Probabilistic-based assessment of existing steel-concrete composite bridges – Application to Sousa River Bridge

José C. Matos¹, Vicente N. Moreira², Isabel B. Valente³, Paulo J. S. Cruz⁴, Luís C. Neves⁵, Neryvaldo Galvão⁶

ISISE, Department of Civil Engineering, University of Minho, Guimarães, Portugal

¹ Assistant Professor, ISISE, Department of Civil Engineering, University of Minho, Campos de Azurém, 4800-058 Guimarães, Portugal. Phone: +351 253 510 200, E-mail: jmatos@civil.uminho.pt (corresponding author)

² PhD student, ISISE, Department of Civil Engineering, University of Minho, Campos de Azurém, 4800-058 Guimarães, Portugal. Phone: +351 253 510 200, E-mail: vicente.nmoreira@gmail.com

³ Assistant Professor, ISISE, Department of Civil Engineering, University of Minho, Campos de Azurém, 4800-058 Guimarães, Portugal. Phone: +351 253 510 200, E-mail: isabelv@civil.uminho.pt

⁴ Full Professor, Lab2PT, School of Architecture, University of Minho, Campos de Azurém, 4800-058 Guimarães, Portugal. Phone: +351 253 510 505, E-mail: pcruz@arquitectura.uminho.pt

⁵ Lecturer, Resilience Engineering Research Group, University of Nottingham, NTEC Building, NG7 2RD, UK. Phone: +44 0115 84 67365, E-mail: luís.neves@nottingham.ac.uk

⁶ PhD candidate, ISISE, Department of Civil Engineering, University of Minho, Campos de Azurém, 4800-058 Guimarães, Portugal. Phone: +351 253 510 200, E-mail: neryvaldo.galvao17@live.com

9 **ABSTRACT**

10 This paper presents a framework to assess the safety of existing structures, combining deterministic
11 model identification and reliability assessment techniques, considering both load-test and complementary
12 laboratory test results. Firstly, the proposed framework, as well as the most significant uncertainty sources
13 are presented. Then, the developed model identification procedure is described. Reliability methods are
14 then used to compute structural safety, considering the updated model from model identification. Data
15 acquisition, such as that collected by monitoring, non-destructive or material characterization tests, is a
16 standard procedure during safety assessment analysis. Hence, Bayesian inference is introduced into the
17 developed framework, in order to update and reduce the statistical uncertainty. Lastly, the application of
18 this framework to a case study is presented. The example analyzed is a steel and concrete composite bridge.
19 The load test, the developed numerical model and the obtained results are discussed in detail. The use of
20 model identification allows the development of more reliable structural models, while Bayesian updating
21 leads to a significant reduction in uncertainty. The combination of both methods allows for a more accurate
22 assessment of structural safety.

23
24 **Keywords:** Probabilistic-based assessment; Uncertainty sources; Steel-concrete composite bridges;
25 Existing structures; Bayesian inference; Model identification

1. Introduction

Structural assessment comprises all activities required to evaluate the condition of structures for future use, namely their safety. Several authors have used probabilistic-based procedures to assess the safety of existing structures, having shown that conclusions can be dramatically different from those obtained by using existing codes [1-6]. When assessing an existing structure, the available information regarding materials and geometry is usually limited. In order to overcome this drawback, model identification techniques may be used to estimate structural parameters based on measured performance, such as deflections. More recently, Bayesian inference was introduced to improve the quality of the probabilistic models for both resistance and effect of loadings, by using data collected from the structure under analysis [7, 8].

In this work, a probabilistic-based structural assessment framework, combining deterministic model identification and reliability assessment, is presented and tested on a composite steel-concrete bridge subjected to a performance load test. In the first step, a sensitivity analysis is used to identify the most influential parameters on the overall structural response at both service and ultimate loading conditions. Then, these parameters are found considering a model identification algorithm, which consists in an optimization procedure minimizing the difference between observed performance (e.g. vertical displacements collected during the load tests) and performance predicted using a non-linear numerical model. A convergence criterion which addresses the expected accuracy of experimental and numerical results, is considered [9]. This procedure yields a set of near optimal solutions, from which the best model is selected considering the probability of each solution occurring based on previous knowledge, followed by an engineering judgment procedure. A reliability assessment algorithm is then applied, considering the selected model. In some circumstances, complementary tests are developed to increase the reliability of the estimation of input parameters. An updated resistance probability density function (PDF) is computed through the use of a Bayesian inference procedure, and considering obtained data from performed complementary tests. The proposed framework is applied to the assessment of a steel-composite bridge built in Portugal.

2. Framework

The proposed safety assessment framework comprises two steps. Initially, a deterministic analysis is used to quantify the numerical model critical parameters, based on the combination of the results obtained by nonlinear finite element method (NL-FEM) models and data obtained with experimental tests and inspection or monitoring assignments. This procedure, denoted as model identification, searches for mean values of the mechanical and

geometrical properties of the structure, which is fundamental to define the probabilistic distributions of structural parameters that will be used in the reliability assessment of the structure.

The model identification procedure can be computationally expensive due to the need to evaluate a large number of NL-FEM models. To minimize the impact of this, a sensitivity analysis is used to identify the critical parameters, minimizing the complexity of the model identification procedure [10, 11]. This analysis consists of evaluating the fitness function variation with each input parameter [12]. An importance measure, b_k , is obtained for each parameter as,

$$b_k = \sum_{i=1}^n (\Delta y_{i,k} / y_{m,k}) / (\Delta x_{i,k} / x_{m,k}) \cdot CV_k \quad [\%] \quad (1)$$

where b_k is the importance measure of parameter k , $\Delta y_{i,k}$ is the variation in structural response parameter, $\Delta x_{i,k}$ is the variation of input parameter around its average value $x_{m,k}$, $y_{m,k}$ is the average response, n is the number of data points to be considered on the computation procedure and CV is the coefficient of variation of the assessed parameter. For the assessed model parameter importance measure, it is added or subtracted a standard deviation value to its mean value, keeping the remaining parameters values with their mean values. Then, each set of assessed parameter values is analyzed through structural analysis software, being then applied Equation (1) to obtain the parameter importance measure. After this procedure is applied to all model parameters, obtained importance measure values are normalized with respect to the highest one.

2.1. Model identification

Most likely values for critical parameters are evaluated using an optimization procedure, minimizing the difference between numerical and experimental data as:

$$f = \sum_{i=1}^n |y_i^{num} - y_i^{exp}| / \max(y^{exp}) \cdot 1/n \quad [\%] \quad (2)$$

where y_i^{exp} and y_i^{num} are the numerical and experimental result i , and n is the number of comparing points to be used in the algorithm, which usually corresponds to the maximum number of measurements at the real structure. If more than one measurement is made, independently of being the same type or not, then the standardized values should be added and divided by the total number of measurements, in order to obtain a final standardized value. As such, by normalizing the value of each parameter, it is possible to use different transducers, measuring different parameters in any section of the structure and load case (LC).

In order to limit the probability of overfitting, optimization is conducted, not to find the best solution, but

a group of solutions associated with a fitness under a given threshold. It is assumed that when computing the difference between numerical and experimental data, results associated with a fitness below the expected amplitude of errors are considered as optimal. The threshold value, ε , is calculated using the law of propagation of uncertainty [9], combining both measurement and modelling errors. Among different optimization methods, evolutionary strategies [13] have shown to be the most efficient and robust in this type of problem [12].

2.1.1. Quantification of error

When using a model identification procedure, two sources of errors should be considered: related to experimental measurements (difference between real and measured quantities in a single measurement) and numerical analysis (difference between the response of a given model and that of an ideal model which accurately represents the structural behavior). Consequently, when computing the difference between numerical and experimental data, results should be considered not as deterministic but as a range of values, following a Uniform PDF [9]. Based on the law of propagation of uncertainty [9] and assuming independent between error sources, the total error, u , can be estimated as a combination of measurement and modelling errors:

$$u = \sqrt{\sum_{i=1}^n (\partial f / \partial x_i)^2 \cdot u(x_i)^2} \quad (3)$$

where $u(x_i)$ is the error associated with each source of uncertainty and $\partial f / \partial x$ is the partial derivative of the fitness function in order to each component x . The partial derivative, in relation to each term, can be determined as $\partial f / \partial y^{num} = \partial f / \partial y^{exp} = 1 / \max(y^{exp})$. Once the expected error is computed, it is used: (1) to define the convergence criteria for the optimization algorithm; and (2) to define potential solutions. The optimization algorithm is considered converged if the improvement in the fitness of solutions between two generations, i.e., the convergence criterion, Δf , is smaller than a threshold value, ε , as defined by equation (4),

$$\Delta f = |f_{i+n} - f_i| \leq \varepsilon \quad (4)$$

with f_i and f_{i+n} , respectively, the fitness function values for generation i and $i+n$, and n the defined gap between two generations. In this case, a threshold value, ε , is a measure of accuracy, and it is considered to be equal to the total error, u , defined by equation (3).

2.1.2. Expert judgment procedure

Global optimization algorithms, as evolutionary strategies [13], when incorporated in model identification, result in a population of optimal or near optimal models. A decision regarding which of these set of parameters is the most accurate must be made using either experience or more robust algorithms. However, even in this latter case,

an expert judgment criterion might be necessary. In this work, the used algorithm is based on the principle that the most suitable model is that which assessed parameter values are close to initial mean values, unless some accidental situation is detected. Therefore, the likelihood of each model, f_d , is computed through:

$$f_d = \prod_{i=1}^n f(x_{id}) \quad (5)$$

where x_{id} is the value of the assessed parameter i , and $f(x_{id})$ is the PDF value for this parameter, assuming a PDF from bibliography [14] or based in experience. Then the product of all PDF values, for all assessed parameters, and for all extracted models, is computed (f_d). The updated model, from proposed model identification procedure, is that which presents the highest value. Herein, expert judgment is used, in combination with the likelihood of each model, to identify and select the most likely model [12].

2.2. Probabilistic-based assessment

In the second step of the proposed algorithm, reliability analysis is used to evaluate, from a probabilistic point of view, the structural safety condition through the computation of the reliability index or, the corresponding failure probability. Accordingly, the previously updated numerical model is converted into a probabilistic model by considering the randomness in model parameters. The use of gradient-based methods, like FORM, in conjunction with NL-FEM is complex, while simulation methods are simpler and robust, but computationally expensive. Variance reduction simulation techniques allow a significant reduction in the required number of simulations to compute a specific variance value. One of these techniques is the Latin Hypercube Sampling (LHS) [15]. Herein, Latin Hypercube Sampling (LHS) [15], with an in-built Iman and Conover correlation method [16], in order to consider structural parameters correlation, is used to sample numerical models. Then, for the set of obtained failure load factors, a distribution fitting procedure was performed, being obtained the resistance curve (R).

In safety assessment, a comparison between resistance, R , and loading, S , distributions is performed [17]. Accordingly, the failure probability, p_f , corresponds to the case in which the structural resistance is lower than the applied load. In this situation, the limit function may be defined by $Z(R,S) = R - S$. The correspondent reliability index, β , is given by $\beta = -\Phi^{-1}(p_f)$, being Φ^{-1} the inverse cumulative distribution function for a standard Normal distribution.

Bayesian methods provide tools to incorporate external information into data analysis process, with the aim of reducing the statistical uncertainty. As more data is collected, Bayesian analysis is used to update the prior into a posterior distribution. The Bayes theorem, which weights the prior information with evidence provided by new data, is the basic tool for the updating procedure. This way, the reliability index is continuously updated. The

structural safety assessment [14, 18] consists of computing the obtained reliability index and comparing it to a target value, β_{target} , proposed by existing standards [12].

3. Case study

The Sousa River Bridge, a composite steel-concrete bridge built in 2010, on highway A43, Gondomar to Aguiar de Sousa (IC24), in Portugal (Figure 1a), is analyzed herein. The bridge presents a total length of 202 m between abutments – from 6+722.50 km to 6+924.50 km – divided in four spans of 44 m and an extreme span, near abutment A2, of 26 m, as shown in Figure 1b. This bridge consists of two adjacent and independent structures, with an identical typology. The continuous deck is composed of a precast reinforced concrete slab supported on two longitudinal steel welded I-beams, as shown in Figure 1c. The longitudinal girders present a constant height of 2.0 m, with exception of the extreme span in which height varies with the deck inclination.

Transversally, these girders are fixed by stringers, evenly spaced of 5.5 m in each 44 m span, and of 5.2 m in the extreme span (Figure 2a and Figure 2b). These stringers are composed of IPE600 laminated steel profiles that are welded to half IPE600 steel profiles for connection with the longitudinal beams. These half profiles are welded to the longitudinal girder flanges. The reinforced concrete slab, the metallic girders and the stringers constitute a transversal and rigid framework.

Nelson headed studs [19], welded to the top flange of metallic girders, are used to connect concrete slabs and steel girders. To improve web stability, vertical steel plates were placed at thirds of the distance between stringers, in the regions that are close to the supports, see Figure 2. In both columns and abutments, symmetrical interior web plates were included. Over the supports, the IPE600 stringers are replaced by welded rectangular hollow sections, as represented in Figure 2a and Figure 2b. The reinforced concrete columns have a maximum height of 35.0 m (average of 25.0 m). A constant I-section is adopted, with maximum dimensions 2.50 m x 4.80 m. The abutments are independent from the rest of the structure, as expansion joints allowing longitudinal movement due to temperature and other environmental effects, were introduced in the bridge ends (Figure 1b). The pavement is bituminous, with 20 mm thickness of regularization and a 30 mm thickness wear layer. C30/37 concrete [20] was used for bridge foundations, abutments and columns, and C40/50 concrete [20] was used for precast slabs and cast *in-situ* concrete. S500 NR SD steel [21] was used for reinforcement bars and S355 steel [21] was used for steel profiles. S355J0 is used in plates with a thickness lower than 50 mm, S355J2 is used for plates with a thickness between 50 and 75 mm, S355K2 for plates with a thickness between 75 and 90 mm and S355ML for plates between 90 and 110 mm. For laminated steel profiles, S355J0 is used. An elasticity modulus of 210 GPa (reinforcing steel,

$E_{s,b}$, and steel profile, $E_{s,p}$, modulus of elasticity) was considered for all steel materials. The headed studs are produced of S235 J2 G3 + C450 steel [19], with a yield strength (f_y) of 350 MPa, a ultimate limit strength (f_u) of 450 MPa and a limit strain (ϵ_{lim}) of 18 %.

3.1. Load test

3.1.1. Description

In order to evaluate the bridge behavior before entering in service, a load test was carried out twenty eight days after the last concrete casting [22]. Both vertical displacement and temperature were measured during the test through an automatic data acquisition system. Load-tests took place between the 9:18am and 12:31pm, being the overall load-test time of 3 hours and 14 minutes. The temperature was measured at both inferior and superior faces of the deck, using PT100 resistive detectors. All transducers are electric based and were tested and calibrated in laboratory, before the load test. The vertical displacement measurements were measured with reference to the ground level, using invar wires, and linear variable differential transformers (LVDTs). These transducers present a precision of 0.05 mm (maximum value) for a measurement field of ± 25 mm (full scale), corresponding to a linearity of 0.10%. Figure 3a shows the location of all sensors. A frequency of 10 Hz was designed for registering the vertical displacement data. Two displacement transducers were installed in span A1 - C1, designated by VD1 and VD2, and other two at span C1 - C2, denoted as VD3 and VD4 (Figure 3a). The load was applied using four identical vehicles (with four axles), each vehicle loaded with sand in order to obtain a total weight close to 32 tons. The two front axles support 40% (20% each – 6.4 ton) of the load, while the two rear axles support 60% (30% each – 9.6 ton) of the total weight [23-26].

Three different load cases (LC) are considered, as represented in Figure 3b: (1) LC1: maximum displacement in span A1 - C1; (2) LC2: maximum displacement in span C1 - C2 and rotation at C1; and (3) LC3: maximum rotation at C2. In each situation, the vehicles are immobilized on the bridge deck for 5 minutes, eliminating any dynamic effects while avoiding environmental effects (temperature, humidity). The temperature effects may be neglected, as it was verified that during the test the temperature was kept almost constant, significantly limiting its impact on obtained results [22].

3.1.2. Experimental results

The results gathered on the unloaded bridge are used to control the temperature effect on the structure and in the monitoring system along the test. The temperature effects may be neglected, as it was verified that during the test the temperature was kept almost constant, significantly limiting its impact on obtained results [22]. The vertical

displacements registered are shown in Table 1. The maximum vertical displacement was registered at the extreme span A1 - C1. Since all spans have the same geometry, the small rotation stiffness of the abutment makes this span critical in terms of vertical displacements.

3.2. Numerical analysis

3.2.1. Numerical model

In order to evaluate the bridge performance, a numerical model was developed using ATENA® nonlinear structural analysis software [27]. The bridge is modelled using a 2D plane stress model elements. Vertical displacements are restricted at all supports, while deformation of piers is modelled using linear springs.

The precast slab presents a non-uniform geometry (Figure 1c). This non-uniformity is considered in the numerical model by introducing several concrete layers. As the number of layers increase, the model's geometry becomes more accurate, but also more complex. For the purpose of this paper, two rectangular layers are used. The reinforcing steel is considered to be embedded in precast concrete slab [12].

Concrete material was described by a SBETA material model, which is defined by the elasticity modulus, E_c , the compressive strain at compressive strength, ε_c , the compressive strength, f_c , the tensile strength, f_t , the critical displacement, w_d , and the fracture energy, G_f [27]. Steel was modeled by a bilinear with hardening Von Mises material model, being described by the elasticity modulus, E_s , the yield strength, σ_y , the limit strain, ε_{lim} , and the ultimate strength, σ_u [27]. Both these constitutive material laws are detailed at ATENA® library [27].

There are two distributions of headed studs along the bridge: low (groups of 6 studs) and high (groups of 10 studs). The space between each group of studs, 0.50 m, is the same for both low and high stud densities [28] (Figure 2). From the models available in ATENA [27] for interface elements, the Mohr-Coulomb [27] was selected, as it allows the definition of a very rigid interface until the strength of the connection, corresponding to the cohesion (c) in the Mohr-Coulomb model, is reached. After this, the tangential stiffness (K_{TT}) becomes very low. The small impact of the normal force on the interface is modelled by using a small friction angle (ϕ). It is assumed that the connection between steel and concrete is very rigid until plastification of the head studs, given by the tensile strength ($f_{t,stud}$). After this, the normal stiffness (K_{NN}) drops significantly. Accordingly, both the compression stiffness and the tensile strength parameters are assumed to present high values in order to guarantee the full composite behavior. The cohesion is computed based on the stud maximum load capacity and on expressions from EN 1994-1-1 [29], being obtained the values of 3.24 and 1.94 MPa for the situations of high and low density of studs, respectively (see Figure 2). According to EN 1994-1-1 [29], the characteristic stud maximum

load capacity is 102.07 kN (P_{Rk}), and the mean value ($P_{Rm} = 113.41$ kN) is obtained by dividing the previous value per 0.90 [29]. By considering this value for one stud, it is then possible to determine the cohesion value based on the number of studs and their spacing [29], i.e., by multiplying the mean stud load capacity by the number of studs per unit area of interface. The shear stiffness is computed based on the stud stiffness value. The stud stiffness value is very difficult to quantify as it depends from several factors [30], such as the type of used concrete and its modulus of elasticity, as well as on the stud's dimensions. Therefore, results obtained from experimental tests (as the push-out tests described in EN1994-1-1 [29]) with the same type of concrete and stud geometry might be used to quantify this parameter. In this case, the value of 325 kN/mm was defined based in expert knowledge, gathered from tests previously developed by the authors [30], and in existing literature [31, 32]. By taking this value into consideration, it is then possible to determine the value of the shear stiffness, 9.29×10^3 and 5.57×10^3 MPa/mm, respectively, for high and low density of studs.

The finite element mesh is mainly composed of quadrilateral elements. Additionally, interface elements are used to simulate the steel to concrete interface and spring elements try to simulate the horizontal support conditions. Reinforcement bars are modelled using nonlinear truss elements embedded in the concrete slab, in order to simulate the web reinforcements and both top and bottom flanges of the steel profile, resulting in a simpler and lighter numerical model.

The trucks are modelled as a load per axle. The load position varies with the LC. These vehicles are loading half of the bridge cross section, considering the respective symmetry. The dead load is firstly applied in 10 steps, with a factor of 0.1, and then the vehicle load is added in 10 steps. The differences in vertical displacements between the loaded and unloaded structure are compared to the experimental values in Table 1. The structure is then loaded up to failure by progressively increasing the vehicle load.

3.2.2. Numerical results

After the bridge is modelled, a calibration procedure is performed by comparing numerical results with those obtained on field test, allowing to validate the developed model and considered assumptions. In order to do that, the obtained numerical results given by Figure 4 and Figure 5 are analysed in detail.

Figure 4a presents the bridge vertical deformation for the dead load only (step 10). The most critical sections are located at the interior support and at 40% of the span length, respectively, for negative and positive bending moment.

Figure 4b shows the bridge deformation for dead load plus live load for LC1, step 20 (vehicles are located at the first span). Figure 4c represents the beam deformation for load step 70 close to collapse. By comparing on Figure 4b it is possible to verify an increase on the first span deformation. Figure 4d presents the bridge deformation for step 186 (bridge collapse). By comparing this figure with Figure 4c, it is possible to verify a higher deformation at first span while all the others are being progressively relieved. The collapse mechanism is characterized by two plastic hinges, respectively, at column C1 (step 70) and at 40% of the span length (step 186). Applied loads are redistributed from the first to the second hinge.

Figure 4e shows the bridge deformation obtained for LC2, in which the vehicles are positioned in the second span. In this situation the collapse mechanism is defined by three hinges, respectively, at column C1 and C2 (step 70) and at middle span (step 104).

Figure 4f shows the obtained bridge deformation with LC3, in which the vehicles are positioned in the third span. In this case, the collapse mechanism is defined by three hinges, respectively, at column C2 and C3 (step 70) and at middle span (step 210).

Strain values on the first span are shown in Figure 5a. Localized cracking is detected close to supports, where the concrete slab and part of the steel profile are in tension. Figure 5b shows the stresses in the interface. Under sagging moment, the interface stress value is 0.66 MPa (low density) while for hogging bending moment region this value is 1.44 MPa (high density). Such results are far from the interface cohesion values computed in Section 3.2.1.

Figure 5c shows the strains values at the critical span. An increase in cracking at hogging bending moment region, above the support, is observed. For the sagging bending moment region, part of the concrete slab is in compression and part is in tension, which means that the neutral axis moved in the upward direction. As shown in Figure 5d the maximum interface stresses is 0.93 MPa (low density) under sagging moment and 1.47 MPa (high density) in the hogging moment region, which are lower than the interface cohesion values.

Figure 5e shows the strain for the critical span, in the support region. The steel profile is partly in tension and partly in compression. The maximum tensile strain is verified at sagging bending moment region, at the bottom fibers of the steel profile. The steel profile is, in this region, in tension and the concrete slab is partly in compression and partly in tension. In this situation, localized cracking, due to concrete crushing, is detected at sagging bending moment region. Figure 5f presents the interface tangential stresses. In this situation, a value of 1.37 MPa (lowest

density) is obtained for sagging moment and a value of 2.20 MPa (highest density) for hogging bending moment, which are closer to the interface cohesion values.

The strain values presented in Figure 5g show that cracking in the concrete slab occurs in both hogging and sagging bending moment regions. Over the supports, the concrete slab is completely in tension, whereas the steel profile is partly in tension and partly in compression. The steel profile and a portion of the concrete slab are in tension, which indicates that the neutral axis is positioned in the top fibers. Figure 5h presents interface stresses for the same load step. A maximum value of 1.62 MPa (low density) is verified for positive bending moment region and a maximum value of 3.24 MPa (high density) is measured for negative bending moment region. This means that the cohesion value for high density region is attained and a redistribution of tangential stresses is produced.

The analysis stops, for the three LCs, when the reinforcement limit strain at hogging bending moment region is reached. This corresponds to a bending failure mode with concrete crushing, and yielding of both reinforcement bars and steel profile. Moreover, it is verified that the ultimate moment depends on the LC considered. It also varies with the parameter values defined. In this situation, the developed model will be applied in a probabilistic analysis, considering different LCs, for which the parameter values are randomly generated. Therefore, a maximum number of 300 load steps is established, in order to take into account all possibilities.

Table 2 presents the computed displacements at VD1 and VD2 for the three considered LCs. In this situation, there are four comparison points (VD1 and VD2 correspond to VD1*; VD3 and VD4 correspond to VD2*) and three LC, which results in twelve components. The error between numerical and experimental data, as presented in Table 1, is computed for each case. It is important to note that the developed numerical model is less stiff than the real structure.

Figure 6 presents the load-test vertical displacements and temperature. Based on these experimental results, and in the numerical results presented in Table 2, it is possible to confirm the good correlation between both, with the numerical vertical displacements being, in average, 17.44% higher than the experimental ones. Sousa *et al.* [23] described this difference and justified it as a result of considering the concrete elasticity modulus (E_c) based on EN 1992-1 [20], which is an underestimation of the real value. Also, neglecting the reinforcements at support sections and at bridge span, as well as all the other non-structural elements (e.g. safety guards, cornices, etc.), lead to a less stiff structure. These modelling assumptions result in a conservative assessment, associated with a lower

reliability index and, therefore, a higher failure probability. Despite that, a good compromise between cost and accuracy is achieved.

3.2.3. Sensitivity analysis

Sensitivity analysis is performed to identify the critical parameters in the structural performance of the bridge, considering the three LCs and both service and failure loadings. Studied parameters are related to material, geometry and mechanical properties. If importance measure (b_k) defined in equation (1) is equal or higher than 10% (b_{lim}), the corresponding parameter will be considered as critical.

A total of 20 parameters are considered as follow: (a) concrete modulus of elasticity (E_c), tensile strength ($f_{t,c}$), compressive strength (f_c), fracture energy (G_f) and concrete specific weight (γ_{conc}); (b) reinforcement steel yield strength ($\sigma_{y,l}$), ultimate limit strength ($\sigma_{u,l}$) and strain ($\varepsilon_{lim,l}$); (c) laminated steel profile yield strength ($\sigma_{y,p}$) and hardening modulus (H_p); (d) steel-concrete interface - shear stiffness (K_{TT}) and cohesion (c); (e) concrete slab width (b_{slab}) and height (h_{slab}); (f) laminated steel profile web thickness (b_{web}), and both top ($A_{fl,sup}$) and bottom ($A_{fl,inf}$) flanges area; (g) reinforcing steel area ($A_{s,l}$); (h) top concrete cover (c_{sup}); (i); and (j) pavement weight (p_{pav}).

The evaluated parameters and corresponding CVs and standard deviations (σ), used to compute the importance measures are given in Table 3. For some of these parameters, such values are provided in bibliography [14, 33]. However, for others parameters, it is possible to sampling the input parameters, to compute the value of interest parameter through provided analytical expressions by bibliography [21, 29], and perform a fitting curve procedure to obtain the CV and σ . Thus, and following the previous procedure, the CV and σ are obtained for the following parameters: (1) for the steel profile hardening modulus (H_p), they are computed through the CV of yield strength, limit strength and limit strain; (2) for the interface parameters (K_{TT} and c), they are computed through the CV of concrete [20] and headed stud material and geometry [19] parameters; and (3) for the pavement self-weight (p_{pav}), a combination of the CV of the pavement thickness and of bituminous specific weight is considered.

The results obtained from the sensitivity analysis under service loads are shown in Figure 7. The importance measures are normalized relative to the concrete tensile strength ($f_{t,c}$). For low intensity loadings, concrete is stressed in the elastic region and its elastic properties are critical. The influence of both reinforcing steel ($\sigma_{y,l}$, $\sigma_{u,l}$ and $\varepsilon_{lim,l}$) and laminated steel profile ($\sigma_{y,p}$ and H_p) material properties is very low. In this situation, the critical parameters are: (1) concrete elasticity modulus (E_c); (2) concrete tensile strength ($f_{t,c}$); (3) reinforced concrete slab height (h_{slab}); (4) concrete density (γ_{conc}); and (5) pavement weight (p_{pav}). Accordingly, from 20 parameters, only

5 are considered to be critical.

Obtained results, from sensitivity analysis under failure loads, are shown in Figure 8a, except for the results for the steel profile yield strength ($\sigma_{y,p}$), which are given in Figure 8b. The computed importance measures are normalized in relation to the steel profile yield strength of plate 2 ($\sigma_{y,p2}$). In this case, a large variability in importance measure values is obtained for the six assessed steel plates, being each yield strength importance measure considered independently.

According to Figure 8b, the laminated steel profile yield strength ($\sigma_{y,p}$) presents a high importance on the structure behavior. Such influence is stronger in plate 1 ($\sigma_{y,p1}$) and plate 2 ($\sigma_{y,p2}$) located in the first and second span, for the considered LCs. Obtained results indicate as critical parameters: (1) concrete elasticity modulus (E_c); (2) concrete tensile strength ($f_{t,c}$); (3) concrete compressive strength (f_c); (4) reinforcing steel yield strength ($\sigma_{y,l}$); (5) yield strength for plate 1 ($\sigma_{y,p1}$) and for plate 2 ($\sigma_{y,p2}$). Therefore, from 20 evaluated parameters, 5 of them are considered as critical.

3.3. Model identification

In this stage, the most likely values for the parameters identified in the previous sections through a model identification process using vertical displacements under service loads. Two additional parameters for which there is limited information (horizontal spring stiffness at supports, k_1 and k_2) are also included.

An evolutionary strategies algorithm in its plus version is used to find the optimal parameter values [13]. A parent population, μ , and a parent for recombination, ρ , of 10 individuals, and an offspring population, λ , of 50 individuals were defined. The algorithm will run until the fitness function criteria is reached. The generation gap, n , used for the fitness function tolerance criterion was established as 2% of the maximum generation's number (1000). Therefore, the improvement on minimum fitness value is evaluated from a gap of 20 generations.

The fitness function relates numerical and experimental vertical displacements, at 17 m and 66 m of the bridge length, for the three LCs considered. In order to perform the model identification, it is necessary to determine the threshold value, ε , that defines the fitness function convergence criteria. Thus, it is first necessary to identify and quantify the different sources of error [12, 23-25, 34-36], see Table 4.

The fitness value criterion establishes that its improvement (Δf) should be less than or equal to a threshold value (ε), which can be understood as the model identification procedure precision [12, 37]. By applying the law

of propagation of uncertainty [9], a threshold value (ε) of 25.84% is obtained.

The model identification procedure is executed five times, considering different randomly generated starting points, as to limit the probability of underperforming results. Each analysis provides a final population of 10 models, resulting in a total of 50 models. Based on the principle that the most suitable model is that with smaller deviation from the initial mean values (see Table 5), unless some accidental situation is detected, the best model is that which presents the highest likelihood value [12, 37]. Figure 9 presents the obtained normalized values for the maximum likelihood for all the selected models. In this situation, model 20, from the second analysis, presents the highest value, being thus the selected model.

Table 5 indicates initial and identified values for the critical parameters considered in the model identification procedure, showing that the used concrete presents a higher quality than initially expected. With respect to horizontal spring stiffness results indicate that the identified k_1 and k_2 values are respectively lower and higher, respectively, than the initial prediction. The slab height (h_{slab}) is slightly higher, around 3%, than the design value. The concrete self-weight (γ_{conc}) is practically unchanged. However, the obtained pavement load (p_{pav}) is 15% higher than the design value. This might be due to the irregularity in bituminous thickness.

The comparison between the fitness function, considering initial and identified critical parameters value shows a reduction in error from 67.33% to 53.74%, being an improvement of more than 20%. Table 6 presents VD1* and VD2* displacement values before and after model identification for model 20. The results show that very small errors are obtained for all sensors and load, with the exception of VD1* under LC3.

3.4. Probabilistic analysis

The numerical model previously developed is now enhanced by defining the critical parameters as random variables. Non-critical parameters are considered to be deterministic. The assigned PDF and CV for each critical parameter are given in Table 3. After generating the random values for each critical parameter, a set of failure load factors is obtained for each LC. A curve fitting procedure is then developed in order to determine the most suitable PDF as described in section 2.2. According to this process, the Normal distribution is considered to be that which better represents the obtained results.

3.4.1. Complementary tests

During construction, complementary tests were developed in order to control the quality of the concrete used in the precast slab and to classify the structural materials used (concrete, reinforcing steel and steel used in

laminated steel profiles). In order to assess the concrete material quality, uniaxial compressive tests were performed in cubic specimens according to NP EN 13747 [38] for precast concrete slab, and according to NP 206-1 [39] for cast in-situ concrete. The reinforcing steel quality was controlled through uniaxial tensile tests, according to LNEC E 456 specification [40]. The steel profile quality was assessed through uniaxial tensile tests, according to EN 10002-1 [41].

The results obtained are shown in Table 7. Regarding concrete, obtained results indicate that the quality is slightly superior than the predicted, confirming the model identification results. With respect to reinforcing steel, results confirm the steel quality considered in the design phase. The steel profile material quality is slightly superior to that considered in design.

3.5. Bayesian inference

The results obtained from complementary tests are then used to update the critical parameters, through a Bayesian inference algorithm [37, 42, 43]. The main objective of Bayesian inference algorithm is the consideration of new collected data into analysis procedure, in order to reduce the statistical uncertainty of each assessed parameter [12, 37, 42, 44]. This is achieved by the Bayes theorem, which weights the prior information and new collected data (likelihood), obtaining a posterior distribution. The prior distributions, which are those that have as a mean value the initial parameter value or the ones obtained from model identification, may be updated. An important aspect of these techniques is the choice of the adopted prior distribution. A non-informative prior is useful when no prior information is available, being, however, necessary to verify if the computed posterior distribution is proper [42]. The Jeffrey's non-informative prior is a good choice for the non-informative prior distribution, once it returns a proper posterior distribution. On the contrary, if some data is available, then the informative prior may be employed instead. In this situation, conjugate families are advantageous, from a mathematical standpoint, once the posterior distribution follows a known parametric form. A more detailed explanation is given at [12, 37]. Accordingly, four different analyses are respectively developed: initial values (Analysis 1); model identification values (Analysis 2); initial values + Bayesian inference (Analysis 3); and model identification values + Bayesian inference (Analysis 4). The mean values (μ) from the initial model are those considered in the design phase, while the CVs are those presented in Table 3. The updated model is respectively based on the initial one, but considering the mean values (μ) obtained from model identification (Table 5). In this case, the CVs are obtained in a similar way by using the CVs from Table 3.

Bayesian inference procedure was developed by considering an informative and a non-informative

(Jeffrey's) prior, being the adopted posterior PDF that with the lowest standard deviation [12, 37]. Table 8 gives the probabilistic models for the critical parameters resulting from each of the analysis performed.

The analysis of these results confirms the complementary tests, once the obtained mean is higher than the initial prediction. The uncertainty is lower than the initial one, once the CV has been reduced.

3.6. Loading curve

In order to assess the bridge safety, the resistance and loading PDF must be compared. In this analysis, the loading PDF is defined based on load model LM71, which is the standard load model for normal roadway traffic presented by the European code [45]. The LM71 is a road bridge static vertical load model intended for the determination of road traffic effects, being composed by double-axle concentrated loads and uniformly distributed loads. This model can be used on both local and global verification of bridge elements.

The considered LCs will correspond to those established at the load tests [22]. The load model LM71 is modelled as a Gumbel distribution, considering a 95th percentile and a return period of 50 years [33]. Additionally, a CV of 15% is adopted [33], corresponding to a mean value of the total applied load 4939.40 kN and a standard deviation of 740.91 kN. The loading values are then randomly generated through a LHS algorithm.

3.7. Safety assessment

The safety assessment consists of comparing resistance (R) and loading (S) PDF for the bridge in analysis, according to the limit state function ($Z=R-S$). The load model is introduced in the previous developed numerical models [27] and then, the bridge is loaded up to failure. This analysis is developed for each LC and for several randomly generated models. Then, a curve fitting procedure is developed to compute the resistance PDF parameters. Obtained mean (μ) and standard deviation (σ) values are given in Table 9, being then computed the failure probability, p_f , and the corresponding reliability index, β , as a comparison between the resistance and the effect of loads curves.

An overall analysis of those results allows to conclude that, for the considered LCs, and for the developed numerical model, the overall bridge resistance is substantially higher than the applied load model, by comparing the resistance PDF mean of each analysis, from Table 9, with the loading PDF mean (4939.40 kN). By comparing the obtained resistance PDF for the four probabilistic models, it is possible to conclude that model identification practically did not change the obtained results. This is due to the fact that the majority of assessed parameters in model identification, in service phase, do not influence the bridge behavior up to failure. The application of a

Bayesian inference procedure leads to an increase in the failure load, confirming an additional structural resistance capacity which was not initially identified. When evaluating the CV, it is possible to conclude that both initial and model identification models provide similar results. A slight decrease on this value is verified with the Bayesian inference procedure. This is due to a decrease on the standard deviation value of some of the updated parameters (Table 8).

The values obtained with this safety assessment procedure, respectively, the probability of failure, p_f , and the reliability index, β , are indicated at Table 9. By analyzing these values, it is confirmed what was previously specified, namely: (1) obtained reliability index (β) values are high according to fib target reliability values [46]; (2) obtained results from the probabilistic numerical model, considering the initial and the identified parameter values, are close; and (3) the application of a Bayesian inference procedure increases the reliability index (β).

According to fib Task Group 5.1 [46], and considering that an overall analysis of the structure is developed, it is possible to conclude that the assessed bridge is in very good situation ($8 < \beta \leq 9$). This is in agreement with Tabsh and Nowak [47] guidelines, which indicate that a β -value higher than 5-6 corresponds to a structure with a very good performance.

4. Conclusions

This paper presents a framework for the probabilistic-based assessment of existing structures. This framework accurately evaluates the structural safety and condition, contemplating all sources of uncertainty. It is composed of two main steps. In the first step the numerical model is updated through a model identification procedure. In the second step, the updated deterministic model is converted into a probabilistic model and a probabilistic analysis is developed. Finally, each parameter distribution may be updated, as complementary data is obtained through a Bayesian inference algorithm. The developed algorithm presents a high computational cost. In order to minimize it, a sensitivity analysis, in which the most important parameters are selected, should be previously applied.

The developed probabilistic assessment framework is applied to a composite steel-concrete bridge (Sousa River Bridge). The developed numerical model and a sensitivity analysis, executed both under service and ultimate loading conditions, are also presented. Then, the model identification algorithm is applied with the results obtained during the load test in the service phase. A probabilistic analysis is further developed by introducing randomness in each critical parameter. A Bayesian inference procedure is also applied to update some parameters distributions

with results from complementary tests. The obtained results are used to evaluate the reliability of the bridge.

The main conclusions taken from developed framework and its application are: (1) model identification in service phase improves the numerical model results, by predicting more accurately the load-deflection behavior in around 20%. In fact, as the load test aims at not damaging the structure, information gathered can only inform on parameters relevant to in-service condition rather than ultimate states; (2) the model identification influence is small when comparing all probabilistic models, due to the fact that the majority of the assessed parameters in service phase do not influence the bridge behavior in failure phase. In this sense, an additional model identification process could be used, but one that considers complementary tests results for critical parameters describing failure region; (3) complementary tests, as non-destructive or material characterization tests, are recommended when model identification is only performed in service phase; (4) obtained values from model identification confirmed that used materials quality is close, or slightly higher, than the initial estimates; (5) the Bayesian inference increases the accuracy of probabilistic models by reducing the statistical uncertainty, once all posterior computed CVs are lower than the initial ones.; and (6) the bridge failure load was higher than the expected, considering the mean and the nominal values from design. In line with these conclusions, the present work allowed the prediction of the structural behaviour of Sousa River bridge with higher accuracy, based on collected data from field tests and by applying the developed framework. Furthermore, the fitness function allows to contemplate various measurement sources at the same time, making the model identification more robust and precise, particularly when studying the interface, for which large uncertainty exists. Additionally, Bayesian Inference allows the continuous updating of the reliability index, based on new information from monitoring devices. Accordingly, with this framework it will be possible to assess the structural behaviour through a more robust, accurate and continuous process. Therefore, the obtained results pointed out a relevant improvement in reliability assessment, allowing a more fundamental decision regarding the repair and strengthening of existing structures.

Although the presented framework was applied to a composite steel-concrete bridge, it is possible to employ it to any type of structures, such as reinforced concrete [37] or masonry bridges, providing basis for more robust and accurate decision-making analysis. Also, the application of the presented probabilistic-based framework to such a massive structure allows the identification and consideration of additional uncertainties and errors, which cannot be considered in controlled environments (e.g. laboratory tests), enhancing the advantages of the developed framework.

Additionally, to this work, it is pointed out the connection between service and failure regions as a topic of future developments, since most of the parameters obtained in service cannot be used for failure. Thus some dynamic

tests or non-destructive tests would be useful to characterize some structural parameters in service region, which can be correlated to others on failure regions. Another relevant drawback is the computational cost, especially when applied to more complex structures, such as the Sousa River bridge. Regarding the field tests, this analysis was performed for a particular load configuration, i.e., with a well-known and particular load magnitude and position. For the operation stage, the load model will also change, and real time vehicle measurement (counting and weighting) would be relevant for performing the structural assessment on operation stage.

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a)

b)

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a)

b)

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a)

b)

c)

d)

e)

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635

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Figure 7. Sensitivity analysis under service loads [12].

a)

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653 Table 1. Registered vertical displacements*† [22].

LC	VD1 [mm]	VD2 [mm]	VD3 [mm]	VD4 [mm]
LC1	16.01 (0.25)	14.48 (0.50)	-4.11 (-)†	-3.51 (-)†
LC2	-4.10 (-)†	-3.84 (-)†	14.00 (0.20)	13.40 (0.12)
LC3	1.86 (-)†	1.84 (-)†	-3.47 (-)†	-2.92 (-)†

654 *Negative value corresponds to a displacement in upward direction. The CV of displacements, in percentage [%],
655 is provided between brackets.

656 †Non-available data on the load-test report [22].
657

658 Table 2. Obtained displacement values for calibrated model[†] [12].

LC	VD1* [mm]	Error [%]	VD2* [mm]	Error [%]
LC1	17.77	16.86	-5.09	34.43
LC2	-4.90	23.56	14.32	4.58
LC3	1.40	24.32	-4.82	51.99

659 [†]Negative value corresponds to a displacement in upward direction.

660

661 Table 3. Parameter variation in sensitivity analysis [14, 19, 20, 33].

Parameter	PDF	CV [%]	Parameter	PDF	CV [%]	Parameter	PDF	CV [%]	Parameter	PDF	CV [%]	Parameter	PDF	σ [mm]
Concrete elasticity modulus (E_c)	Normal	10.00	Reinforcing steel yield strength ($\sigma_{y,l}$)	Normal	5.00	Steel profile hardening modulus (H_p)	Normal	20.00	Laminated steel profile dimensions - bottom flanges area ($A_{fl,inf}$)	Normal	2.00	Reinforced concrete slab width (b_{slab})	Normal	5.00
Concrete tensile strength ($f_{t,c}$)	Normal	20.00	Reinforcing steel limit strength ($\sigma_{u,l}$)	Normal	5.00	Steel to concrete interface - shear stiffness (K_{TT})	Normal	10.00	Reinforcing steel area ($A_{s,l}$)	Normal	2.00	Reinforced concrete slab height (h_{slab})	Normal	10.00
Concrete compressive strength (f_c)	Normal	10.00	Reinforcing steel limit strain ($\varepsilon_{lim,l}$)	Normal	15.00	Steel to concrete interface - cohesion (c)	Normal	12.50	Concrete specific weight (γ_{conc})	Normal	3.00	Laminated steel profile web thickness (b_{web})	Normal	1.00
Fracture energy (G_f)	Normal	10.00	Steel profile yield strength ($\sigma_{y,p}$)	Normal	5.00	Laminated steel profile dimensions - bottom flanges area ($A_{fl,sup}$)	Normal	2.00	Pavement weight (p_{pav})	Normal	10.00	Superior reinforcement concrete cover (c_{sup})	Normal	1.50

662

663 Table 4. Errors: sources and quantification.

Error sources		Quantification method	Error [%]
Experimental uncertainties	Sensor accuracy	Manufacturer (includes cable and acquisition equipment losses)	$1.71 \cdot 10^{-1}$ (VD1 and VD2); $2.98 \cdot 10^{-1}$ (VD3 and VD4)
	Stability	Static load test (null fatigue problems)	$\rightarrow 0.00$
	Robustness	Short term test (null environmental effects)	$\rightarrow 0.00$
	Load positioning	Test assembly perfectly controlled	$\rightarrow 0.00$
	Load intensity	Precisely measured	$\rightarrow 0.00$
Numerical uncertainties	Finite element method	Based on preliminary study (by comparing to a refined mesh model)	1.80% (VD1*) ^a ; 9.77% (VD2*) [*]
	Inaccurate assumptions	Based on preliminary study (by comparing to a short load step model)	$3.53 \cdot 10^{-1}\%$ (VD1*) ^a ; 2.81% (VD2*) [*]
	Model exactitude	Model “as built”	$\rightarrow 0.00$
	Considered hypothesis	Introduction of five reinforced concrete slab layers	3.64% (VD1* and VD2*)
		Introduction of a medium density region at interface	5.75% (VD1* and VD2*)
		Introduction of a pavement macro element	1.82% (VD1* and VD2*)
		Removing the web reinforcements	1.07% (VD1* and VD2*)

664 ^aValues calculated for service phase [12].

665 Table 5. Obtained initial and model identification parameter values for service region [12].

Numerical model			Initial value	Model identification
Parameter	Concrete elasticity modulus (E_c)	[GPa]	35.00	35.98
	Concrete tensile strength ($f_{t,c}$)	[MPa]	3.50	4.03
	Horizontal spring stiffness at support (k_1 – C1 axis)	[kN/m]	56.69	36.98
	Horizontal spring stiffness at support (k_2 – C2 axis)	[kN/m]	9.93	12.90
	Reinforced concrete slab height (h_{slab})	[m]	0.15	0.16
			0.25	0.25
	Concrete specific weight (γ_{conc})	[kN/m ³]	24.00	24.34
	Pavement weight (p_{pav})	[kN/m]	6.50	7.38
			6.81	7.73

666

667

668 Table 6. Obtained displacement values for calibrated model considering model identification[†] [12].

LC	VD1* [mm]		Error [%]	VD2* [mm]		Error [%]
	Before model identification	After model identification		Before model identification	After model identification	
LC1	17.77	15.43	5.02	-5.09	-3.57	7.87
LC2	-4.90	-3.64	8.31	14.32	12.06	11.97
LC3	1.40	1.04	43.78	-4.82	-3.48	8.92

669 [†]Negative value corresponds to a displacement in upward direction.

670

671 Table 7. Obtained material properties from complementary tests [12].

Concrete (no. samples = 10)										
Parameter		Initial value			Mean value (μ)			Standard deviation (σ)		
Elasticity modulus (E_c)*		[GPa]	35.00			37.04			0.63	
Tensile strength ($f_{t,c}$)*		[MPa]	3.50			3.98			0.14	
Compressive strength (f_c)*		[MPa]	48.00			56.86			3.21	
Reinforcing steel material (no. samples = 10)										
Parameter		Initial value			Mean value (μ)			Standard deviation (σ)		
Yield strength ($\sigma_{y,l}$)*		[MPa]	560.00			562.94			21.42	
Limit strength ($\sigma_{u,l}$)		[MPa]	644.00			645.49			20.36	
Limit strain ($\varepsilon_{lim,l}$)		[‰]	80.00			96.39			35.78	
Steel profile material (no. samples = 10)										
No. of steel plate	Thickness	Yield strength ($\sigma_{y,p}$)* [MPa]			Tensile strength ($\sigma_{u,p}$) [MPa]			Tensile strain ($\varepsilon_{lim,p}$) [%]		
	[mm]	Initial Value	Mean value (μ)	Standard deviation (σ)	Initial Value	Mean value (μ)	Standard deviation (σ)	Initial Value	Mean value (μ)	Standard deviation (σ)
1*	≤ 16	355	388.32	17.52	470-530	540.39	18.18	20-22	28.71	2.33
2*	≤ 40	345	377.38	17.02	470-530	540.39	18.18	20-22	28.71	2.33
3	≤ 60	335	366.44	16.53	470-530	540.39	18.18	19-21	27.35	2.22
4	≤ 80	325	355.51	16.04	470-530	540.39	18.18	18-20	25.98	2.11
5	≤ 100	315	344.57	15.54	470-530	540.39	18.18	18-20	25.98	2.11
6	≤ 110	295	322.69	14.56	450-600	567.41	19.09	18-18	24.61	2.00

672 *Data considered as likelihood in Bayesian inference.

673

674 Table 8. Input parameter values for reliability analysis [12].

Parameters		PDF	Analysis 1		Analysis 2		Analysis 3*		Analysis 4*	
			μ	σ	μ	σ	μ	σ	μ	σ
Concrete elasticity modulus (E_c)	[GPa]	Normal	35.00	3.50	35.98	3.60	37.04	0.63	36.51	0.52
Concrete tensile strength ($f_{t,c}$)	[MPa]	Normal	3.50	0.70	4.03	0.81	3.99	0.15	3.99	0.15
Concrete compressive strength (f_c)	[MPa]	Normal	48.00	4.80	48.00	4.80	56.86	3.24	56.86	3.24
Reinforcing steel yield strength ($\sigma_{y,l}$)	[MPa]	Normal	560.00	28.00	560.00	28.00	562.92	21.61	562.92	21.61
Laminated steel profile yield strength ($\sigma_{y,p}$)	[MPa]	Normal	355.00	17.75	355.00	17.75	387.93	18.35	387.93	18.35
Steel plate 1 yield strength ($\sigma_{y,p1}$)	[MPa]	Normal	355.00	17.75	355.00	17.75	387.93	18.35	387.93	18.35
Steel plate 2 yield strength ($\sigma_{y,p2}$)	[MPa]	Normal	345.00	17.25	345.00	17.25	387.93	18.35	387.93	18.35

675 *Posterior data, obtained from Bayesian inference.

676

677 Table 9. Resistance PDF (R) [12].

Numerical model	PDF	LC1		LC2		LC3		p_f^*	β^*
		μ [kN]	σ [kN]	μ [kN]	σ [kN]	μ [kN]	σ [kN]		
Analysis 1	Normal	24796.00	902.40	39294.00	700.82	35991.00	659.80	3.59×10^{-16}	8.32
Analysis 2	Normal	24749.00	936.94	39550.00	780.70	35990.00	665.32	4.26×10^{-16}	8.30
Analysis 3	Normal	26770.00	904.49	41210.00	751.58	37148.00	648.64	1.17×10^{-17}	8.73
Analysis 4	Normal	26769.00	911.05	41188.00	742.84	37270.00	649.74	1.19×10^{-17}	8.72

678 *Considered the most critical value from all LCs

679