustainable railway infrastructures, *Sustainability* 12, 9428 (2020); doi: 10.3390/su12229428
- [3] R. Rabadán-Arroyo, E. Simó, F. Aguiló-Gost, F. Hernández-Ramírez, X. Masip-Bruin, An adaptive IoT-based forecasting framework for structural and environmental risk detection in tailings dams, *Electronics* 15, 658 (2026); doi: 10.3390/electronics15030658
- [4] S. Hochreiter, J. Schmidhuber, Long short-term memory, *Neural Computation* 9, 1735-1780 (1997); doi: 10.1162/neco.1997.9.8.1735
- [5] R. Killick, P. Fearnhead, I. A. Eckley, Optimal detection of changepoints with a linear computational cost, *Journal of the American Statistical Association* 107, 1590-1598 (2012); doi: 10.1080/01621459.2012.737745

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