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ABSTRACT

Reclassification of bridges, i.e., a change in load rating, using reliability-based methods and a direct update with proof load information has been presented by many authors. However, bridge reclassification has hardly been studied from a decision analytic perspective, i.e., with quantification of the risks and benefits of different classification choices, and the expected benefit gain from proof loading. We derive, explain and exemplify a decision analytic approach for bridge reclassification along with models for (1) elastic and ultimate capacity and their adaptation with proof load information, (2) proof load information with classification outcomes accounting for target reliabilities and, (3) utilities including socio-economic benefits from reclassification. The approach and models are exemplified with a case study based on reclassification of bridges with a low existing classification. Decision rules, for practical use by a highway authority to find the optimal classification, are identified and documented based on: (1) the measurement of the capacity at elastic limit by proof loading, (2) the bridge reclassification benefits, and, (3) the required annual reliability level. From a Value of Information analysis, it is concluded that the proof load information is highly valuable for reclassification in cases of high socio-economic benefits and high reliability requirements.

1. Introduction

Sufficient classification levels (or load rating) of bridges is of high importance to society in order to ensure the future service life of a traffic infrastructure that suffers from increasing traffic demand and aging structures. From the bridge owner's perspective, the goal is to allow transport of more and heavier goods with a higher classification, i.e., increasing the traffic efficiency of the bridge. It is often observed that existing bridges were designed using conservative methods and without explicit consideration of the distribution of internal forces, interaction between structural elements, redistribution of stresses, etc., leading to a huge potential for reclassification [1,2]. Here, proof load testing may be used to obtain information about a bridge's load carrying capacity.

The information gained from the proof load test can be incorporated in the probabilistic model of the bridge capacity and used in reliability assessment. Many researchers have presented approaches for modeling proof loading information (see e.g., [3–6]), and of bridge reclassification with proof loading using a reliability based approach (see e.g. [7–11]). Even the calibration of measurement systems may be achieved via a proof loading [12]. A review of proof loading monitoring approaches and technologies can be found in [13].

Decision analyses, by quantifying, the Value of (obtained or predicted) Information (VoI), enable identifying cost and risk efficient strategies for acquiring information (see e.g. [14–16]). In the context of decision support for infrastructure systems, VoI based decision analysis have been applied e.g., in inspection and maintenance planning (see e.g. [17–21]), design and optimization of sensor systems (see e.g. [22–24]), structural maintenance using condition assessment (see e.g. [25,26]. Implications of regulatory policies on the value of information are discussed in [27]. Chadha et.al. discuss, model and integrate risk perception in the monitoring and maintenance planning [28]. Proof loading has been investigated in a decision theoretical context yet solely in the pre-construction phase for offshore structures [29].

It is noted that in both fields namely reliability-based proof load

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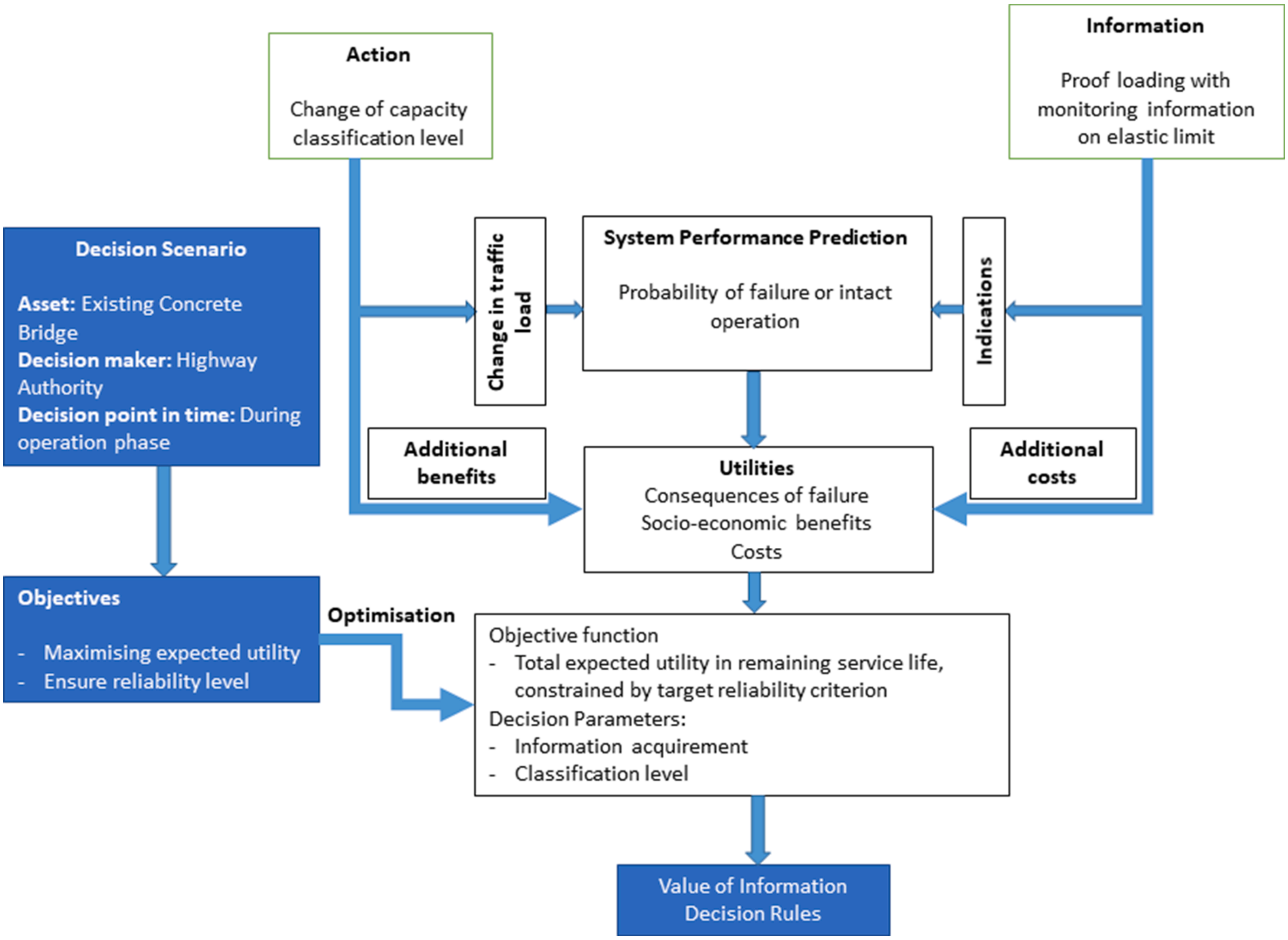

Fig. 1. Flowchart on reclassification decision scenario with elastic limit information from proof loading.

modeling research, and decision analyses and Value of Information research, a bridge reclassification has not been studied. The focus of the present study is thus in developing a decision analytic approach and a case study for bridge reclassification using information from proof loading by building upon and extending [2]. The decision analytic approach is based on Bayesian decision theory [30,31] and utility theory [32].

Proof load tests demonstrate the ability of the bridge to carry a specific load but do not directly provide information about the ultimate capacity of the structure. The structural response to the loading is closely monitored and the loading is stopped when either the elastic limit or a target proof load level is reached. Hence, the information from proof loading is within the elastic range of structural system behaviour. On the other hand, the state-of-the-art for concrete structure design at ultimate limit is based on ultimate capacity including plastic methods [33]. Modeling the proof loading information for reliability updating while accounting for the specifics of structural reliability modeling and the underlying mechanical behaviour and design approaches, i.e. the elastic and ultimate limit state modeling and information, has to the knowledge of the authors hardly been studied in the scientific and engineering research literature. This challenge is addressed in this paper by developing a model for the distinction of elastic level proof load information and the ultimate capacity of the bridge in conjunction with the introduction of a pre-posterior structural reliability updating approach.

Following the outline of current challenges, the decision analytic approach for reclassification of bridges is developed for in-situ and in-service proof loading in combination with monitoring during the proof load test. The proof load information is modelled by discretization of (continuous) distributions following a recently introduced approach [34,35]. In the referenced work, monitoring information is modelled as realizations of model uncertainty within pre-calibrated thresholds. The thresholds are calibrated by setting the posterior probability of structural failure equal to target values (from e.g., EN 1990 [36] or the Probabilistic Model Code of the Joint Committee on Structural Safety (JCSS) [37]. The probability of an indication is obtained as the probability of a realization within the thresholds discretizing the continuous distribution. For the present purpose, the approach for modeling structural measurements is extended for modeling the elastic limit information from proof loading.

The paper is structured such that the individual elements for the decision analysis, i.e., the decision analytic approach and the probabilistic models for structural reliability analysis and information modeling (Section 2), are described first. This is followed by a detailed reclassification case study in Section 3. The bridge classification approach and load modeling in the case study specifically relates to the Danish classification system [38,39] that was developed for the administration of heavy vehicles requiring permits. The system is based on a series of heavy “standard” vehicles, which are distinguished by their gross vehicle weight ranging from 20 t – 500 t. The classification of the bridge is equal to the class of the heaviest “standard” vehicle for which an adequate reliability can be demonstrated. Finally, Section 4 presents a summary of the contents and conclusions are drawn.

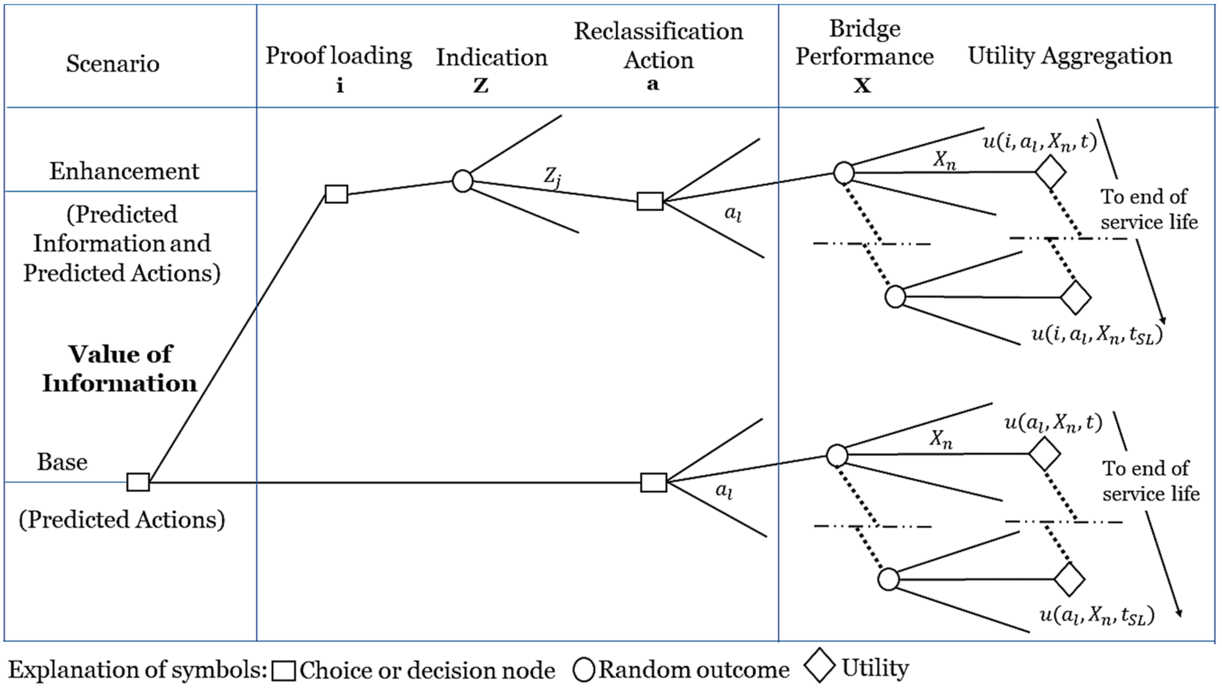

Fig. 2. Illustration of the decision analysis with a decision tree.

2. Decision analytic approach for reclassfication of bridges

The decision scenario is modelled from the perspective of a highway authority (the Decision Maker: DM) who has to choose and adapt the classification for an existing bridge (Fig. 1). The choice of capacity classification i.e., the permitted traffic load is modelled as the action available to the DM. The DM may use in situ and in service proof loading testing for acquiring information and deciding the optimal action, i.e., the optimal choice of the (re-)classification.

The optimal action is identified by maximizing the aggregated expected value of the utility - in this way the analysis represents a normative decision analysis [30] - and ensuring compliance with code-based requirements on minimum reliability level. Utility, as considered in this paper, is a function that assigns a monetary value to the DM choices (of classification level and acquiring information from proof loading), and the uncertain bridge performance.

The DM may choose to (re-)classify the bridge with or without acquiring information. The choice of acquiring information is performed by quantifying the Value of Information (VoI) defined as the difference in maximum aggregated expected utility from a decision scenario with and without information. The cost of proof loading information is explicitly modelled and included in the utilities. Obtaining a positive or zero VoI implies that acquiring information will be beneficial to the DM while a negative VoI implies that the cost of the information exceeds any expected utility gain to the DM from a change of classification.

The decision analysis is illustrated using a decision tree in Fig. 2. A base scenario without any proof load information is considered. The base scenario is formally defined as a predicted action (PA) decision analysis [40], where the action is reclassification ($a_l \in \mathbf{a}$). The performance of the bridge ($X_n \in \mathbf{X}$) is modelled by calculating the annual probability of the system states, such as e.g., failure (X_1) and intact (X_2) states. The probabilities of failure and intact state with different classification choices is calculated and a decision analysis is performed to identify the optimal classification as the one leading to the highest expected utility, within reliability constraints (i.e. for classification choices a_l for which probability of failure $P_{X_1}(a_l)$ is less than or equal to a required target value P_F^T).

The enhancement scenario includes an information strategy ($i \in \mathbf{i}$) i.e., the information from in situ and in service proof loading and is formally defined as a Predicted Information and Predicted Action (PIPA) analysis. In the PIPA decision analysis, the indication from the proof loading ($Z_j \in \mathbf{Z}$) is predicted and the reclassification is optimized in compliance with the minimum reliability criterion.

The expected Value of Information is calculated as the difference between the expected utility from the PIPA and PA analysis, respectively (see Eq. (3) with $E[\ldots]$ as the expectation operator). It should be noted that the information costs are here per definition included for consistency with the expected utility theorem (see e.g. [16]).

$$U^*_{PA} = \max_{\mathbf{a_l}} \sum_{t}^{t_{SL}} E_{X_n}[u(a_l, X_n, t)] \text{ s.t. } P_{X_1}(a_l) \leq P_F^T \tag{1}$$

$$U^*_{PIPA} = E_{Z_j}\left[\max_{\mathbf{a_l}} \sum_{t}^{t_{SL}} E_{X_n|Z_j}[u(i, a_l, X_n, t)]\right] \text{ s.t. } P_{X_1|Z_j}(a_l) \leq P_F^T \tag{2}$$

$$VoI = U^*_{PIPA} - U^*_{PA} \tag{3}$$

In Eqs. (1)–(3), U^*_{PA} and U^*_{PIPA} are the maximum aggregated expected utilities within reliability constraints from PA and PIPA decision analyses, respectively . The utilities $u(\ldots)$ include the failure consequence, the benefits from intact operation following (re-) classification to a_l, and information cost. The expected utility is aggregated over a service life period, i.e., from the year t to the end of the service life in year t_{SL}. In Fig. 2, the dotted lines symbolize the temporal dependency in the annual system performances and the expected utility aggregation. The utility modeling also accounts for the temporal value of money by using the discount rate to discount the future costs/benefits to the decision point in time [41].

As mentioned above, the probabilistic modeling includes quantifying the bridge performance in terms of annual probability of failure. The annual probability of failure with respect to the annual maximum traffic load, S_{L,a_l}, is calculated with Eq. (4).

$$P_{X_1}(a_l) = P\left(M_{R_F} \cdot R_F - M_S \cdot \left(S_D + \phi \cdot S_{L,a_l}\right) \leq 0\right) \tag{4}$$

In the above, R_F represents the ultimate load bearing capacity, M_{R_F} is the model uncertainty related to the ultimate capacity model, S_D

represents the permanent load effect, S_{L,a_l} represents the annual maximum traffic load effect due to a vehicle of class a_l, ϕ represents the dynamic amplification factor applied to the traffic loading, and M_S represents the uncertainty related to the load model. The annual probability of failure over time is calculated as the failure rate (see [37]). The probabilistic modeling also includes information modeling (see Section 2.3), which is used, along with Eq. (4), to obtain updated estimates of the failure probability. The reliability and information modeling takes basis in [37,42,43]. Further studies and examples of model uncertainty quantification can be found in [44–46].

2.1. Load modeling

The most important load variables to be modelled for bridge classification are the dead load (self-weight and permanent fixtures) and traffic load. The traffic load modeling includes both static and dynamic components. The static component of the traffic load effect is calculated from a static analysis considering the gross vehicle weight, axle weights, axle spacing and vehicle width. However, the actual load effect due to a moving vehicle is typically larger than the static live load effect due to dynamic interaction between the vehicle and bridge. To this end, a Dynamic Amplification Factor (DAF) is used to convert a static to a dynamic load effect.

2.2. Capacity modeling

In this and the following section, we introduce a distinction between the elastic and ultimate capacity model and the proof loading information, which is on elastic level. The approach and models described are developed specifically for structures exhibiting an identifiable elastic limit that is lower than the ultimate capacity (e.g., stocky steel beams in bending or shear, under- reinforced concrete in bending, decks, etc.). This excludes, for instance, stability induced failure mechanisms below the elastic limit (e.g., buckling).

The ultimate capacity R_F is defined as a function of parameters, including the concrete compressive strength, reinforcement ultimate strength, concrete ultimate strain, geometry, reinforcement ratios etc. (vector $\mathbf{V}_F$) and the elastic range parameters, $\mathbf{V}_E$. The elastic limit capacity R_E is a function of parameters contained in vector $\mathbf{V}_E$, which includes e.g., the concrete compressive strength, reinforcement yield strength, strain at yielding, etc. The ultimate load carrying capacity is modelled as a function of the elastic limit of capacity, and other additional parameters affecting the ultimate capacity, denoted with the function $g(\ldots)$, (Eq. (5)).

$$M_{R_F}\cdot R_F = M_g\cdot g(M_{R_E}\cdot R_E(\mathbf{V}_E),\mathbf{V}_F) \quad (5)$$

Here, R_E is the capacity at the elastic limit, R_F is the ultimate capacity, M_{R_E} is the model uncertainty related to the elastic capacity model, M_g is the model uncertainty related to the function $g(\ldots)$. This relation builds upon the usual situation that a statistically significant number of elastic and failure load tests is available. Additionally, the model uncertainty M_g has been quantified according to [37], based on these tests.

2.3. Proof load information modeling

In proof loading, the structural response to the loading is monitored to ensure that the structure continues to behave in the linear elastic range. With the proof loading and monitoring up to the elastic limit, a measurement of the capacity at elastic limit i.e., $m_{R_E}\cdot r_E$ can be obtained. With the measurement $m_{R_E}\cdot r_E$, the ultimate capacity (Eq. (5)) can be calculated using the function $g(\ldots)$, subjected to the model uncertainty, M_g (Eq. (6)).

$$M_{R_F}\cdot R_F(m_{R_E},r_E) = M_g\cdot g(m_{R_E}\cdot r_E,\mathbf{V}_F) \quad (6)$$

Note that m_{R_E} represents a realisation of the random variable M_{R_E} and, similarly, r_E is a realisation of the random variable R_E.

The uncertainty in the measurement owing to the limited precision of the monitoring equipment may also be included in Eq. (6). However, as pointed out by Olaszek & Casas [47], the magnitude of the monitoring related measurement uncertainty in proof loading is insignificant if proper loading protocol is followed and the instruments are well calibrated. This is assumed to be the case and measurement uncertainty is neglected in the information modeling.

2.3.1. Discretization of probability distribution function

A significant computational effort would be required to perform the decision analysis and optimization for each sampled realization of M_{R_E} and R_E. To overcome the computational challenge in such a brute force optimization, we discretise the distribution of $(M_{R_E}\cdot R_E)$ i.e., the elastic limit capacity distribution using thresholds. By using the discretized form of the distribution function, the outcomes for the proof loading are modelled with a discrete number of indication events. The discretization of the elastic limit distribution allows compliance with target reliabilities and that in a practical application, the decision maker, on obtaining an elastic limit measurement $(m_{R_E}\cdot r_E)$, can refer to the derived thresholds and decision rules [34,35]. The procedure for deriving the thresholds is described in the following Sections 2.3.1.1 and 2.3.1.2, while the derivation of decision rules is illustrated in the case study in Section 3.

Indication events and threshold calibration. The indication events $Z_j \in \mathbf{Z}$ correspond to the yet unknown realisations of the elastic limit capacity, $M_{R_E}\cdot R_E$, within calibrated thresholds. For example, indication event Z_j would be observed if the elastic limit measurement $m_{R_E}\cdot r_E$ is within the lower (b_{j,a_l}) and upper threshold $(b_{j+1,a_{l+1}})$. The probability of the indication event P_{Z_j} is calculated by integrating the elastic limit capacity distribution between the thresholds (Eq. (7)).

$$P_{Z_j} = \int_{b_{j,a_l}}^{b_{j+1,a_{l+1}}} f_{M_{R_E}\cdot R_E}(m_{R_E}\cdot r_E)d(m_{R_E}\cdot r_E) \quad (7)$$

Considering again the indication event Z_j corresponding to the random variable for the elastic capacity measurement $(M_{R_E}\cdot R_E)\big|_{b_{j,a_l}}^{b_{j+1,a_{l+1}}}$, the posterior probability of failure $P_{X_1|Z_j}(a_l)$ for a load from vehicle class a_l is calculated using Eq. (8).

$$P_{X_1|Z_j}(a_l) = P\left(M_g\cdot g\left((M_{R_E}\cdot R_E)\big|_{b_{j,a_l}}^{b_{j+1,a_{l+1}}},\mathbf{V}_F\right) - M_S\cdot(S_D+\phi\cdot S_{L,a_l})\leq 0\right) \quad (8)$$

Here, $(M_{R_E}\cdot R_E)\big|_{b_{j,a_l}}^{b_{j+1,a_{l+1}}}$ is modelled using the j^{th} discretization of the normalized elastic capacity distribution.

The thresholds are calibrated such that the indication events $Z_j \in \mathbf{Z}$ classify proof loading information of whether the posterior failure probability (Eq. (8)) satisfies the target value for a specific classification. The above means that the thresholds $(b_{j,a_l}, b_{j+1,a_{l+1}})$ are obtained such that the posterior failure probability $P_{X_1|Z_j}(a_l)$ for load S_{L,a_l} due to vehicle class a_l is equal to the target annual failure probability P_F^T (Eq. (9)).

$$P_{X_1|Z_j}(a_l) = P\left(M_g\cdot g\left((M_{R_E}\cdot R_E)\big|_{b_{j,a_l}}^{b_{j+1,a_{l+1}}},\mathbf{V}_F\right) - M_S\cdot(S_D+\phi\cdot S_{L,a_l})\leq 0\right) = P_F^T \quad (9)$$

Note that the subscript 'a_{l+1}' implies a vehicle class higher than a_l: the upper threshold $b_{j+1,a_{l+1}}$ for indication Z_j is the lower threshold for the next indication Z_{j+1} that indicates acceptable performance for load $S_{L,a_{l+1}}$. If the next indication event is not defined, the upper threshold $b_{j+1,a_{l+1}}$ is the maximum value of the random variable $M_{R_E}\cdot R_E$ in its domain.

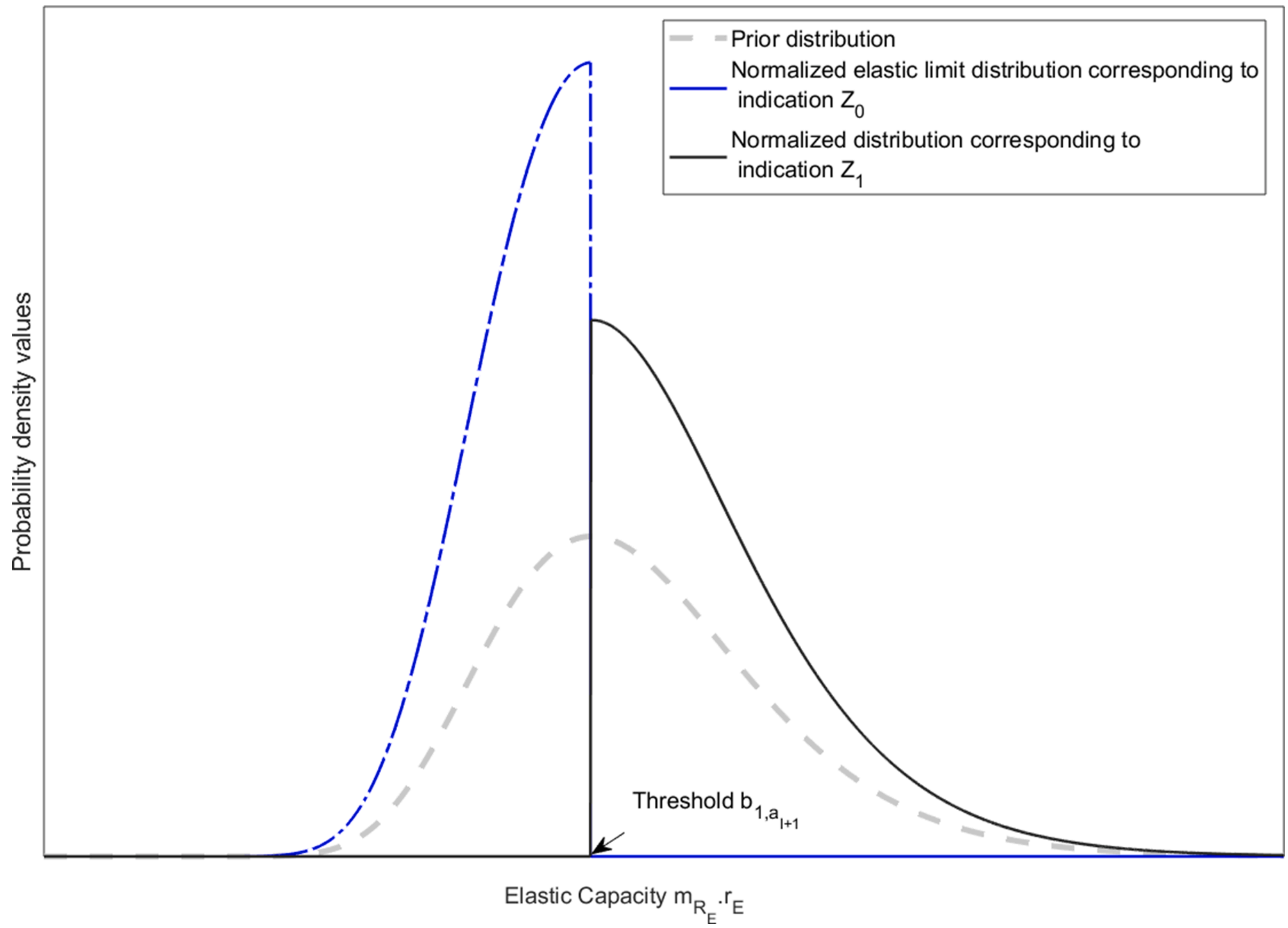

Fig. 3. Illustration of discretised distribution of elastic limit capacity and indication events.

Illustration. As an illustration, a discretization of the distribution function for $M_{R_E}{\cdot}R_E$ is performed (Fig. 3). It is assumed that, based on the prior information on the ultimate capacity, the bridge performance i.e., failure probability is acceptable for classification a_l, which it was designed for. Now, information, in the form of measurement of capacity at the elastic limit, can be obtained from the proof load test. This information is predicted using two indication events: Z_1, which indicates that the bridge ultimate performance is adequate for a higher classification a_{l+1}, and Z_0: which indicates that the performance is not adequate for the higher classification. The distribution, corresponding to event Z_1, has a lower limit $b_{1,a_{l+1}}$ calibrated such that the posterior failure probability for a load due to vehicle class a_{l+1} satisfies the target reliability criterion (Eq. (10)).

$$P\left(M_g{\cdot}g\left((M_{R_E}{\cdot}R_E)|_{b_{1,a_{l+1}}}^{\infty}, \mathbf{V}_F\right) - M_S{\cdot}\left(S_D + \phi{\cdot}S_{L,a_{l+1}}\right) \leq 0\right) = P_F^T \quad (10)$$

The distribution corresponding to indication Z_0 has the thresholds $b_0 = 0$ and $b_{1,a_{l+1}}$ (see Fig. 3).

The corresponding updated ultimate capacity distributions are illustrated in Fig. 4, (see Eq. (6)).

2.4. Utility model

The utility model for a bridge reclassification should encompass the total benefits, costs and consequences to the -DM throughout the bridge's remaining service life.

The failure consequence is modelled with a cost (C_F) including direct consequences of loss of investment and costs of replacement as well as the indirect consequences due to diversion and restriction of traffic, increased travel time, etc. [48]. The costs also include the costs of information i.e., the proof load test cost (C_{Test}).

The socio-economic benefits from intact bridge operation with a reclassification (B_{a_l}) are attributed to an increased efficiency in goods transport. Increased bridge carrying capacity implies that more and heavier goods can be transported, leading to a higher ton-volume per kilometre for the goods transport vehicles. By modeling the monetary impact of increased goods transport efficiency from an increase in the classification level, a quantification and direct comparison between benefits for different classifications is performed. It may be noted that such socio-economic benefits related to transport efficiency are also conventionally included in cost-benefit analysis of traffic infrastructure projects [49,50].

All costs and benefits are discounted to their present value, i.e., the decision point in time. As the decision maker for the reclassification of bridges constitutes usually a public authority, the discounting rate (r) should correspond to the real rate of economic growth per capita [41].

3. Case study

3.1. Decision scenario

Let us consider an existing single span bridge that has initial capacity classified as Class 50, i.e., the capacity was initially designed for a load from a vehicle of Class 50. The span of the bridge is 8 m. For the purpose of illustration, we consider loading from the heavy vehicle in one lane only. This can be, for example, a conditional passage situation according to the Danish classification approach [39].

The decision point in time is at the end of the bridge's service life when an assessment has to be made for the next 15 years of service. The

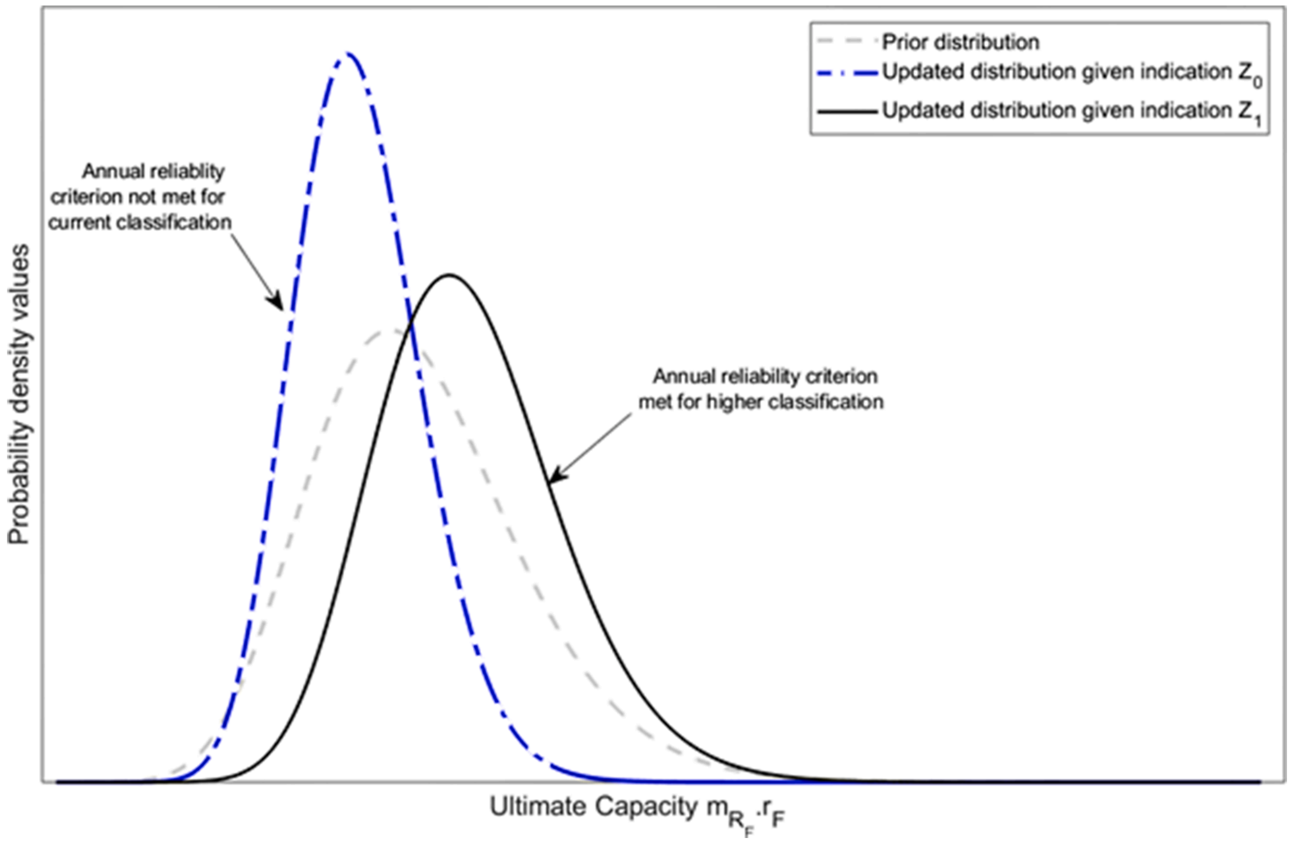

Fig. 4. Illustration of ultimate capacity distribution and updating following indications.

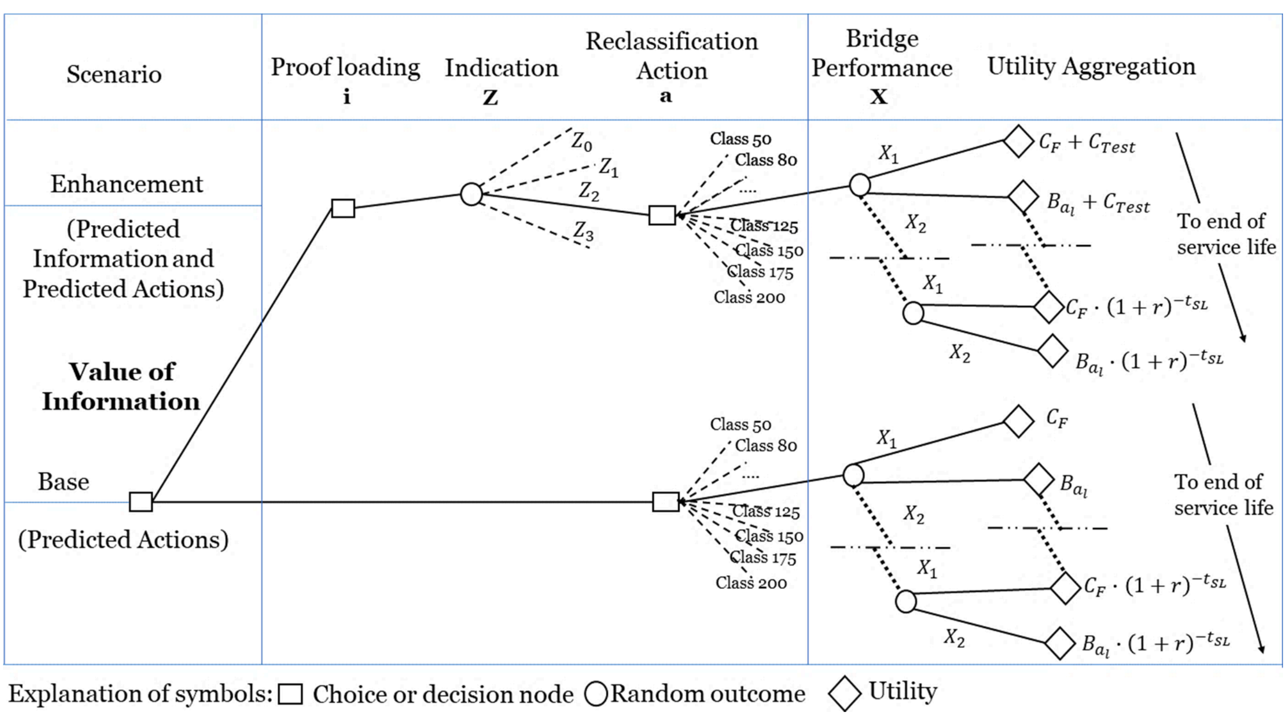

Fig. 5. Visualisation of the decision scenario in case study.

highway authority has the choice (contained in set of actions, **a**) of classifications between 50 and 200 Fig. 5) as well as the choice of acquiring proof load information. The information is modelled with the definition of indication events Z_j, as described previously. The bridge performance, with respect to the load due to the different classification choices, is modelled with the probabilities of failure (event X_1) and survival (event X_2) until the end of the projected service life. The expected utilities are calculated by aggregating the annual failure risks and

Table 1
wt and annual frequency for heavy "standard" vehicles [39].

Vehicle Class a_l	Gross Vehicle Weight (in tons and kN (in brackets)) Mean	Standard Deviation	Number of yearly crossings N_{a_l}
Class 50	53.1 (520.4)	5 (49)	200
Class 80	82.5 (808.5)	5 (49)	150
Class 90	95.4 (934.9)	5 (49)	150
Class 100	109.2 (1070.2)	5 (49)	100
Class 125	131.4 (1287.7)	5 (49)	50
Class 150	157.6 (1544.5)	5 (49)	50
Class 175	170.2 (1668)	5 (49)	50
Class 200	201.0 (1968.9)	5 (49)	50

expected annual benefits (see Eqs. (1) and ((2), Section 2). This is symbolized in Fig. 5 with dotted lines between the bridge performance outcome and utility nodes in the years following proof loading.

The models used in the case study for calculating the probabilities of system failure and intact operation are detailed below and summarized in Tables 1 and 2.

3.2. Capacity modeling

The considered bridge was initially designed as a Class 50 bridge. This is the prior information available to the DM and is used for the prior failure probability calculations. Hence, the mean of the prior model for R_F is calibrated such that annual failure probability for traffic load due to a Class 50 vehicle (Eq. (4)) is equal to a target value $\approx 10^{-7}$, corresponding to $\beta^T \approx 5.2$ for new bridges in Consequence Class 3 for a 1 year reference period, see EN 1990 DK NA [52]. This prior model (based on the calibration to β^T and implying no gross errors in the design and construction) is later updated with in situ proof loading information facilitating an uncertainty reduction in regard to the conservativeness of engineering models and potential design and as-built deviations.

The ultimate capacity model is related to the elastic capacity using a function $g(\ldots)$ (Section 2.2, Eq. (5)). As a starting point, the function $g(\ldots)$ is defined generically with a linear relation between the ultimate and elastic capacity and omitting an explcit model of the variables in vector $\mathbf{V}_F$ (Eq. (11)).

$$M_{R_F} \cdot R_F = k \cdot M_g \cdot M_{R_E} \cdot R_E \tag{11}$$

The model of the ultimate capacity $M_{R_F} \cdot R_F$ is used along with k and M_g to model the distribution for the elastic capacity, $M_{R_E} \cdot R_E$. This distribution is required for sampling the elastic limit measurements (Section 2.3).

Following Eq. (11), k is by definition the bias in the ultimate capacity prediction, when extrapolating from elastic capacity estimate. $k = 1.5$ is chosen considering experimental evaluations of elastic limit and failure load in short span concrete bridges [53,1]. For practical application, its value would require to be quantified with laboratory and in-situ load tests on similar bridges. In the extrapolation, it would be required to account for uncertainties related to the failure mode (different realizations of the physical uncertainties: e.g., concrete compression strength, may trigger different failure modes) and type of bridge. These (model) uncertainties are accounted for in the modeling by M_g.

The resistance model uncertainties, M_{R_F} and M_g are modelled with a lognormal distribution [37]. The prior model for R_F is assumed to be conservative, hence a bias is included in the model uncertainty (see e.g. [44,45]). The model uncertainty M_{R_F} is modelled with a CoV of 0.15 following JCSS Probabilistic Model Code Part 3.9 [37] for concrete resistance models.

3.3. Load modeling

For load modeling on bridges, the ratio of dead to live loads in design varies with the span. Live loads dominate for short spans [54]. This fact is represented by modeling the characteristic value of the dead load effect S_D as $\rho = 1/2$ times the characteristic value of the annual maximum live load effect due to a Class 50 vehicle, $S_{L,50}$ [8]. The characteristic values for the heavy vehicles are defined in Vejdirektoratet [39] and e.g., are used as basis for the calibration of partial factors in the Danish National Annex to EN 1990 (part relevant to applications for bridges). It is to be noted that the characteristic value in the Eurocode EN 1991–2 is defined on the basis of a 1000-year return period. However, this definition is for ordinary traffic, not for heavy vehicles in Load Model 3 as introduced in the Danish National Annex.

For traffic load modeling, only the load effects due to individual heavy vehicles are considered as the critical loading events in short spans (up to 20 m) can be attributed to transits of heavy vehicles [55]. The modeling for the heavy vehicles includes the Gross Vehicle Weight (GVW), its distribution to the individual axles, axle configuration and spacing. The probabilistic models for the vehicle weight as recommended in the guideline for assessment of existing bridges by the Danish Road Directorate are used [39]. Fig. 6 shows the representative axle configuration and width of selected vehicles, according to this document. The probabilistic model for the GVW is presented in Table 1. The load effect due to a single heavy vehicle Q_{a_l} is calculated using the probabilistic model for the GVW and an axle configuration equivalent to those illustrated in Fig. 6. Samples from the distribution function Q_{a_l} is obtained in three steps: i) random GVWs are sampled using the probabilistic model in Table 1, ii) for each sampled value, random axle loads are simulated assuming the same ratio to the GVW as in the Fig. 6, iii) the load effect is calculated by longitudinally and laterally positioning the vehicle for maximum bending moment in the span.

Considering N_{a_l} yearly crossings of a heavy vehicle of a specific class, the distribution of the annual maximum load effect S_{L,a_l} due to the class a_l vehicle is obtained by modeling the vehicle crossings using a thinned Poisson distribution (Eq. (12)). It is assumed with the modeling that the vehicle crossings are independent and that the number of passages per year (N_{a_l}) is constant [56]. The 'thinning' of the Poisson process implies that the distribution accounts for loads due to vehicles of a specific type (class a_l).

Table 2
Probabilistic model used in the case study for bridge performance modeling.

Quantity	Symbol	Distribution	Mean	Std. Dev.	Reference
Ultimate capacity	R_F	Lognormal	Calibrated	$0.14 \cdot \mu(R_F)$	[7]
Model uncertainty	M_{R_F}	Lognormal	1.1	0.15	(M [44]; Milan [45]; Probabilistic Model Code Part 3.9)
Model uncertainty	M_g	Lognormal	1	0.10	(JCSS Probabilistic Model Code)
Load model uncertainty	M_S	Normal	1	0.10	[39]
Dead Load	S_D	Normal	$\rho \cdot S_{L,50,k}$	$0.05 \cdot \mu(S_D)$	[39]
Live load due to Class a_l vehicle	S_{L,a_l}	According to Eq. (13)			
DAF for	ϕ	Normal	1.091* / 1.024**	0.0348* / 0.0015**	[51]

* For Class 50 Vehicle.
** For Class 80 – 200 Vehicle.

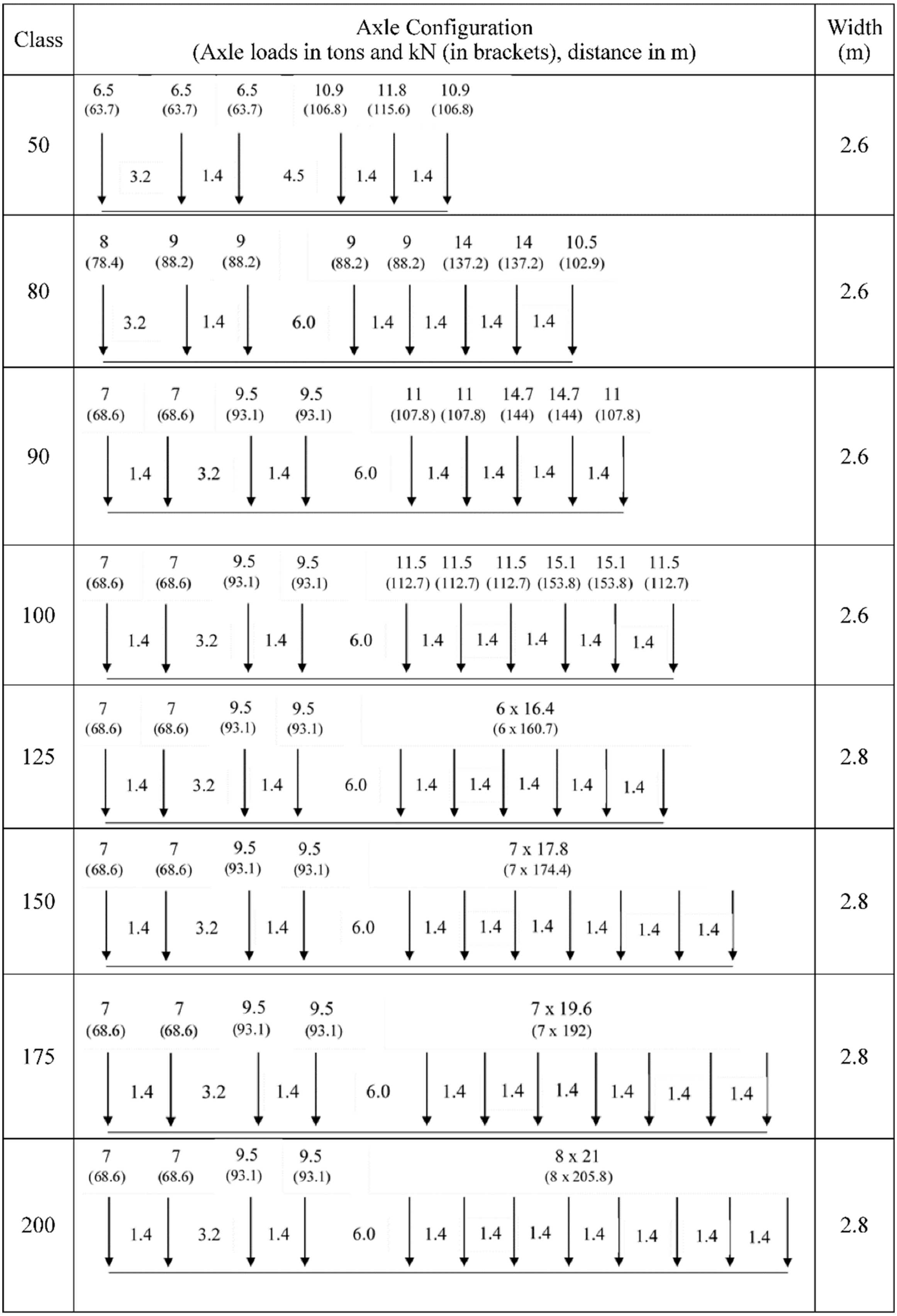

Fig. 6. Configuration of “standard” vehicle classes according to Danish classification system [39].

Table 3
Benefit model for bridge classification.

Benefit Model	Annual benefit/ vehicle	Annual traffic volume of heavy vehicles* Bridge Class 80 750	Bridge Class 90 900	Bridge Class 100 1000	Bridge Class 125 1050	Bridge Class 150 1100	Bridge Class 175 1150	Bridge Class 200 1200
		Total benefit in remaining service life (Monetary Unit $= 10^5€$)						
Model 1	10^{-6}	1.04E-02	1.25E-02	1.38E-02	1.45E-02	1.52E-02	1.59E-02	1.66E-02
Model 2	10^{-5}	1.04E-01	1.25E-01	1.38E-01	1.45E-01	1.52E-01	1.59E-01	1.66E-01
Model 3	10^{-4}	1.04E+00	1.25E+00	1.38E+00	1.45E+00	1.52E+00	1.59E+00	1.66E+00
Model 4	10^{-3}	1.04E+01	1.25E+01	1.38E+01	1.45E+01	1.52E+01	1.59E+01	1.66E+01
Model 5	10^{-2}	1.04E+02	1.25E+02	1.38E+02	1.45E+02	1.52E+02	1.59E+02	1.66E+02

* Sum of yearly crossings of "standard" vehicles on bridge span with a specific classification.

$$F_{S_{L,a_l}}(q_{a_l}) = \exp\Big(-\Big(1 - F_{Q_{a_l}}(q_{a_l})\Big)N_{a_l}\Big) \tag{12}$$

The Dynamic Amplification Factors used are based on models developed by Kirkegaard et al. [51] from a simulation study of the transit of heavy transport vehicles on a simply supported bridge with the road roughness profile of a typical Danish road. The study presented the dynamic amplification of load effects due to a heavy vehicle with gross weight ~100 tons at different speeds. Alternatively, the probabilistic models in the Danish Road Directorate guideline [39] may be used. However, the DAF from those models may be conservative with respect to the heavy vehicles, which have a low dynamic impact [57] A low load model uncertainty is used since the model is limited to loading in one lane [39] .

3.4. Information indication events and calibration of thresholds

As described in Section 2.3, indication events $Z_j \in \mathbf{Z}$ are modelled such that they categorise the proof load information in terms of the performance for load from different vehicle classes. In Denmark, classification of existing bridges to Class 100 is of interest to the Danish Road Directorate. This is because the bridge can then be included into the so-called 'Blue road' network, comprising of bridges with Class higher than 100. The network includes all motorways and major roads and provides ease of administration for goods transport using heavy vehicles [38]. Hence, an adequate reliability level for load from vehicle Class lower than 100 and for vehicle Class(es) higher than 100, respectively, is used to categorize the information.

The indication events are distinguished as follows:

- Z_3: Posterior failure probability is acceptable for the load due to a vehicle Class 200. The threshold $a_{3,200}$ is calculated such that:

$$P\Big(k\cdot M_g\cdot(M_{R_E}\cdot R_E)\big|_{a_{3,200}}^{\infty} - M_S\cdot(S_D + \phi\cdot S_{L,200}) \leq 0\Big) = P_F^T \tag{13}$$

- Z_2: Posterior failure probability is acceptable for the load due to a vehicle Class 150. The threshold $a_{2,150}$ is calculated such that:

$$P\Big(k\cdot M_g\cdot(M_{R_E}\cdot R_E)\big|_{a_{2,150}}^{a_{3,200}} - M_S\cdot(S_D + \phi\cdot S_{L,150}) \leq 0\Big) = P_F^T \tag{14}$$

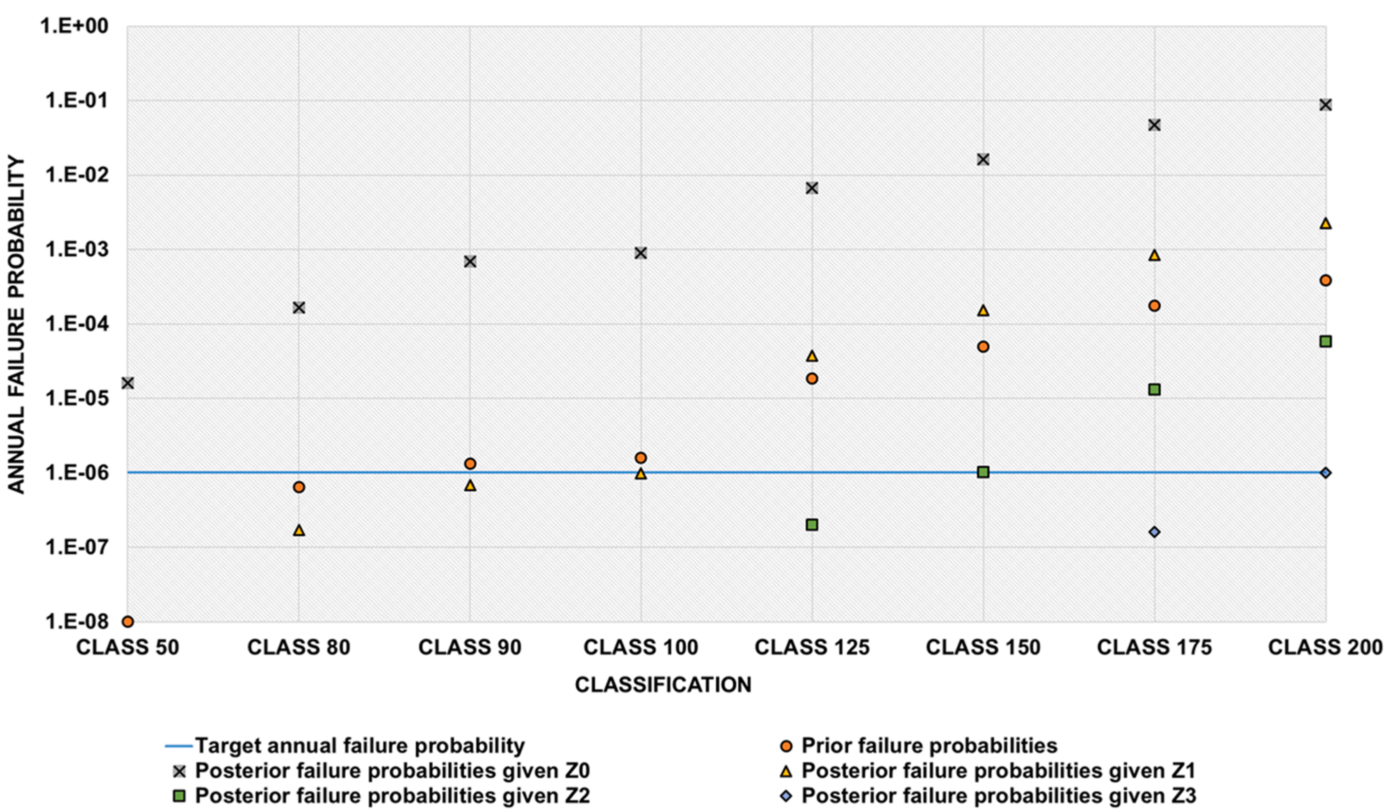

Fig. 7. Annual failure probabilities with target $P_F^T = 10^{-6}$.

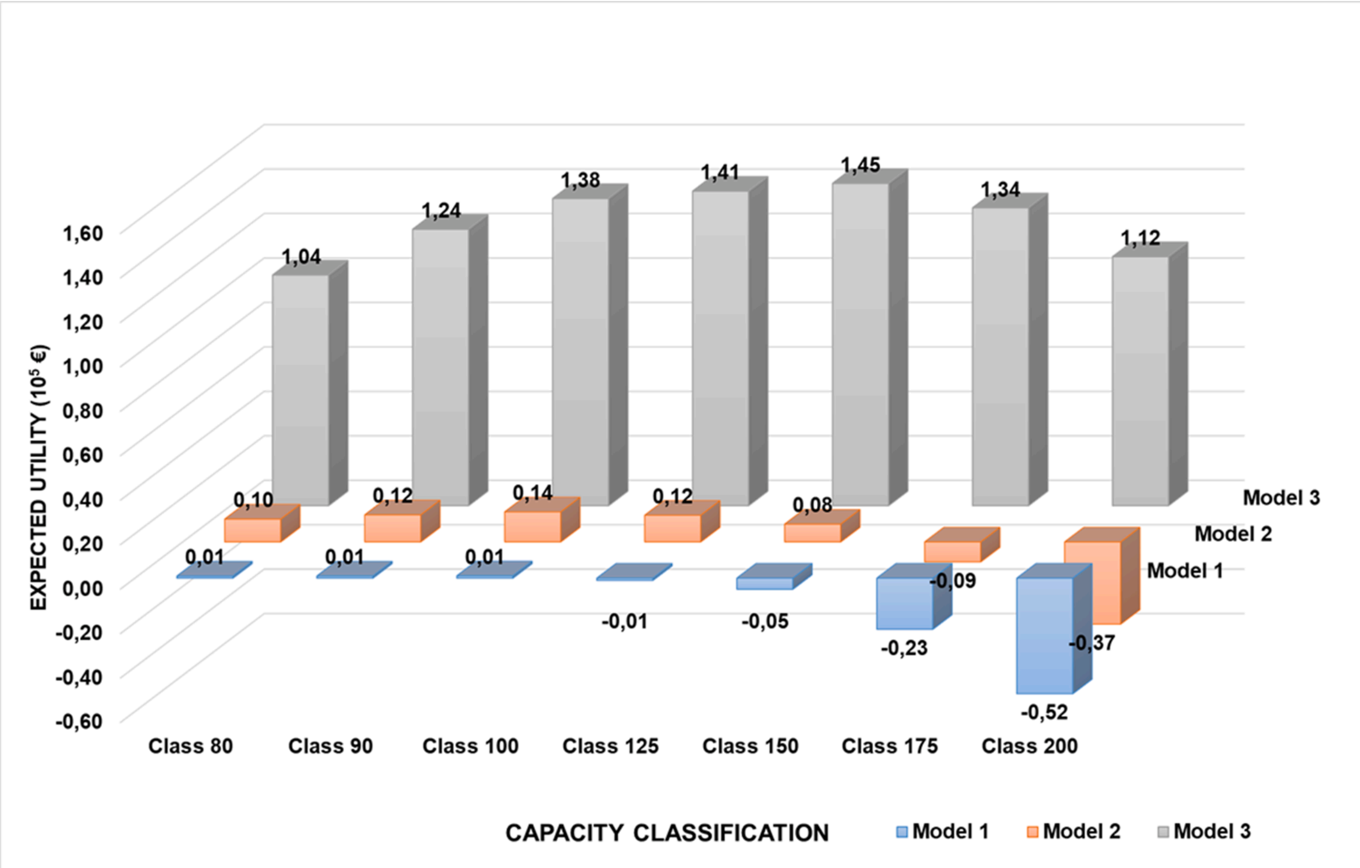

Fig. 8. Expected utilities from the PA analysis as a function of benefit models 1–3 and classification.

- Z_1 : Posterior failure probability is acceptable for the load due to a vehicle Class 100. The threshold $a_{1,100}$ is calculated such that:

$$P\left(k \cdot M_g \cdot (M_{R_E} \cdot R_E)|_{a_{1,100}}^{a_{2,150}} - M_S \cdot (S_D + \phi \cdot S_{L,100}) \le 0\right) = P_F^T \tag{15}$$

- Z_0 : Posterior failure probability not acceptable for the load due to a vehicle Class 100

The annual target failure probability of $P_F^T = 10^{-6}$ is used for the above calibration, based on Danish National Annex to the EN1991 [58]. The national annex states that, for existing bridges, the target reliability level can be calculated with one Consequence Class lower than for a new bridge structure. Assuming that the new structure was designed for CC3, the value for P_F^T is based on the reliability criterion for CC2.

3.5. Consequence, cost and benefit model

The total expected utility corresponding to a choice of classification $a_l \in \mathbf{a}$ is calculated by aggregating the expected annual failure consequence and the expected annual benefit accruing over the remaining 15 years' service life of the bridge.

The failure consequence is modelled with a cost $C_F = 10^7€$, taken as an estimate from studies in Denmark for monetary consequences of bridge failure and replacement (see [59,60]).

The cost of information C_{Test}, inclusive of the costs of loading and monitoring equipment and the human resources involved in performing the test and processing results, is chosen equal to $10^4€$ [1].

The annual benefit from bridge operation B_{a_l} is modelled using the annual benefit per goods vehicle (see e.g., Thoft-Christensen [50], De Brito et al. [61]) multiplied by the annual traffic volume of goods vehicles for a specific classification level. The annual traffic volume of goods vehicles for a specific bridge classification level is obtained by summing the number of yearly crossings of the heavy "standard" vehicles that can be allowed on the bridge (last column, Table 1). In this way, the socio-economic benefits are modelled proportional to the traffic volume of goods vehicles, allowing a quantification and comparison of benefits from different classification levels.

Five values are modelled for the annual benefit per goods vehicle and labelled "Benefit Model", see Table 3, to represent the effects of negligible reclassification benefits (Benefit Model 1) to very high benefits (Benefit Model 5) on the expected utilities. The total remaining service life benefit i.e., the aggregation of the annual benefits B_{a_l} over 15 years remaining service life for each bridge classification level and Benefit Model is also shown in Table 3. A discount rate $r = 2\%$, considered to be representative of the rate of economic growth per capita in Denmark is used, see also Section 2.4.

3.6. Results & discussion

3.6.1. Reliability analysis

The reliability analysis is performed for the consideration of bridge failure probability constraints, to which the DM may by law and regulations be restricted to. These failure probability constraints can be complied with by prior and posterior failure probabilities, which necessitates the utilization of the extensive form of decision analysis or the separate calculation of posterior probabilities in a normal form decision analysis.

In Fig. 7, the prior and posterior annual failure probabilities for each capacity classification are plotted. For comparison, the recommended minimum target value is also shown. From the figure, the maximum classification that satisfies the reliability criterion is identified for each

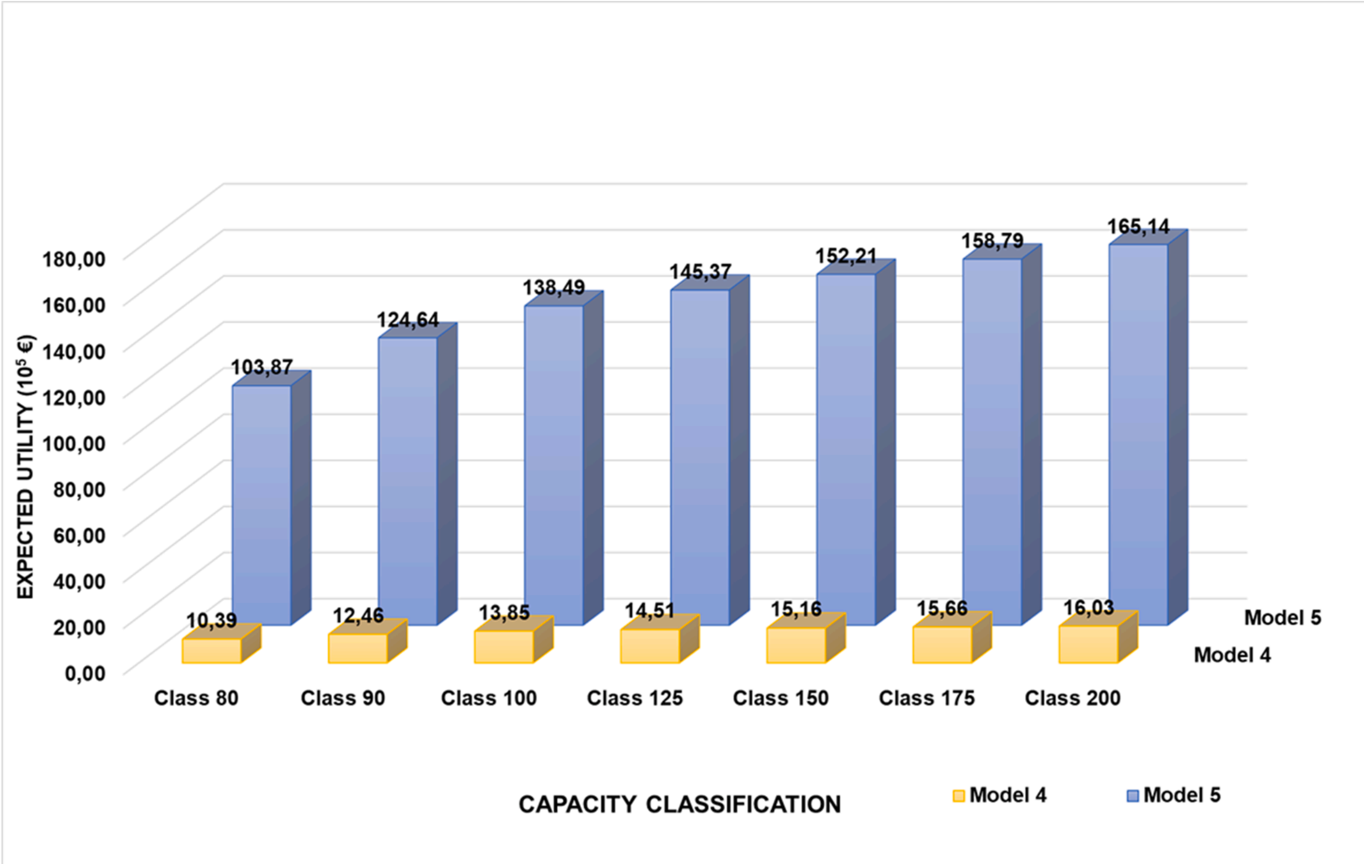

Fig. 9. Expected utilities from the PA analysis as a function of benefit models 4–5 and classification.

Table 4
Decision Rules: Optimal choice of classification for different indications with constraints on annual failure probability.

Benefit Model	Decision Rules ($\beta^T = 4.7$ or $P_f^T \cong 10^{-6}$)			
	Without Information (Base Scenario)	With Indication Z_1 (Enhancement Scenario)*	With Indication Z_2	With Indication Z_3
Model 1	Class 80	Class 100	Class 125	Class 175
Model 2	Class 80	Class 100	Class 150	Class 200
Model 3	Class 80	Class 100	Class 150	Class 200
Model 4	Class 80	Class 100	Class 150	Class 200
Model 5	Class 80	Class 100	Class 150	Class 200

* Indication Z_0 implies a replacement due to exceedance of P_f^T for existing classification.

indication. It is observed that the classification may not be increased to Class 80 or above for indication Z_0 (indication of unsafe performance for Class 100 vehicle). The posterior failure probabilities given indication Z_0 are high as compared to the prior failure probabilities. For example, the posterior failure probability $P_{X_1|Z_0}$ is $\approx 10^{-5}$ for Class 50. This means that the initial classification cannot be maintained in order to comply with the minimum reliability level and the expected utilities are calculated assuming a replacement with costs C_F. However, the DM may alternatively opt – if at all possible - for analysing and planning adaptive actions such as reducing the classification level, repairs or replacement.

3.6.2. *Expected utility calculation and decision rules*

Figs. 8 and 9 present the expected utilities as a function of the classification and benefit model from the PA decision analysis (base scenario). It can be observed that the expected utility is sensitive to the socio-economic benefits. The structural failure risks contribute more to the expected utility when the annual benefit/vehicle is low. As the benefit increases (as indicated by the Benefit Model indices), the expected benefits from reclassification dominate over the structural failure risks from allowing a higher vehicle load. The expected utility is directly proportional to the benefits for Benefit Models 4 & 5 (Fig. 9).

For the enhancement scenario (PIPA decision analysis), the classification choices leading to the maximum aggregated expected utility and

Table 5
Classifications for maximum aggregated expected utility from PIPA analysis without constraints on annual failure probability.

Benefit Model	Classification levels for maximum aggregated expected utility from PIPA analysis				
	Without Information (Base Scenario)	With Indication Z_0 (Enhancement Scenario)	With Indication Z_1	With Indication Z_2	With Indication Z_3
Model 1	Class 100	Class 80	Class 100	Class 125	Class 175
Model 2	Class 100	Class 80	Class 100	Class 150	Class 200
Model 3	Class 150	Class 80	Class 125	Class 200	Class 200
Model 4	Class 200	Class 100	Class 150	Class 200	Class 200
Model 5	Class 200	Class 100	Class 200	Class 200	Class 200

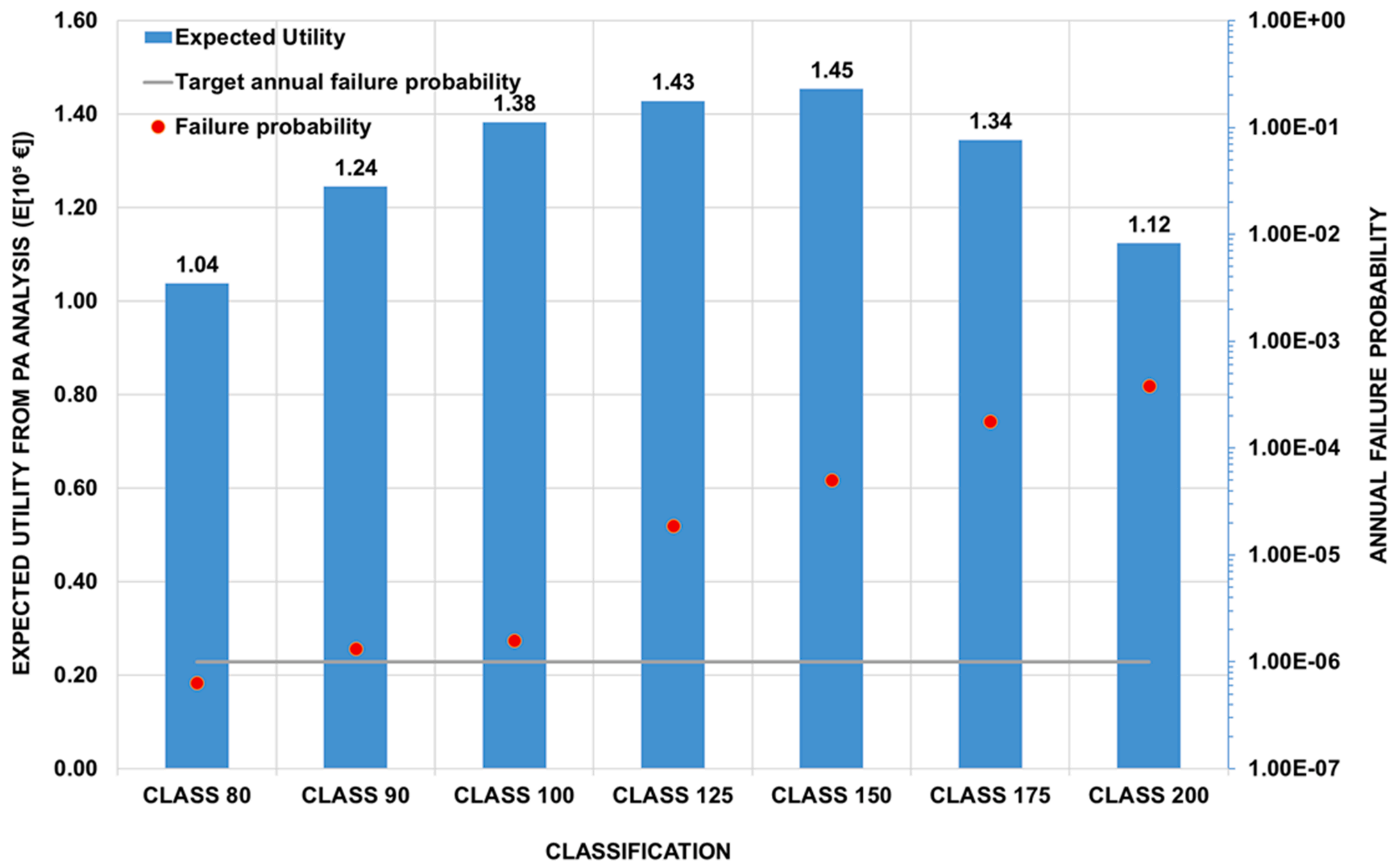

Fig. 10. Expected utility and annual failure probability for base scenario with Benefit Model 3 (Monetary unit $= E[10^5 €]$).

satisfying the target reliability criteria, are identified for each indication (Table 4). Substantial increase in classification levels is observed when using proof loading information (Table 4). This is often seen in practice as load tests reveal capacities much higher than expected with conservative design or assessment methods [1,62].

The Benefit Model influences the classification choice, as would be explained by the relative contributions of the risks and expected benefits to the expected utility, which vary with the Benefit Model. In comparison with the classifications leading to the maximum aggregated expected utility in the enhancement scenario (Table 5), we can observe that the optimal classification choice is governed by the target reliability criterion. For example, with indication Z_0 (performance not safe for Class 100), the classification can be increased to Class 80 and higher from the perspective of maximizing expected utility (Table 5). However, this does not meet the target reliability boundary condition, as the posterior failure probability is quite high (Fig. 7) and would rather point to a replacement of the bridge.

A further example that target reliability constraints lead to a decrease in the classification choice is depicted in Fig. 10. Here, the expected utilities for the base scenario calculated with Benefit Model 3 are depcited together with the failure probability values. The target reliability criterion is satisfied only for Class 80, whereas the maximum expected utility corresponds to Class 150.

The initial target reliability calibration of the ultimate capacity model (see Section 3.2) has minor influence due to the relatively high precision of proof load information.

Two cases can be identified where the optimal choice of classification is governed by maximization of the expected utility rather than the target reliability criterion:

(1) The classification following indication Z_2 (acceptable performance for the Class 150 vehicle) may not be increased to Class 150, even though the target reliability criterion is met, because the expected utility with Class 150 is not maximum (Fig. 11). With a different Benefit Model (e.g., Benefit Models 2 – 4), the increase in classification to Class 150 is optimal from the perspective of expected utility maximization as well.

(2) With indication Z_3 (indication of acceptable performance for load due to Class 200 vehicle) and Benefit Model 1, the optimal classification is not Class 200, even though the target reliability criterion is met (Fig. 12).

3.6.3. Value of information

The Value of Information obtained from proof loading is presented in Table 6. The VoI increases with increase in the socio-economic benefit from reclassification. The expected utility gain from proof load information is attributed to the facts that 1) a higher classification may be obtained using the proof load information, as compared to the base scenario, and 2) a higher classifications are allotted to a higher utility in the form of a higher total service life benefit (see Table 3). With increasing classification level, the expected benefits and structural failure risks both increase. However, for the cases of high reclassification benefits, specifically as considered in Benefit Models 3–5, the structural failure risks are dominated in magnitude by the expected benefits (see also Section 3.6.2, Figs. 8 and 9). In these cases of high reclassification benefits, the proof load information lead to higher classifications and is thus highly (monetarily) valuable (Table 6). The expected utility U^*_{PIPA} is lower than the cost of the proof load test C_{Test} for Benefit Models 1 & 2, causing the VoI to be negative. Even though the proof load information leads to higher classifications, the low magnitude of the reclassification benefits (Benefit Models 1 & 2) lead to U^*_{PIPA} being exceeded by the proof load test costs. This results in the optimal decision to not perform proof loading when the socio-economic benefit from the reclassification action is low.

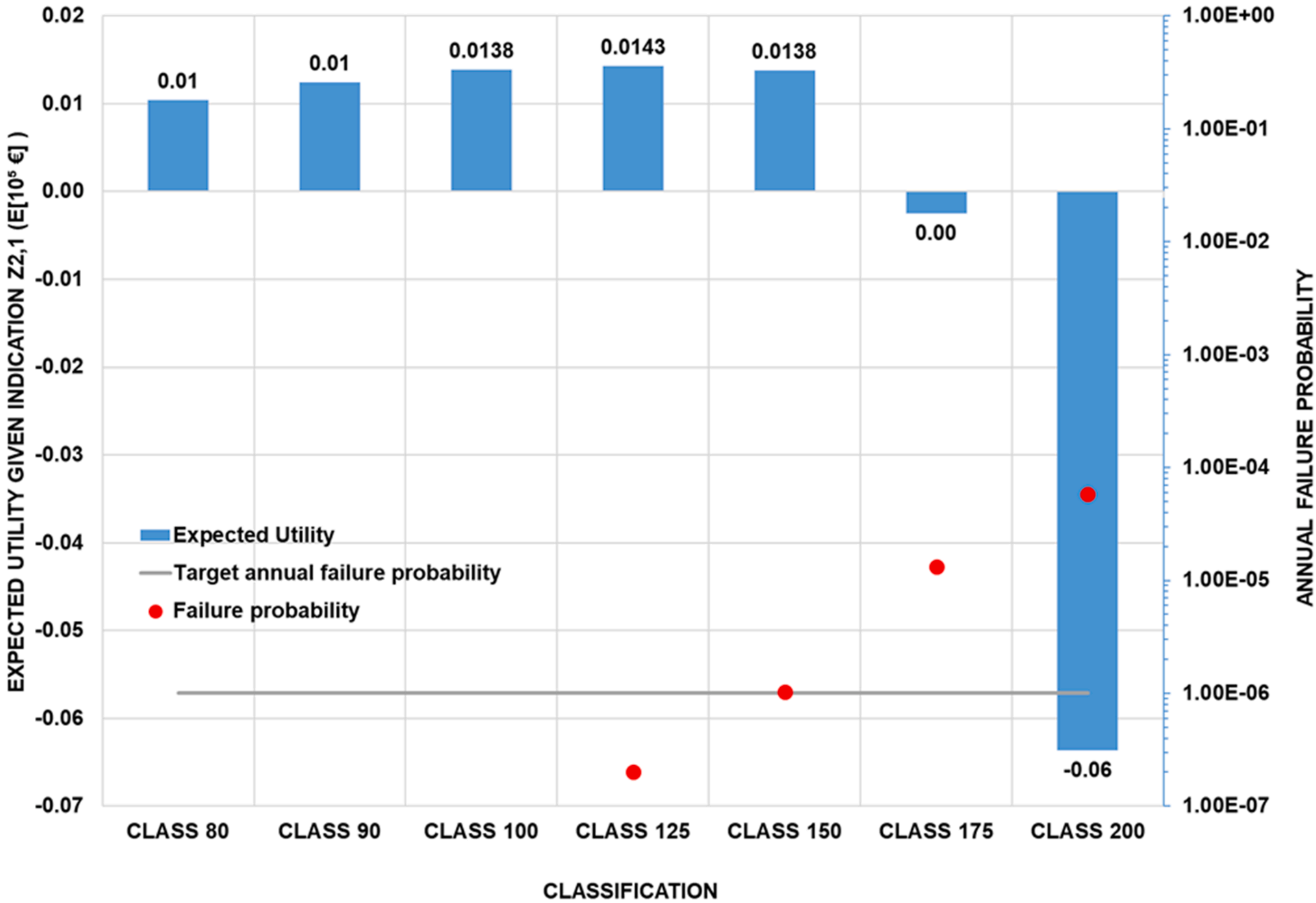

Fig. 11. Expected utility and annual failure probability given indication Z_2 and Benefit Model 1 (Monetary unit $= E[10^5 €]$).

The target annual reliability level affects the analysis results on two levels: i) calibration of the thresholds, and ii) as constraints on the decision analysis. In order to examine the influence of the target reliability boundary condition on the results, the thresholds are re-calibrated for a lower target annual reliability level $\beta^T = 3.7$, corresponding to a structure in Consequence Class 3 with large relative costs of safety measure [41]. The threshold recalibration is followed by re-calculation of the posterior probabilities of failure and intact system state, expected utilities, and optimal classification levels.

With a target annual reliability level of $\beta^T = 3.7$, the optimal classification level in the base scenario is Class 100 (Benefit Models 1 & 2) and Class 150 (Benefit Models 3–5). This is because with a lowering of the minimum annual reliability level, the classification level can be increased even without using information from proof loading (see also Fig. 7 for the prior reliability analysis). Consequently, the VoI decreases considerably (Table 7).

The proof load test costs, relative to the failure cost of the bridge, considerably affect the Value of Information, see Tables 8(a) & (b) for the VoI for different ratios of test costs C_{Test} to the failure costs C_F. The test cost range represents testing costs from 5000 € to 500,000 €. We can observe that, for high socio-economic benefit (e.g., Benefit Model 5), the optimal decision for the highway authority is to obtain information with proof loading, even with very high test costs.

4. Summary and conclusions

This paper contains the development and application of a decision analytic approach for the reclassification of the bridge capacity with quantification of the structural risks and socio-economic benefits. The approach enables identifying an optimal capacity reclassification with quantification and maximization of expected service life utility, including structural risks and expected benefits from bridge operation.

The approach includes a novel and explicit differentiation of modeling and adaptation of elastic and ultimate capacity models with elastic limit information from proof load testing. In this way – beyond the current common scientific literature in this field – a model is introduced, which explicitly accounts for the fact that in-situ and in-service proof loading is on elastic level and the bridge capacity including the determination of target reliabilities relies on its ultimate capacity. In this way, the developed approach contributes – in the view of authors – to a more rational modeling of proof load information and to harmonizing structural design, reliability and decision analytic principles.

In-situ and in-service proof load testing constitutes in conjunction with monitoring, information about the capacity at elastic limit. The proof load testing outcomes are defined by discretizing the distribution of the elastic capacity and calibrating the discretization thresholds to satisfy target reliability for different traffic loads. This facilitates that the proof loading information are modelled as indications of load bearing classes, which can be directly used as decision rules and account at the same time for reliability requirements based on a macroeconomic and life safety optimization ([36], and the JCSS Probabilistic Model Code, Part I), and eventually Life Quality Index considerations [41,63].

An illustrative decision analysis for a highway authority, responsible for strategy development for the reclassification of bridges with a low existing classification, is performed. The benefit from bridge reclassification is modelled proportional to the traffic frequency and allowable weight of goods vehicles i.e., that an increase in allowable weight

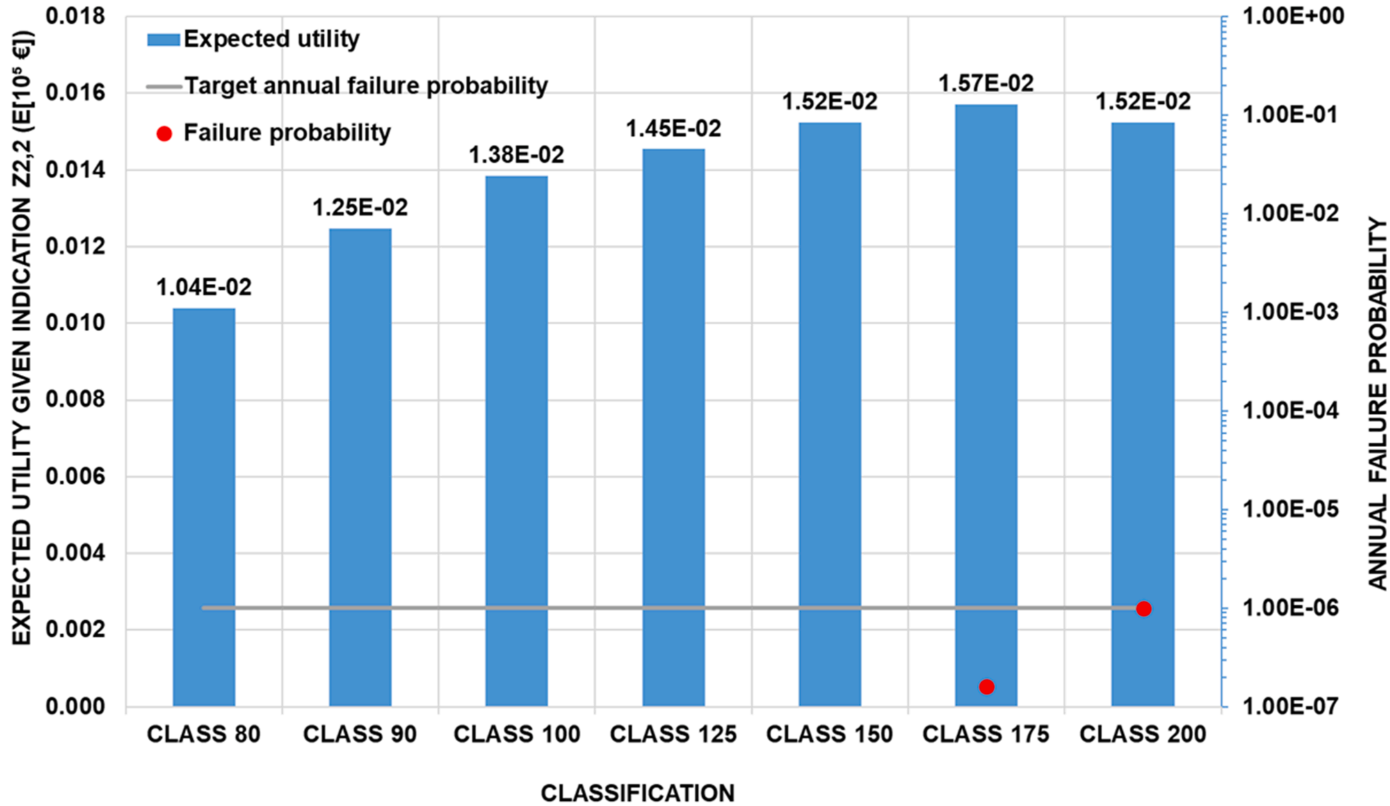

Fig. 12. Expected utility and annual failure probability given indication Z_3 and Benefit Model 1 (Monetary unit $= E[10^5\epsilon]$).

Table 6
Expected and Relative Value of Information (Monetary unit $= E[10^5\epsilon]$.

Benefit Model	Expected Value of Information $(U^*_{PIPA} - U^*_{PA})$	Relative Value of Information $\frac{U^*_{PIPA} - U^*_{PA}}{U^*_{PA}}\%$
Model 1	−0.295	–
Model 2	−0.242	–
Model 3	0.290	27.9%
Model 4	5.614	54.0%
Model 5	58.858	56.8%

Table 7
Value of Information in relation to target annual reliability level (Monetary unit $= E[10^5\epsilon]$).

Benefit Model	Expected Value of Information $(U^*_{PIPA} - U^*_{PA})$		Relative Value of Information $\frac{U^*_{PIPA} - U^*_{PA}}{U^*_{PA}}\%$	
	$\beta^T = 4.7$	$\beta^T = 3.7$	$\beta^T = 4.7$	$\beta^T = 3.7$
Model 1	−0.295	−0.030	–	–
Model 2	−0.242	−0.019	–	–
Model 3	0.290	0.095	27.9%	6.7%
Model 4	5.614	1.118	54.0%	7.3%
Model 5	58.858	12.550	56.8%	8.3%

Table 8
(a) Value of Information in relation to testing costs, annual target reliability level 4.7 (Monetary unit $= E[10^5\epsilon]$).

$\frac{C_{Test}}{C_F}$	Benefit Model 1	Benefit Model 2	Benefit Model 3	Benefit Model 4	Benefit Model 5
0.05%	−0.25	−0.19	0.34	5.66	58.91
0.10%	−0.30	−0.24	0.29	5.61	58.86
0.20%	−0.40	−0.24	0.19	5.51	58.76
0.50%	−0.70	−0.64	−0.11	5.21	58.46
1.00%	−1.20	−1.14	−0.61	4.71	57.96
2.50%	−2.70	−2.64	−2.11	3.21	56.46
5.00%	−5.20	−5.14	−4.61	0.71	53.96

Table 8
(b) Value of Information to testing costs, annual target reliability level 3.7 (Monetary unit $= E[10^5\epsilon]$)

$\frac{C_{Test}}{C_F}$	Benefit Model 1	Benefit Model 2	Benefit Model 3	Benefit Model 4	Benefit Model 5
0.05%	0.02	0.03	0.14	1.17	12.60
0.10%	−0.03	−0.02	0.09	1.12	12.55
0.20%	−0.13	−0.12	−0.01	1.02	12.45
0.50%	−0.43	−0.42	−0.31	0.72	12.15
1.00%	−0.93	−0.92	−0.81	0.22	11.65
2.50%	−2.43	−2.42	−2.31	−1.28	10.15
5.00%	−4.93	−4.92	−4.81	−3.78	7.65

extends the heavy vehicle traffic volume and leads to higher benefits. Using five benefit models, the effects of negligible to very high reclassification benefits on the expected utilities are modelled allowing for flexibly adapting to different highway network utilization scenarios.

With a pre-posterior decision analysis and by utilizing the (1) elastic and ultimate capacity models and its adaptation with elastic proof load information, (2) the proof load information model with classification outcomes accounting for target reliabilities and (3) the utility model including the socio-economic benefits from reclassification, the optimal classification choice is identified. For the practical use of the decision analyses for a highway authority, decision rules are identified and documented. The decision rules can help a highway authority to find the optimal classification or load rating, based on (1) the measurement of the capacity at elastic limit by proof loading, (2) the bridge reclassification benefits, and, (3) the required annual reliability level.

A value of information analysis revealed that proof loading for reclassification may only be used when the socio-economic benefits are high i.e., higher than 10^5 ϵ for the projected 15 years remaining bridge service life, relative to a bridge failure cost of 10^7 € and proof load test costs of 10^4 €. For the information to be (monetarily) valuable, the proof loading should lead to higher classifications, and the expected benefits from the higher classification should also compensate for the structural failure risks due to the increased load level and proof load test costs.

With a parametric study, it is concluded that the expected utility gain from the proof load information is sensitive to (1) the costs of proof loading relative to the bridge failure cost and (2) the target reliability requirements. The target reliability level requirements, which serve as constraints to the decision analysis, generally lead to choosing a classification level lower than what would be the optimum if only expected utility maximization is considered. If a lower target annual reliability level is used as the constraint, a higher classification level can be chosen in the base scenario itself i.e., without the need for proof loading. This has a significant impact on the Value of Information from proof loading, which is reduced by 75% on average following a reduction in target annual reliability level requirement from 4.7 to 3.7. This further implies that proof loading for reclassification has a high value when the target reliability requirement is high.

CRediT authorship contribution statement

Medha Kapoor: Conceptualization, Methodology, Formal analysis, Visualization, Writing – original draft, Writing – review & editing. **Christian Overgaard Christensen:** Writing – review & editing. **Jacob Wittrup Schmidt:** Supervision, Writing – review & editing. **John Dalsgaard Sørensen:** Methodology, Supervision, Writing – review & editing. **Sebastian Thöns:** Conceptualization, Methodology, Supervision, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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