Vulnerability Assessment of Existing Bridges to Scour: An Indirect Monitoring Approach

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ABSTRACT: Detecting scour in railway bridges is possible by locating accelerometers and GPS on carriages of passing trains and processing the resulting signals. This research aims to detect scour based on these drive-by measurements, obtained from an instrumented passing vehicle. Signals from multiple train passages will be collected before and after scour repair to determine the change in bridge behavior. Measurements from a train in the UK passing over the Carlisle Bridge will be provided through In2Track3, an ongoing Horizon 2020 project.

In the first stage of the numerical approach, off-bridge conditions are considered. The carriage vibrational responses to track with different ground conditions – represented by altering the stiffnesses in a Winkler spring model – are calculated. In second stage, the bridge 'apparent profile'(AP), which is made up of the true profile on the bridge plus components of bridge/track deflection, will be computed. The Moving Reference Influence Line, i.e., deflection per unit load at a moving reference point, is found from the measured deflections. Bridge support stiffnesses will be modified to represent the loss of stiffness due to scour. Then, signals from the instrumented in-service train carriage i.e., measured AP, will be processed. Finally, an optimization algorithm will find foundation stiffnesses by minimizing the sum of squared differences between the calculated AP and the corresponding measured AP. The presence of scour will be determined by the difference between the stiffness values in the scoured and repaired cases. The results will help to optimize retrofits or develop mitigation measures to scour.

KEYWORDS: Bridge Scour; Indirect Monitoring, Influence Line; Optimization.

1 INTRODUCTION

The Federal Highway Administration defines scour as a washout or discharge of material stored in the river bed by water flow, over a long period [3]. There are different types of scour seen around a bridge pier: natural, contraction and local scour [4], having different formations and triggered by different mechanisms. Local scour is the most influential and therefore one of the most frequently researched scour types on bridges. When the water flow is obstructed by structures, centred turbulence is induced-which is the main mechanism behind local scour [4].

Scour is a slowly developing destructive process for bridges and one of the major factors in many bridge collapses. For example, researchers have determined that 3 out of 5 bridge failures in the United States between 1960 and 1990 were caused by scour [1]. Moreover, in the United Kingdom, the annual cost of railway bridge scour damage has been evaluated to be more than about £1 million [2]. The situation is exacerbated by the changing climatic conditions (such as rainfall regimes) which, in the bridge's lifetime, are likely to be different from those assumed in the bridge's original design.

This study is aimed at finding the flexural rigidity of an existing railway bridge, which minimizes the sum of squared differences between measured and calculated displacements using optimization methods. This research seeks to identify foundation scour by combining drive-by SHM methods with ML algorithms. An experimental campaign in the UK, a partner of an international project, is providing indirect monitoring data for the study. Measurements will be used from multiple batches of passing train runs. A methodology is being developed to identify scour based on the bridge's response. In the first step, a numerical method that consists of 2 stages will be conducted to find deflections, i.e., the APs. The AP is the profile experienced by the train and consists of the pre-existing profile of the track plus elements of bridge deflection. In the first stage, the off-bridge will be used to consider soil conditions and to calibrate the vehicle. In the second stage, the model will compute the displacements under the instrumented carriage and will use them to find the Influence Line of the bridge, i.e., the deflection due to a unit load. Reductions in support stiffnesses will be used to represent the effects of foundation scour. To inspect the impact of scour, before and after repairing a scoured bridge, signals from various batches of train passes will be acquired. Later, to find the bridge stiffness, ML-based algorithms will be applied to minimize the difference between measured and simulated influence lines. The long-term impact of the study will be developing possible repair or mitigation countermeasures. The flowchart in Figure 1 summarises the study. This paper was mainly focused on the background, methods, case study characterization, and numerical model of the study.

2 BACKGROUND AND METHODS

Structural Health Monitoring (SHM) is one of the methods to detect scour. SHM is a term used to cover a range of electronic techniques for health monitoring, including the scour damage state. It has the major advantage of ensuring improvement in public safety, early risk detection, and minimizing downtime. SHM can be divided into two main categories: direct and indirect monitoring. Direct monitoring involves instrumenting

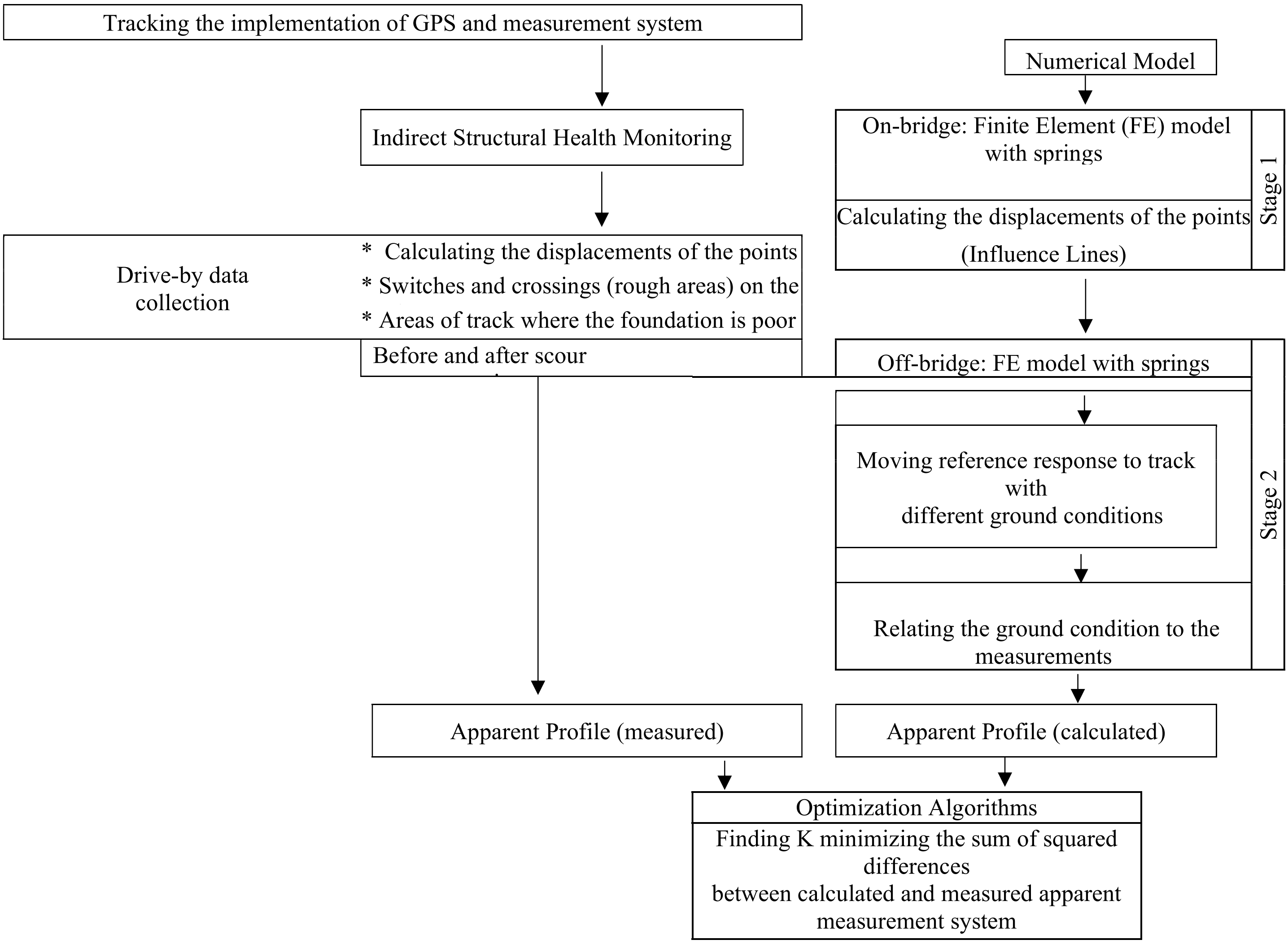

Figure 1. Flowchart of the study.

the bridge with sensors. It has some disadvantages of the total process being costly and requiring periodic maintenance or replacement of sensors [5]. On the other hand, indirect monitoring, i.e., instrumenting a passing vehicle, has the potential to be more economical at the network level, as one vehicle can be used to monitor many bridges. Furthermore, it causes no service disruption and has the potential to provide updated information frequently. It is possible to process collected vehicle data to obtain the bridge's frequencies by numerical techniques and, possibly also mode shapes. Eigen frequency analysis [6] and closed-form mode shape derivation [7] are methods proposed to identify scour in a bridge but further research is required before these methods can be used routinely in the industry. It was possible to identify the presence of scour by applying Continuous Wavelet Transformation to simulated acceleration measurements. The difference in the average CWT coefficients between healthy and scoured bridges from sets of train crossings was the scour indicator [8]. Other researchers have applied Wavelet Transforms to acceleration signals directly [9, 10]. O'Brien & Keenahan propose the AP [11], derived from measured accelerations in passing trains, to detect the presence of scour. The AP is the profile experienced by the train so it consists of any pre-existing profile plus elements of track and bridge deflection.

Machine Learning (ML) algorithms and optimization techniques have also been used in scour detection by taking advantage of its capability to deal with a large number of inputs. For example, Zhang and Zhao [12] by training Convolutional Neural Networks and Dong et al. by utilizing the Multiple Linear Regression method [13] predicted local scour depth around piers better than empirical formulas. Hybrid K-star models [14] were outperformed the scour equations in the literature in the prediction of relative scour depth around abutments. Reduced Error Pruning Tree-Base Classifier [15] predicted local scour depth at complex piers, whereas Extreme Learning Machines [16, 17, 18] predicted pier local scour depth better than frequently used ML algorithms such as Support Vector Machines and Artificial Neural Networks and empirical formulas. A combination of Gradient Tree Boosting with the Group Method of Data Handling technique [19] predicted scour depth around piers with different shapes. Evolutionary Radial Basis Function Neural Network [20] outperformed several algorithms and equations in predicting equilibrium scour depth. Non-dominated Sorting Genetic Algorithm [21] was used for predicting critical scour depth and studies adopting Gaussian Process-based models [22, 23, 24] performed more accurate predictions of local scour around piers and piles than empirical formulas. The empirical scour depth formulas mentioned above were Hydraulic Engineering Circular No. 18, Melville [25]-Sheppard [26], 65-1, and 65-2 (Chinese).

More recently, heuristic optimization methods have been applied in civil engineering to predict scour depth around a pier [27]. In fact, heuristic optimization algorithms are competent in solving complex, non-linear civil engineering problems. Some of most widely used are genetic algorithm, ant colony algorithm, simulated annealing and particle swarm optimization [28]. The latter one has been adopted in several studies addressing scour depth prediction, being defined as particle swarm optimization method. In this method, when the swarm readjusts itself to the ambient by reappearing in the previously explored areas, the current location of every particle is updated by a vector of velocity, according to the social attitudes of individuals [29]. Particle swarm optimization method was used for updating the FE model of an existing bridge to obtain a more robust one [30], and in another study, for the analysis of a suspension bridge installation [31]. Considering its performance in past studies, it is thought to be an adequate candidate to solve the sum of the squared roots-minimization problem of this study in the latter period.

3 CASE STUDY CHARACTERIZATION

The bridge monitored is the Eden Viaduct, located in Carlisle, United Kingdom, in Figure 2**Error! Reference source not found.** [32]. It is a 7-span simple span bridge, each span 12.7 m in length. It has 5 masonry piers, in-situ a concrete deck, and each span has 8 prestressed concrete beams with a prestressed parapet unit and a reinforced concrete parapet upstand unit on each side. Continuously welded rails rest on concrete sleepers on one end of the structure (to the High Mileage end), while there are timber sleepers at the other end of it (to the Low Mileage end) [33]. There are 2 up and down fast lines with a speed of about 160 km/h [34]. The bedrock was scoured throughout the pier faces, the piers were lifted off the bedrock that surrounds them, and the overhanging foundation courses were identified by underwater examinations [32]. For this reason, between July-October 2015, scour protection was applied to foundations and the masonry piles by implementing permanent sheet piles and concrete backfill [33]. The bridge also experienced a flood in 2015.

Figure 2. Eden Viaduct bridge. [32].

The data collection system is called RILA. It is built for measuring the track's longitudinal level and is located at the back of the train carriage [35, 36]. The traditional way to measure the geometry of a track is through track geometry cars, also called loaded measurement, which has high associated costs, including service disruption. RILA is an alternative, cheaper solution which increases the frequency of measurements. Track geometry monitoring sensors are located further away from the axle. This type of measuring is called unloaded (static) measurement [35]. Although it was proven by the field tests that unloaded measurement resulted in small disparities from loaded measurements, it satisfies all the requirements of the measurement standards [35].

4 NUMERICAL MODEL

To find the pseudo-static bridge response due to the moving train, Moving Reference Influence Lines (MR-IL)s were calculated. A simulation model was generated in the MATLAB environment for this purpose. First, a single span was considered. Then, it was upgraded to the 7-span simple supported case, which is the real condition of the bridge monitored. The bridge was modelled as an Euler-Bernoulli beam [37] and divided into several smaller elements. The Foundation stiffness value was calculated with the FEMA 2000 [38, 39] formula, which includes foundation dimensions as an input:

$$k_f = [G_B/(1-\upsilon)][1.55\left(\frac{L}{B}\right)^{0.75} + 0.8] \tag{1}$$

where G is the soil shear modulus, L is foundation length and B is its width. The train carriage is Vehicle 66 and has 6 axles. The location of the measurement point is at a distance x from the start of the bridge and axle loads are behind point x, as illustrated in Figure 3**Error! Reference source not found.Error! Reference source not found.**.

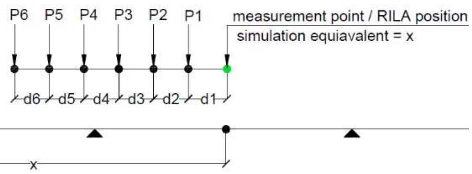

Figure 3. Axle loads and the measurement point.

There are 2 components of δ_x, the first is the bending of the beam, which will be called δ_{x1} and for which the Unit Load Theorem was applied. δ_{x1} is computed with equation 2, where M_R and M_V represent the moment diagrams of the virtual and real systems respectively.

$$\delta_{x1} = \int M_R M_V / EI \tag{2}$$

The second component of δ_x is the support deflection, i.e., δ_{x2}. Both components could be seen in Figure 4**Error! Reference source not found.**, for the single load case. k_{f1} and k_{f2} are spring stiffnesses, computed with equation 6. Total displacement is equal to:

$$J(x, d_i) = \delta_x = \delta_{x1} + \delta_{x2} \tag{3}$$

The moving reference response of the beam is computed as the sum of the contributions due to each axle:

$$\delta_{xR} = \sum_{i=1}^{n} P_i \, J(x, d_i) \tag{4}$$

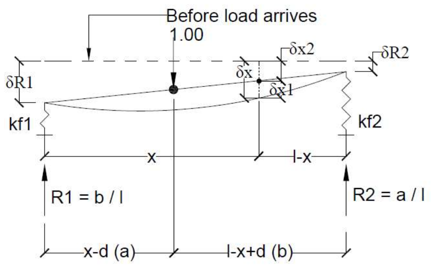

Figure 4. δ_x and components.

4.1 Single span 1-axle case

The model was developed gradually. First, a single-span one-axle case was studied. Figure 5**Error! Reference source not found.** demonstrates the MR-IL of the 1-axle case. The black curve represents the support deflection component (δ_{x2}), while the magenta line belongs to the beam deflection component (δ_{x1}). The moving reference response to the train is illustrated in Figure 6**Error! Reference source not found.**. Both MR-IL and response are zero until load enters the bridge, i.e., x equals to d_1.

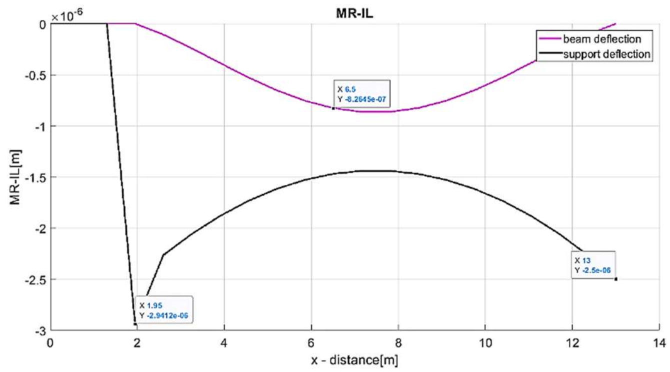

Figure 5. MR-IL for 1-axle single-span case.

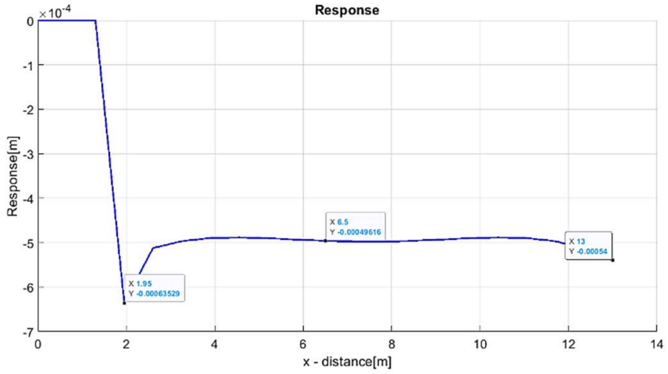

Figure 6. Response for 1-axle single-span case.

5 FINAL REMARKS AND CONCLUSIONS

Results obtained so far through simulation belong to the MR-ILs and responses, representing the calculated APs due to a moving train carriage. The values are verified through hand calculations or the computations performed with the structural analysis program. The shapes of the bending moment and deflection graphs, local maxima points, etc. are compatible with the expectations.

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