A value of information framework for quantifying the value of reliability assessment for a steel railway truss bridge

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ABSTRACT: Infrastructure is frequently subject to various loading and environmental stressors that cause degradation of its performance with time. Management of such degrading infrastructure is conditioned upon its estimated performance. The conventional methodologies of infrastructure performance assessment, such as the rating factor assessment, employ semi-probabilistic (or deterministic) techniques. It is known that the problem of infrastructure performance assessment is subject to various errors and uncertainties. Therefore, probabilistic approaches such as structural reliability assessment are recommended for performance assessment due to their ability to quantify and incorporate uncertainties of infrastructure performance. However, such probabilistic assessments require additional time and monetary costs while their potential monetary benefits are not apparent to the asset manager. In this article, the authors present a Bayesian decision framework and methodology to quantify the potential monetary benefits of probabilistic assessments. The framework is based on the value of the information (VoI) framework. The prior analysis focuses on infrastructure management using a semi-probabilistic code-based rating factor assessment, and the preposterior analysis focuses on a reliability-based probabilistic assessment using a proposed conditional distribution of reliabilities. It is found that a probabilistic assessment can have significant benefits relative to a load rating factor assessment. A comparison of the conditional distribution of reliabilities with in-situ reliability estimates reveals the adequacy of the distribution. Infrastructure asset managers can utilize this framework to decide on probabilistic assessments over rating factor assessments.

1. INTRODUCTION

Degrading infrastructure is a challenging issue for structural engineering practitioners, scientists, and large infrastructure asset owners (ASCE, 2021). Load rating factor approaches are commonly adopted to evaluate the adequacy of degrading bridge infrastructure (AASHTO MBE-3, 2018; AS 5100.7, 2017). However, such semi-probabilistic approaches fail to capture the full extent of the reserve structure capacity (Melhem and Caprani, 2020). Therefore, probabilistic approaches should be investigated for degrading infrastructure assessment.

There exists a variety of different indicators based on probabilistic approaches for infrastructure assessment (Frangopol, 2011). The reliability index is a useful metric which serves as a basis for many other probabilistic indicators (Ghosn et al., 2016). It can be used to tie the structural performance with a probability of failure for a given basis (e.g. annual probability of failure). The primary advantage of full-probabilistic assessments such as reliability assessment is that they help capture the reserve structural capacity stemming from a highly conservative design process (Melchers and Beck, 2017). However, the widespread adoption of reliability assessments is impeded by the high complexity, lack of familiarity, and lack of clarity on their potential monetary benefits (Melhem and Caprani, 2022). Therefore, in this study, the authors propose a value of information (VoI) framework to quantify the potential monetary benefits of reliability assessments.

The VoI framework can be utilized to estimate the potential monetary benefits of procuring any source of information (Iannacone et al., 2022). Within structural engineering, most VoI applications are located within a structural health monitoring (SHM) context (Zhang et al., 2021). Therefore, there exists many studies which either quantify the potential monetary benefits of SHM or optimize SHM information acquisition (Khan, 2022; Giordano et al., 2023; Zhang et al., 2023). However, there have not been any investigations that propose a VoI framework to quantify the potential monetary benefits of full probabilistic assessments relative to semi-probabilistic assessments. Therefore, this study proposes a VoI framework to quantify the potential monetary benefits of a reliability assessment over a conventional rating factor assessment.

The decision problem in this study consists of an asset manager considering a reliability assessment over a rating factor assessment. Section 2 proposes the VoI framework approach, elaborating on the prior and preposterior analysis of the framework. Section 3 demonstrates the framework on a case study of degrading steel railway truss bridge. Finally, Section 4 concludes the study and identifies the research gaps for future work.

2. Benefits of Probabilistic Assessment Using Value of Information

The value of information (VoI) framework is a widely utilized approach for quantifying the amount a decision-maker would be willing to pay to acquire information prior to making a decision. It is based on Bayesian preposterior analysis framework (Raïffa and Schlaifer, 1961). The expected VoI, EVI is estimated as the difference between expected utilities (or cost) with and without the information as shown in Equation (1). For this study, the source of information is a probabilistic assessment resulting in a reliability index β, and associated probability of failure, P_f.

$$EVI = C_{\text{prior}} - C_{\text{prepost}} \tag{1}$$

where C_{prior} represents prior costs and C_{prepost} represents preposterior costs.

To estimate the expected benefit of a probabilistic assessment using VoI, it is necessary to construct the corresponding prior and preposterior decision scenarios. The prior analysis represents the decision situation when the asset manager decides regarding the asset management without probabilistic assessment information, i.e. using a code-based rating factor assessment. In preposterior analysis, the asset management decision is made using postulated reliability indices, β, resulting from a probabilistic assessment. In the situation when information is actually available, the corresponding costs are called the posterior costs. Therefore, this study estimates three costs: prior costs, preposterior costs, and conditional costs. The difference between the prior costs and conditional costs is referred to as the conditional value of information (CVI) (Zhang et al., 2021) as shown in Equation (2).

$$CVI = C_{\text{prior}} - C_{\text{post}} \tag{2}$$

The analyses are explained in detail in the following sections.

2.1. *Prior Analysis*

The prior analysis involves the estimation of expected prior costs based on the rating factor assessment for a range of structural sections. Based on the rating factor assessment, the asset manager decides whether the section is structurally inadequate, thus necessitating repairs. When the RF indicates adequate structural capacity, the asset manager decides to do nothing for the particular structural section. Based on the number of sections that require intervention, the prior costs are estimated. The various aspects of this decision-analysis are elaborated in the following sections.

2.1.1. *Rating factor assessment*

Similar to many international codes, AS 5100.7 (2017) defines RF as the ratio of the available bridge capacity for traffic load effects to the traffic load effects resulting from a load rating vehicle. The available bridge capacity for traffic load effects can be estimated by subtracting the load effects due to static non-traffic loads from the resistance of the structural section. Thus, the rating factor can be estimated.

Bridges, particularly railway bridges, are subject to a variety of structural actions. These include static non-transient loads such as dead loads (DL), superimposed dead loads (SDL), and railway track loads (TL). Furthermore, there exist transient loads such as vertical train loads from wagons and locomotives (NCW/NCL), braking forces (BF), nosing forces (NO), wind on bridge (WB), and wind on train (WT). Separating the load effects associated with the traffic with those not associated with traffic loads, the *RF* of a structural section for the ultimate limit state under combined action can be estimated as:

$$RF_S = \frac{\phi R - \left|\gamma_g \times S_{\text{DL}} + \gamma_{gS} \times (S_{\text{SDL}} + S_{\text{TL}} + S_{\text{WB}})\right|}{\left|\gamma_Q \times (S_{\text{NCW/ NCL}} + S_{\text{BF}} + S_{\text{NO}} + S_{\text{WT}})\right|} \quad (3)$$

where $S \in \{M_z, M_y, N\}$ for giders, $\phi = 0.9$, $\gamma_g = 1.1$, $\gamma_{gS} = 2$, and $\gamma_Q = 1.6$ as per AS 5100.7 (2017) recommendations.

2.1.2. *Prior decision-costs*

The management decisions for prior analysis are given in Figure 1. If $RF \geq 1$, then the structure is deemed safe and no repair action is taken. However, $RF \geq 1$ does not preclude the possibility of structural failure. Therefore, in such a case, a probability of failure is postulated on the basis of the corresponding *RF* to estimate the risk, i.e. $P_f(RF)$. The basis of this postulation is elaborated in Section 2.2.1. Similarly, when the $RF < 1$, then the structure is deemed unsafe and therefore, repair costs are incurred. The corresponding costs are specified in Table 1.

A general approach to infrastructure repair costing involves fixed as well as variable costs (Frangopol, 2011). The fixed costs typically include costs of tendering, contracting, and machinery. The

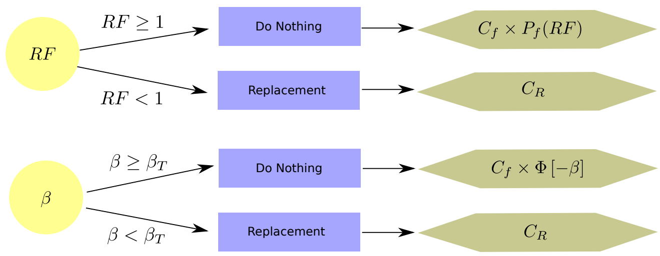


Figure 1: Decision scenario for Prior (RF) and Preposterior (Reliability) analysis

Table 1: Management costs for prior analysis

Symbol	Description	Cost (Australian Dollars [AUD])
C_R	Cost of repair of a section	30,000
C_{fixed}	Fixed costs of repair intervention	100,000
C_f	Cost of unexpected failure	10,000,000

variable costs vary with the volume of repair work. In this study, a fixed and variable cost model is adopted for estimating the management costs related to infrastructure assessment as shown in Table 1.

The total costs of infrastructure management for multiple structural sections can be estimated by adopting an appropriate utility model. These utility functions can be additive or diminishing (Maes and Faber, 2007). In case when the utility function is additive, the total costs are obtained by estimating the cost for all n_s sections and summing, as given by Equation (4).

$$\begin{aligned} C_{\text{prior}} = C_{\text{fixed}} + \sum_{n=1}^{n_s} C_R \, \mathrm{I}[RF_n < 1] \\ + \sum_{n=1}^{n_s} C_f \, P_f(RF) \, \left(1 - \mathrm{I}[RF_n < 1]\right) \end{aligned} \quad (4)$$

where I is an indicator function that is equal to 1 if the rating factor for n-th section is less than 1, i.e. $RF_n < 1$. Otherwise the indicator function is 0.

2.2. *Preposterior analysis*

In order to estimate the value of probabilistic assessment relative to a rating factor assessment, reliability indices are hypothesized based upon a chosen functional relationship between the prior rating factors and reliability indices. Such a functional relationship to determine the distribution of the "information" conditioned on the prior can be established using previous scientific studies as well as expert judgement. Previous studies have indicated the strong sensitivity of the adopted prior probabilistic model on the consequent VoI (Li and Pozzi, 2019; Khan et al., 2018, 2020). Therefore, it is important that the adopted functional relationship is adequate.

Using the postulated reliabilities, the management decisions are taken and preposterior costs are estimated. The following sections elaborate the methodology for preposterior analysis.

2.2.1. Conditional distribution of reliabilities

Melhem and Caprani (2020) reports rating factors and reliability indices for a range of prestressed concrete bridges. Using this data, an approximate relationship between the rating factors and corresponding probability of failure is modelled as,

$$RF = -0.12\ \log_{10} P_f + 0.25 \tag{5}$$

The rationale for the second condition is that the engineer deems that a rating factor of 0.5 would indicate a near certain failure, e.g. $P_f = 0.90$. Furthermore, we know that,

$$\beta \approx -\Phi^{-1}\left[P_f\right] \tag{6}$$

Therefore, RF can also be related with β.

Equation (5) represents a perfect model which assumes a perfect (i.e. non-erroneous) relationship between RF and P_f. However, in reality there exist numerous uncertainties which need to be accounted. Therefore, in this study a normally distributed error is considered in the model. Therefore, we have,

$$RF = -0.12 \log_{10} P_f + 0.25 + \varepsilon \tag{7}$$

or

$$P_f = 10^{-\frac{RF-0.25-\varepsilon}{0.12}} \tag{8}$$

and,

$$\varepsilon \sim \mathcal{N}\left(\mu = 0, \sigma = 0.2\right), \tag{9}$$

where μ represents the mean, and σ represents the standard deviation of the random variable. Therefore, the conditional distribution of RF (or P_f and β) can be established using Equation (7).

Finally, to sample from the conditional distribution of reliabilities, a Monte Carlo strategy can be adopted as follows:

1. Generate a bootstrap realization of rating factors of size n_s using the rating factors estimated in the prior analysis.
2. Generate a realization of errors of size n_s
3. Using the realizations in Equations (6) and (7), estimate a potential realization of β

The above procedure can be repeated to generate samples from marginal distribution of β.

2.2.2. Preposterior decision-costs

As specified earlier, Figure 1 presents the decision scenario for preposterior analysis. The two management actions, i.e. "Do Nothing" and "Repair" are decided on the basis of the reliability index. If reliability is greater than or equal to a specified target reliability (i.e. β_T), then the asset manager does nothing. Otherwise, the manager initiates a repair at the section. ISO 2394 (2015) recommends optimization of costs of safety improvement and marginal costs of failure. Using the optimization principle, JCSS (2001) recommends different target annual reliability indices depending upon the cost of safety measure and consequences of failure.

Similar to prior analysis, the posterior costs are:

$$\begin{aligned} C_{\text{prepost |RF}} = \\ C_{\text{fixed}} + \\ \sum_{n=1}^{n_s} C_R\ \mathrm{I}\left[\beta_{|RF} < 1\right] + \\ \sum_{n=1}^{n_s} C_f\ P_f \Phi\left[-\beta_{|RF}\right]\ \left(1 - \mathrm{I}\left[\beta_{|RF} < 1\right]\right). \end{aligned} \tag{10}$$

The distribution of $\beta_{|RF}$ can be determined using Equations (6) and (7) as outlined in Section 2.2.1. Thus, the expected preposterior costs are:

$$C_{\text{prepost}} = \mathrm{E}_{RF}\left[C_{\text{prepost |RF}}\right] \tag{11}$$

Using the prior and preposterior costs, the expected VoI can be estimated using Equation (1).

Through this process, the following comments can be made between the prior and the preposterior analyses:

1. By conditioning the sampled reliabilities upon the corresponding rating factor of the section, preposterior analysis is centred around the prior knowledge, as is the case in a typical VoI analysis.

2. The primary difference between the prior and preposterior analysis is the decision rule and corresponding acceptable threshold and the corresponding costs as shown in Figure 1.

3. In case the possible error in Equation (8) is assumed to be zero, the analysis corresponds to the case of perfect information in a VoI analysis in which the measurements are assumed to be obtained "perfectly", i.e. with zero error. The corresponding expected value of information (EVI) is also called the expected value of perfect information and generally represents the upper limit on the EVI for an unbiased VoI analysis.

2.3. *Posterior Analysis*

Preposterior analysis are compared with the results from a posterior analysis. For posterior analysis, a reliability analysis for the structural elements is conducted for the ultimate limit state under combined action. Load effects for the bridge are found using a suitable structural model. Then the probability distributions of the load effects were estimated. Using relevant load combinations, the critical reliabilities can be obtained using a load combination rule, e.g. Turkstra's rule (Melchers and Beck, 2017). Finally, the critical reliabilities are used to estimate the conditional costs by utilizing Figure 1 and Equation (10).

3. Case Study: Railway Steel Truss Bridge

This section applies the framework presented in Section 2 to quantify the potential value of probabilistic assessment for a steel railway truss bridge girder located in Queensland, Australia. In this case study, the two longitudinal girders a 61 m Pratt Truss bridge are considered for assessment as shown in Figure 2.

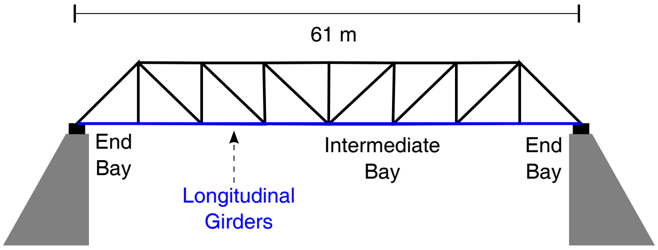
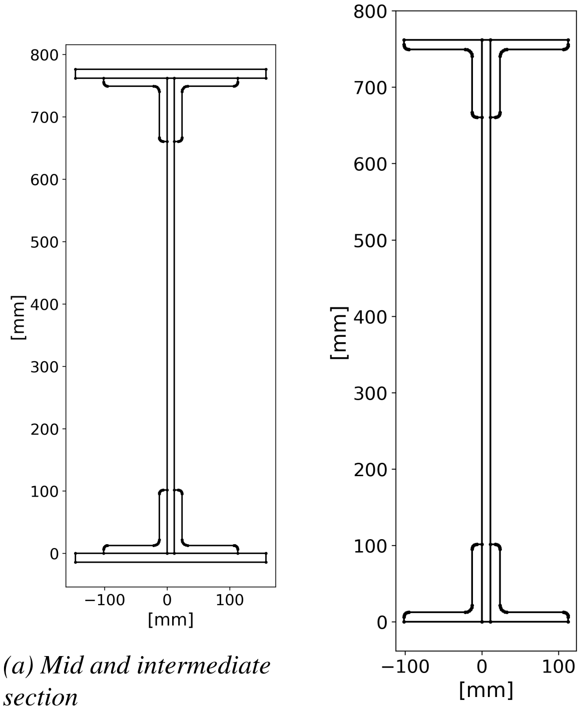


Figure 2: Illustration of the case study railway steel truss bridge



(a) Mid and intermediate section

(b) End section

Figure 3: Steel girder cross section

There are eight bays along the span and the girders are assessed at three sections along each bay: (i) end section, (ii) one-third span, and (iii) mid-span. Therefore, the total number of sections to be assessed are $2 \times 8 \times 3 = 48$ sections. The cross sections of the girders are shown in Figure 3.

3.1. *Prior Costs*

As specified in Section 2.1.1, the girder sections are assessed using a load rating factor approach and

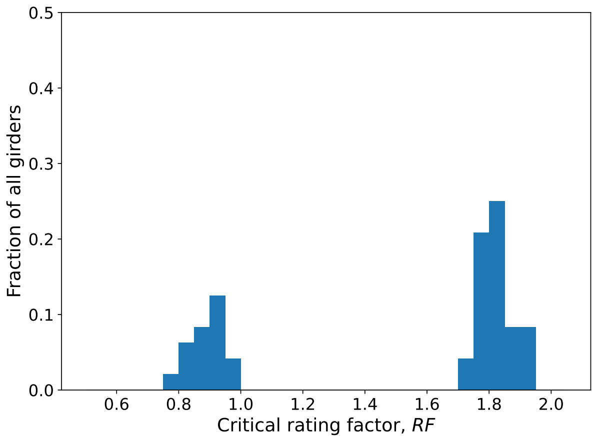


Figure 4: Histogram of Rating Factors of girders

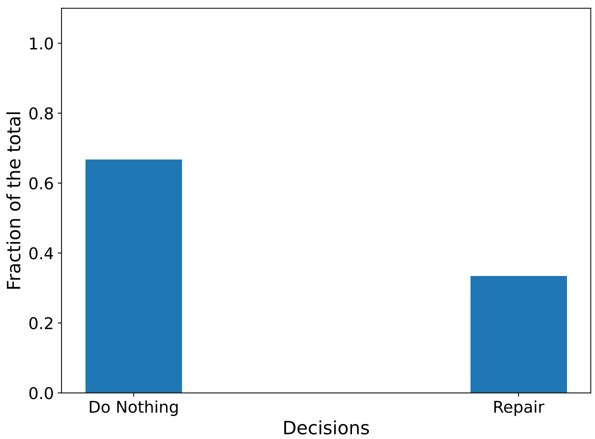


Figure 5: Prior management decisions based on rating factor results

the prior costs are estimated. Figure 4 present the estimated rating factors of the 48 sections.

The results indicate a minor axis bending inadequacy of the weaker end sections, while the mid and intermediate sections are adequate. Therefore, we see two populations of results in Figure 4. Owing to the rating factor inadequacy of end sections, the asset manager decides to repair in 33% of the 48 cases as shown in Figure 5, resulting in a prior cost of 580K AUD.

3.2. Preposterior and Conditional Costs

Using the procedure outlined in Sections 2.2 and 2.3, the preposterior and posterior costs are estimated. Using JCSS (2001) recommendations, a target reliability index of 3.7 is adopted for management decisions. A Monte Carlo approach for estimating the preposterior costs is specified below,

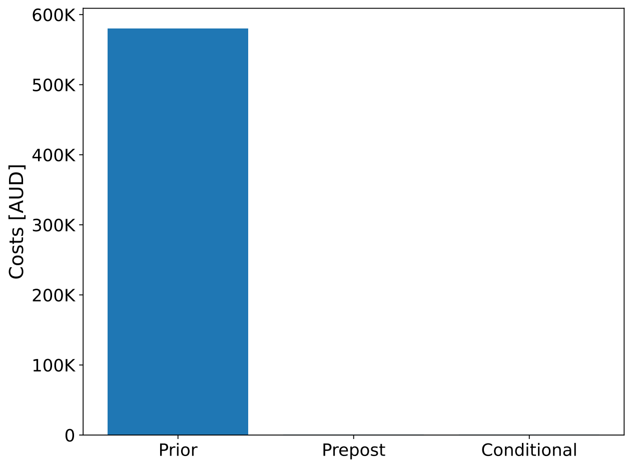


Figure 6: A comparison of estimated prior, preposterior, and conditional costs

1. Postulate reliability indices conditioned on *RF* as specified in Section 2.2.1;
2. Estimate corresponding costs using Equation (10);
3. Repeat steps 1 and 2 10^4 times, and;
4. Estimate the expected preposterior costs using Equation (11).

For estimation of the conditional costs, a detailed reliability analysis of the girder sections is conducted as elaborated in Section Section 2.3. The resulting reliabilities are utilized by the asset manager to identify repair interventions as specified in Figure 1 and corresponding posterior costs are obtained using Equation (10).

Figure 6 presents a comparison of the prior, preposterior, and conditional costs. The resulting preposterior and posterior costs are 0.5K AUD, approximately. Therefore, the VoI framework indicates a high potential monetary benefit of probabilistic assessment. Such a high EVI is further corroborated by a high CVI as the conditional costs are estimated to be 0.6K AUD, approximately.

3.3. Management Decisions

Figure 7 presents the histogram of preposterior management decisions. Contrasting Figure 7 with

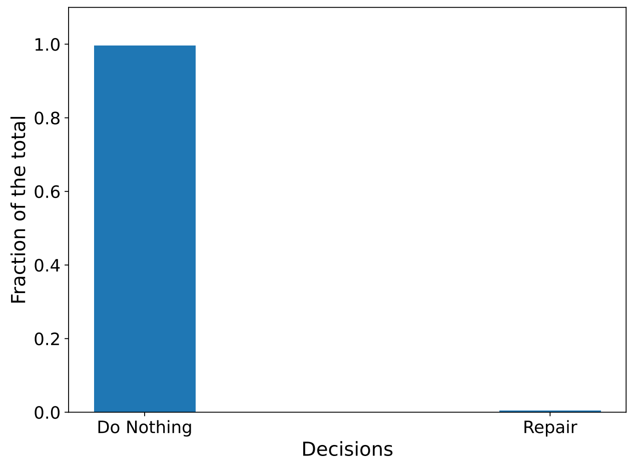


Figure 7: Preposterior management decisions based on reliabilities

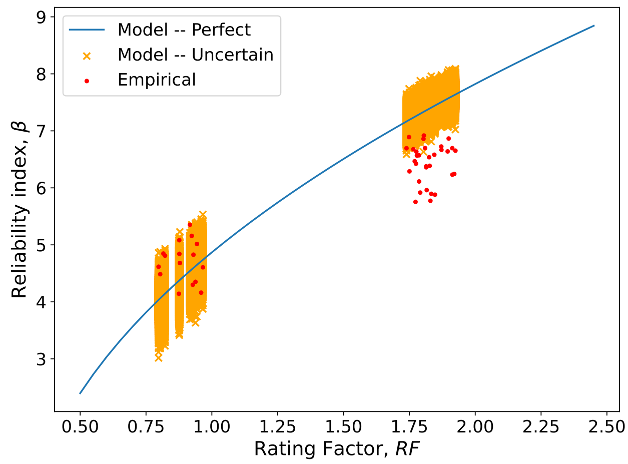


Figure 8: Comparison of prior relationship between rating factor and probability of failure with estimated data

Figure 5, it is found that the low preposterior costs are caused by the low number of structural inadequacy cases with structural reliability. Considering the high level of conservatism within typical structural designs, it is expected that a detailed probabilistic assessment should uncover the reserve capacity of structural sections.

3.4. *Model and Empirical Reliabilities*

Figure 8 presents a comparison of the marginal reliabilities predicted by Equations (5) and (7), and the conditional/empirical reliabilities estimated using the detailed reliability analysis model. It is evident that the conditional relationship between rating factors and reliabilities is accurate for low rating factors but overestimates reliabilities for higher rating factors. Therefore, care must be taken when utilizing the VoI framework to quantify potential monetary benefits of probabilistic assessments.

4. Conclusions and Future Scope

In this study, the authors propose a Bayesian decision theory based value of information (VoI) framework to quantify the potential monetary benefits of probabilistic assessments, relative to the conventional load rating factor assessments. The prior analysis utilizes rating factor assessment results to identify an appropriate management decision, i.e. do nothing or repair. For preposterior analysis, a probabilistic model to estimate the distribution of reliability index (or probability of failure) conditioned upon rating factor is proposed. Adopting a Monte Carlo strategy, the expected preposterior costs are evaluated. Additionally, a detailed reliability assessment is also conducted for the structural sections to estimate the conditional costs. The framework is demonstrated on two longitudinal girders of a steel Pratt truss railway bridge.

The prior costs are estimated to be 580K AUD while the preposterior and conditional costs are estimated to be quite low, 0.5K AUD approximately. Therefore, the results indicate a high EVI of 579.5K AUD, i.e. potential monetary benefit, for probabilistic assessment. The high EVI results from the high structural adequacy determined by the probabilistic assessment, leading to minimal repair interventions in the preposterior analysis. A comparison of the estimated in-situ reliabilities of girder sections with the probabilistic model for conditional distribution of reliabilities indicate the adequacy of the probabilistic model with further scope for refinement.

The results of the study are subject to the underlying modelling choices and assumptions of the constituting structural analysis, decision-cost, and conditional distribution models. In particular, the utility model, the choice of target reliability index, and the uncertainties of the conditional distribution of reliability index can influence the results significantly. Therefore, future investigations will seek to quantify some of these sensitivities and propose further refinements. Nevertheless, the potential monetary benefit of probabilistic assessment of aged structures is clear.

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