Drive-by damage detection in railway bridges subject to operational variabilities using deep autoencoder

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Abstract. One of the major challenges in the design and management of railway bridges is ensuring their safety and structural integrity throughout their lifespan. This is due to the fact that the loss of structural function and eventual failure of these structures have catastrophic consequences. Additionally, climate change projection which permeate the present show a tendency towards an increase in the frequency and intensity of extreme events, accelerating the deterioration process of railway infrastructure. In this context, there is a demand to define strategies in structural health monitoring (SHM) in order to minimize disruptions in railway operations and maximize its profitability through the safe operation of the system. There are two approaches to acquiring structural data for evaluating integrity: the direct monitoring approach and the indirect monitoring approach, or drive-by. In direct monitoring of railway bridges, sensors are installed directly on the bridge to capture responses caused by train excitations on the structure. On the other hand, in the drive-by monitoring approach, sensors are installed on the train to capture vibrational responses from the dynamic interaction of the train-bridge system during its passage. The advantages of the indirect approach over the direct approach involve the ability to obtain spatial information along the entire length of the bridge without the need to interrupt train operation, in addition to a substantial decrease in the cost associated with monitoring an entire railway line. However, one of the main challenges of indirect monitoring is dealing with the variability of operational and environmental conditions which affect monitoring data and result in false negatives or false positives in damage identification process. This study focuses on the indirect structural health monitoring of railway bridges using deep autoencoder model. For this purpose, numerical simulations of the dynamic train-via-structure interaction (TTBI) are performed. These simulations aimed to gather acceleration responses as trains crossed the target bridge under different levels of bridge foundation scour damage. Operational variability involving train speed and track irregularity, and measurement data noise are considered to simulate conditions closer to reality. The results show that the applied methodology is highly effective for detecting the scour damage of railway bridge foundations.

Keywords: Structural health monitoring, Drive-by, Data analysis, Autoencoders, Train-track-bridge interaction

1 Introduction

The maintenance of ageing railway bridges is essential to ensure the safe and efficent operation of this transport infrastruture during your service life. This is intensified in the current scenario in which the railways are being operated at the limit of their structural integrity due to the increase in traffic speed and axle load and the increase in the frequency of operation of the system [1]. In addition to operational causes, environmental factors, which tend to be aggravated by the climate changes, such as the increase in the recurrence and intensity of extreme events and the exposure of bridges to aggressive environments, are directly related to the mostly negative effects on structural safety railway [2]. In this scenario, some of the damage mechanisms that may cause the collapse of the bridge structure involve scour around bridge piers and abutments, degradation of reinforced concrete, corrosion of metallic components and bearing deterioration [3].

In recent years, structural health monitoring (SHM) strategies are an important non-destructive assessment methodology that involves the integration of sensors, data transmission and computational robustness in order to identify the integrity of the monitored structure [4]. The collected data from sensors is processed through finite element numerical model and/or data-driven techniques to extract useful features. In this sense, the early detection of damage is characterized as one of the main goals of SHM and it is usually based on vibrational responses of the structure [5].

In the data acquisition stage, two approaches are applied to monitoring of bridges, the traditional approach, based on direct monitoring, and the approach based on indirect monitoring, also known as mobile sensing or drive-by monitoring. Direct monitoring of railway bridges, whose sensors are installed directly on the bridge to capture responses caused by the train excitation on the structure, can involve several drawbacks in data acquisition. An example is the acess difficulty to install sensors due to the presence of vegetation or large span lengths. The spatial information obtained by the sensors system fixed on the structure is limited to certain discrete positioning, which can affect the efficiency of damage detection of the bridge as a whole. In addition, there is often a need to stop trains running during the installation process. On the other hand, drive-by monitoring assumes the installation of sensors on the train, rather than the bridge, which capture the operational and environmental response of the train-bridge system during its passage. This monitoring can be done by the passage of an individual train or a batch of trains, so that accelerometers are installed on suspended and/or non-suspended masses to capture vertical and/or lateral acceleration [6]. In this approach, the bridge data acquisition process becomes more economical and, due to the trains acting as mobile sensors, the responses obtained involve the spatial information of the entire continuity of the bridge and consequently improves the efficiency of the SHM [7].

Once the quality of data acquisition has been ensured, machine learning techniques, a subgroup of artificial intelligence, have gained attention in the field of structural monitoring due to their efficiency in operating large datasets, identifying patterns and making predictions [8]. Machine learning algorithms are classified into supervised and unsupervised learning algorithms [9]. In the field of structural safety, supervised learning requires datasets inferred by inspection agents corresponding both to the healthy structure and the damaged structure. Then, supervised approach can be challenging such as in cases of structures with multiple damage sites, as it requires collecting structural damage data for all possible combinations of damage locations to make predictions. On the other hand, unsupervised learning does not require data from the damaged structure, so it does not need to be labeled by human knowledge [10]. Since the lack of information about the damaged structure is the most recurrent scenario in structural integrity monitoring, unsupervised learning algorithms are more applicable. Thus, machine learning tools make it possible to process with multidimensional datasets, in order to guarantee high flexibility in data fitting and recognizing statistical patterns to assess health state of the monitored structure.

To adress some challenges which envolves railway bridge health monitoring, this paper presents a damage detection method considering the dynamic response from a batch of trains traversing the target bridge. The idea is explored numerically with a bidimensional train-track-bridge interaction (TTBI) model, developed by Cantero [11], considering a range of vehicle speeds, as well as the presence of track irregularities and measurement noise. An autoencoder based machine learning framework is applied to extract damage-sensitive features based on bogie vertical accelerations while vehicle crossing the bridge. The difference between model-based and actual vehicle responses is the prediction error evaluated by the mean absolute error (MAE). The damage index is based on the distance between the distribution of prediction error using Kullback-Leibler divergence. The numerical study evaluates the performance of the method for a range of different bridge scour damage scenarios.

2 Structural health monitoring for damage detection

SHM systems provide information about the condition of structures, their performance, and the demands they are subjected to. Thus, SHM can aid in predicting the future performance of the infrastructure and in planning preventive and corrective actions. In this sense, SHM can be divided into four main stages, in general: operational assessment, data acquisition, data processing, and data analysis [9]. Figure 1 shows a flowchart of the SHM stages applied in this paper for railway bridge damage detection.

The operational assessment stage is also characterized by understanding the excitation sources to which the monitoring system is subjected. These sources involve knowledge of the variability of operational and environmental conditions that can cause changes in the measurement system. It is imperative that these changes are not misinterpreted as indications of damages during data analysis to avoid false positives. In the railway system, track irregularities, variability of the vehicle speed and mechanical properties of the train such as mass and suspension systems can significantly influence the dynamic quantities measured during the damage detection process [12].

The data acquisition stage of the SHM system involves the types and quantities of sensors, their positioning along the system, and the data storage and transmission system. The primary goal of any SHM sensing system is to make the sensor readings more directly correlated and sensitive to damages. In this sense, it is expected that the sensors readings and the damage-sensitive features extracted from the data will change monotonically with the increasing severity of the damages [9]. The data collection in this work assumes that train responses are measured

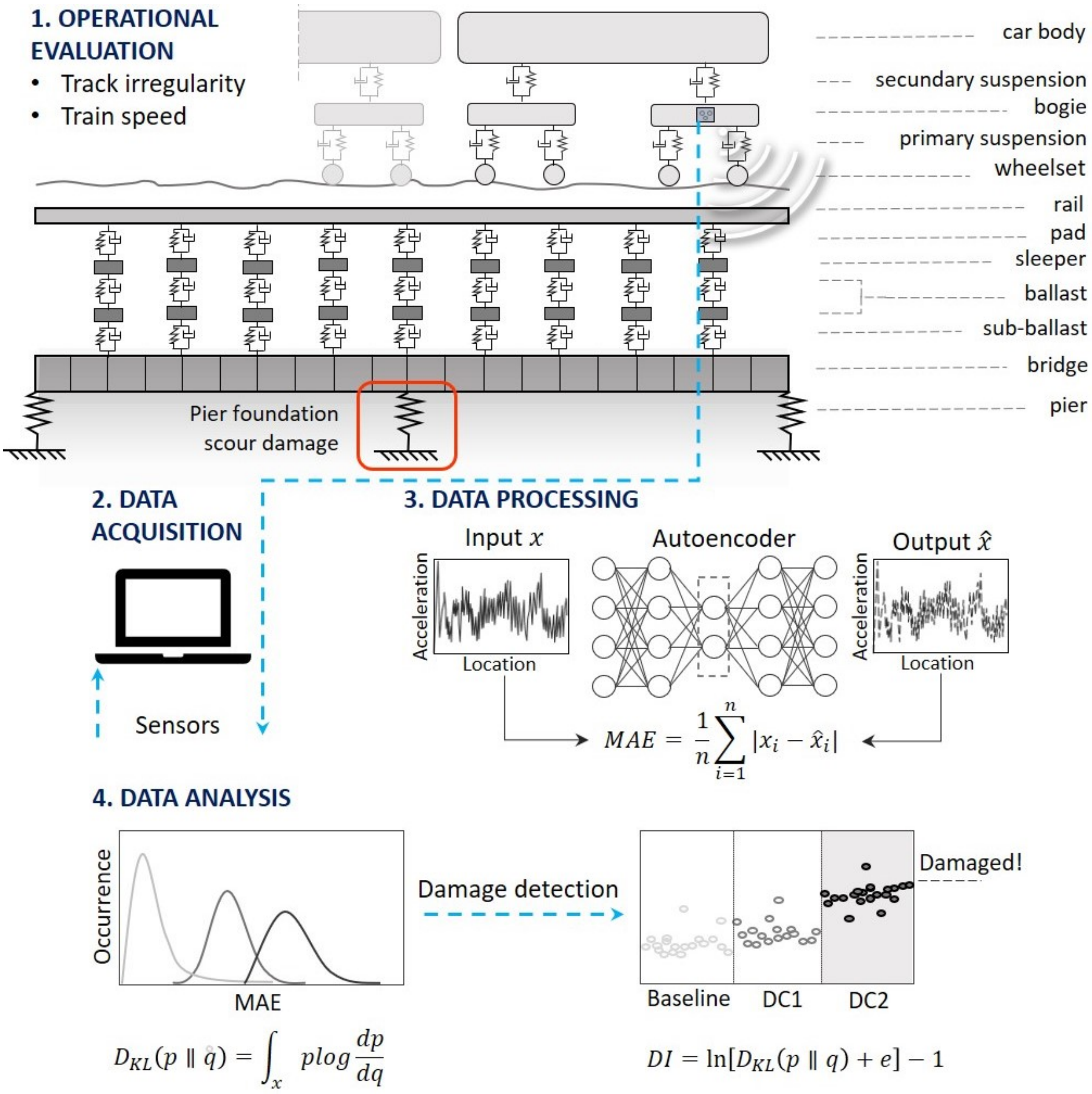

Figure 1. Overview of the proposed framework

using on-board systems, information that could be acessed remotely by a central management system. Due to low cost and ease of installation, this study assumes that accelerometers are installed in frontal bogie of the first vehicle on each passing train.

Autoencoders are explored in many applications for dimensionality reduction and/or anomaly detection in SHM systems [13]. Autoencoders are a subgroup of neural networks, with a two-level framework. The first level, known as the encoder, plays the role of reducing the dimensionality of the input data by projecting it through one or multiple layers into a latent space. The second part, known as decoder, projects the signal back to its original space. The objective function reconstruct the original signal to create a suitable latent space for compressing the training data. Compress and denoise a signal different from the training signals results in a larger reconstruction error, which is used as a feature for anomaly detection. In this way, anomaly detection, which can also be described as outlier detection is the recognition of observations that do not fit an estimated pattern of the data [14].

Data analysis stage of SHM involves the application of statistical tools to analyze the features and evaluate the structural integrity. After feature extraction, it is necessary to use metrics to assess the error between the testing and training data for damage detection. Typically, in the case of SHM, this metric can be referred to as a damage indicator. The damage indicator can be based on a threshold that distinguishes between the health and damaged state of the structure.

For damage detection, the reconstruction error is evaluated by mean absolute error (MAE) using eq. (1). The MAE calculates for each vehicle-crossing, given by the difference between the measured response and the reconstructed response estimated by the trained autoencoder model.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|x_i - \hat{x}_i| \tag{1}$$

where x_i and $\hat{x}_i$ are the measured and reconstructed responses respectively at sample i for a total of n samples.

When considering a batch of trains, the MAE error varies between crossing events because of different train speed and measurement noise. However, batches of these events result in distributions of MAE values that can be used do differentiate a health bridge (baseline) from a damage one. It is possible to assess the bridge condition by evaluating the difference between MAE distributions from different batches. In this study, the KL divergence is applied to quantify how different two distributions are [10]. In this paper the MAE distributions are assumed to follow the log-normal distribution for each batch of trains crossing the bridge. These distributions are defined in terms of their corresponding mean μ and standard deviation error σ for the baseline condition ($p_0 = logN(x|\mu_0, \sigma_0)$) an unknown condition ($q_1 = logN(x|\mu_1, \sigma_1)$). Thus, the KL divergence between two distributions can be written as:

$$D_{KL}(p_0||q_1) = ln\left[\frac{\sigma_1}{\sigma_0}\right] + \frac{\sigma_0^2 + (\mu_0 - \mu_1)^2}{2\sigma_1^2} - \frac{1}{2} \tag{2}$$

To obtain a robust damage index the eq. (2) is transformed into a linearized relationship as eq. (3):

$$DI = ln[D_{KL}(p_0||q_1) + e] - 1 \tag{3}$$

where e is Euler number.

3 Numerical Modeling

This section presents the numerical model that simulates the responses of a TTBI system. The numerical model is used to generate dataset for training and testing of autoenconder. This study considers single train events consisting of five vehicles traversing along the bridge structure. Numerical simulations are performed using software that calculates the two-dimensional train-track-structure interaction system, developed in Matlab language by Cantero [11].

The train model is performed using concatenated individual vehicles in the TTBI-2D model, each defined individually [11]. Each vehicle is performed using the same fully parameterized model. The implemented model for the vehicle comprises a combination of lumped masses, rigid bars, springs, and dampers, as shown in Fig. 1. The property values and critical dimensions of the Irish Rail Hyundai Rotem Intercity train vehicle are calibrated through instrumentation by OBrien et al. [15] and used in this study for data simulation. The track is modelled as a beam resting on periodically spaced sprung mass systems [11]. The rail is modeled by beam elements in a finite element model (FEM), while the masses represent the sleepers and ballast. The beam and masses are connected by spring/damper systems representing the rail pad, ballast, and sub-ballast, with values based on the study by Zhai et al. [16]. The bridge is modeled as two spans, each with a length of 20 meters. For this purpose, Euler-Bernoulli beam model is employed using finite element discretization with vertical springs that represent the effects of the bridge's foundation stiffness. Its section and material properties are: second moment of area I=0.33 m^4, modulus of elasticity E=3.5 $\times$ 10^{10} N/m^2 and mass per unit length ρ=9600 kg/m. A 3% damping factor is considered for all modes. By assuming that the bridge is founded on a rigid footing overlying a soil profile corresponding to medium dense sand with Young's modulus E=100 MPa the spring stiffness is found to be 344 $\times$ 10^3 kN/m, such as model studied by Fitzgerald et al. [17]. The finite element model is discretised into 133 elements (each element 0.3 m length). The TTBI system of a coupled equations of motions can be expressed as:

$$M_s\ddot{u}_s + C_s\dot{u}_s + K_s u_s = f_s \tag{4}$$

where M_s, C_s and K_s are the time-varying system mass, damping and stiffness matrices respectively and u is the vector of combined train, track and bridge displacements. The vector f_s contains the external forces applied to the coupled system [18] . The dynamic problem is then solved by direct integration using the Newmark-β algorithm [11].

In this study, four scenarios of the structural condition of the vertical stiffness (k_{v2}) of the central support are considered to simulate the effect of scour at a pier foundation, from the model of the structure illustrated in Fig. 1: baseline (k_{v2}=344×10^3 kN/m), damage case 1 (DC1) with a corresponding stiffness loss of 5% ($DC1$=326.8×10^3 kN/m), DC2 with a corresponding stiffness loss of 10% ($DC2$=309.6×10^3 kN/m) and DC3 with a corresponding stiffness loss of 20% ($DC3$=275.2×10^3 kN/m).

In order to simulate operational variabilities, the track irregularity simulated is an FRA Class 4 rail profile that is randomly generated using Power Spectral Density functions, based on US Federal Railroad Administration Standard [19]. For each damage scenario, 500 passes of the train at different speeds are simulated to obtain vertical acceleration responses of the frontal bogie. Consequently, 2000 sets of vertical acceleration data are generated, with speeds randomly selected from within a range with an average of 80 km/h and a standard deviation of 10% of the average for each pass. Measurement noise is also simulated, with a correspondevalue of SNR=20 (signal-to-noise ratio), which corresponds to a standard deviation of 5% of the data's mean. The vertical acceleration of the train is obtained for a train passage frequency of 1000 Hz, meaning that for every 0.001 seconds, a sensor acceleration response is captured at that instant. The monitoring is considered from the moment when the first wheel of the first vehicle enters the bridge until the last wheel of the first vehicle exits the bridge, resulting in a monitoring length of 58.3 meters.

4 Results

The autoencoder is trained with 100 acceleration signals from the baseline scenario, which accounts for 20% of the baseline dataset. Neural network training is performed through three hidden layers in the encoding step and three hidden layers in the decoding step. The ReLU function is employed as activation function for all hidden layers, except for the last layer—the decoder's output layer—where the sigmoid activation function is used. A total of 400 epochs are employed for model training. Figure 2 shows the graph of the training loss function set for the 400 epochs. The determination of the number of epochs is based on the decay of the cost function, specifically the reconstruction error of the signal as measured by the MAE metric. This error reaches an asymptotic region where there is no improvement in solution quality as shown in Fig. 2.

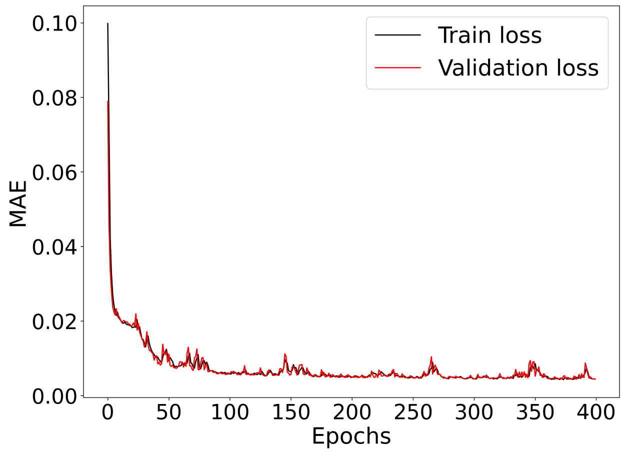

Figure 2. Mean absolute error over training epochs

After training the model based on the undamaged scenario data, the model is then tested for four damage conditions (baseline, DC1, DC2 and DC3). This is achieved through events spanning from 50 train passes up to 400 passes, designed to evaluate the influence of the number of passes based on the DI. Figure 3 shows the fitted distributions to the MAE to 400 vehicle-crossing events. Each distribution has distinct statistical parameters (μ, σ) that are then used to compute the corresponding DI following eq. (3). As shown in Fig. 3, the MAE distribution for each scenario with 400 passes each is skewed slightly to the right and has a long tail because of outliers. For each damage scenario, it is easy to visualize the increase in the MAE value as a function of the increase in damage severity. Figure 4 shows the influence of number of vehicle-crossing in the calculation of the DI.

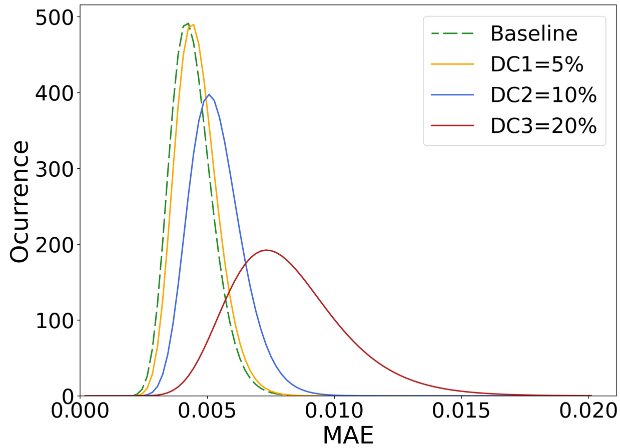

Figure 3. Comparison of log-normal distributions of reconstruction loss for different damage cases

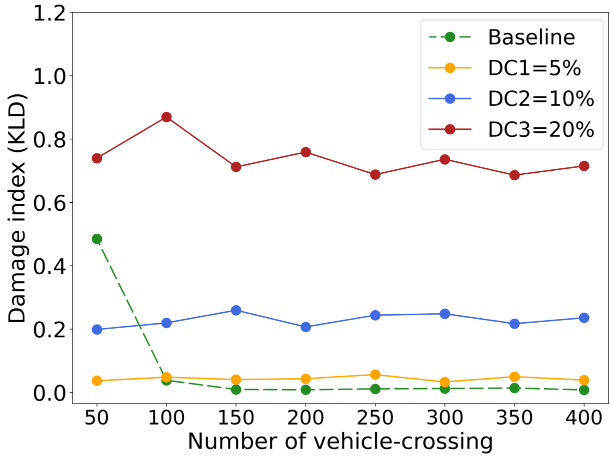

Figure 4. Influence of number of vehicle-crossing events in the calculation of the damage index

As shown in Fig. 4, the DI fluctuates quite significantly for small vehicle-crossing events sizes. However, with increasing number of vehicles, variations in DI decrease. This shows that for a sufficiently large fleet size, the effect of operational conditions can be reduced. In this study a batch size of 150 vehicle-crossing events are deemed appropriate because it results in sufficiently small variations in DI. From 150 vehicle crossings onward, the DI values are distinctly different for various bridge conditions. In the baseline scenario, the DI magnitude is small and close to zero. As the severity of damage increases, the DI grows significantly, especially for the 10% and 20% damage scenarios. Operational speed conditions impact the DI magnitude, leading to variations in each scenario. The index's sensitivity to damage severity is evident, enabling damage identification even with slight variability in the scenario outcomes.

5 Conclusions

The results show that the methodoly applied in this work can successfully be used to monitor the evolution in time of the condition of a bridge damaged by scour considering operational conditions (track irregularities, train speed variability and measurement noise) using deep autoencoder. Additionally, this methodology has the potential to become a practical tool, as a high number of train passages is not required for damage detection. In order to achieve operational conditions even closer to real-world applications, it is suggested to include variability in the mechanical properties of the vehicles (primary and secondary suspension, for example) and mass variability in this applied methodology. Furthermore, other damage indices can also be tested to evaluate their effectiveness in damage detection.

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