Chapter 2

Robust Output Only Health Monitoring of Steel Railway Bridges:

Analysis of Applicability of Different Sensors

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ABSTRACT

This chapter extends application of a framework proposed by the authors (73, 74) for automated damage detection using strain measurements to study feasibility of using sensors that can measure accelerations, tilts, and displacements. The study utilized three-dimensional (3D) finite element models of double track, riveted, steel truss span, and girder bridge span under routine train loads. The chapter also includes three instrumentation schemes for each bridge span (65) to investigate the applicability of the framework to other bridge systems and sensor networks. Connection damage was simulated by reducing rotational spring stiffness at member ends and various responses were extracted for each damage scenario. The methodology utilizes Supervised Machine Learning to automatically determine damage location (DL) and intensity (DI). Simulated experiments showed that DLs and DIs were detected accurately for both spans with various structural responses and using different instrumentation plans.

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INTRODUCTION

Monitoring aging infrastructure performance under various loading and environmental conditions continuously via an automated monitoring system that evaluates their structural health quantitatively is very significant to ensure safety and avoid progressive collapses. One of the important elements in any transportation system are bridges which currently subjected to increased traffic load and frequency. In the United States, bridges structural health is usually assessed via visual inspection which is costly, might be unsafe and subjected to human interpretation as examined by Phares et al. (Phares et al., 2001). Structural Health Monitoring (SHM) often involves detecting structural damages automatically which explored previously by Farrar and Worden (Farrar & Worden, 2012). SHM involves extracting structural health information via signal processing layer from responses collected with a set of sensors deployed on a structural system. Significant information features usually extracted from the data using damage identification methods and integrated into analyses or probabilistic models to evaluate the structure health and expected service life (Achenbach, 2009).

SHM systems usually incorporate one or more of strains, accelerations and displacement where acceleration measurements provide insights on the structural global behavior while strain measurements provide unique understanding of structural local behavior. Research work was conducted to investigate the effectiveness of certain types of strain sensors in damage detection within SHM applications (Glisic & Inaudi, 2008; Glisic & Inaudi, 2012; Harmanci et al., 2016). Fiber Optic (FO) sensors application in SHM damage detection was investigated using two main FO techniques, where the first technique was based on fiber Bragg-gratings and the other was based on Brillouin optical time-domain analysis. The first technique allows the use of long gage FO sensors and the second one allows for distributed FO sensors. Glisic et al. (2013) applied the framework to a full-scale reinforced concrete structure and it was found that both sensing techniques are suitable for SHM damage detection (Glisic et al., 2013). To locate structural damage from dynamic strain measurements using local modal filters, a framework was proposed and validated experimentally in the laboratory by Tondreau and Deraemaeker (2014) on a steel beam with a dense array of strain sensors (Tondreau & Deraemaeker, 2014).

Material degradation and geometry changes are usually associated with structural damage, which influences structural dynamic characteristics which was examined by naby researchers. Shokrani et al., (2018) examined the effect of structural damage on modal curvature (Shokrani et al., 2018). Ashory et al., and Tan et al., (2017) investigated structural damage effect on modal strain energy (Ashory et al., 2017, Tan et al., 2017), and; structural damage influence on Eigenmodes was examined by Moaveni et al., and Taciroglu et al., (Moaveni et al., 2010; Taciroglu et al., 2017). In a vibration-based damage detection, modal identification and model updating are usually included where damage intensity is determined using an optimization process that minimizes discrepancies between field and updated model results. Detecting localized deficiencies using fault detection methods is achieved by implementing a framework that combines vibration properties and Machine Learning tools which was investigated by multiple researchers (Bellino et al., 2010; He et al., 2011; C. Kim et al., 2015). Bellino et al., (2010) examined site condition effects such as train velocity and mass effects on structural frequencies which were eliminated using Principle Component Analysis so that frequency variations would be solely caused due to damage (Bellino et al., 2010). To verify this approach, a laboratory testing using a single moving mass on a short cantilever beam subjected to damage was conducted where various level damages were detected successfully (Bellino et al., 2010). However, Loads applied to the bridge were from a single bullet train car that did not simulate trains actual loading configurations where train axle loads variations were not involved as well. Kim et al., (2015) examined a steel multi-girder bridge deficiencies detection from a long-term SHM recorded data with collected accelerations, temperature and vehicle weights were studied (C. Kim et al., 2015). Detecting damage procedure involved three steps: extracting damage-sensitive features from collected accelerations using autoregressive model coefficients; analyzing damage-sensitive features regressively to consider environmental and vehicle weights variations, and using Bayesian hypothesis testing with a 95% confidence interval for differences between observed and predicted damage-features to make decision about the bridge health (C. Kim et al., 2015). The study found that including environmental and vehicle loading variations in the Bayesian regression yielded more reliable results when compared against situations where these items were excluded; however, the framework damage detection methodology did not include determine damage location (C. Kim et al., 2015). HE et al., (2011) used Genetic Algorithm in detecting damage location and intensity for a coupled FEM model of a simply supported single span bridge under induced vibrations from a crossing train (He et al., 2011).

One of the major challenges with modal based damage detection is their sensitivity to modeling error where analysis models with high accuracy should be generated. Moaveni et al., (2010) examine uncertainties in well-known damage detection methods with dynamic tests carried on a full-scale seven-story reinforced concrete building (Moaveni et al., 2010). The study concluded that uncertainty in identified modal parameters such as spatial density of measurements and modeling errors such as mesh size influenced the level of confidence in detected damage results. Hu et al., (2017) and Moaveni (2012) investigated another major concern associated with Operational Modal Analysis (OMA) which is environmental conditions such as temperature and wind which shown to influence identified modal properties dramatically (Hu et al., 2017; Moaveni & Behmanesh, 2012). Identified modal parameters could also be influenced by the ambient excitation which is often assumed as stationary white noise in OMA algorithms. Abazarsa et al., and Ghahari et al., examined the influence of non-stationary external inputs on damage detection (Abazarsa et al., 2015; Ghahari et al., 2017). It can be concluded that a reliable SHM system requires high precise models, stationary excitations and low noise-to-signal ratio which might be difficult to achieve. High accuracy models require time and experience, while low noise-to-signal ratio requires high-quality sensors, which increases the SHM system cost.

Data-driven methods in SHM applications research was recently motivated due to several concerns. Those concerns stated by Farrar and Worden (2012) include: considering unknown and non-stationary excitations; the effectiveness of extracting damage features under operational conditions automatically; and the low accuracy related to the use of global damage features in detecting localized damages (Farrar & Worden, 2012). Developing SHM system that determines damage features by analyzing recorded sensor data is the main objective related to previous issues (Worden et al., 2000). Many studies investigated the development of SHM system output-only damage detection requirements. Thiene and Galvanetto (2015) developed an innovative damage localization framework bhy implementing Proper Orthogonal Decomposition (POD) (Thiene & Galvanetto, 2015). Y. Kim and Eun (2017) developed an algorithm based on POD of the structure Frequency Response Function (FRF) was examined to detect damage of simulated beam experiments where damage was shown to be detected effectively with POMs of FRFs within specific frequency range (Y. Kim & Eun, 2017). O'Connor et al., (2017) carried a study that incorporated a combination of Statistical Process Control (SPC) and Gaussian Process Regression (GPR) for detecting damage based on novelty detection where continuous monitoring system was deployed on a highway bridge(O'Connor et al., 2017). To detect damage, GPR was used to mitigate environmental conditions and vehicle-bridge interaction with SPC threshold being determined using a long measurement window. Dervilis et al., (2014) studied the use of multivariate numerical methods such as Artificial Neural Networks (ANNs), Principle Component Analysis and Radial Basis Functions. The study methodology was validated experimentally using a wind turbine blade laboratory fatigue tests where measurements were recorded under harmonic excitations (Dervilis et al., 2014). Ou et al., (2017) conducted a study on wind turbine blades to examine and compare statistical damage features and modal parameters based SHM systems, which concluded that statistical-based damage feature methods were more effective in detecting damage (Ou et al., 2017). El Kadi et al., (2017) examined textile reinforced cement self-healing behavior and structural conditions using acoustic emission measurements (El Kadi et al., 2017).

Current output-only damage detection methods are based on stationary excitations and require a low noise-to-signal ratio. To include non-stationary loading conditions, the authors developed a damage detection methodology based on POD and ANNs (Eftekhar Azam et al., ; Rageh et al., 2018). An output-only structural response classification based on a supervised learning method was performed to reduce POMs variations and keep those variations related to DI and DL only where the relation between POMs variation, DI and DL was determined vis ANNs regression analysis.

In the research work completed in this study is an extension to the framework developed by Eftekhar Azam et al., and Rageh et al., (2018) where the former work involved a simply supported steel riveted truss double-track bridge span (Eftekhar Azam et al., 2018; Rageh et al., 2018). Responses included in the earlier proposed framework were predicted strains based on an analytical model (Eftekhar Azam et al., 2018) or measured strain responses under routine loadings (Rageh et al., 2018) where ILs (i.e., locations where strains were extracted or measured) were stringer ends. The current work includes analytically applying POMs and ANNs framework to: (i) two different steel riveted double-track bridge segments with a truss and a plate girder systems; (ii) various structural responses which are strains, strong-axis rotations, vertical displacement and vertical accelerations; and (iii) three different instrumentation plans with varying sensors numbers and locations. It was observed that the developed framework was robust and applied to various structural systems, extracted responses and instrumented plans.

STUDIED BRIDGE SPAN, INSTRUMENTATION, NUMERICAL MODEL

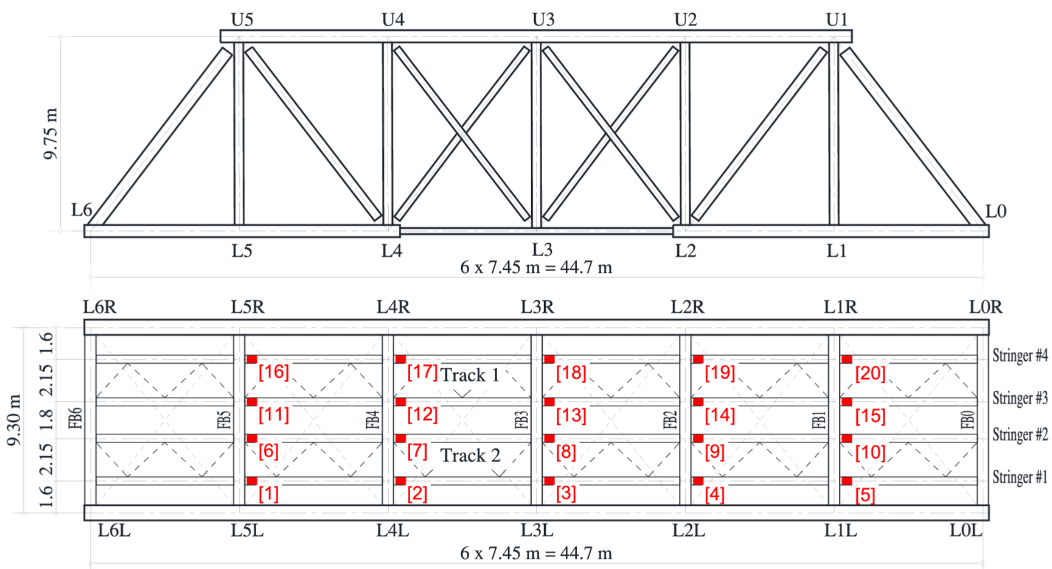
The research focused on in-service steel, riveted, double track, bridge having five truss and six through plate girder spans. One truss and one through plate girder span were selected as the testbeds. The current study focused on assessing feasibility of using time histories of strains, member strong-axis rotations, vertical displacements or accelerations at locations that were part of 3 instrumentation plans (IP). The selected quantities of structural response were selected as there are off the shelf solutions for measuring them. The selected instrumentation plans best reflected one of the most likely damage scenarios, namely stringer-to-floor beam connection degradation, which were reported by the bridge owner to be prevalent locations for damage in these types of structures.

Studied Bridge Spans

The bridge spans are simply supported and composed of rolled and riveted built-up steel elements. Each span supports two tracks spaced laterally at 3.95 m center-to-center. The rails rest on wood ties that are supported by stringers spaced laterally at 2.15 m on center. Lateral bracing systems are provided with the truss having top and bottom lateral bracing while the through girder had bottom lateral bracing only. The truss span description was given in Section 2.5 and is shown in Figure 1.

The through plate girder has a 22.0 m span divided to 7 panels with floor beams longitudinally spaced at 3.14 m. The main plate girders and floor beams are riveted, built-up-I-sections having a web plate and flanges constructed using angles and cover plates of varying number and thickness. Stringers are rolled S 24x80, I-beams. Bottom lateral bracing is composed of single angles with varying dimensions. A girder elevation and span framing plan view are shown in Figure 2. More details about cross-sectional dimensions can be found in (Rageh & Linzell, 2018).

Figure 1. Studied truss span elevation view and plan views



Numerical Model

Three-dimensional frame finite-element models were developed in SAP2000 for the bridge spans under study. The constructed models contained the trusses and plate girders, stringers, floor beams and bracing systems. Train loads were applied via a set of point moving loads. Riveted truss elements and floor beams were modeled as rigidly connected at their ends while truss eyebars and bracing members were pinned. Stiff rotational springs were used at the ends of each stringer span to facilitate simulating connection damage via reduction of their stiffness. Isometric views of the developed models are shown in Figure 3. More details about constructed models are provided in (Rageh & Linzell, 2018).

Multi-step static and time history analyses were used to obtain the desired static and dynamic response for each train passage and damage scenario. Strains, strong-axis rotations and vertical displacements were extracted from the multi-step static analyses while vertical accelerations were extracted from the time-history analyses. The maximum number of modes defined in the modal analyses were 50 and 25 for the truss and the plate girder spans, respectively, and were selected based on comparing strain and displacement results of both analyses cases.

Figure 2. Through plate girder span elevation and plan view

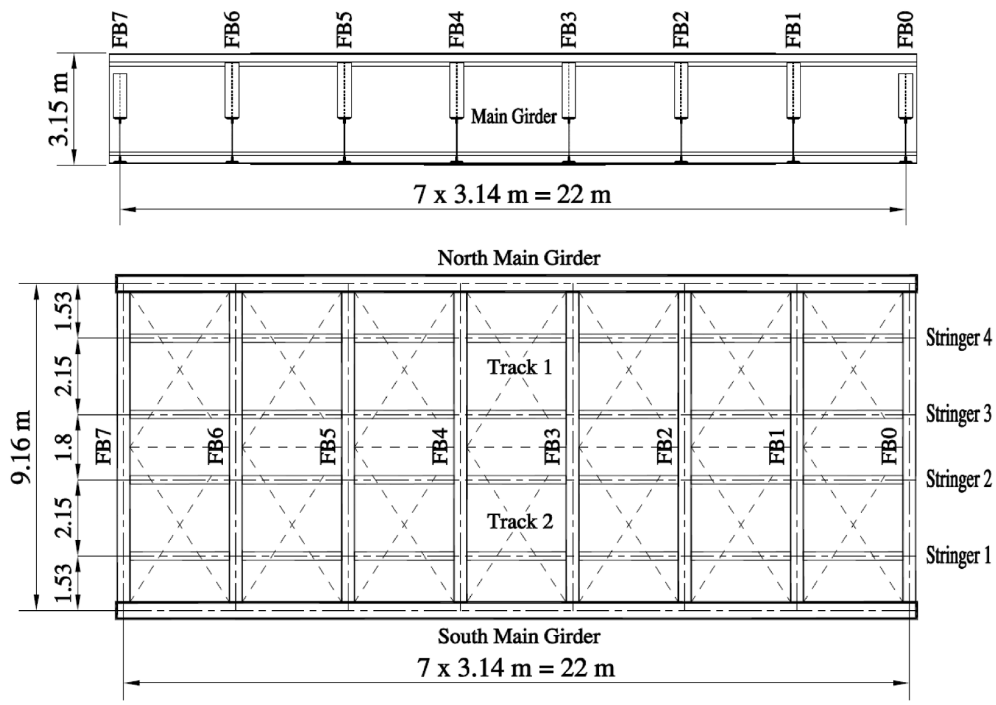
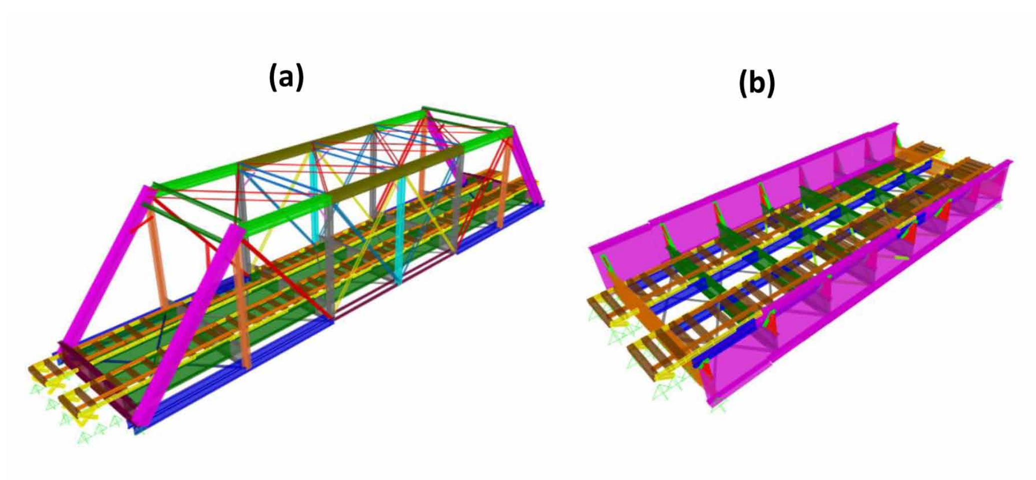


Figure 3. SAP2000 isometric view: (a) truss span; and (b) plate girder span



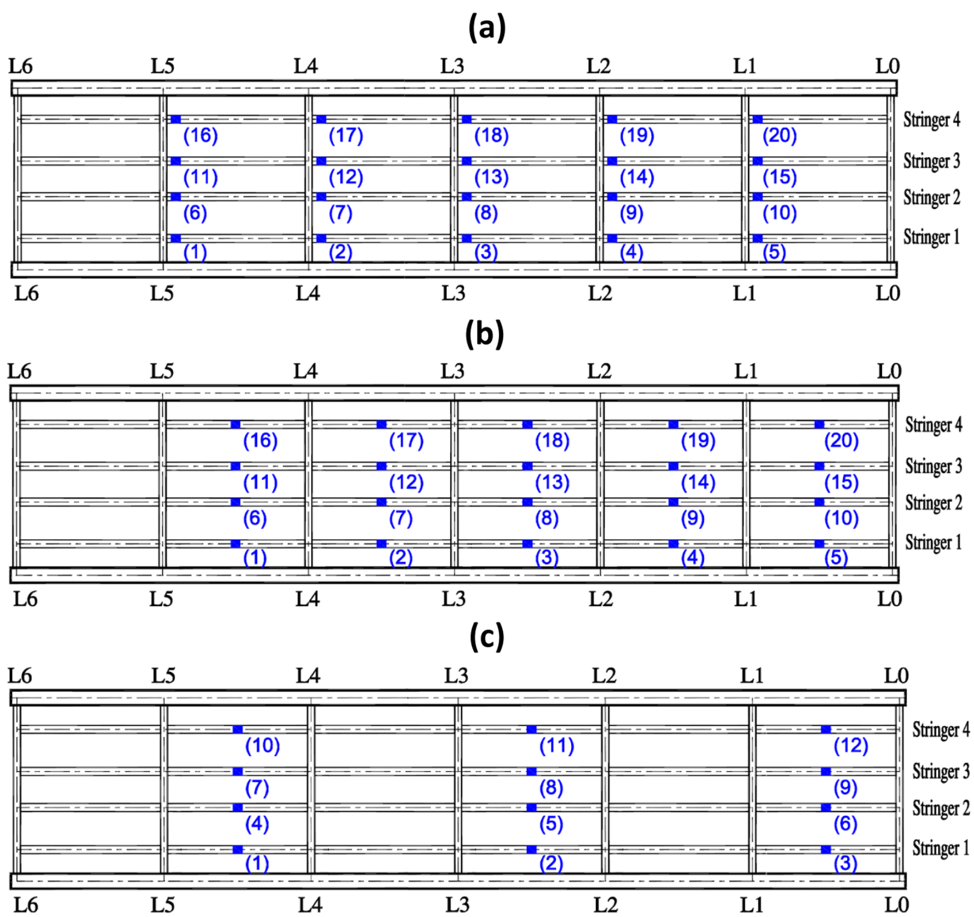
Matlab and the SAP2000 OAPI Open Application Programming Interface (OAPI) were used to automate each type of analysis. Automation was implemented to (i) model selected trains; (ii) simulate damage locations and intensities, of which there were 201 scenarios for the truss and 241 for the through plate girder, for each train passage; and (vi) extract internal effects that included loads (strains), strong-axis rotations, vertical displacements and accelerations.

ANALYTICAL "INSTRUMENTATION" PLANS AND SIMULATED DAMAGE

Commonly reported deficiencies for these types of railway bridges include: stringer-to-floor beam connection deterioration and damage; stringers and bottom laterals connection deterioration and member failure; and frozen supports (Rageh & Linzell, 2018). For the bridges understudy, stringer-to-floor beam connection deterioration was one of the more prevalent and important deficiencies to identify and track and, as a result, "instruments" in the models were placed to detect changes of various responses due to damage at or near those locations.

Three instrumentation schemes were examined analytically and are shown in Figure 4 for the truss span and Figure 5 for the through plate girder span. For the truss span, IP-1 in Figure 4 (a) had 20 sensors at stringer ends, IP-2 in Figure 4 (b) had 20 sensors at stringers midspans and IP-3 in Figure 4 (c) had 12 sensors at stringers midspan. For the through plate girder span, IP-1 in Figure 5 (a) had 24 sensors

Figure 4. Truss instrumentation plans: (a) Instrumentation plan 1 (IP-1); (b) Instrumentation plan 2 (IP-2); and (c) Instrumentation plan 3 (IP-3)



at stringer ends, IP-2 in Figure 5 (b) had 24 sensors at stringers midspans and IP-3 in Figure 5 (c) had 12 sensors at stringers midspan. Selected instrument locations were based on sensitivity analyses and those analyses are reported elsewhere (Rageh & Linzell, 2018).

For each of the examined instrumentation plans, the damage was simulated at 20 stringer ends in the truss span and 24 in the through plate girder. Differences between the number of simulated damage locations were due to the number of panels and stringers (i.e., the truss span has 24 stringers while the through plate girder has 28 stringers). Connection deterioration would reduce rotational stiffness and, as a result, a "rigid" connection would revert to semi-rigid connection and, ultimately a pinned connection (Al-Emrani, 2005). Continuous reduction in rotational stiffness was used to simulate crack propagation through connecting clip angles. Simulated Damage Locations (DL) are shown in Figure 6.

To select loadings for the analyses, the bridge owner provided Weigh-In-Motion (WIM) data for 81 trains of varying loadings, axle spacing, lengths and travel speeds. Preliminary analyses, which assumed that the bridges were undamaged, subjected to the 81 trains were completed using Matlab and the SAP2000 Open Application Programming Interface (OAPI) to extract structural responses at locations marked in IP-1 shown in Figure 4 (a). Of the 81 trains, 24 were selected for validating the framework expanded herein, where those 24 trains used because they have the highest strain RMS among the 81 trains (Eftekhar Azam et al., 2018).

ANN Training Using POMs

ANN training data was generated for 10 DIs between 10% and 100% in 10% increments at each DL, with each increment representing progressive damage at a stringer-to-floor beam connection. A total of 4800 (truss) and 5760 (plate girder) damage scenarios were analytically studied using this approach for the 24 selected train passages. Matlab coding showing rotations, displacement and acceleration extraction for IP-1.These damage scenarios helped train ANNs using the MATLAB *Neural Net Fitting* function, where various numbers of internal neurons were explored to ensure ANNs were accurately generalized for damage identification. ANNs could detect DL and DI once trained with the available data. A nonlinear regression ANN was selected to establish damage detection with POMs for each DI/DL scenario. It was decided that 70% of the input POMs would be used for training, 15% for ANN validation and 15% for testing with 18 trains strain POMs being used to train the ANNs. The number of trains selected for ANN training was based on a trial and error approach using 6, 12 or 18 trains.

A representative comparison between ANNs testing under 6 train passages using 6, 12 or 18 train passages in training are shown in Figure 7 for the truss span with a DI 50% at DL 8. ANNs trained and tested with POMs developed using stringer end bending rotations. Figure 7 (a) shows testing of ANNs trained with 6 train passages, Figure 7 (b) shows the testing of ANNs trained with 12 train passages and Figure 7 (b) shows testing of ANNs trained with 18 train passages. As expected, the figure indicates that increasing the number of events in the training process increased DI/DL prediction accuracy and reduced false positives and negatives. More detail on selected trains can be found in (Eftekhar Azam et al., 2018).

Figure 5. Through plate girder instrumentation plans: (a) Instrumentation plan 1 (IP-1); (b) Instrumentation plan 2 (IP-2); and (c) Instrumentation plan 3 (IP-3)

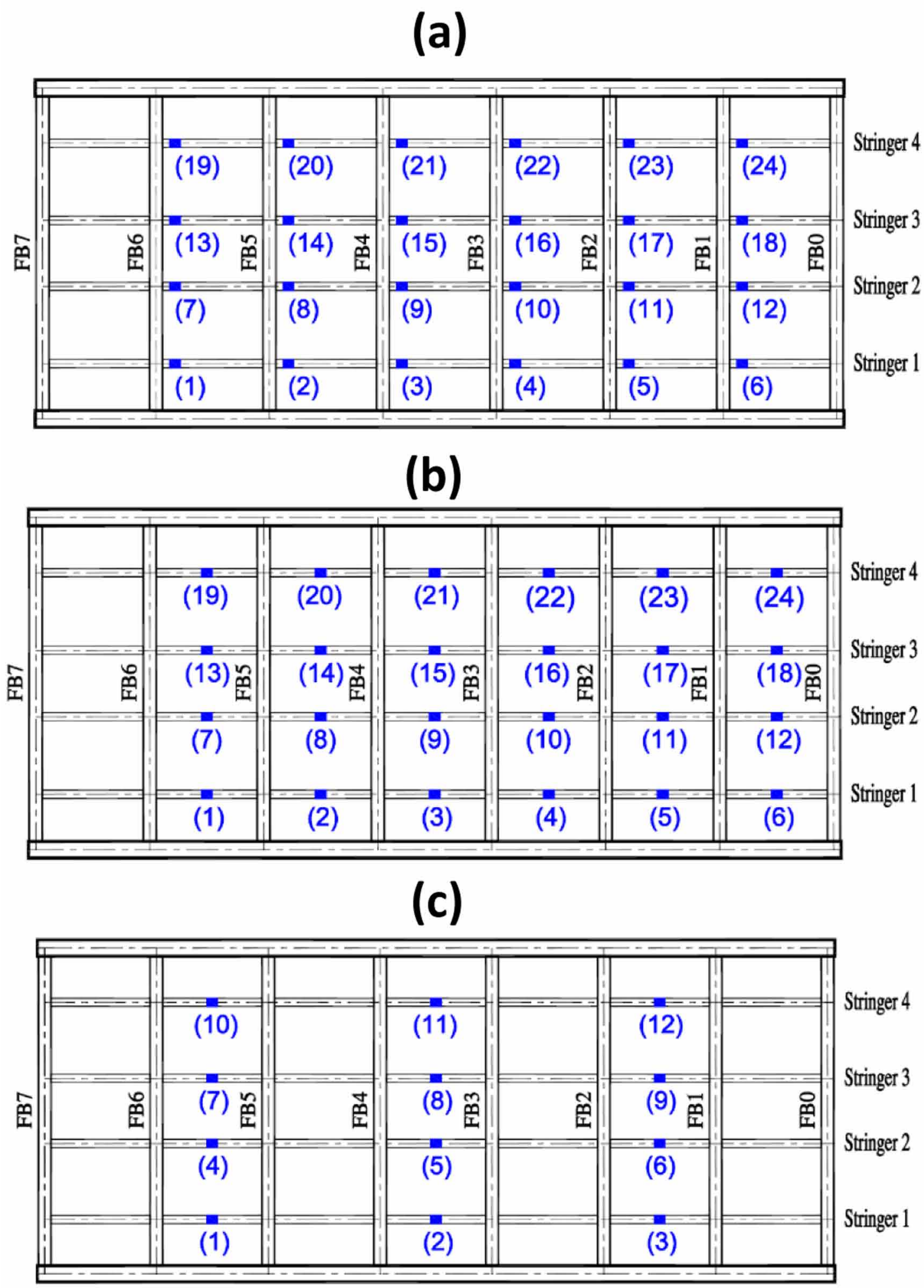


Figure 6. Simulated damage locations (DL): (a) truss span; and (b) through plate girder span

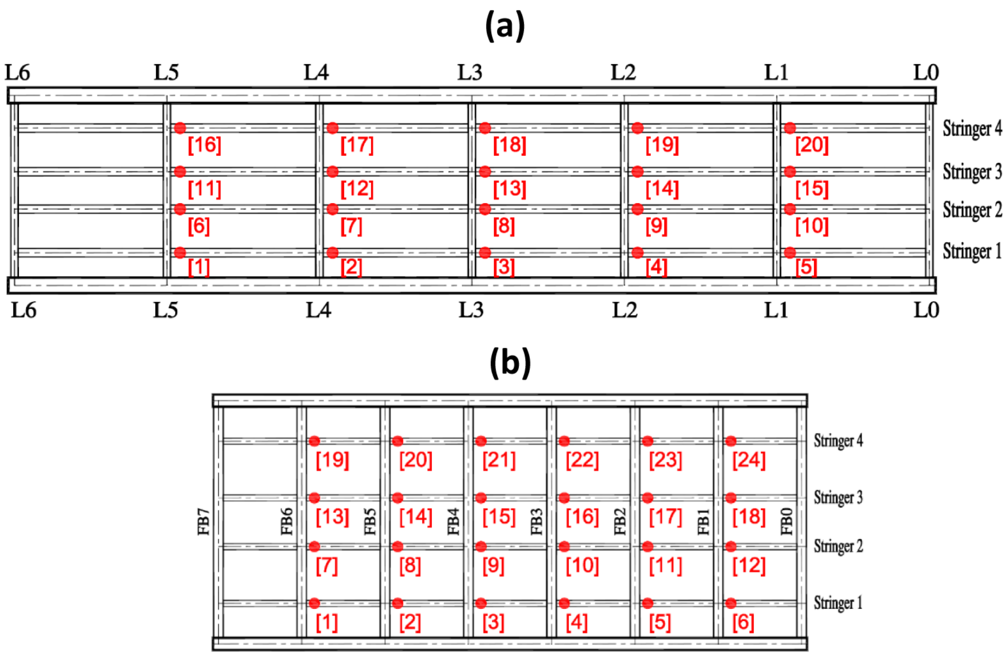
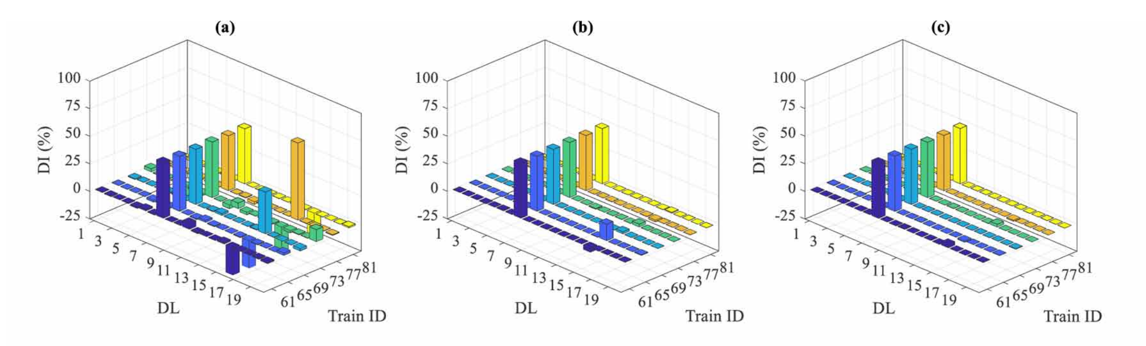


Figure 7. Influence of number of train events used in training process, DI=50% at DL 3, rotation POMs, truss span: (a) Training with 6 trains; (b) Training with 12 trains; and (c) Training with 18 trains



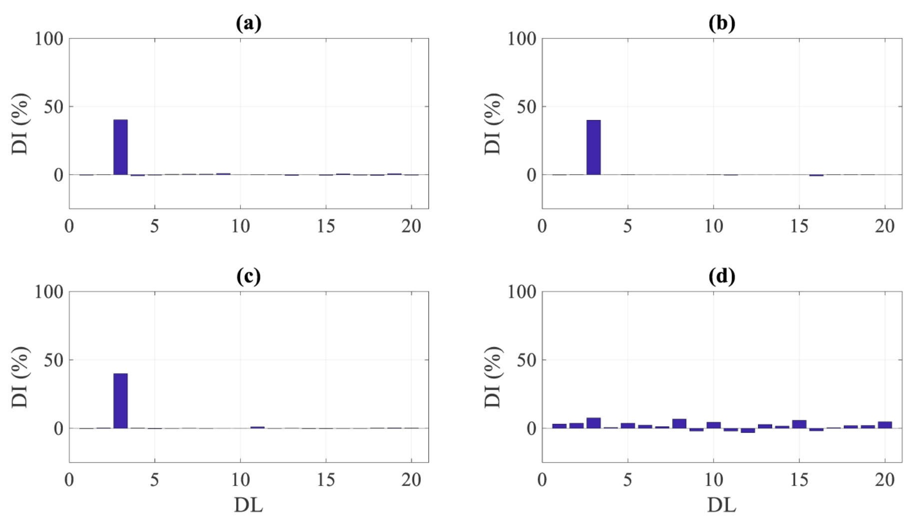
ANN Testing, Truss Span

As stated earlier, 75% of DI/DL scenarios were used for ANN training, with training and testing proportions being selected based on trial and error. This provided 3600 damage scenarios for training and 1200 for testing with extracted strain, rotation, displacement and acceleration POMs. Representative results that detail the effectiveness with which each response POM detects damage are presented in the following section for IP-1.

IP-1

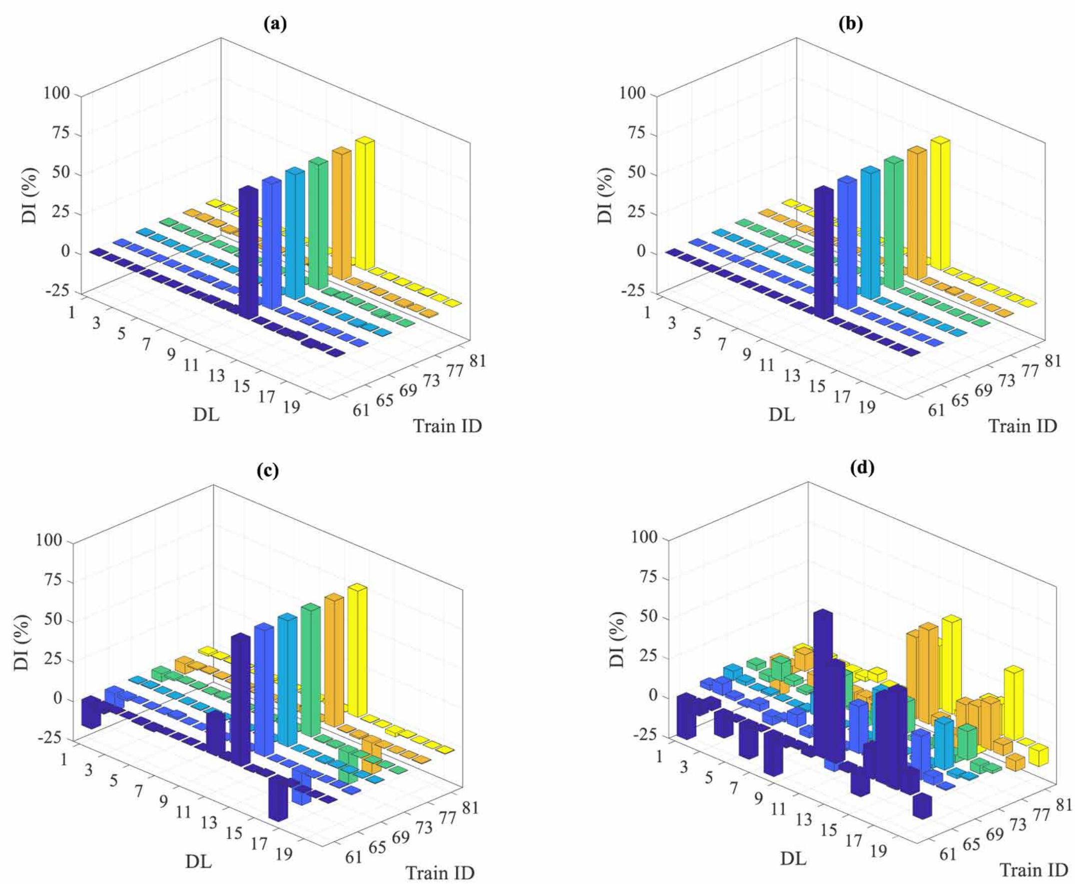
Representative results for a single train (Train 69) at DL 3 for a DI of 40% are shown in Figure 8. The figure details detected DI/DL for ANNs tested and trained with POMs extracted from various structural responses. As shown in the figures, DI/DL were detected with very good accuracy with ANNs trained with various responses POMs except for acceleration, which showed very low DIs at all locations. Predicted damages for various responses were: (i) DI =40.3% at DL 3 for strains POMs, Figure 8 (a); (ii) DI= 40% at DL 3 for rotation POMs, Figure 8 (b); (iii) DI= 40% at DL 3 displacement POMs, Figure 8 (b); and (iv) for acceleration POMs, DI and DL were not captured where 15 DLs indicated false positives and 4 DLs indicated false negatives with a maximum DI = 7.5%, Figure 8 (b).

Figure 8. Truss span ANNs testing, IP 1, Train 69, DI=40% at DL 3: (a) strain; (b) rotation; (c) displacement; (d) acceleration



To investigate the efficiency and the effectiveness of using POMs/ANNs to detect damage under different train loads, results from 6 train events at DL 13 for a DI of 80% are shown in Figure 9. The results indicated that strain POMs accurately predicted the DI and DL for all trains. Predicted DI for strain POMs ANNs testing ranged from 79.2% to 81.0% with maximum false positive and negative of 1.0 and 1.2%, respectively, which showed reliable results for detecting damage under a wide variety of train loadings, Figure 9 (a). Rotation POMs/ANNs also showed reasonable accuracy, Figure 9 (b). ANN testing of displacement did not demonstrate similar accuracy levels with false negatives and positives being observed, Figure 9 (c).ANNs testing with acceleration POMs were not reliable for determining DLs or DIs for any of the considered trains, Figure 9 (d). As a result of the studies that were completed, POMs extracted from strain or rotation measurements were recommended for the framework with truss span IP-1.

Figure 9. Truss span ANNs testing, IP 1, all testing trains, DI=80% at DL 13: (a) strain; (b) rotation; (c) displacement; and (d) acceleration



ANNs Testing, Plate Girder Span

As stated earlier, 75% of DI/DL scenarios were used for ANN training, with training and testing distribution proportions being selected based on trial and error. This provided 4320 damage scenarios for training and 1440 for testing with extracted strain, rotation, displacement and acceleration POMs. Representative results that detail the effectiveness with which each response POM detects damage are presented in the following section for IP-3.

IP-3

Representative results for a single train (Train 69) at DL 3 for a DI of 40% are shown in Figure 10. The figure details detected DI/DL for ANNs tested and trained with POMs extracted from various structural responses. As shown in the figures, DI/DL were detected with very good accuracy with ANNs trained with various response POMs except for acceleration, which showed very low DIs at all locations. Predicted damages for strain, rotation and displacement POMs at DL 3 varied between 36.8 to 39.9% with maximum false positive and negative of 9.3 and 4.0%, respectively, Figure 10 (a-c). Acceleration POMs ANNs testing showed false positives at multiple locations with magnitudes between 3.1 to 0.40%, Figure 10 (d).

To investigate the efficiency and effectiveness of using POMs/ANNs to detect damage under different train loads, results from 6 train events at DL 15 with a DI of 80% are shown in Figure 11. The results indicate that using strain, rotation and displacement POMs predicted DI and DL accurately for all trains. Predicted DI at DL 15 for strain, rotation and displacement POMs ranged from 77.1 to 82.7% with false positives and negatives less than 5.0%, which showed reliable results for detecting damage under a wide variety of train loadings and responses, Figure 11 (a-c). However, ANNs testing for acceleration POMs detected neither DL nor DI accurately where DI detected at DL 15 were between 18.6 to 20.0% with additional false positives at DLs 5 to 8 of with magnitudes between 2.9 and 19.8%, Figure 11 (d).

As a result of the studies that were completed, POMs extracted from strain, rotation and displacement measurements were recommended for the framework with through plate girder span IP-3.

Figure 10. Plate girder span ANNs testing, IP 3, testing Train 69, DI=40% at DL 3: (a) strain; (b) rotation; (c) displacement; and (d) acceleration

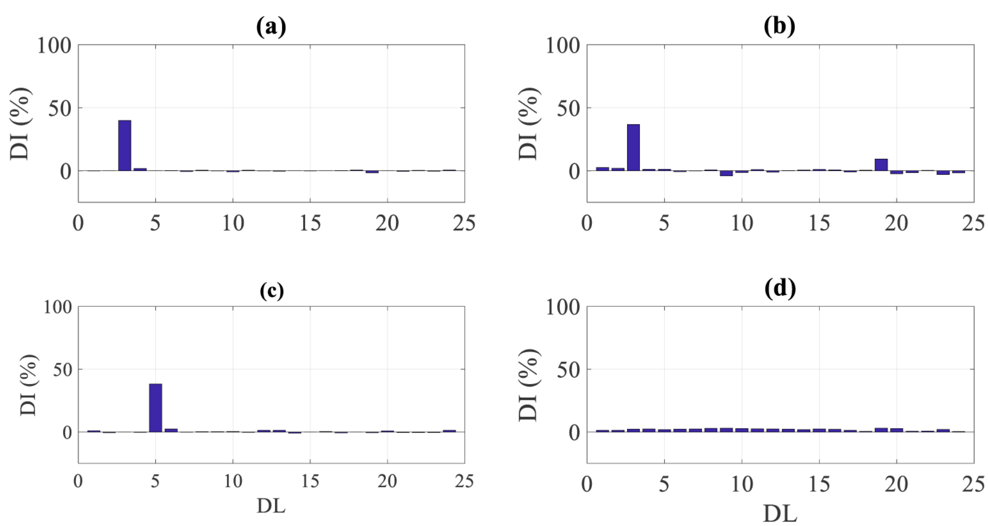
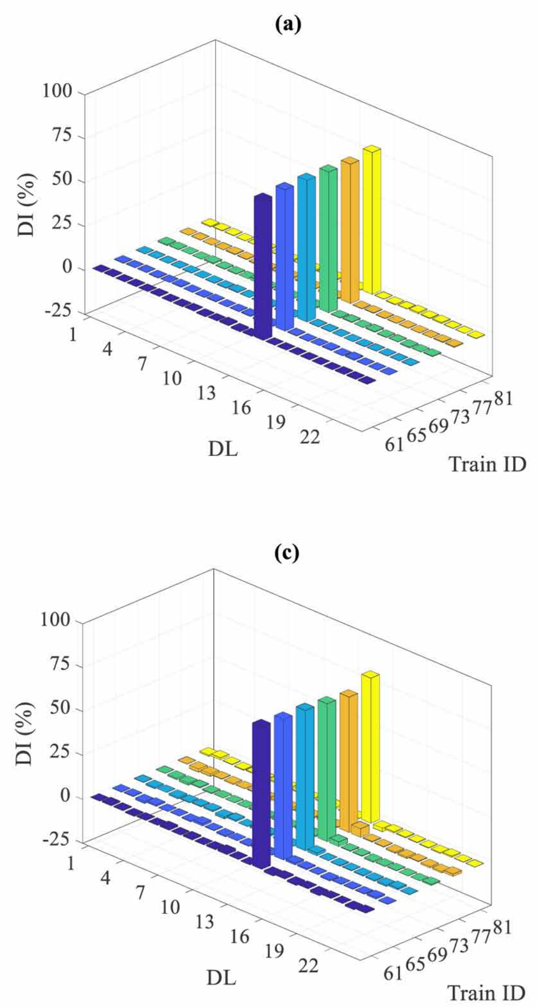


Figure 11. Plate girder span ANNs testing, IP 3, all testing trains, DI=80% at DL 15: (a) strain; (b) rotation; (c) displacement; and (d) acceleration



CONCLUSION

The viability of expanding an output-only, automated, strain-based damage detection framework that utilized POD/POMs and ANNs, see (Eftekhar Azam et al. 2018, ; Rageh et al., 2018) to include other response parameters (rotations, displacements and accelerations) was studied. The expanded framework was examined via its application to an in-service steel truss span and an in-service through plate girder span in Nebraska. Optimizing instrumentation schemes were concurrently studied; with 3 proposed sensors schemes being examined for each bridge span, see (Rageh & Linzell, 2018).

A set of 24 routine train loading events and combinations of damage locations (DLs) and intensities (DIs) were simulated using Matlab and the SAP2000 OAPI. Results demonstrated the efficiency and applicability of the proposed framework for detecting localized stringer-to-floor beam damage for a wide variety of responses, train events and instrumentation plans. The proposed methodology could be extended further to include other structural systems or deficiencies.

It was concluded that:

- Damage detected accurately for involved bridge spans where damage location and intensity were captured.
- Investigated instrumentation plans were shown to be very informative in railway bridges SHM applications where instrumented locations provided sufficient information to assess the structural health.
- Strain, rotation, displacement or acceleration sensors could be used in monitoring the investigated bridge.

Ongoing work includes:

- Investigating applying the framework to in-service bridges with a filed data-based framework.
- Developing ANNs training set based on continuous SHM field measurements.
- Investigating modeling errors to allow for training ANNs with damage scenarios using field measurements.
- Studying the effects of environmental variations on framework accuracy.

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