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Impact Rating System for Vehicle–Railway Bridge Collision

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ABSTRACT

Overhead collisions of trucks with low-clearance railway bridges cause more than half of the railway traffic interruptions over bridges in the United States. Railroad owners are required to characterize the damage caused by such events and assess the safety of subsequent train crossings. However, damage characterization is currently visual (subjective) and becomes difficult in remote locations where collisions are not reported and inspections are not performed following the impact. To mitigate these shortcomings, this paper presents a new impact definition and rating strategy for automatically and remotely quantify damage. This research proposes an impact rating strategy based on the information that best describes the consequences of vehicle-railway bridge collisions. A series of representative impacts were simulated using numerical finite element models of a steel railway bridge. Railway owners provided information about the bridge and impact characterization based on railway industry experience. The resulting nonlinear dynamic responses were evaluated with the proposed rating strategy to assess the effect of these impacts. In addition, a neural network methodology was implemented on a simplified numerical model to identify spatial characteristics of the impact damage.

Keywords: railway bridges, structural health monitoring, finite element model, impact detection, neural networks.

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1. Introduction

Today nearly half of railway bridge-related service interruptions are attributed to strikes of highway traffic [1]. Out of 8,563 reported interruptions in railway services, half are caused by strikes of highway vehicles with railroad bridges (Fig. 1). Annual risk created by vehicle-bridge collision is estimated to be as much as $10.2 million for the industry. The consequence of an impact can vary from negligible damage in structural members to disturbance in the alignment due to supports being pushed beyond their capacity limits. In the least serious events, traffic is delayed only until an inspection is conducted. In the most serious cases, destruction of the bridge and even loss of a train may occur.

In general, highway truck impact with the bottom flange of a girder does not have an immediate effect on the structural capacity of the bridge. Nevertheless, after a highway truck collision, bridge inspectors need to conduct a detailed visual inspection to ensure the bridge is safe for subsequent train crossings even when a minor impact is reported. A minimum estimated cost for minor service interruption and negligible damage after impact is calculated to be $10,000 [2]. As a result, the railway industry is interested in a method that can rate the damage of vehicle-railway bridge collisions

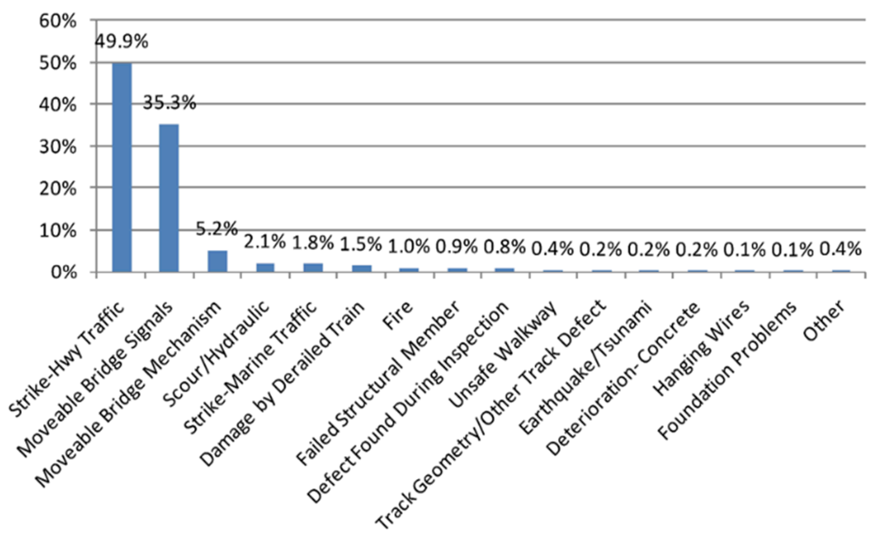


Fig. 1: Frequency of railway reported events causing traffic interruptions [1]

With the same interest, three critical objectives of this research are identified as: (a) impact modeling, (b) impact assessment, and (c) impact rating. To achieve these objectives, an extensive literature review has been conducted. Various damage detection techniques and structural health monitoring methodologies [1, 3-13] are studied. Different finite element models focusing on the simulation of impact events have also been reviewed [8, 14-17]. None of the previous literature addressed a realistic vehicle-bridge collision event. Likewise, a consequence-based rating system was overlooked.

In this study, a rating strategy for quantifying damage is proposed. This research develops a three dimensional finite element (FE) model of a railway bridge (ANSYS 17.2) and simulates nonlinear overhead collision events. Results include structural stresses and permanent deformations, and strains under vehicular impacts running at different speeds. Researchers linked the nonlinear dynamic responses with a preliminary rating strategy to assess the effect of impact on the bridge model. In addition, researchers investigated the potential application of neural network systems for impact ratings using a simplified beam model of the bridge.

2. Impact modeling

For the impact modeling, this research utilizes a railway bridge owned by one of the Class I railways in North America. This bridge is a single span deck plate girder system that carries one railway track. The bridge is 5 meters (16.4 feet) wide and 24 meters (78.7 feet) long, crossing over a two lane road. The main structure consists of two plate girders connected with transverse cross beams carrying the train track. Multiple vertical stiffeners are added to the two webs to prevent the web from buckling under heavy train loading. Fig. 2 shows the bridge plan and elevation views.

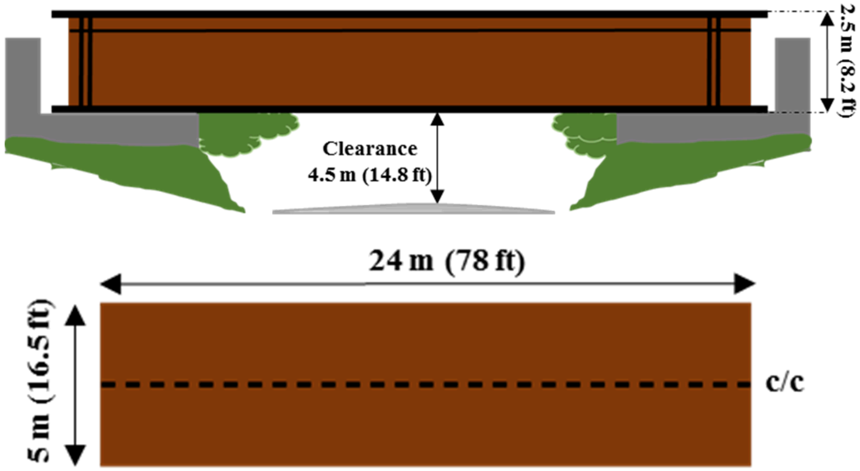
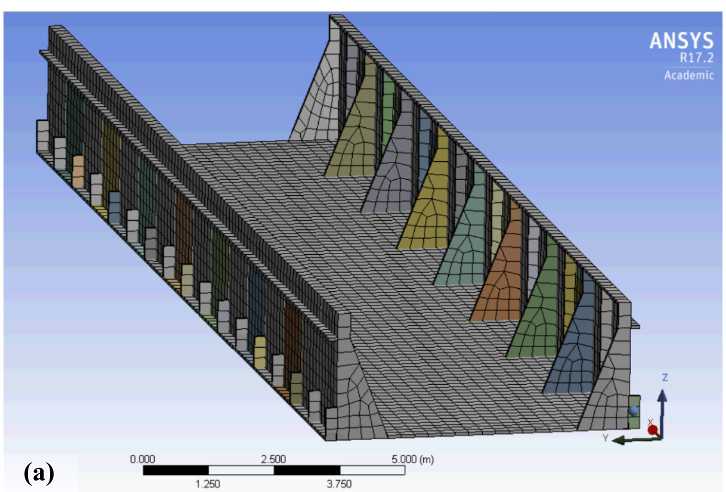


Fig. 2: Plan and elevation of the simulated bridge.

In this study, an FE model of the target structure is constructed using ANSYS/Autodyn software [18] to (1) simulate a vehicle impact with the railway bridge, (2) study resulting nonlinearities on the bridge, and (3) quantify its dynamic deflection characteristics during and after impact. The FE model is developed based on the plans and pictures of the railway bridge. Bridge plans are used to determine the material properties of steel such as Young's modulus, yield str ess, tangent modulus and yield strains. All steel components, including the girder web, top and bottom flanges, and the main deck plate, are structural steel with bilinear hysteresis observing elasto-plastic behavior based on American Standard for Testing and Materials (ASTM) A572/A572M [19]. The Cowper-Symonds material deformation law [20] with parameters appropriate for the steel material is utilized for all the structural components. The elastic modulus is estimated to be 200 GPa (29,000 ksi). The geometry of each component such as girders, including web, flange and stiffeners, and the deck plate is modeled in accordance with technical drawings. Those components are meshed automatically with 3-node triangular and 4-node quad shell elements by ANSYS' mesh module. To simplify the modeling procedure, the cross beams are condensed as a continuous diaphragm connecting the two girders in the direction of the impact. Consequently, this approach allows better observation of stresses distributions in the equivalent horizontal plate. The boundary conditions are assumed pin-roller support which is often used in classical single span bridge designs. A typical FE mesh and plot for material properties is shown in Fig. 3(a) and 3(b) respectively.



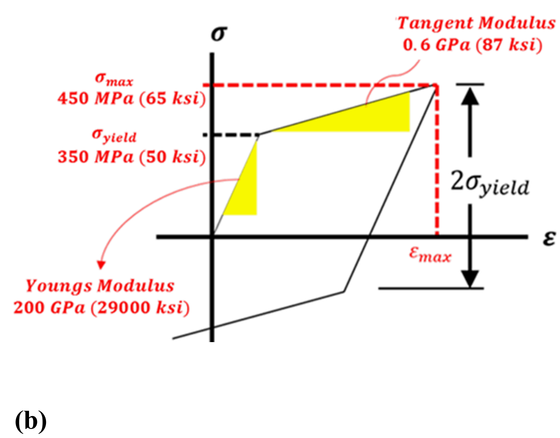


Fig. 3: (a) FE model of the railway bridge, and (b) the steel stress-strain curve [20]

For impact, a semi-trailer truck, simplified as a solid mass box, is modeled with 8-node hexahedron solid elements and impacts are simulated with the bridge. The box, assumed as a steel solid rigid body, has a height of 0.5 m (1.6 feet), length of 3.5 m (11.5 feet) and width of 2 m (6.6 feet). The mass of this box is calculated as 27,475 kg based on the dimensions and the density of steel (7850 kg/m^3) which is equivalent to the weight of a representative semi-trailer truck. The surface area facing towards the bridge is calculated as 1 m^2. The typical mesh for the mass box is given in Fig. 4.

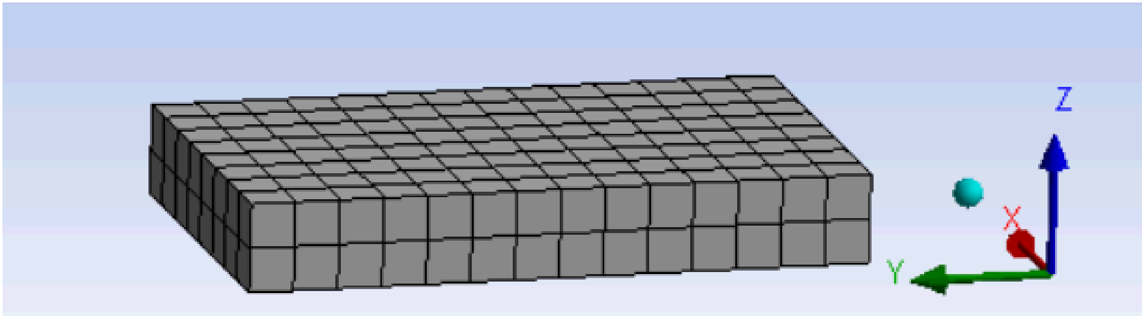


Fig. 4: Finite element mesh for the mass box.

3. Impact assessment

Autodyn has an explicit numerical solver that yields accurate results for short duration contact problems. Since impact is also a small time step problem, Autodyn is a suitable platform to simulate vehicle-bridge collision event. A series of impact simulations are performed with varying speeds of 20 km/h (12 mph), 40 km/h (24 mph), 40 km/h skewed at a 5-degree angle and 60 km/h (37 mph). The location of impact is 10 m (29.5 feet) from the right end of the bridge. The resulting equivalent (von Mises) stress responses for vehicle speed of 40 km/h are provided at impact times of 0, 0.05, and 0.1 seconds in Fig. 5. The maximum stress observed at the impact location throughout the simulation for a vehicle speed of 40 km/h is determined 337 MPa.

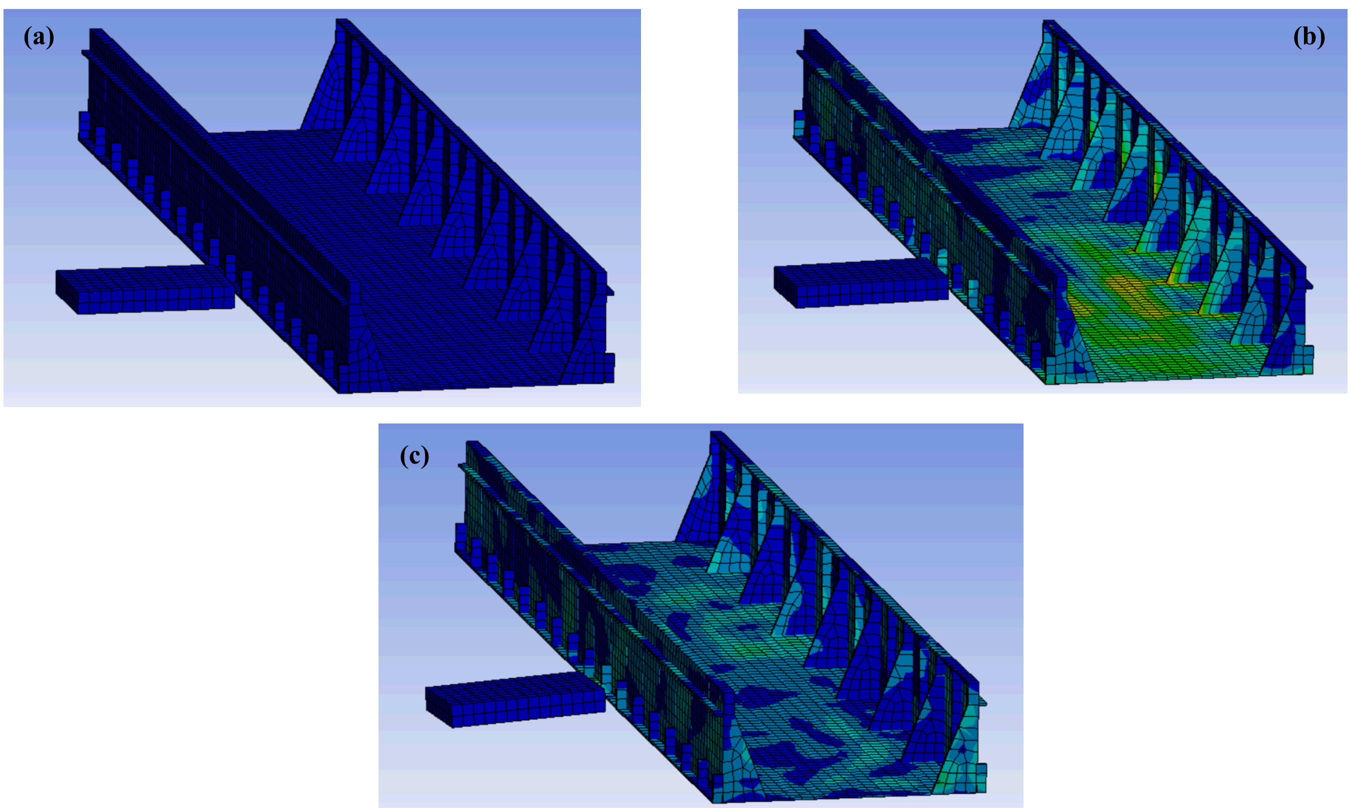
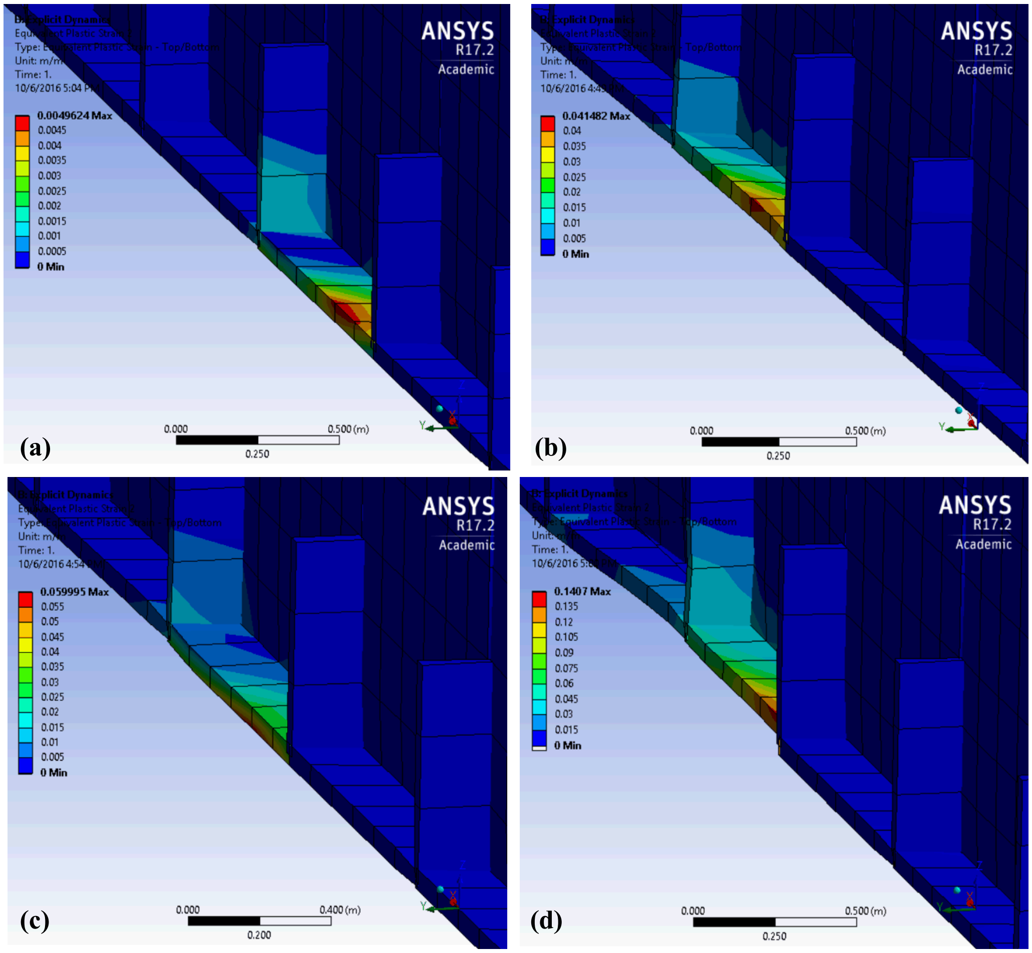


Fig. 5: von Mises equivalent stress patterns for vehicle speed of 40 km/h at impact time of (a) 0 seconds, (b) 0.05 seconds, and (c) 0.1 seconds.



Additionally, at the end of each impact, the structure experiences localized equivalent plastic strain (Fig. 6).

For all impact events, the bridge experienced nonlinear plastic deformation at varying levels. As shown in Fig. 6, visible permanent deformation is observed in the bridge web. The values of permanent deformations compared to the maximum deformations are given in Table 1. The presence of permanent deformation is an indication of the severity of damage in a bridge whereas the maximum deformation is considered as a design criteria relevant to the load capacity of the bridge. Since the aim of this study is to improve the serviceability of railroad bridges after impact, permanent deformation is considered for rating which is discussed in the next section.

Table 1: Deformation values for series of impacts

Impact Speed (km/h)	Maximum Deformation (mm)	Permanent Deformation (mm)
20	9.1	2.5
40	26.6	14.9
40 – skewed 5-degrees	27.1	16
60	101	75

4. Impact rating

To rate the aforementioned impact events, the following consequence based rating system has been proposed. The description of rating categories and the cost of consequences are shown in Table 2. The category descriptions have been established in reference to previous literature (severity rating, service interruption, consequence and lost estimate) [2], and discussions of this approach with railroad bridge engineering staff about the threshold limit.

Table 2: Description of Rating Categories

Rating of Impact Severity	Level of Service Interruption	Condition of Damage	Threshold Limit Permanent Disp.	Consequence	Loss Estimate
1	No Interruption	No Damage	5 mm	No consequence	**$0**
2	Minor	Negligible	10 mm	Visual inspection	**$10,000**
3	Moderate	Repairable	30 mm	Minor repair	**$100,000**
4	Major	Significant	60 mm	Extensive repair	**$300,000**
5	No Service	Bridge collapse	300 mm	Bridge replacement	**>$1,500,000**

For preliminary layout of the quantification of impacts and consequences using objective data, the following general scenario is proposed: With truck speeds of 20 km/h, the permanent deformation in the model is observed to be 2.5 mm. For such small deformations, the bridge will still remain in operational condition with no negligible damage. Therefore, this impact is classified as category 1. Due to the increased momentum of vehicle in 40 km/h skewed and non-skewed impact cases, higher deformations are observed in the model. The elevated deformation increases the severity of the collision to category 2. Thus, this bridge would experience some temporary service interruptions such as train speed reduction. A significant permanent deformation of 75 mm is experienced by the bridge in the impact case with truck speed of 60 km/h. With such nonlinearities, the bridge department would have to avoid potential service interruptions, causing permanent train speed reductions until the repair. The severity of this case has therefore been classified as category 4 in the rating system. The trends observed from the results of the numerical simulations indicate that higher velocity impacts have the potential to create impact severity of category 5. These proposed thresholds are the first preliminary effort to "rate" measured consequences with current railroad bridge management decisions. For the application of this theoretical effort to railroad environments and decisions, future research will be conducted in coordination with the railroad departments input, including workshops and small scale tests.

5. Future direction: spatial identification of impact damage

In order to evaluate the severity of a collision after the impact event, the energy inserted into the system must be identified. The level of energy depends on variables such as the speed of the truck and the location of impact. Based on previous studies, which demonstrate the potential of neural networks for detection and characterization of nonlinearities in dynamic systems [21, 22], an effective and simple approach for identification of damage location of bridge-vehicle collisions is proposed here. To demonstrate the identification procedure and represent the dynamic response of a TPG, a simplified FE model of a fixed-pinned beam is considered. Since this response is governed by the six modes, the beam model consists of six elements, where each node has a translational and rotational degree of freedom. The beam has properties representative of the three-dimensional bridge considered above. This has been achieved by adjusting the mass, stiffness and damping matrix. The damping matrix has been computed as Rayleigh damping proportional to the mass and stiffness matrix, respectively. The modal damping ratio of the first mode is tuned to 0.02. The aim is to detect the spatial location of damage. Therefore, the model has been split into six sections as illustrated in Fig. 7.

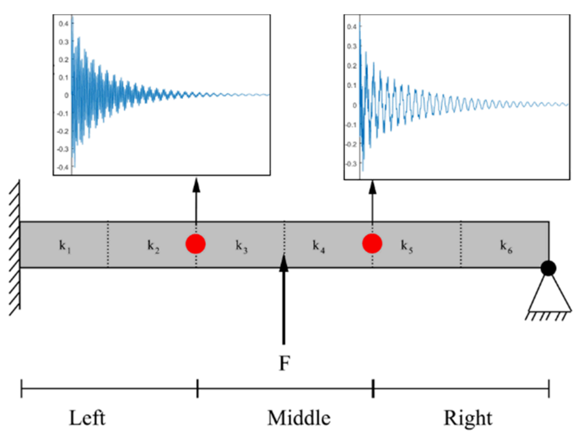


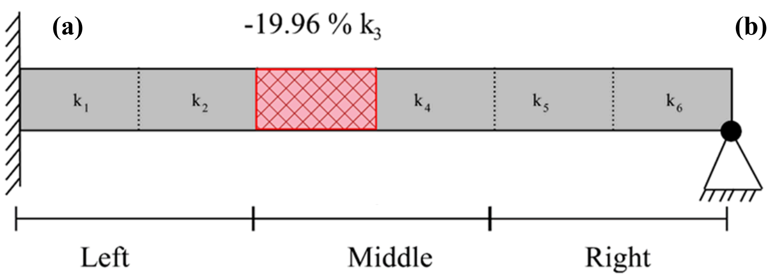
Fig. 7: Simplified beam model of the railway bridge used for the neural networks approach.

Each of the six elements is given stiffness properties denoted by k, with the subscripts 1 to 6. Damage caused by an impact event is assumed to cause local stiffness reduction. This has been simulated numerically by weakening the stiffness of subsequent elements. The initial step of the identification is to select the damage sensitive features. These are listed in Table 3 and consist of statistical quantities achieved from the dynamic response of the numerical model. The dynamic response is obtained from the two reference signals from the locations indicated in Fig. 7. Furthermore, the modal parameters for the first and second mode are selected as features. The patterns of the features selected in response to stiffness reduction have been classified to train and validate the neural network. For training, 230 data sets are simulated by individually reducing the stiffness of k_1 to k_6 by 10, 20, 30, 40, 50, 60, 70, 80 and 90%. The data set contains the features obtained from the impact at the middle of the beam. Forty-nine samples each are employed for validation and testing.

Table 3: Selection of damage sensitive features of the beam model.

Feature	Damage Sensitive Features
1	Difference between displacement time history at reference location
2	Root-mean-square of reference response
3	Correlation coefficient of reference response
4	Mean of reference response
5	Standard deviation of reference response
6	Natural frequency, f_1 and f_2
7	Modal damping ratio, ζ_1 and ζ_2
8	Euclidian norm of normalized mode shape, $\|\|\phi_1\|\|_2$ and $\|\|\phi_2\|\|_2$

To improve training of the neural network, a feature space reduction step is performed. The space reduction is achieved by applying principal component analysis as in [22]. It is desirable to have the largest possible data set for training of neural networks where the size of the data set grows with an increasing number of features. The training is performed using MATLAB Neural Network Toolbox with 9 neurons. A single neuron act as a correspondence to the input-output mapping by regression. The extension to multiple neurons is achieved by establishing a neural network, such that the output of a neuron can be the input of another [22]. The training of the network has been performed to obtain weighting functions that correlate to the features with the damage location. After completion of training, an additional data set has been generated. This data set has been used to test the robustness of the identification procedure. The stiffness in the middle region of the beam has been decreased by 19.96% instead of 20% as in the training data set, shown in Fig. 8 (a). The outcome probability for the damage to be in the middle of the beam model is 100%, as given in Fig. 8 (b). Other combinations of stiffness reduction of the beam elements have also been tested. The true location has been consistently identified with a probability ranging from 80-100%. This indicates that the proposed procedure for the spatial identification of damage is reasonable for the developed numerical model. Similar procedure can be adopted for a detailed numerical model, such as the above ANSYS model. This would in particular require an extensive dataset, containing features as proposed in Table 3. The extent of this dataset depends on which accuracy of stiffness reduction due to vehicle impact is sought.



Categories	Probability
No damage	0%
Left	0%
Middle	100%
Right	0%

Fig. 8: (a) Beam model of the bridge span, where the red element indicates stiffness reduction. (b) The probability of the damage location found by the proposed procedure.

6. Conclusions and future work

This paper emphasizes the type of accidents occurring due to impact between highway trucks and railway bridges. In order to study the effects of these impacts and rate them, we developed: (1) a preliminary FE model to understand the deformation processes associated with and impact event, and (2) an idealized neural network model to demonstrate its applicability in detecting damage. The results presented herein represent an initial attempt to quantify truck-bridge impact phenomena and develop techniques to detect and mitigate future impact events. In our future work, the FE model will be improved by developing a higher fidelity mesh to more accurately capture the internal mechanical behavior of the bridge. In addition, we will develop a more accurate representation of a typical semi-truck. A mesh convergence study will be conducted in order to obtain an accurate and computationally efficient model. Furthermore, a more complex neural network system will be developed to rate the impacts when railway bridges are hit by highway traffic. A hybrid approach will be considered where both the location and the magnitude of the impact detected by neural networks are utilized as inputs to the simulation. Accordingly, structural integrity will be assessed using hybrid simulation results. Additionally, permanent displacements at the supports due to an impact will be evaluated. Finally, the effectiveness of crash beams in protecting the bridge against impacts will be investigated.

7. Acknowledgment

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