Received: 13 April 2024 | Accepted: 13 September 2024

DOI: 10.1111/mice.13349

RESEARCH ARTICLE

COMPUTER-AIDED CIVIL AND INFRASTRUCTURE ENGINEERING WILEY

Prediction of approaching trains based on H-ranks of track vibration signals

Ugne Orinaite[1] | **Rafal Burdzik**[2] | **Vinayak Ranjan**[3] | **Minvydas Ragulskis**[1]

[1]Department of Mathematical Modeling, Faculty of Mathematics and Natural Sciences, Kaunas University of Technology, Kaunas, Lithuania

[2]Faculty of Transport and Aviation Engineering, Silesian University of Technology, Katowica, Poland

[3]Division of Physical and Computational Sciences, University of Pittsburgh, Bradford, Pennsylvania, USA

Correspondence

Minvydas Ragulskis, Department of Mathematical Modeling, Faculty of Mathematics and Natural Sciences, Kaunas University of Technology, Studentu st. 50, Kaunas, 51368, Lithuania.
Email: minvydas.ragulskis@ktu.lt

Vinayak Ranjan, Division of Physical and Computational Sciences, University of Pittsburgh, Bradford, PA, USA.
Email: vir105@pitt.edu

Abstract

This paper introduces a method for forecasting the arrival of trains by analyzing track vibration signals. The proposed algorithms, based on H-ranks of track vibration signals, can generate early alerts for approaching trains. These algorithms are robust to additive noise and environmental conditions. The theoretical foundation of the method involves the application of matrix operations to detect significant changes in vibration patterns, indicating an approaching train.

1 | INTRODUCTION

The methods of acquiring knowledge about the current state of processes and devices determine the quality of the decisions made. In this respect, in engineering issues, the dynamic development of measurement systems and sensors is visible. The current possibilities of registering many signals with high precision and sampling frequency mean that the possibilities of correctly describing the physical quantities representing the analyzed physical phenomena are almost unlimited. Big Data denotes vast, intricate, expanding datasets sourced from various independent origins. (Wu et al., 2014). When processing such datasets, a new challenge is to make proper choices regarding the number of signals and to find suitable algorithms for the extraction of useful information from those signals. The existing limitations of information extraction techniques used for data pre-processing, data extraction, transformation, and representation are discussed in Adnan and Akbar (2019). Based on the systematic literature review, Adnan and Akbar (2019) conclude that noise, missing data, incomplete, and low-quality data are primary challenges that degrade the process of extracting information. The additive noise can affect the extraction of the information from vibration and audio signals (Heittola et al., 2013; Tian, 2017). As a result, the development of novel signal-processing methods continues to be an active research topic.

The detection of approaching trains on a relatively closed railway line is essential for enhancing overall safety. This method serves as an additional layer of technical protection to mitigate human–vehicle conflicts and sensor failures. By implementing this detection system, we can ensure a higher level of safety for maintenance workers and road vehicle drivers who might otherwise be unaware of an approaching train due to visibility limitations or other factors.

Safety is a critical part of developing, manufacturing, and utilizing technical goods. Every engineer prioritizes safety when it comes to transportation systems. This paper addresses safety concerns within rail transportation, particularly focusing on the motion of rail vehicles. Railway-level crossings pose the highest risk of accidents within the transportation network (Szaciłło et al., 2021). This increased risk stems from the convergence of rail and road traffic streams. Usually, railway-level crossings safety is ensured by the separation of these traffic flows. However, the safety of crossings without a barrier system depends on the individual decisions of car drivers. The accident prediction model presented in Borsos et al. (2016) defines the geometry (the road pavement width, the crossing angle) as a significant risk factor at railway and road level crossings. The weights of the safety ranking components are also determined in Borsos et al. (2016) for given estimates of the recognizability and drivability. But in terms of driver behavior at an unprotected railway crossing, the main deciding factor for safety is that the driver can see an approaching train. The information about the approaching train may not reach the driver in time due to limited visibility resulting from buildings in the vicinity of a railway level crossing, a bend of a road or a railway line, trees, roadside advertisements, large-size vehicles standing on the roadside, weather conditions, and so forth. The late reaction can result in a serious accident, unfortunately often fatal.

This paper attempts to solve this problem by developing a technique for obtaining warning information about an approaching train, regardless of the factors that may limit visibility. The importance of the problem is backed by strong social significance. As already stated in Schoppert et al. (1968), railway crossings with limited lateral visibility present greater hazards, compared to crossings with unobstructed visibility. The hypothesis of risk homeostasis theory, which suggests compensatory behavior in reaction to perceived risks linked with limited visibility, is examined in Ward and Wilde (1996) and Gerald et al. (1987). One of the study's discoveries indicates that the origin of this driver behavior is methodological and lies in the positioning on the area leading to the level crossing. However, it should be noted that current social habits and high trust in warning systems mean that the behavior of drivers is different and much more focused on available support in the decision-making processes.

From an engineering perspective, the investigated problem is called the rail vehicle detection problem. As a result, the specific scientific topic addressed in this study is the prediction of the railway vehicle approach based on data from an independent source. The primary aim of this paper is to develop a signal processing algorithm capable of predicting approaching trains based on track vibration signals (track vibration information is measured by devices not used in the standard railway traffic control systems).

TABLE 1 A table outlining the characteristics of various train detection methods.

Detection method	Characteristics
Inductive loop	Reliable, requires installation in tracks (Borsos et al., 2016)
Magnetic sensors	Sensitive to metal objects, requires calibration (Szaciłło et al., 2021)
Treadle systems	Mechanical, prone to wear and tear (Borsos et al., 2016; Schoppert et al., 1968)
Radar technologies	Long-range detection, affected by environmental factors (Gerald et al., 1987; Ward & Wilde, 1996)
Ultrasonic methods	High accuracy, limited by line-of-sight (Heittola et al., 2013; Tian, 2017)
Computer vision	Advanced, requires visual data (Adnan & Akbar, 2019; Wu et al., 2014)
Vibration-based (proposed)	Robust, independent of existing systems, early detection

A table outlining the characteristics of various train detection methods is provided in Table 1.

The need for accurate and timely information about the state of railway transportation is paramount for safety and efficiency. This study aims to develop a method for detecting approaching trains using track vibration signals. The proposed method addresses the limitations of existing systems by providing an independent and early warning system that enhances safety at railway crossings.

While it is true that many level crossings are equipped with comprehensive signal systems, there are specific scenarios where these systems alone may not be sufficient. For instance, at unmanned or remote crossings, the absence of active monitoring can increase the risk of accidents. Additionally, technical failures, whether due to system malfunctions or external factors such as hacking, can render traditional systems ineffective.

Our proposed method serves as an independent, redundant safety layer that operates independently of the existing rail infrastructure. This redundancy is crucial in ensuring that even if the primary system fails, there is still a reliable mechanism in place to detect and warn of an approaching train. The vibration-based system is particularly effective because it is not susceptible to the same vulnerabilities as signal-based systems, such as electromagnetic interference or software hacking.

The proposed method adds an extra layer of safety by providing early detection of approaching trains using track vibration signals. This serves as a redundancy measure, ensuring safety even in cases where traditional systems may fail due to technical issues or environmental factors. The simplicity and robustness of vibration-based detection make it a valuable addition to existing safety measures.

The primary motivation for our work is rooted in the increasing complexity and vulnerability of modern railway systems. Traditional methods of train detection, while effective in many scenarios, can be compromised by electromagnetic interference, hacking, and other technical failures. Moreover, they are dependent on infrastructure that, while generally reliable, does not provide a fail-safe in all situations.

Our research seeks to fill this gap by developing an alternative, independent detection system that leverages track vibration data. This system is designed to be robust against the aforementioned vulnerabilities and to operate effectively in scenarios where traditional methods might fail, such as in unmanned or remote crossings, or during maintenance operations in challenging environments. The simplicity and robustness of vibration-based detection, combined with the innovative application of the H-rank algorithm, provide a critical safety layer that is both independent and complementary to existing systems.

1.1 | The historical background

To trace the evolution of vehicle detection solutions, the overview of the existing solutions for the prediction of an approaching train is presented for the decades of the 20th and 21st centuries. This approach enables the contribution of this paper to be contextualized within both the historical literature and the latest advancements in the field.

Already in the 20th century, the use of electricity in railway signaling and track circuits became an important factor. Methods for the elimination of the human aspect in terms of the signalman and exercising total control over traffic are explored in Hookham (1925). However, it is noted that in the absence of an automatic train control system, the engine driver may disregard signals. The growing necessity for track circuits and autonomous train control is emphasized in Peter (1936). Innovative and alternative techniques for autonomous train detection have already been proposed at the beginning of the 20th century. For example, an interesting solution is proposed in Rice (1932) where the autonomous train control system uses an alternating magnetic Wheatstone bridge to receive signals from the inert track inductors. Upon receiving these signals, when a train enters a dangerous area, its air brakes are automatically engaged to bring the train to a halt (Rice, 1932). Vehicle identification and signaling are also considered in road transit.

An innovative concept for train vehicle detection is presented by McAulay (1974). The track is considered as the communication channel capable of transmitting information on the passing train. The techniques used in McAulay (1974) are based on crossover wires capable of measuring the surface electromagnetic waves (the numerical results obtained through the finite element method are consistent with the analytical findings).

Numerous studies on future vehicle detection systems have been conducted since the 1970s. An overview of the vehicle detection concepts is given in Mills (1970). Back then, four types of vehicle detection technologies were considered: inductive loop, magnetic, treadle, and radar technologies (the radio frequency type vehicle detectors are highlighted are future technologies). Barker (1970) examines three distinct physical phenomena relevant to the detection of vehicular traffic. These sensors supply data inputs for controlling vehicle-activated traffic signals, managing control systems, monitoring freeways, and conducting statistical analysis. The paper examines radar detectors, which utilize microwave radio frequencies between 2.5 and 10 MHz, detailing their operating principles, design considerations, and real-world applications. Moreover, the paper explores acoustical detectors functioning at 20 kHz and low-flux density change magnetic detectors. Furthermore, the paper undertakes a comparative assessment of radar, acoustical, and magnetic sensors, in addition to mechanical, magnetic, induction, and optical detectors.

Singleton and Ward (1977) describe the systems and devices utilized until the 1970s in their report titled “Comparative study of various types of vehicle detectors,” prepared for the US Department of Transportation Office of the Secretary of Systems Development and Technology. Additionally, an automated ultrasonic rail flaw detection system is presented by Abonyi et al. (1988) for the real-time detection and assessment of rail flaws. While this system pertains to a different application, it signifies a novel approach to the development of rail-mounted measurement systems.

A new trend in vehicle identification utilizing vision-based approaches may be seen in the 1990s (Bertozzi et al., 2000). The whole strategy is founded on powerful image processing and pattern-matching algorithms (Michalopoulos, 1991). During this decade, researchers began investigating the feasibility of utilizing neural networks in the detection of approaching vehicles (Dougherty, 1995).

Since the early 2000s, innovative unorthodox approaches to train detection have been introduced. The conceptual viability of utilizing fiber optic sensors to detect trains is discussed in Kuen and Ho (2006). A fiber Bragg grating (FBG) sensor, which is an optical instrument, measures and quantifies strain by detecting variations in the reflected wavelength of light (Hill et al., 1993). A FBG sensor device may also be utilized to count train axles (Wei et al., 2010). The FBG sensors may also be used to check the condition of trains in real time. Optical systems facilitate real-time monitoring of trains during regular operation owing to their rapid responsiveness (Lai et al., 2012). A system that uses wireless power transmission to transmit train location information through a source coil section is presented in Hwang et al. (2019). The system comprises onboard sensor coils, ferrite blocks fabricated with precise location data, and a detector. A study by Reiff (2003) presents an evaluation of five potential detection methods of trains at highway-rail junctions (the evaluation criteria encompass detecting approaching trains, identifying train islands, detecting stationary highway vehicles, and detecting moving highway vehicles).

The advantage of optical fiber sensors is electromagnetic immunity, which is a major issue in the context of track circuits. Vibration signals created by a railway car also help to ensure electromagnetic immunity. Most of the publications (Gómez et al., 2018; Kaynia et al., 2017) propose a vibration application for the detection of defects. Alahakoon et al. (2018) provide an in-depth examination of cutting-edge rail defect-detecting methods. Chen et al. (2022) describe a vibration-based detection approach for detecting invisible fastener deterioration. A self-powered nanofiber vibration sensor is used to monitor the safety tightness of railway fasteners (Meng et al., 2022). Zhao et al. (2022) analyze and examine existing conventional rail detection systems exploiting techniques based on vibration, ultrasonics, electromagnetic, and optics.

The study by Sun et al. (2021) describes a real-time vibration-based approach for detecting the order and rough degree of railway wheel polygonization faults. The most prevalent local surface problems in railway wheels are wheel flats. During the operating operation, this sort of fault might generate a cyclic wheel-rail collision. The publication by Li et al. (2017) describes a flaw detection approach for flat railway wheels based on a rail vibration adaptive multiscale morphological filter. The study by Suharjono et al. (2017) gives a preliminary examination of vibration signal recognition for rail train arrival. Burdzik et al. have provided various studies of rail vibration signal information capacity and its use for train identification: studies for train traffic control (Burdzik et al., 2017), studies for vehicle image analysis, and track condition monitoring (Celiński et al., 2022). Some studies have been done on railway lines using the sound approach (Burdzik et al., 2022).

Previous studies have explored various methods for detecting trains, including light-based and electricity-based technologies. However, vibration-based detection methods offer distinct advantages due to their robustness against electromagnetic interference and hacker attacks. Studies such as in Suharjono et al. (2017) have demonstrated the feasibility of using vibration signal recognition for detecting train arrivals. This study expands on these findings by applying the H-rank algorithm to enhance the detection accuracy and reliability of vibration-based methods.

In recent years, modern train detection systems have become crucial elements of safety systems of railway safety, especially with the progress of high-speed railway infrastructure (Yang et al., 2011). Sensors on trains activate signaling devices as they approach the crossing level. Wheel sensors play a significant role in detecting the location and movement direction of the rail vehicle, influencing the activation of these devices (Burdzik et al., 2016). The limitations associated with these techniques include the high costs involved in installing track circuits, axle counters, and managing related equipment.

Presently, transponders stand out as the foremost technologies for accurately detecting the position of rail vehicles, particularly high-speed trains. However, transponder telegrams are susceptible to corruption from electromagnetic interference originating from onboard electric train power equipment or wayside devices (Park et al., 2016). In the current geopolitical situation and the importance of rail transport as a critical infrastructure, hacker and hybrid attacks cannot be ruled out. Current transponder-based systems are at high risk for such threats. An innovative method is being tested and validated to assess the practicality of using radio frequency identification technology (RFID) to accurately position vehicles at switch and crossing points within the railway infrastructure Olaby et al. (2022).

All these systems enable the detection of a rail vehicle when passing through a checkpoint (sensor); additionally, an RFID-based system enables the identification of vehicles that want to be identified and have an RFID tag. The presented vibration method is distinguished by the fact that it detects the approaching train in advance (prediction), is independent and does not require additional devices built into the rail vehicle, and is resistant to electromagnetic interference and hacker attacks. Given the characteristics of vibration signals generated by moving trains, the development of a signal processing methodology necessitated addressing nonstationary and random vibrations using novel time-series analysis methods.

Recent advancements in train detection technologies include the use of fiber optic sensors, wireless communication systems, and advanced signal processing techniques. These modern approaches offer significant improvements over early 21st-century technologies by providing more accurate and reliable detection under various environmental conditions. This study builds on these advancements by proposing a novel method that utilizes track vibration signals to detect approaching trains, offering a complementary solution to existing systems.

1.2 | The main objective of this paper

The primary objective of this paper is to introduce a novel method for predicting approaching trains using track vibration signals. This method leverages the H-rank algorithm to process vibration data, providing early warnings of approaching trains. The innovations of this approach include its robustness to environmental noise, independence from existing rail traffic control systems, and the ability to function without additional onboard devices. These innovations address the challenges of sensor failures and the need for enhanced safety at railway crossings.

Despite the extensive history spanning over a century in rail vehicle detection and numerous recent publications exploring new detection methods, track circuits with simple open/close circuit principles remain the most popular system for detecting rail vehicles moving on tracks. However, it's crucial to highlight that railway engineers frequently encounter unstable or faulty operations of track circuits due to electromagnetic interference. This issue inevitably poses risks to the safe operation of trains. Therefore, this paper introduces a novel approach utilizing vibration signals, which are immune to electromagnetic interference, for predicting approaching trains. Given the characteristics of vibration signals generated by moving trains, the development of a signal processing methodology necessitated addressing nonstationary and random vibrations using time-series methods.

It is crucial to highlight that the suggested method for the detection of approaching trains must be validated using real-world experimental data. This experimental validation is critical, as the signal processing approach will account for all possible disturbances of the vibration signal, confirming the practical feasibility of implementing the proposed system. Such a predictive system constitutes an innovative contribution to both the historical literature and the current state of the art. The proposed scheme not only enables the detection of a passing train but also helps to forecast its arrival. This prediction opens up new possibilities for use in railway safety systems, particularly at railway crossing levels, where there are no measures to separate road and rail traffic. It also suggests innovative ways to improve the railway safety system and train traffic control.

2 | MATERIAL AND METHODS

The scientific issue tackled in this paper is the prediction of the railway vehicle approach based on an alternative source of information such as the train vibration signal. The main goal is to introduce a signal processing algorithm capable of performing an early prediction of an approaching train. The vibration generated by rolling wheels encompasses interactions between the vehicle, track, and soil, as well as variations in track geometry and dynamic axle loads (Xu et al., 2022). The irregular profile of a railway line stands as a crucial source of vibrations for both vehicles and tracks.

FIGURE 1 The measurement setup showing the vibration sensors mounted on the surface of the rail. Photographs courtesy of Rafal Burdzik.

The research on the information capacity of rail vibration signal for different forces and railway system devices reflecting the real vibrational conditions within the railway infrastructure is presented in Burdzik and Nowak (2017). The high capacity of information and the ability to choose components of the signal, indicating diverse modes of propagation of vibration waves on the rail, have been provided in Burdzik and Nowak (2017). This enables the continuation and expansion of the study for the feasibility of forecasting an approaching rail vehicle.

Rail vibration acceleration is measured utilizing an analog input module, specifically the NI 9233 from National Instruments. These data acquisition device features a universal serial bus (USB) interface and four channels of 24-bit analog inputs, complete with integrated signal conditioning. The Dytran series 3023 is a small triaxial integrated electronic piezoelectric (IEPE) accelerometer with a sensitivity of 10 mV/g that is available in transducer electronic datasheet (TEDS) and high-temperature conditions. The study is conducted on real railway lines in a typical working setting. The measuring system is designed with the purpose of not affecting the functioning of the railway traffic management system or track infrastructure, thus eliminating a possible impact on transport safety (Figure 1).

As previously stated, the aim of this study is to verify the possibility of predicting an approaching rail vehicle from a distance so that it is safe for a car located on a railroad-level crossing to exit or warn the driver enabling him to stop safely before the crossing. An impulse-based sensor is installed on the rail, positioned 400 m away from the vibration-measuring sensor. The diagrammatic representation of the experimental scheme is depicted in Figure 2.

The sensor system is designed to detect the presence of an approaching train when it is approximately 400 m away

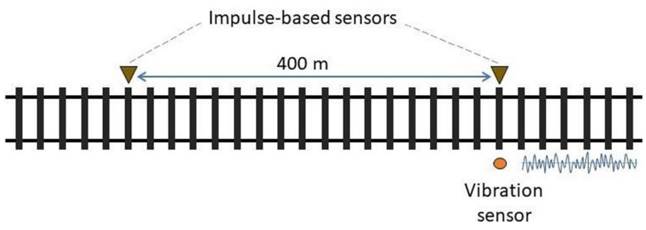

FIGURE 2 The schematic diagram illustrating the experimental setup.

from the vibration accelerometer. This means that the system starts identifying the train's approach at this distance. The vehicle's first axle is the point at which the vibration caused by the train's axle is directly detected by the sensor. The initial detection occurs when the train is 400 m away, and as the train moves closer, the system continues to monitor the vibrations until the train passes over the sensor. This continuous monitoring ensures early detection and consistent tracking of the train's approach.

The system is designed to detect and confirm the presence of a train from 400 m but does not classify the type of train, measure its speed, or provide detailed information about the train. The primary goal is to provide an early warning of an approaching train to enhance safety at railway crossings and other critical points along the track.

As a rule, for unguarded rail and road crossings (without barriers and traffic lights) or with a system failure in Poland, it is recommended to limit the train speed during the passage to even 20 km/h. In the case of a larger traffic index, the speed limit is 50 km/h. On railway lines managed by Polish Rail lines Company, for the purposes of positioning the signals, the following braking distances are assumed, resulting from the maximum possible speed on a given line section; for speeds up to 60 km/h, the assumed braking distance is 400 m. However, the most important thing is that the concept of using this method of predicting the approach of a train is not about informing the locomotive driver and initiating braking, but about informing road vehicle drivers or employees working on the tracks and enabling them to evacuate from the danger zone, in this case, 400 m is significantly sufficient.

The prediction of an oncoming rail vehicle can be given as a function of distance or time. Therefore, during the experimental investigations, the speed of the train was also recorded using radar, making it possible to analyze the impact of instantaneous speed on the total prediction time (Figure 3). The horizontal axis represents the time in seconds. The prediction time is converted into prediction distance using the instantaneous speed of the approaching train. This conversion is critical for accurately determining the distance at which the train will arrive based on the vibration signals detected.

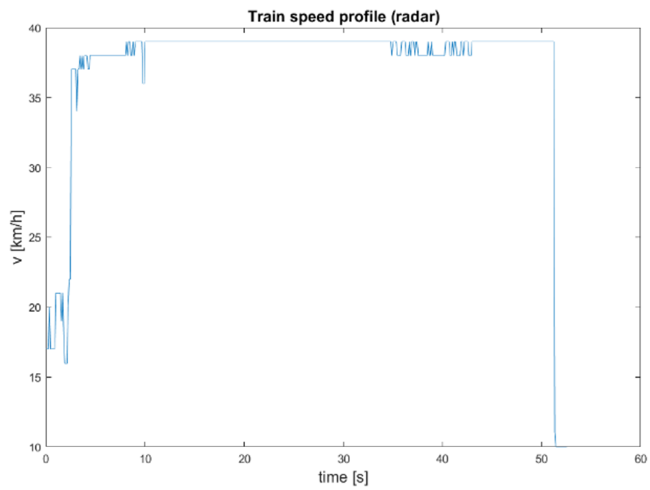

FIGURE 3 A typical train speed profile measured during a typical experiment.

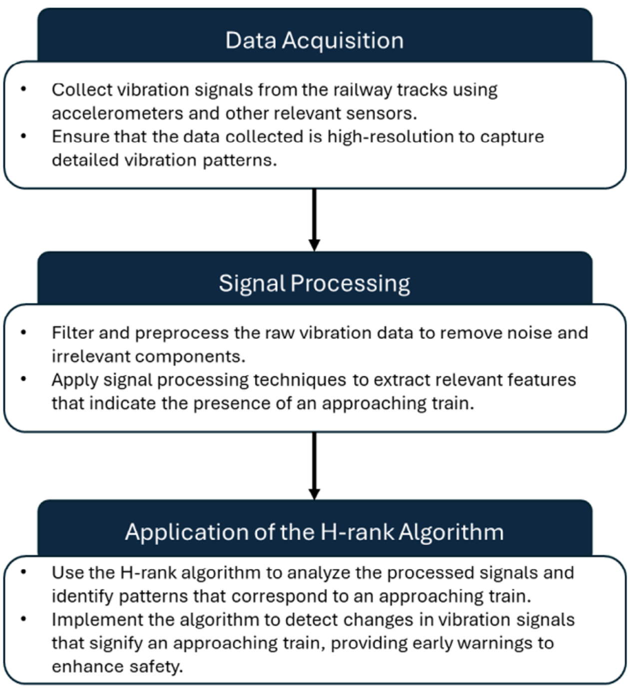

FIGURE 4 A technical roadmap illustrating the proposed methodology.

Continuous registration of the instantaneous speeds of the approaching train enables the conversion of the prediction time into the predicted distance. Ultimately, this may facilitate the installation of rail vehicle detection devices in specific locations of the railway network for known parameters of railway lines and permissible speed.

A technical roadmap illustrating the overall methodology of the study is provided in Figure 4. This roadmap outlines the key steps involved in the detection process, including data acquisition, signal processing, and the application of the H-rank algorithm to identify approaching trains.

Technical route: The detection system follows a clear and systematic process: (1) Data Acquisition: Sensors collect vibration signals from the railway tracks; (2) Signal Processing: Raw data are filtered and preprocessed to remove noise; (3) Feature Extraction: Relevant vibration features indicative of an approaching train are extracted; (4) H-rank Algorithm Application: The extracted features are analyzed using the H-rank algorithm to detect approaching trains. Each step is optimized for real-time processing and accuracy.

3 | THE PROPOSED COMPUTATIONAL APPROACH

3.1 | Overview of the H-rank algorithm

The H-rank method, previously described in the literature, is briefly introduced here. This study focuses on the customizations and modifications made to the H-rank algorithm to specifically address the challenge of detecting approaching trains using track vibration signals. These modifications include adapting the algorithm to handle high-frequency vibration data and optimizing its parameters for early and accurate detection.

The transformation of a sequence of real numbers using the Hankel transform $(x_k)_{k=1}^{\infty}$ yields a sequence $(h_k)_{k=1}^{\infty}$, where $h_k = \det(H_k)$ and H_k is a kth order Hankel matrix (V. L. Kurakin et al., 1995)

$$H_k = \begin{bmatrix} x_1 & x_2 & \cdots & x_k \\ x_2 & x_3 & \cdots & x_{(k+1)} \\ \vdots & \vdots & \ddots & \vdots \\ x_k & x_{(k+1)} & \cdots & x_{(2k-1)} \end{bmatrix} \tag{1}$$

If there exists such $m > 1$ that $h_m \neq 0$, but $h_j = 0$ for all $j > m$, then $(x_k)_{k=1}^{\infty}$ is a mth order linear recurrence sequence (LRS; A. Kurakin et al., 1995).

However, calculating the order of an LRS by computing a series of determinants is both impractical and imprecise. The utilization of the singular value decomposition (SVD) of a Hankel matrix is a well-established method for effectively determining the rank of a linear model governing the evolution of a time series (Klema & Laub, 1980). The count of non-zero singular values in a Hankel matrix of an LRS matches the number of non-zero roots present in the characteristic polynomial of the linear recurrence. The SVD algorithm can also be used to determine the order of linear recurrences affected by noise (Palivonaite & Ragulskis, 2014). Furthermore, the quantity of squared singular values of the Hankel matrix that exceeds the threshold ε can be utilized to assess the algebraic complexity of any time series, regardless of whether it is a linear recurrence or not (Navickas et al., 2017). Computing the count of singular values greater than a certain threshold ε value constitutes the principle of the H-rank algorithm (Navickas et al., 2017). Choosing the appropriate dimensions for the Hankel matrix, denoted by d, and the threshold parameter ε, aids in evaluating the algebraic complexity of any given time series (Landauskas et al., 2017; Petkevičiute-Gerlach et al., 2020).

The singular values of the Hankel matrix are calculated using the SVD algorithm. The threshold parameter ε is selected based on empirical testing to balance sensitivity and robustness. In our experiments, a threshold value of 0.1 provided the best results for detecting approaching trains.

While the H-rank algorithm relies on matrix operations, its application to vibration data involves complex signal processing techniques that enhance detection accuracy. The method's innovativeness lies in its ability to process large datasets efficiently and to detect subtle changes in vibration patterns of approaching trains.

The H-rank algorithm quantifies the changes in vibration patterns, which are indicative of an approaching train. The physical significance lies in the algorithm's ability to detect subtle increases in vibration intensity and specific frequency changes that occur as the train gets closer. By mapping H-rank values to the distance and speed of an approaching train, the algorithm uses a combination of signal amplitude and frequency analysis to distinguish train vibrations from environmental noise. Detailed results from controlled experiments demonstrate that as the train distance decreases, the H-rank value increases in a predictable manner, allowing for accurate train detection.

The H-rank algorithm's feasibility has been demonstrated through extensive testing with real-life vibration datasets. To handle large-scale computations, we utilize optimized numerical libraries and efficient specialized algorithms. These optimizations reduce the computational complexity and enable real-time processing of vibration data on standard computing hardware. Specifically, the computation of the SVD for a 100×100 matrix was completed in 0.003041 s on a laptop equipped with an Intel Core i3 (10th Gen) 1005G1 processor, 4 GB DDR4 SDRAM, and a processor frequency ranging from 1.2 to 3.4 GHz. For a 100×100 matrix, the SVD computation corresponds to 200 data points within an observation window from the dataset, covering a 0.004-s signal. This method is a feasible approach using standard computer hardware.

For the purpose of consistency and to ensure sufficient data for accurate analysis, the observation window throughout this study is standardized to 380,000 data points, which corresponds to a duration of 7.6 s of vibration signal recording.

The H-rank algorithm represents a significant advancement in vibration signal processing by enabling the detection of subtle pattern changes that simpler algorithms might miss. This capability is particularly important in ensuring the reliability of detection systems in scenarios where human vigilance or traditional systems might fail.

The innovation of our approach lies in its ability to function independently of the existing rail infrastructure and human factors, offering a consistent and accurate detection mechanism. This is particularly valuable in scenarios where traditional systems may be compromised or where human error could lead to catastrophic consequences. By automating the detection process, our system reduces the risk of human error and provides an additional layer of protection.

3.2 | Computational examples and results

As previously stated, the H-rank algorithm is useful not just for identifying the sequence order in a linear recurrence but also for assessing the algebraic intricacy of any time series (Petkevičiute-Gerlach et al., 2020, 2022). Therefore, before analyzing the rail vibration data, we will demonstrate the H-rank algorithm using a synthetic chaotic time series. The paradigmatic master–slave coupled (MSC) logistic map (Brown et al., 1994) is used to demonstrate how the H-rank algorithm can reveal the varying complexity of the MSC model. Specifically, we will consider a system in which the degree of synchronization between two subsystems (the master and the slave) can be controlled, and we will show that the H-rank algorithm is able to efficiently determine this degree of synchronization.

The equations governing the MSC model are as follows:

$$\begin{aligned} X_{k+1} &= r_X \cdot X_k \cdot (1 - X_k), \\ Y_{k+1} &= r_Y \cdot q_k \cdot (1 - q_k), \\ q_k &= \Delta \cdot X_k + (1 - \Delta) \cdot Y_k, k = 0, 1, 2, \ldots \end{aligned} \tag{2}$$

where X represents the master system, Y represents the slave system, and the parameter Δ denotes the strength of the master–slave coupling.

We select a value of $r_X = 3.9$ for the master system and $r_Y = 3.89$ for the slave system to ensure that both systems operate in a chaotic state (Brown et al., 1994). The initial conditions for the master and slave systems are set to $X_0 = 0.1$ and $Y_0 = 0.2$, respectively. As a result, when the coupling parameter Δ is set to 0, the two logistic maps produce completely different time series. In this study, the values of parameter Δ for the computational experiments are set to $\Delta = \{0.01; 0.3; 0.4; 0.5\}$.

Increasing the magnitude of the coupling parameter Δ leads to master–slave synchronization between the two coupled maps. The time series produced by the master and slave systems exhibit significant divergence at $\Delta = 0.01$ (Figure 5). As the value of Δ increases, the time series generated by the master and slave systems start to resemble each other more closely. For example, at $\Delta = 0.3$ (Figure 5) and $\Delta = 0.4$ (Figure 5), the likeness of the master and the slave systems is indicated by the smaller differences between X and Y. The master and the slave systems become almost identical when Δ is large enough (Figure 5), though small intermittent bursts can still be observed in the time series of the difference between the two systems.

The coupling parameter Δ can be utilized to control the complexity of the time series representing the difference between the master and slave $(X_k - Y_k)$. The MSC model does not only allow the generation of a chaotic time series $(X_k - Y_k)$ but also is capable to control its complexity. We will demonstrate that the H-rank algorithm can provide a meaningful evaluation of the algebraic complexity of this synthetic chaotic time series.

The master–slave system serves as a model for generating synthetic vibration data of an approaching train. The master–slave system is used to model the interaction between the track and the approaching train. The master system represents the track's baseline vibration pattern, while the slave system captures the variations caused by the approaching train. This setup allows for the effective application of the H-rank algorithm to detect significant deviations indicative of an approaching train.

For further computations, parameter Δ is chosen as a slowly varying function of time in the form of a cubic spline interpolant over 10,000 discrete time steps (Figure 6). The master (X) always remains the same, it is not influenced by the variation of Δ (Figure 6). However, the slave (Y) does respond to the variation of Δ. The difference $(X_k - Y_k)$ becomes almost equal to zero when $\Delta = 0.5$ and does represent a violent chaotic behavior at $\Delta = 0$ (Figure 6). In fact, the variation of Δ is chosen in such a way that the difference time series $(X_k - Y_k)$ would represent the computational approximation of the rail vibration of the approaching and distancing train.

The parameter Δ represents the coupling strength between the master and the slave systems. In our experiments, Δ is varied according to Figure 6 to simulate different levels of interaction between the track and the train. This variation helps to fine-tune the H-rank algorithm for optimal detection performance.

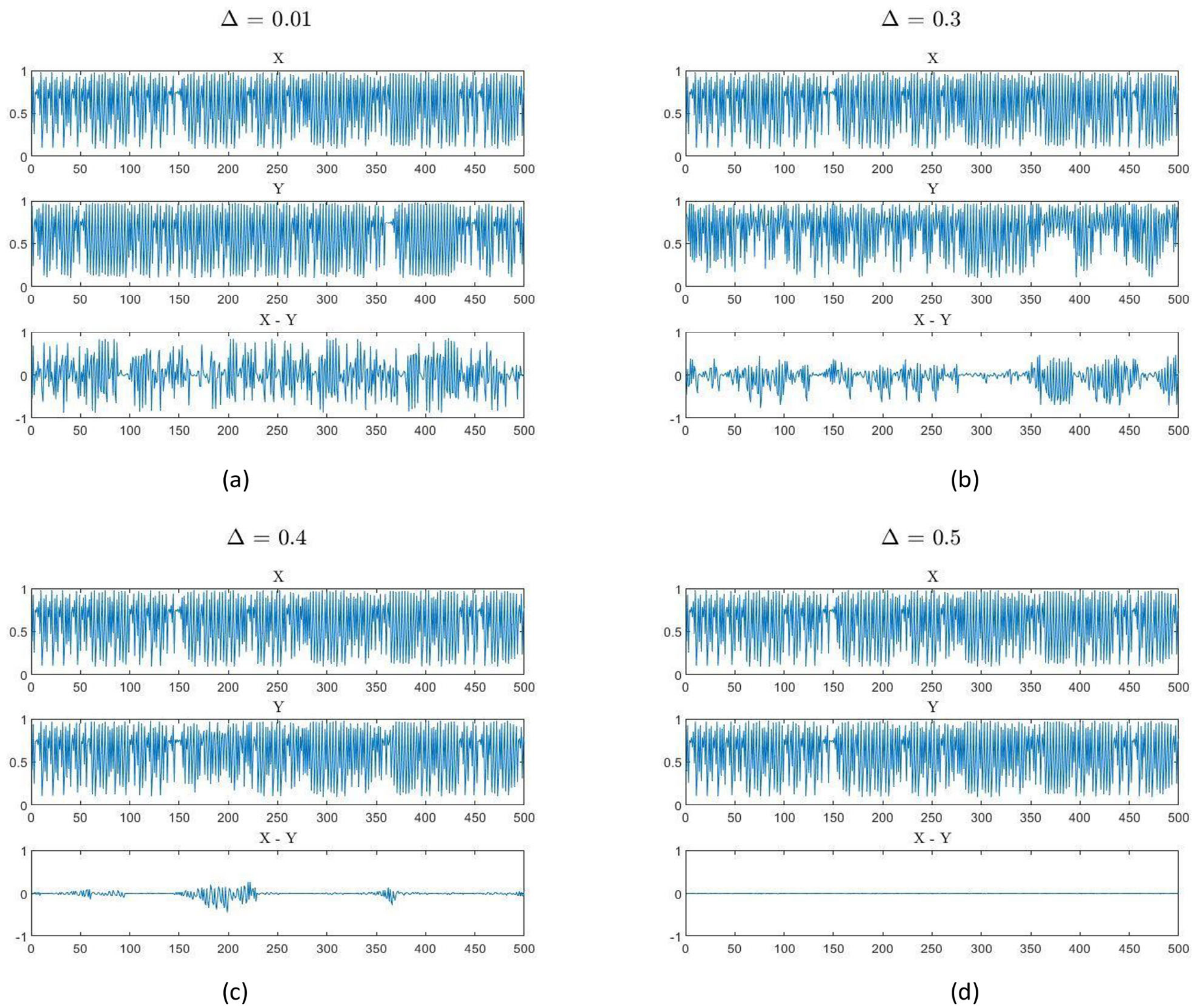

FIGURE 5 The experimental computation results of the master–slave coupled (MSC) logistic map at different constant values of Δ for time series X, Y, and $(X - Y)$. The results at $\Delta = 0.01$ in panel (a) show complete chaos at the difference between master and slave $(X - Y)$. Increasing Δ corresponds to the increasing similarity between the time series of master and slave in panels (b) and (c). At $\Delta = 0.5$ in panel (d) the difference between master and slave is almost equal to zero, thus master has high control over the behavior of the slave.

The dimensions of the Hankel matrix utilized to calculate the H-ranks are established as 100×100 (resulting in an observation window length of 200-time forward iterations); the threshold parameter is set to $\varepsilon = 0.1$. Each observation window (each Hankel matrix) results in a single numerical value representing the H-rank of that matrix (Ragulskis & Navickas, 2011). We use overlapping observation windows to produce the continuous variation of the H-ranks throughout the whole domain (represented by a thin blue line in the H-rank panel of Figure 6; note that the maximal possible H-rank at this size of the Hankel matrix is 100). It can be noted that the reconstructed H-ranks provide a good approximation of the varying complexity of the difference time series $(X_k - Y_k)$ (Figure 6).

4 | THE DETECTION OF THE APPROACHING TRAIN BASED ON TRACK VIBRATION SIGNAL ANALYSIS

The primary goal of the proposed method is to detect the presence of an approaching train. While the current implementation focuses on presence detection, future enhancements could extend the method to estimate the train's distance, speed, and speed variations. This would involve additional signal processing techniques to analyze the frequency and amplitude of the vibration signals in more detail.

Three types of experimental train track vibration signals generated by different types of moving trains are investigated in this paper: freight train with 12 wagons, electric

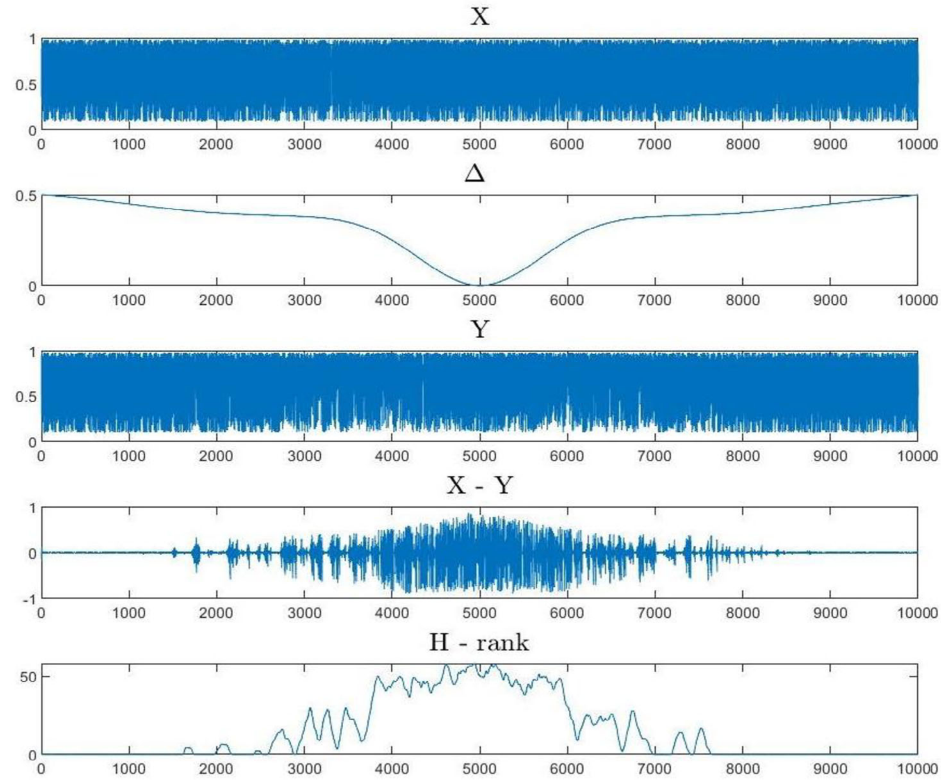

FIGURE 6 The results of the computational experiment of the MSC logistic map while parameter Δ is described as a function of the interpolated cubic spline. The slave (time series Y) behaves in respect of the master (time series X) corresponding to the value of Δ. The difference between the master and the slave is shown in the panel of $(X - Y)$ and demonstrates that two time series are becoming almost the same at high Δ values and evolve into almost chaotic time series at Δ equals zero. H-ranks computed for the time series of the difference between the master and the slave $(X - Y)$ denote the chaotic behavior: H-ranks are high when the signals X and Y are different and H-ranks become close to zero otherwise.

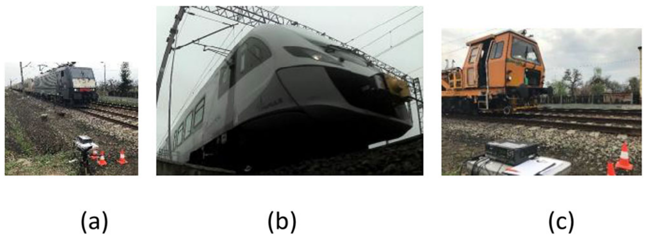

FIGURE 7 Different types of trains investigated in the paper: (a) the freight train, (b) electric multiple units, and (c) the railcar. Photographs courtesy of Rafal Burdzik.

multiple units (EMU), and solo (single) railcar. These three types of railway vehicles are illustrated in Figure 7. The dataset of recorded vibration signals has 5,796,000 data points for the freight train, 3,864,000 data points for the EMU, and 3,066,000 data points for the solo railcar. The sampling rate for all signals is 50,000 Hz, so each file of vibration signals contains vibration records for 115.92 s (freight train), 77.28 s (EMU), and 61.32 s (solo railcar; Figure 8). The accelerometer mounted on the train track is set to measure the track vibration in the direction of the X-axis.

The radar installation location is carefully selected based on the expected speed range of approaching trains and the geometry of the track. The radar is positioned to maximize its field of view and ensure accurate speed measurement. The relationship between radar and sensor systems is designed to optimize detection performance by aligning the radar's detection range with the sensor's vibration sensitivity. Instantaneous speed measurements are used to dynamically adjust detection parameters, enhancing the system's accuracy and responsiveness.

The chosen sampling rate of 50,000 Hz is necessary to capture the high-frequency components of the track vibration signals accurately. This high sampling frequency ensures that even subtle changes in the vibration patterns, indicative of an approaching train, are detected reliably. While this increases computational requirements, the benefits of early and accurate detection outweigh the costs.

As mentioned previously, the rail track is equipped with standard impulse-based sensors used to detect the approaching train. The output of the impulse-based sensors is depicted in Figure 8 in green solid lines. The first peak of the impulse-based sensor shows the train

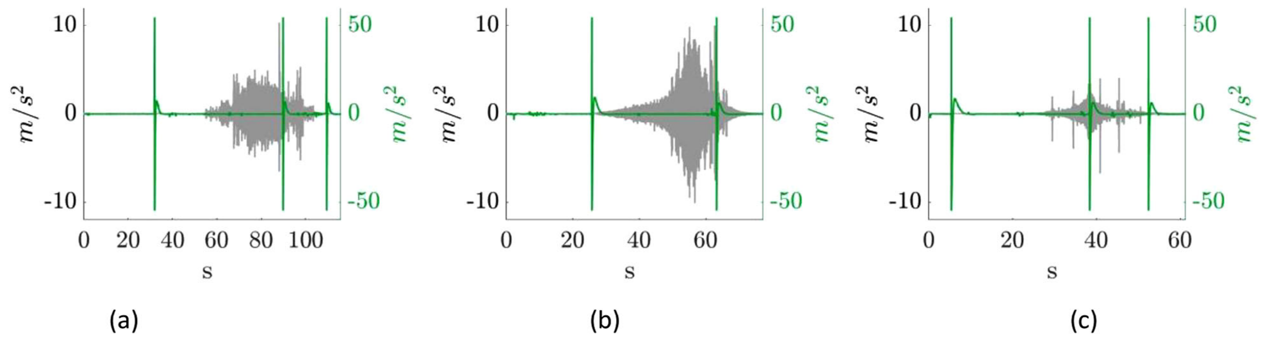

FIGURE 8 Track vibration data measured for three different types of trains. The track vibration signal is shown in gray, and the signal of the impulse-based sensor is plotted in green. Panels (a), (b), and (c) show the measurement results of the freight train, the EMU, and the solo railcar respectively.

passing over the point located 400 m ahead of the vibration measurement accelerometer (Figure 1).

Three impulses generated by the impulse-based sensor can be observed in Figure 8. Those impulses do determine the successive times of the position of the train. The first impulse is when the wheels of the first axle of the train are 400 m from the place where the vibration accelerometer is mounted. The second impulse is registered when the wheels of the first axle of the train approach the place where the vibration accelerometer is located (the moment of the train entry). The third impulse is when the wheels of the last axle of the train approach the place where the vibration accelerometer is mounted (the train exit). These impulses are marked in green lines in Figure 8.

As mentioned previously, the primary aim of this study is to demonstrate that the H-rank algorithm can predict the approaching trains earlier than the existing impulse-based sensors. The Hankel matrix dimension is specified as $d = 100$, leading to an observation window comprising 200 data points. The value of the threshold parameter ε is set to 0.1 (the same as used for the identification of the complexity of the MSC model).

4.1 | The selection of the length of the observation window

The experimental track vibration signals are inevitably contaminated by different types of noise (especially around the railroad crossings). Hence, it is crucial to adjust the algorithms for detecting approaching trains. A single random peak in the vibration signal should not be detected as an approaching train. On the other hand, the algorithms should be sufficiently sensitive to detect even smaller approaching train vehicles. In any case, the sensitivity of the proposed algorithm should be high enough to detect an approaching train further than 400 m away (the standard distance of the train markers).

The proposed method has been tested under a variety of track conditions and environmental factors, including different rail types, weather conditions, and noise levels. Results show that the H-rank algorithm effectively adapts to these varying conditions by adjusting its sensitivity to the specific vibration signatures associated with different train types and environmental influences. This adaptability ensures reliable train detection across diverse scenarios.

As mentioned earlier, a single calibration is sufficient for each specific location. For detailed steps and considerations involved in this calibration process, refer to Section 4.2, where we outline the calibration procedure comprehensively

Let us consider the experimental vibration signal of the track vibration measured without the approaching train. The first 380,000 data points of the vibration signal (7.6 s) are depicted in gray in Figure 9a–c. The selection of the length of the observation window is critical in our analysis. The H-ranks computed for this vibration signal are shown in blue in Figure 9. Clearly, the stochastic nature of the vibration signal leads to considerable fluctuation in the reconstructed H-ranks (Figure 9). Clearly, it would be difficult to exploit the values of H-ranks for a straightforward prediction of an approaching train.

In this study, it is demonstrated that the methodology is independent of the type of approaching train. A single calibration ensures reliable computation under challenging environmental conditions. This is the primary advantage of the proposed method. While a fixed window interval of 7.6 s was used in the initial experiments, future work will explore adaptive window intervals that vary based on train weight, speed, rail condition, and weather. This adaptation aims to improve the accuracy and reliability of the detection system under varying conditions.

The proposed model is effective under conditions where early detection of approaching trains is critical for safety, such as at unmanned railway crossings or maintenance areas. The model is particularly useful in scenarios where

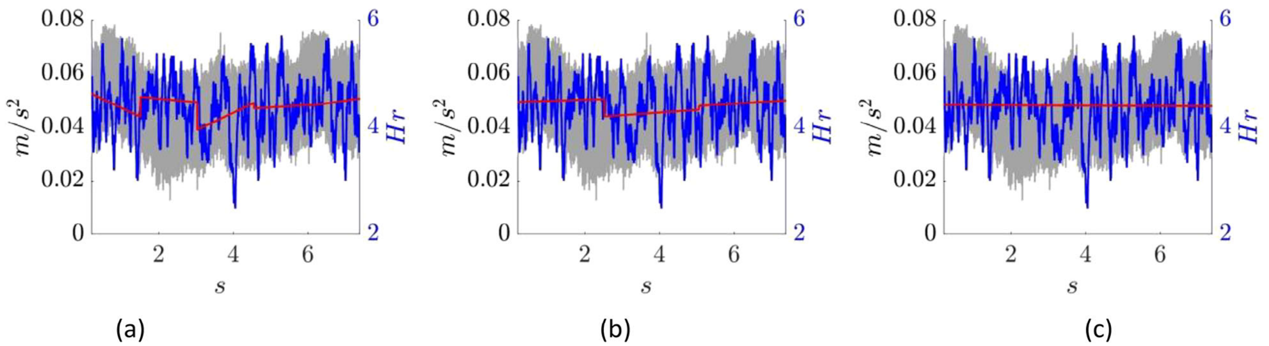

FIGURE 9 The selection of the length of the observation window. The vibration signal is divided into different intervals, showing varying slope coefficients. The whole observation window is used for linear regression in panel (c), resulting in a slope coefficient $\alpha = -0.11449402 \cdot 10^{-4}$.

visibility is limited, and existing detection systems may not provide adequate warning. By detecting the train's presence from 400 m, the model ensures sufficient time for vehicles or personnel to react, even at speeds up to 60 km/h.

It is well known from the theory of stochastic processes that statistical tests for stationarity in time series require an observation window of a certain length (Davydov, 1968). Therefore, the whole vibration signal in Figure 9 is split into several non-overlapping intervals of equal length, and the variation of H-ranks is approximated by linear regression in each of the intervals (marked in red in Figure 9).

Linear regression models are commonly used to explore the connection between a continuous outcome and independent variables (Swamy & Tinsley, 1980). The reconstructed model of the linear regression reads $y = \alpha x + \beta$, where y is defined as the approximated H-rank of the track vibration signal, and the x is time. The slope coefficient α can be used to detect the approaching train. When the slope coefficient α is equal to around zero, the track vibration signal corresponds to the random noise. The higher slope coefficient α denotes the increasing values of the H-ranks, which can be interpreted because of the approaching train.

Therefore, the first task is to choose a proper length of the interval for the computation of the slope coefficient α. A stationary random signal should result in $\alpha = 0$. If the vibration signal in Figure 9 is divided into five parts (panel a), the slope coefficients are different in each sub-interval. That is a clear indication that the process is not stationary, and implementing the proposed algorithm for detecting approaching trains might pose challenges.

Next, the vibration signal is segmented into three parts (Figure 9). The differences between the slope coefficients are smaller, but it would be still difficult to construct a reliable algorithm for the detection of the approaching train. Finally, if the vibration signal in Figure 9 is approximated by the linear regression in the whole observation window, the slope coefficient reads $\alpha = -0.11449402 \cdot 10^{-4}$. This value of the slope coefficient is considered sufficiently small, and all further computational analysis of vibration signals is performed using non-overlapping observation windows equal to 380,000 data points (7.6 s).

To calibrate the system, two parameters are required: the width of the observation window and the threshold, ε. We have extensively discussed the choice of observation window; however, it is worth noting that it may need to be adjusted based on the non-stationarity of environmental noise. This adjustment does not require the presence of a moving train. Instead, sensors need to be installed on the tracks at a specific location, and L can be calibrated based on the results obtained using the described methodology.

The calibration of ε, however, is more complex. It necessitates the measurement of vibration signals from at least one passing train. Additionally, a sensor needs to be placed at a specific distance (typically 400 m) to measure the exact moment of the train's passage. At least one vibration record is required. Based on this record and the described methodology, ε is calibrated.

There is always a lower bound for the value of ε. If ε is too low, the system will operate unstably and generate false alerts. Conversely, ε should not be too high, as the system would then only detect the passing train when it is very close. The goal is to find a reliable compromise between noise resistance and sensitivity to an approaching train.

4.2 | The calibration of the slope coefficient

Figure 10 shows H-ranks computed for all three different types of trains (freight train in panel (a), EMU in panel (b), and solo railcar in panel (c)). Afterward, the time series of H-ranks is divided into intervals of 7.6 s. Since the

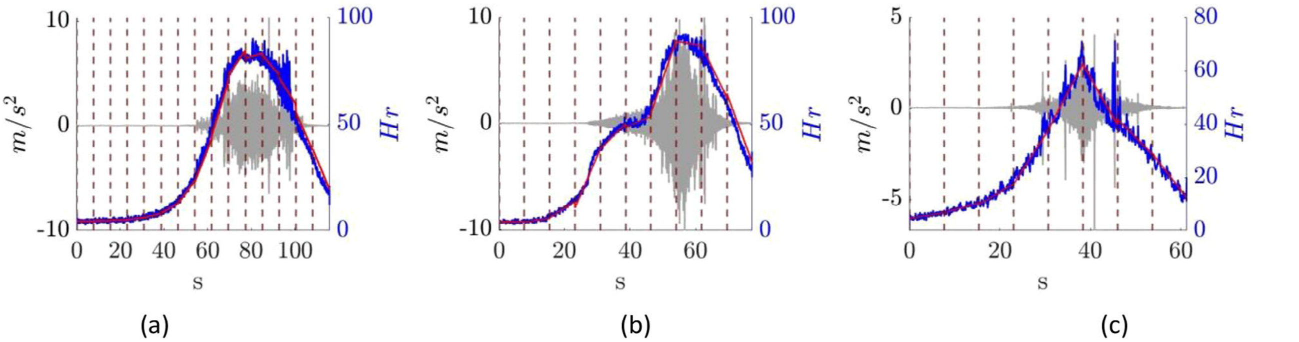

FIGURE 10 The reconstruction of slope coefficients from the track vibration signals recorded for different types of trains (the freight train, EMU, and the solo railcar vibration signals. Railcar vibration signals are gray. H-ranks for track vibrations are in blue (right blue scales). Red dashed lines indicate sub-intervals for H-rank linear regression: 15 in (a) (freight train), 10 in (b) (EMU), and eight in (c) (solo railcar).

TABLE 2 The slope coefficients of H-ranks are approximated by the linear regression for track vibration signals generated by different types of passing trains.

Slope coefficient		
Freight train	**EMU**	**Solo railcar**
−0.0114	0.0081	1.1783
−0.0119	0.9115	1.9107
0.0286	4.0409	4.0794
0.3741	14.5960	10.6448
1.0496	6.2254	13.1414
2.4673	2.5940	−11.9728
5.7050	18.0439	−6.9073
10.6117	−1.0988	−8.8009
13.6492	−12.7204	
6.1539	−16.9926	
1.1997		
−4.9164		
−6.5852		
−9.3314		
−9.9389		

Note: The computed values of the slope coefficients are multiplied by 10^3 for clarity. Note that the duration of recorded vibration signals for different types of trains is different. Coefficients colored in red denote sub-intervals where the proposed technique could not detect the approaching train. Coefficients colored in green represent sub-intervals when the approaching train is detected earlier by the proposed technique than by the impulse-based sensor mounted 400 m away from the vibration accelerometer.
Abbreviation: EMU, electric multiple units.

vibration records are of different lengths, such a division results in 15 sub-intervals in Figure 10a, 10 sub-intervals in Figure 10b, and eight sub-intervals in Figure 10c. The slope coefficients of the linear regressions computed for the variation of H-ranks in each sub-interval are depicted in Table 2 (note that the values of slope coefficients are multiplied by 1000 for clarity).

Now, the calibration of the proposed technique must be done in terms of the minimum slope coefficient signaling about the approaching train. It can be observed that the threshold value of the slope coefficient equal to $0.02 \cdot 10^{-3}$ does serve as a reliable indicator for an approaching train.

Calibration is performed once immediately after the installation of the measurement hardware. This calibration ensures that the sensors are accurately aligned and responsive. These calculations clearly demonstrate that calibration for different types of trains is unnecessary. A single calibration ensures the successful operation of the system. Comparative experiments have been conducted to test the applicability of the method across different types of trains, velocities, and environmental conditions. These experiments demonstrate the robustness and reliability of the proposed detection system.

Table 2 shows that from the first sub-interval of H-ranks linear regressions train can be detected only by the signal of solo railcar (Figure 10c) as the slope coefficient for this sub-interval $1.1783 \cdot 10^{-3}$ is greater than the threshold parameter $0.02 \cdot 10^{-3}$ (the third column in Table 2). The train can be detected from the second sub-interval of the linear regression (the second column in Table 2) of the EMU train vibration signal (Figure 10b) since the slope coefficient is $0.9115 \cdot 10^{-3} > 0.02 \cdot 10^{-3}$. The third sub-interval of the linear regression (the first column in Table 2) denotes the approaching train for the vibration signal of the freight train since the slope coefficient $0.0286 \cdot 10^{-3}$ is greater than $0.02 \cdot 10^{-3}$ (Figure 10a).

Regarding the presented methodology the train can be detected from 38 to 60.8 s before driving across the crossing. This algorithm is better for the train detection system than previous methods, using physical sensors while detecting an approaching train 33 s before it drives across the road.

The calibration process is performed once per location to account for the specific track and environmental characteristics. During calibration, the system measures baseline vibrations and environmental noise, adjusting its sensitivity and thresholds accordingly. This allows the algorithm to remain effective across different train types without the need for recalibration, as it is designed to recognize the unique vibration patterns of all trains passing through the calibrated location.

Calibrating the slope coefficient is directly linked to choosing the appropriate observation window. The primary goal of this calibration procedure is to enable the proposed algorithm to distinguish track vibrations induced by the approaching train from the environmental noise. It is important to observe that this calibration is performed only once right after the installation of the specific measurement hardware and is usable for all three types of trains investigated in this paper. No doubt, different types of accelerometers and different vibration signal acquisition hardware and software would require a re-calibration of the slope coefficient. But the results of this study show that once this calibration is done, it can be used for different kinds of trains, for different train velocities, and for different environmental parameters.

5 | DISCUSSION

Increasing the prediction range of an approaching rail vehicle requires the use of new devices and advanced methods of signal processing. Existing devices dedicated to the detecting of moving objects, both those used in rail transport and vehicle detectors (Feng et al., 2017; based on magnetoresistive sensors, fiber optic sensors, current sensors, voltage sensors, or even temperature sensors), or radars are increasingly being tested. However, the successful implementation of such techniques has several limitations in their application. The sensors used in the train traction system enable the detection of a vehicle located above the sensor or in its immediate vicinity. Axle counters, also referred to as rail vehicle detection sensors, stand as the primary component of the rail traffic control system. The task of these devices is to constantly control the unoccupied sections of the track necessary for the safe operation of rail traffic both on the railway line and at the station. Information on which of the supervised sections is free or occupied is necessary to determine a safe route, and thus allow the train to enter the controlled zone. Therefore, they constitute the sectional control points whose possibilities of predicting the approach of a train are limited due to the length of specific linear sections.

Radars, on the other hand, allow the detection of vehicles from certain distances, but they are exposed to many unwanted effects, and their effectiveness strongly depends on the location and topography as well as barriers that are often present in the vicinity of the railway crossings.

Therefore, the search for new sources of information about approaching trains is an important scientific issue with great potential for practical applications. The technique described in this paper is based on rail vibration measurements and enables independent predictions from other information systems used in rail transport. The difficulty in using vibration signals for these purposes results from the large information capacity, which results in redundancy and sensitivity to the inevitable environmental noise. That is why the development of an original and dedicated mathematical algorithm for signal processing to extract information about the approaching train as early as possible is so important.

The proposed method utilizes durable sensors with a low maintenance requirement, making it a cost-effective solution for railway safety. Initial installation costs are offset by the system's longevity and low operational costs. Additionally, the system's ability to reduce accidents and improve safety at railway crossings provides significant economic and social benefits, further enhancing its cost-effectiveness.

Whenever a new technique is developed, its limitations should be considered. One such limitation is the type of rail vehicle. Of course, the type, size, weight, and speed of the rail vehicle do affect the generated track vibrations. Therefore, as part of the measurements, signals of rail vibrations generated by the passage of various types of trains are recorded. Then, as part of analytical experiments, calculations are carried out for extremely different types of rail vehicles: a freight train, a passenger train (EMU), and a single handcar. The train types are selected in such a way that the differences in the construction, weight, and size are very large. Additionally, rail vehicles moving at different speeds are considered too. Due to the use of the signal processing method developed using the H-rank algorithm, it is shown that in each of these very different situations, satisfactory prediction rates are achieved. This is a very important achievement of the developed method, which reduces the fundamental limitation of the method for different rail vehicles moving at different speeds.

Another limitation is related to the location of the railway network and the resulting differences in the track geometry and the type of track infrastructure. In this respect, the same measurement setup was installed in different geographical locations. The obtained results confirmed the satisfactory results for different locations. Similarly, the influence of the ambient temperature, which could potentially impact the propagation characteristics of the vibration wave on the steel rail, is verified too. Satisfactory results are also achieved for different meteorological and environmental conditions. Therefore, as limitations of the developed method of predicting an approaching rail vehicle using vibration signals and the H-rank algorithm, which require further verification, the type of vibration sensors used and the place of mounting on the rail should be indicated. An additional limitation may be the presence of other railway crossings, stations, or carrying out works on the railway infrastructure within the prediction range converted into distances from the location of the vibration sensor.

It takes a long time to achieve 100% separation of road and rail traffic flows using railroad crossings levels with barriers. Additionally, this process will progress at different rates in different countries. So far, there is not a single country in the entire world that has all rail and road crossings with barriers. For example, in Poland, there are over 8740 crossings without barriers (ca. 70% of all). Moreover, the presented research shows the potential and possibilities of using rail vibration signals, which can be used in many areas of rail transport and in the entire railway network, not only at railroad crossings.

In experimental tests, rail vibration accelerations were recorded during the passage of several dozen trains. Long-term signals were always recorded, which included at least 5 min of recording before the train passage and a few minutes after the train passage. The article presents only representative results for three types of trains (passenger—EMU, freight, and single railcar), whose construction is so different that they constitute separate experimental groups. For each of these groups, several dozen passages of various trains were recorded. In addition, the concept of the signal processing methodology is based on tools that determine relative measures and trends, which makes it possible to reduce the impact of the environment (different tracks) and different types of trains on the prediction time of an approaching rail vehicle.

The concept and prototype of the system are completely independent from other systems currently used in railway infrastructure. The sensor is powered autonomously and by battery, the battery life is over 12 months. Tracking sensor for rail vehicles was patented in Tracking sensor for rail vehicles (2021). The signal transmission system is based on LoRa technology, independent of the railway transport transmission system. LoRa is a radio interface operating, among others, in the ISM 434 MHz and 868 MHz bands, enabling long-range communication with low power consumption. The data processing and results archiving unit is built into the measurement sensor. The prototype of the system was developed by the Polish company DR-TECH and has been installed for over 2 years at a railroad crossing level as a completely independent and autonomous system.

The developed method for predicting an approaching train was designed with the assumption of being independent of the technical state of the railway infrastructure and superstructure, including the condition and type of tracks and rail vehicles.

Knowing how much influence the parameters, type and technical condition of ballast, railway sleepers and rail joints have on the recorded vibration signals, as well as the size, type of train, type of suspension, technical condition of wheels and bogies of rail vehicles (locomotives and wagons), it was assumed that all these factors would be reduced as a vibration background. Therefore, relative measures have been proposed that analyze the increases in subsequent iterations of the computational algorithm, which reduces the impact of infrastructure and temperature. In the case of the technical condition of rail vehicles, any anomalies from the standard condition result in an increase in the dissipation of vibration energy, which further highlights the upward trends, making it easier to predict the vehicle from a greater distance.

It is difficult to compare the obtained results of research experiments with the research of other authors because there are no articles in the literature presenting calculations for predicting the approach of a rail vehicle based on rail vibration signals. It is true that there are many publications on the measurement of rail vibrations: Cui et al. (2021, 2022) and Kaewunruen and Remennikov (2006) alongside the anticipation of vibrations triggered by train passage and the emission of vibrations into the ground, Auersch (2020), Kouroussis et al. (2017), Lombaert et al. (2006), and Picoux & Houedec (2005), but it is not possible to directly relate these results to the described experiments.

Our research demonstrates that such methods are often insufficient in complex environments characterized by high levels of noise and other vibrations. The H-rank algorithm we propose is specifically designed to address these challenges by analyzing large datasets to detect subtle changes in vibration patterns that simpler algorithms might miss.

In environments with significant noise, such as urban areas or near industrial sites, the precision of our method becomes critical. The advanced algorithm we developed is capable of distinguishing between different types of vibrations, ensuring that the system can reliably detect an approaching train even under these challenging conditions. This accuracy and robustness are not achievable with simple vibration detection methods, particularly when the train is far from the detection point, and the signal-to-noise ratio is low.

While simple vibration detection methods can identify the presence of a train, they may not provide the accuracy needed in complex environments with high noise levels. The H-rank algorithm enhances detection reliability by processing large datasets efficiently, ensuring robust performance even in challenging conditions.

6 | CONCLUDING REMARKS

This paper introduces a novel technique for detecting approaching trains through the analysis of track vibration signals. The proposed method relies on the H-ranks of vibration signals obtained from a real experimental setup, where the vibrations produced through the interaction of the wheel with the track are inevitably affected by environmental noise. It appears that the predictions performed by the proposed method do outperform standard techniques for the detection of approaching trains.

The presented approach for the detection of the approaching trains can be easily implemented on the existing track infrastructure without compromising any safety standards or regulations. All presented experimental measurements, computations, and predictions are performed when the vibration accelerometer is installed directly on the track at the crossing location. The prediction time for the approaching train could be seriously improved if the vibration accelerometer were mounted ahead of the crossing (e.g., 400 m away from the crossing). Then, the proposed technique should either comprise wireless vibration signal transmission to the computer performing the prediction, or all the real-time computations should be performed in the vicinity of the vibration accelerometer (then only the warning signals for the approaching train should be transmitted to the location of crossing). The concrete goal of future research is to practically implement such a distributed infrastructure.

While direct comparisons with other studies are challenging due to the lack of similar research, our experimental results indicate that the proposed method provides reliable early detection of approaching trains. The method's robustness to noise and environmental conditions further supports its potential for practical application.

For practical implementation, the proposed technique can be enhanced by incorporating wireless vibration signal transmission to a central processing unit or performing real-time computations locally near the vibration accelerometers. This would ensure timely and efficient detection, improving overall safety.

CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

REFERENCES

Abonyi, Z., Dobrowiecki, T., & Tóth, K. (1988). Dedicated multiprocessor system for automatic rail flaw detection. *Periodica Polytechnica Electrical Engineering*, *32*(1), 33–41.

Adnan, K., & Akbar, R. (2019). An analytical study of information extraction from unstructured and multidimensional big data. *Journal of Big Data*, *6*(1), 91. https://doi.org/10.1186/s40537-019-0254-8

Alahakoon, S., Sun, Y. Q., Spiryagin, M., & Cole, C. (2018). Rail flaw detection technologies for safer, reliable transportation: A review. *Journal of Dynamic Systems, Measurement, and Control*, *140*(2), 020801.

Auersch, L. (2020). Simple and fast prediction of train-induced track forces, ground and building vibrations. *Railway Engineering Science*, *28*(3), 232–250.

Barker, J. L. (1970). Radar acoustic, and magnetic vehicle detectors. *IEEE Vehicular Technology Transactions*, *19*(1), 30–43. https://doi.org/10.1109/T-VT.1970.23429

Bertozzi, M., Broggi, A., Fascioli, A., & Nichele, S. (2000). Stereo vision-based vehicle detection. *Proceedings of the IEEE Intelligent Vehicles Symposium*, Dearborn, MI, (pp. 39–44). https://doi.org/10.1109/IVS.2000.898315

Borsos, A., Gabor, M., & Koren, C. (2016). Safety ranking of railway crossings in Hungary. *Transportation Research Procedia*, *14*, 2111–2120. https://doi.org/10.1016/j.trpro.2016.05.226

Brown, R., Rulkov, N. F., & Tracy, E. R. (1994). Modeling and synchronizing chaotic systems from time-series data. *Physical Review E*, *49*, 3784–3800. https://doi.org/10.1103/PhysRevE.49.3784

Burdzik, R., Celiński, I., & Kłaczyński, M. (2022). Railway line occupancy control based on distance determination sound method. *Sensors*, *22*(13), 5003. https://doi.org/10.3390/s22135003

Burdzik, R., Konieczny, L., & Nowak, B. J. R. (2017). Research on vibration employed for the train traffic control. *Vibroengineering Procedia*, *14*, 227–232. https://doi.org/10.21595/vp.2017.19237

Burdzik, R., & Nowak, B. (2017). Identification of the vibration environment of railway infrastructure. *Procedia Engineering*, *187*, 556–561. https://doi.org/10.1016/j.proeng.2017.04.414

Burdzik, R., Nowak, B., Młyńczak, J., & Deuszkiewicz, P. (2016). Analysis of the detection and crossing signaling system in safety terms. *Diagnostyka*, *17*(4), 65–72.

Celiński, I., Burdzik, R., Młyńczak, J., & Kłaczyński, M. (2022). Research on the applicability of vibration signals for real-time train and track condition monitoring. *Sensors*, *22*(6), 2368. https://doi.org/10.3390/s22062368

Chen, Y., Wang, J., Chen, J., Wang, P., Xu, J., & An, B. (2022). A novel three-dimensional wheel–rail contact geometry method in the switch panel considering variable cross-sections and yaw angle. *Vehicle System Dynamics*, *60*(9), 3174–3197. https://doi.org/10.1080/00423114.2021.1941140

Cui, X., Cheng, Z., Yzng, Z., Huang, B., & Du, Z. (2022). Study on the phenomenon of rail corrugation on highspeed rail based on the friction-induced vibration and feedback vibration. *Vehicle System Dynamics*, *60*(2), 413–432.

Cui, X., He, Z., Huang, B., Chen, Y., Du, Z., & Qi, W. (2021). Study on the effects of wheel-rail friction self-excited vibration and feedback vibration of corrugated irregularity on rail corrugation. *Wear*, *477*, 203854.

Davydov, Y. A. (1968). Convergence of distributions generated by stationary stochastic processes. *Theory of Probability & Its Applications*, *13*(4), 691–696. https://doi.org/10.1137/1113086

Dougherty, M. (1995). A review of neural networks applied to transport. *Transportation Research Part C: Emerging Technologies*, *3*(4), 247–260. https://doi.org/10.1016/0968090X(95)00009-8

Feng, J., Xu, J., Liao, W., & Liu, Y. (2017). Review on the traction system sensor technology of a rail transit train. *Sensors*, *17*(6), 1356. https://doi.org/10.3390/s17061356

Wilde, G. J. S., Hay, M. C., & Brites, J. N. (1987). Video-recorded driver behaviour at railway crossings: Approach speeds and critical incidents. Kingston Ont: Canadian Institute of Guided Ground Transport; Dept. of Psychology Queens University.

Gómez, M. J., Corral, E., Castejón, C., & García-Prada, J. C. (2018). Effective crack detection in railway axles using vibration signals and WPT energy. *Sensors*, *18*(5), 1603. https://doi.org/10.3390/s18051603

Heittola, T., Mesaros, A., Eronen, A., & Virtanen, T. (2013). Context-dependent sound event detection. *EURASIP Journal on Audio, Speech, and Music Processing*, *2013*(1), https://doi.org/10.1186/1687-4722-2013-1

Hill, K. O., Malo, B., Bilodeau, F., Johnson, D. C., & Albert, J. (1993). Bragg gratings fabricated in monomode photosensitive optical fiber by UV exposure through a phase mask. *Applied Physics Letters*, *62*(10), 1035–1037.

Hookham, F. J. (1925). Automatic train control. *Journal of the Institution of Locomotive Engineers*, *15*(70), 243–279. https://doi.org/10.1243/JILE_PROC_1925_015_022_01

Hwang, K., Cho, J., Park, J., Har, D., & Ahn, S. (2019). Ferrite position identification system operating with wireless power transfer for intelligent train position detection. *IEEE Transactions on Intelligent Transportation Systems*, *20*(1), 374–382. https://doi.org/10.1109/TITS.2018.2797991

Kaewunruen, S., & Remennikov, A. M. (2006). Sensitivity analysis of free vibration characteristics of an in situ railway concrete sleeper to variations of rail pad parameters. *Journal of Sound and Vibration*, *298*(1-2), 453–461.

Kaynia, A. M., Park, J., & Norén-Cosgriff, K. (2017). Effect of track defects on vibration from high speed train. *Procedia Engineering*, *199*, 2681–2686. https://doi.org/10.1016/j.proeng.2017.09.551

Klema, V., & Laub, A. (1980). The singular value decomposition: Its computation and some applications. *IEEE Transactions on Automatic Control*, *25*(2), 164–176. https://doi.org/10.1109/TAC.1980.1102314

Kouroussis, G., Vogiatzis, K. E., & Connolly, D. P. (2017). A combined numerical/experimental prediction method for urban railway vibration. *Soil Dynamics and Earthquake Engineering*, *97*, 377–386.

Kuen, L. K., & Ho, S. L. (2006). Unconventional method of train detection using fibre optic sensors. *HKIE Transactions*, *13*(1), 16–21. https://doi.org/10.1080/1023697X.2006.10668026

Kurakin, A., Kuzmin, A., & Nechaev, A. (1995). Linear complexity of polinear sequences. *Journal of Mathematical Sciences*, *76*, 2793–2915.

Kurakin, V. L., Kuzmin, A. S., Mikhalev, A. V., & Nechaev, A. A. (1995). Linear recurring sequences over rings and modules. *Journal of Mathematical Sciences*, *76*(6), 2793–2915. https://doi.org/10.1007/BF02362772

Lai, C. C., Kam, J. C. P., Leung, D. C. C., Lee, T. K. Y., Tam, A. Y. M., Ho, S. L., Tam, H. Y., & Liu, M. S. Y. (2012). Development of a fiber-optic sensing system for train vibration and train weight measurements in Hong Kong. *Journal of Sensors*, *2012*, 1–7. https://doi.org/10.1155/2012/365165

Landauskas, M., Navickas, Z., Vainoras, A., & Ragulskis, M. (2017). Weighted moving averaging revisited: An algebraic approach. *Computational and Applied Mathematics*, *36*, 1545–1558.

Li, Y., Zuo, M. J., Lin, J., & Liu, J. (2017). Fault detection method for railway wheel flat using an adaptive multiscale morphological filter. *Mechanical Systems and Signal Processing*, *84*, 642–658. https://doi.org/10.1016/j.ymssp.2016.07.009

Lombaert, G., Degrande, G., Kogut, J., & François, S. (2006). The experimental validation of a numerical model for the prediction of railway induced vibrations. *Journal of Sound and Vibration*, *197*(3-5), 512–535.

McAulay, A. D. (1974). *Detection of track-guided ground vehicles using the track as an electromagnetic surface waveguide*. Carnegie Mellon University. Report.

Meng, Y., Yang, J., Liu, S., Xu, W., Chen, G., Niu, Z., & Li, X. (2022). Nano-fiber based self-powered flexible vibration sensor for rail fasteners tightness safety detection. *Nano Energy*, *102*, 107667.

Michalopoulos, P. G. (1991). Vehicle detection video through image processing: The autoscope system. *IEEE Transactions on Vehicular Technology*, *40*(1), 21–29. https://doi.org/10.1109/25.69968

Mills, M. K. (1970). Future vehicle detection concepts. *IEEE Transactions on Vehicular Technology*, *19*(1), 43–49. https://doi.org/10.1109/TVT.1970.23430

Navickas, Z., Vainoras, A., Ragulskis, M., & Landauskas, M. (2017). Weighted moving averaging revisited: An algebraic approach. *Computational and Applied Mathematics*, *36*, 1545–1558.

Olaby, O., Hamadache, M., Soper, D., Winship, P., & Dixon, R. (2022). Development of a novel railway positioning system using RFID technology. *Sensors*, *22*(6), 2401.

Palivonaite, R., & Ragulskis, M. (2014). Short-term time series algebraic forecasting with internal smoothing. *Neurocomputing*, *127*, 161–171.

Park, S., Lee, J. H., & Kim, S. J. (2016). Performance assessment of high-speed transponder system for rail transport on high-speed line. *Journal of the Korean Society for Railway*, *19*(3), 304–313.

Peter, L. H. (1936). Modern developments in railway signaling. *Journal of the Institution of Electrical Engineers*, *78*(472), 353–371.

Petkevičiute-Gerlach, D., Timofejeva, I., & Ragulskis, M. (2020). Clocking convergence of the fractional difference logistic map. *Nonlinear Dynamics*, *100*, 1–11.

Petkevičiute-Gerlach, D., Šmidtaite, R., & Ragulskis, M. (2022). Intermittent bursting in the fractional difference logistic map of matrices. *International Journal of Bifurcation and Chaos*, *32*(1), 2230002. https://doi.org/10.1142/S0218127422300026

Picoux, B., & Houedec, D. L. (2005). Diagnosis and prediction of vibration from railway trains. *Soil Dynamics and Earthquake Engineering*, *25*(12), 905–921.

Ragulskis, M., & Navickas, Z. (2011). The rank of a sequence as an indicator of chaos in discrete nonlinear dynamical systems. *Communications in Nonlinear Science and Numerical Simulation*, *16*(7), 28942906. https://doi.org/10.1016/j.cnsns.2010.10.008

Reiff, R. P. (2003). *Evaluation of alternative detection technologies for trains and highway vehicles at highway rail intersections*. DIANE Publishing.

Rice, P. X. (1932). Automatic train control based on magnetic bridge. *Journal of the Franklin Institute*, *213*(4), 381399. https://doi.org/10.1016/S0016-0032(32)90446-3

Schoppert, D. W., Hoyt, D. W., Voorhees, A. M., & McLean, V. A. (1968). *Factors influencing safety at highway-rail grade crossings*. NCHRP Report No 50. Washington, D.C.: Highway Research Board, National Cooperative Highway Research Program (NCHRP).

Singleton, M., & Ward, J. E. (1977). *Comparative study of various types of vehicle detectors*. Report No. DOT-TSC-OST77-09. United States Department of Transportation, Office of the Secretary.

Suharjono, A., Wardihani, E. D., & Hardani, Y. F. K. (2017). Analysis of the vibration signal detection for rail train arrival. *IEEE International Conference on Communication, Networks and Satellite (Comnetsat)*, Semarang, Indonesia (pp. 85–87). https://doi.org/10.1109/COMNETSAT.2017.8263578

Sun, Q., Chen, C., Kemp, A. H., & Brooks, P. (2021). An onboard detection framework for polygon wear of railway wheel based on vibration acceleration of axle-box. *Mechanical Systems and Signal Processing*, *153*, 107540. https://doi.org/10.1016/j.ymssp.2020.107540

Swamy, P. A. V. B., & Tinsley, P. A. (1980). Linear prediction and estimation methods for regression models with stationary stochastic coefficients. *Journal of Econometrics*, *12*(2), 103–142. https://doi.org/10.1016/0304-4076(80)90001-9

Szaciłło, L., Jacyna, M., Szczepański, E., & Izdebski, M. (2021). Risk assessment for rail freight transport operations. *Eksploatacja i Niezawodnosc–Maintenance and Reliability*, *23*(3), 476–488. https://doi.org/10.17531/ein.2021.3.8

Tian, X. (2017). Enhanced information extraction from noisy vibration data for machinery fault detection and diagnosis *[Doctoral dissertation*, University of Huddersfield].

Tracking sensor for rail vehicles. (2021). Tracking sensor for rail vehicles. https://patents.google.com/patent/PL237398B1/en?inventor=burdzikŹoq=burdzik+.

Ward, N. J., & Wilde, G. J. (1996). Driver approach behaviour at an unprotected railway crossing before and after enhancement of lateral sight distances: An experimental investigation of a risk perception and behavioural compensation hypothesis. *Safety Science*, *22*(1-3), 63–75. https://doi.org/10.1016/0925-7535(96)00006-9

Wei, C. L., Lai, C. C., Liu, S. Y., Chung, W. H., Ho, T. K., Tam, H. Y., Ho, S. L., McCusker, A., Kam, J., & Lee, K. Y. (2010). A fiber Bragg grating sensor system for train axle counting. *IEEE Sensors Journal*, *10*(12), 1905–1912. https://doi.org/10.1109/JSEN.2010.2049199

Wu, X., Zhu, X., Wu, G. Q., & Ding, W. (2014). Data mining with big data. *IEEE Transactions on Knowledge and Data Engineering*, *26*(1), 97–107. https://doi.org/10.1109/TKDE.2013.109

Xu, L., Li, Z., Zhao, Y., Yu, Z., & Wang, K. (2022). Modelling of vehicle-track related dynamics: A development of multi-finite-element coupling method and multi-timestep solution method. *Vehicle System Dynamics*, *60*(4), 197–1124. https://doi.org/10.1080/00423114.2020.1847298

Yang, J., Tao, W., Liu, M., Zhang, Y., Zhang, H., & Zhao, H. (2011). An efficient direction field-based method for the detection of fasteners on high-speed railways. *Sensors*, *11*(8), 7364–7381. https://doi.org/10.3390/s110807364

Zhao, Y., Liu, Z., Yi, D., Yu, X., Sha, X., Li, L., Sun, H., Zhan, Z., & Li, W. J. (2022). A review on rail defect detection systems based on wireless sensors. *Sensors*, *22*(17), 6409. https://doi.org/10.3390/s22176409

How to cite this article: Orinaite, U., Burdzik, R., Ranjan, V., & Ragulskis, M. (2024). Prediction of approaching trains based on H-ranks of track vibration signals. *Computer-Aided Civil and Infrastructure Engineering*, 1–18. https://doi.org/10.1111/mice.13349