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A Generalized Framework for Reliability Assessment of Bridges using Adjusted Partial Safety and Combination Factors

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ABSTRACT: Assessment of degrading infrastructure, particularly bridges, represents a growing challenge for structural engineers. While traditional strategies for bridge assessment, such as a code-based rating factor assessment, are still frequently utilized by practitioners, the advantages of a probabilistic approach are now well-recognized. However, the applicability of probabilistic assessments for large infrastructure is impeded by many factors including high dimensionality, high computational costs, and the difficulty of incorporating advanced structural analysis models for estimation of resistance. In this paper, the authors propose a generalized framework for reliability assessment of bridges using adjusted partial and combination factors. The framework is conceptualized using six indepent modules, operating in mutual interaction and cooperation: structural properties, linear elastic analysis, reliability analysis, Bayesian data assimilation, rating factor adjustment and calibration, and non-linear analysis module for a final performance check. The framework addresses the shortcomings of typical semi-probabilistic assessments by leveraging the strengths of each analysis module and enables the application of probabilistic assessment methods on large infrastructure. The main challenge for the practical applications of probabilistic assessments relates to uncertainty quantification and data collection, that would facilitate establishing the probabilistic models for resistance (including degradation effects) and load effect parameters well reflecting bridge-specific conditions.

1. INTRODUCTION

The adequacy of degrading infrastructure is a globally-recognized problem. ASCE (2021) noted that 42% of all American bridges were more than 50 years old, while 7.5% were structurally deficient. Establishing the performance adequacy of such degrading structures is a significant challenge for structural engineering practitioners, researchers, and asset managers. Assessment of degrading infrastructure is complicated by a range of factors. Firstly, there exist a range of different methods for structural analysis and assessment. Asset managers typically adopt a tiered system of performance analysis and assessment where the analysis methods vary significantly in terms their accuracy, complexity, and time-cost (COST 345, 2004; ISO 13822, 2010; Khan et al., 2022).

Secondly, the assessment of large infrastructure such as buildings and bridges brings a problem of scale. This problem exists in terms of both, the number of structural elements constituting the system and the number of different load effects acting simultaneously on the elements as combined action. Scaling-up the advanced methods for structural analysis and assessment, such as non-linear finite element analysis and reliability assessment, respectively, presents numerous difficulties. While metamodelling strategies have enabled reduction of computational costs, integrating the practical reliability analysis of large infrastructure with existing non-linear analysis software using metamodelling is yet to be done (Sudret, 2012; Khan et al., 2018).

Finally, a major issue with such deterministic analysis and semi-probabilistic assessments is that they are unable to capture the full range of uncertainties within the underlying parameters (Melhem and Caprani, 2022). Consequently, any reserve structural capacity stemming from a highly conservative code-based structural design may not be uncovered (Sýkora et al., 2013; Caspeele et al., 2013). Furthermore, it becomes difficult to take full advantage of the widespread availability of engineering data using Bayesian techniques without full consideration of uncertainties (Khan et al., 2020). A generalized approach for a thorough probabilistic assessment of bridges that utilizes the strengths of various structural analysis methods can help address these challenges, thereby enabling widespread adoption of probabilistic methods for degrading infrastructure assessment.

Therefore, in this study the authors present a scalable and generalized framework for probabilistic assessment of bridge. This framework utilizes a linear-elastic analysis methods and reliability assessment to develop adjusted partial and combination factors for a non-linear structural analysis. Section 2 proposes the framework in detail. Section 3 discusses some of the challenges and complexities of this approach. Concluding remarks and recommendations for further research and practical applications are provided in Section 4.

2. SCALABLE GENERALIZED RELIABILITY ASSESSMENT FRAMEWORK

2.1. *Overview*

The overall flow diagram of the proposed framework is illustrated in Figure 1. The framework involves utilization of six distinct analysis or modules, namely: structural properties, linear elastic analysis, reliability analysis, Bayesian data assimilation, factor adjustment, and non-linear analysis modules. These modules work and interact together to obtain a final performance check on the various structural elements.

The structural properties module generates a section database consisting of the structural properties of the various constituting structural elements with due consideration to its degradation. The linear elastic analysis module identifies the critical load positions of the moving loads and estimates the maximum load effects at various structural elements. The section database and load effect values are used in conjunction with the design code specifications in the reliability analysis module. Any site-specific measurements and information can be utilized via the Bayesian data assimilation module. The reliability analysis module is paired with a factor adjustment module to obtained adjusted and optimized combination and partial factors. These factors are then utilized in the non-linear analysis module to obtain a final performance check for all structural sections. The following sections explain the proposed framework in detail.

2.2. *Structural Properties and Linear Elastic Analysis Modules*

Infrastructure, such as bridges, is subject to a variety of different structural actions (AS 5104, 2017). These structural actions can be static (or non-transient) and dynamic (or transient) loads. In this study, a static load is that which does not change in its magnitude, position, and direction with time, such as dead, superimposed dead, and track/pavement loads. Otherwise, the load is referred to as a dynamic load, such as traffic, rail, wind, and earthquake loads. Within the context of probabilistic assessment, a similar distinction is made depending upon whether a load changes its probability distribution with time (i.e. transient or

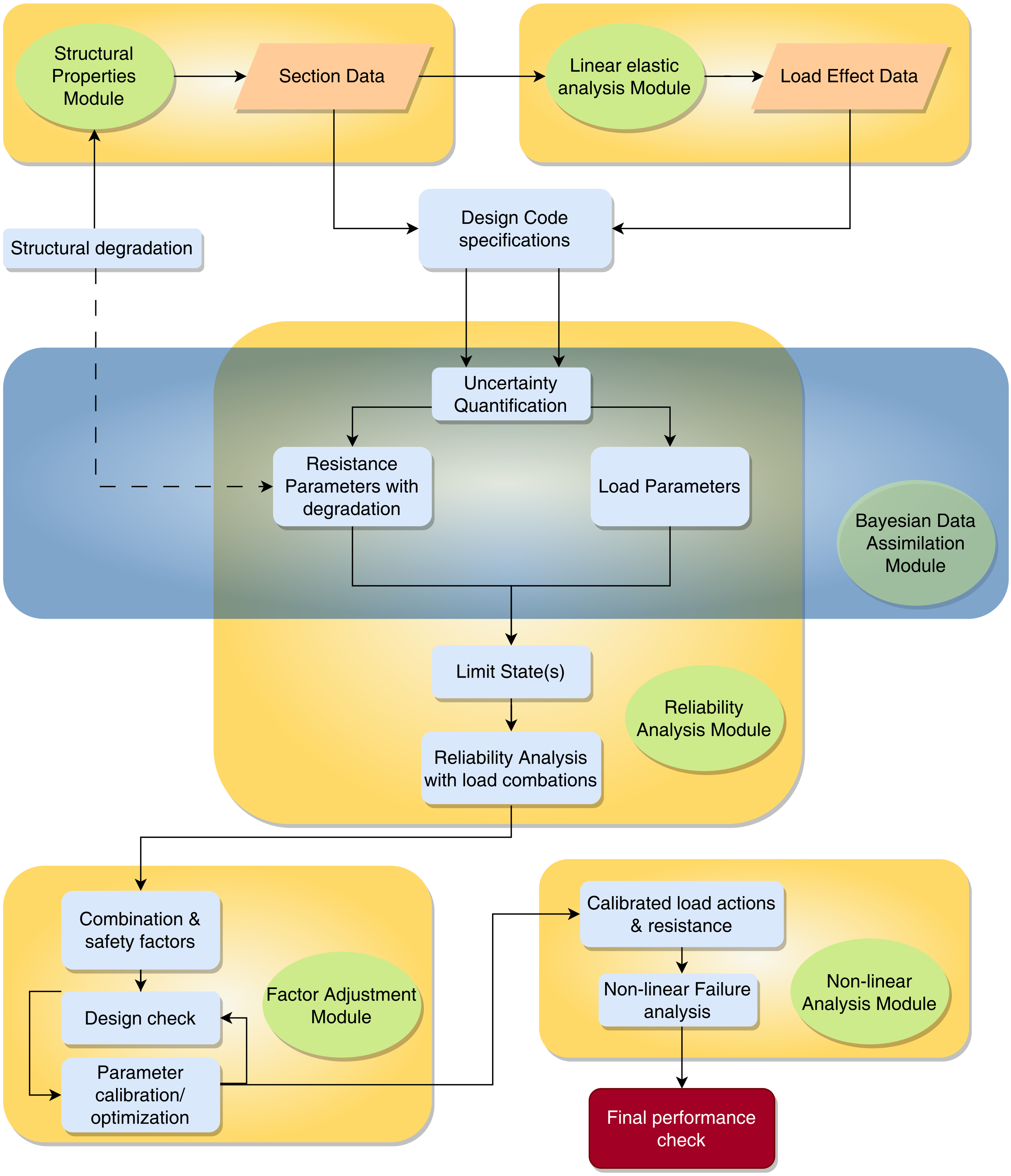

Figure 1: Proposed scalable generalized framework for probabilistic bridge assessment.

time-varying) or not (i.e. non-transient or quasi-static) (Melchers and Beck, 2017).

For any performance assessment, it is necessary to, first, determine the resulting load effects. 3D finite element (FE) frame models are quite useful to quickly determine the load effects. Their strengths include ability to incorporate different kinds of load actions simultaneously. Such frame models can also be used to determine the critical load positions of any moving loads. However, a more feasible approach is to estimate the influence lines corresponding to each moving load and estimate the maximum load effects corresponding to any design vehicle. The 3D FE models can also be used to investigate alternative load-paths after accounting for degraded structural elements. Furthermore, the results of a linear elastic analysis of the 3D FE can be used to conduct an initial screening of potentially critical members for further analysis.

Such 3D FE models need to be supplemented with a module for evaluating the structural properties. Most 3D FE finite element software come with inbuilt section analysis modules. However, in cases when the design code provisions are not specified within the software, or a range of structural degradation scenarios need to be investigated, an independent structural properties module may be required.

2.3. *Reliability Analysis Module*

The section properties database and the load effect data can be used in conjunction with design code and other specifications for a thorough uncertainty quantification to load and resistance distributions. The structural design code provides much useful information for a reliability assessment. Firstly, the desired return period of load actions can be established. Secondly, design code specifications can be used to establish the performance requirements on the sections, which assist establishing the limit state(s) for a reliability assessment (e.g. ultimate, serviceability, and fatigue limit states). Finally, the design code specifications on the load combination factors can be used to identify the transient load effects occurring concurrently and, therefore, the relevant load combination cases for the reliability assessment (Caprani et al., 2017).

Utilizing the design code, site-specific information, and other technical reports, the bias and Coefficient of Variation (CoV) can be established for the various acting load effects (Nowak and Rakoczy, 2012; ABCB, 2019; JCSS, 2001). That is:

$$\lambda = \frac{\mu_X}{X_k}, \tag{1}$$

where X_k is the nominal or characteristic value (e.g. the 95-percentile or a loading for a return period specified by the design code) of the variable, and

$$CoV = \frac{\mu_X}{\sigma_X}, \tag{2}$$

where μ is the mean, and σ is the standard deviation. Therefore, utilizing the maximum load effects from the 3D FE model as the nominal or characteristic value along with the bias and CoV, it is possible to determine the parameters of and specify any chosen probability distribution for a reliability analysis for a given load case.

2.4. *Bayesian Data Assimilation Module*

Bayesian statistics provides a formal mathematical framework to systematically update prior knowledge about engineering parameters using measurements. The updated distribution incorporating the prior knowledge as well as the measurements is termed as the *posterior* distribution. The primary advantages of Bayesian parameter estimation over typically adopted frequentist approaches is that valuable prior knowledge is also incorporated and more accurate estimations are obtained, especially in most infrastructure assessment cases where only few measurements are generally available.

The acquisition of site-specific information can significantly improve the accuracy of degrading infrastructure assessment results. Such information can be regarding that which affects any load and resistance parameter such as historical traffic load data, material properties, wind drag coefficient, and structural degradation. The load and resistance distributions resulting from the uncertainty quantification can be updated using Bayesian techniques using any such acquired information. While such information usually comes at a cost, it is now possible to determine the potential monetary benefits of and optimize acquisition of stuctural health monitoring (SHM) information using Bayesian preposterior analysis (Khan et al., 2020).

2.5. *Factor Adjustment Module*

For the assessment of existing structures, the partial factors in structural design codes are expected to be typically conservative for an individual structure, since those factors are calibrated for the governing situations across the entire population of structures covered by the code. So for an individual bridge, such conservative assessments can lead to unnecessarily expensive structural interventions. Therefore, using reliability analysis, these partial and load combination factors can be adjusted to achieve a target reliability index. The factor adjustment module adjusts or updates the partial and load combination factors from the code using the reliability analysis module. Using these adjusted factors, a targeted assessment of the structural sections for a chosen reliability level can then be done.

The adjusted factors can be obtained by using expert judgement, design value method, or optimization (Sørensen, 2002; Caspeele et al., 2013). Factor adjustment using optimization involves adjusting the limit state function to a target reliability index and identifying the design point, i.e. most probable failure point Nadolski et al. (2019); Lenner and Sýkora (2016); Sykora et al. (2017). For example, consider the limit state function $G(X)$:

$$G(X) = zR - Q_1 - Q_2, \tag{3}$$

where z is a scalar design parameter, R is the resistance variable, and Q_i are the transient loads. Therefore, the problem consists of two load cases. First, Q_1 has the maximum distribution for a chosen basis (e.g. annual maximum) and Q_2 has the point in time distribution for a chosen basis (e.g. daily maximum), then vice versa for the second. The design parameter z is adjusted, such that the probability of failure corresponds to that of the target reliability index (β_T), i.e. $z = z*$ such that:

$$-\Phi^{-1}\left[\mathbb{P}\left[G(z*) \leq 0\right]\right] = \beta_T. \tag{4}$$

The design point at β_T for the two load cases can be represented as,

$$X^*_{\beta_T} = \begin{bmatrix} z_1 & R^*_1 & S^*_{11} & S^*_{12} \\ z_2 & R^*_2 & S^*_{21} & S^*_{22} \end{bmatrix} \tag{5}$$

A typical semi-probabilistic design seeks to ensure that the design resistance R_d is greater than the design loads S_{di}, i.e.

$$R_d \geq \sum_i S_{di} \tag{6}$$

and,

$$\begin{aligned} S_{di} &= \psi_i \gamma_i \, S_{ki} \\ R_d &= \phi \, R_k \end{aligned} \tag{7}$$

where S_{ki} is the characteristic value of the ith load, R_k is the characteristic value of the resistance, ϕ is the resistance factor, ψ_i are the combination factors, and γ_i are the load factors. Therefore, by comparing the corresponding terms in Equations (5) to (7), estimates of ϕ, ψ, and γ adjusted to β_T can be obtained.

It is important to ensure that the adjusted partial factors are checked to reach β_T so that any effects of rounding off are accounted. This can be done by using Equation (6) to obtain a design resistance for each load case. A forward reliability analyses using the maximum of the so obtained design resistances is then conducted to verify actual reliability levels (validation).

The above procedure results in unique values of partial load factors, while the estimates of partial resistance factors and combination factors differ per load case. Furthermore, a large number of structural sections and load cases may lead to a large set of partial factors, thereby making the assessment problem unmanageable for the asset manager. Therefore, these adjusted partial factors can be further calibrated for all (or a subset) of sections to obtain an optimized set of partial factors (Nadolski et al., 2021). Therefore, the optimization of partial factors and the design check are conducted iteratively as shown in Figure 1.

2.6. *Non-linear Analysis Module*

Using the adjusted and calibrated partial factors, the calibrated load effects acting at a section can be estimated. These calibrated load effects can be applied to a non-linear analysis model of the section and corresponding resistance at failure can be estimated. Therefore, utilizing Equation (6), the final performance check of the section using the adjusted and calibrated partial factors.

3. CHALLENGES AND DISCUSSION

By selectively deploying the different strategies for structural analysis and assessment in the proposed generalized framework presented in Section 2 and Figure 1, the primary challenge of applying probabilistic assessment methods to large infrastructure, i.e. the scale of the assessment problem, can be effectively addressed. However, considerable challenges and modelling considerations for a particular infrastructure type, such as bridges, require addressing as discussed below.

3.1. Critical Section Identification

The 3D FE models can be utilized to identify a preliminary set of critical sections for reliability assessment. However, their identification is complicated by factors such as varying structural geometry, localized degradation, and moving loads. Their identification can be facilitated by adopting heuristics such as evaluation of girders at mid-span, 1/3 span, and end span. However, the choice of critical sections for analysis must be adequately justified.

3.2. Load Reversal

The characterization of the load effects at the critical sections, such as wind and other horizontal loads, requires considerations of load direction reversal. Depending upon the cross girder and bracing arrangements, under some special circumstances, the load effects due to change in load application direction may be mirrored across an axis of symmetry. However, in most cases, both direction cases need to be investigated.

Within the design code and research literature, it is more common to find recommendations regarding the annual maximum distribution of load effects. Under such circumstances, the utilization of extreme value theory to infer the point-in-time distributions of the transient load effects may result in a change of the type of effect (e.g. from positive/sagging bending to negative/hogging bending). Under some cases, such a reversal may imply a change of load application direction, which may not be physically justified. Therefore, care must be taken to ensure consistency of loads across the 3D FE analysis and reliability analysis.

3.3. Uncertainty Quantification

Quantifying the uncertainties with the probabilistic models adopted in a reliability analysis can be a significant impediment in the application of structural reliability. In particular, the uncertainties within structural analysis and assessment models may not be readily available. Furthermore, the performance of structures, such as steel structures, under combined axial tension/compression and biaxial bending is a complex phenomenon. AS 4100 (2020) recommend a performance function with an exponent. However, the uncertainties within this performance model, particularly that in the exponent, are not known, despite having a significant influence on the overall performance of the section. Furthermore, uncertainties within load actions such as axle weight and spacing uncertainty may also be unknown. In spite of the technical advances made, considerable engineering judgement remains a requirement for proper consideration and characterization of these uncertainties. Indeed, in the era of artificial intelligence and machine learning, such heuristics and empiricism will become increasingly highlighted.

3.4. Correlations

Another crucial input to reliability assessments is the correlations between various load types and effects. Due to general lack of information on correlations, the engineer is generally forced to assume uncorrelated or perfectly correlated load effects. However, both situations may be misleading and significantly different from the reality. In some cases, expert judgement and knowledge can be utilized to postulate a possible set of correlations based on the phenomenological understanding of the problem. However, such a postulated correlation matrix may satisfy requirements such as the positive definiteness of the correlation matrix for a successful application of first order reliability methods (FORM). Therefore, the proper modelling of correlations requires meticulous investigations and studies for an accurate reliability estimation. However, in practical applications it might be sufficient to identify the basic variables dominating structural reliability for the critical failure modes, then define lower and upper bounds for correlation coefficients for these basic variables, and then verify sensitivity of reliability levels to these bounds on correlation coefficients.

3.5. Horizontal Loads

Bridges, such as steel railway bridges, are subject to various horizontal loads such as braking forces and nosing forces. More clarity on the phenomenological behaviour of these forces is required for a thorough uncertainty quantification and characterization of these forces. Some aspects of further scientific investigations can be: (i) the frequency of high speed braking events, (ii) probabilistic characterization of nosing forces and their correlations with vertical train loads, and (iii) effect of railway line operator decisions on reliability.

3.6. Partial Factor Calibration

The calibration of adjusted partial factors can become a significant challenge depending upon the scale of the assessment problem. For example, consideration of combined major bending, minor bending, and axial forces of six different loads can lead to 18 estimates of partial load factors for a single load combination. This problem is compounded by increasing number of load combinations, structural sections for assessment, and degradation scenarios. Therefore, calibration of the partial factors is necessary so that a partial factor adjustment using nonlinear analysis can be done.

However, there exist complexities with partial factor calibration. Firstly, a crude calibration (e.g. taking the maximum partial factors) can lead to a very conservative design, reducing the benefit of reliability assessment. Secondly, the identification of the beneficial load effects for a given load combination is necessary so that the partial factor can be enveloped appropriately. Finally, the identification of groups (and sub-groups) with the structural section for efficient and optimal enveloping is a challenge.

4. CONCLUSIONS

Practical applications of structural reliability methods raise issues such as high computational costs and difficulty of integration with non-linear analysis methods. Therefore, this study proposes a generalized framework for reliability assessment of bridges using adjusted partial and combination factors. The proposed generalized framework consists of six independent, mutually cooperating, and interacting modules: (i) structural properties for generating section properties database based on noted degradation; (ii) linear elastic analysis using a 3D FE structure; (iii) reliability analysis; (iv) Bayesian data assimilation for updating probabilistic distributions based on structure-specific data; (v) factor adjustment for obtaining adjusted and calibrated partial factors; and; (vi) non-linear analysis for obtaining a final performance check of the section based on the calibrated load actions and resistance.

The proposed scalable and generalized framework address a major problem of scale of large degrading infrastructure such as bridges. However, many challenges are encountered within different aspects of the generalized framework. Firstly, the identification of critical elements for a probabilistic assessment is difficult. Secondly, load direction reversals, either due to the phenomenological variability or due to statistical characterizations, need to be investigated and accounted. Thirdly, uncertainty quantification, particularly related to the horizontal loads and correlations, remains a significant challenge. Finally, the adjusted partial factor calibration and optimization while maintain design efficiency is another challenge.

The proposed generalized framework enables the application of probabilistic assessment methods for large infrastructure. The main challenge for the practical applications of probabilistic assessments relates to uncertainty quantification and data collection, that would facilitate establishing the probabilistic models for resistance (including degradation effects) and load effect parameters well reflecting bridge-specific conditions. Future investigations would focus on addressing some modelling challenges identified in this study.

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