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Decision theoretic approach for identification of optimal proof load with sparse resistance information

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ABSTRACT: Proof load testing may be performed to confirm the reliability of the bridge for an existing classification or to prove the reliability for a higher classification. In this paper, a probabilistic decision analysis approach is applied to the scenario for the evaluation of target proof load in the situation where information on the bridge resistance model is lacking. In this case, the resistance model is established by proof loading and taking very basic prior knowledge into account. The decision scenario is modelled in the context of the proof load test planner who shall choose the required load level for assessment of a bridge. The choice of the load level depends on the risks due to the testing and the expected benefit gain from the test. Information acquired about the loading response from monitoring during the proof load testing is modelled by taking basis in the model uncertainty formulation. The optimal proof load level for classification of a single lane, simply supported bridge of 8m span subjected to live load from very heavy (gross weight > 80 tons) transport vehicles was calculated. The optimal proof load level was identified as leading to a positive expected benefit gain to the decision maker while also satisfying target reliability criteria for remaining service life. The analysis was performed for the evaluation of bridge performance with respect to five classifications of very heavy transport vehicles with different vehicle weights and configurations.

1 INTRODUCTION

The accurate determination of bridge capacity is important for decisions regarding the load rating or classification of bridges. Assessment of bridge classification can be achieved with deterministic or probabilistic methods involving models to describe the traffic loading and the bridge capacity. It has been noted that the use of probabilistic methods may lead to a higher classification of the bridge capacity than what may be achieved with deterministic methods (Lauridsen et al., 2007). In the situation where the capacity of the bridge cannot be estimated due to a lack of information about the design and material, non-destructive testing methods may be employed. One of the testing methods which can be directly used in the bridge capacity classification is proof load testing.

In the past, the development of decision analysis and its application to structural integrity management has lead to the identification of risk informed actions for asset management (Faber et al., 2000; Sørensen et al., 1991; Straub & Faber, 2005). Building upon these methods, a probabilistic decision

analysis approach was described for decision support for proof load tests providing decision rules for a safe and efficient in-situ testing (Kapoor et al., 2019). The study analyzed the proof load testing of bridges and provided an approach for optimization of the choices available to the proof load test planner with respect to the load level, monitoring technology, and stop criteria. In this paper, the probabilistic decision analysis approach is applied to the scenario for the evaluation of target proof load in the situation where information on the bridge capacity model is lacking. This situation is considered by using a uniform distribution for the resistance model which takes very basic prior knowledge of the capacity into account. The analysis is performed in the context of capacity evaluation of short span bridges subjected to loads from very heavy transport vehicles.

2 PROOF LOAD TESTING

Proof load testing may be performed to confirm the reliability of the bridge for an existing classification or to prove the reliability for a higher classification. The latter is relevant for situations where the bridge capacity is estimated to be higher than that assessed

with standard theoretical methods which, due to conservatism in design practices, do not account for complexities in structural behavior. Often, the transport authority or evaluator is faced with the situation where the actual capacity of a bridge cannot be sufficiently documented due to incomplete or non-existing documentation. Even in such cases, the bridge capacity can be assessed with a proof load test.

2.1 Description of testing method

The testing procedure involves loading the bridge with a gradually increasing load from a test vehicle or test rig while measuring the structural response for signs of damage from the applied loading. The choice of the maximum load level is crucial as the higher the chosen load level, the greater the information about the capacity that can be obtained. However, applying a heavy load may cause damage to the bridge. Additionally, proof testing also requires precise load application and monitoring systems that can provide accurate information about the structure response. The choice of the maximum or target proof load level can be obtained utilizing structural reliability methods. The procedure involves modelling the uncertainties in the loads and resistance of the bridge and quantifying the probability of failure or reliability level. A target reliability level for the remaining life of the bridge is considered (usually obtained from the relevant codes). The required proof load is then calculated such that the bridge, following survival with the proof load, can be assessed to satisfy the target reliability criteria (see, among others, Casas & Gómez, 2013; Faber et al., 2000; Lantsoght et al., 2017; Tzyy Shan Lin & Nowak, 1984). However, the above approaches do not consider a risk based optimization for the target proof load levels. The approach used in this paper considers the risk due to testing as well as the service life risk reduction following successful test outcome (see section 3).

2.2 Reliability assessment with proof load test information

Broadly, from literature, two approaches may be outlined for incorporating the test survival information in the bridge reliability model. In the former, the probability distribution function of the resistance is truncated at the value equal to the survived proof load. By doing so, it is indicated that the resistance is at least equal to the applied proof load. The second approach utilizes a formulation where the event of the bridge (or its component) surviving a certain proof load level is modelled with a limit state function and used to update the prior failure probability with Bayesian updating. However, both of the above

approaches require that a formulation of the resistance distribution is known.

For the derivation of target proof load in the case of no documentation of the bridge resistance, a conservative estimate of the required proof load may be obtained utilizing only the load model. In the limit state function for calculating the annual failure probability of the bridge, the variable representing the resistance is replaced with the yet unknown proof load and the equation is solved such that the failure probability is equal to a target value (Casas & Gómez, 2013). However, this approach does not allow for the quantification of risks associated with the testing. In this paper, it is proposed to model the prior distribution of the resistance with a uniform distribution to represent the lack of information. The parameters of the uniform distribution may be selected based on e.g. site information or assumptions about the lower and upper limit of the bridge capacity for live load. For instance, if the bridge is open to traffic, then the resistance can be considered to be at least equal to the load due to current traffic.

Following successful test outcome with a certain proof load level, the resistance distribution is truncated at the survived proof load (see Fig. 1).

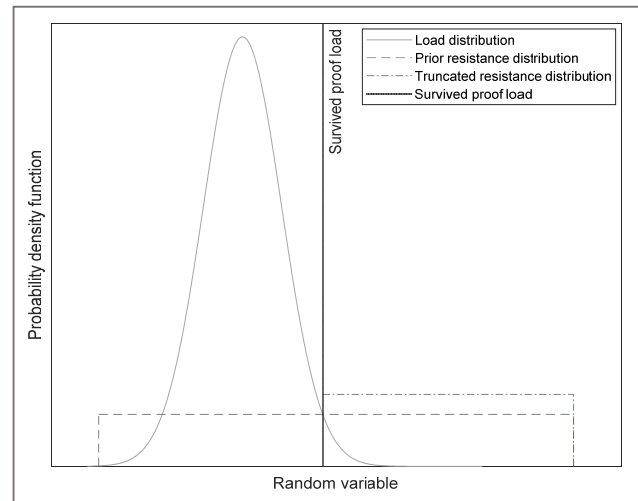


Figure 1. Graphical illustration of resistance distribution modelling and updating with proof load test outcome information

It is to be noted here that the resistance distribution models the capacity of the bridge with respect to the live load. It follows from this assumption that the derived proof load level is to be understood as the load additional to the load due to self-weight, permanent fixtures and other non-variable loads on the span.

3 DECISION ANALYTIC APPROACH

The decision scenario is modelled in the context of the proof load test planner who shall choose the required load level for assessment of classification of a bridge. The choice of the load level depends on the

risks of the testing and the expected benefit gain from the proof load test and monitoring information in the form of a risk reduction in the remaining service life of the bridge. The base scenario is the bridge performance with respect to the live load due to the vehicle without any testing and monitoring information. The performance of the bridge is modelled by calculating its annual probability of failure. The outcome of proof load testing with different proof load levels is predicted and a decision analysis is performed to identify the optimal proof load level as the one leading to the highest expected benefit gain. Here, the expected benefit gain is quantified as the difference between the expected utilities with and without any proof load testing. Additionally, information from the monitoring system deployed during the proof load testing is predicted. The information is modelled taking basis in the load model uncertainty formulation. It is considered that information obtained from the monitoring leads to knowledge of the realization of the model uncertainty related to the load effects. The additional benefit gain due to the monitoring information is calculated with the quantification of the value of information. An important part of the decision analysis is that the optimization is performed with consideration to the target reliability levels, obtained based on code requirements, which serve as boundaries for the decision analysis (see section 5).

The decision scenario is visualised in Figure 2 in the form of a decision tree. Here, the choice of utilizing a monitoring strategy is represented by \mathbf{i} with the outcomes of the monitoring information contained in the set \mathbf{Z} . The modelling of monitoring information, information outcomes and the actions following the outcomes are described in detail in section 6.

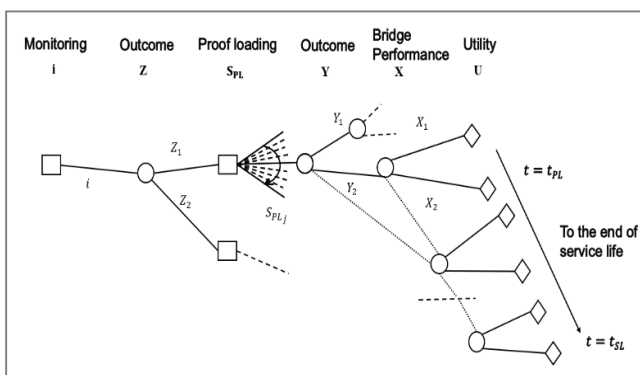


Figure 2. Visualization of the decision scenario

The proof loading is modelled as the action available to the decision maker with the choice of proof load levels $S_{PL,j}$ varying as a ratio of the characteristic value of the annual maximum live load. The outcomes of the loading are contained in set \mathbf{Y} and include the events of test failure (Y_1), or success (Y_2). The probability of test success is given by:

$$P(Y_2) = P(R - M_S \cdot S_{PL,j} > 0) \quad (1)$$

Following the test outcome of success, the resistance distribution is truncated at the survived proof load level (refer Fig. 1). The updated failure probability of the bridge in any year ' t ' following successful test outcome is obtained by,

$$P(X_1(t) | Y_2) = P(R'' - M_S \cdot \Phi \cdot Q_{\max,1} \leq 0) \quad (2)$$

In the Equation above, R'' is the truncated distribution of the resistance following successful proof load test with a certain load level $S_{PL,j}$, M_S is the load model uncertainty, Φ is the dynamic amplification factor and $Q_{\max,1}$ is the distribution of the annual maximum (static) load effect due to the traffic. Here, it is to be noted that the model uncertainty is assumed to be the same for the applied proof load and the traffic loading on the bridge.

The decision analytic approach accounts for the capacity information obtained with the proof load testing (through truncation of the resistance distribution, Eq. 2) as well as the uncertainty associated with the testing through the formulation of the test outcome events (Eq. 1).

The utility distribution \mathbf{U} models the costs associated with the testing and monitoring and the consequences associated with the test outcomes and bridge life cycle performance. The dimension of time is added to illustrate the effect of the proof load testing on the risk reduction in the remaining service life of the bridge. It is to be noted here that the deterioration of the bridge resistance is not considered in the temporal modelling.

In the following sections, the probabilistic models used in the analysis are expanded upon along with an example to highlight the application of the approach.

4 LOAD MODELLING

For short span bridges with one lane or considering only the main girder of a short span bridge, it is sufficient to consider only the loads due to individual heavy vehicles (Hellebrandt et al., 2014). The principle is that only one heavy vehicle can be expected to pass on the bridge, due to its short length and hence it is not required to model the headway between successive vehicles. In this paper, the load modelling is limited to single lane bridges only.

Therefore, for this situation, the most important parameters for the load modelling are the vehicle weight (along with the weights of the individual axles) and configuration, along with the frequency of

the vehicle. The load effect due to the vehicle is modelled using a distribution that describes the maximum load effect experienced by the bridge in a reference period e.g. one year. The distribution involves models for the weight of the vehicle and its distribution to the axles, a response function (e.g. an influence line or surface) to convert the vehicle load to a load effect, dynamic amplification factor and model uncertainty. In the following sections each constituent of the traffic load model used in this paper is elaborated upon.

4.1 Vehicle load

The modelling of the vehicle load is the most important aspect in the traffic load modelling. The models for the vehicles must describe the weight of the vehicle, its distribution to the individual axles and the configuration of the vehicle. The procedure for developing these models involve statistical analysis of vehicle weight data obtained from e.g. weighing stations, vehicle permit records, weigh-in-motion systems, etc.

The Danish Road Directorate employs a classification system for the administration of heavy vehicles, based on a set of standard vehicles. The classification of the bridge is equal to the class of the heaviest standard vehicle for which adequate capacity shall be demonstrated. In this paper, the load effects are calculated using the vehicle load models for these standard vehicles (Vejdirektoratet, 2004). The vehicle configurations for vehicle class 80 – 150 and their annual frequency are presented in Table 1. Further, for the assessment of bridge classification, the reliability of the bridge with respect to the extreme load effect by a standard vehicle belonging to a particular class is calculated.

Vehicle Class	Configuration	Number/year
Class 80	8.0 9.0 9.0 3.2 1.4 6.0 9.0 9.0 14.0 14.0 10.5 1.4 1.4 1.4 1.4	150
Class 90	7.0 7.0 9.5 9.5 1.4 3.2 1.4 6.0 11.0 11.0 14.7 14.7 11.0 1.4 1.4 1.4 1.4	150
Class 100	7.0 7.0 9.5 9.5 1.4 3.2 1.4 6.0 11.5 11.5 11.5 15.1 15.1 11.5 1.4 1.4 1.4 1.4	100
Class 125	7.0 7.0 9.5 9.5 1.4 3.2 1.4 6.0 6 * 16.4 1.4 1.4 1.4 1.4	50
Class 150	7.0 7.0 9.5 9.5 1.4 3.2 1.4 6.0 7 * 17.8 1.4 1.4 1.4 1.4	50

Table 1. Configuration of special vehicles according to Danish classification system (Vejdirektoratet, 2004)

The static load effect due to a single heavy vehicle is calculated using the following equation,

$$Q = \sum_i^{N_{axle}} z(x_i) \cdot W_i \quad (3)$$

Here, Q is the load effect, $z(x_i)$ is the influence coefficient with x_i being the position of the i^{th} axle on the bridge and W_i is the weight of the i^{th} axle.

Considering N yearly passages of the heavy vehicle, the distribution of the annual maximum load effect due to the vehicle is obtained by assuming that the load effects due to each passage are independent and identically distributed (note that often it is additionally assumed that the truck passages follow a Poisson process):

$$F_{Q_{\max,1}}(q) = F_Q(q)^N \quad (4)$$

4.2 Dynamic amplification factor

Moving vehicles interact dynamically with a bridge such that the actual load effect is typically larger than that calculated from a static analysis. The dynamic amplification factor (DAF) is used to transform the load effect calculated with a static analysis to the actual load effect due to the moving vehicle. Determination of the DAF is however a complicated problem due to the large number of influencing parameters. Since this study is focused on a particular type (heavy transport) of vehicle and bridge geometry (short span bridges), we focus on only those parameters that are relevant to the situation.

For short bridges, Ludescher & Bruhwiler (2009) noted that the governing scenario for maximum load effects was due to the amplification of the heavy axles or axle groups. They further noted a negative correlation between vehicle weight and the dynamic amplification. Deng et al. (2015) reviewed various models for the DAF and highlighted its relationship with a number of parameters. For short span bridges the authors noted the vehicle speed to be relevant for DAF models, especially when the length of the vehicle is larger than the bridge length. They further recommended that the influence of road roughness be considered, particularly in the assessment of in-service short span bridges. Further literature review has highlighted the dependency of the DAF models for short span bridges on the considered load effect, and the presence of multiple vehicles (Nowak & Szerszen, 1998).

Various models for the DAF for specific situations have been developed theoretically or numerically using, e.g. FEM methods, and also through experimental investigations and measurements. In this paper, models for the DAF developed by Kirkegaard et al. (1998) with basis in a simulation study of the passage of heavy transport vehicles on a simply supported bridge are used. The study calculated the dynamic amplification of load effects due to a heavy vehicle with gross weight ~100 tons at different vehicle speeds and passage condition.

4.3 Model uncertainty

The uncertainty in the traffic load model can arise due to two reasons: i) the model of the vehicle itself, and, ii) the simplifications in the calculation model used to convert the load to the load effect. The model uncertainty for traffic loads is defined in the report Reliability-Based Classification of the Load Carrying Capacity of Existing Bridges (Vejdirektoratet, 2004) as a Normal distributed random variable with mean 1.0 and coefficient of variation dependent on the traffic situation and its influence on the bridge safety. As a starting point, a coefficient of variation of 10% is used in this paper and is assumed to account for simplification in the calculation model used to calculate the load effect. The uncertainty in the model of the vehicle itself is assumed to be accounted for in the probabilistic model of the vehicle weight.

5 TARGET RELIABILITY FOR EXISTING BRIDGES

Target values for annual reliability indices are recommended in the JCSS Probabilistic Model Code (Joint Committee on Structural Safety (JCSS), 2001) based on an economic optimization that accounts for both the relative cost of safety measures and consequence class of the structure. For existing short span bridges, the relative costs for safety measures can be considered to be medium to large, depending on costs of repair and consequence of restricting traffic on bridge due to repair. Further, the failure consequence can be regarded to belong to ‘Moderate Consequences’ or ‘Large Consequences’. The reliability indices with the above considerations correspond approximately to the recommended values for existing constructions with Consequence Class 1 to 3 according to the Eurocode. However, the Danish National Annex to the Eurocode 1990 recommend that bridges be considered as a minimum to belong to Consequence Class 2. From the above arguments, annual target reliability indices of 3.8, 4.2 and 4.4 (from JCSS PMC) are proposed for use in this study.

Furthermore, in choosing a target reliability level, the type of failure should also be considered wherein the classifications according to ductile failure (with or without reserve capacity) and brittle failure may be employed. Considering the type of failure, two additional annual target reliability levels of 4.75 and 5.2 (Vejdirektoratet, 2004) are also adopted in the analysis.

6 MONITORING INFORMATION

Information acquired from the monitoring systems (deployed during the proof load testing) can be

modelled by taking basis in the model uncertainty formulation. The measurement of the bridge response to the loading can reveal information about the realization of the model uncertainties related to the load effect. It is here assumed that the structure behavior during testing is linear and hence a measurement of the loading response at critical locations during the testing can lead to knowledge of the realization of the load model uncertainty.

The information obtained from the monitoring is subject to the measurement uncertainty of the system employed. The effect of the measurement uncertainty can be modelled by multiplying the model uncertainty realizations with a random variable having distribution parameters according to the precision of the measurement equipment.

The yet unknown monitoring information is modelled with threshold-truncated distributions of the model uncertainty and the measurement uncertainty (Thöns, 2019). The thresholds may be assumed, derived through calibration with respect to target failure probabilities, or optimized with a decision analysis (Kapoor et al., 2019). In the context of proof load testing, the threshold can be linked to the stop criterion for the test. The realization of the model uncertainty can be i) close to the threshold, ii) lesser than the threshold or, iii) higher than the threshold. For realizations of the model uncertainty close to or lower than the threshold, the implication is that the performance during the testing is as expected. This outcome (Z_1) is linked to the application of a higher loading level. Realizations of the model uncertainty higher than a threshold imply that the performance of the structural components is not as expected and are associated with high risks and adaptive (repair) actions. The adaptive actions following an indication of performance not as expected (Z_2) is not modelled explicitly in this paper.

The probability of successful test outcome with the information outcome that the model uncertainty realizations are lower or close to the threshold is calculated with:

$$P(Y_2 | Z_1) = P\left(R - M_s \left[-\infty; \hat{M}_{s_{th}}\right] \cdot U_{meas} \cdot S_{PLj} > 0\right) \quad (5)$$

In the above $M_s \left[-\infty; \hat{M}_{s_{th}}\right]$ is the truncated distribution of the load model uncertainty with realizations lesser than or close to the threshold and U_{meas} is the measurement uncertainty in the monitoring system.

The updated probability of failure of the bridge in the year ‘ t ’ following a successful proof load test and information outcome Z_1 is modelled with the truncated resistance distribution R and the truncated model uncertainty distribution (assuming that the model uncertainty for the test load is the same as the model uncertainty for the traffic load),

$$P\left(R'' - M_s \left[-\infty; \hat{M}_{s_{ph}} \right] \cdot U_{meas} \cdot \Phi \cdot Q_{\max,1} \leq 0 \right) \quad (6)$$

7 APPLICATION

An 8 m long single span bridge having one lane is considered with the critical failure mode due to bending. In this case, the bridge classification is based on the extreme load effect due to the heavy transport vehicle only, as discussed in section 4. The load effects are calculated by modelling the bridge as a simply supported beam and using influence line diagram based on linear elastic analysis. The considered load effect is the maximum bending moment. The probabilistic model for the vehicle weight is obtained from the Danish Road Directorate's guideline document on the reliability assessment of existing bridges (Vejdirektoratet, 2004). The gross vehicle weight is assumed to be normally distributed with the parameters as described in Table 2. The distributions for the static load effect and the annual maximum static load effect are obtained using the probabilistic models presented in Table 2 and Equations 3 & 4. The inverse transform method is used to randomly sample from the distribution $F_{Q_{\max,1}}(q)$.

Property	Distribution	Mean	CoV
Gross Vehicle Weight	Normal		
Class 80	Normal	82.5 tons	0.0606
Class 90	Normal	95.4 tons	0.0524
Class 100	Normal	109.2 tons	0.0458
Class 125	Normal	131.4 tons	0.0381
Class 150	Normal	157.6 tons	0.0317
Dynamic Amplification Factor	Normal	1.024	0.0015
Load model uncertainty	Normal	1	0.1
Measurement uncertainty	Normal	1	0.05
Resistance	Uniform	1350 kNm	0.3635
Proof Load Level	Deterministic	0.8-1.5 times char. value $Q_{\max,1}$ due to vehicle	

Table 2. Distribution type and properties of the parameters used in the analysis

The DAF model for mid-span bending moment due to a single heavy transport vehicle with weight ~100 tons and speed 60 km/h is used (Kirkegaard et al., 1998). The reliability calculations are performed numerically using Monte Carlo simulations.

The bridge is considered to be in the 85th year of service life when the proof load test is to be performed. The total service life of the bridge is 100 years. The analysis is performed for choice of proof load $S_{PL,j}$ varying from 0.8 to 1.5 times the characteristic value (0.98 fractile) of the annual maximum live load effect due to a vehicle belonging to a particular class. The bounds for the resistance distribution are assumed such that the lower bound is at least equal to the maximum bending moment due to a heavy vehicle with gross weight 50 tons and the upper bound is assumed to be higher than 1.5 times the characteristic value of the annual maximum bending moment due to class 150 vehicle. Hence,

the lower limit for the resistance distribution is chosen as 500 kNm and the upper limit is 2200 kNm.

The information from the monitoring system is modelled using Equations 5 & 6. The measurement uncertainty of the monitoring system U_{meas} is modelled using a normal distributed random variable with mean 1.0 and a CoV of 0.05. The threshold $\hat{M}_{s_{ph}}$ is assumed to correspond to the expected value of the model uncertainty i.e. $\hat{M}_{s_{ph}} = 1.0$.

The expected utilities are quantified with the accumulation of the risks over the remaining service life of the bridge as well as the risk due to the proof load testing. The (annual) risks of structural failure are obtained with the multiplication of the annual probability of failure with the failure consequence ($C_f = 100$). The failure probabilities following a proof load testing outcome and/or information outcome are modelled using Equations 2 & 6. In the scenario with proof load testing and monitoring information, the cost of testing and monitoring is also added. The costs associated with the proof loading and monitoring system is modelled as a 0.1% C_f and 0.01% C_f , respectively. A depreciation in the modelled costs is considered to discount the future costs to present value, with a discount rate of 2%. The required proof load is derived for annual target reliability levels of 3.8, 4.2, 4.4, 4.75 and 5.2.

8 RESULTS & DISCUSSION

The expected benefit gain from the proof load testing alone is calculated as a function of the proof load level choices. The expected benefit gain is quantified as the difference of the total expected utilities with and without the proof load testing. The analysis is performed for the bridge performance with respect to five vehicle classes (see Table 2). The results from the decision analysis for the class 80 vehicle are plotted in Figure 3. It is observed that the expected benefit gain increases with the increasing proof load level up to a point and then decreases.

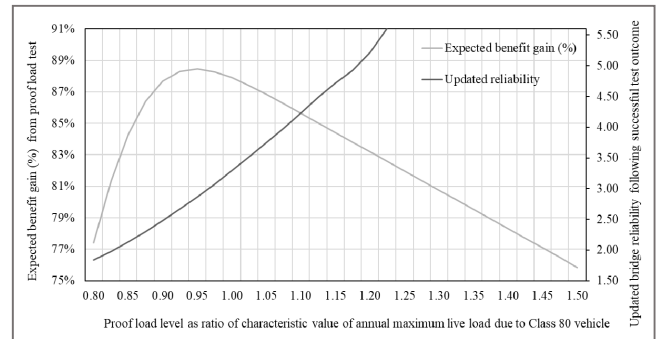


Figure 3. Expected benefit gain and updated bridge reliability as a function of proof load level

The increase is explained by the potential risk reduction in the remaining service life of the bridge fol-

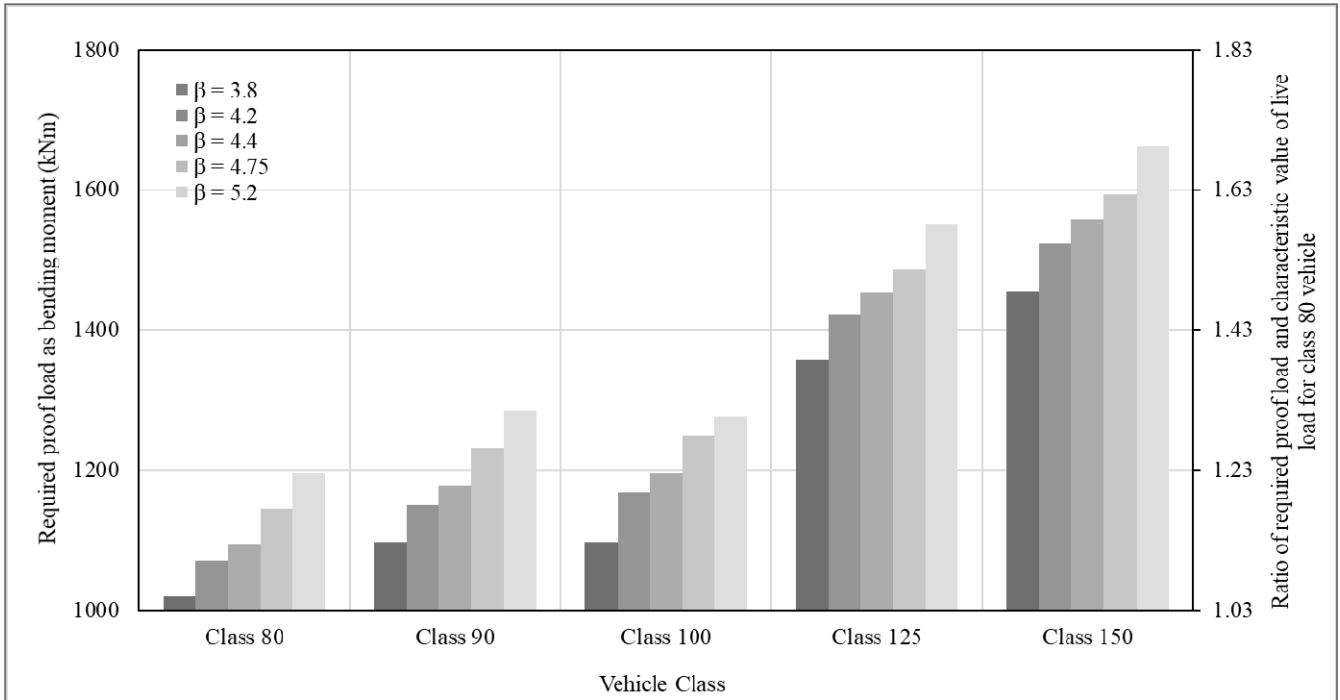


Figure 4. Required proof loading effect to satisfy reliability criteria for different vehicle classes as a function of the target reliability level (without inclusion of monitoring information)

lowing the test survival outcome and updated resistance distribution. At higher proof load levels, however, the risks from the testing outweigh the benefits from risk reduction and the total expected benefit gain decreases. From the decision analysis, the optimal proof load level is identified as 0.95 times the characteristic value of the annual max. load effect due to the class 80 vehicle. However, the updated annual reliability level of the bridge following successful test outcome with this load level is ~ 3 , which is below the target level. In order to satisfy the target reliability criterion, proof load levels higher than this level are required, as can be also observed in Figure 3. These are obtained for each vehicle class and target reliability level and plotted in Figure 4. The ratio of the required proof load effect to the characteristic value of the annual max. load effect due to a class 80 standard vehicle is also plotted in the figure. It can be observed from the figure

that classifications corresponding to class 80 to class 100 can be achieved with proof loads that are within 10% of each other. Whereas, classifications higher than class 100 require $\sim 30\%$ (for class 125) and $\sim 40\%$ (for class 150) proof load as compared to the proof load required for class 80.

This is illustrated in Figure 5 for a target reliability level of 4.4. Here, the percentage increase in required proof load is plotted with respect to the percentage increase in gross vehicle weights and weight of the rear (last 5) axle group. It is observed that the required proof load is highly dependent on the weight of the rear axle group whereas increase in the gross vehicle weight does not produce a large difference. The influence of the information acquirement on the required proof load levels for target reliability level of 4.4 is illustrated in Figure 6.

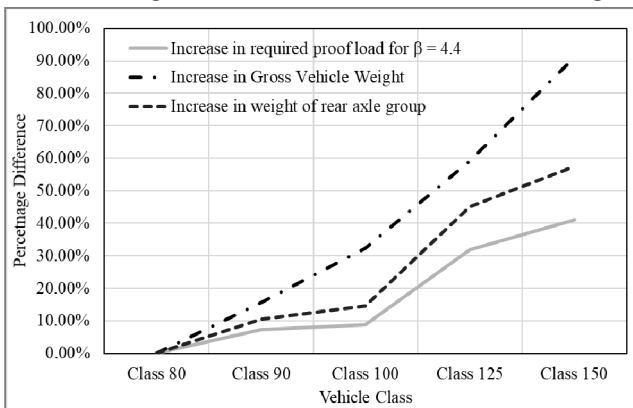


Figure 5. Percentage increase in required proof load corresponding to different vehicle classes in comparison with the percentage increase in the vehicle weights

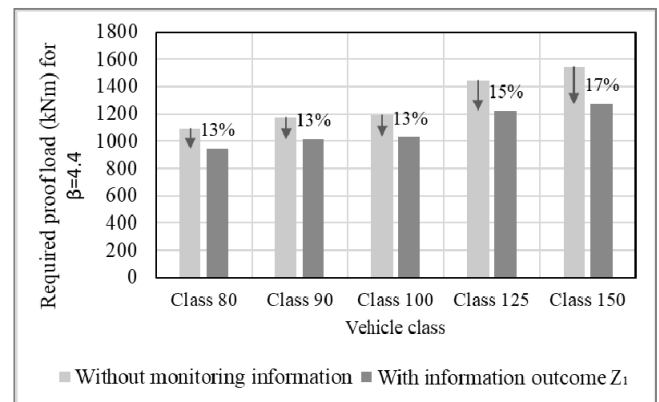


Figure 6. Required proof load to satisfy target reliability level of 4.4 with and without inclusion of monitoring information in the models

The required proof load to satisfy the reliability criteria for a certain classification are on average lowered by 15%, in comparison with the proof load levels without any information on the load models. Consequently, we can also infer that, given successful test outcome with a certain load level, the capacity of the bridge can be assessed to satisfy the reliability criteria for a higher classification if monitoring information is included in the load models. The information acquirement also leads to an exp. benefit gain due to risk reduction. This is illustrated in Figure 7. The total expected costs (inclusive of test risks, risks along remaining service life and costs of testing and monitoring) with the optimal load level required for a target reliability level of 4.4 for different vehicle classes is plotted in the situation without monitoring information and following monitoring outcome Z_1 .

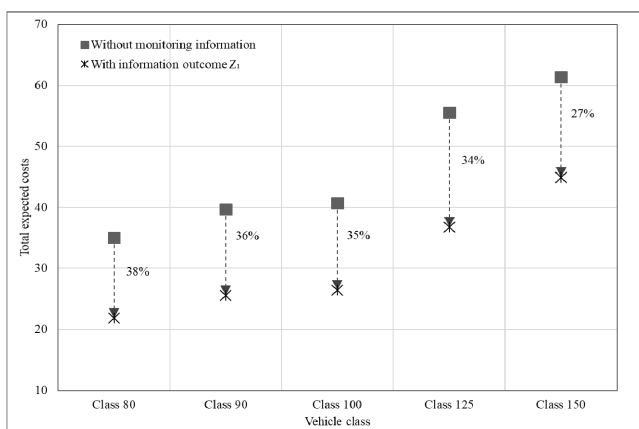


Figure 7. Illustration of reduction in expected costs following monitoring information outcome Z_1 with the optimal load level required for a target reliability level of 4.4

9 SUMMARY & CONCLUSION

A methodology to derive the required proof load for the classification of short span bridges in the situation of lacking capacity documentation was presented. The resistance model was established by information from the proof load testing and basic prior knowledge about the capacity. The methodology takes basis in a decision analytic approach where the expected benefit gain from the proof load testing was quantified to derive the load required in order to verify the bridge capacity with respect to loading from heavy transport vehicles with specific configurations. The optimal load level was identified as leading to a positive expected benefit gain to the decision maker while also satisfying the target reliability criterion. The decision analytic approach further considered the inclusion of information from monitoring systems deployed during the testing.

The methodology and models can be further refined with the inclusion of more information from bridge management systems in the models. These

may include vehicle models based on actual weight and configuration data of the heavy transport vehicles. Further, the methodology can be extended to consider different bridge geometries (span lengths and lane conditions), more choices of vehicle types and different precision related to monitoring systems.

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