TRB Annual Meeting

Development and Implementation of a Novel Technique for In-Motion Track Change Detection and Identification

--Manuscript Draft--

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ABSTRACT

With nearly 140,000 miles of track, railroads are central to North America's transportation infrastructure, carrying over 40% of freight by ton-miles and serving millions of passengers annually. Maintaining the structural integrity of the track is essential for operational safety and economic efficiency. Integrity is compromised by stiffness changes due to ballast degradation, subgrade settlement, aging ties, temperature-induced stresses, and repeated loading. Proactive track health monitoring systems are needed to detect such changes continuously under dynamic train loads. This paper presents a novel in-motion system for detecting track stiffness irregularities (TSI), serving as a proxy for identifying potential defects. The proposed system uses onboard vibration measurements processed through advanced signal processing techniques. The system consists of three modules, i.e., Data Acquisition, Change Detection, and Classification. It operates on an edge computing platform allowing real-time processing and achieves over 95% data compression. The Change Detection module, emphasized in this paper, combines wavelet packet analysis, variational mode decomposition, and Hilbert transform to extract instantaneous energy features from vertical acceleration signals. These features act as sensitive indicators of track stiffness variations. The method was validated through both simulation and offline field data. Simulations captured a wide range of TSI scenarios including abrupt changes, gradual transitions, and localized soft zones. Field validation using public light rail datasets confirmed the model's ability to detect known problem areas, including bridge transitions and settlement zones, with strong spatial consistency. These results demonstrate the robustness, scalability, and real-world applicability of the proposed approach for continuous rail infrastructure monitoring.

Keywords: Track Stiffness change, In-Motion Sensing, Onboard Vibration Measurement, Track Condition Monitoring, Instantaneous Energy, Wavelet Packet Analysis, Hilbert Transform

INTRODUCTION

Background and significance

Track performance is typically evaluated through structural and geometric changes along the track that play a crucial role in how the track responds to dynamic train loads. These changes are broadly attributed to Track Geometry Irregularities (TGI) and Track Stiffness Irregularities (TSI). Track stiffness refers to the track resistance to deformation under load, while track geometry involves the alignment and shape of the track. Both TGI and TSI are crucial for assessing the overall health of the track and determining when maintenance activities should be scheduled to ensure safe and efficient rail operations. Existing research has shown that both TGI and TSI significantly impact wheel-rail interactions [1, 2] and contribute to long-term track degradation [3, 4]. Track defects, particularly TSI, are responsible for over 30% of derailments, as reported by the U.S. Federal Railroad Administration (FRA) [5]. In 2020, for example, a train derailment near Temple, TX that caused over $3 million in estimated damage was attributed to poor track stiffness conditions [6].

While there is an extensive body of literature focusing on TGI monitoring and its correlation with safety indices [7-9], the development of scalable, real-time systems for monitoring TSI remains a challenge. A common measure of the vertical stiffness of the rail foundation is the track modulus that is defined as the ratio of vertical support force per unit length of rail to vertical deflection [10]. This measurement excludes the effects of the rail itself, providing a focus on the substructures and superstructures (such as fasteners and sleepers) that support the rail. Track stiffness, on the other hand, includes the contribution of the flexural rigidity of the rails [11]. TSI is influenced by several factors, including the compactness and thickness of the ballast, the properties of the subgrade soil, ballast contamination, and moisture content in the subgrade soil. It is extremely difficult to maintain these factors consistent along the track even over short sections. In fact, as highlighted by Shi et al. [12], the geotechnical properties of the substructures can vary significantly from one location to another, leading to inevitable changes in track stiffness and non-homogeneous stiffness along the track. In this context, changes in TSI are often used as a proxy of changes of the track modulus. Spatial and temporal changes in dynamic track stiffness are fundamental to understanding long-term degradation issues under train operation. These changes, in addition to contributing to immediate wear and tear, accelerate the deterioration process, making it crucial to proactively detect and address them [12]. Given these challenges, the long-term performance of railway tracks becomes increasingly important in reducing downtime and operational disruptions, and the shift from corrective to predictive maintenance has become the focus of current track integrity assessment efforts.

Current practice challenges

Track stiffness measurement methods are broadly grouped into spot-check and in-motion techniques, each with their own set of advantages and limitations. Spot-check techniques of overall track stiffness involve pre-selecting a measurement point, where the excitation and track reaction are recorded to calculate track stiffness. This can be done using several methods, including the Track Loading Vehicle (TLV), which applies loads through a specialized vehicle to assess track deflection [13], the traditional hydraulic jack loading method, which applies controlled vertical forces [14], the impact hammer method, which uses hammer strikes to measure the track response [15, 16], and the Falling Weight Deflectometer (FWD) method [17-20], which measures track deflection under a controlled load. Spot-check methods, such as TLV, achieve high accuracy at multiple loading points with precise laser-based measurements. However, this method is limited by a low-speed range (up to 10 mph) and high operational costs, and they can only be used on specialized vehicles. The loading jack method is affordable, simple and reliable, but is time-consuming and labor-intensive and requires track shutdowns. The impact hammer test is a simple and fast method effective for localized measurements, with high-frequency resolution. However, it requires precise placement of the hammer and is unsuitable for low-frequency responses below 50Hz. Additionally, it is limited to short sections of track. The FWD method simulates the impact of trains and

measures track energy absorption. However, its limited frequency range and high operation costs make it impractical for large-scale monitoring. Trackside technology continuously records data as trains pass. Although it provides real-time or near-real-time information, it is prone to background noise and requires calibration. Furthermore, it only monitors small sections of the track, which limits its coverage.
In-motion techniques like the China Academy of Railway Sciences (CARS) system, introduced for measuring track elasticity [21], can adjust axle load ranges and control vibrations through energy-absorbing air bladders. It offers comprehensive stiffness measurements, but it is expensive and requires specialized vehicles. In early 2000's FRA sponsored research at the University of Nebraska Lincoln that led to the development of the MRail track modulus measurement system [22-24]. The MRail system uses precise laser-based measurements and high-speed tests, making it suitable for real-time monitoring. However, it requires expensive equipment, and field validation at high speeds is limited, as it relies on a fixed setup and assumptions about rail surface smoothness. Ground Penetrating Radar (GPR) detects subsurface issues, useful for identifying problems not visible on the surface. While it can detect issues in ballast or subgrade, it does not measure track stiffness directly, and it requires expertise to interpret results which are sensitive to system calibration. Other methods, such as the Swedish Rolling Stiffness Measurement Vehicle (RSMV) system, provide dynamic responses under realistic conditions with high accuracy but are expensive to operate and limited in capturing high-frequency components. The Swiss Railways (Schweizerische Bundesbahnen, SBB) method achieves high accuracy in displacement measurements but is limited by low vehicle speeds (10–15 km/h) and requires a specific vehicle setup, making it costly to operate. Another FRA-funded project led by Ensco and the Volpe Center [25] used split axles with different static loads and onboard accelerometers to estimate track stiffness via double integration. While cost-effective and quickly deployable, the method is sensitive to noise, low resolution, and drift errors introduced by the integration process. Finally, the Portancemetre [26], sponsored by the Innotrack project, uses high-accuracy sensors for track stiffness measurement but is complex with multiple components and requires a limited speed range for measurements, making it expensive to operate. **TABLE 1** provides a comprehensive overview of various track stiffness measurement methods.

TABLE 1 Overview of various track stiffness measurement methods

	Method	Pros	Cons
Spot-check	**TLV**	Accurate, laser-based, static & dynamic	Slow (≤10 mph), costly, special vehicle needed
	Impact hammer test	Fast, simple, localized, high-frequency resolution	Placement-sensitive, ineffective <50Hz, short-range
	FWD	Simulates train loads, portable	Costly, surface-only, low frequency, slow
	Loading jack	Reliable, detailed data, low-cost	Track closure, static only, labor-intensive
	Trackside tech.	Continuous data, no wiring along the track, real-time	Noisy, calibration needed, small area (1–2 sleepers)
In-motion techniques	**CARS**	Adjustable load, vibration control, full stiffness range	Expensive, location-specific, special vehicle
	MRail	High-speed, laser-based, real-time capable	Costly, low-speed validation, fixed setup, rail smoothness assumption
	GPR	Detects subsurface issues	Not direct stiffness, expertise needed, clay-sensitive
	RSMV	Realistic loads, high accuracy, temporal variation	Costly, poor high-freq. capture, vehicle-specific setup
	SBB	Accurate displacement, dual systems	Slow (10–15 km/h), vehicle-specific, costly
	FRA/ Ensco/ Volpe Center	Fast setup, low cost	Integration error, noise-sensitive, low resolution
	Portancemetre	High accuracy sensors	Complex system, speed-limited, expensive

In summary, while current track stiffness monitoring techniques have advanced significantly, challenges related to speed, cost, scalability, real-time data processing, infrastructure requirements and the ability to capture accurate, high-resolution data still exist. Overcoming these challenges will be key to developing more effective and widespread solutions for ensuring track integrity and safety across extensive rail networks. The proposed system aims to address these challenges by improving the accuracy, scalability, and cost-effectiveness of track stiffness monitoring, while also ensuring the system is suitable for real-time, large-scale applications.

Study objectives

Given the limitations of existing track stiffness monitoring systems, this research aims to advance a solution that is accurate, scalable, and deployable in real-world operating conditions. This study addresses the challenges of current technologies by introducing an in-motion system capable of detecting TSI in real time using onboard vibration measurements, identifying, thus, track stiffness changes over space and time. This paper discusses a hybrid signal processing framework for robust feature extraction from vertical acceleration signals recorded onboard during revenue service. The proposed approach is validated through multi-scale simulation studies, including both simplified 3DOF vehicle models and a high-fidelity 3D train–track interaction simulator using real track profile data. The effectiveness of the system is demonstrated using field data available in the literature. These records are collected from in-service light rail vehicles operating under realistic conditions, including pre- and post-maintenance operations. It is demonstrated that the proposed method is capable of detecting different types of TSI scenarios, such as abrupt stiffness changes, gradual transitions, and localized weak zones and effectiveness of maintenance. By achieving these objectives, the research contributes to the development of a scalable, intelligent track condition monitoring system that supports predictive maintenance and enhances the safety and durability of railway infrastructure.

METHODOLOGY

Methodology overview

The proposed research enables rapid in-motion track stiffness detection through a hybrid signal processing framework implemented at the edge and designed to improve accuracy, efficiency, and scalability. The methodology is structured into three primary modules shown in **FIGURE 1**, i.e., Data Acquisition, Change Detection, and Classification. This paper focuses on the development and implementation of the second module for change detection and identification. This module uses onboard acceleration measurements, the train speed profile, and GPS data. The acceleration records are then subjected to Wavelet Packet Analysis (WPA) for decomposition, denoising, and reconstruction of the signal. Subsequently, the reconstructed signal is further processed using Variational Mode Decomposition (VMD), which extracts oscillatory modes while addressing the nonlinearity of the signal. Finally, TSI detection is accomplished using instantaneous energy derived by Hilbert Transform (HT). Further information about the proposed method is discussed in the following sections.

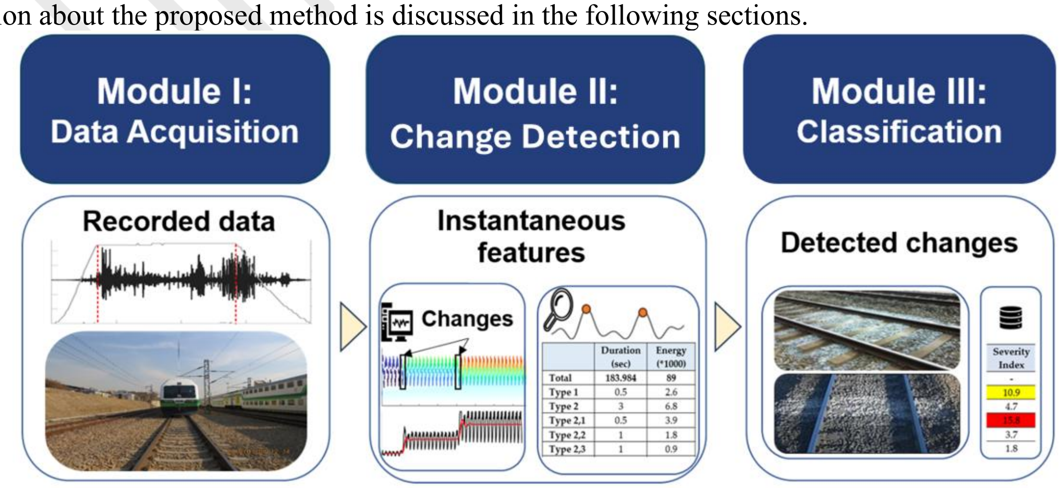


FIGURE 1: Workflow of the proposed hybrid algorithm for TSI detection

Module I: Data Acquisition

Module I (Data Acquisition) collects acceleration and positional data using railcar-mounted accelerometers and GPS sensors. These sensors continuously capture vertical accelerations. The data is transmitted to an edge computing platform, ensuring faster anomaly detection with reduced reliance on centralized processing. This step of the proposed method involves equipping trains in regular traffic with accelerometers mounted on bogies. The choice of bogie instrumentation plays a key role in the accuracy and effectiveness of this data acquisition process. The bogie, being part of the wheelset, experiences the full impact of track changes and dynamic properties. By placing sensors directly on the bogies, the data collected directly reflects the interaction between the train and the track, capturing better vibration patterns, referred to as signatures, generated by changes in track stiffness. These signatures are closely tied to localized changes in track stiffness. The measurements are then synchronized with the train speed profile and GPS. The integration of GPS ensures precise georeferencing of the measurements, which is vital for tracking the exact locations where stiffness changes occur. In the current stage of this algorithm accurate detection of TSI relies heavily on maintaining a consistent train speed during data acquisition. This consistency ensures that the measurements correspond directly to localized stiffness changes without introducing additional changes from speed-related dynamics.

Module II: Change Detection

This module is designed to handle large volumes of data efficiently and to extract meaningful features that will allow for accurate detection of TSI. This module is designed for implementation on an edge computing platform since the algorithms enable local, onboard analysis without relying on raw data transfer to centralized processing units. This non-centralized architecture reduces data transmission load and allows anomaly detection on the edge in real time, making it suitable for continuous in-service monitoring. This paper focuses on the algorithm development and offline application and validation. The edge computing implementation is the focus of current work and will be reported in forthcoming publications. The feature extraction process in this module involves three key steps, each playing a vital role in isolating the relevant information needed to assess track stiffness changes and anomalies. These steps are outlined in the following sections.

Background and significance

Wavelet Packet Analysis (WPA)

WPA breaks the signal into subsets at various frequency levels, filtering out noise and isolating the frequency ranges associated with track stiffness. The theoretical formulation of the wavelet packet function is derived from a multi-layer wavelet packet decomposition, which can be expressed as follows [27]:

$$\psi_{j,k}^{i}(t) = \sqrt{2^j}\psi^j\left(2^j t - k\right) \quad , i = 0,1,2, \ldots \tag{1}$$

Where $\psi_{j,k}^{i}(t)$ represents the wavelet packet function; ψ^j denotes the wavelet basis function; i, j and k are the modulation coefficient, scale coefficient, and translation coefficient of the wavelet function, respectively, with t as the time parameter of the wavelet function. For a signal sampled at f_s, when the minimum frequency of interest is f_{min}, the maximum level of decomposition (DL_{max}) can be determined using the formula below:

$$DL_{max} = \log_2(f_s/f_{min}) \tag{2}$$

When a signal $y(t)$ undergoes j-layer WPA, it yields 2^j wavelet packet coefficients as follows:

$$c_{j,k}^{i}(t) = \int_{-\infty}^{\infty} y(t)\psi_{j,k}^{i}(t)dt \tag{3}$$

To effectively remove background noise from the signal, wavelet coefficients below a specified threshold are classified as noise and set to zero, while those exceeding the threshold are retained as part of the signal. This process is founded on the observation that the energy of a signal is generally concentrated in a few wavelet coefficients of high magnitude, whereas the energy of noise tends to be scattered across a large number of wavelet coefficients of low magnitude [28]. The hard threshold function is defined as follows:

$$\tilde{c}_{j,k}(t) = \kappa c_{j,k}(t) \tag{4}$$

Where $\tilde{c}_{j,k}$ is denoised wavelet packet decomposition coefficient, $\kappa = \begin{cases} 1 & |c_{j,k}| \geq \lambda \\ 0 & else\ where \end{cases}$; and λ is the threshold value equal to $\lambda = \sigma\sqrt{2\ln(N)}$ defined by Donoho et al. [29]. The noise standard deviation is taken as $\sigma = \frac{median(|c_{j,k}|)}{0.6745}$ and N is the number of data points. This hard thresholding method is typically used in conjunction with a noise reduction filter. Subsequently, the denoised data is organized into distinct frequency bands and the signal is reconstructed while retaining essential signal components as:

$$\tilde{y}_j^i(t) = \sum_{k=-\infty}^{\infty} \tilde{c}_{j,k}^i(t)\psi_{j,k}^i(t) \tag{5}$$

Where $\tilde{y}_j^i(t)$ is the reconstructed signal derived from the corresponding denoised coefficients.

Variational Mode Decomposition (VMD)

VMD is a powerful signal processing technique used to decompose complex, nonstationary signals into intrinsic modes with different frequency characteristics. This method was first introduced by Dragomiretskiy and Dominique [30]. Unlike traditional methods such as Fourier Transform, which rely on global frequency analysis, VMD performs an adaptive decomposition by separating a signal into several modes (IMFs). Each IMF is compactly localized around a center frequency, f, without any frequency overlap. The *ith* oscillatory mode (IMF_i) and its central frequency (ω_i) are derived by minimizing the constrained variational problem as follows:

$$\min\,(IMF_i, \omega_i)\left\{\sum_{i=1}^{K}\left\|\partial_t\left[\left(\delta(t)+\frac{j}{\pi t}\right)*IMF_i(t)\right]e^{-j\omega_i t}\right\|_2^2\right\} \tag{6}$$

Where $\delta(t)$ is the Dirac delta function, "$*$" denotes the convolution and K represents the number of oscillatory modes. The decomposition process is guided by a set of parameters, such as the number of modes to extract and the trade-off between mode sharpness and bandwidth. The details are discussed in [30].

Hilbert Transform (HT)

Hilbert transform is a fundamental tool in signal processing, primarily used for extracting the analytic signal of a real-valued signal. The analytic signal provides a convenient way to extract time-varying features such as instantaneous phase, frequency, and amplitude, which are critical for understanding dynamic changes in the system. The HT is particularly effective for analyzing signals that are nonstationary and have time-varying frequency content, such as those caused by dynamic changes in track stiffness. For instance, when a train moves over track sections with varying stiffness, the frequency content of the resulting vibrations changes dynamically. HT allows for the precise tracking of these changes, which is essential for detecting TSI and other track-related defects. In this proposal, it is applied to each IMF derived from VMD to compute instantaneous features of the signal. Conventionally, HT of each $IMF(t)$ is defined as:

$$H(t) = \frac{1}{\pi}P\int\frac{IMF(\tau)}{t-\tau}d\tau \tag{7}$$

Where P denotes the Cauchy principal value. Using the HT, the instantaneous amplitude ($a(t)$), phase ($\theta(t)$), and frequency ($\omega(t)$) of the signal $IMF(t)$ can be calculated as follows:

$$a(t) = \sqrt{IMF^2(t) + H^2(t)} \tag{8}$$

$$\theta(t) = \tan^{-1}\left(\frac{H(t)}{IMF(t)}\right) \tag{9}$$

$$\omega(t) = \frac{d\theta(t)}{dt} \tag{10}$$

Finally, the instantaneous energy spectrum can be defined by **Equation 11**. This spectrum can be particularly insightful in analyses where energy changes in the signal are of interest.

$$IE(\omega, t) = \int H^2(\omega, t) d\omega \tag{11}$$

Where $H(\omega, t)$ is the Hilbert amplitude spectrum defined as:

$$H(\omega, t) = Re \sum_{j=1}^{n} a(t) exp \ (i \int \omega_j(t) dt) \tag{12}$$

Module III: Classification

The instantaneous frequency, energy, amplitude, and phase features, that were extracted from the dynamic response in Module II for TSI detection, serve as the primary inputs in Module III. This module identifies, classifies, and quantifies the severity of TSI in real time. By integrating these features with train speed, a robust severity index can be established, allowing for defect classification with respect to location and type. Initial model development and training are in progress using data collected from a custom-built track rig and its digital twin, which allowed for controlled simulation of various TSI scenarios. The classification logic, including adaptive filtering and severity estimation, builds on that training framework to support generalization across real-world conditions. Further technical details, including the full training pipeline, algorithmic parameters, and validation results, are beyond the scope of this paper and will be presented in forthcoming publications [31].

NUMERICAL IMPLEMENTATION AND VALIDATION OF MODULE 2

To assess the feasibility of the proposed approach for detecting and identifying TSI, a numerical model was developed to simulate the dynamic behavior of a track system under varying conditions and generate on-board acceleration time history records. These simulated records are used subsequently as inputs in the proposed workflow to produce the instantaneous energy of the signal at every location and demonstrate the feasibility of using the instantaneous energy as a proxy of TSI changes.

Simulation Model

The simulation model serves as the foundation for testing the ability of the system to detect changes in track stiffness using onboard measurements. As shown in Error! Reference source not found., the moving vehicle is modeled using a 3-degree-of-freedom (3-DOF) auxiliary mass system used in [32], which includes a car body mass (m_c), bogie mass (m_t), and wheelset mass (m_w). The vertical interaction between components is defined through a layered spring-damper system, capturing both primary (k_1, c_1) and secondary (k_2, c_2) suspension dynamics.

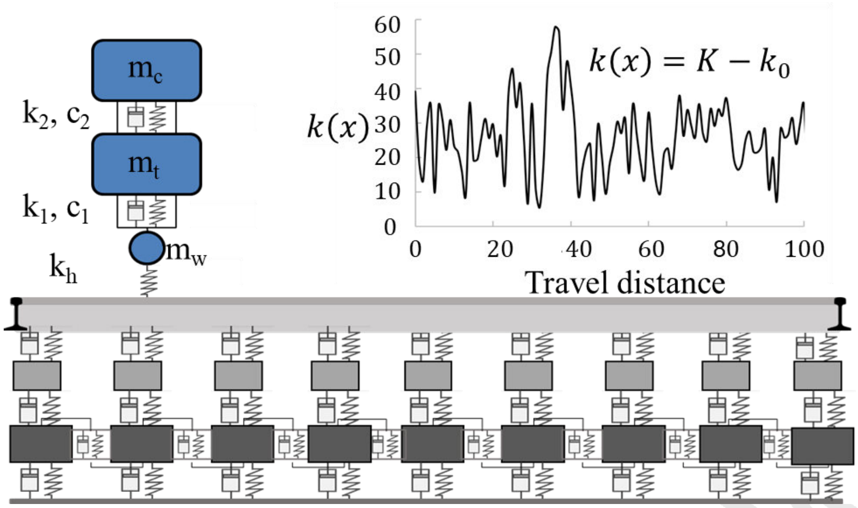


FIGURE 2: Schematic of vehicle system over track

The wheel-rail contact is modeled as a stiff spring to represent the Hertzian contact relationship. This method is based on mapping the contact point and allowing for dynamic interaction modeling as described in [33]. The rail track in the simulation is modeled as a Euler-Bernoulli beam, supported by multiple layers of distributed spring-damper elements that represent the track structure. These spring-damper elements are distributed at intervals corresponding to the spacing of sleepers. The stiffness of these spring elements can be adjusted to represent different track conditions. These elements represent the varying stiffness and damping properties of the track under different conditions. TSI noted by *k(x)* is defined as the difference between the nominal stiffness k_0 and the actual stiffness K at each position x.

Generation of simulated on-board acceleration time histories

A series of track stiffness variations were programmed into the simulation to assess the algorithm's robustness across different types of TSI conditions. Four representative cases of stiffness variations are considered:

1) *Abrupt Stiffness Change:* Simulates a sudden increase in stiffness at a given location.
2) *Multiple-Step Stiffness Increases:* Represents a gradual upgrade in subgrade conditions through multiple discrete increases.
3) *Localized soft Zone:* Models a significant dip in stiffness across a short segment.
4) *Linear Stiffness Gradient:* Represents a gradual increase and then decrease in track stiffness.

For each case, the vehicle moves over the track at a speed of 60 km/h, the dynamic response of the vehicle was computed using a time resolution of 1 millisecond (sampling rate of 1 kHz) and the acceleration of the bogie mass is recorded. To simulate realistic onboard conditions, the acceleration signals are embedded in Gaussian noise with a signal-to-noise ratio (SNR) of 15 dB. **FIGURE 3** shows the four track stiffness profiles and the recorded acceleration of the bogie mass as a function of the vehicle position on the track. It is evident that the stiffness changes cannot be identified by a simple visual inspection.

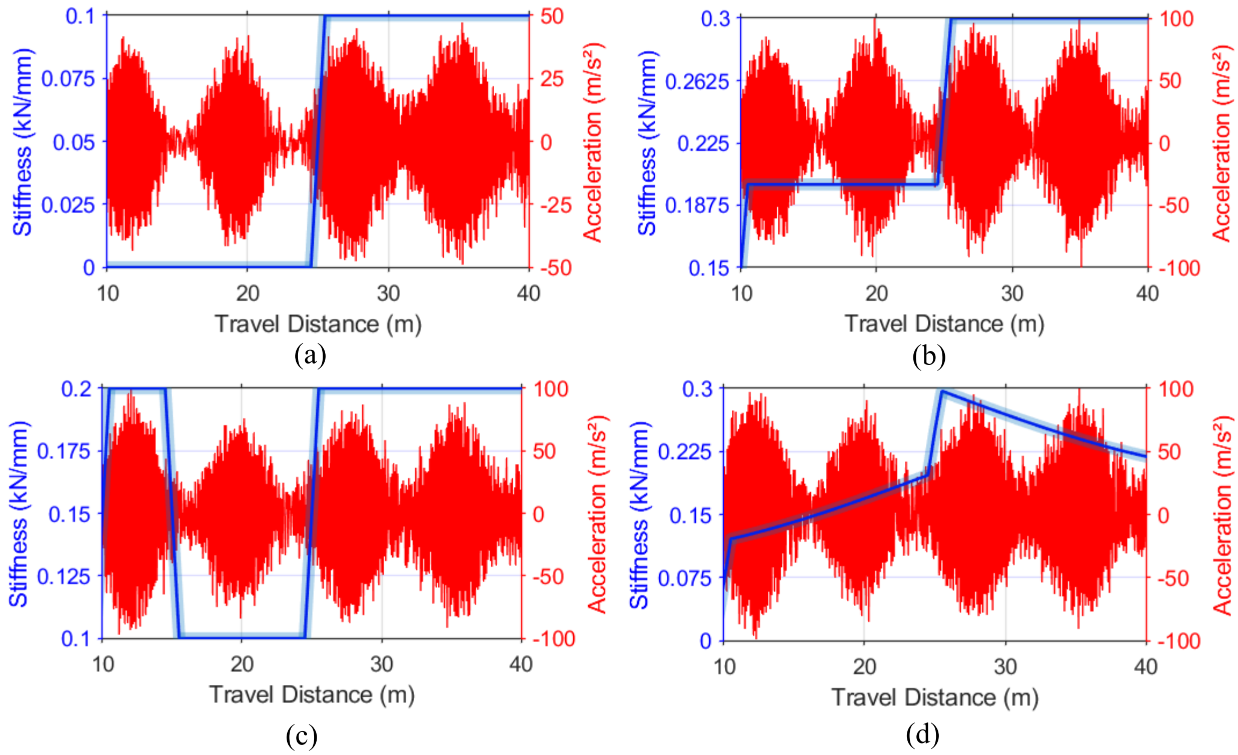


FIGURE 3: Simulated track stiffness profiles (blue) and corresponding bogie acceleration responses (red) versus travel distance for four stiffness variation cases

TSI detection

The simulated acceleration records are used next in Module 2 for TSI detection. It is noted that only low-frequency content (below 25 Hz) was retained for analysis, aligning with typical onboard accelerometer sensitivity and stiffness-induced vibration features. The signal is first processed using WPA to denoise the data and isolate frequency bands associated with stiffness-related responses. At this stage, a data compression rate exceeding 95% is achieved through thresholding of wavelet decomposition coefficients, where critical features were preserved with minimal information loss. This approach has previously demonstrated strong performance in preserving critical vibration features in related applications, such as rail squat detection [34]. Subsequently, the denoised signal is decomposed using VMD to extract oscillatory modes, and HT is applied to compute instantaneous amplitude, frequency, and energy. The resulting instantaneous energy, calculated from the vertical acceleration of the bogie, is used as a proxy for identifying localized stiffness changes and shown in **FIGURE 4**. In order to reveal underlying trends in the instantaneous energy, a moving average filter is applied to each instantaneous energy profile. A consistent and strong correlation between the instantaneous energy and stiffness changes is observed in all cases. Specifically, in abrupt transitions, the energy signal shows sharp, well-localized peaks, accurately reflecting the location of the stiffness change. In gradual trends, the energy increases progressively, tracking the overall stiffness trend reliably. In dip-shaped deficiencies, the energy drops distinctly within the affected region and recovers after, indicating its ability to detect soft spots. In noisy conditions, the method retains its detection capability due to its reliance on time-frequency features rather than absolute values. Importantly, the proposed framework is resilience to inherent signal fluctuations and dynamic variability, with minimal distortion or lag. These results confirm that the instantaneous energy of bogie vertical acceleration can serve as a robust proxy for onboard detection of TSI.

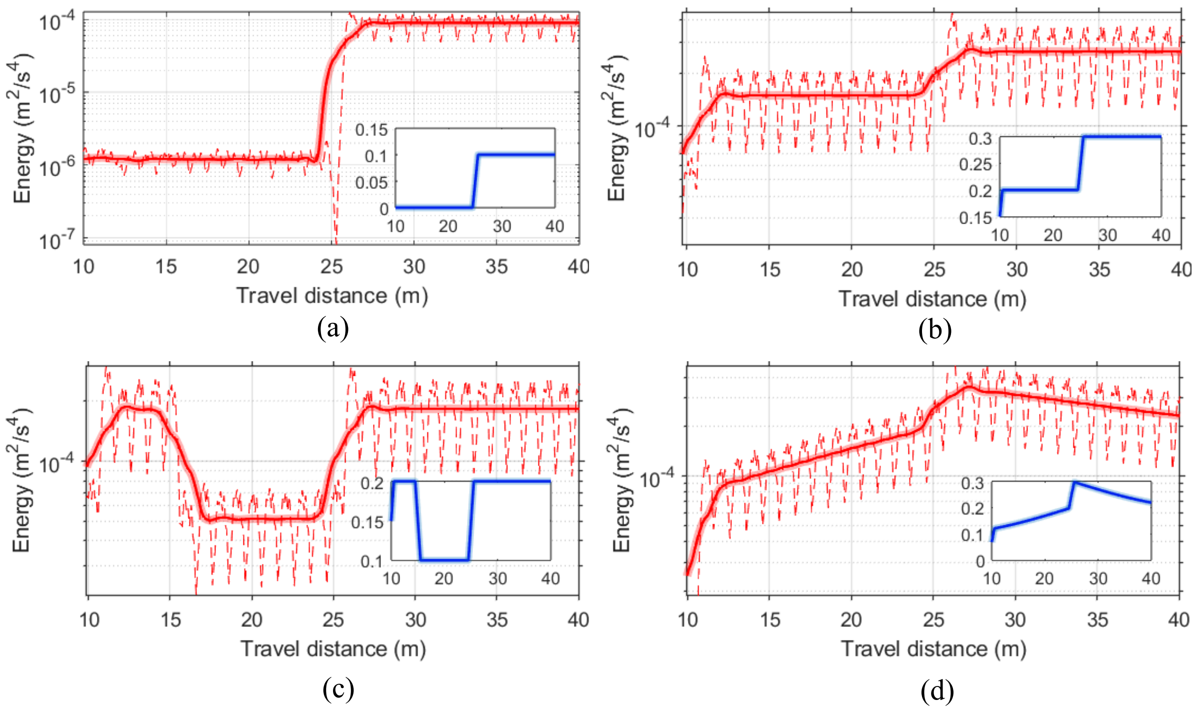


FIGURE 4: Instantaneous energy profiles (red) derived from bogie acceleration signals across four simulated cases. Insets show corresponding track stiffness profiles (blue).

VALIDATION THROUGH A HIGH-FIDELITY 3D SIMULATION

Model overview

To further assess the performance of the proposed onboard monitoring system, a 3D train–track interaction simulator developed in our previous study [35] was employed. This high-fidelity model represents a single-carriage train equipped with three bogies, each modeled with 24 degrees of freedom (DOFs), as illustrated in **FIGURE 5**. The configuration closely mirrors the rail vehicle used in the field validation study detailed in the subsequent section. The total track length modeled is 250 meters, with vertical vibration responses recorded at the middle bogie while the train moves at a constant speed of 60 km/h. Parameters for the train and track are derived from references [35] and [36], respectively.

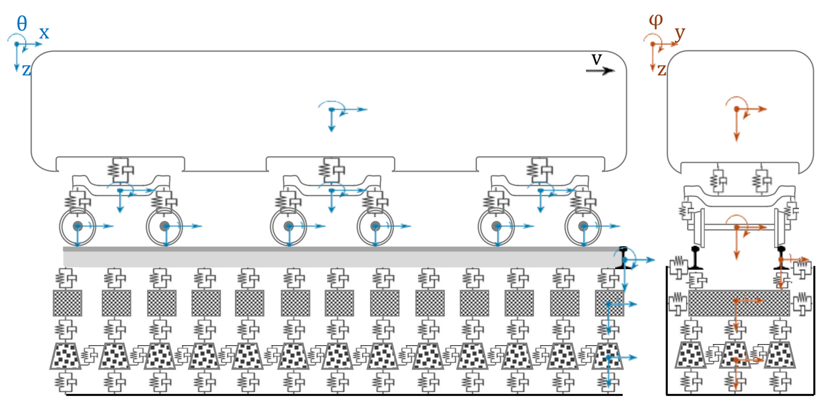


FIGURE 5: Schematic of the 3D train-track interaction model

To increase realism, the vertical track profile was extracted from actual measurements recorded on ballasted tracks using the DOTX 220 inspection vehicle. These data were collected over a segment of the Precision Test Track (PTT) at the FRA's Technology Testing Center (TTC), shown in **FIGURE 6**.

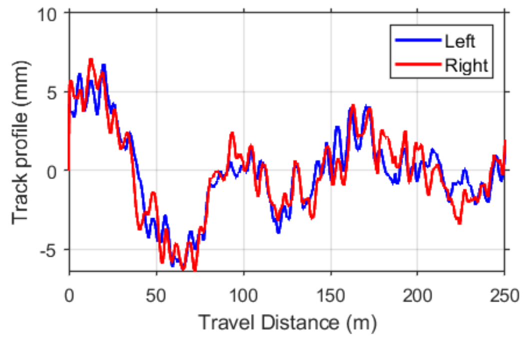


FIGURE 6: DOTX220 recorded track profile

To account for operational uncertainty and sensor noise, white Gaussian noise with a SNR ratio of 15 dB was added to the simulated acceleration data. The simulation scenarios were benchmarked against standard railway engineering guidelines as introduced in literature. These include:

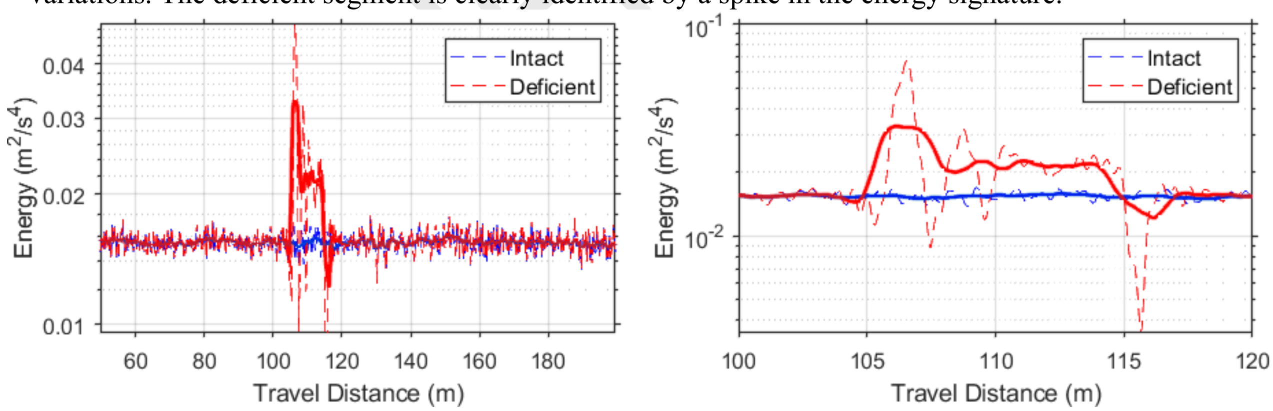
1) Maximum allowable vertical deflection: 6.4 mm [37]
2) Acceptable track stiffness range: 50–90 kN/mm (optimal ≈ 75 kN/mm) [38]
3) Sleeper-to-sleeper stiffness variation: less than a factor of 5 [12]

The baseline (intact) model was configured with a uniform stiffness of 78 kN/mm, while three distinct stiffness-deficient cases were designed, each corresponding to one of the benchmark thresholds, to evaluate the sensitivity of the proposed detection method under various structural conditions.

Analysis results

Deflection threshold analysis

Segments exhibiting excessive vertical deflection are often precursors to serious structural failures. To examine the detection framework's sensitivity to such cases, a 10-meter-long section was modeled with reduced subgrade stiffness to produce deflections exceeding the 6.4 mm threshold. The reference case (k = 78 kN/mm) maintained deflections around 1.4 mm, whereas the deficient case resulted in 6.6 mm deflection. **FIGURE 7** shows the instantaneous energy used as a proxy for detecting dynamic stiffness variations. The deficient segment is clearly identified by a spike in the energy signature.

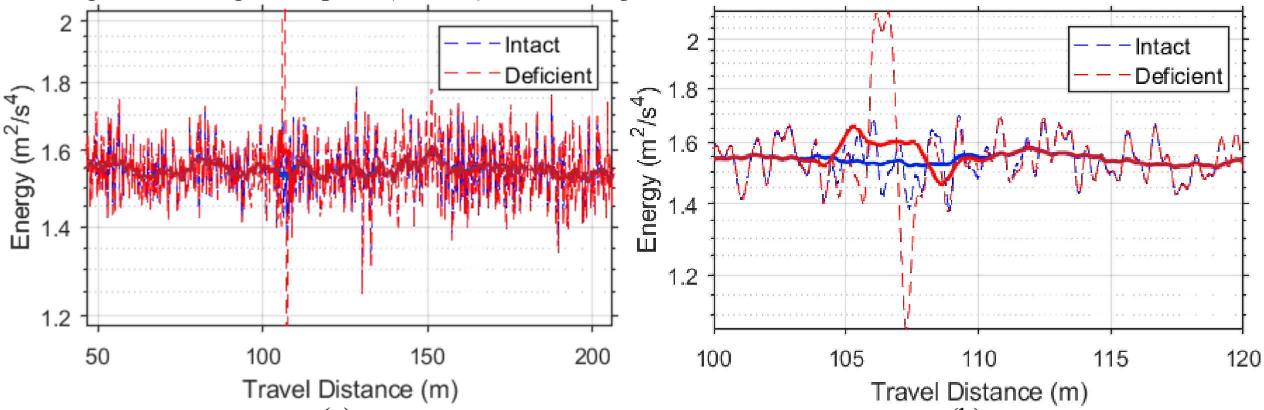


(a) (b)

FIGURE 7: Instantaneous energy variation before and after applying deflection threshold criteria a) across the full track segment and b) zoomed-in view of the deficient region (100–120 m)

Track stiffness ratio between adjacent sleepers

This scenario simulates a sharp drop in stiffness between adjacent sleepers, where the track stiffness at one sleeper drops from 75 kN/mm to 15.6 kN/mm, exceeding the threshold ratio of 5. Such conditions often indicate localized ballast washout or foundation degradation. As shown in **FIGURE 8**, a localized and abrupt change in the energy metric is observed over the affected sleeper length (~1 m), persisting throughout the bogie footprint (~2.5 m), confirming successful detection.

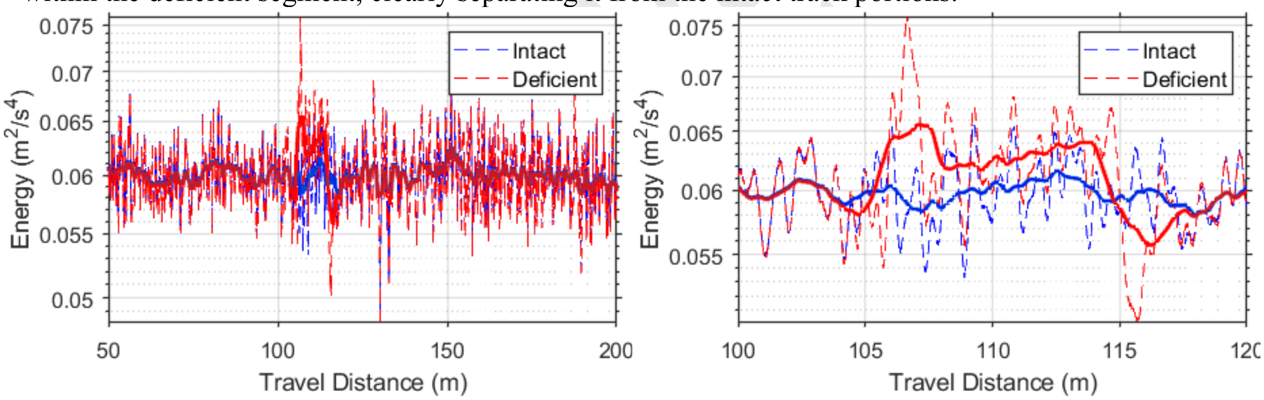


(a) (b)

FIGURE 8: Instantaneous energy variation before and after applying sleeper-to-sleeper stiffness change: a) over the full segment b) zoomed-in at the critical location.

Stiffness range compliance

The final test evaluates whether the system can correctly identify stiffness values falling outside the recommended range of 50–90 kN/mm. A 10-meter-long deficient section with stiffness k = 30 kN/mm was simulated. The results, shown in **FIGURE 9** , highlight a measurable increase in energy response within the deficient segment, clearly separating it from the intact track portions.



(a) (b)

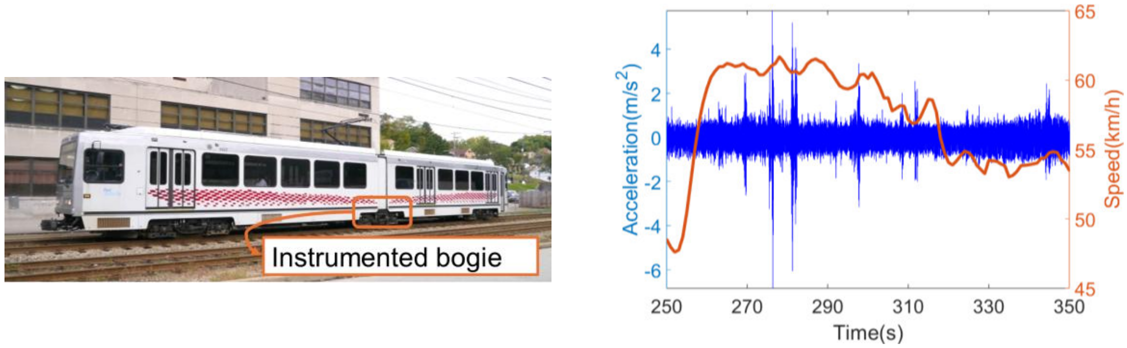
FIGURE 9: Instantaneous energy variation before and after applying stiffness range compliance: a) over the full segment b) zoomed-in at the critical location.

OFFLINE VALIDATION THROUGH FIELD MEASUREMENTS

This section presents offline validation of the proposed TSI detection framework using publicly available field datasets. The objective is to evaluate the system's effectiveness in real-world conditions without the need for customized instrumentation or proprietary vehicle models. Notably, the proposed method requires only acceleration measurements and corresponding vehicle speed data that are commonly available in many open-access monitoring operations. Since the detection algorithm operates on the dynamic response of the vehicle–track system, the specific mechanical properties of the test vehicle are not required for this phase of validation.

Field data overview

To evaluate the effectiveness of the proposed stiffness variation detection framework, field data collected from Pittsburgh's light rail system were utilized. The field measurements were conducted by researchers at Carnegie Mellon University in collaboration with the Port Authority of Allegheny County [39]. This dataset offers a rich source of vertical acceleration and GPS information recorded from two in-service light rail vehicles (LRVs) operating under normal service conditions. As shown in **FIGURE 10 (a)**, the experiment involved instrumenting the non-tractive bogie frame of each vehicle with tri-axial accelerometers capable of capturing high-frequency vibrations. Acceleration data were recorded at a sampling rate of 1.6 kHz, while GPS positions were logged at 1 Hz, providing precise spatial correlation of track responses. **FIGURE 10 (b)** shows a sample time-history of acceleration overlaid with the vehicle's speed profile. In addition, environmental parameters such as ambient temperature were also collected to support contextual interpretation of the measurements. This field implementation serves as a valuable benchmark for testing the proposed signal processing techniques and validates the system's ability to detect localized stiffness changes using onboard measurements in realistic operating environments.



(a) (b)

FIGURE 10: Field implementation: (a) instrumented light rail vehicle; (b) vertical acceleration and speed profile during an in-service run [39]

Data were collected over a period of several weeks, encompassing more than 40 full passes on selected track segments before and after scheduled maintenance interventions. For this study, Region 5, a segment between Bon Air and Denise stations, was selected. This stretch, shown in **FIGURE 11**, includes a bridge structure with transition zones with two intermediate piers and clearly defined transition zones where the ballasted track interfaces with the bridge superstructure. These characteristics make it an ideal benchmark for evaluating vertical stiffness variations. The transition zones, approximately 10 meters in length on each side of the bridge, are common sites of settlement and degradation due to abrupt changes in track support conditions. The layout in **FIGURE 11** highlights the track path, station locations, and bridge geometry, providing spatial context for interpreting dynamic responses and identifying weak spots in the infrastructure.

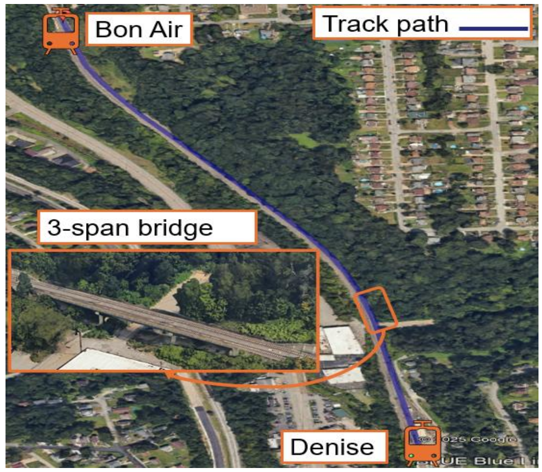


FIGURE 11: Annotated satellite view of Region 5 from Bon Air to Denise station (Taken from Google Map)

Analysis results

The test vehicles were modern LRVs, commonly used for urban passenger service, which allowed for capturing typical loading conditions. The availability of pre- and post-maintenance data also enabled comparative analysis to quantify the impact of tamping and resurfacing on track dynamic behavior. **FIGURE 12** presents the variation of instantaneous energy along the analyzed track segment between Bon Air and Denise stations. Using the proposed method, the results were derived from acceleration signals compacted by over 95% of their original volume in an offline implementation, enabling efficient yet highly informative representation of the vehicle–track interaction. The plot displays both pre- and post-maintenance conditions to assess the impact of tamping and resurfacing. The instantaneous energy, computed through Hilbert-based transformation, highlights localized zones of elevated dynamic response. Peaks 2 and 5, observed around 4890 m and 4990 m respectively, represent the bridge transition zones, points where track structure shifts from ballasted to the bridge superstructure. These transition regions, marked in yellow, show distinct energy spikes due to abrupt stiffness changes. The region between these two spikes (~80 m) corresponds to the three-span bridge, where fluctuations 3 and 4 are linked to the intermediate piers, illustrated in gray. Despite superstructure maintenance, the bridge area exhibited minimal energy reduction after tamping, indicating persistent stiffness transitions and structural dynamics inherent to bridge components. In contrast, a notable energy drop is observed along the remaining ballasted track, confirming the effectiveness of the tamping and resurfacing operations in restoring track support and uniformity. Before the bridge, spike 1 coincides with a track switch, denoted in purple. The persistent energy elevation at this location, even after maintenance, suggests unresolved stiffness imbalance or degradation, possibly warranting further attention. Downstream of the bridge, anomalies 6, 9, and 10, highlighted in green, remain prominent in the post-maintenance data. These localized energy peaks likely correspond to zones of recurrent settlement or insufficient compaction, which are known precursors to accelerated degradation. Conversely, anomalies 7 and 8, which were elevated before maintenance, were effectively mitigated, indicating localized success of the intervention.

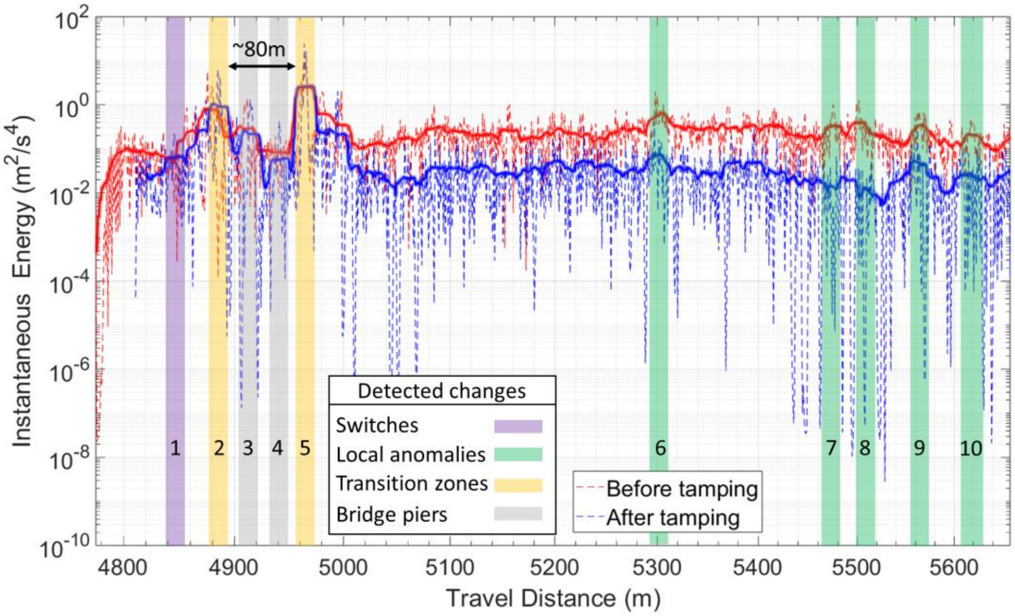


FIGURE 12: Instantaneous energy before and after maintenance

The combined analysis confirms that the proposed energy-based approach can successfully detect and localize stiffness-related issues and monitor the site-specific impact of maintenance. The ability to distinguish between persistent, improved, and emerging weak spots provides valuable guidance for prioritizing future maintenance and inspections.

CONCLUSIONS

This paper introduced a novel in-motion framework for detecting track stiffness irregularities (TSI) using onboard vertical acceleration measurements and a hybrid signal processing approach. The proposed method integrates wavelet packet decomposition, variational mode decomposition, and Hilbert transform to extract instantaneous energy signatures indicative of track stiffness changes. The system is designed for edge computing implementation. It achieves data compression exceeding 95%, enabling, thus, real time change detection. A key innovation lies in its modular design, which allows for scalable deployment and adaptation to both simulation environments and publicly available field datasets, without the need for vehicle-specific mechanical models. The preliminary results obtained from both simulation and field experiments strongly support the efficacy of the proposed onboard TSI detection approach. Across varying track stiffness conditions, ranging from abrupt discontinuities to gradual stiffness trends, instantaneous energy of the vertical acceleration signal demonstrated high sensitivity to underlying track structural variations. These findings were consistent in both the simulations and the field test. The effectiveness of the method under varying noise levels and different stiffness patterns highlights its robustness and adaptability to real-world scenarios. A key insight from these early findings is that even relatively small changes in substructure stiffness result in detectable dynamic signatures at the vehicle level. This underlines the potential of vibration-based onboard sensing systems for routine track condition monitoring without the need for extensive ground instrumentation. Moreover, the combination of real-time and offline analysis modes enables flexibility in implementation, allowing for immediate exception flagging during operation or more comprehensive diagnostics during scheduled maintenance

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AUTHOR CONTRIBUTIONS

The authors confirm contribution to the paper as follows: study conception and design: R. Naseri, D.C. Rizos; data collection: R. Naseri; analysis and interpretation of results: R. Naseri, D.C. Rizos; draft manuscript preparation: R. Naseri, D.C. Rizos, B.L. Gedney. All authors reviewed the results and approved the final version of the manuscript.

DECLARATION OF CONFLICTING INTERESTS

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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