Railway Bridge Self-Assessment Using Real-Time Loading Data

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ABSTRACT: This paper describes a case study outlining the development of a system in which rail infrastructure may continuously "self-assess" using Weigh-In-Motion (WIM) data and probabilistic techniques. The case study concerns an ageing steel rail bridge spanning 24.4m across the Ebbw River in South Wales. The bridge was constructed in 1966 and is under the management of Network Rail in the UK. Increased volumes of rail traffic, train velocities and axle weights can result in altered structural behaviour of older rail bridges such as this one. The ability to predict impending failure of infrastructure at the Ultimate, Serviceability and Fatigue Limit States allows owners to implement proactive maintenance approaches, resulting in lower costs of repair and increased safety levels for rail users. This case study consisted of the deterministic assessment of the bridge, followed by a probabilistic assessment using a code load model. Software was then developed which autonomously reads train WIM data obtained from the nearby monitoring locations as it becomes available and calculates the load effect of running these trains across the bridge. The results of the probabilistic assessment showed that the structure had sufficient capacity at the Ultimate Limit State (ULS), despite low utilisation values obtained from a traditional deterministic assessment. It was found that, as expected, deterministic assessment was the most conservative approach in determining the structural integrity of the bridge. Probabilistic assessment using the WIM data was found to produce higher values of reliability for the bridge than the equivalent assessment using a code load model, indicating that the code model may be overly-conservative in this case.

KEY WORDS: Railway Bridge; Weigh-In-Motion; Probabilistic Assessment; Structural Health Monitoring; Train Loading; Structural Safety

1 INTRODUCTION

One of the challenges facing the owners and managers of rail networks today is the preservation of ageing rail infrastructure. Maintenance of structures such as rail bridges can be labour intensive and high cost. The past 50 years has seen many advancements in train technology as well as social and industrial developments which have led to changes in the rate and magnitude of loading of rail infrastructure. These changes may lead to structural behaviour that has been accounted for at the time of design. This can be exacerbated by the degradation of materials over time including reduced cross sections caused by rusting of metallic members or weakened elements and connections as a result of fatigue. With these intrinsic and extrinsic structural changes comes the possibility of an increased failure probability when compared to the context of the original design.

Assessment of ageing rail infrastructure may be carried out deterministically using design and assessment standards relevant to the area in question. However, these standards can often be overly conservative and indicate limit state failure where it is not present in reality. While suitable for maintaining a sufficient level of safety in infrastructure, carrying out overly-regular maintenance and repair work on structures can lead to unnecessary disruption and higher costs for the network managers [1]. Hence it is desirable to obtain a more accurate interpretation of the state of the structure through use of assessment techniques tailored to the structure in question. This can be done using probabilistic assessment methods combined with site-specific monitoring data.

This case study deals with a simply-supported steel railway bridge that was constructed over 50 years ago. The bridge span is 24.4m over the Ebbw River in South Wales and is under the management of Network Rail. It is situated on the South Wales main line and is located between the cities of Cardiff and Newport. It consists of two independently-spanning welded girder bridges, each carrying a single track. The superstructure consists of two welded steel main girders with cross sections as shown in Figure 1. The rails and sleepers are supported by cross girders at 2' centres (approx. 610mm) which are either of T or I-section. These girders span 2.8m between the main girders and are welded along their length to a 15mm thick steel plate which is continuous across the length of the bridge. The end girders of the bridge are steel T-sections encased in concrete.

The tracks in question are considered "main" tracks [2] and have a speed limit of 75 mph (approximately 120 km/h) over the bridge, as opposed to an adjacent bridge which is intended for slower-moving trains. There is a nearby monitoring station which is used to detect wheel defects [3], located at Marshfield, approximately 5.7km from the bridge. Data from this monitoring station also includes axle weight and spacing information for individual trains as well as train classification details; essentially Weigh-In-Motion (WIM) data. This loading data will allow for a more tailored approach to load modelling as opposed to the use of generalised models from the assessment standards, hence leading to a more accurate representation of the structural behaviour.

The objective of this case study was to create a software with the ability to continuously run a probabilistic analysis of the bridge, using a load model based on train WIM data. The nature of the monitoring system, where trains are monitored in real time [3], lends itself to the possibility of setting up a constant influx of train data that can be used in assessment. The advantage of this when coupled with an automatic assessment software is that the bridge can essentially "self-assess" in real-time in response to train loading. The results of this analysis consists of a calculation of the reliability of the bridge based on its reliability index (β), probability of failure (Pf) and its most probable point of failure (β-point) at a given limit state. Using statistical techniques to continuously update stochastic models allows for the prediction of future failure at Ultimate Limit State (ULS), Serviceability Limit State (SLS) or Fatigue Limit State (FLS).

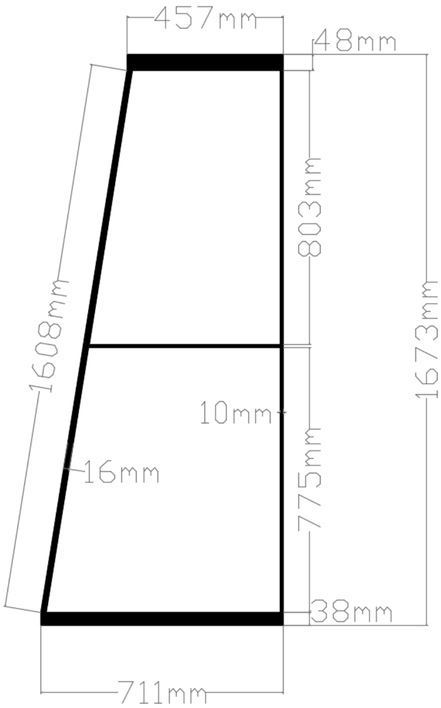

Figure 1. Cross-section of the steel main girders

2 DETERMINISTIC ASSESSMENT

2.1 Finite Element Model

The deterministic assessment of the bridge began with the development of a finite element (FE) model using the Midas Civil software package (see Figure 2) [4]. The model was developed based on pre-construction drawings supplied by Network Rail and does not take into account any possible defects or degradation of materials. As previously noted, the bridge consists of two independently-spanning structures. Only one of these structures was modelled due to symmetry of the spans. The chosen span carries the main line track with trains travelling towards Cardiff. A superimposed dead load of 3kN/m^2 was applied to the bridge deck to account for ballast and a 3kN/m load was applied to each rail to account for the weight of the rail and sleepers. These values were calculated based on the material weight per unit bed length [5].

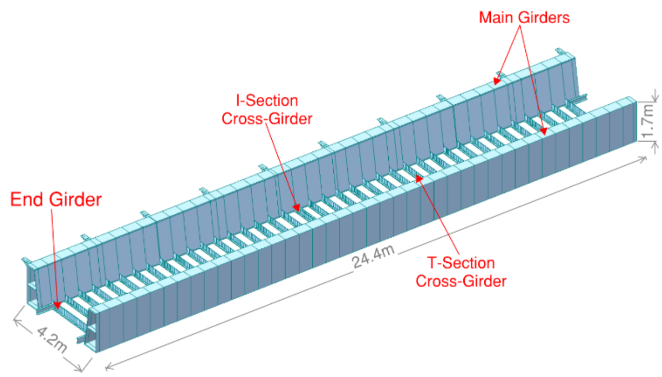

Figure 1. FE model of the bridge over the Ebbw River - deck plate and track removed for clarity

The moving load applied to the bridge was Load Model 71 (LM71). This is the prescribed load model for railway bridges in Eurocode 1 [6]. This load model was arranged in a combination with the dead loads (DL) and superimposed dead loads (SDL) with partial load factors at ULS as outlined in the Design Manual for Roads and Bridges (DMRB) [7] (see Table 1). The point of highest stress was obtained from the FE model for each critical member of different cross section and the force and moment details at this high stress point were taken from the model for use in the deterministic assessment.

Table 1. ULS Partial Load Factors

Load Type	γ_{fl1}	γ_{fl3}
Live	1.5	1.1
Dead	1.05	1.1
Superimposed Dead	1.2	1.1

The FE model was also used to perform an eigenvalue analysis and determine the first natural frequency of the bridge. This value was needed in order to ensure that the frequency fell within the limits set by EN 1991-2 [6] such that a dynamic analysis would not have to be performed. The first natural frequency value was found to be 7.08Hz which falls within the specified limits of 3.86-8.69Hz, hence a detailed dynamic analysis was not needed.

2.2 Deterministic Analysis

The deterministic analysis of the bridge was carried out to BS 5400 design standards and DMRB assessment standards [8][9][10]. The main objective of this assessment was to identify the most critical members of the bridge structure at ULS so that these may be further investigated in the probabilistic analysis.

The bridge drawings used in the creation of the FE model specified the structural steel as being compliant with BS 15 which defines steelwork up to 20mm thickness as having a characteristic yield strength of 247 MPa and 230 MPa for steelwork 21-51mm thick [8]. Given the thickness variation within the structural sections, the yield strength was conservatively taken to be 230 MPa for all members

The DMRB calls for the application of the RU load model in assessment for all combinations of rail vehicles in Europe and the UK [7]. This load model matches the LM71 model that was used in the FE model of the bridge (see Figure 3). This model consists of 4 axle point loads of 250kN each at 1.6m spacing. These axle loads are preceded and succeeded by an infinite UDL of 80kN/m, spaced at 0.8m from the outside axle loads. Dynamics were taken into account in this assessment through the use of a Dynamic Amplification Factor (DAF) as defined in BS 5400-2 [10]. This factor in bending was defined as 1.705 and 1.198 for the cross girder and main girder elements respectively. When considering shear effects, these values were 1.470 and 1.132 for the cross girders and main girders respectively.

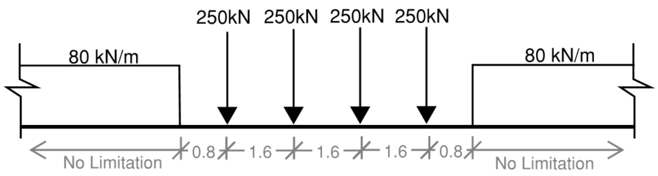

Figure 3. Load Model 71

Table 2 outlines the deterministic results for the structural members of the bridge. In this table, the deterministic check that proved to be most critical for that element is noted along with the associated utilisation value.

Table 2. Deterministic Results (ULS)

Member	Tension/ Compression	Most Critical Check	Utilisation
Main Girder	Compression	Yielding	21.7%
Cross Girder (T-Section)	Tension	Yielding	6.0%
Cross-Girder (I-Section)	Tension	Yielding	38.8%
End Girder	Tension	Yielding	27.6%

This assessment clearly shows the T-section cross girder to be the most critical bridge member with an additional capacity of only 6.0%. The second lowest utilisation was seen in the main girder with a value of 21.7%. Hence these two bridge members were chosen for use in the probabilistic analysis. As the most critical check for both members was yielding, the probabilistic assessment would be centred on element stresses and yield strengths.

3 PROBABILISTIC ASSESSMENT

The probabilistic analyses of the critical bridge elements at ULS were performed considering both the RU load model as described previously and a model based on WIM data values obtained from the "WIM" monitoring site. These loads were applied to the influence lines extracted from the FE model for the critical bridge elements as defined in the deterministic assessment in order to obtain the load effects. These were then combined with stochastic permanent load effects

Influence lines were generated for the right and left rails independently and were combined in the assessment software. In cases where the influence lines contain a relieving effect [7], this portion of the influence line was set to zero. Given that yielding was deemed the most critical load effect, only the stress influence lines were used in the analysis. These may be seen in Figures 4-5 for the two critical bridge members.

3.1 Permanent Load and Resistance Modelling

Probabilistic assessment of structures involves the stochastic modelling of certain load and resistance variables so that reasonable variation of these parameters may be taken into account in calculations. Each of the relevant parameters was modelled with respect to distribution guidelines published in the Reliability-Based Classification guideline document by the Danish Road Directorate (DRD) [11]. The details of these load models are outlined in the following sections.

3.1.1 Dead Load

The DL consisted of the self-weight of the bridge. It was modelled stochastically as a normal distribution with a coefficient of variation (CoV) of 5%. Uncertainty in the model was taken as 5% [11]. This uncertainty is based on uncertainty in the load definition and could be reduced if testing was carried out on the bridge to determine the actual self-weight. The mean (μ) of the distribution was obtained from the FE model for each member that was considered. These values are summarised in Table 3.

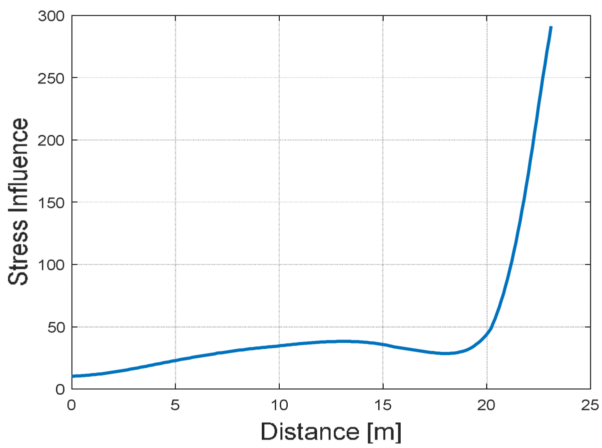

Figure 4. Stress Influence Line for the T-Section Cross Girder

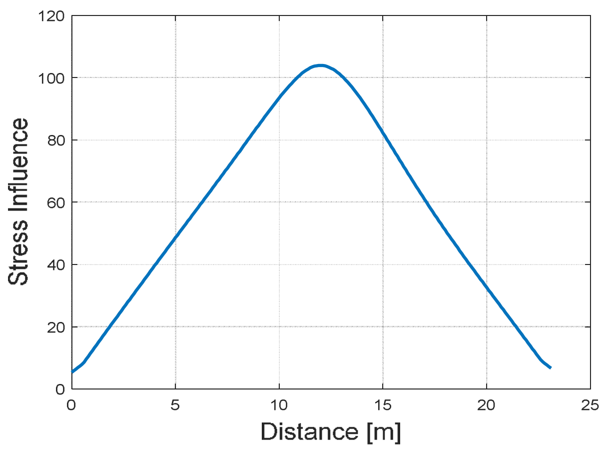

Figure 5. Stress Influence Line for the Main Girder

3.1.2 Superimposed Dead Load

The SDL consisted of the load induced by the ballast, the sleepers and the rails. This was modelled stochastically as a normal distribution with a CoV of 10%. Uncertainty in the model was considered 5% [11]. Again, this uncertainty could be reduced if values taken from field tests were used. The mean value for this distribution was the sum of the stress values due to the ballast weight and the track weight and was obtained directly from the FE model. These values are summarised in Table 3.

Table 3. Mean Values for Stochastic Load Models

Member	Variable	μ [MPa]
Cross-Girder (T-Section)	DL	8.19
	SDL	6.79
Main Girder	DL	14.45
	SDL	9.05

3.1.3 Material Parameters

In order to model the resistance capability of the bridge members in question, the yield strength of the steel was considered a stochastic variable. The steel strength was modelled according to a lognormal distribution with parameters as defined in the DRD guideline document. The mean (μ) and standard deviation (σ) parameters are summarised in Table 4. The steel type used in construction was not specified in the bridge drawings and so a type St.37 was assumed based the characteristic value of 230 MPa mentioned previously.

Table 4. Distribution Parameters for Steel Yield Strength

Member	μ [MPa]	σ [MPa]
Cross-Girder (T-Section)	304	25
Main Girder	283	25

The uncertainty in the stochastic model of the material capacity was based on three variables: the uncertainty in the accuracy of the computation model (I_1), the uncertainty in determining the material parameters (I_2), and the uncertainty in identifying the materials used in the bridge (I_3). In this case study, I_1 was considered to be "normal", I_2 was considered to be "medium" and I_3 was "good" [11]. These evaluations resulted in a CoV of uncertainty of 0.087 for the structural material. This uncertainty was modelled stochastically with a lognormal distribution.

3.2 RU Load Model

3.2.1 Load Modelling

The uncertainty in the RU model was taken to be a normally distributed stochastic variable with a mean of 1.0. The CoV of this uncertainty model was dependent on the confidence in the accuracy of the applied variable load. In the case of the RU load model, this uncertainty was considered to be 'medium', implying an assumed accuracy of ±25% [11]. This led to a CoV value of 0.15.

As previous research has outlined, RU loading may be modelled stochastically assuming a Gumbel distribution and using the 98% fractile value of the RU load model as defined in BD 37/01 [1][7]. Conservatively assuming a coefficient of variation of 0.2, the mean value of the wagon weight was taken to be 0.659 times the RU load model [12].

3.2.2 Dynamic Amplification

The dynamic amplification factor (DAF) was modelled as in the following equation, where K is the modelled DAF and ε is the dynamic increment [11].

$$K = 1 + \varepsilon \tag{1}$$

The dynamic increment was considered a stochastic variable and was modelled as normally distributed with a CoV of 1.0. The mean of the distribution was calculated as the 98% fractile value of the deterministically-calculated dynamic factor [1]. These mean values were 0.231 for the cross girder and 0.039 for the main girder.

3.3 WIM Data Model

3.3.1 Extrapolation of Data

The train WIM data that was used for the purpose of this case study consisted of approximately one month (28 days) of data. When considering assessment at ULS, the main interest lies in the loading scenario that results in the maximum load effects for a given bridge member as these are the loads that are most likely to cause failure. Modelling the train loads based on a distribution of maximum load effects allows the month of data to be extrapolated into a year of maximum values which can give greater insight into the type of loading that the bridge experiences over this period of time [13]. For the purpose of this case study, the maximum load effect caused by each individual train passing over the bridge was assessed. These values were then used in order to determine the train that causes the maximum load effect on a given day. A distribution was then fitted to these maximum daily load effect values which served as a parent distribution from which extrapolated maximum yearly distribution could be obtained.

The extrapolation of this data in order to determine the maximum distribution was carried out using Extreme Value Theory (EVT) which may be represented by the formula [14]:

$$F_Y(y) = [F_X(x)]^n \tag{2}$$

Where the parent distribution, F_X, is raised to a power n in order to produce a maximum distribution F_Y. This maximum distribution will hence consist of n independently distributed samples of x [13]. In this case, the parent distribution was a distribution of maximum values per working day, so in order to obtain a distribution of maximum values per year the distribution was raised to an n value equal to the number of working days in a year. This value was taken to be 303, i.e. the number of days in a year neglecting Sundays and holidays. A histogram of the maximum daily load effects for the real train data is shown below for the T-section cross girder (Figure 6) and the main girder (Figure 7) and both are compared to the equivalent load effect under RU loading.

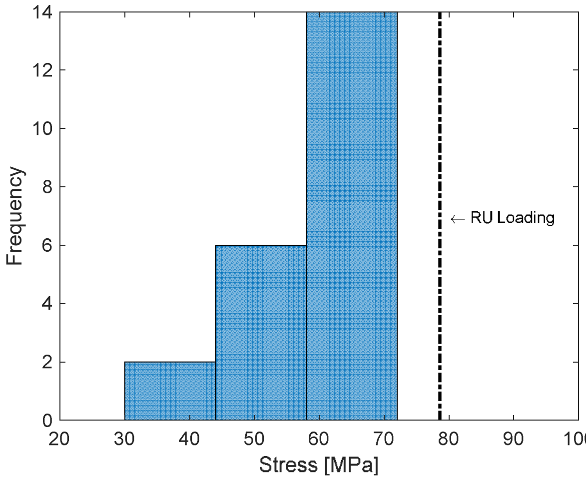

Figure 6. Distribution of maximum daily stress effects for the T-section cross girder

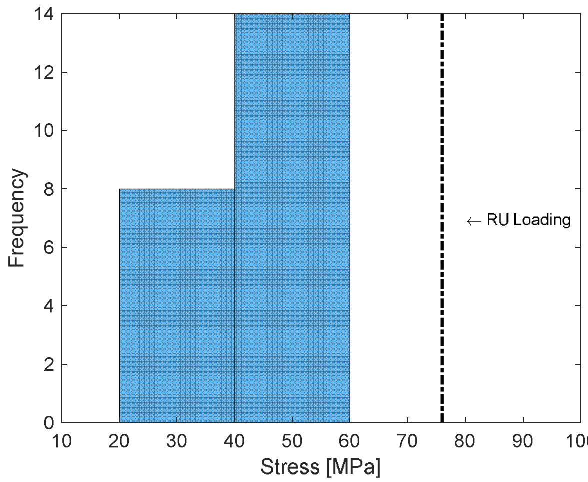

Figure 7. Distribution of maximum daily stress effects for the main girder

It can be seen clearly from Figures 6-7 that the stress effect caused by RU loading is conservative when compared to those caused by real trains passing over the bridge.

3.3.2 Uncertainty Modelling

As in the RU model, uncertainty in the axle weights obtained from the WIM data was modelled as a stochastic variable with a mean of 1.0. However there was a higher level of confidence in the applicability of the loading to the structure in this case due to the fact that the actual train loading on the bridge was included. Hence the level of uncertainty could be considered 'low', leading to a CoV value of 0.1 [11]. This uncertainty model was applied to the load model after extrapolation. In fact, it may be argued that this level of uncertainty is conservatively high, considering the only uncertainty in question is the accuracy of the monitoring station.

3.3.3 Dynamic Amplification Factor

When considering real train data, the DAF must conform to Annex C of EN 1991-2 and take into account the maximum permitted vehicle speed over the bridge [6]. A study of the Western Sectional Appendix [2] showed that the speed limit over the bridge in question is 75 mph (approximately 120km/h). Assuming standard maintenance of the track, the DAFs were calculated as 1.880 and 1.119 for the T-section cross girder and the main girder respectively.

These DAF values were modelled as in the probabilistic RU model, where the dynamic increment ε was modelled as a stochastic variable with normal distribution with a mean derived from the 98% fractile value of the calculated DAF. In this case, these mean values were 0.039 and 0.289 for the cross girder and main girder respectively. The K value obtained from Equation 1 was then applied to the load effects.

3.4 *Reliability*

Structural safety may be quantified by calculating the reliability at a certain limit state. The reliability index (β) of a structure is related to its probability of failure (P_f) and may be estimated using the First Order Reliability Method (FORM) [15]. Analysis using FORM is based on a performance function *g(X)*. In the case of ULS analysis for the current assessment, this function is as defined below.

$$g(X) = R(X) - S(X) \tag{3}$$

Where R and S are the resistance and loading of the system respectively. Hence when $g(X) < 0$, the load exceeds the resistance capability of the structure and failure occurs.

The Hasofer-Lind (HL) method of carrying out a FORM analysis was chosen due to its stability when dealing with larger CoV values in comparison to other methods [15]. This method involves the transformation of stochastic variables into standard normal space. The shortest distance between the origin of this normalised space and the failure surface of the limit state function is equal to the reliability index. Hence the reliability index may be calculated with respect to the mean and standard deviation of the load and resistance distributions using the formula:

$$\beta = \frac{\mu_R - \mu_S}{\sqrt{\sigma_R^2 + \sigma_S^2}} \tag{4}$$

The point on the failure surface at which this distance is measured is known as the Most Probable Point (MPP), also referred to as the β-point.

One drawback to the use of the HL method is that it assumes normal distributions. In cases such as this one where the load and resistance variables are likely to follow non-Gaussian distributions, it is necessary to transform these into equivalent normal distributions before performing the HL analysis. This can be done using the Rackwitz-Fiessler method [15].

The target reliability index of a structural component varies based on a number of considerations including economic, social and sustainability factors [13]. EN 1990:2002 calls for the definition of the structure into one of three reliability classes. These classes are dependent on the consequences of failure of the structure in question. The railway bridge that is under consideration in this case study falls under the RC2 category. This indicates a medium level of consequence for loss of human life and considerable economic, social or environmental consequences [16]. The target reliability indices for a structural member of this class as defined in EN

1990:2002 is outlined in Table 5 for reference periods of 1 year or 50 years.

Table 5. Target Reliability Indices for Class RC2 structural members as per EN 1990:2002

Limit State	Target Reliability	
	1 Year	50 Year
ULS	4.7	3.8
FLS	-	1.5 to 3.8
SLS (irreversible)	2.9	1.5

As this analysis is assessing the bridge at ULS with a one-year reference period, the target value for the reliability index is 4.7.

4 RESULTS OF ANALYSIS

As shown previously, the results of the deterministic analysis showed some relatively low utilisation values for certain bridge members at their most highly-stressed point. Two of these members with the lowest utilisations, the T-section cross-girder and the main girder, were probabilistically assessed using both the typical RU load model and train WIM data from the site. The reliability results of this assessment are outlined in Table 6 below.

Table 6. Results of Probabilistic Analysis

Member	Live Load Model	β	P_f
Cross-Girder (T-Section)	RU	5.0	1.54×10^{-7}
	WIM	5.5	1.87×10^{-8}
Main Girder	RU	5.6	7.27×10^{-9}
	WIM	9.5	1.28×10^{-21}

The above results clearly show that for both load models used in the probabilistic assessment, both bridge members have reliability indices greater than the target value of 4.7. This indicates that the most critical elements of the bridge in question are compliant at ULS in accordance with the Eurocode [16]. Table 6 also clearly shows that, as expected, the use of real train WIM data in the probabilistic analysis proved to be a less conservative approach than the use of the RU load model as prescribed in the codes.

5 CONCLUSIONS

The objective of this research was to develop a software that can take WIM data of trains that have passed over a rail bridge as an input and use this to continuously assess the reliability and probability of failure of that bridge using probabilistic methods.

The results of this case study showed that the software that was developed was capable of performing probabilistic analysis of the critical elements as defined by a deterministic assessment. As expected, the deterministic analysis was found to be more conservative than the probabilistic analysis. This is due to the fact that the codes used in the deterministic assessment were developed to take into account a broad range of bridges whereas the probabilistic assessment incorporated an individualised approach tailored to this particular bridge.

In addition to this, it was seen that the use of WIM data in the calculation of the reliability index led to less conservative values than in a similar analysis where RU loading was used. Given that the WIM data presents a more accurate picture of the type and pattern of loading that passes over the bridge, it can be said that these values are more representative of the reality of the structure than those obtained using RU loading. Hence it can be concluded that the use of this software in conjunction with train WIM data can give network operators a more reliable measure of the probability of failure of the structure, allowing for the potential of increased maintenance efficiency.

Finally, an online data storage platform has been developed which can read WIM data directly from the infrastructure owner as it becomes available. This platform has been designed to interface with the Matlab software developed and discussed in this paper. Therefore, the bridge can be considered "self-assessing" as it can automatically re-evaluate its reliability over time as more data becomes available.

ACKNOWLEDGMENTS

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