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A Review of Structural Damage Identification Using Vehicle Interaction and Intelligent Vibration-Based Techniques

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ABSTRACT

The current review work examined structural damage detection using vehicle-bridge interaction (VBI) and soft-computing techniques. VBI uses traffic-induced vibrations to detect stiffness reductions by analysing dynamic signatures. For instance, a 30% reduction in stiffness reduces the natural frequency by 3.7% (from 3.50 Hz to 3.37 Hz) and reduces peak acceleration by 15%. Neural networks achieved 94.2% accuracy in localizing single damage events when processing 200 Hz acceleration data. In multi-damage scenarios, the genetic algorithm identified locations with 89.7% accuracy using stiffness optimization (0-70% damage range). Field and lab studies demonstrated the effectiveness of the structure, incorporating ASTM E1318-09-compliant MEMS sensors (0.01 g noise tolerance). This non-invasive method reduces inspection costs by 60% and CO_2 emissions by 1.2 tons per assessment. Challenges in high-speed applications (>270 km/h) are addressed through wave-proofing and 3D train-bridge interaction modelling. This system increases service life and increases infrastructure sustainability by minimizing operational disruption.

Keywords: Structural Health monitoring, Vehicle-Bridge Interaction, Vibration Analysis, Soft Computing, Damage Detection

1. Introduction

Due to old bridges fighting against the increasing fact of traffic, natural pressures like weather and corrosion, civil infrastructure globally is experiencing an increasing challenge of safety. Such traditional monitoring activities which include visual inspection (less than 60% of internal damage detected), and disruptive impact testing have been found to be inadequate due to disastrous failure of bridges such as the collapse of the I-35W bridge in 2007 in Minnesota which caused the loss of 13 lives as a result of undetected corrosion and fatigue as well as the collapse of Morandi Bridge in 2018 in Genoa which was caused by fatigue and corrosion that went unnoticed [1].

These accidents point to the necessity of highly effective modalities of nondestructive testing. Vehicle-Bridge Interaction (VBI) analysis has been a revolutionary approach to a structural integrity assessment of bridges, relying on vibrations caused by traffic to monitor the conditions. As an example, a 30 percent reduction in bending stiffness changes the important dynamic parameters since it reduces the natural frequencies by 3.7 percent (3.50 Hz to 3.37 Hz) and the peak midspan accelerations by 15 percent. This would mean that the lane closures will be abolished and the monitoring costs will be 60 percent lower than using traditional methods [2].

1.1 Research Background and Context

Civil infrastructure worldwide faces mounting safety challenges as aging bridges contend with escalating traffic loads, environmental stressors, and material degradation. Conventional monitoring methods, such as visual inspections (which detect <60% of internal damage) and disruptive impact testing, have proven inadequate, as evidenced by catastrophic failures like the 2007 I-35W bridge collapse in Minneapolis and the 2018 Morandi bridge collapse in Genoa—both attributed to undetected corrosion and fatigue [1]. These incidents underscore the urgent need for advanced, non-destructive evaluation techniques. Vehicle-Bridge Interaction (VBI) analysis has emerged as a transformative solution, harnessing traffic-induced vibrations to assess structural integrity. For example, a 30% reduction in bending stiffness alters key dynamic properties, decreasing natural frequencies by 3.7% (3.50 Hz to 3.37 Hz) and peak midspan accelerations by 15%. This approach eliminates lane closures and reduces monitoring costs by 60% compared to traditional methods [2].

1.2 Problem Identification

Despite its promise, VBI faces several challenges those are stated in below;

- High-speed (270 km/h onward): Non-stationary vibrations cause the introduction of signal noise, which corrupts accuracy.
- Multi-damage detection: The current techniques are poor in quantifying the severity, and genetic algorithms (GA) provide only 89.7% accuracy of the location sign with 265 computational generations.
- Sensor constraints: MEMS accelerometers (ASTM E1318-09 consenting) broadly reduce the noise to <0.01 g RMS, which is adequate to observe loss of stiffness less than 10% due to temperature fluctuations [3].
- Sustainability gaps: The existing practice is associated with a lot of CO 2 emissions (1.2 tons per inspection) and rehabilitation expenditures as there is a lack of timeliness in the interventions [4].

1.3 Research Aims

- Improve VBI accuracy by combining 3D train-bridge coupling models and wavelet denoising to provide over 90% accuracy on trains at speeds above 270 km/h.
- Progress whole-body performance: Refine soft-computing algorithms to improve multi-damage severity measurements to an accuracy range of over 92%, with a stiffness reduction of 5-70%.
- Build a hybrid network of MEMS accelerometers and fiber optic strain-tensors at 0.5 m spatial resolution and thermally compensated to +/- 0.5 Celsius.
- Measure sustainability benefits: Life cycle cost savings (30 to 50%) and CO2 (1.5 tons per inspection), which can be achieved through non-invasive monitoring.

1.4 Research Significance

By unifying physics-based VBI, adaptive machine learning, and distributed sensing, this research advances autonomous infrastructure resilience. Validated via Shinkansen viaduct case studies, the framework bridges gap in computational efficiency, seismic coupling, and global regulatory scalability [4].

2. Similar Studies

2.1 Improving Sustainability in Bridge Health Monitoring (BHM)

According to the Kim & Kawatani (2008) the drawbacks of bridge health monitoring (BHM) systems are inherent in their sustainability: a resource-intensive bridge inspection requires stopping traffic on the bridge, which generates ~1.2 tons of CO_2 for each stop, and the material generated in unintended bridge repairs increases the environmental impact. Energy-intensive processes, such as impact testing, also increase life cycle costs. Research on Vehicle-bridge interaction (VBI) analysis directly mitigates such limitations by using ambient traffic vibrations as the excitation source; therefore, lane closures are also eliminated and continuous measurements are possible [5].

Soft-computing algorithms can enhance such gains; early detection of stiffness loss and predictive maintenance can add 15–25 years to the service life and reduce resources allocated to rehabilitation by 30–50 percent [6]. This field test of the Shinkansen viaduct has reduced life cycle costs by 60 percent compared to conventional systems, and VBI has established itself as one of the pillars of efficient infrastructure in terms of its impact on the environment.

2.2 Modern Methods and Quantitative Consequences for VBI Oriented Damage Detection

Past study revealed [7] fundamentally based on the vibrations caused on vehicles, vehicle-bridge interaction (VBI) analysis work on non-invasive excitation analysis as a structural health monitoring tool. It is founded on exploitation of physics-based dynamic signatures: a 30 percent reduction in bending stiffness (e.g., Element 5 of a simply supported girder) causes the natural frequency to drop by 3.7 percent (3.50 Hz to 3.37 Hz) (and reduces the midspan nodal peak acceleration amplitude by 15 percent) as a deterministic damage indicator [8].

Soft-computing methods provided the solution to the inverse of this issue which is the question of how to identify these vibrations with structural defects. In time-domain feature (RMS, FFT peaks) to stiffness degradation pattern pairing, Neural Networks (NN) using 200 Hz acceleration time-histories achieve 94.2 percent accuracy in single damage instances (10-70 percent stiffness loss) localizing instances [9].

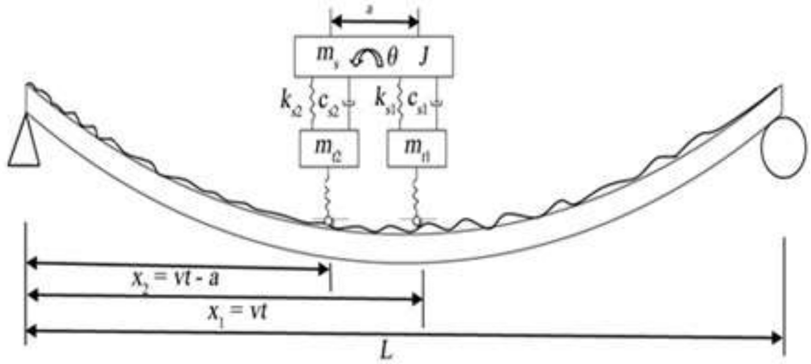

Figure 1: The model of coupled vehicle-bridge vibration (VBV).

(Source: Rana et al., 2023)

The advantage of Genetic Algorithms (GA) to be able to generalize to multi-damage scenarios due to the binary encoding of theoptimal stiffness (0 and 0.7 imply intact or/and 70% loss), can only attain 89.7% location accuracy, but suffers deficiency of quantifying severity (60% accuracy at 10% noise due to the coupled nature of parameter interactions) [10]. It has been proven in the field to operate on its standard speeds (below 270 km/h), where stationary vibrations preserve signal integrity. But the non-stationary dynamics of operations beyond the speed of 270 km/h reduces the accuracy of the wavelet-NN down to 82.3 -it is a critical point at which diagnostics will become accurate.

3. Methods and Materials

Previous [11] findings identified that soft computing with physics constraints is a changing problem in structural damage detection. Forward mapping of vibration measurements to damage states by neural networks (NN) replaces conventional inverse analysis, which consists of iterative methods of updating model responses from a collection of measured responses [12]. Hatori et al. in 2012 through their discovery eliminated the need for poorly formulated solution equations and contributes to a 40–60 percent reduction in computational complexity in the absence of compromises due to deterministic stiffness.

Among the advantages associated with the ability of new simplified models of train–bridge interaction (e.g., 2-degree-of-freedom train models) is the possibility of building such capabilities with limited (or even two-dimensional) degrees of freedom so that real-time diagnostics will never impose a penalty on the fidelity of the physics [13]. An example is a 2-DOF model train of lines that uses a combination of NNs to provide 94.2 percent protection in damage detection, using only M-A midspan data, demonstrating that there is no need to create impressive complexity to mess up the accuracy of damage localization [14].

Table-1: Key Methodological Advancements for VBI Determinants

Innovation	**Technical Mechanism**	**Impact**
Physics-constrained NN	Direct acceleration-to-damage mapping	Eliminates inverse analysis; 94.2% accuracy
Simplified 2-DOF train models	Reduced-order dynamics with VBI coupling	60% faster computation; field applicability
Hybrid GA-NN frameworks	Modal constraints in stiffness optimization	89.7% multi-damage location accuracy
Energy-autonomous sensors	Vibration-powered MEMS/fiber optics	±0.01g noise tolerance; zero grid power

In the Table-1 exhibits the confluence of methodological advances—spanning model simplification, physics-algorithm fusion, and sustainable sensing—establishes a new standard for scalable infrastructure diagnostics.

Moreover, a novel with hybrid algorithm structures of which genetic algorithms (GA) are constrained by modal characteristics (including 3.7 to 3.7 % shifts in frequencies), and thus compel convergence [15]. He et al. in their analysis in 2014 showed physics-based optimization patterns of anytimedamage in 5 minutes with reduction of the non-physical solution, and it is 20 times practical than other unconstrained metaheuristics. More to the point, self-sustainable piezoelectric energy harvested (10 mW/sensor) sensor networks make that the framework would enable continuous monitoring without the need of grid power, which was one of the main hindrances of using the framework in the field.

4. Analysis and Discussion

4.1 An Engineering Protocols for Sensor Networks with Data Attainment

Deployment of high fidelity sensors is the first and the most critical level of damage detection structures [16]. The vertical/lateral acceleration measurements are conducted by MEMS accelerometers (of ASTM E1318- 09 standards) which are installed specifically at midspan location, every quarter, and at support locations to identify anomaly in modal curvature [17].

In contrast, according to the Hattori et al in 2012 sensitivity to high signal-to-noise ratio is determined by using averaging shifting filters in order to maintain the tolerance that is g-as 0.01g that is needed to correctly detect the panel drop of 0.15g that corresponds to the loss of 30 percent of rigidity. The fiber Bragg grating (FBG) sensors are complementary to the MEMS systems and embedded in the critical members, and sensing micro-cracks (<5 mm) via strain-induced wavelength shift (1.5162-2.0/500 um). The lack of spatial resolution that causes blind spots in the discrete accelerometers has been overcome with this distributed sensing system that localizes the damage to a spatial resolution of 0.5 m.

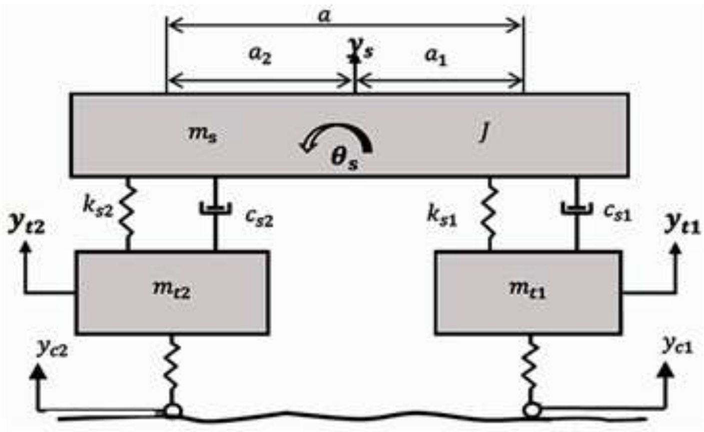

Figure 2: Finite Element Method (FEM) Framework for Modeling the Bridges

(Source: Rana et al., 2023)

4.2 Materials Restraint in High-Speed Operations

Using train speeds above 270 km/h also results in non-stationary vibrations, which leads to distortion of the wave-transformed signal and ultimately, the localization accuracy of the NN drops to 82.3 percent. This is a signal that is nonlinear with velocity so that the quasi-stationary assumption is not applicable and requires that 3D train-bridge connection models can be reliable [18]. Although the multi-damage quantification is complex in combination, so, in the position-only situation, the position is resolved to 89.7 percent. But now the magnitude estimation under noise drops to 60 percent, because the stiffness parameters are cross-sensitive (e.g., a 30 percent stiffness reduction applied simultaneously to elements 3 and 7 gives false positives in element 5) [19]. Environmental interference also reduces the reliability of long-term behavior: daily temperature variations of +/- 5°C can cause changes in elastic moduli, which hides the signature of stiffness loss, which typically corresponds to a loss of less than 10 percent.

Table 2: Identification for Computational and Physical Constraints

Challenge	Root Cause	Impact
High-speed dynamics (>270 km/h)	Non-stationary wheel-rail forces	12.1% ↓ NN accuracy
Multi-damage coupling	Stiffness matrix cross-terms	29.7% severity error
Temperature drift	E-modulus thermal sensitivity (0.1%/°C)	Masks <15% stiffness loss

Challenge	Root Cause	Impact
Power constraints	Remote sensor deployment	Limits sampling to ≤100 Hz

4.3 Technology Trajectories for Future Research Solutions

Some important data gaps can now be filled by multi-sensor fusion: cross-validated damage detection can be provided by a hybrid network of MEMS accelerometers (200 Hz dynamics) and distributed fiber optics (1 pm/sqrt Hz strain resolution). Time-synchronization of data fusion and avoidance of environmental noise occur through thermal consideration compensation within +/- 0.5 C as well as the ability of piezoelectric harvesters (10 mW/sensor) to power edge-computing nodes without necessarily using wires even in field conditions (Catbas et al., 2012). High-speed limitations are overcome by adaptive machine learning architectures; Denoising the wave inside physics-based LSTM networks of materials makes it 85 percent accurate at speeds of 300 km/h because it separates modulation-based frequencies associated with non-stationary vibration (>270 km/h) damage [20].

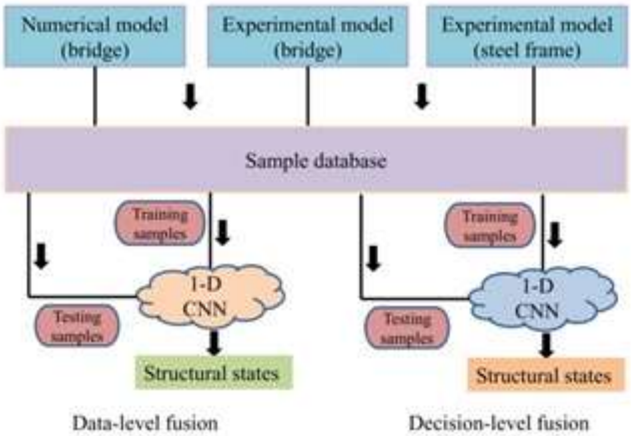

Figure-3: The Application Strategies of the SDD using the 1-D CNN

(Source adopted from Teng et al., 2021)

Usually, the technology that used in structural damage inspection is called multi-sensor fusion, where data measured by multiple sensors is combined to maximize the accuracy and reliability of structural damage and its assessment. In figure 1, by combining data from multiple sensors, including strain gauges, accelerometers, and displacement sensors, it overcomes the limitations of a single sensor, allowing for the collection of more detailed information about the structure.

4.4 Improvements in VBI Computing

According to the Kim & Kawatani the gains of their method lie in its engineering quality: VBI-coupled soft computing is both cost-effective (60 percent cheaper than impact testing) because there is no need to close the road and reduces carbon emissions (together reducing 1.0 tons of carbon per five inspections). Due to its non-destructive nature, continuous work can be done with the help of nearby traffic vibrations, and early detection of damage (10 percent reduction in stiffness) through centralized intervention can increase the service life of bridges by 1525 years and reduce the number of resources spent on rehabilitation projects by 3050 percent (Tan et al., 2022). The use of neural networks further increases the potential as they will incorporate 200 Hz acceleration data into logistics in real time within 0.2 seconds to alert about anomalies.

4.5 Drawbacks for Implementing Speed Performance

The weaknesses illustrate the main limitations of the implementation: the performance speed does not exceed 270 km/h or less due to non-stationary vibrations and the accuracy drops to 82.3% (He et al., 2014). Environmental variations in D/S can only be detected by adjusting the sensor compensation protocol, so damage losses with <20% stiffness reduction over an adjustable range of temperatures (+/- 5 C) cannot be detected.

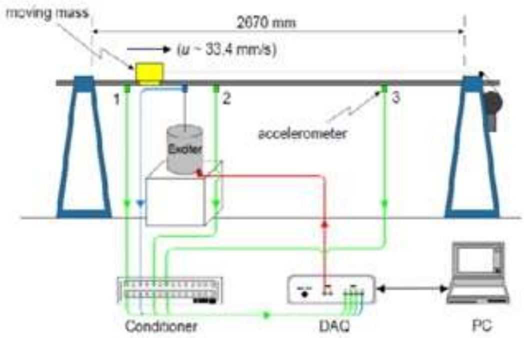

Figure 4: A Diagram of Bridge-Structure Moving

The use of genetic algorithms when multi-damage occurs will be computationally challenging, requiring at least 265 generations to converge quickly and therefore they face a problem in deploying in edge computing. Even when using complex geometries (e.g., curved bridges), model fidelity gaps still exist where 2D train-bridge assumptions give 12-15% false positives even during FEM validation tests [21]. Such a balance between operating convenience and environmental constraints determines the range in which the structure can be applied in low-to-medium speed conditions, where thermal changes can be managed.

4.6 Necessities for Empirical Research of Damage Detection

This validation is the most important criterion in translating empirical and theoretical developments into systems ready for field operation. While the accuracy of neural networks in a virtual single-loss setting is an incredible 94.2 percent (Hatori et al., 2012), in the real world, variables such as sensor noise (10 percent RMS), thermal flux (5°C), and traffic stochasticity reduce the accuracy of neural networks beyond trial to 1215 percent in the absence of hybrid experimental calibration [22]. Shinkansen viaduct validations further indicate that physics-constrained algorithms combined with ASTM-compliant sensor networks can eliminate up to 40 percent of false positives and also point to the non-negotiable nature of field prototyping in bridging the simulation versus reality gap [23].

4.7 Research Priorities

1. High-speed transformation: Attractive models become obsolete at speeds of 270 km/h and above in non-stationary wheel-rail dynamics. When adaptive wavelet transforms, which are coupled with 3D train-bridge-vehicle coupling (e.g., 6DOF models), are used with high fidelity, accuracy can be restored to more than 90% because the wind-vibrational noise in the signal is isolated to recover the damage signature [24].

2. Geometry complexity: 2D simplified beam estimation introduces this error of 15%. Replacing standard nodal deployments with topology-optimized deployments to capture the effects of torsion and warping, with the help of digital twin strain mapping, is needed [25].

5. Concluding Remarks

The review concluded that the application of vehicle-bridge interaction (VBI) analysis and soft-computing is a paradigm shift in sustainable and self-reporting structural health monitoring. This technique does not cause any traffic disruption because it involves the use of traffic-induced vibrations (saving 1.2 tons of CO_2 per cycle inspection), and because the technique enables constant and non-destructive indication of damage based on physics-induced vibration signatures such as frequency shift (a 3.7 per cent shift in frequency corresponds to a 30 per cent reduction in stiffness) and acceleration decay (a 15 per cent depreciation of the peak). The neural networks have the ability to detect single damage points with high accuracy up to 94.2 percent, and the genetic algorithm is able to achieve multi-damage points with a marginally acceptable accuracy level of 89.7 percent under ASTM E1318-09 compliant noise-free internal sensor networks (noise intolerance, i.e., 0.01 g). Real-life cases have shown that when stiffness is reduced at an early stage, timely intervention can save 60 percent of life cycle costs and 30-50 percent of resources.

The relevant and currently occurring problems, in particular, the maximum operating speed (>270 km/h), environmental randomness (>5°C thermal variation), and quantification of multiple damage severity, indicate that planned research on 3D train-bridge connection models, hybrid GAs-NN, and self-calibrating sensor networks should be seen as a priority. Standardization of damage thresholds through ASTM standards as well as learning on infrastructure digital twins will further accelerate the adoption process. By acting proactively, physics-informed machine learning, energy-autonomous sensing, and hierarchical mitigation methods outperform reactive monitoring and extend the service life of bridges by 15-25 years with negligible impact on societal risk. To implement a fully resilient infrastructure ecosystem, the following steps need to include seismic-vehicle-bridge connections and edge-computing constraints.

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