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Real-Time Damage Assessment of Bridge Strike Events Using a Bayesian Digital Twin

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Abstract

Bridge strikes represent a persistent and growing challenge for rail infrastructure in the UK with an average of five incidents occurring daily and up to ten during peak periods. Approximately 2,000 strikes annually lead to significant service disruption and an estimated economic cost of £23 million. This paper presents a real-time Digital Twin framework for post-impact structural assessment of railway bridges. The proposed system integrates LiDAR sensing, AI-enhanced computer vision for real-time telemetry, synchronised via edge computing with a Bayesian inference model informed by high-fidelity finite element (FE) simulations. A total of 144 impact scenarios were simulated for a representative heritage steel bridge, enabling the construction of a Bayesian Inference Table capable of rapidly estimating damage states in terms of rail alignment and permanent steel deformation. The framework translates probabilistic damage predictions into operational decisions using a Red-Orange-Yellow-Green (ROYG) classification, supporting immediate and risk-informed post-strike interventions.

Keywords: bridge strike, finite element, digital twin, Bayesian, railway bridge dynamics, collision risk assessment.

1 Introduction

The rail infrastructure in the UK is characterized by a significant population of legacy assets, many of which were not originally engineered to withstand the loading profiles or vehicle dimensions of modern transport. Consequently, vehicle-bridge strikes have become a systemic issue, occurring at a frequency of approximately once every five hours-totalling nearly 1,900 incidents annually [1]. Under current Network Rail (NR) protocols—specifically standard NR/L3/CIV/076 [2]—reported strikes trigger an immediate and often conservative operational response.

Despite the severity of the issue, prevention strategies remain largely reliant on passive measures, such as the design and evaluation of enhanced visual warnings and physical signage aimed at driver behaviour [3]. Furthermore, while Structural Health Monitoring (SHM) has advanced significantly, most existing systems are designed for general health monitoring that tracking long-term degradation like fatigue or corrosion, rather than the high-energy, transient nature of bridge strikes. Current monitoring technologies are largely reactive, focused on simple event detection rather than real-time structural prognosis. Recent efforts have explored supervised machine learning to categorize collision events [4], yet there remains a critical gap in translating sensor data into an immediate assessment of residual structural capacity.

Based on the National Bridge Strike Instruction (NBSI) framework, bridges are categorized by their structural robustness. While Green-rated structures may allow continued operation at line speed, most incidents involve Red or Amber-rated assets where trains are either stopped or restricted to cautionary speeds until a physical examination is conducted by a Bridge Strike Nominee (BSN). These manual inspections are the primary driver of massive operational costs under the Schedule 8 performance regime, which functions as a system of liquidated damages. Under this framework, Network Rail must financially compensate Train Operating Companies (TOCs) for every minute of service disruption attributed to infrastructure availability.

The threshold for reopening a line is traditionally binary and manual. Structural integrity is assessed based on specific damage limits: if a steel girder sustains significant section loss, such as damage exceeding 50% of the bottom flange, the bridge is deemed unsafe for loading, resulting in a "Red" status and total line closure. Conversely, if the damage is less severe—retaining at least 75% of the flange (maximum 25% loss)—the bridge may be downgraded to "Amber" status, allowing trains to proceed at a restricted speed of 20 mph. Any visible track misalignment, however, triggers an immediate "Red" status regardless of girder condition.

While these measures prioritize passenger safety, the reliance on manual inspection leads to substantial service delays and significant liquidated damages, with annual costs across the network often exceeding £20 million [1]. This paper proposes a Digital Twin framework to address these limitations. By integrating real-time sensing with physics-based simulation and probabilistic inference, the system provides an instantaneous estimation of damage states, potentially allowing for the safe, rapid resumption of rail services and the mitigation of avoidable financial penalties.

2 Real-Time Monitoring System

The monitoring system uses localised data processing to minimise data delay and ensure rapid alerts. The core hardware integrates LiDAR and camera sensors for real-time vehicle tracking, as shown in the Figure 1 below. The LiDAR provides 3D dimensions and speed data, while a synchronised camera uses AI-based detection to classify the vehicle type (e.g., distinguishing vans from heavy trucks). This classification helps the system more accurately estimate the vehicle's mass for kinetic energy calculations.

All data processing is performed locally by a trackside edge computer. In the event of a collision, wireless MEMS accelerometers mounted on the bridge girders trigger immediately. These sensors confirm the strike and record the bridge's vibration response. This data is then analysed alongside results from the perception system and the numerical simulations detailed in the following sections. The result enables infrastructure maintenance teams to rapidly assess the severity of the damage and coordinate targeted inspections or necessary closures, thus ensures that maintenance plans are efficiently managed, minimising the impact of service disruptions on both rail and road networks.

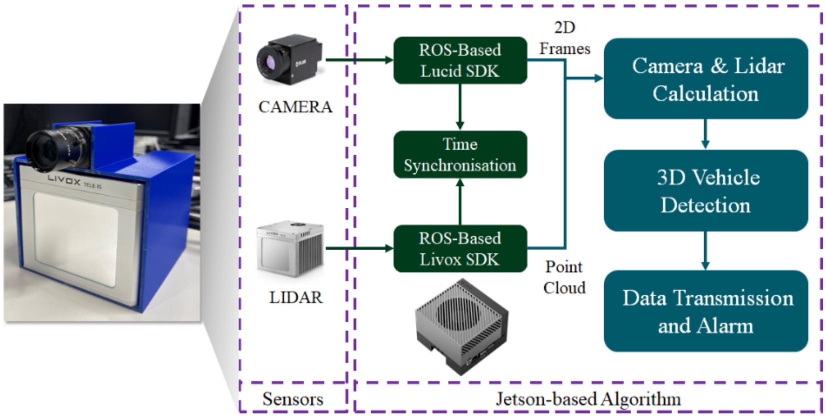


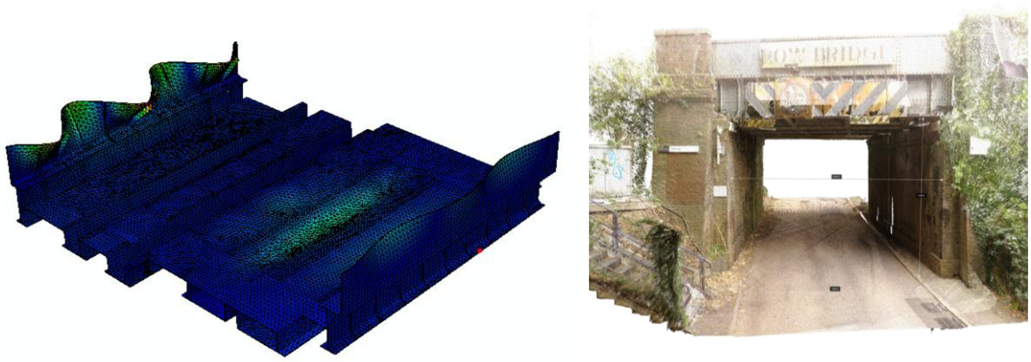
Figure 1: Real-time monitoring system

3. Numerical Simulation

3.1 Bridge Model

The study utilizes a 7-girder steel railway bridge as a representative case study, as illustrated in Figure 2. This structure is a common bridge type within the UK rail network and was specifically selected due to its history of significant and frequent vehicle-bridge strikes. Figure 2(a) illustrates the bridge's first vertical mode, occurring at approximately 20 Hz, while Figure 2(b) displays the high-resolution 3D scan data captured at the site. The finite element model incorporates transverse brackets between the primary girders to accurately capture lateral load distribution.

In this analysis, the masonry brick walls were excluded from the model, as bridge strikes predominantly result in damage to the bridge deck rather than the substructure. Furthermore, while the bridge deck is susceptible to lateral displacement upon impact, the brick walls remain effectively stationary. To investigate rail misalignment resulting from such strikes, translator connectors were utilized to model the mechanical interaction between the bridge girders and their supports (bearings and abutments). To account for environmental variables—such as moisture levels and agerelated surface degradation—friction coefficients (μ) were defined at 0.2, 0.45, and 0.6. The resulting friction force is dynamically coupled to the bridge's dead weight to ensure a high-fidelity representation of the structural response during an impact event.



(a) (b)

Figure 2: Trail Railway Bridge; (a) 3D FE model; (b) 3D scan model

3.2 Material Properties

The structural steel was modelled using S235 structural steel to reflect the material properties of heritage bridge assets. A von Mises yield criterion with isotropic hardening was employed. To account for large-strain kinematics during high-energy impacts, the material was defined using a True Stress-Strain relationship, initiated at a yield strength of 235 MPa.

3.3 Impact Scenarios

The mechanical response of the bridge is highly sensitive to the collision morphology, which is governed by the structural stiffness of the impacting vehicle. As illustrated in Figure 3, three primary impact scenarios were identified and replicated within the numerical model:

(a) (b) (c)

Figure 3: Strike scenarios; (a) peeling; (b) overturning; (c) crush and stop

- Peeling (Continuous Displacement): Characterized by the vehicle passing beneath the girder without coming to a complete rest. This is common in strikes involving double-decker buses, where the relatively deformable upper deck undergoes significant plastic deformation. In this scenario, energy is dissipated over a longer impact duration (t), resulting in a lower peak force but a sustained loading cycle.
- Overturning (Rotational Impact): Typically observed in rigid-body trucks. Due to the high structural hierarchy of the vehicle frame, the kinetic energy is converted into a rotational moment upon contact. This results in a high-intensity, localized impact force concentrated at a specific point of the girder.
- Crush and Stop (Impulsive Impact): Associated with heavy goods vehicles (HGVs) and semi-trailers. This scenario represents the most severe loading condition, where a high initial impulse occurs as the vehicle's momentum is rapidly arrested. The lack of structural flexibility in the vehicle leads to a shorter impact duration and a significantly higher peak impact force.

The force-time history F(t) applied to the 7-girder model is governed by the relationship between the vehicle's kinetic energy and its structural stiffness. While the Impulse-Momentum Theorem defines the transient loading, the partitioning of energy differs significantly based on the collision morphology.

For rigid vehicles (e.g., HGVs in "Crush and Stop" or "Overturning" scenarios), the lack of sacrificial deformation results in a near-instantaneous transfer of kinetic energy. This necessitates a high-amplitude, short-duration force profile in the simulation. Conversely, for flexible vehicles such as double-decker buses, the extended deformation phase facilitates energy dissipation, thereby increasing the impact duration (t) and reducing the peak impulsive load.

Vehicle	**Mass (kg)**	**F_{peak}(N) V=20 mph**	**F_{peak}(N) V= 27 mph**	**F_{peak}(N) V=34 mph**	**F_{peak}(N) V=40 mph**
Van	2,000	133,230	243,145	385,036	532,919
	2,800	186,522	340,403	539,050	746,087
	3,500	233,152	425,504	673,812	932,609
Box Truck	5,000	499,612	911,794	1,443,884	1,998,448
	8,500	849,340	1,550,050	2,454,602	3,397,361
	12,000	1,199,068	2,188,306	3,465,321	4,796,274
Double Bus*	12,000	400,000	400,000	400,000	400,000
	15,000	600,000	600,000	600,000	600,000
	18,000	800,000	800,000	800,000	800,000
Semi-Trailer	15,000	2,997,671	5,470,766	8,663,302	11,990,686
	30,000	5,995,343	10,941,532	17,326,605	23,981,372
	40,000	7,993,790	14,588,710	23,102,140	31,975,163

Table 2: Simulation case scenarios

The peeling scenario, however, requires a distinct application of the work-energy principle. Unlike stationary impacts, peeling is a path-dependent process where work is done continuously as the vehicle moves beneath the girder. The energy dissipated is defined by the integral of the crushing force over the contact length. Therefore, the yield force (constant load) represents the "threshold-limited" force governed by the controlled failure of the vehicle's roof. A transient analysis were used, and the peak forces are applied at the contact surface of the girders for different scenarios. To ensure the robustness and predictive reliability of the Bayesian Inference Table (will introduced in Section 4), a comprehensive parametric study comprising 144 distinct simulation cases was conducted. This systematic approach allows the Digital Twin to account for a wide range of impact variables and environmental uncertainties (friction coefficient mentioned in Section 3.1). The full matrix of the simulated scenarios is summarized in Table **Error! Reference source not found.**.

4. The Bayesian Inference Framework for Damage Quantification

The Digital Twin employs a Bayesian Inference Framework to provide a probabilistic mapping between observed impact kinematics and structural damage states. This framework is designed to bridge the gap between high-level site data and localized structural degradation while accounting for the critical safety requirements of rail operations.

4.1 Probability of Damage States

The framework operates on the principle of Bayes' Theorem, allowing the system to update the probability of a specific structural damage state based on real-time evidence:

$$\mathrm{P(D|V,M,t)} = \frac{\mathrm{P(V,M,t|D)\ P(D)}}{P(V,M,t)}$$

Where

- P(D|M,V,t) (Posterior): The probability of a specific damage state (D) given the vehicle mass (M), vehicle velocity (V), and impact duration (t) detected by the site sensors.
- P(M,V,t|D) (Likelihood): The probability of observing these specific impact parameters for a given damage state, derived from the 144-case numerical database.
- P(D) (Prior): The initial probability of damage based on the bridge's structural robustness classification.

4.2 Decision Logic: Rail Alignment and Steelwork Damage

The model predicts the permanent lateral shift of the bridge deck by simulating the interaction between the 7-girder system and its supports via translator connectors. Because the rails are fixed to the bridge deck, any lateral movement (Δx) directly translates to a change in track geometry. Therefore, if Δx exceeds the permissible limit defined by the standards for the specific line speed, the system triggers an immediate "Red" status, regardless of whether the steelwork has yielded. This reflects the reality that rail misalignment is an immediate derailment risk.

For steelwork damage logic in the Bayesian Table, the model utilizes the Equivalent Plastic Strain (PEEQ) which represents the measure of the plastic part of the component. The total steelwork damage is calculated by integrating the volume of all elements where plastic deformation has initiated, normalized by the total volume of the critical flange.

4.3 Operational Status Matrix

The results of the 144 cases were mapped to the following operational decision logic as shown in Table 3. This logic ensures that the Digital Twin prioritizes the most restrictive safety condition. By automating the assessment of both rail alignment and steelwork integrity, the system significantly mitigates liquidated damages, providing a high-confidence decision in seconds that would otherwise require hours of manual site attendance by a Bridge Strike Examiner (BSE).

Damage State	**PEEQ-Based Steel Loss**	**Lateral Shift**	**Operational Response**
Green	< 10%	< 2 mm	Normal Operations: No structural risk detected.
Yellow	10-25%	2-5 mm	Caution: Manual inspection required within 24h.
Orange	25-50%	5-10 mm	Restriction: 25% Speed Reduction for all trains.
Red	> 50%	> 10 mm	Danger: IMMEDIATE LINE STOP.

Table 3: Operational status matrix

5. Conclusion

This paper demonstrates that a Bayesian Table approach allows for a nuanced, risk-based response to bridge strikes. By moving away from "Pass/Fail" inspections and toward a probabilistic Digital Twin, UK rail operators can reduce unnecessary delays while maintaining a strict safety ceiling.

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