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Railway Bridge Scour Detection Using Drive-By Track Profiles and Machine Learning Algorithms

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This research introduces a practical, non-intrusive method for detecting scour in railway bridges using drive-by monitoring with in-service trains. The approach is first validated on a case study railway bridge in the UK, where longitudinal track profiles are collected by the Rail Infrastructure Alignment Acquisition (RILA) unit mounted on a 6-axle locomotive. Measurements belong to the healthy stage of the bridge; scoured stage measurements are synthetically generated using a Vehicle–Bridge Interaction model. For both scoured and healthy stages of the bridge, a Cross-Entropy algorithm is then employed to optimize pier stiffnesses by minimizing the discrepancies between measured and theoretical track profiles. The theoretical track profiles combine bridge displacements from a Finite Element model with Moving Reference Influence Lines and rail irregularities. Differences in optimized pier stiffness between the healthy and damaged states are interpreted as quantitative indicators of scour.
Building on this methodology, the study develops a Machine Learning framework that generalizes the scour-detection concept to a broader set of bridges and operating conditions. Synthetic RILA-measured track profiles are generated for multiple bridge and scour scenarios and used to train classifiers based on Artificial Neural Networks, Random Forests, and Support Vector Machines. These models are tasked with identifying scour and, in extended configurations, localizing the scoured supports using features derived from simulated track profiles. The proposed framework shows that indirect, train-based measurements can provide valuable early indicators of scour, supporting risk-informed management of railway bridge networks.

Keywords: Bridge scour, drive-by monitoring, RILA, Moving Reference Influence Lines, Cross-Entropy optimization, Vehicle–Bridge Interaction, Discrete Wavelet Transformation (DWT), Auto-Regressive Models with Exogenous Output (ARX), Markov Parameters, Machine Learning, Artificial Neural Networks, Random Forest, Support Vector Machines.

1. Background and Introduction

Bridge scour is broadly recognized as a major contributor to bridge failure worldwide, since erosion around foundations can precipitate abrupt collapse, particularly during severe flood events. Documented scour-driven failures illustrate how rapid foundation undermining can escalate into loss of structural capacity during floods. The 1987 collapse of the New York State Thruway bridge over Schoharie Creek followed severe erosion around Pier 3 and exposure of shallow foundations (National Transportation Safety Board 1988). The 1989 failure of the US Route 51 bridge over the Hatchie River occurred after flooding and channel changes undermined pile-supported bents (National Transportation Safety Board 1990). The 1995 collapse of the I-5 bridges at Arroyo Pasajero was attributed to floodinduced scour at the foundations (Richardson, Jones, and Blodgett 1997), and the 2009 Malahide Viaduct partial collapse was linked to scour-related undermining of the protective works supporting Pier 4 (Railway Accident Investigation Unit 2010). Together, these incidents underscore how bridge foundations can remain highly susceptible to scour-driven failure, reinforcing the need for monitoring strategies and early-warning systems to identify scour before collapse.

The monitoring techniques employed can be categorized into two distinct methods: direct and indirect. In direct monitoring, fixed sensors are installed on bridge components to measure their response. In contrast, in indirect (drive-by) monitoring, sensors are placed on vehicles crossing the bridge to assess the condition without interrupting service. (Tola et al., 2023). Drive-by monitoring can reduce sensor maintenance and site-access demands via operating under normal service conditions, improve safety by limiting in-water and trackside work, and enable frequent, network-wide screening without the need for underwater inspections or disruptions to bridge use. McGeown et al. (2024) investigate a drive-by scour-monitoring concept based on the pitch, i.e., the rotation of a passing railway vehicle. Scour-driven stiffness loss alters the bridge deflection component of the apparent profile experienced by the vehicle. The method is examined using vehicle–bridge interaction modelling, with scour represented as a reduction in pier stiffness. The developed methodology is supported by scaled laboratory experiments in which reduced-stiffness spring supports mimic scour; in both settings, the pitch response shows a consistent divergence between healthy and scoured cases. Key limitations are that the evidence is currently confined to modelling and laboratory validation rather than full-scale deployment, and that practical application requires handling of operational variability and a suitable baseline for comparison. Zhang et al. (2022) propose a drive-by method that processes vehicle accelerations via a wavelet transform to obtain wavelet energy and then extend this to a statistical-wavelet approach to improve robustness to sensor noise and environmental variability. They introduce a pier index based on component energy to support localization, demonstrating its feasibility through numerical simulations and laboratory experiments. The study also notes that wavelet-energy features can be sensitive to operating conditions, motivating the need for batching/statistical treatment and careful control of variability when translating to practice.

Machine learning (ML) is increasingly used in structural health monitoring because it can learn damage-related patterns directly from monitoring data, reducing reliance on explicitly defined physical or mathematical models to describe complex structural behavior. When sufficiently diverse datasets are available, ML methods can extract informative features, capture nonlinear relationships, and generalize to operating conditions not seen during training, supporting tasks such as anomaly detection, damage classification and localization, and performance prediction under varying environmental and operational influences. In addition, ML can combine heterogeneous inputs such as data from different sensors or feature families and provide probabilistic scores that can be mapped to alert thresholds for decision-making. Fernandes et al. (2024) propose a machine-learning drive-by approach for scour detection in railway bridges using raw train vertical accelerations analyzed with a deep autoencoder. Scour is represented as a local stiffness reduction in a pier–foundation system, and detection relies on the autoencoder prediction error (mean absolute error), complemented by a Kullback–Leibler divergence damage index to assess how many crossings are needed and ROC curves to evaluate classification performance. Their results indicate effective detection of 5% and 10% scour levels, particularly when sensors are placed on the front and rear bogies of the first and last vehicles, without requiring preprocessing. Huang et al. (2023) introduce a simulation-to-field framework that combines a 3D bridge–vehicle–wave interaction model with a Siamese neural network, in which real bridge vibration signals are compared with simulated scour scenarios to infer both scour location and damage level. In a field test, they report accuracies of 81.11% for scour location and 78.06% for damage-level classification and discuss sensitivity to vehicle speed and sensor arrangement. Both studies depend on repeated passes and require careful consideration of transferability across bridge types, operating conditions, and modelling assumptions.

The present study proposes a drive-by monitoring framework to detect and localise scour in existing railway bridges. The methodology is validated using a combination of field measurements and synthetically generated track profiles, building on earlier studies (Prendergast et al., 2016; Fitzgerald et al., 2019). In contrast to many previous works that rely on vehicle accelerations, this study uses drive-by displacement measurements collected with an alternative sensor system, rather than conventional geometry cars. As scoured-condition field measurements are unavailable, synthetic displacement responses for scour scenarios are generated using a vehicle–bridge interaction model. A cross-entropy (CE) optimization algorithm is then applied to infer pier stiffness by minimizing the sum of squared differences between measured and theoretical track profiles, and the relative stiffness change is adopted as the scour indicator. The framework is subsequently extended to a network-level application using multiple ML models. ML classifiers are trained and tested using features extracted from simulated track profiles, derived from discrete wavelet transformation (DWT) and autoregressive with exogenous input (ARX) model coefficients. This combined approach supports generalizable scour detection and localization across multiple bridges, providing a basis for an early-detection system that can enhance transport-network resilience and reduce the risk of sudden service disruptions.

2. Proposed method

2.1 Modelling framework

The displacement responses required for scour detection are replicated using two numerical models. The primary model is a static finite element (FE) model that determines the bridge displacement component relative to the theoretical track profile. By utilizing Moving Reference Influence Lines (MR-ILs) and representing bridge piers as elastic springs, the moving reference displacement is calculated. In the healthy state, vertical pier stiffness is derived from the foundation contact area, incorporating the embedment correction factor as specified in FEMA 356 (2000). Scour-induced damage is subsequently simulated by decreasing this initial vertical stiffness. To account for different sensor placements, the model is configured for both the front and rear of the train. An off-bridge FE model of the train, supported by Winkler springs, is also utilized; due to its lower sensitivity to mass fluctuations, this track-only model serves to calibrate the vehicle and synchronize soil properties with the moving reference displacement response.

The second model involves the dynamic vehicle–bridge interaction tool, TTB-2D v4.4 (Cantero, 2022). This software is used to generate synthetic datasets for scour scenarios when field data is unavailable. This tool, validated by prior research, allows highly flexible adjustments to train, track, and bridge parameters. Using this methodology, bridge displacements under various scour conditions are simulated and integrated with rail irregularities sourced from in-service measurements to develop comprehensive theoretical scoured track profiles. This approach ensures the creation of consistent, comparable datasets for both healthy and compromised bridge states, maintaining alignment with RILA-based measurements.

2.2 Case study bridge and field measurements

The suggested methodology has been applied to a case study involving a multi-span railway bridge situated in the northern United Kingdom. This structure features a concrete superstructure supporting two tracks, resting on masonry piers that cross a river. Since the completion of scour remediation efforts following a major flood in December 2015, the bridge has exhibited no signs of scouring (Figure 1) and is therefore classified as being in a healthy, unscoured state.

Figure 1. Scour repair works of the case study bridge, reproduced from Tola et al. (2025).

The Rail Infrastructure Alignment Acquisition System (RILA), developed by Fugro, is a modern advancement in track monitoring. In contrast to standard track geometry cars—which are bespoke vehicles requiring independent scheduling—RILA can be attached to the front or rear of standard in-service trains for rapid use. This adaptability enables ongoing data collection during routine traffic, providing a much higher measurement frequency than conventional methods. While the sensor unit's positioning away from the axle results in minor differences compared to axle-based recordings, the data remains fully compliant with the longitudinal standards of EN 13848 (CEN, 2019). The RILA sensor suite incorporates a Global Navigation Satellite System (GNSS) antenna, an Inertial Measurement Unit (IMU), laser-vision rail scanners, a 360° LiDAR scanner, and three video cameras providing 165° views (Figure 2) (Network Rail, 2021). The final track geometry output is produced by merging GNSS, IMU, and laser scanner data, with GNSS coordinates reprocessed alongside IMU accelerations to enhance spatial precision (Network Rail, 2021). The integration of IMU data is vital, as it ensures that the system records bridge-specific responses in addition to rail surface defects. Consequently, the relative track geometry provided by RILA represents a combination of bridge-induced displacements and rail surface irregularities.

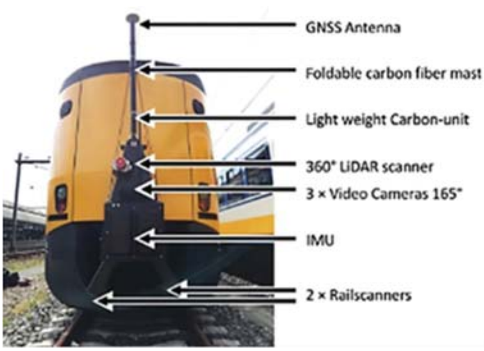

Figure 2. Sensors of the RILA implemented on a train (Network Rail, 2021).

2.3 *Stiffness inference with Cross-Entropy algorithm*

Operational displacement data, specifically track profiles for the bridge under study, were gathered using a RILA system installed on a six-axle locomotive. Ideally, longitudinal level profiles would be captured for both pre-damage and post-damage intervals. However, in this application, the sixteen available measurements were recorded following scour repair works, during a timeframe when underwater inspections confirmed the absence of scour. Thus, these data points are assumed to represent the bridge's healthy state. These field recordings were organized into four categories based on the train's direction of travel and the specific RILA orientation (front- or rear-mounted). To address the lack of field data at the damaged stage, synthetic track profiles for scoured conditions have been generated using the TTB-2D model to account for dynamic interactions. In this process, bridge displacements under scour conditions have been simulated and subsequently merged with rail surface defects identified from actual operational data.

This research identifies the variation in pier stiffness between the scoured and healthy bridge conditions as a primary scour indicator. To determine optimized stiffness parameters, a Cross-Entropy (CE) algorithm (Botev et al. 2013) has been applied. For each bridge condition, the objective function identifies the pier stiffness that minimizes the sum of squared residuals between the measured and theoretical track profiles across all data points and train passages in that group. Theoretical profiles have been derived by integrating the static bridge model, as detailed in Section 2.1, with the recorded rail surface defects. The notable disparity between the CE-optimized values for damaged and undamaged states confirms the presence of scour (Tola et al., 2025). Ultimately, the track profile damage index is calculated as the delta between the optimized pier stiffness values for the healthy and scoured stages. Sensitivity assessments have been performed across various scour magnitudes. For scour levels ranging from 5% to 25%, damage indexes have been defined as the sum of squared differences between healthy and scoured profiles. These sensitivity analyses yield a noise threshold, confirming the technique's reliability for detecting scour-related damage.

3. Machine Learning Scheme

The ML component of this research broadens the scour detection framework described in Section 2, transitioning it from a single-bridge analysis to a network-scale application suitable wherever drive-by longitudinal track profiles are available. The initial phase of the ML scheme focuses on feature extraction, where specific descriptors are identified from longitudinal level profiles to capture structural response signatures linked to scour. These extracted features serve as inputs for ML classifiers, facilitating scour identification across diverse railway bridge types.

The dataset for training and validating the ML models consists of track profiles generated from simulated train crossings equipped with RILA. Two years of traffic across four distinct bridges have been synthetically generated using the TTB-2D vehicle–bridge interaction tool, with representative rail profiles for Class 6 tracks. Monte Carlo simulations have been used to introduce stochasticity into variables such as vehicle speed, body mass, and scour magnitude, with scour levels ranging from 0% to 20%. The simulations considered both localized scour at a single pier and more complex scenarios involving up to three piers. The four bridges in the training set encompass concrete and steel superstructures and diverse span configurations. Additionally, both single-coach and multi-coach vehicle configurations have been modelled. To ensure the synthetic data realistically mirrors field conditions, measurement noise has been incorporated. Finally, front-mounted and rear-mounted sensor scenarios have been addressed as independent models within the ML framework.

3.1 Feature engineering

To establish the input parameters for the ML models, scour-sensitive descriptors were extracted from an analysis of simulated track profiles. Initially, a Daubechies Discrete Wavelet Transform (DWT) has been applied to the profiles. Given that the resulting coefficients vary with scour presence, their statistical moments and the total energy—calculated via Parseval's theorem—have been evaluated as potential ML inputs. However, relying solely on these parameters compromised the model's robustness; consequently, the feature set has been broadened. Autoregressive with Exogenous Input (ARX) modeling has been utilized to generate further descriptors from the simulated profiles. In this setup, rail irregularities serve as the exogenous input while track profiles functioned as outputs, with a one-sample input–output delay implemented to maintain causality. For each simulation, ARX models have been individually fitted by testing various model orders and selecting the configuration that optimized the Akaike Information Criterion (AIC). To produce more stable and interpretable indicators of the input–output relationship, these ARX models were transformed into Markov parameters, representing each model's impulse response. These sequences were then organized into feature matrices to serve as the primary inputs for the ML classifiers.

3.2 Classification models

To address scour detection and localisation, Artificial Neural Networks (ANNs), Random Forests (RFs), and Support Vector Machines (SVMs) have been utilized. A scour threshold of 5% has been established, whereby simulations below this limit have been classified as undamaged, while those at or above it have been categorized as scoured. Two distinct modelling approaches have been implemented: a bridge-based model used for scour detection, where a single row of input parameters represents each simulation; and a pier-based model, which computes parameters for specific scour-prone zones surrounding each support. In the pier-based approach, the number of data rows per simulation has corresponded to the number of piers, naturally facilitating location-specific detection. Feature selection for the ML classifiers has been conducted using a relative-importance methodology, and hyperparameters have been optimized via a combination of grid and random searches. To resolve data imbalance issues within the pier-based models, the Synthetic Minority Oversampling Technique (SMOTE) has been applied.

4. Results and Final Remarks

The established scour detection strategy has been validated using a combination of operational RILA track-profile measurements from a UK railway bridge and synthetic scour scenarios generated with a vehicle–bridge interaction model. A primary contribution is the use of displacement signals from the RILA system; because the instrument is mounted away from the axle, the framework can be applied to standard in-service operational data rather than relying on bespoke inspection vehicles. To support risk assessment and resilience planning at network scale, ML classifiers have been trained and validated on a comprehensive synthetic dataset, allowing repeated in-service passages to be translated into decision-ready outputs that can prioritise bridges and piers for follow-up inspection and mitigation actions. The sliding-window analysis further improves robustness to operational variability, and strong classification performance is obtained for both bridge-level detection and pier-level localisation. Achieved accuracies of the three ML algorithms with varying batch sizes for the RILA front- and rear-mounted scour detection models is provided in Figure 3, and Figure 4, respectively. Across both front- and rear-mounted configurations, all three algorithms deliver very high detection performance across batch sizes. RF is the most accurate and stable, ANN also performs strongly with slightly lower recall, and SVM remains competitive but shows the greatest variability across batch sizes, particularly in the front-mounted case.

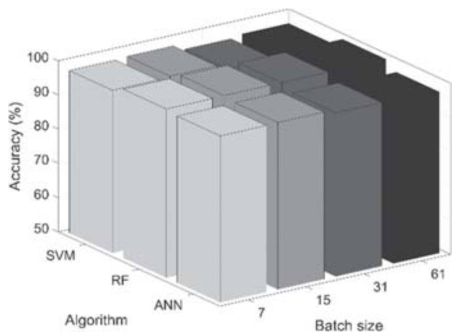

Figure 3. Accuracy of ML algorithms with varying batch sizes.: RILA-front mounted configuration.

Overall, the proposed framework enables scour-related risk to be managed using routine in-service data, supporting timely, support-specific interventions that strengthen railway network resilience under flood-driven hazards. In the presence of a larger field dataset, including continuous monitoring and scoured field cases, an owner-oriented implementation guide could be developed as future work to support routine use. The guide would cover required inputs, basic data preparation, and practical decision rules aligned with inspection practice.

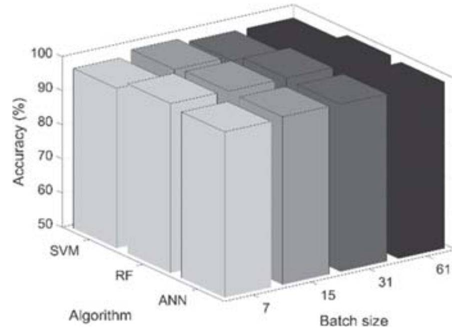

Figure 4. Accuracy of ML algorithms with varying batch sizes.: RILA -rear mounted configuration.

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