Limitations and Future Direction for Structural Health Monitoring of Railroad Bridges Subjected to Over-Height Vehicle Impacts

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ABSTRACT

Low clearance through-plate girder railroad bridges in the United States are highly susceptible to impacts from over-height vehicles, which can lead to structural damage and disruptions in railroad bridge service. Current post-impact inspection protocols require bridge closures, causing unnecessary delays when minor impacts occur. This study presents a low-cost structural health monitoring-oriented framework for automated impact detection, severity classification, and condition assessment using wireless smart sensors. The proposed structural health monitoring framework leverages machine learning models to detect and characterize impact events and estimate resulting residual displacements using acceleration data alone. Although this framework demonstrates promising performance in both numerical and field settings, some limitations remain. The current approach has been validated only for single-span through-plate girder bridges, relies solely on acceleration data, and does not incorporate vehicle speed or visual confirmation. Future directions include integrating additional sensing modalities such as cameras for event verification and visual assessment, expanding applicability to multi-span or alternative bridge types, and incorporating traffic history and near-miss data to support predictive impact risk modeling. These extensions will further enhance the utility, scalability, and resilience of automated post-impact response strategies for railroad infrastructure.

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1. INTRODUCTION

Low-clearance bridges are often prone to frequent impacts from over-height vehicles. Half of the 100,000 railroad bridges in the United States are over 100 years old and were constructed when the minimum vertical clearance requirements were lower than the current standards. Thus, these aging bridges are particularly prone to impact by over-height vehicles [1]. For example, Joy et al. [2] found that nearly half of railroad bridge service disruptions between 1999 and 2010 were caused by over-height vehicle collisions. Structural Health Monitoring (SHM) is a technique used to evaluate the condition and integrity of structures analyzing sensor data collected from various monitoring systems. Conventional SHM systems primarily rely on wired sensors, which have been widely adopted in practice for SHM applications [3]. Recent advances in wireless smart sensor (WSS) technologies offer attractive alternatives to wired systems due to their ease of installation, lower maintenance costs, and scalability [4]. Despite advances in SHM technologies, several key challenges must be overcome to effectively address railroad bridge impact detection and condition assessment. This is because impacts on railroad bridges can exceed the bridge design impact load and can lead to structural damage as well as service disruptions, resulting in danger to public safety, disruption of traffic, and potentially significant loss of revenue for railroad owners [5].

Given these challenges, this paper presents a comprehensive framework integrating WSSs and machine learning techniques to enable near real-time impact detection, impact severity classification, and post-impact condition assessment. Although the framework demonstrates strong performance in simulation and practical implementations, some limitations remain, such as its validation only on single-span through-plate girder (TPG) bridges, lack of visual verification, and exclusion of vehicle speed as a model input.

The purpose of this work is to outline these limitations and propose future directions that address scalability, enhance sensing capabilities, and improve predictive performance across broader bridge inventories. By identifying gaps in the current approach and recommending specific enhancements, this study aims to support the development of more resilient and comprehensive post-impact monitoring systems for railroad infrastructure.

2. FRAMEWORK FOR AUTOMATED IMPACT DETECTION AND CONDITION ASSESSMENT

This section introduces a framework for automatically assessing the structural condition of railroad bridges after impact events. The framework is structured into three stages: identifying the occurrence of impacts, classifying the severity of impacts, and estimating the resulting permanent displacement. Relying on just one accelerometer and three dedicated neural network models, the approach offers a practical and near real-time monitoring solution.

2.1. Impact Detection

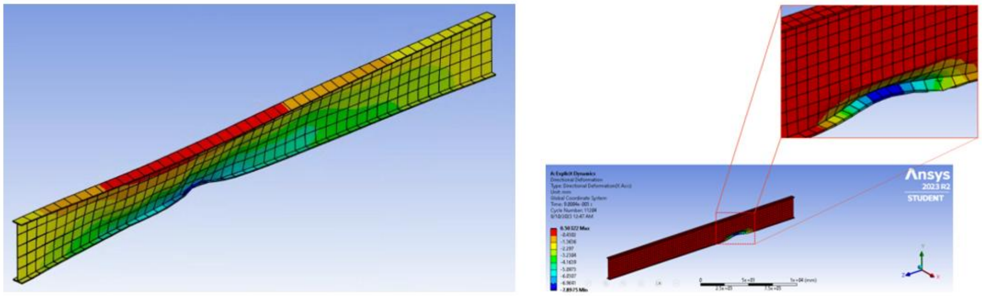
The initial stage focuses on detecting impacts using the event classification neural network introduced in Lawal et al. [6]. This model analyzes acceleration data recorded by sensors mounted on the bridge to differentiate between impact events and routine train crossings. By extracting important features such as peak acceleration, dominant frequency content, and spectral energy, the network achieves high classification accuracy. Accurate detection of impacts is essential, as it underpins the effectiveness of the remaining steps in the assessment process.

2.2. Impact Severity Assessment

For impacts identified by the model in Section 2.1, the second stage of the framework classifies each event as either minor or non-minor using the impact severity assessment model described in Lawal et al. [7]. This model was developed using finite element (FE) simulations of a representative TPG bridge in ANSYS, with Figure 1 showing examples of the deformed girder after simulated impacts. The severity model helps exclude minor impacts (which are unlikely to cause meaningful permanent deformation) from further analysis. This targeted filtering enhances the efficiency of the framework by ensuring that only significant events trigger additional structural evaluation, allowing for more effective allocation of inspection and maintenance resources.

2.3. Permanent Displacement Estimation

The final step involves predicting the resulting permanent displacement for non-minor impacts. For estimating permanent displacements following non-minor impacts, a neural network model is trained using data generated from FE simulations of TPG railroad bridge impacts using the model introduced in Section 2.2. These simulations cover a range of vehicle masses, speeds, and damping conditions to capture realistic response behavior. The key input to the model is the peak dynamic displacement measured in the transverse direction, which has shown a strong correlation with permanent displacement for significant impacts (see Figure 2). Although Figure 2 shows a generally linear trend and a linear regression model performs reasonably well, the artificial neural network model (ANN) used in this study still achieves a 2% increase in performance. However, more importantly, an ANN is employed because of its advantages in terms of flexibility and scalability. ANNs are well suited to capturing complex nonlinear data that may arise when this method is applied to other bridges. Additionally, the ANN allows the use of transfer learning, allowing the existing model to be finetuned for new bridges with minimal retraining. In contrast, a linear regression model would need to be retrained from scratch for each new application, limiting its adaptability and efficiency for widescale implementation. By leveraging this relationship, the model enables reliable displacement estimation using only acceleration-derived data. This estimate is critical for rapid condition assessment and maintenance prioritization in the aftermath of over-height vehicle impacts. An overview of the proposed framework is provided in Figure 3.



(a) (b)

Figure 1. Examples of deformed girder from FE model after impact: (**a**) Full-span view; (**b**) Zoomed-in view.

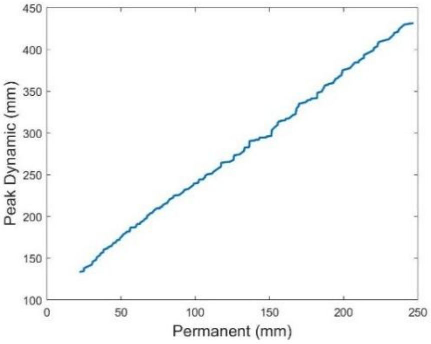


Figure 2. Peak dynamic vs permanent displacement for non-minor impacts.

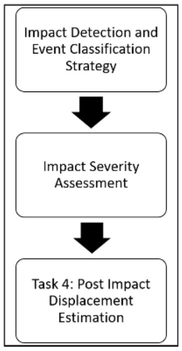


Figure 3. Framework for automated condition assessment.

The hierarchical structure of the framework was adopted instead of a single multi-task neural network because the individual models are not executed for every detected event. Each neural network is designed for a specific task with unique input features and outputs tailored to that task. Using a single model to handle all classification and prediction functions would significantly increase model complexity and computational cost, reducing the suitability for resource-constrained edge deployment. Additionally, the hierarchical design allows for each model to be independently updated or fine-tuned without affecting the performance of the others. While the proposed framework provides a scalable and low-cost approach for impact detection and condition assessment of TPG railroad bridges, there are certain limitations to consider. First, the current implementation relies on a single accelerometer, which has been shown to be sufficient to capture global responses on short, simply supported bridges. However, for multi-span structures or more complex bridge geometries, deploying additional accelerometers may be necessary to ensure adequate spatial coverage and accurate assessment. Additionally, the current approach uses acceleration data as the sole input for impact detection and severity assessment. In practice, other sensing modalities such as cameras could be integrated to enhance system capabilities. For example, video footage could help estimate the speed of an impacting vehicle, which can then be used to better inform FE simulations of impact scenarios. These extensions, which would further enhance the robustness and practicality of the proposed system are discussed in the next section.

3. FUTURE WORK

While this paper has discussed significant contributions to railroad bridge impact monitoring, several avenues for future research remain to further enhance railroad bridge impact monitoring. The following subsections discuss research directions that can build upon the work presented in this paper.

3.1.Multimetric Approach for Impact Detection

The current impact detection approach primarily relies on acceleration-based sensing to classify events. While effective, integrating additional sensing modalities such as camera-based monitoring can enhance the reliability of impact detection. Some bridge owners have already installed closed-circuit television cameras near bridges to capture the license plates of offending vehicles involved in bridge strikes [8]. However, these cameras can be used in combination with WSSs.

The integration of wireless sensor networks with vision-based systems presents several promising enhancements to bridge impact monitoring. WSSs deployed on bridges can be configured to trigger a nearby camera upon detecting an impact event. The camera system can be activated when the ANN model proposed in this study detects an impact. The captured images will be useful for confirming the occurrence of impacts and recording the offending vehicles. This information can help authorities locate and hold drivers accountable, potentially mitigating financial losses incurred by railroad bridge owners.

One potential approach for implementing this multimetric sensing system is through the OpenMV module [9]. The OpenMV module has a camera sensor which can easily be integrated into the board. The OpenMV has already been successfully integrated with the Xnode WSS platform [10], making it a promising candidate for the proposed research. However, one key challenge that must be addressed is establishing wireless communication between OpenMV and Xnode. Unlike previous implementation where OpenMV and Xnode were connected through board pins, an alternative method will be needed for wireless data exchange. Future research should investigate suitable wireless communication protocols such as LoRaWAN [11], to enable seamless interaction between the two platforms without the need for a direct physical connection.

Beyond serving as evidence for liability enforcement, the use of vision-based techniques offers an opportunity for local condition assessment, complementing the WSS-based global assessment approach in the framework presented in this paper. While the current approach focuses on detecting structural responses at a global level, cameras can provide direct visual confirmation of localized damage such as local flange deformation (bending, nicks, gouges, etc.) or bolt shear following an impact event. By applying deep learning computer vision algorithms, the recorded images can be analyzed to identify potential structural damage, providing a more holistic evaluation of bridge health.

3.2. Generalization of Event Classification System

The framework presented in this paper is primarily for TPG railroad bridges, which are the most frequently impacted bridge type in North America [12]. However, to ensure broader applicability, future work should focus on deploying and validating the approach across multiple railroad configurations, including truss and box girder bridges. Conducting large-scale field deployments would allow for a comprehensive assessment of model generalization and performance under different structural dynamics, traffic loads, and environmental conditions.

One of the key challenges in deploying machine learning models for impact detection and assessment on multiple bridges is the requirement for extensive labeled datasets. To mitigate this, transfer learning techniques can be employed, allowing pre-trained models from one bridge to be adapted for another with minimal additional training. Transfer learning reduces the burden of data collection by leveraging knowledge gained from a previously trained model, making it possible to generalize impact detection models across multiple bridge types without the need for an entirely new dataset.

Future research should focus on leveraging the pre-trained model from the impact detection step in the framework presented in this study as a foundational model for transfer learning applications. By fine-tuning this model on new bridge configurations with limited new data, a scalable framework can be developed that ensures high-impact detection accuracy across different bridge types. Domain adaptation techniques should be explored to refine models based on the structural and environmental characteristics unique to each bridge, ensuring that impact classification remains robust even with variations in bridge design and material properties.

Additionally, integrating active learning frameworks can enhance model adaptation by selectively incorporating new data points from different bridges that improve the model accuracy. Incremental learning techniques should be explored to allow models to adapt gradually using small batches of new data rather than retraining from scratch. By implementing an incremental learning approach, where models continuously update as new impact events are recorded, the classification system can evolve over time, reducing the risk of model drift and maintaining high detection accuracy in various operational conditions. Simulations and experimental tests can be conducted to refine deployment strategies and minimize hardware costs.

3.3. Predictive Impact Risk Assessment Using Historical Data

While this study focuses on impact detection, the ultimate goal for railroad bridge owners is to prevent bridge impacts altogether. Although various protective systems have been proposed to mitigate bridge impacts caused by over-height vehicles, including warning signs [13], over-height vehicle detection systems [14], and crash beams [12], the deployment of these solutions for every bridge in a network is impractical due to resource constraints. Therefore, an effective strategy is needed to prioritize the most vulnerable bridges, allowing limited resources to be allocated where they are most needed.

This paper has already presented an established impact detection framework using Xnode WSSs, which continuously monitor railroad bridges for impact events. A natural extension of this work is to leverage the collected impact data and integrate with historical impact records, traffic patterns, and structural characteristics to develop a predictive risk assessment model.

Future research should focus on training machine learning models to identify patterns in the occurrence of bridge impacts, helping railroad owners anticipate structures which are the highest risk. Factors such as impact frequency, impact severity and traffic volume can be incorporated into a predictive framework. By analyzing these variables, a risk prioritization model can be developed to rank bridges based on their likelihood of experiencing future impacts.

The ability to forecast bridge impact risk would provide railroad bridge owners with valuable decision-making tools. Instead of reacting to impacts as they occur, preventative measures could be strategically implemented before significant damage occurs.

Future work should also examine the feasibility of integrating risk prediction with the existing impact detection framework. By combining impact event monitoring with predictive analytics, railroad authorities could receive automated risk alerts, flagging bridges that may require immediate intervention.

4. CONCLUSION

This paper presented a scalable SHM framework for automated impact detection and condition assessment of TPG railroad bridges using WSSs. The framework integrates three machine learning models to sequentially detect impact events, assess their severity, and estimate resulting permanent displacements, using data from only a single accelerometer to enable a cost-effective SHM solution. The proposed approach was validated using both simulation data and field deployments, demonstrating its effectiveness in enabling near real-time post-impact structural evaluation.

Despite the promising results, limitations remain. The current implementation has been tested only on single-span TPG bridges and does not incorporate additional sensing modalities or contextual data. Future SHM research directions include: (a) integration of camera-based systems for event verification and local damage assessment, (b) generalization of models to other bridge types through transfer learning, and (c) development of predictive impact risk models using historical impact and traffic data. These extensions will improve the robustness, adaptability, and preventative capabilities of SHM systems for critical railroad infrastructure.

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