Probabilistic evaluation of road bridges under heavy load platforms

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ABSTRACT: Road bridges are one of the most important infrastructure assets for global transportation. With the growing freight demands, traffic loads on bridges are also increasing. Specifically, the increase of heavy load platforms (superloads) may impose an unacceptable risk for existing bridges. Because these events are statically-significant, they offer a unique opportunity to determine the true behaviour of the bridge. Notably, measurements from these events can be used to determine statistical parameters which are commonly used in reliability assessement. These measurements can also be very useful for calibrating a model of the bridge, as may be used for bridge assessment. Intuitively, heavy vehicle crossings have inherit randomness in their properties – such as nominal axle loads, vehicle speed, and travel paths. This paper evaluates the variations in model updating performance when considering the random nature of heavy load platforms movements. This paper also provides statistical parameters determined based on measurements for reliability assessment. For this work, bridge load effects were measured for multiple heavy load platforms across a reference bridge. Statistical evaluation of the bridge load effects of multiple heavy load platforms is conducted. Grillage analysis is used to simulate the crossing of these heavy load platforms. Following this, model updating is conducted for each heavy load platform measurement by tuning key model parameters (e.g., longitudinal stiffness of beams). The variations in the updated models (i.e., updated parameters and model outputs) are then evaluated. The findings should inform users on the variability in bridge load effect due to heavy load platforms and its influence on bridge model errors.

1. INTRODUCTION

Road bridges are constantly exposed to varying traffic loads over their lifespan. With the growing freight demands, traffic loads on bridges are also increasing (Hung, 2014; Decò and Frangopol, 2013). Specifically, the increase of heavy load platforms (superloads) may impose unacceptable risk for existing bridges. Because these events are statically significant (load magnitude greater than normal traffic), they offer a unique opportunity to determine the true behaviour of the bridge.

The reliability assessment of bridges is an important part of road asset management throughout the life cycle of bridge structures. Reliability assessment has an extensive literature and the statistical parameters, specifically the bias factor (λ) and coefficient of variation (CoV), are important inputs towards reliability assessments. However, the bias factor and CoV are typically uncertain parameters estimated based on engineering experience. To this, measurements of statistically-significant heavy loads crossing road bridges can be valuable in determining benchmark bias factor and CoV for use in heavy load reliability assessments.

Model calibration of bridge structures using measurement data aims to enhance existing numerical models such that the computed results have reasonable fidelity with the measurements. Studies of Okasha et al. (2012) and Polanco et al. (2016) are a few examples of model calibration applications in bridge assessments, both which subsequently contribute towards bridge structural reliability. Evaluating the model calibration procedure of bridges also allow for assessment of properties properties, including corrosion effect (Heitner et al., 2019), non-destructive damage indicator, and bridge capacities (Sipple and Sanayei, 2015; Costa et al., 2015). Concerning model calibration procedures, measurements of bridge load effects from crossings of superloads are also valuable inputs. However, heavy platform loads have inherit randomness in their properties – such as nominal axle loads, vehicle speed, and travel paths - which can affect the performance of model calibration.

Accordingly, the aim of this paper is two fold: (1) to evaluate the effects of heavy load vehicles on the model updating performance of bridge numerical models, and; (2) to provide bias factor and CoV obtained from measurements of heavy load vehicles, of which can be useful for practitioners in reliability assessment. A road bridge located in Melbourne is subjected to heavy platform loads and chosen for the purpose of this study. Monitoring systems installed during the crossings of heavy platform loads allow bridge load effect measurements to be obtained. Statistical parameters for reliability assessment (bias factor and CoV) are determined from these measurements. Additionally, model updating procedures are carried out for the bridge numerical model using the measurements. The influence of heavy platform loads on the model updating performance were also evaluated and discussed.

2. SUPERLOAD MONITORING DATA AND NUMERICAL SIMULATION

2.1. *Strain measurement*

Strain measurements were collected from a long term monitoring system of a road bridge located along the Hamilton Highway, Melbourne, Australia. The bridge is a three-span, simply-supported I-girder bridge illustrated in Figure 1.

The bridge was subjected to scheduled heavy platform crossings (Figure 2) for a period between Jan 2019 to Nov 2020. The magnitude of heavy platform loads ranged from 76 Tonne to 138 Tonnes. Taking account the maximum recorded load (138 Tonnes), a total of 55 individual measurements containing the heavy platform load were used for this study. The measurements are treated as a probabilistic database to determine statistical parameters as well as measured inputs for model calibration.

Table 1 outlines the sensor channels that were placed along the superstructure of the bridge in Figure 1. Strain gauges were primarily placed at top and bottom flanges of beam girders to determine the midspan bending moments.

Table 1: Strain gauge location and identification.

Channel ID	Strain gauge location
S2-B1-T	Span 2, Beam 1, Top flange
S2-B1-B	Span 2, Beam 1, Bottom flange
S2-B2-B	Span 2, Beam 2, Bottom flange
S2-B3-B	Span 2, Beam 3, Bottom flange
S2-B4-T	Span 2, Beam 4, Top flange
S2-B4-B	Span 2, Beam 4, Bottom flange

Figure 3 summarises the strain readings for the 55 individual crossings of the heavy platform load. It is observed that the strain data of top flange strain gauges (Table 1) are very small relative to the bottom strains. This can suggest that the top flange strain gauges are located close to the neutral axis of the beam girders. As can be seen, the magnitude of strain values appear consistent throughout the 55 moves albeit having slight variations in magnitude. Since the time axis is normalised, this suggest that the variations of strains between moves can be due to other varying factors such as travel path, site conditions, and axle loads.

2.2. *Grillage modelling*

Grillage modelling is adopted for the numerical study of this work as it is commonly adopted by practitioners due to its rapid modelling means whilst providing reasonable analysis accuracy (American Association of State Highway and Transportation Officials (AASHTO), 2012). The grillage model is a two-dimensional (2-D) representation of three-dimensional (3-D) structure of the bridge using linear elements aligned in a grid.

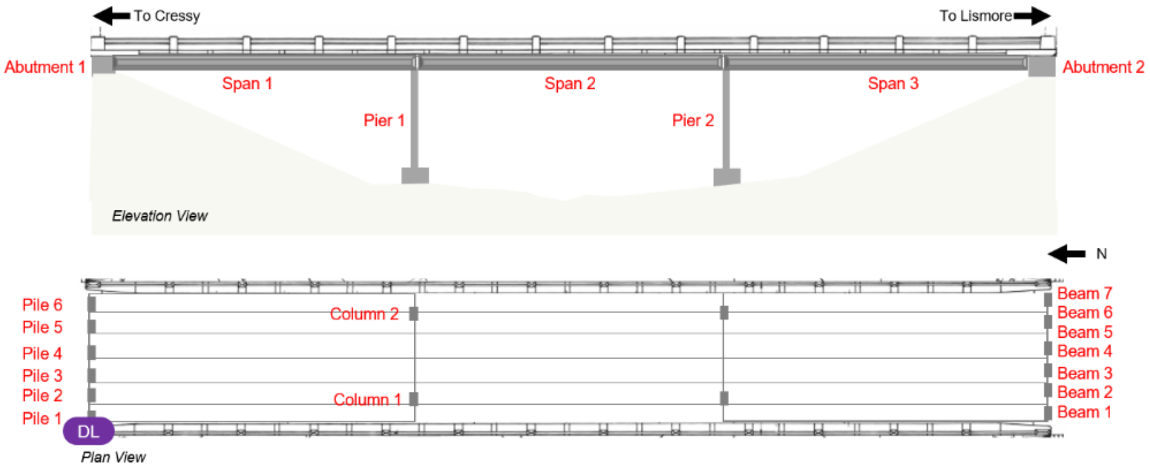

Figure 1: Components of the subjected road bridge. DL indicates the location of its data acquisition station.

Figure 2: Heavy platform loads along the highway.

A grillage consist of longitudinal and transverse elements connected to one another in a grid form that represent the deck and its main structural elements. Typically, longitudinal elements are used to model the supporting girders while transverse elements are used to represent the slab deck. Supports are placed at nodes of grillage model to represent the position of boundary conditions such as piers or abutments.

Figure 4 shows the grillage model of the bridge deck. The grillage model is created using the free and open-source `ospgrillage` python package developed by the authors (Ngan and Caprani, 2022). This is used to quickly create and perform bridge deck grillage analyses. `ospgrillage` wraps `OpenSeesPy`, which is a Python interpreter of `OpenSees` - an open-source structural analysis framework well-suited for various structural and geotechnical systems (McKenna, 2011). The girders and slabs are aligned in the global x and z-axis respectively. All grillage members are modelled using elastic beam elements. Nodal restraints are placed at pier locations to simulate the supports. The mesh for each spans are segregated and non-continuous along the pier support node lines since there is minimal deck continuity between the spans. The grillage model is discretized into an even number of grid spacings such that the nodes along the mid-span of each beam girder position correspond to the locations of sensors in Table 1.

The top and bottom longitudinal strains are computed from the bending moments extracted at the mid-span node locations using the relationship for bending stress and Hooke's law, giving:

$$\sigma_y = \kappa y = \frac{\varepsilon_{\text{top}} - \varepsilon_{\text{btm}}}{h} \cdot y = \frac{My}{EI} \qquad (1)$$

where the symbols have their usual meanings and are all stated for the longitudinal direction.

2.3. *Statistical evaluation of heavy loads*

The probability density function (PDF) for the maximum absolute strains values of each channel in Figure 3 are given in Figure 5.

The statistical parameters of the strain measurements are given in Table 2. Here, the strains of each

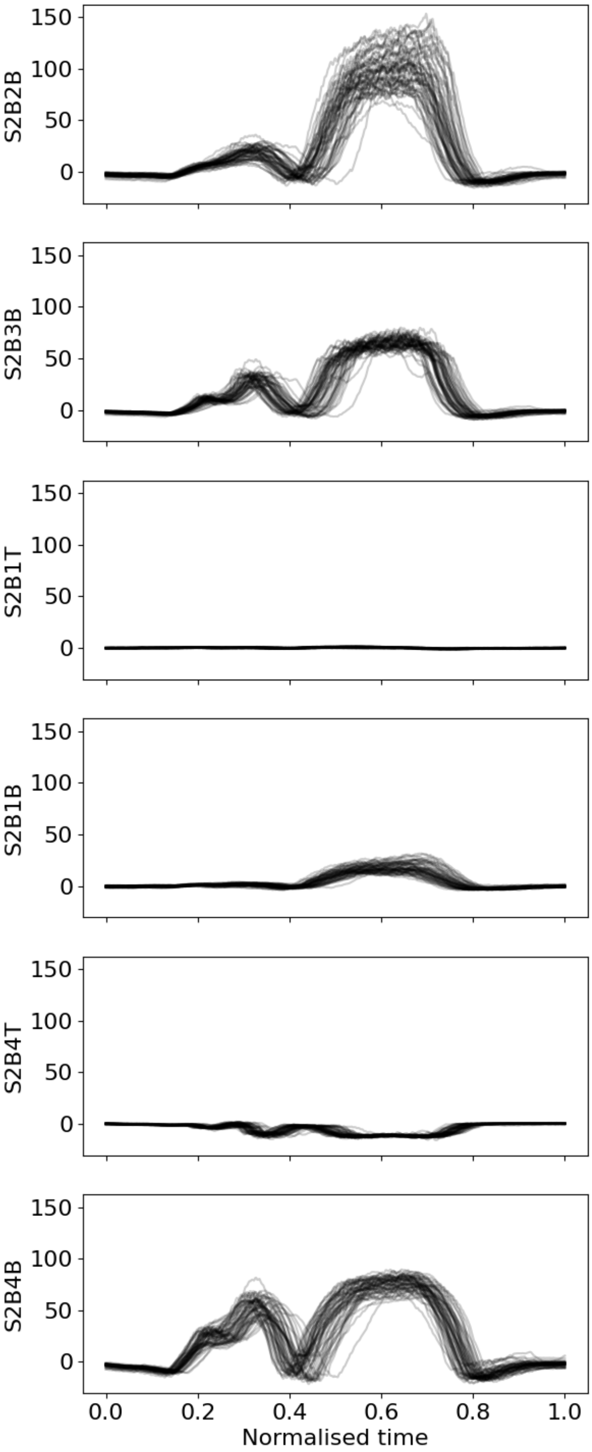

Figure 3: Strain gauge readings from 55 heavy platform crossings (138 Tonnes). Strain readings are in microstrain ($\mu\varepsilon$) and normalised across time.

beam girder computed using the grillage model are considered as the nominal values, as that is what an assessor would determine. The bias is calculated as the ratio of mean and nominal values. For top flange strain channels in Table 1, the bias is not determined due to the very small near zero nominal values. The calculated bias factors in Table 2are generally lower than one - which is typically the case for load effect. The CoV is the ratio of standard deviation and mean.

Table 2: Statistics of the absolute maximum strains for strain channels. Units in microstrain, $\mu\varepsilon$

Sensor	Mean	Std. dev.	Bias	CoV %
S2-B2-B	107.89	20.80	0.98	0.19
S2-B3-B	68.95	4.93	0.64	0.071
S2-B1-T	1.089	0.422	-	0.387
S2-B1-B	19.39	5.08	0.57	0.261
S2-B4-T	1.04	0.51	-	0.484
S2-B4-B	78.14	6.51	1.03	0.083

3. MODEL CALIBRATION

3.1. *Sensitivity-based model updating*

The sensitivity-based model updating procedure is used, which is an iterative process that tunes model parameters to minimise the error between strain measurements and corresponding strains calculated from grillage models (Mottershead et al., 2011). Here, the grillage models is treated as a function (black box) that calculate the corresponding strain values of the measurements. This relationship between calculated strains and model parameters can be defined as:

$$\mathbf{R} = f(\mathbf{P}) \tag{2}$$

where **R** and **P** are vectors containing model parameters and model responses respectively. Here, the black box that describes the relationship between **R** and **P**, f, is the numerical grillage model. The parameter and response vectors can be shown as:

$$\mathbf{P} = \left[p_1, p_2, ..., p_{(j-1)}, p_j\right] \tag{3}$$

$$\mathbf{R} = \left[r_1, r_2, ..., r_{(i-1)}, r_i\right] \tag{4}$$

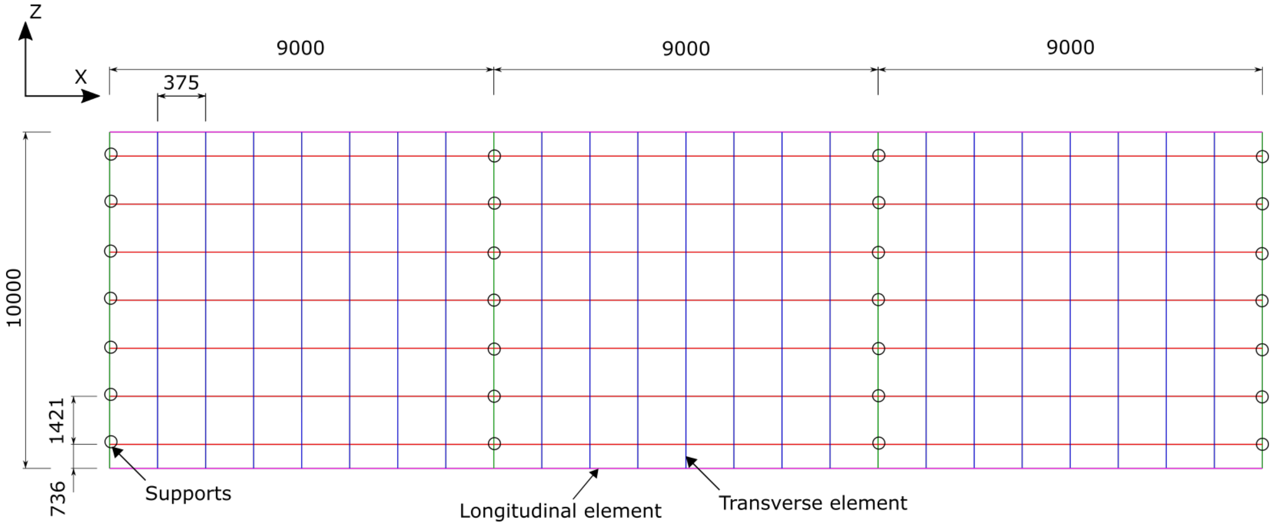

Figure 4: Plan view of grillage model, detailing dimensions (in mm*)*

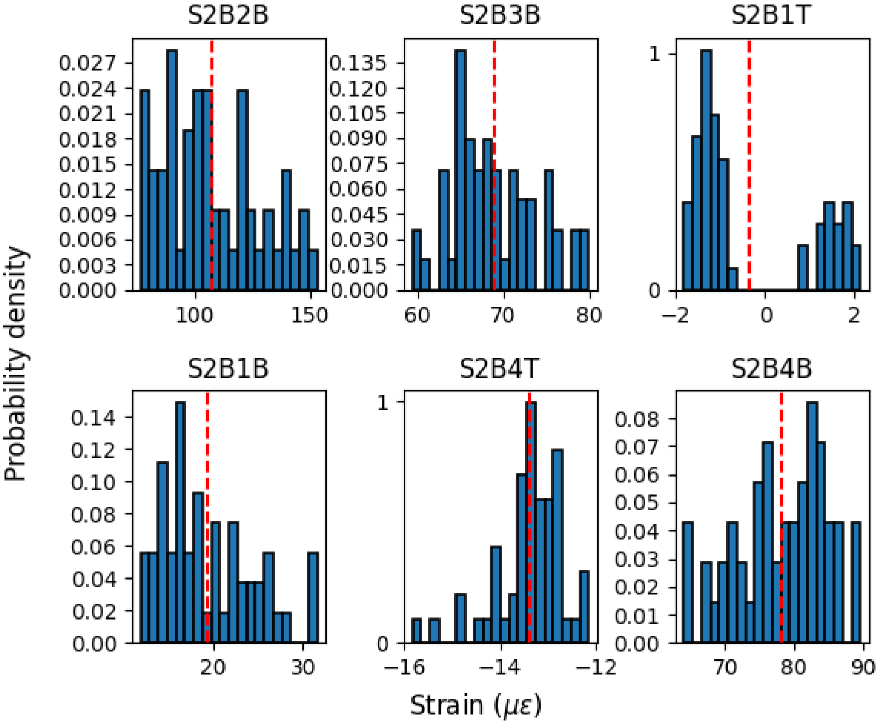

Figure 5: Probability density of updating parameters. Mean value for each channel are also indicated.

where **R** and **P** has i and j number of elements respectively. From 2, sensitivity can be calculated for all responses with respect to all parameters. A sensitivity matrix of dimension $(i \times j)$, **S**, is then obtained:

$$\mathbf{S} = \mathbf{S}_{ij} = \left[\frac{\delta \mathbf{R}_i}{\delta \mathbf{P}_j}\right]. \tag{5}$$

The sensitivity matrix is calculated during each iteration to optimise the sensitivity-based objective function. Upper and lower bound constraints can be applied to updating parameters to prevent unreasonable solutions for the physical parameters. Convergence is achieved once the average parameter change is below the defined tolerance of 1%.

3.2. Selection of model parameters

A parametric study is first performed to identify model parameters of the grillage model that are sensitivity towards the computed strains. This is important as the selection of parameters should be carefully considered as they potentially result in non-convergence or non-unique solutions. The parametric study is conducted by manually tuning and adjusting the model parameters (primarily the stiffness or elastic modulus), which influence the bending moment behaviour since the measured strains attributes to bending strains (top and bottom flanges). It is found that the elastic modulus - while being a proxy for adjusting the bending stiffness - is sensitive towards the bending moments (and strains) at midspans of Beams 1 to 4. Consequently, the concrete elastic modulus of Beams 1 to 4 (E_{b1} to E_{b4}) are chosen to be updated during model calibration. It should be note that the concrete elastic modulus acts as a proxy to tuning the bending stiffness of the beam girders, amongst other sources of stiffness. The selected parameters allow a functional yet minimal model calibration as the number of chosen parameters is kept as low as possible (four parameters to match six measurements) to avoid ill-conditioned numerical solutions (Jaishi et al., 2007). The updating parameters are given a lower bound of 5 to avoid deviating to negative values and lose their physical meaning. An upper bound of 1000 is also in place to avoid any extreme non-convergence of parameters.

The target **R** matrix of Equation (4) comprise of: (1) the maximum absolute strain value of the midspan bending (top and bottom strain) channels, and (2) the root-mean-square error between measured and calculated strain from grillage model. The latter is considered to correlate the shape profiles of the strain time histories between measured and computed strain readings.

3.3. Calibration Results

Figure 6 shows the strain time histories from the initial model and calibrated model for a single simulation of load crossing. The respective strain measurement used in the calibration procedure are also plotted alongside each channel in Figure 6. As can be seen, the model calibration procedure improves the prediction of absolute maximum strains. Overall, the updated responses captures the behaviour of the bridge deck reasonably well - notably the maximum strains at each beam as well as the deck continuity

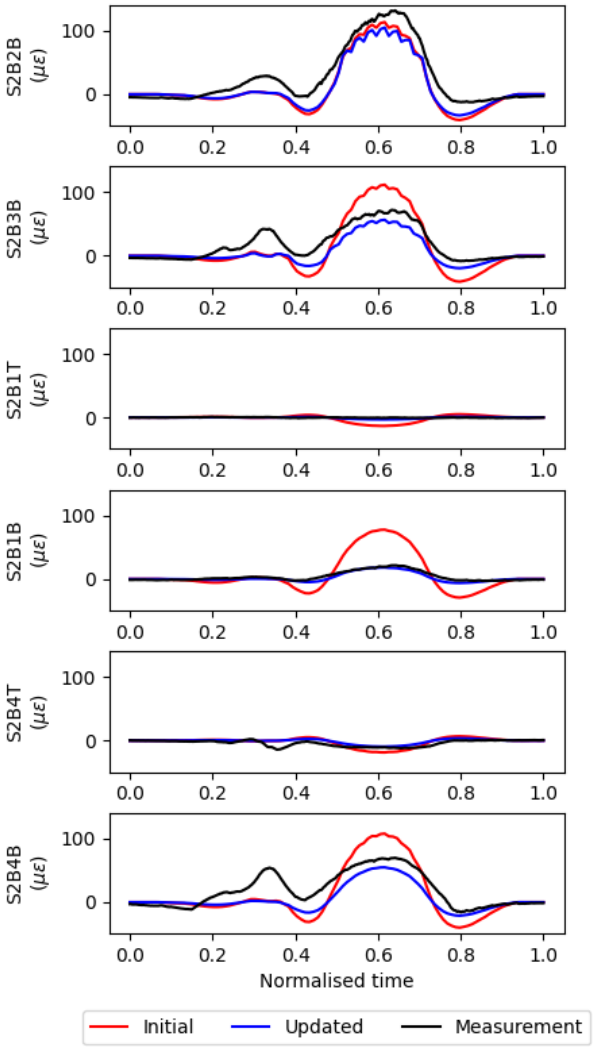

Figure 6: Comparison of model responses from calibration with measurements for a single movement.

Table 3 summarises the average initial and updated parameters for all 55 heavy load moves. The statistics of the updated parameters are also summarised alongside Table 3. Based on the updated model, the parameter values attained physically non-meaningful values for Beams 1 and 4 for both span 1 and 2. This is expected since the concrete elastic modulus acts as a proxy in capturing at best other phenomenon which are not represented by grillage model. Such phenomenon can include cracked concrete behaviour, additional stiffness from non-structural components, and so forth. Overall, the higher order of magnitude observed in the final parameters values are attained in order to correspond to the lower strain values in measurements.

The PDF of updated parameters is shown in Figure 7. As can be seen, the updated parameters follow a non-normal distribution.

4. CONCLUSIONS

In this paper, a road bridge located in Melbourne is subjected to heavy platform loads. A total of 55 strain measurements from the heavy platform crossings were obtained from the data acquisition system of the bridge. The strain measurement from heavy platform moves (138 Tonnes) can be significant to determine the statistical parameters for reliability assessments. Additional, the heavy platform prove to be statically-significant for model calibration procedures to determine the true behaviour of the bridge.

Grillage modelling approach is adopted to model the bridge deck. The bending moments at midspan of the instrumented beams (Beam 1 to 4) was obtained by moving the 138 tonne heavy platform load across the grillage model. The concrete elastic modulus of four beam girders (Beam 1 to 4) were chosen to be updated during model calibration due to their sensitivity towards the strain measurements.

The following conclusions were made:

1. The bias factor and CoV of strain sensor measurements for top and bottom beam flange during heavy load vehicles were provided in this paper.
2. The updated grillage model of the bridge showed good correlation in strain measurements albeit some parameters attained physically non-meaningful values. This indicates that these parameters act as surrogate for phenomenon not captured in the simple grillage model.

Overall, the results in this study should inform practitioners and researchers on both the assessment and model calibration of bridges using heavy vehicle data. In particular, the statistical parameters in this paper which are determined on the basis of measurements can be useful for practitioners in reliability assessment.

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Table 3: Statistics of updated parameters across all 55 heavy load crossings.

Member	Initial (GPa)	Updated (GPa)	Standard deviation (GPa)
Beam 1, E_{b1}	56.7	70.35	20.06
Beam 2, E_{b2}	36.7	19.57	3.25
Beam 3, E_{b3}	36.7	32.59	2.82
Beam 4, E_{b4}	31.17	174.2	3.07

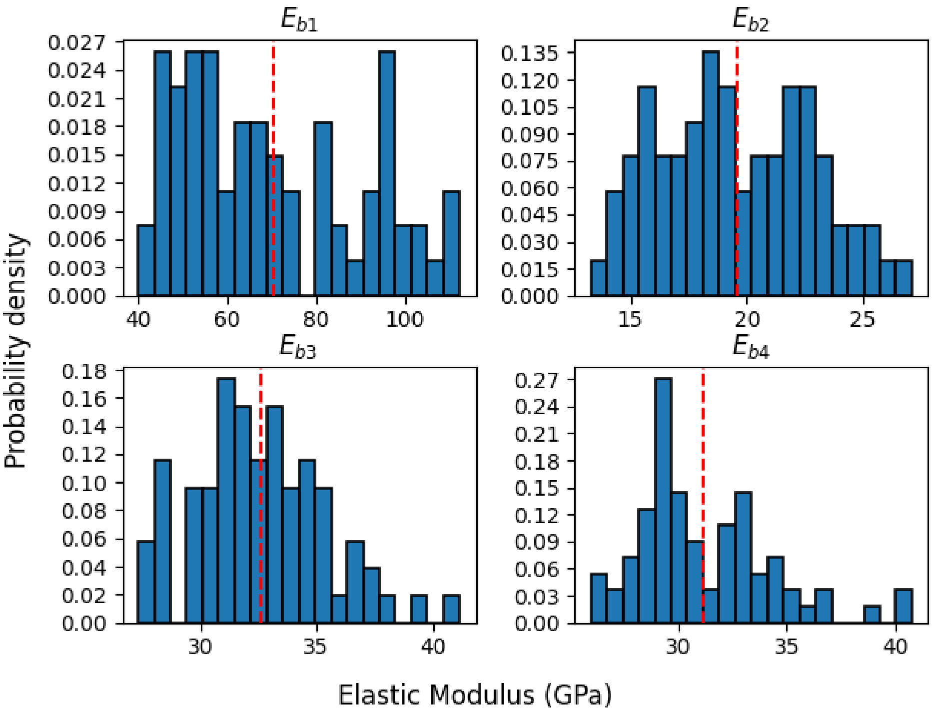

Figure 7: Probability density of updating parameters with mean values indicated.

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