

Ranking bridge intervention scenarios with a risk-based predictive decision support system

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ABSTRACT

Advancing infrastructure management practices requires innovative decision-support tools to enhance the functionality, safety, and sustainability of infrastructure assets. This paper introduces the fundamentals of a Decision Support System (DSS) that integrates a risk-based prioritization framework with a streamlined probabilistic structural reliability model, providing data-driven and cost-effective operational scenario rankings. By leveraging probabilistic deterioration Markov Chains models, the DSS accounts for correlation effects between several present and potentially new defects, ensuring an accurate representation of the degradation processes and future structural risks. Such, through a streamlined structural reliability assessment methodology, intended to bridge the gap between rigorous and data-hungry structural reliability assessments and real-world decision-making constraints. The DSS also includes key decision-making factors such as the exposure and the operational scenarios costs. The proposed framework empowers infrastructure managers with a scalable and adaptable tool for proactive maintenance strategies, resource allocation optimization and intervention planning.

1. Introduction

Effective decision-making relatively to the management of structural and infrastructural assets is epitomized by optimal resource allocation to guarantee (1) the upkeep of assets and (2) satisfactory levels of functionality and user safety. Decision-making and asset management are rapidly increasing in relevance due to the aggravating global crisis of aging infrastructure. For instance, 42 % of American bridges aged 50 years or more are structurally deficient [1,2]. Along these lines, the tragic collapse of Italy's Morandi Bridge in Genoa in 2018 highlighted the need of addressing the vulnerabilities of aging bridges in the short term. As society grapples with these challenges on a global scale, the demand for rapid, effective and data-grounded decision-making tools has never been more relevant to ensure public safety and economic stability.

In recent years, a growing number of infrastructure managers are tackling such demand with the adoption of advanced Management Systems [3,4] integrated with a Decision Support System (DSS) [5,6]. In Brighenti et al. [7] comprehensive literature review on the DSS strategies implemented in the Bridge Management Systems of various

countries is presented. Generally talking, a DSS refers to a digital architecture that conceptualizes an articulated interactive system (bridge management) and identifies objects of particular relevance (data on structural-related risks) in such a way as to enable the final user (infrastructure managers) to discern between various options related to a given context (asset upkeep-oriented courses of action).

Among the possible design philosophies of a Decision Support System, the Multi Attribute Utility Theory (MAUT) properly fits the underlying systems of the infrastructural management environment [8,9]. Indeed, the key advantage of the MAUT approach is the explication of otherwise implicit judgments (probability of asset failure, expected losses in case of asset failure [10], maintenance intervention costs, asset reconstruction costs) [8]. MAUT, by assigning specific values to information helps to simplify, streamline and accelerate the decision-making process. As such, this philosophy represented the framework in which the proposed Decision Support System was developed.

Generally, effective decision-making for infrastructural asset management translates in the optimization of maintenance activities and strategies (generally subdivided into corrective, preventive, condition-based, and predictive) [11–13]. Two of the most commonly employed

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approaches to said optimization are the determination of maintenance priority indices and cost-benefit analyses [14–16]. However, traditional approaches to infrastructure management primarily rely on the evaluation of the Condition State of assets, often treating it as the primary factor in maintenance decision-making [17]. This oversimplification overlooks critical aspects of structural reliability, which encompasses not only the current condition of an asset but also its probabilistic degradation and external risk factors [10,18]. Additionally, existing models frequently neglect the correlation between different structural defects, assuming independent deterioration mechanisms despite evidence suggesting otherwise [18]. This assumption leads to inaccurate failure risk predictions and suboptimal maintenance prioritization. While sophisticated methodologies for comprehensive structural reliability evaluation exist, many are computationally demanding and time-intensive, making them impractical for large-scale infrastructure networks [13]. This represents a significant limitation for swift structural health assessments, urgent decision-making, and timely intervention planning—critical aspects of infrastructure management.

To address these challenges, this study proposes a Decision Support System that integrates a risk-based prioritization framework with a probabilistic structural reliability model, explicitly incorporating defect correlations into intervention ranking. Unlike traditional approaches that prioritize interventions based solely on current asset conditions, the proposed methodology accounts for projected deterioration trends, structural reliability assessments, and the modeling of operational and intervention scenarios, ensuring a more data-driven and predictive approach. Furthermore, a low-input, high-efficiency model is introduced to enhance computational feasibility, reducing the reliance on extensive data while maintaining analytical robustness. By leveraging Markov Chain-based degradation modeling, Bayesian forecasting, and custom-made Exposure functions, this system achieves a balance between computational efficiency and predictive accuracy, making it adaptable to large-scale infrastructure networks. Additionally, the modeling of intervention efficiency ensures that prioritization not only considers risk reduction but also the effectiveness and impact of different maintenance strategies over time. The presented framework bridges the gap between theoretical structural reliability assessments and real-world decision-making needs, offering infrastructure managers a scalable tool for optimizing intervention planning. By integrating probabilistic deterioration modeling, defect correlation analysis, streamlined computational approaches, and advanced modeling of intervention effectiveness, the proposed DSS enhances risk-informed prioritization while remaining feasible for practical infrastructure management.

In their previous work [13], the authors tackled the above issue with the introduction of an effective Decision Support System based on a swift Structural reliability assessment and advanced probabilistic deterioration models. On this last point, the proposed Decision Support System wholly pertains to the recent infrastructure management landscape transition towards the adoption of probabilistic frameworks, treating structural parameters as random variables with probability density functions [19–21]. Crucially, such tool enabled not only the assessment of the asset reliability at the present instance (accounting for its degradation state and risk of overload) but also the projection of said reliability to any time horizon selected by the user. This was achieved through (1) a degradation model rooted in Markov Chains capable of projecting the worsening of already present damage and (2) a Bayesian Theory-rooted model to predict the surge of new structural defects in the years to come.

The present article stands as a direct continuation to the authors' previous work [13]. Building upon this foundation, the present study represents a significant advancement of the authors' prior work by extending the capabilities of the DSS beyond structural reliability assessment to risk-informed maintenance prioritization. While the previous DSS provided a robust framework for reliability evaluation and deterioration forecasting, it did not explicitly address how to prioritize

maintenance actions in a resource-constrained environment. This work directly tackles that gap by introducing a structured methodology for ranking intervention scenarios. Unlike previous models, which primarily focused on reliability projections, the proposed DSS integrates risk-based prioritization, explicitly incorporating intervention costs and risk reduction potential into decision-making. Specifically, the contribution of this procedure lies in the formulation of a priority index, which ranks maintenance interventions based on: 1) current and projected asset risks, incorporating both the condition state of the bridge and its exposure to potential failure consequences; 2) the risk reduction achieved through intervention, ensuring that decision-making is risk-informed rather than solely condition-based; and 3) the associated intervention costs, enabling a cost-effective optimization of maintenance resources.

By integrating probabilistic risk assessment with an intervention ranking system, this study extends the functionality of the previous DSS from a predictive reliability tool to a fully operational decision-making framework. Additionally, this work introduces an explicit treatment of defect correlations, recognizing that the presence of specific defects can influence the development of others, further refining the prioritization process. Moreover, while maintaining the computational efficiency of the original model, this study enhances its practical applicability by ensuring scalability to large infrastructure networks, making it more adaptable to real-world bridge management needs.

In conclusion, the present article provides the final pieces of the puzzle laid down in Brighenti et al. [13], detailing the development of a Decision Support System that is both swift in its use and comprehensive in its content. Through such a tool, infrastructure managers are empowered to make informed decisions on both current day and future courses of action, thus guaranteeing the functionality and reliability of their assets in a period of time characterized by a growing distrust in the populace towards infrastructural asset management.

Glossary

R	Risk
C	Capacity Index
D	Damage Index
Z	Exposure
G	Permanent Load
Q_d	Traffic Load
i	Projected year
I	Intensity
E	Extension
j	Case study defect
j_k	Current Defect
V_z	Coefficient of Variation
β	Reliability Index
T_i	Transition Matrix
P_{DL}	State Probability Vector
P_{IE}	State Probability Matrix
P_F	Probability of Failure
P_F^i	Projected Probability of Failure at year i
$P_{F, int}^i$	Projected Probability of Failure at year i after an intervention
P_{app}	Intrinsic Defect Appearance Probability
P_D	Defect Presence Probability
P_U	Defect Absence Probability
$R_{w/o int}$	Pre- intervention Risk
$R_{w/ int}$	Post-intervention Risk
$Cost_{int}$	Cost intervention
α_{int}	Priority Index

2. Objective and structure of the proposed decision support system

A considerable gap exists between comprehensive but complex theoretical structural reliability assessments and the world of infrastructure management. It is apparent how complex and time-consuming analyses match very little with urgent decision-making processes for the

upkeep of entire infrastructural assets. This becomes even more evident if to account for the:

- Non-negligible duration of rigorous structural reliability assessments (especially considering the notable complexity of certain assets).
- Substantial frequency with which said assessments should be performed (every time the data on the state of the bridge is updated i.e., every time a routine inspection is performed, which can be multiple time per year).
- Substantial size of most infrastructural assets.
- Need of planning interventions as early as possible for both logistical purposes and in order to prevent damage escalation.

In light of all the above, the present work intends to fill the above-mentioned gap through the introduction of a Decision Support System (DSS) that meets the following requirements:

- Providing decision makers with an efficient tool for infrastructural management optimization.
- Suggesting the optimal course of action and resource allocation based on structural reliability evaluations.
- Performing structural reliability evaluations:
 - o In a swift manner (versus traditional complex and time-consuming structural reliability analyses) by means of targeted simplifications and assumptions.
 - o Based solely on straightforward and intuitive parameters.
 - o With the least amount of input parameters (thus bypassing the requirement of extensive documentation, technical information, and testing data).
 - o All the above without compromising the correctness of the assessments.
- Providing decision makers with a structural reliability-based ranking of the assets requiring the most urgent intervention.
- Accommodating both reactive and preventive asset maintenance approaches through asset degradation projections.

- Being as versatile as possible, thus providing speedy and cost-effective management solutions for the entirety of the asset instead of a single structure/structural technology.

Having clarified the objectives of the proposed DSS, the authors will now present its overall structure with the support of Fig. 1. The colour code in Fig. 1 distinguishes those processes performed by infrastructure managers decision-maker (in green) from those internal to the DSS (in blue). Those frames containing both colours indicate hybrid processes that can be performed by both infrastructure managers and the DSS itself.

Focusing momentarily on the righthand frames of Fig. 1, the reader can immediately spot the cardinal parameter of the DSS i.e., the Priority Index α_{int} . As the name implies, this index quantifies the urgency of each possible action/intervention, thus permitting their ranking and chronological distribution. Guided by the said simple and straightforward parameter the infrastructure manager acknowledge the optimal course of action and most cost-efficient intervention scenario. As visible in the bottom-right frame of Fig. 1, α_{int} is a function of the intervention-induced reduction of Risk (Risk before the intervention $R_{w/o\ int}$ subtracted by the Risk after the intervention $R_{w/int}$) and the cost of the intervention itself $Cost_{int}$. What transpires is the main philosophy behind the DSS: the intervention with highest priority is the one that maximizes the Risk reduction whilst keeping the costs as low as possible. Both $R_{w/o\ int}$ and $R_{w/int}$ are projections of the current-day Risk R and their assessment involves not only the projection of the deterioration of existent defects (detected during asset inspections) but also the forecasting of the appearance of new ones. As delved into later, regardless of the examined Risk, all are calculated as a multiplication of the Probability of Failure P_F and the Exposure Exp of the asset at hand, as visible on the left-hand of Fig. 1. The former is a function of the conservation state of the bridge (the higher the number and gravity of defects, the higher is P_F) and of the bridge age whilst the latter is a function of the expected losses in case of asset failure (human lives, reparation costs,

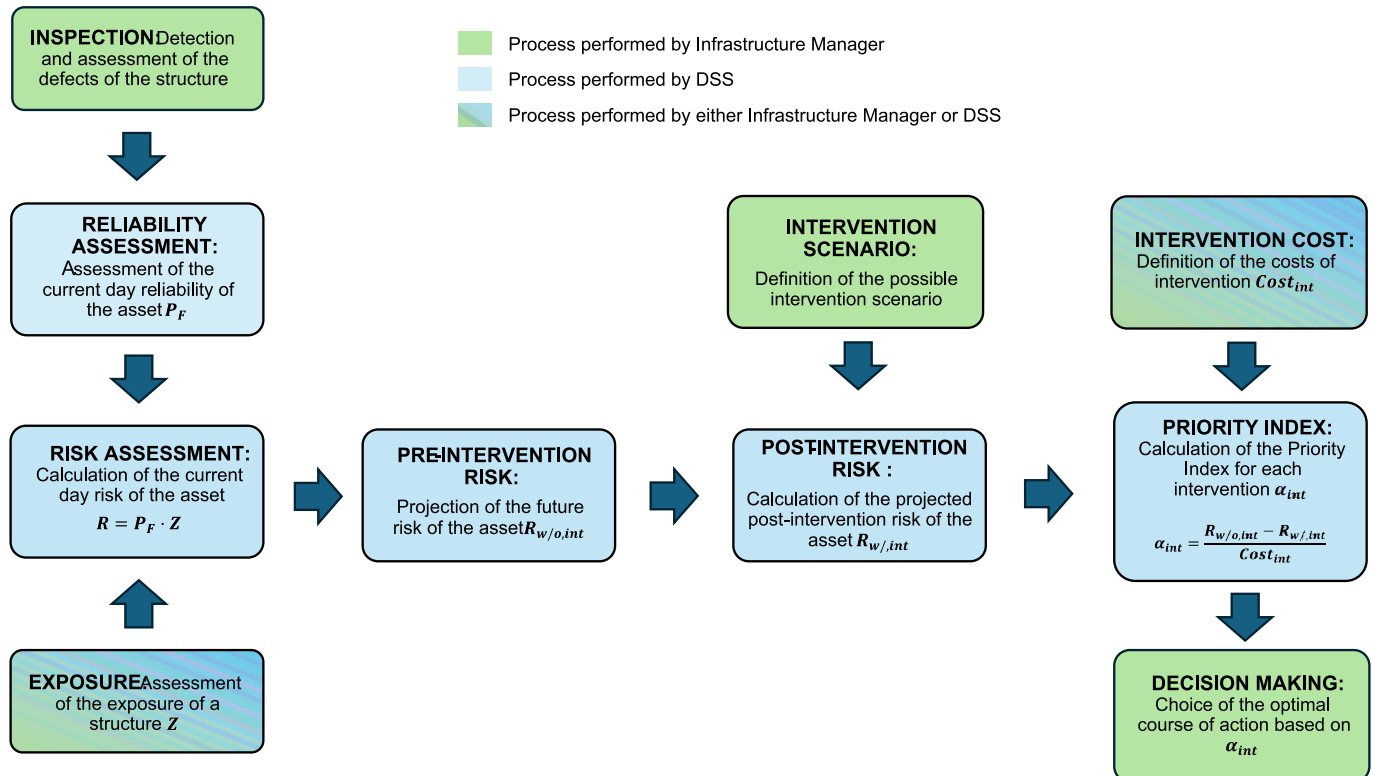


Fig. 1. Decision Support System (DSS) structure.

indirect costs, etc.).

All the assessment of the above parameters will be described in the following Sections, but with a varying degree of depth. Indeed, the present publication is a follow-up to the authors' previous work [13] which focused in great detail on those processes that lead to the Pre-intervention Risk, with exception made for the Exposure parameter. Hence, said processes will be described here in a concise fashion. Oppositely, the processes leading to the Post-intervention Risk and to the Priority Index evaluation, along with the Exposure parameter and an improved methodology for considering defect correlations, will be tackled in a thorough manner.

3. Risk assessment in the decision support system

The proposed methodology hinges upon the conceptualization of Risk (R), as apparent in Fig. 1. In the proposed DSS, the Risk is considered through the well-trodden path of combining three factors unique to each analyzed asset: Hazard, Vulnerability, and Exposure. As previously anticipated, R is determined by combining the Probability of Failure P_F of the asset, which accounts for both Hazard and Vulnerability, and the Exposure Z as per Eq. (1):

$$R = P_F \cdot Z \quad (1)$$

Please note that the Probability of Failure associated to a risk factor x is commonly expressed as the product of Hazard P_x (i.e., the probability of a hazardous event occurring) and Vulnerability (i.e., the likelihood of an undesirable event (in our case the bridge failure) occurring given the incidence of a hazardous event): $P_F = P_{(F|x)} \cdot P_x$. However, due to the inherent strong correlation between the two for the bridge failures, the proposed model chooses to incorporate both Hazard and Vulnerability within a unique term, P_F .

The previously mentioned risk factors x for civil engineering structures are most commonly considered to be Overload and Degradation ($P_{F,D}$), Seismic risk ($P_{F,S}$), Hydraulic risk ($P_{F,H}$) and Landslides risk ($P_{F,L}$) [22–25]. In the following, these risk factors will be considered uncorrelated to guarantee the analytical expediency and overall swiftness of the model. Such is an acceptable simplification in light of the reduced probability that a structure fails because of two simultaneous causes (which does not mean that said two phenomena cannot occur simultaneously, but rather that it is much more likely that only one of them is the culprit behind the failure of the structure). With this assumption in place, the Total Probability of Failure P_F of a structure can be determined as $P_F = P_{F,D} + P_{F,S} + P_{F,H} + P_{F,L}$. In the present article the authors describe the determination of $P_{F,D}$ only, as the most impactful and widespread cause of failure of the four.

3.1. Determining the asset structural reliability

To determine $P_{F,D}$ (henceforward just P_F), the calculation of the Reliability Index β is required. Indeed, the latter can be formally defined as the negative value of the inverse of the standardized normal distribution function Φ calculated for the Probability of Failure P_F , as per Eq. (2) [26].

$$\beta = -\Phi^{-1}(P_F) \rightarrow P_F = \Phi(-\beta) \quad (2)$$

Given the commonly adopted Limit State Function: $Z = R - S = 0$ [27] with R and S the Resistance and Load Effect respectively, it was assumed that R and S are mutually independent and follow a log-normal probabilistic distribution $Z = \ln(R) - \ln(S)$. As a matter of fact, the log-normal distribution better describes the probabilistic distribution of R and S compared to a normal distribution [13]. On such fundamental assumption, the authors built the swift structural reliability assessment methodology as described in Brighenti et al. [13], which culminated in the definition of a Reliability Index β as per Eqs. (3)–(5).

$$\beta = \left[\beta_0 + \frac{\ln(D \cdot C)}{V_{z,0}} \right] \cdot \frac{V_{z,0}}{V_z} \quad (3)$$

$$D = \frac{R_{d,D}}{R_{d,U}} \in (0, 1) \quad (4)$$

$$C = \frac{R_{d,U}}{R_{d,0}} = \frac{1 + \frac{Q_{d,U}}{G}}{1 + \frac{Q_{d,0}}{G}} \in (0, 1) \quad (5)$$

Being β_0 the original/as-built value of the Reliability Index; D the Damage Index; C the Capacity Index; V_z and $V_{z,0}$ the Coefficient of Variation of the Limit State Z under current and reference conditions, respectively; $R_{d,D}/R_{d,U} \in (0, 1)$ the difference between the resistance of a bridge in its damaged ($R_{d,D}$) and undamaged ($R_{d,U}$) states; $R_{d,U}/R_{d,0} \in (0, 1)$ the difference between the resistance/carrying capacity of an undamaged bridge designed according to the actual (and potentially outdated) design code of the case study asset ($R_{d,U}$) versus its resistance if it were designed with the reference current-day code ($R_{d,0}$); G the effect of Permanent Load; $Q_{d,U}$ the effect of the Traffic Load calculated according to the actual design code; $Q_{d,0}$ the effect of Traffic Load calculated according to the reference current-day code. Please note that all these load effects must be evaluated for both the bending and shear collapse mechanisms; the final Capacity Index to be considered is the lowest among the two: $C = \min(C_V; C_M)$. Poli et al. [10] offer valuable insights into the Capacity Index C for highway bridges designed under Italian codes. Naturally, the formulation they propose can be adapted to other national codes and various bridge types. Notably, Brighenti et al. [28] had previously employed the same parameter to assess Italian railway masonry arch bridges, demonstrating its broader applicability.

Crucially, Eq. (3) suggests that the β of a case study bridge is equals to its original value β_0 decreased (indeed, $\ln(\dots)$ of an integer comprised between 0 and 1 is negative) by the natural logarithm of $D = R_{d,D}/R_{d,U}$ and $C = R_{d,U}/R_{d,0}$. As previously anticipated, C and D embody the reduction in structural reliability of an asset due to the presence of damage (and its yearly degradation) and to the increased overload risk whenever a bridge is designed with outdated codes that did not account for the modern ever-growing traffic loads. Such parameters are capable of capturing potential vulnerabilities related to outdated design practices or design flaws which can translate into observable defects. Indeed, whenever assessing the C of a bridge designed with current-day codes $R_{d,U} \equiv R_{d,0} \rightarrow C = 1$, whilst $C < 1$ for prior codes.

Please note, that the commodity of modeling the damage-induced and overload risk-induced β reductions with simple ratios ($D = R_{d,D}/R_{d,U}$ and $C = R_{d,U}/R_{d,0}$) stems from having chosen to work with log-normal distributions. Indeed, taking for example D , if normal probabilistic distributions had been chosen to describe it instead, the absolute values of $R_{d,D}$ and $R_{d,U}$ would have to be singularly determined in order to obtain $\Delta R = R_{d,D} - R_{d,U}$; a much tougher sale compared to simply using the $R_{d,D}/R_{d,U}$ ratio, $\ln R_{d,D} - \ln R_{d,U} = \ln(R_{d,D}/R_{d,U})$. Furthermore, the C and D ratios are very tangible and engineer-friendly parameters.

3.2. Evaluating the asset damage

The present subsection succinctly tackles the Damage Index D and its effect on the P_F , essential for the “Reliability Assessment”, “Current Risk” and “Projected Risk” processes of Fig. 1.

To determine the P_F of a defect, for the sake of the preestablished goal of analytical swiftness, pre-established values of D are associated to a specific scale of “Damage Level” of said defect (itself function of the extent and gravity of the defect as detected during bridge inspection). These associations are established directly by infrastructure managers according to their risk-proneness/aversion management approach [13], as illustrated in Table 1 for the case of a medium-sized Italian infrastructure manager.

Table 1

Infrastructure Manager-specific correlation of each Damage Level to corresponding values of D , P_F , β and V_z .

Damage Level	DL1	DL2	DL3	DL4	DL5	DL6
Damage Index D	1	1	0.99	0.96	0.92	0.8
Probability of Failure P_F	10^{-8}	10^{-7}	10^{-6}	10^{-5}	10^{-4}	10^{-3}
Reliability Index β	5.61	5.20	4.75	4.26	3.72	3.09
Coefficient of Variation V_z	0.16	0.17	0.20	0.21	0.23	0.26

It is worth noting that the Italian infrastructure manager in question has opted for a notably conservative/safe approach to risk. Indeed, the reliability of a new/undamaged bridge (DL1) corresponds to a $\beta_0 = -\Phi^{-1}(P_{F,D} = 10^{-8}) = 5.61$, differently, for example, from Eurocode 0 [29] which considers a $\beta_0 = 4.7 \rightarrow P_{F,D} \cong 10^{-6}$. The other Damage Levels follow suit with similar conservative values.

The determination of the P_F of an entire infrastructural asset passes through the aggregation of multiple P_F -s, one per each defect detected on the asset. In other words, the DSS determines a P_F value per each risk detected on the structure, whose combination provides the complete picture of the current state of the asset.

Now, let us understand how the Damage Levels are applied to the defects. During routine inspections the operator assigns an extent (henceforward referred to as Extension E) and a gravity (henceforward referred to as Intensity I) to the observed defects, each subdivided in four distinct levels (a commonly employed methodology among infrastructure managers). The parameter I captures the magnitude of the defect, regardless of the extent of the affected area, while the parameter E encapsulates the spatial scope of the defect, regardless of its magnitude. An example of these parameters for an exemplary defect is presented in Fig. 2a. On the basis of these two parameters, an I - E -Damage Level matrix is developed for each defect, which enables the correlation of any I - E pair to specific Damage Levels (see the example in Fig. 2b-c).

Please note that the I - E -Damage Level matrix is the result of a

meticulous calibration process described in depth in Brighenti et al. [13]. Briefly, the calibration of a specific defect was developed under the assumption of “Dominant Defect” (i.e., its Probability of Failure is order of magnitude higher than any other defect), entailing that the Probability of Failure of the entire asset coincides with the one of the defect in question (and vice-versa). With this assumption in place, given the dominant defect in question and a single I - E pair, the calibration consisted in determining the specific Probability of Failure of the asset and associating it to a Damage Level through Table 1. This process is then repeated for each I - E pair until the completion of the I - E -Damage Level matrix. Finally, this was developed for each possible defect. As visible in Fig. 2c, multiple I - E combinations can lead to identical Damage Level (and, through Table 1, to identical P_F values) e.g., $[I = 1; E = 4]$ and $[I = 2; E = 1] \rightarrow \text{DL3}$.

These matrices can be differentiated for individual structural elements, allowing for a more precise assessment of the defect impact based on the element’s criticality within the bridge system. In particular, when defects are identified in vulnerable zones [23]— such as post-tensioning systems or Gerber joints, which are fundamental to the bridge’s overall resistance — the corresponding matrix values can be raised by an order of magnitude or adjusted using a multiplication factor. This adjustment ensures that defects in highly critical areas receive appropriate prioritization, reflecting their disproportionate influence on structural reliability [25].

Hence, the defect state observed during the inspection is described using two four-row column vectors for Intensity and Extension parameters, which range from 1 to 4. These vectors, called the Intensity State Vector (I) and Extension State Vector (E), have a value of one at the position corresponding to the Intensity observed during inspection, with all other positions set to zero. For example, if a defect is detected with Intensity and Extension both equal to 1, then $I = E = [1; 0; 0; 0]$. If a defect has an Intensity of 2 and Extension of 3, the vectors would be $I = [0; 1; 0; 0]$ and $E = [0; 0; 1; 0]$.

With this approach, it is possible to define the asset damage

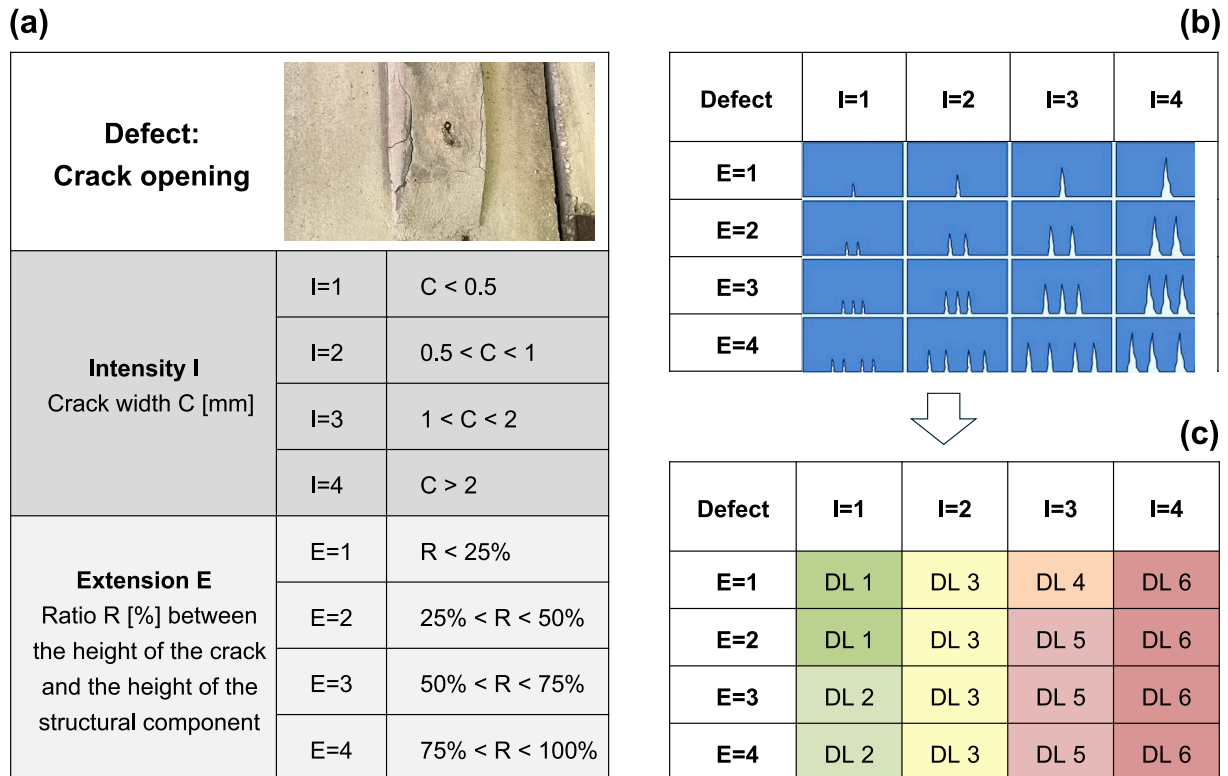


Fig. 2. Exemplary crack opening defect with its: a) respective Intensity I and Extension E descriptions; b) symbolic I - E -Damage Level matrix depiction; c) specific I - E -Damage Level matrix.

condition at the moment of the inspections, thus determining the “Current Risk”. From this starting point, the next sections will present the method to project the asset damage condition over time. This process will update the Damage Index D and thereby provide the “Projected Risk”.

3.3. Projecting the asset damage

The present subsection succinctly addresses the scenario in which a particular defect is identified on the structure during an inspection and, in particular, how this one evolves over time (i.e., a Degradation Model). This subsection embodies the “Projected Risk” processes of Fig. 1.

3.3.1. Degradation model

After having defined the current state of a defect through the Intensity State Vector and the Extension State Vector, its future projection is assessed using transition probabilities governed by the Markovian equation $P_{q \rightarrow r} = 1 - 0.5^{\frac{1}{N}}$. Here, $P_{q \rightarrow r}$ represents the probability of transitioning from a generic state q to a consecutive state r , and N is the time period after which there is a 50 % probability of transitioning to the next state. Considering three transition time periods of 20, 15 and 15 years respectively (see the left side of Fig. 3), to have 50 % transition probability to the successive state, the yearly values of $P_{q \rightarrow r}$ end up being 0.034 for transitioning from state 1 $\rightarrow$ 2, and 0.045 for both states 2 $\rightarrow$ 3 and 3 $\rightarrow$ 4. The authors wish to clarify that such transition model, despite being statistically derived from empirical data – as outlined in previous studies – and validated through practical applications, represents a simplification and the defect manifestation remains probabilistic.

The transition probabilities, along with their complements, form a Transition Matrix T_i (see right side Fig. 3) of which is, importantly, raised to the power of i to reflect the evolution over i years. The matrix values follow two key assumptions: transitions cannot skip states, and states cannot regress without external intervention. The main diagonal of the matrix indicates the probability of remaining in the initial state. Multiplying the Transition Matrix iteratively depicts the progression over time of a defect.

Consecutively, the evolving state is captured in the State Probability Vectors I_i and E_i for Intensity and Extension, respectively: $I_i = T_i \times I$ and $E_i = T_i \times E$. These vectors provide the probability distribution of the defect’s Intensity and Extension after i years. Finally, the State Probability Matrix P_{IE}^i is then derived by multiplying the Extension State Probability vector E_i by the transpose of the Intensity State Probability vector I_i as $P_{IE}^i = E_i \times I_i'$. This matrix P_{IE}^i offers a comprehensive view of the defect’s trajectory over time. Importantly, similarly to what happened in Fig. 2c, multiple P_{IE}^i cells can correspond to a singular Damage Level, according to the nature of the defect itself and their consequence on the carrying capacity. Thus, by summing the probabilities of the State Probability Matrix corresponding to the same Damage Level, P_{DL}^i can be condensed in a Damage Level Probability Vector P_{DL}^i for any year i as per Eq. (6) and Fig. 4:

$$P_{DL}^i = \left[\sum P_{IE,DL1}^i; \sum P_{IE,DL2}^i; \sum P_{IE,DL3}^i; \sum P_{IE,DL4}^i; \sum P_{IE,DL5}^i; \sum P_{IE,DL6}^i \right] \quad (6)$$

Next, the key Structural Reliability assessment parameters are

	N [years]	$P_{q \rightarrow r}$
State 1 to 2	20	$P_{s1 \rightarrow s2} = 3.4\%$
State 2 to 3	15	$P_{s2 \rightarrow s3} = 4.5\%$
State 3 to 4	15	$P_{s3 \rightarrow s4} = 4.5\%$

$$T_i = \prod_{j=1}^i T = \begin{bmatrix} 1 - P_{s1 \rightarrow s2} & 0 & 0 & 0 \\ P_{s1 \rightarrow s2} & 1 - P_{s2 \rightarrow s3} & 0 & 0 \\ 0 & P_{s2 \rightarrow s3} & 1 - P_{s3 \rightarrow s4} & 0 \\ 0 & 0 & P_{s3 \rightarrow s4} & P_{s4 \rightarrow s4} \end{bmatrix}^i$$

Fig. 3. On the left, the probability $P_{q \rightarrow r}$ of transitioning from a state q to a state r with their associated time periods N after which there is a 50 % transitioning probability for each of the 4 Intensity and Extension states, thus forming the Transition Matrix T_i (on the right).

forecasted. The Forecasted Damage Index D^i and the Forecasted Coefficient of Variation V_z^i are calculated at year i as in Eq. (7):

$$\begin{cases} D^i = \sum_{m=1}^6 P_{DLm}^i \cdot D_{DLm} \\ V_z^i = \sqrt{\frac{\sigma^2}{D}} = \sqrt{\sum_{m=1}^6 \left\{ P_{DLm}^i \cdot \left[V_{z,DLm}^2 \cdot \left(\frac{D^i}{D_{DLm}} \right)^2 + \left(1 - \frac{D^i}{D_{DLm}} \right)^2 \right] \right\}} \end{cases} \quad (7)$$

Please note that the values of D_{DLm} and $V_{z,DLm}$ can be found in Table 1 distinctly for each DL value under consideration (e.g., for DL3, $D_{DL3} = 0.99$ and $V_{z,DL3} = 0.20$). These indices provide a dynamic depiction of the structural system’s degradation over time. The Forecasted Probability of Failure $P_{F,i}$ are then determined cumulating the Probability of Failure of each year $P_{F,\Delta i}$ (from year $i=1$ to a target year n), as per Eq. (8):

$$P_F^i = \sum_{i=1}^n P_F^{\Delta i} = \sum_{i=1}^n \Phi \left(- \left\{ \beta_0^1 + \frac{\ln(D^i \cdot C)}{V_{z,0}} \right\} \cdot \frac{V_{z,0}}{V_z^i} \right) \quad (8)$$

Where β_0^1 is the Scaled Reliability Index of the structure in undamaged state, gauged over a 1-year Reference Period, and derived from a

Scaled Probability of Failure P_F^1 as $\beta_0^1 = -\Phi^{-1}(P_F^1) = -\Phi^{-1} \left(1 - e^{\frac{\ln(-P_F^{Tr})}{T_r} \cdot T} \right)$ [13]. Where T represents the Reference Period considered –

for P_F^1 , $T = 1$ year –; T_r is the Reference Period of the mathematical model, assumed to be 50 years; and P_F^{Tr} denotes the Probability of Failure corresponding to the reference period T_r considered to be $P_F^{Tr} = 1 \cdot 00 \cdot 10^{-8}$.

Fig. 5 provides a demonstrative application of the assessment of the Probability of Failure – through Eq. (8) – of the defect “Crack opening” (correspondent Defect Matrix in Fig. 2) over different time frames. In particular, the plots of Fig. 5 represent the evolution $P_{F,i}$ over time for all possible I-E defect combinations and the forecasted Defect Matrices at $i = 1$ year and $i = 50$ years. As visible, this methodology offers the possibility of understanding the evolving reliability of a structural system affected by a defect at any desired time frame.

3.3.2. Forecasting defect appearance accounting for defect correlations

The present section addresses the asset damage projection whenever a defect is not observed during an inspection. Under such condition, one must still consider that said defect has an intrinsic probability of manifesting itself in the upcoming years (for instance, defect “Joint deterioration” sooner or later surely appears). Clearly, said probability depends on the surrounding conditions of the defect in question, such as the current presence of defects that might directly promote its appearance (e.g., the “Water infiltration through joints” might promote the appearance of water induced “Concrete degradation”). Indeed, the current presence of defects on the asset might promote the appearance of one or more defects (henceforth referred to as “Triggered Defects”) in the long haul or even in the close future (see Fig. 6), given a certain degree of correlation between the two defects.

Notably, as visible in Fig. 6, said Triggered Defects might also trigger

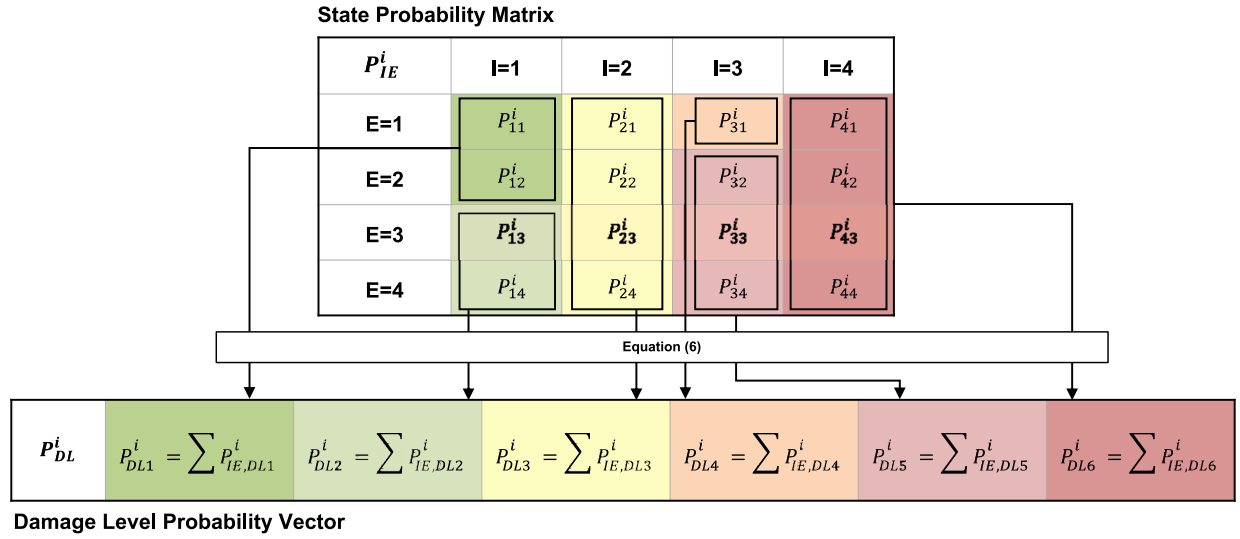


Fig. 4. Graphic representation of the aggregation of the State Probabilities (found in the State Probability Matrix P_{IE}^i) for the different Damage Levels and the consequent creation of the State Probability Vector P_{DL}^i .

other defects, despite it being increasingly less probable as the number of consecutive correlations increases. The above key aspects must be considered in a DSS as the appearance of new defects prompted by the defects currently present on the asset (henceforth referred to as Current Defect) can singularly or jointly accelerate the overall asset degradation, thus significantly compromising its structural reliability. As can be deduced from Fig. 6, whenever assessing the evolving Probability of Failure of a currently present defect (described in Section 3.3.1), one must also take in consideration the number and gravity of Triggered Defects that it may bring in the long run, along with their manifestation

probability. The proposed DSS model tackles this problematic by tying together the Probability of Failure of the Current Defect – see the degradation model of Section 3.3.1 – and the an additional Probability of Failure contribution from the consequential correlated Triggered Defects, according to Eq. (9):

$$P_{F,j}^i = P_{F,current\ defect}^i + \sum P_{F,triggered\ defect}^i \quad (9)$$

Being $P_{F,j}^i$ the Probability of Failure of a generic currently present defect j at year i encompassing both its degradation and the contribution

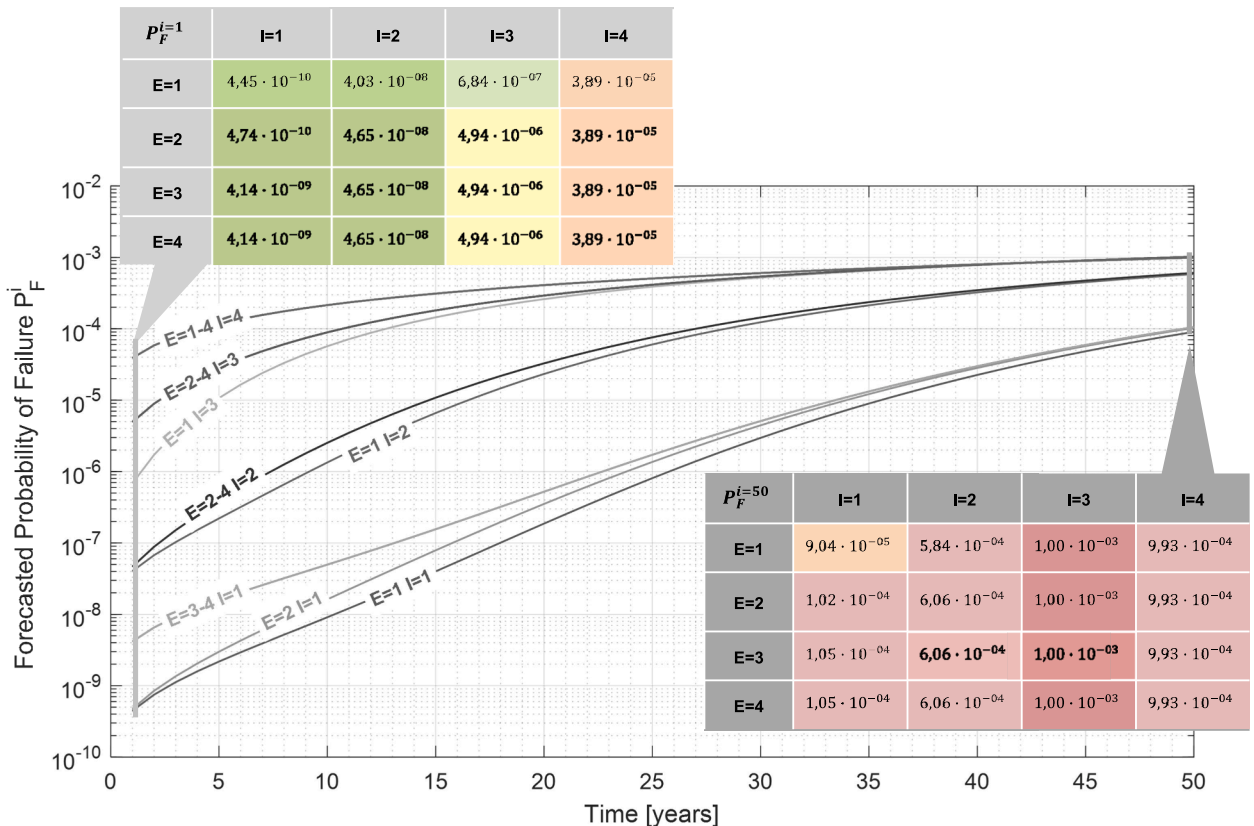


Fig. 5. Forecasted Probability of Failure P_F^i curves for each initial state (I-E combinations) of the “Crack opening” defect.

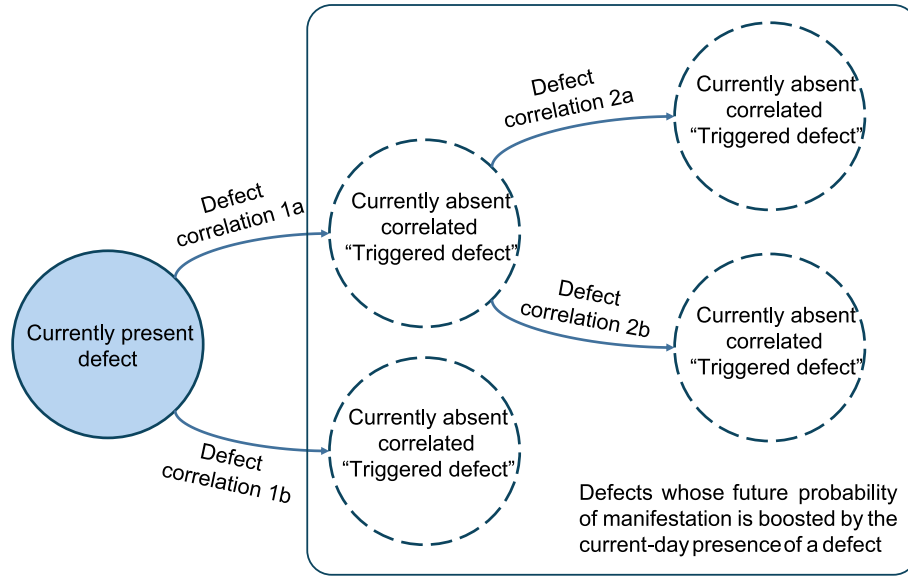


Fig. 6. DSS mechanism of correlation between defects.

of its Triggered Defects, $P_{F,j}^{i, \text{current defect}}$ the Probability of Failure of the Current Defect at year i (calculated according to the procedure of Section 3.3.1) and finally $\sum P_{F, \text{triggered defects}}^i$ the additional Probability of Failure contribution of all the Triggered Defects at year i , whose manifestation is promoted by the currently present defect j . The following paragraphs will elucidate how to determine the $\sum P_{F, \text{triggered defects}}^i$ of all Triggered Defects.

In brief, the proposed DSS methodology considers the probability that a currently absent defect will be present at a future time frame is the combination of its (1) intrinsic probability of manifesting itself after a certain amount of time and (2) the effect of other defects that might accelerate its appearance (illustrated in Fig. 6).

Starting from the former, to determine the annual probability of a defect manifesting itself, henceforth referred to as Intrinsic Defect Appearance Probability P_{app} , a statistical analysis was conducted on a set of bridges affected by several kinds of defects – refer to Brighenti et al. [13] –, following these steps:

- I. Analysing present and historic inspection reports of each bridge in the set.
- II. Cataloguing the identified defects jointly with the year they first appeared, compared to the year the bridge was constructed.
- III. Extracting the Intrinsic Defect Appearance Probability P_{app} by means of the Bayesian Theory and the Principle of maximum Likelihood of each reported defect.

Let us now move on to the quantification of the manifestation-boosting effect of currently-absent defects induced by other Triggered Defect. This phenomenon is modelled through the introduction of a Defect Presence Probability $P_{D,j}^i$ i.e., the probability that a generic Triggered Defect j is “present on the asset” at a future instance i , given its absence in the previous year or at the time of the latest visual inspection. As delved into later, $P_{D,j}^i$ jointly computes: (1) the Intrinsic Defect Appearance Probability of the Triggered Defect j : $P_{app,j}$, (2) the $P_{D,j}^i$ increase caused by the presence of other Triggered Defect, and (3) the possibility that the defect has already been triggered ($P_{D,j}^i \geq 50\%$). Please note that whenever referring to “Triggered Defect” the authors refer to both directly and indirectly Triggered Defect. In particular, as seen in the exemplative Fig. 6, some defects are consequential in nature whilst others aren’t. Fig. 7 provides a demonstrative practical example

to clarify this difference:

- A direct connection occurs when the analyzed defect consequentially leads to another defect (e.g. defect D1 is tied by a single connecting line to defect D2).
- An indirect connection occurs when two defects are not directly tied, but present one or more defect in the middle (e.g. defect D7 is connected to defect D1 through defects D2 and D5 i.e., D7 is indirectly connected to D1 and vice versa).

Noteworthy, Fig. 7 displays how a Current Defect (D1 in the figure) forms branches of correlated Triggered Defects (D2–D8), resulting in a “Correlation Tree” stemming from D1.

Moving back to the Defect Presence Probability $P_{D,j}^i$, the transition from the “defect absent” condition to the “defect present” condition occurs whenever $P_{D,j}^i$ exceeds 50 %, analogously to the definition of the state transition of Section 3.3. Quantifying $P_{D,j}^i$ entails quantifying the consequential connections between defects (labelled as “defect correlation” in Fig. 6 and represented as blue lines in Fig. 7) through a Correlation Probability $P_{Dj|jk}$, where j represents the Triggered Defect under consideration and jk the defect that could potentially expedite its appearance. Bear in mind that each defect jk is characterized by its own Defect Presence Probability $P_{D,jk}$. Now, to account for the evolution of $P_{D,j}$ in future years, an iterative process is necessary. This was achieved in Brighenti et al. [13], through Eq. (10).

$$P_{D,j}^i = 1 - \left\{ (1 - P_{app,j}) \cdot \prod_{k=1}^n (1 - [P_{Dj|jk}] \cdot P_{D,jk}^{i-1}) \right\} \mid i = 1, 2, \dots \quad (10)$$

$P_{D,j}^i$ of Eq. (10) operates in a vector space and encapsulates the evolution of the Defect Presence Probability of all defects j . In particular, the vector $P_{app,j}$ represents the annual Intrinsic Defect Appearance Probability of each defect j , whilst the $\left\{ \prod_{k=1}^n (1 - [P_{Dj|jk}] \cdot P_{D,jk}^{i-1}) \right\}$ component encapsulates the influence of all Triggered Defect jk correlated to each defect j . Note that, each term of the matrix $[P_{Dj|jk}]$ was calibrated for each defect correlation in such a way that the consequent $P_{D,j}^i$ reached 50 % (i.e., defect appearing) after a specific time interval. This interval represents the amount of time required by a specific Triggered Defect j to appear after having observed a specific defect jk . It is specific to each j –

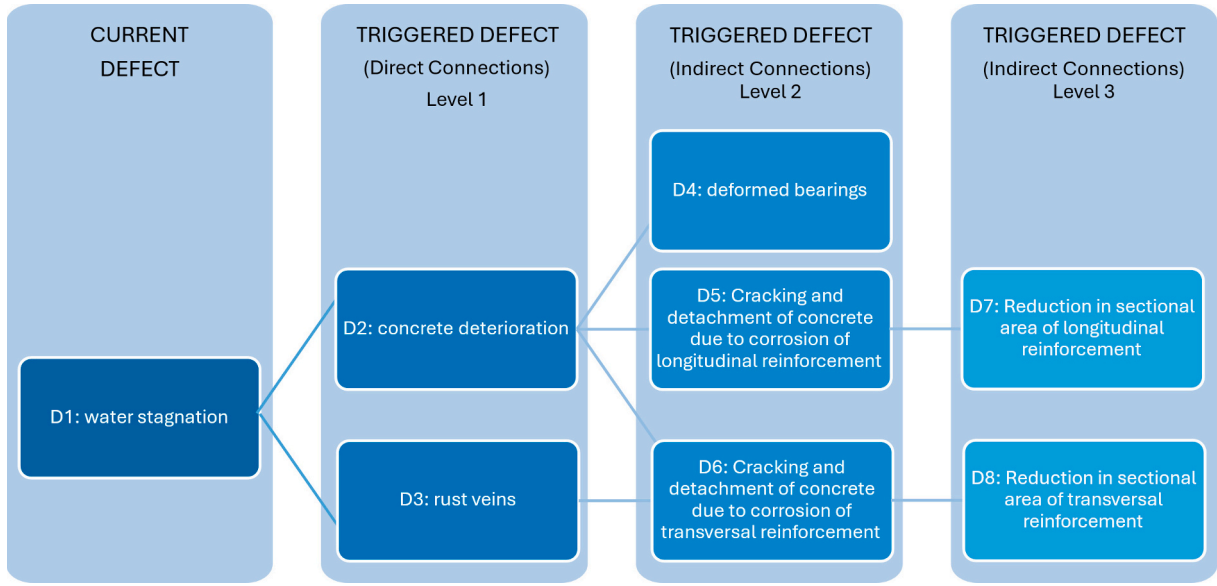


Fig. 7. Correlation branches stemming from the currently present defect “D1 – water stagnation”, forming defect D1 Correlation Tree.

j_k correlation and is established by infrastructure managers on the basis of the environmental and structural features of their asset.

Moving back to Eq. (10), if a defect is detected during an inspection, their associated P_{Dj} and P_{Djk}^{i-1} terms become =1 (whereas when the defect is absent during the latest inspection $P_{Dj}^i < 1$) regardless of the value extracted from the iteration. Whenever the defect has reached $P_{Dj}^i = 1$ the iterative process is interrupted.

Now, all pieces are in place to determine the $\sum P_{F, \text{triggered defects}}^i$ component of Eq. (9). In particular this is achieved through the summation of Eq. (11) over the total number of Triggered Defects – correlated to a specific Current Defect – and for the i -th year of temporal progression.

$$\sum P_{F, \text{triggered defects}}^i = \sum \sum_i \left\{ P_{D, \text{triggered defect}}^i \cdot \left[P_{F, \text{triggered defect}(1-1)}^i \right] \right\} | i = 1, 2, \dots \quad (11)$$

Being $P_{D, \text{triggered defect}}^i$ the Defect Presence Probability of the Triggered Defect under analysis and $P_{F, \text{triggered defect}(1-1)}^i$ the Probability of Failure of the Triggered Defect under analysis, considering it in the $I = 1$ and $E = 1$ conditions in light of the defect not yet being manifest. Indeed, $I = 1$ and $E = 1$ are considered to be the conditions in which a defect first manifests itself on the asset ($I < 1$ and $E < 1$ coincides with an absent defect). The two terms $P_{D, \text{triggered defect}}^i$ and $P_{F, \text{triggered defect}(1-1)}^i$ are cumulated for the projection years i , and then again for each Triggered Defect correlated to the current defect, so as to obtain a global contribution $\sum P_{F, \text{triggered defects}}^i$ of the Triggered Defects at the year i .

As example, let us consider the bottom branch of the Correlation Tree graphically represented in Fig. 7, namely D1-D3-D6-D8. Here, the Current Defect is “D1 – water stagnation” promotes an acceleration in the future manifestation of the following Triggered Defects, within a pre-determined time frame:

- Defect D3, indicating the presence of rust veins, observed 2 years after the formation of D1, with a Correlation Probability $P_{D3|D1} = P_{D,D3|D1} = 30\%$.
- Defect D6, describing the presence of cracks and concrete detachments due to corrosion of the transverse reinforcement, is consequent to defect D3 appearing after 2 years, with a Correlation Probability $P_{D6|D3} = P_{D,D6|D3} = 30\%$.

- Defect D8, or the reduction of the transverse reinforcement section, appears 14 years after the emergence of defect D6, with a Correlation Probability $P_{D8|D6} = P_{D,D8|D6} = 5\%$.

The Triggered Defect will bring a contribution to the Probability of Failure $P_{F,D1}^i$ associated to the Current Defect D1, as shown in Fig. 8.

Please note that in order to integrally determine the $P_{F,D1}^i$, the process shown in Fig. 8 should be performed for each and every branch of the correlation tree of Fig. 7 stemming from defect D1. Therefore, the contribution of defects $P_{F,D2}^i$, $P_{F,D4}^i$, $P_{F,D5}^i$ and $P_{F,D7}^i$ should be summed to $P_{F,D1}^i$. Given the Correlation Tree represented in Fig. 8, the values of $P_{F,D1}^i$ at the 50th year of temporal transition are reported in Table 2 for all conditions of Intensity and Extension, both in the presence and absence of correlations.

From the comparison between the two tables of Table 2, it is evident that considering defect correlations results in a Probability of Failure at the 50th year of temporal evolution that is up to five orders of magnitude higher than in the case without correlations. This highlights the critical importance of accounting for defect consequentiality to properly assess the degradation progression of a structure.

It is worth noting that in Table 2, the Probability of Failure $P_{F,D1}^{50}$ varies according to Extension (E) but not Intensity (I). This is because the original Defect Matrix for defect “D1 - Water Stagnation” manifests with different Extensions but not with varying Intensities. Indeed, water stagnation cannot be more or less intense, what matters is the area of the element affected by the stagnation, which explains why $P_{F,D1}^{50}$ varies per E but remains constant across all levels of I .

3.4. Exposure

As stated in Eq. (1), risk assessment can be defined as a mathematical function of the probability of an event – in our case the Probability of Failure – P_F and the Exposure Z of that event. This subsection addresses the modeling of the latter. The general logic behind the Exposure evaluation is based on a formal analysis consistent with the Expected Utility Theory and on several simplifying assumptions:

- The failure F in question coincides with the collapse of the structure;
- The consequences of a collapse are determined (there is no uncertainty on the consequences of a collapse);

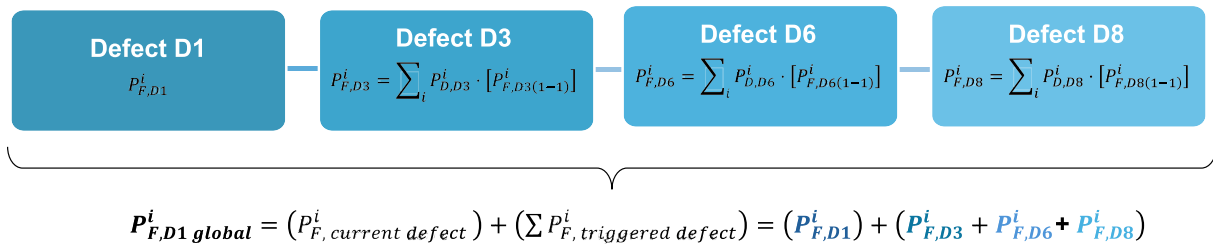


Fig. 8. Effect of Triggered Defects on the Forecasted Probability of Failure of the Current Defect.

Table 2

Probability of Failure of the defect “D1 – Water stagnation” at the 50 years timeframe $P_{F,D1}^{50}$ without (on the left) and with (right) the contribution of Triggered Defects.

$P_{F,D1}^{50}$ without contribution from Triggered Defects					$P_{F,D1}^{50}$ with contribution from Triggered Defects				
	I = 1	I = 2	I = 3	I = 4	I = 1	I = 2	I = 3	I = 4	
E = 1	1.404·10 ⁻⁸	1.404·10 ⁻⁸	1.404·10 ⁻⁸	1.404·10 ⁻⁸	4.908·10 ⁻⁷	4.908·10 ⁻⁷	4.908·10 ⁻⁷	4.908·10 ⁻⁷	
E = 2	2.487·10 ⁻⁸	2.487·10 ⁻⁸	2.487·10 ⁻⁸	2.487·10 ⁻⁸	4.984·10 ⁻⁷	4.984·10 ⁻⁷	4.984·10 ⁻⁷	4.984·10 ⁻⁷	
E = 3	4.941·10 ⁻⁸	4.941·10 ⁻⁸	4.941·10 ⁻⁸	4.941·10 ⁻⁸	5.159·10 ⁻⁷	5.159·10 ⁻⁷	5.159·10 ⁻⁷	5.159·10 ⁻⁷	
E = 4	1.008·10 ⁻⁷	1.008·10 ⁻⁷	1.008·10 ⁻⁷	1.008·10 ⁻⁷	5.527·10 ⁻⁷	5.527·10 ⁻⁷	5.527·10 ⁻⁷	5.527·10 ⁻⁷	

- x is the variable expressing the consequence of the collapse (scalar x or vector $\vec{x}$);
- x does not vary depending on the risk factor;
- The consequences of a collapse are considered as “disutility” or loss according to the utility function $U(\vec{x})$ (e.g., number of casualties, costs for the operator, costs for users, etc.), being $D_{\vec{x}}$ the domain of the variable $\vec{x}$;
- The variable $\vec{x}$ and the failure F – the collapse – are independent;
- The uncertain consequences of the collapse can be represented by a joint probability density $f_{\vec{x}|F}$.
- Casualties is the dominant consequence $\vec{x}$ predominating over the others, therefore the only one considered.

Under the above assumptions, the Exposure Z can be expressed through an integral – in the domain of the variable $\vec{x}$ – of the product of $f_{\vec{x}|F}$ and $U(\vec{x})$. Under the last listed assumption of a single predominant consequence (casualties), the variable $\vec{x}$ of the consequences can be considered as a scalar variable x and no longer a vector. Finally, the Utility Function $U(x)$ of such scalar variable is assumed to be an exponential function dependent on α , the risk aversion parameter [19–23]. As such, the Exposure takes the following form of Eq. (12):

$$Z = \int_{D_{\vec{x}}} f_{\vec{x}|F} \cdot U(\vec{x}) d\vec{x} = \int_0^\infty f_{x|F} \cdot U(x) dx = \int_0^\infty f_{x|F} \cdot e^{-\alpha x} dx \quad (12)$$

Please note that $U(x)$ assumes different meanings depending on the value of the exponent α , in particular: $\alpha = 1$ Risk Neutral, $\alpha < 1$ Risk Prone and $\alpha > 1$ Risk Adverse. The values of α adopted by different countries are shown in [30–34]. In this article, the authors have chosen the Risk Neutral hypothesis, thus $\alpha = 1$. Let us now consider the possible exposure factors Z specific to the collapse of a bridge, evaluated as monetary amounts (i.e., costs) as per Eq. (13):

$$Z = Z_D + Z_V + Z_T + Z_I \quad (13)$$

Where:

- Z_D : direct costs related to a bridge reconstruction;
- Z_V : direct costs related to potential casualties;
- Z_T : direct costs related to potential damage to the surrounding area;
- Z_I : indirect costs associated with the lack of functionality of the bridge.

Considering human casualties as the dominant consequence entails that Z can be evaluated solely as a function of this one. The number of

potential casualties is assessed separately for (1) vehicle transit over the structure x_V – associated to the factor Z_V – and (2) entity being crossed over (road, watercourse, built-up area, etc.) x_T – associated to the factor Z_T –. On the exposure factors Z_D and Z_I , these do not lead to potential casualties, so their consequences can be neglected when compared with the possible loss of life. For Z_I , this is even more valid when considering that the presence of alternative routes is oftentimes verified.

Starting with the Z_V model, this one is derived from the general definition of Exposure as per Eq. (12) and is a function of the number of vehicles passing over the bridge. Considering $\alpha = 1$, the term $\int_0^\infty f_{x_V|F} \cdot x_V dx_V$ can be re-written as the Vehicular Density crossing the bridge at a specific instance d_V [35] [$n_{vehicles}/span$]. Moreover, considering a Poisson distribution of the Vehicular Density, one can define d_V as the ratio between the Average Daily Traffic (ADT) [35] and the mean velocity of the vehicles on the road v , as shown in Eq. (14).

$$Z_V = \int_0^\infty f_{x_V|F} \cdot x_V dx_V = d_V \cdot L_{max} \cdot n_{ppl/vehicle} \cdot \lambda_V = \frac{ADT}{v} \cdot L_{max} \cdot n_{ppl/vehicle} \cdot \lambda_V \quad (14)$$

Being L_{max} the length of the longest span of the bridge; $n_{ppl/vehicle}$ the average number of people per vehicle (in absence of accurate studies the parameter can be assumed equal to 2) and λ_V the probability of death for people exposed to risk in the event that the hazardous event occurs, defined as “Lethality”. Being this one a function of the bridge’s height, the authors defined the Lethality function as constant at 1 % up to 5 m, then linearly increasing from 1 % to 100 % between 5 and 10 m, and finally remaining constant at 100 % beyond 10 m.

Moving on to the evaluation of Z_T , this one is a function of the number of people under the bridge and exposed to risk in the event that the hazardous event occurs. Given once again the base Eq. (12) and $\alpha = 1$, Z_T can be modelled as per Eq. (15).

$$Z_T = \int_0^\infty f_{x_T|F} \cdot x_T dx_T = \lambda_T \cdot d_T \cdot s \quad (15)$$

Being λ_T the probability of death for people exposed to risk (from above this time) in the event that the hazardous event occurs, defined as “Lethality” and it is arbitrarily assumed to be constantly 100 %; d_T the occupancy density of the area of the entity being crossed [$n_{ppl/spatial\ quantity}$], which can be for example industries, commercial activities, residences, parking lots, roads, water courses and valleys, etc. and s the spatial quantity [length or area] of interest under the bridge.

4. Intervention efficiency and COST-based prioritization

The present section focuses on comprehending and modeling the way structural interventions improve the structural condition of a bridge, along with its reliability. Essentially, structural interventions reduce the risk associated with a specific defect which singularly – or jointly with other defects – represents a reduction in asset performance and reliability. Maintenance processes that target and mitigate progressive degradation play a crucial role in this. Generally, following the detection of one or more defects on a bridge, three main possible scenarios are considered by infrastructure managers and decision-makers:

- Intervention Scenario 1: Not intervening;
- Intervention Scenario 2: Performing Maintenance, Repair, and Rehabilitation (MR&R);
- Intervention Scenario 3: Reconstructing the whole bridge.

The latter scenario would drastically improve the bridge structural behaviour, albeit at considerably different costs compared to addressing the individual defects. Understanding whether it is more cost-efficient to address the defects with the highest risk contribution or opting for a full reconstruction is a crucial component of the bridge management practice, especially over a long-term period. The preferable scenario among these three is not always as intuitive as one might think. For example, whilst MR&R always seems preferable to reconstructing a bridge, sometimes the scale and grievousness of the asset defects make the latter scenario a more efficient, cost-effective and safety-boosting scenario. Not intervening too is a worthwhile decision in certain scenarios. For example, in the commonplace situation of a limited budget being allocated for the upkeep of a large bridge asset, infrastructure managers need to select a certain number of assets that will not receive any intervention to guarantee the execution of proper MR&R works on the asset that most urgently require intervention. As such, to design a DSS model capable of identifying the optimal upkeep strategy, it is necessary to consider the effect that these interventions may have on the presence and/or subsequent development of a defect.

As explained above, to design a DSS model capable of identifying the optimal upkeep strategy, it is necessary to consider the effect of possible interventions on the presence and/or subsequent development of one or more defects (a single intervention scenario could tackle more defects). Clearly, as represented in Fig. 9 given “Intervention Scenario 1: not intervening”, the defect/s Probability of Failure remains unvaried. Hence, its evaluation at future time-frames coincides with the

assessment of P_F^i (as per Section 3.3).

Instead, given “Intervention Scenario 2: MR&R” and “Intervention Scenario 3: Reconstruction” the defect/s post-intervention Probability of Failure $P_{F,int}^i$ is considerably reduced from its pre-intervention one. The evaluation of $P_{F,int}^i$ at future time-frames is performed analogously to the procedure of Section 3.3, except its starting point isn’t anymore the damaged state – currently present defect – but, instead, its repaired – thus absent – state ($P_{D,j}^{i=0} = 0$). Noteworthy, as represented in Fig. 9, three types of intervention consequences (on the basis of which $P_{F,int}^i$ is assessed) are considered:

- Intervention consequence 1: The defect is completely removed;
- Intervention consequence 2: The defect is eliminated, but there is an increase in the Annual Intrinsic Defect Appearance Probability $P_{app,j}$ by one order of magnitude (e.g., application of mortar over deteriorated or spalling concrete which does eliminate the defect, but in such a way that there is a high chance that defect will represent itself in little to no time);
- Intervention consequence 3: Not only the defect is eliminated but, additionally, a reduction in the Annual Intrinsic Defect Appearance Probability $P_{app,j}$ by one order of magnitude is included (e.g., removal of rust from a beam – chemically first and mechanically after – and, finally, application of a rust-inhibiting primer, creating a protective barrier that enhances the resistance of the beam to moisture and to environmental factors that can lead to rust formation).

Clearly, whenever evaluating the efficiency of “Intervention Scenario 3: Reconstructing the whole bridge”, one must consider “Intervention consequence 1”, where all existing defects on the asset are entirely removed and the original values of $P_{app,j}$ preserved. In contrast, when MR&R scenarios are considered, the $P_{app,j}$ values might change. For instance, repairing a corroded reinforcement bar and applying an anti-corrosion treatment before restoring the covering concrete, will eliminate the defect “Reinforcement corrosion” and decrease its $P_{app,j}$ in such area; whereas, simply restoring the detached concrete without addressing the underlying corrosion will cause the $P_{app,j}$ of the defect “Concrete detachment” to increase.

On the basis of the intervention scenario selected by the infrastructure manager – not intervening versus MR&R/Reconstruction – it is possible to define two distinct conditions of progressive defect degradation. Each one is tied to different Bridge Reliability conditions i.e., with and without the intervention effect – P_F^i and $P_{F,int}^i$ – respectively (see

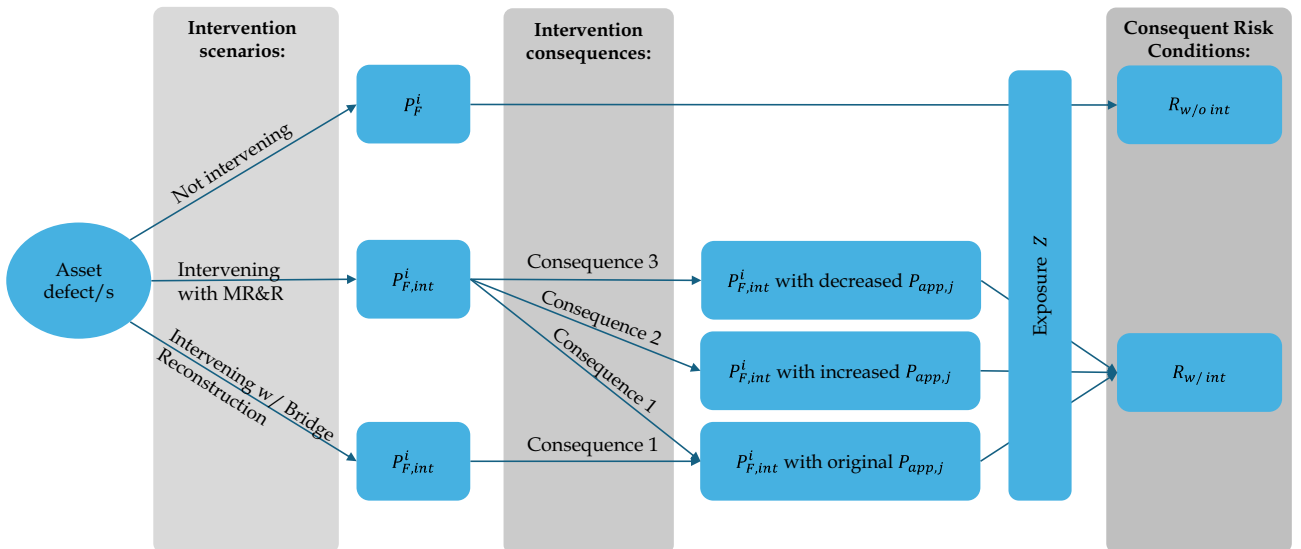


Fig. 9. Intervention scenarios effect on Risk.

Fig. 9), and each leading to a different Risk value:

- Risk condition without intervention ($R_{w/o\ int}$): characterized by the un-altered temporal evolution of the defect and its correlations with other defects.
- Risk condition after the intervention ($R_{w/int}$): defect is considered removed, effectively altering the defect progression analysis by treating the defect as non-existent (Defect Presence Probability $P_{Dj}^i < 1$).

As per Eq. (1) and Fig. 9, to define the pre- and post-intervention risk of a specific defect – $R_{w/o\ int}$ and $R_{w/int}$ respectively –, one needs to cumulatively sum the Probabilities of Failure – P_F^i and $P_{F,int}^i$ – to the studied year (n) and multiply the obtained value by the Exposure Coefficient Z i.e., $R_{w/o\ int} = \sum_{i=1}^n P_F^i \cdot Z$ and $R_{w/int} = \sum_{i=1}^n P_{F,int}^i \cdot Z$. Now, assuming the goal of infrastructure management to be the efficient allocation of resources towards interventions that maximize the risk-reduction ΔR while minimizing its costs $Cost_{int}$, the cost-effectiveness of a specific intervention scenario can be evaluated through a coefficient called Priority Index α_{int} , as per Eq. (16).

$$\alpha_{int} = \frac{\Delta R}{Cost_{int}} = \frac{R_{w/o\ int} - R_{w/int}}{Cost_{int}} = \frac{\sum_{i=1}^n P_F^i \cdot Z - \sum_{i=1}^n P_{F,int}^i \cdot Z}{Cost_{int}} \quad (16)$$

Clearly, as anticipated in Section 2, the interventions that better meet this cost-efficiency criteria ($\Delta R / Cost_{int}$) gain increased priority towards the others, thus the name Priority Index α_{int} . In other words, said index allows the assessment, on a yearly basis, of the comparative benefit of addressing one defect over others. Indeed, per Eq. (16), given an identical intervention cost $Cost_{int}$, it is more cost-efficient to carry out the intervention that results in a higher risk reduction ΔR between the pre- and post-intervention situations, hence with a higher α_{int} value.

Crucially, the Priority Index of an entire asset is evaluated as the difference between the sum of the Risk pre- and post- intervention

associated to every defect j , normalized by the sum of all the costs associated to every intervention scenario, as per Eq. (17):

$$\alpha_{asset} = \frac{\sum_j R_{w/o\ int} - \sum_j R_{w/int}}{\sum Cost_{int}} \quad (17)$$

As reported in Bortot et al. [36], in line with the formulations presented by [37,38], the life-cycle cost $Cost$ associated with each bridge is estimated as in Eq. (18), being:

$$Cost = C_0 + C_I + C_M + C_R + C_F \quad (18)$$

- C_0 the new construction or replacement costs: these are calculated based on euros per square meter ($\text{€}/\text{m}^2$) of the replacement area, varying according to the type of structural elements considered, linearly related to the span length L .
- C_I the inspection costs: these are based on the geometry and accessibility of the bridge in exam.
- C_M and C_R the bridge maintenance and repair costs, respectively: these are estimated based on the unitary costs of the element to be repaired, similar to the PONTIS procedure [39]. These unitary costs are derived from official bulletins and agency records and are typically independent from the quantity of the elements, with few exceptions.
- C_F the failure costs: these account for all structural and functional costs associated with potential failures and is estimated by integrating the annual probability of failure with the total cost C_{F0} due to the bridge deficiency caused by the failure. In the current DSS, it is simply estimated as a percentage of the reconstruction cost.

Depending on the chosen intervention scenario, it is possible to calculate the pre- and post-intervention difference of $Cost$. Please note that C_I and C_F remain unchanged before and after intervention (they are functions of the bridge's geometric characteristics, location, and socio-economic importance), leaving only the intervention costs (C_M and C_R) and reconstruction costs (C_0) as the varying ones. These costs are

Table 3
Case study bridges inventory information, and Capacity Index (C) and Exposure (Z) values.

Attribute	Bridge 1	Bridge 2
Capacity Index		
Design Year	1970	2000
Construction Year	1975	2005
Design Code	Italian code of 1962	Italian code of 1980
Material	prestressed concrete	mixed steel-concrete
Spans	5 spans (23 m each)	27 spans (27 m each)
L_{max}	23 m	27 m
Width	12 m	15 m
Maximum bending moment for dead load G_M [kN/m^2]	11,846.82	11,074.57
Maximum shear force for dead load G_V [kN]	2057.63	1640.68
Maximum bending moment for live load $Q_{d,U-M}$ [kN/m^2]	796.54	1047.53
Maximum shear force for live load $Q_{d,U-V}$ [kN]	159.32	155.19
Maximum bending moment for reference live load $Q_{d,0-M}$ [kN/m^2]	983.07	1280.65
Maximum shear force for reference live load $Q_{d,0-V}$ [kN]	173.87	192.39
Shear Capacity Index C_V	0.993	0.980
Bending Capacity Index C_M	0.985	0.981
Capacity Index C	0.985	0.980
Exposure		
Bridge Height	8 m	8.5 m
Highway Network	Yes	Yes
ADT (Average Daily Traffic)	50,000 vehicles	20,500 vehicles
Average Speed (v)	110 km/h	110 km/h
Location	Over a small canal	Over a river
Passage of people underneath	No	No
Assumed $n_{ppl/vehicle}$ (see Section 3.4)	2	2
Assumed lethality (as a function of "Bridge Height" as per Section 3.4)	0.604	0.703
Exposure Z	0.526	0.295

zero whenever assessing the pre-intervention risk scenario and correspond to the intervention cost in the post-intervention scenario. Hence, in Eq. (16), the difference between the risks with and without intervention is normalized only by the cost of the intervention scenario itself ($Cost = Cost_{int}$).

In the above sections, the authors have illustrated how to obtain two important decision-making tools (α_{int} for single intervention scenarios and α_{asset} for entire assets) which jointly address the limitations of current-day classic methods, ensuring the long-term safety and reliability of critical infrastructure.

5. Application to case studies

The present section guides the reader through each step of the DSS, providing a clear overview of the contributions of each term within the DSS framework. We consider two case studies with the characteristics detailed in Table 3:

In regards to the Capacity Index C , it was calculated according to Eq. (5) using the loads effect of Table 3 (as a function of the related design code of each asset). The Capacity Index was evaluated for both shear and bending – noted as V and M respectively – and the minimum index was finally assumed, in accordance with Section 3.1.

As for the Exposure, it was evaluated by means of Eq. (13) as the sum of: Z_D direct costs related to a bridge reconstruction, Z_V direct costs related to potential casualties, Z_T direct costs related to potential damage to the surrounding area, and Z_I indirect costs associated with the lack of functionality of the bridge, where, as explained in Section 3.4, Z_V and Z_I are neglectable. Moreover, being both bridges over a small canal with no passage of people, Z_T , associated with casualties under the bridge can be considered equal to 0. Therefore, in both cases the Exposure was evaluated by means of solely Z_V of Eq. (14) and the parameters of as per Table 3.

Following a visual inspection on the bridge asset, Bridge 1 was found to have seven defects after, each requiring specific interventions. Similarly, Bridge 2 was found to have 5 defects, also with specific correlated interventions. The result of said visual inspections, namely the defects type, Intensity, Extension and Location, along with the proposed interventions and their consequences are reported in Table 4.

Table 4

Result of visual inspection on the two case study bridges: (1) Defect code and description, (2) Intensity level (I), (3) Extension level (E), (4) Location on the asset, (5) Suggested intervention code and description and (6) Consequence of the intervention.

Defect	I	E	Location	Intervention	Consequence of intervention (§4)
BRIDGE 1					
D0 – Water drainage malfunction	1	2	Span 1	R2 - Downspout cleaning/restoration of water collection system	1st consequence
D5 – Cracking and detachment of concrete due to transversal reinforcement corrosion	3	4	Span 2 overhang	R3 - Conservative restoration of concrete portions in correspondence of exposed reinforcement (concrete cover)	2nd consequence
D6 – Cracking and detachment of concrete due to longitudinal reinforcement corrosion	3	4	Span 3 overhang	R1 - Structural restoration of reinforced concrete elements with exposed reinforcement	3rd consequence
D9 - Bearing corrosion	1	2	Bearing 4	M1 - Maintenance or replacement of supports/insulators or components (e.g. anchors, Teflon, skids)	1st consequence
D19 – Cracks at the edges	2	4	Impost block 1	R4 - Conservative restoration of concrete surfaces (no exposed reinforcement)	3rd consequence
D20 – Deterioration of bearing's concrete support	4	3	Bearing pedestal 1	R1 - Structural restoration on reinforced concrete elements with exposed reinforcement	2nd consequence
D22 – Deformation or detachment of joint pad	2	2	Joint 1	M2 - Joint line reconstruction	1st consequence
BRIDGE 2					
D0 – Water drainage malfunction	1	1	Span 1	R2 - Downspout cleaning/restoration of water collection system	1st consequence
D10 – Elastomer deterioration	1	2	Bearing 3	M1 - Maintenance or replacement of bearings/insulators or components (e.g. anchors, Teflon, skids)	1st consequence
D13 - Erosion	1	1	Foundation 1	R6 - Restoration of foundations in riverbed	1st consequence
D21 – Bearing generic defect	1	1	Bearing 2	M1 - Maintenance or replacement of supports/insulators or components (e.g. anchors, Teflon, skids)	1st consequence
D23 – Obstruction for material in riverbed	1	1	Pile 2	M3 - Cleaning material in riverbed	1st consequence

5.1. Risk pre- and post-intervention evaluation

As elucidated in Section 3.3, the Forecasted Probabilities of Failure P_F^i of the asset is composed of two elements: the contribution of defects present during the inspection and the contribution of defects absent during the inspection but that might appear later on the asset service life. Both contributions converge in the determination of the P_F^i associated to a present defect through Eq. (9). Starting from the former contribution, the Forecasted Probabilities of Failure of the defects were determined at two exemplary timeframes $i = 5, 50$ (a short-term and long-term time horizon of 5 and 50 years, respectively), following the steps presented in Section 3.3 and by means of the Defect Matrices of the defects detected during the inspections (illustrated in Fig. 10).

The contribution of the defects absent during the inspections (but potentially appearing later on as Triggered Defects, due to the presence of the Current Defects) are calculated by means of the steps of Section 3.3.2, the Correlation Tree of Fig. 11 and the Defect Appearance Probabilities of each defect (on the right hand of Fig. 11). Please note that, once again, the number of years before the appearance of Triggered Defects is the choice of each infrastructure manager and, therefore, may be subjected to variation. Crucially, as visible in Fig. 11, all the D19-D23 defects do not present any Triggered Defects in light of their intrinsic nature.

The Defect Matrices of Fig. 10 and the Correlation Tree & Defect Appearance Probabilities of Fig. 11 allow for the evaluation of the Forecasted Probability of Failure P_F^i at 5 and 50 years for all the defects of Bridge 1 and 2, according to Section 3.3, culminating in Eq. (11). Table 5 reports both the non-intervention scenario Forecasted Probabilities of Failure P_F^i and the ones considering the intervention consequences pertinent to each defect $P_{F,int}^i$, as per Table 4 and Section 4.

Some considerations can be made when observing the results at the 5 years time-frame. For the sake of conciseness, a code system will be used henceforward to refer to the different defects, interventions and bridge where they are located. For example, (Br1 – D0) stands for (Bridge 1 – Defect D0).

- (Br1 – D20): Its high Probability of Failure $P_F^i = 9.36 \cdot 10^{-5}$ and its severe state of deterioration ($I = 4$, $E = 3$) suggest that (Br1 – D20) is the most critical defect in the short term. This was clear also from the

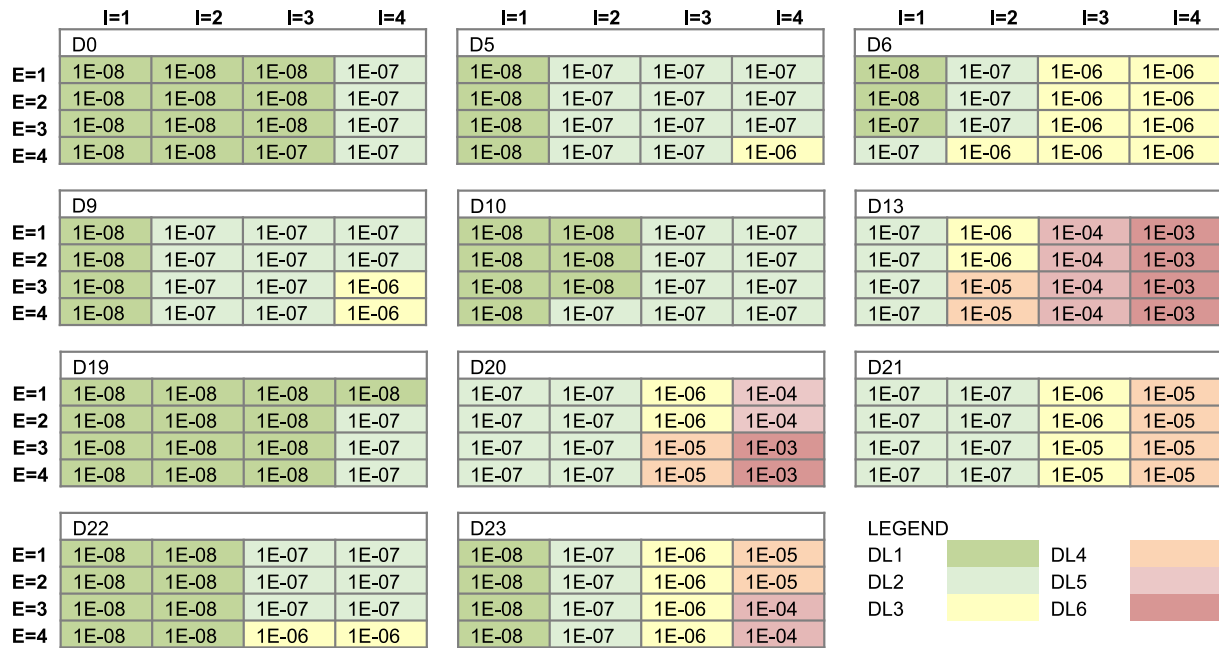
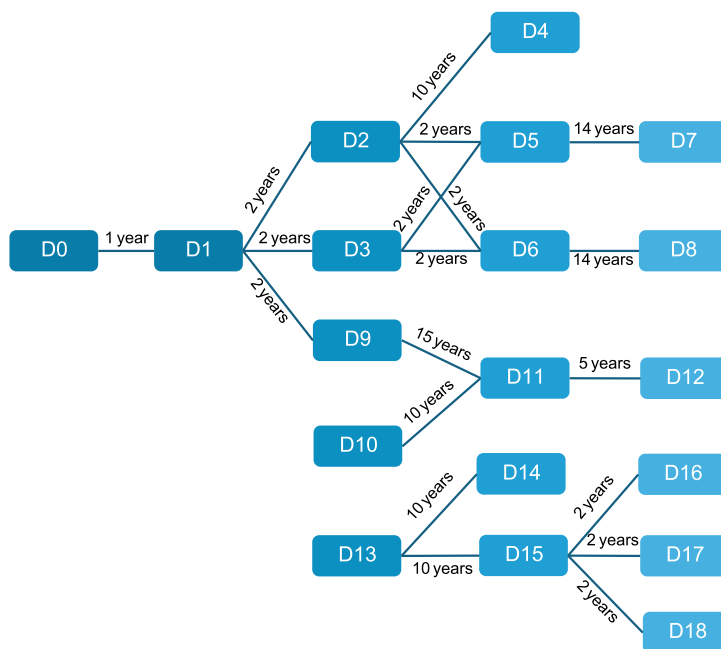


Fig. 10. Defect matrices of all the defects found on the two case study bridges.

severity of the Defect Matrix of D20 (see Fig. 10). Furthermore, D20 is the only defect with a post-intervention $P_{F,int}^5 > 10^{-9}$.

- (Br1 – D0) and (Br2 – D0): These are the second most critical defects ($P_F^5 = 1.61 \cdot 10^{-5}$), despite being characterized by a much lighter deterioration state ($I = 1$, $E = 2$) than (Br1 – D20). (Br1 – D0) and (Br2 – D0) further distinguishes themselves from (Br1 – D20) in their Defect Matrix (see D0 Defect Matrix in Fig. 10). In particular, the former has a significantly more severe Defect Matrix (mainly 10^{-8} and 10^{-7} for maximum Intensity conditions) compared to the latter (values ranging from 10^{-7} to 10^{-3}). Yet, the extensive correlations of D0 with 11 other Triggered Defects (see the entire correlation tree of Fig. 11) significantly amplify its severity.

- (Br1 – D19): this defect has the most severe Defect Matrix of Fig. 10 which, combinedly with the fact that it has no defect correlations, results in (Br1 – D19) having the lowest P_F^5 of Table 5. Interestingly, D0 has the second most conservative Defect Matrix of Fig. 10 after D19, yet, as seen above, the defect correlations lead (Br1 – D0) and (Br2 – D0) to a much harsher $P_F^5 = 1.61 \cdot 10^{-5}$ compared to (Br1 – D19): $P_F^5 = 8.30 \cdot 10^{-10}$.
- Bridge 1 and 2 - General Intervention Impact: Despite varying initial P_F^5 levels, the selected interventions bring all defects to a similar low-risk $P_{F,int}^5$ level within 5 years, showing uniform effectiveness across different intervention types.



Defect	Description	P_{app}
D0	Water drainage malfunction	8,90E-05
D1	Water stagnation	1,38E-03
D2	Concrete deterioration	5,37E-04
D3	Rust veins	4,10E-04
D4	Deformed bearings	0,00E+00
D5	Cracking and detachment of concrete due to corrosion of transversal reinforcement	5,13E-04
D6	Cracking and detachment of concrete due to corrosion of longitudinal reinforcement	1,20E-03
D7	Reduction in sectional area of transversal reinforcement	5,10E-05
D8	Reduction in sectional area of longitudinal reinforcement	8,90E-05
D9	Bearing corrosion	5,00E-04
D10	Elastomer deteriorated	0,00E+00
D11	Bearing blockage	1,30E-05
D12	Structural connection defect	0,00E+00
D13	Erosion	0,00E+00
D14	Out-of-lead vertical elements	3,80E-05
D15	Differential subsidence of vertical elements	0,00E+00
D16	Height difference between embankment and deck	2,50E-05
D17	Unevenness pavement - joint	0,00E+00
D18	Unevenness between continuous joint elements	0,00E+00
D19	Cracks at the edges	5,53E-04
D20	Deterioration of bearing's concrete support	4,00E-04
D21	Bearing generic defect	1,02E-04
D22	Deformation or detachment of joint pad	0,00E+00
D23	Obstruction for materials in riverbed	0,00E+00

Fig. 11. Correlation tree for the defects of the case study bridges and defect catalogue with Intrinsic Defect Appearance Probability P_{app} of each defect.

Table 5

Probabilities of Failure related to defects detected on Bridge 1 and 2 at two different time horizons (5 and 50 years), with $(P_{F,int}^i)$ and without (P_F^i) intervention. Note, the color scheme follows the same logic as the one in Figure 10.

Defect	I	E	P_F^5	P_F^{50}	Intervention	$P_{F,int}^5$	$P_{F,int}^{50}$
BRIDGE 1							
D0	1	2	$1.61 \cdot 10^{-5}$	$1.35 \cdot 10^{-3}$	R2	$8.33 \cdot 10^{-10}$	$2.48 \cdot 10^{-6}$
D5	3	4	$8.41 \cdot 10^{-8}$	$1.05 \cdot 10^{-6}$	R3	$8.17 \cdot 10^{-10}$	$7.08 \cdot 10^{-9}$
D6	3	4	$9.91 \cdot 10^{-8}$	$2.43 \cdot 10^{-4}$	R1	$8.95 \cdot 10^{-10}$	$1.58 \cdot 10^{-5}$
D9	1	2	$3.85 \cdot 10^{-6}$	$7.64 \cdot 10^{-4}$	M1	$8.31 \cdot 10^{-10}$	$9.92 \cdot 10^{-7}$
D19	2	4	$8.30 \cdot 10^{-10}$	$1.72 \cdot 10^{-8}$	R4	$8.16 \cdot 10^{-10}$	$7.05 \cdot 10^{-9}$
D20	4	3	$9.36 \cdot 10^{-5}$	$7.96 \cdot 10^{-4}$	R1	$1.85 \cdot 10^{-9}$	$2.85 \cdot 10^{-6}$
D22	2	2	$1.18 \cdot 10^{-9}$	$1.57 \cdot 10^{-7}$	M2	$8.16 \cdot 10^{-10}$	$6.93 \cdot 10^{-9}$
BRIDGE 2							
D0	1	1	$1.62 \cdot 10^{-5}$	$1.08 \cdot 10^{-3}$	R2	$8.33 \cdot 10^{-10}$	$1.41 \cdot 10^{-6}$
D10	1	2	$6.45 \cdot 10^{-6}$	$7.76 \cdot 10^{-4}$	M1	$8.16 \cdot 10^{-10}$	$6.93 \cdot 10^{-9}$
D13	1	1	$2.40 \cdot 10^{-7}$	$1.85 \cdot 10^{-4}$	R6	$8.31 \cdot 10^{-10}$	$9.92 \cdot 10^{-7}$
D21	1	1	$8.72 \cdot 10^{-9}$	$5.63 \cdot 10^{-7}$	M1	$8.16 \cdot 10^{-10}$	$7.04 \cdot 10^{-9}$
D23	1	1	$1.05 \cdot 10^{-9}$	$1.71 \cdot 10^{-7}$	M3	$8.16 \cdot 10^{-10}$	$6.93 \cdot 10^{-9}$

- Whereas, when observing the 50 years time-frame, the following observations can be detailed:
- (Br1 – D0), (Br2 – D0) and (Br2 – D13): These defects stand out over a 50-year period due to their significant P_F^i increase, driven largely by the presence of multiple correlations with multiple Triggered Defects. This underscores the need for long-term strategies to address correlated defect clusters early on.
- (Br1 – D20): Although this defect shows a high P_F^{50} – one order of magnitude higher than its P_F^5 –, its relative importance diminishes over time compared to the one of (Br1 – D0) and (Br2 – D0) – two orders of magnitude higher than their P_F^5 –, highlighting the varying priorities in long-term maintenance strategies.
- (Br1 – D6): This one is the defect with the largest $P_F^5 - P_F^{50}$ difference (around 4 order of magnitude), suggesting a large contribution of the Triggered Defect D8 to its own P_F^{50} . (Br1 – D6) perfectly exemplifies those defects that, while not critical in the short term P_F^5 , should still be monitored due to their potential for rapid deterioration/defect propagation.
- (Br1 – D5) vs. (Br1 – D6): The long-term analysis reinforces the idea that R1's effectiveness is limited, being $P_{F,int}^{50} < P_F^{50}$ for intervention R1 on (Br1 – D6) while $P_{F,int}^{50} \ll P_F^{50}$ for intervention R3 on (Br1 – D5). This suggests the need to reassess intervention strategies that heavily rely on R1. Interestingly, defects D5 and D6 both start from $I = 3$ and $E = 4$ values, similar P_F^5 and similar Correlation Tree positions, however, their evolution in time is very different. This is due to the two different Defect Matrices of the defects – more severe for defect D6 – and to the severity of the correlated defects. In fact, the emergence of defect D8 (section reduction of longitudinal reinforcement) has a higher impact on the risk of the structure compared to the emergence of defect D7 (section reduction of transversal reinforcement).
- Bridge 1 - Correlation-Driven Risk: As correlations between defects exacerbate over time, interventions that mitigate multiple related defects, like those affecting D0 (intervention R2), become increasingly beneficial.
- Bridge 1 - Intervention Effectiveness: R4 proves more effective in the long run considering that it decreases the Intrinsic Defect Appearance Probability P_{app} of defect (Br1 – D19).
- Bridge 2 - Intervention Impact Over Time: While all interventions are effective in the short term, their long-term efficacy varies, with some defects like (Br1 – D0), (Br2 – D0) and (Br2 – D13) still presenting substantial risk increases. This highlights the importance of continuous monitoring and possibly additional interventions over time.

5.2. Determining the intervention costs

Being now in possession of the Forecasted Probabilities of Failure P_F^i and Exposure Z parameters, the last Eq. (16) parameter still in need of determination is the intervention cost $Cost_{int}$, relatively to each defect detected on the assets. To achieve said goal, for each intervention proposed on the case study bridges (see Table 4) a cost analysis was performed on the basis of the ANAS intervention pricing lists [40,41]. Please note that all the prices reported below are inclusive of the labour costs. The consideration of the analysis on Bridge 1 and 2, along with the intervention costs, are reported below. Similarly to before, a code is used to indicate the intervention, the defect and the bridge in question, for instance (R2 – Br1 – D0) stands for (Intervention R2 – Bridge 1 – Defect D0).

- (R2 – Br1 – D0): 175 € and (R2 – Br2 – D0): 205.40 €. Intervention R2 involves cleaning the gutters and water drainage system along the full bridge span length (23 m for Bridge 1 and 27 m for Bridge 2), on both sides of the deck.
- (R3 – Br1 – D5): 2665 €. Intervention R3 involves the structural restoration of reinforced concrete portions on overhang elements with exposed reinforcement due to transversal reinforcement corrosion. The intervention involves working on a 6 m² wide, 60 to 100 mm thick area and requires a 4 h long aerial platform rental.
- (R1 – Br1 – D6): 1160 € and (R1 – Br1 – D20): 3408 €. Intervention R1 is a conservative restoration of concrete in correspondence of exposed reinforcement. Regarding (R1 – Br1 – D6), the object of intervention is a free overhang whilst the intervention area is of 6 m² in area and 10 to 50 mm in thickness. The work includes 4 h of aerial platform rental. Regarding (R1 – Br1 – D20), the object of intervention is a bearing pedestal. It involves aerial platform rental for 8 h and rehabilitation using polymer fiber-reinforced concrete. The work also requires lifting the deck, removing the bearing device and, once the restoration is concluded, lowering the deck. The dimensions of the concrete bearing pedestal are assumed to be $0.50 \times 0.50 \times 0.20$ m³, with an affected surface ratio of 60 % considering an Extension $E = 3$ (ratio of affected surface to total element surface: $50\% < R < 75\%$).
- (M1 – Br1 – D9): 3067 €, (M1 – Br2 – D10): 5460 €, (M1 – Br2 – D21): 5460 €. Intervention M1 is focused on the bearing system (pedestal or device) and requires the deck being lifted. The cost of this one depends on the amount of lifted kN , which corresponds to half of the bridge deck weight ~ 460 kN for Bridge 1 and ~ 820 kN for Bridge 2. The intervention is a conservative restoration/replacement of the bearing device, requiring, in addition to the deck lifting/lowering,

the removal of the damaged bearing device and its substitution with a new fixed elastomeric bearing. Please note, no aerial platform rental was required as the bearing system was fully accessible from the road.

- (R4 – Br1 – D19): 511 €. This R4 intervention involves the conservative restoration of the concrete surface of an impost block, without exposed reinforcement. The intervention involves working on a 1 m² wide, 3 to 6 mm thick area and requires a 3 h long aerial platform rental.
- (M2 – Br1 – D22): 11810 €. This M2 intervention involves the reconstruction of a 12 m joint line (correspondingly to the deck width). It includes the demolition and removal of the old joint and the installation of a new reinforced elastomer joint. The cost of an elastomeric joint – with sliding-up to 50 mm – is 875€/m without including labor.
- (R6 – Br2 – D13): 14848 €. This R6 intervention involves the restoration of the foundations in the riverbed. It includes the rental of metal sheet piles, consolidation with inert mixture, water removal using hydraulic pumps, and the driving and extraction of sheet piles. The intervention covers an area of 200 m² and is planned to take three weeks.
- (M3 – Br2 – D23): 2106 €. This M3 intervention involves the cleaning of material from the riverbed, using an excavator or mechanical shovel over two working days.

5.3. Intervention priority index evaluation

Let us move on to the determination of the Priority Index α_{int} of all the interventions suggested in Table 4. Having determined the Forecasted Probabilities of Failure P_f^i of a defect at the desired time frame i with and without intervention – subsection 5.1 –, the Exposure Z of the bridge on which the defect was detected – values indicated in Table 3 – and the intervention cost $Cost_{int}$ to eliminate said defect – subsection 5.2 –, the Priority Index α_{int} can finally be determined through Eq. (16). Table 6 below reports Priority Indices of both study case bridges at 5 and 50 years time horizons.

Some key takeaways from Table 6 regarding the 5 years time-frame are as follow:

- Cost-Effectiveness: Intervention (R2 – Br1 – D0) features the highest Priority Index in the short term $\alpha^5 = 8.41 \cdot 10^{-8}$. This is due to the low intervention cost, combined with the substantial risk reduction ($\Delta R^5 = 1.47 \cdot 10^{-5}$). These two make this one the most cost-efficient intervention, making it a clear priority and underscoring the value of addressing this defect promptly. (R2 – Br2 – D0) also takes the top spot in the intervention ranking of Bridge 2.

- Ranking of (R1 – Br1 – D20): This intervention has a lower α^5 value than the previous one, despite boosting a higher risk reduction: $\Delta R^5 = 8.57 \cdot 10^{-5}$. The reason for such is its higher intervention cost. Still, its substantial risk mitigation, justifies the R1 inclusion in the immediate maintenance plan.
- Ranking of (M3 – Br2 – D23): Despite this intervention costing substantially less than the ones just above, D23's low impact on safety (see Table 5) and M3's low risk reduction ($\Delta R^5 = 2.13 \cdot 10^{-10}$) suggests that intervention (M3 – Br2 – D23) may be deprioritized in favour of other more critical ones.
- Short term Priority Index (α^5): In the short term, the Priority Index emphasizes interventions on defects with higher intrinsic severity and substantial correlations, suggesting that a holistic approach that considers these factors is essential for effective maintenance planning.

Some key takeaways from Table 6 regarding the 50 years time-frame are as follow:

- Long-Term Priorities: Over 50 years, intervention (R2 – Br1 – D0) stays in pole position with the highest $\alpha^{50} = 6.90 \cdot 10^{-6}$ value, reaffirming its long-term importance.
- Sustainability of Interventions: The sustained effectiveness of interventions over 50 years, especially for defects like (R2 – Br1 – D0) and (R2 – Br2 – D0), highlights the importance of early, proactive maintenance strategies that can yield long-term benefits.
- Cost vs. Impact: The interventions (R2 – Br1 – D0), (R2 – Br2 – D0) and (M1 – Br2 – D10) provide the best balance between cost and impact, reaffirming their prioritization for both short and long-term maintenance planning.
- Change in priority: In the long run, the priority of (R1 – Br1 – D20) remains significant $\alpha^{50} = 2.13 \cdot 10^{-7}$ indicating that, despite higher costs, the long-term risk reduction justifies the investment. Yet, over 50 years, the priority of (M1 – Br1 – D9) surpasses the aforementioned one in light of its considerable correlation effects ($\alpha^{50} = 2.28 \cdot 10^{-7}$).
- Long term Priority Index (α^{50}): Generally talking, despite the overall ranking remains mostly unaltered between the two time frames, some ranking positions see some switches (see for example (R4 – Br1 – D19) and (M2 – Br1 – D22)). The mostly unchanged classification between 5 and 50 years suggests stable intervention effectiveness but also points to the importance of addressing defects with high correlation-induced risk increases, as they could disproportionately affect the structure's integrity over time.

The above displayed Table 6 can be considered a fully employable

Table 6

Priority Index of Bridge 1 and 2 at both 5 and 50 years time frames. Note, that the color shade indicate the magnitude of the indexes reported in each column (dark blue corresponds to larger values whilst lighter blue corresponds to smaller values).

Defect	I	E	Intervention	Cost [€]	ΔR^5	ΔR^{50}	Priority Index α^5 [lives/€]	Priority Index α^{50} [lives/€]
BRIDGE 1								
D0	1	2	R2	175	$1.47 \cdot 10^{-5}$	$1.21 \cdot 10^{-3}$	$8.41 \cdot 10^{-8}$	$6.90 \cdot 10^{-6}$
D20	4	3	R1	3408	$8.57 \cdot 10^{-5}$	$7.25 \cdot 10^{-4}$	$2.51 \cdot 10^{-8}$	$2.13 \cdot 10^{-7}$
D9	1	2	M1	3067	$3.53 \cdot 10^{-6}$	$6.99 \cdot 10^{-4}$	$1.15 \cdot 10^{-9}$	$2.28 \cdot 10^{-7}$
D6	3	4	R1	1160	$1.10 \cdot 10^{-7}$	$1.98 \cdot 10^{-4}$	$4.14 \cdot 10^{-11}$	$7.42 \cdot 10^{-8}$
D5	3	4	R3	2665	$9.39 \cdot 10^{-8}$	$1.18 \cdot 10^{-6}$	$8.09 \cdot 10^{-11}$	$1.01 \cdot 10^{-9}$
D22	2	2	M2	11810	$4.72 \cdot 10^{-10}$	$1.76 \cdot 10^{-7}$	$4.00 \cdot 10^{-14}$	$1.49 \cdot 10^{-11}$
D19	2	4	R4	511	$1.81 \cdot 10^{-11}$	$1.31 \cdot 10^{-8}$	$3.54 \cdot 10^{-14}$	$2.54 \cdot 10^{-11}$
BRIDGE 2								
D0	1	1	R2	205	$9.48 \cdot 10^{-6}$	$6.23 \cdot 10^{-4}$	$4.62 \cdot 10^{-8}$	$3.03 \cdot 10^{-6}$
D10	1	2	M1	5460	$3.78 \cdot 10^{-6}$	$4.54 \cdot 10^{-4}$	$6.93 \cdot 10^{-10}$	$8.32 \cdot 10^{-8}$
D13	1	1	R6	14848	$1.64 \cdot 10^{-7}$	$1.07 \cdot 10^{-4}$	$1.11 \cdot 10^{-11}$	$7.18 \cdot 10^{-9}$
D21	1	1	M1	5460	$6.65 \cdot 10^{-9}$	$4.19 \cdot 10^{-7}$	$1.22 \cdot 10^{-12}$	$7.67 \cdot 10^{-11}$
D23	1	1	M3	2106	$2.13 \cdot 10^{-10}$	$1.30 \cdot 10^{-7}$	$1.01 \cdot 10^{-13}$	$6.18 \cdot 10^{-11}$

tool for decision-making support. Indeed, on the basis of this one, an infrastructure manager could very well allocate the available resources for an optimized intervention schedule and overall upkeep of its infrastructural asset.

5.4. Bridges' global priority index evaluation

Having already showcased the innerworkings of the Priority Index for all possible interventions, an additional priority ranking can be extracted to further help the infrastructure managers in their decision-making processes: an intervention urgency ranking for the entire bridge. This is achieved through the Global Priority Index (see Section 4), calculated by means of Eq. (17). The results obtainable per the case study bridges are reported in Table 7.

As previously discussed in Section 4, for broader bridge-level evaluations a different scenario to be considered – parallelly to the reparation of all defects on the asset – is the complete reconstruction of the bridge. This scenario brings along its own Reconstruction Priority Index α_R^i which needs to be evaluated separately. As a matter of fact, the Reconstruction Priority Index values were calculated considering that the cost of reconstruction for the Bridge 1 is € 3713.55/m² (prestressed concrete beam structure as per [42]), whereas for the Bridge 2 the cost would be € 2673.76/m² (as indicated for steel beam structures in [42]). The results are two right-most columns of Table 7.

If to compare the two scenarios – repairing all the defects (Global Priority Index) versus reconstructing the entire bridge (Reconstruction Priority Index) – for both bridges, it is evident that the total reconstruction is not a cost-efficient option ($\alpha^{50} > \alpha_R^{50}$), all the more so in the short timeframe ($\alpha^5 > \alpha_R^5$). This inefficiency likely lays in the reduced number of impactful defects whose reparation cost is significantly oversized by a full-on reconstruction cost. This conclusion could change when considering bridges with a higher number of significant defects, or when considering just a partial reconstruction of the most damaged element. Similarly, it is clear that in both the presented case studies, a total reparation of all the defects on the bridge or a total reconstruction it is far less convenient in the short-term rather than in the long one. This is because, by intervening early on all the defects indistinctly, the manager would sustain high costs to repair also defects that do not affect the bridge in terms of risk yet; whereas in the long term, such defects would have evolved in impactful defect that might be worthy spending money on to be repaired.

6. Conclusions

This article presented the principles and functioning of a comprehensive Decision Support System (DSS) designed to optimize the management and maintenance of structural assets. The proposed DSS leverages advanced probabilistic models and a Structural Reliability framework to provide a robust, data-driven approach to decision-making for asset upkeep. In particular, the following were integrated in the DSS: (1) a degradation model grounded on Markov Chain processes capable of projecting the worsening of already present damage at future timeframes and (2) a Bayesian Theory-based model to predict the rise of new structural defects in the years to come. The ensuing risk assessments and projections of structural reliability over different time horizons offer valuable insights into the optimal timing and prioritization of interventions. The system's versatility in accommodating both

reactive and preventive maintenance approaches provides a comprehensive solution for the optimal management of extensive infrastructural assets.

Through two detailed case studies, the practical application of the DSS in evaluating structural reliability, assessing risks, and prioritizing maintenance interventions was demonstrated:

- The case studies highlighted the effectiveness of the DSS in addressing both immediate and future risks, ensuring that interventions are strategically planned to maximize risk reduction and cost efficiency over any target time frame.
- Whenever assessing the priority of an intervention, the DSS accounts for several aspects: the defect on which the intervention acts and its future evolution, the intervention cost and its ensuing structural risk reduction. For example, the DSS identified the 'D20 defect – overhang deterioration' as in need of urgent intervention given its advanced degradation state and substantial deterioration speed in future timeframes. Despite the elevated costs of the D20-repairing intervention (R1 – Structural restoration on reinforced concrete elements with exposed reinforcement), the DSS inferred that the risk reduction brought forth by said intervention counterweighed its costs, thus making it a priority.
- The DSS can establish when the presence of a particular defect on the asset might trigger the appearance of new defects in the future (e.g., the "water infiltration through joints" defect might promote the appearance of water-induced "concrete degradation"). For example, defect 'D0 – drainage system issues', though initially hardly critical, becomes significant over time due to its high correlation with other defects, highlighting the need for timely intervention. In the case study applications, the DSS prioritized the swift and economical intervention on D0 (R2 - Downspout cleaning/restoration of water collection system) over other significantly more taxing ones.
- In some cases, the priority of some interventions can increase in the long run to such extent that it surpasses other initially more urgent ones. Then again, over a long-term horizon, the interventions priority ranking of the case study application remained mostly unaltered, underscoring the persistent impact of these defects on the bridge's reliability and safety.
- The DSS also assesses the cost-effectiveness of repairing all the asset defects of versus the one of a complete asset reconstruction (more cost-effective whenever the amount and size of defects becomes excessively large). In neither of the case study applications the reconstruction cost-effectiveness outweighed the one of single defect repairing.

While the DSS presents significant advancements in bridge management, some limitations should be acknowledged, along with potential future developments to address them:

- The DSS simplifies risk modeling by treating structural, seismic, hydraulic, and landslide risks as independent, which helps streamline computations but limits the system's ability to reflect compounding effects. To address this, ongoing research is exploring ways to integrate multi-hazard interactions, enhancing the accuracy of risk assessments and better capturing interdependencies between failure mechanisms.
- The DSS is intentionally designed as a simplified, high-efficiency prioritization tool rather than a formal structural reliability

Table 7
Reconstruction Priority Index of case study bridges for both 5 and 50 years.

Bridge	Reconstruction cost	5-Years Global Priority Index α^5	50-Years Global Priority Index α^{50}	5-Years Reconstruction Priority Index α_R^5	50-Years Reconstruction Priority Index α_R^{50}
Bridge 1	5'124'699 €	$4.57 \cdot 10^{-9}$	$1.24 \cdot 10^{-7}$	$6.89 \cdot 10^{-13}$	$1.36 \cdot 10^{-10}$
Bridge 2	29'237'566 €	$4.78 \cdot 10^{-10}$	$4.22 \cdot 10^{-8}$	$2.53 \cdot 10^{-16}$	$1.46 \cdot 10^{-14}$

assessment framework. Instead of providing absolute reliability values, it classifies assets and interventions based on relative risk rankings, ensuring a practical and scalable approach to maintenance decision-making. While this methodology enhances applicability to large-scale infrastructure networks, users should be mindful that it is best suited for comparative prioritization rather than detailed probabilistic reliability analysis. Future refinements will focus on further optimizing this classification method while maintaining its computational efficiency and ease of implementation.

- Since defect assessments rely heavily on visual inspections, results may vary depending on inspector expertise, leading to potential subjectivity and inconsistencies. To mitigate this, future iterations will incorporate AI-driven defect detection and sensor-based monitoring, reducing human variability and improving overall assessment accuracy.
- The DSS currently evaluates only Overload and Degradation risks, leaving out other critical hazards such as Seismic, Hydraulic, and Landslide risks. Expanding the framework to include these additional threats is a priority, ensuring a more comprehensive and multi-hazard approach to structural reliability evaluation.
- The need for region-specific calibration means that differences in materials, environmental conditions, and maintenance practices can affect the transferability of results. To overcome this, efforts are being directed towards refining adaptive calibration methods, enabling the DSS to adjust dynamically to different infrastructure settings without excessive reliance on fixed input parameters.
- While the DSS prioritizes structural reliability and risk-based decision-making, it does not fully account for socio-economic and logistical factors that influence maintenance planning. Addressing this gap, future developments will integrate a more holistic exposure model, factoring in economic, social, and environmental impacts to enhance decision-making beyond purely technical criteria.

In conclusion, the proposed DSS represents a significant advancement in bridge management, offering a versatile and efficient tool for infrastructure managers. The present work delivers a DSS that empowers infrastructure managers with an efficient, scalable and reliability-based tool for the prioritization of intervention scenarios. By integrating structural reliability assessments — enhanced by defect correlation modeling, time-evolving deterioration and exposure quantification — with cost-benefit analyses, the system ensures that maintenance strategies remain both economically viable and technically sound. This holistic approach effectively addresses the pressing challenges of aging infrastructure, enhancing the safety and sustainability of bridge networks. The practical insights gained from the case studies highlight the DSS's potential to transform infrastructural maintenance, ensuring the functionality and reliability of critical assets amid growing infrastructural demands.

Looking ahead, the proposed DSS opens several promising avenues for further development and application. A natural evolution of the proposed DSS lies in its integration with real-time monitoring systems and inspection data streams, enabling dynamic updates of deterioration states, structural reliability, and priority indices. This would allow infrastructure managers to support near real-time, data-informed decision-making, particularly in critical or rapidly evolving contexts. Further enhancements may also involve the incorporation of multi-objective optimization frameworks, where risk reduction is balanced against broader criteria like environmental impact, user disruption, and social equity. To fully leverage this potential, future adaptations could aim to generalize the methodology beyond bridges, extending its applicability to other infrastructure typologies — such as tunnels or retaining walls — through tailored adjustments to defect typologies, deterioration models, and exposure parameters. Such scalability would make the DSS a valuable tool for network-level asset management across heterogeneous systems. In parallel, coupling the DSS with GIS-based visualization platforms or digital twin environments could

significantly improve spatial intelligibility and inter-agency coordination. These directions point to a broader vision in which the DSS not only enhances technical prioritization but also serves as a foundation for transparent, accountable, and sustainability-oriented infrastructure governance.

CRedit authorship contribution statement

Francesca Brighenti: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Mattia Francesco Bado:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Francesco Romeo:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Andrea Rebellato:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Daniele Zonta:** Validation, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

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Data availability

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

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