Smart Integration of Non-Destructive Damage Detection and Life-Cycle Assessment for Sustainable Maintenance of Coastal Bridges

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ABSTRACT

Purpose – This paper proposes a sustainability-oriented method for detecting corrosion-induced damage in long-span reinforced concrete bridges using the power spectral density (PSD) approach. The aim is to enhance the long-term performance and maintenance planning of bridge structures exposed to chloride environments by integrating structural health monitoring with life-cycle sustainability assessment.

Design/methodology/approach – A finite element model is developed for structural health monitoring of a coastal reinforced concrete bridge over a 100-year service life. The model captures the changing dynamic properties resulting from reinforcement corrosion. PSD analysis, adapted for damage caused by chloride corrosion, is used to extract frequency shifts and amplitude variations associated with the progression of internal damage. The results are assessed within a holistic sustainability framework that includes economic, environmental, and social factors. Additionally, multi-criteria decision-making (MCDM) techniques, including TOPSIS and AHP, are utilized to rank and prioritize rehabilitation strategies. To enhance the robustness of the findings, key assumptions, such as the discount rate and deterioration parameters, are examined through sensitivity analysis.

Findings – The results reveal that developed frequency-based analysis can effectively identify corrosion-induced deterioration at early stages, offering a non-destructive and reliable approach to structural health monitoring. Integrating this technique with sustainability assessment provides valuable insights into the cost-effectiveness, environmental performance, and social implications of bridge maintenance interventions. The sensitivity analysis confirms that the overall ranking of maintenance strategies remains stable under reasonable variations in key parameters.

Research limitations/implications – The study is based on a simulation-driven methodology and applied to a single base study of a coastal bridge. Sensitivity analysis is used to address major uncertainties; however, the lack of validation using field monitoring data may limit the applicability of the results. Future research should focus on experimental validation and on extending the framework to diverse bridge typologies and environmental conditions.

Practical implications –The suggested framework serves as a decision-support tool for infrastructure asset managers, transportation authorities, and policymakers by facilitating early damage identification and assessing life-cycle sustainability impacts. That, in turn, enables more informed, proactive, and resource-efficient maintenance planning.

Originality/value – This study advances sustainable infrastructure management by linking vibration-based damage detection methods with life-cycle sustainability and decision-making frameworks. It highlights the developed PSD as a practical tool for predicting and identifying chloride corrosion, thereby supporting proactive, sustainable maintenance planning and optimizing resource allocation for long-term durability.

Keywords: Life cycle assessment (LCA), Multi-criteria decision-making, Non-destructive damage detection, Power spectral density (PSD), Sustainability, TOPSIS

1. Introduction

Sustainable development means meeting today's needs without compromising future generations. It requires balancing economic growth, social progress, and environmental protection (Brundtland and Comum, 1987). When making long-lasting choices in construction, it's essential to consider their impact on people, the planet, and the economy over time (Navarro et al., 2019; Sánchez-Garrido et al., 2024). The construction industry is one of the most significant sources of environmental harm. This is because it consumes approximately 30% of the world's energy, 40% of its natural resources, and generates around 30% of greenhouse gas emissions (Al-Numan, 2024). Life Cycle Assessment (LCA) is a robust and reliable method for evaluating the sustainability of buildings. It carefully examines the environmental and social impacts of a building throughout its entire life cycle, encompassing the stages from raw materials extraction to disposal (ISO 14040, 2006; ISO 14044, 2006). Designers must strike a balance between impact and strive for a sustainable future through thoughtful infrastructure. Given the increasing human impacts on the environment and the need for sustainable solutions, advanced approaches have been proposed as a means to reduce destructive human impacts and support more sustainable infrastructure (Rahimian et al., 2020, 2021; Edwards et al., 2025).

Interest in the sustainability assessment of a wide range of infrastructure types, such as pavements (Kazemeini and Swei, 2023; Kothari et al., 2022), buildings (Sánchez-Garrido et al., 2022; Sánchez-Garrido et al., 2026), railway tracks (Celauro et al.,2023), and others (Ha et al., 2025; Limwibul et al., 2025), has increased despite the significant attention paid to the sustainable design of bridges. Bridges are vital but expensive; recent research aims to reduce their construction and maintenance costs (Navarro et al., 2020a; Zhao and Li, 2022). Modern methods of construction maintenance should be cost-effective, energy-efficient, operationally robust, and safe for workers and residents compared to conventional methods, but unfortunately, cost estimates and infrastructure maintenance are inadequate for today's complex needs (Najafi et al., 2024, 2025).

Choosing the right methods to identify damage in buildings without causing harm is crucial for sustainability and for understanding a structure's lifespan. Damage can be assessed in two ways: destructive methods, which involve removing parts of the building for testing, and non-destructive methods, which do not harm the structure (Bjørheim et al., 2022). Non-destructive methods utilize computer models to assess buildings without causing damage (Jodhani et al., 2023). Predicting rebar durability in salty coastal conditions is essential (Cai et al., 2023; Luo et al., 2024). Improved computers and sensors have enhanced the use of signal-based non-destructive testing (Chaupal and Rajendran, 2023).

Signal-based non-destructive testing methods analyze data in the time domain (Malekghaini et al., 2023), the frequency domain (Hadizadeh-Bazaz et al., 2023a; Cai and Zhu, 2023), or both the time and frequency domains (Liu et al., 2023; Yang et al., 2023). The most popular techniques focus on the frequency domain and include methods like Power Spectral Density (PSD) (Hadizadeh-Bazaz et al., 2023b; Sheng and Fan, 2024), Frequency Response Functions (FRF) (Hassani et al., 2023; Jalali and Rideout, 2022), modal curvatures (Qiu et al., 2025; Jiang et al., 2024), modal strain energies (Nguyen and Livaoğlu, 2023; Pooya and Massumi, 2022), and natural frequencies (Wang, 2020; Khan et al., 2020).

The PSD method operates in the frequency domain by analyzing the power distribution across both periodic (regular) and random signals. It uses a sensitive nonlinear function related to the structure's parts to create a second-order transfer function (Zhang et al., 2025).

In general, previous studies on structural damage detection methods and stability assessment can be classified into three main research streams: The first group focuses on non-destructive vibration-based damage detection techniques, including PSD, FRF, and modal-based methods, which have shown high sensitivity in identifying changes in structural characteristics.

However, these approaches are usually limited to assessing structural performance in detecting the location and extent of damage, and sustainability aspects, such as environmental or economic impacts of these methods at different stages of a structure, especially the destructive and harmful effects of these methods in repair and maintenance, have not been considered. The second group of studies emphasizes life-cycle sustainability assessment but often relies on predefined deterioration models and lacks integration with real-time structural health monitoring throughout a structure's life. The third group uses Multi-Criteria Decision-Making(MCDM) methods, such as AHP and TOPSIS, to support sustainability-based decision-making. However, these methods are more effective in addressing complex decision-making problems and are generally not related to structural health monitoring (SHM) frameworks.

MCDM methods are the most effective way to handle complex sustainability decisions in infrastructure projects involving numerous stakeholders and with long-term implications. These methods help decision-makers weigh different, often conflicting factors by considering expert and stakeholder opinions (Navarro et al., 2020b; Meng et al., 2025). However, truly understanding sustainability means combining knowledge from many scientific fields, a process known as the "orchestration of sciences" (Munda, 2023).MCDM is an effective tool for multidisciplinary sustainability evaluation (Sousa et al., 2021). Researchers employ various MCDM methods to assess infrastructure sustainability, but the most effective approach remains debated; combining methods may enhance results (Hwang and Yoon, 1981).

In this regards Table 1 summarizes the gaps in previous studies compared to this study.

Table 1. Comparative review of previous studies on bridge maintenance, damage detection, and sustainability life cycle assessment.

Study	Damage Detection Method	Sustainability Assessment (LCA/LCCA)	MCDM (AHP/TOPSIS)	Integration Level	Key Limitation
Dong & Frangopol (2016)	None	LCA	No	Low	No structural condition monitoring
Frangopol et al. (2019)	General SHM)	LCA + LCCA	No	Medium	Limited integration with decision-making
Hadizadeh-Bazaz et al. (2023a)	PSD	LCCA	No	Medium	No environmental/social assessment

Hadizadeh-Bazaz et al. (2023b)	PSD (chloride corrosion)	No	No	Low	No sustainability integration
Kothari et al. (2022)	None	LCA + S-LCA + LCCA	No	Low	No structural monitoring integration
Munda (2023)	None	Social sustainability	Yes (general MCDM)	Medium	Not applied to infrastructure systems
Navarro et al. (2020a, 2020b)	None	Sustainability assessment	No	Low	No damage detection
Navarro et al. (2024)	None	Social LCA	No	Low	No integration with engineering models
Renne et al. (2022)	None	LCA + LCCA	No	Low	No link to structural condition
Sánchez-Garrido et al. (2026)	None	Maintenance + sustainability	Yes	Low	No damage detection integration
Wittocx et al. (2022)	None	LCA + LCCA	No	Low	No decision-making framework
Jalali and Rideout, 2022	FRF	NO	No	Low	No sustainability integration
Qiu et al., 2025	modal curvature change	NO	NO	Low	No sustainability integration
Nguyen and Livaoğlu, 2023	Modal strain energy	No	No	Low	No sustainability integration
Khan et al., 2020	Natural frequency changes +FRF	No	No	Low	No sustainability integration
This study	PSD-based detection	LCA + LCCA + Social	AHP + TOPSIS	High	Simulation-based (no field validation)

As shown in Table 1, previous studies have mostly focused on structural damage detection using frequency-based methods or on life-cycle sustainability assessment, with limited integration between these areas. While several studies have applied LCA and environmental and social assessment methods to infrastructure systems, they generally rely more on predefined structural damage models and lack estimates of real-time structural condition data. On the other hand, vibration-based damage detection methods, including PSD approaches, although widely developed, are rarely linked to sustainability and LCA or decision-making frameworks, and the performance of such methods in repair activities and maintenance for corrosion damage, as well as their environmental, social, and even cost impacts, has been investigated. Furthermore, although multi-criteria decision-making techniques have been used in sustainability studies, their integration with SHM remains limited.

Therefore, according to the research gap, there is a need to develop an integrated framework for assessing the performance of a damage detection method on Life Cycle Cost (LCC), Environmental Life Cycle Assessment (E-LCA), and Social Life Cycle Assessment (S-LCA) for maintenance and repair activities of a coastal bridge that was damaged by chloride corrosion.

The main contributions of this study include the following:

(i)linking frequency-based damage detection with LCA and LCC,

(ii) Incorporating economic, environmental, and social impact assessment,

(iii) Applying AHP–TOPSIS for prioritizing rehabilitation strategies and performance,

(iv) Assessing the robustness of the proposed framework through sensitivity analysis in damage detection of a coastal concrete bridge.

2. Methodology

Sustainability must include environmental, economic, and social impacts across all life-cycle stages (Navarro et al., 2024a). Non-destructive methods help detect damage during all life stages of a structure, aiming to reduce harm to people, the planet, and the economy. Figure 1 illustrates how non-destructive methods aid in assessing damage during bridge maintenance.

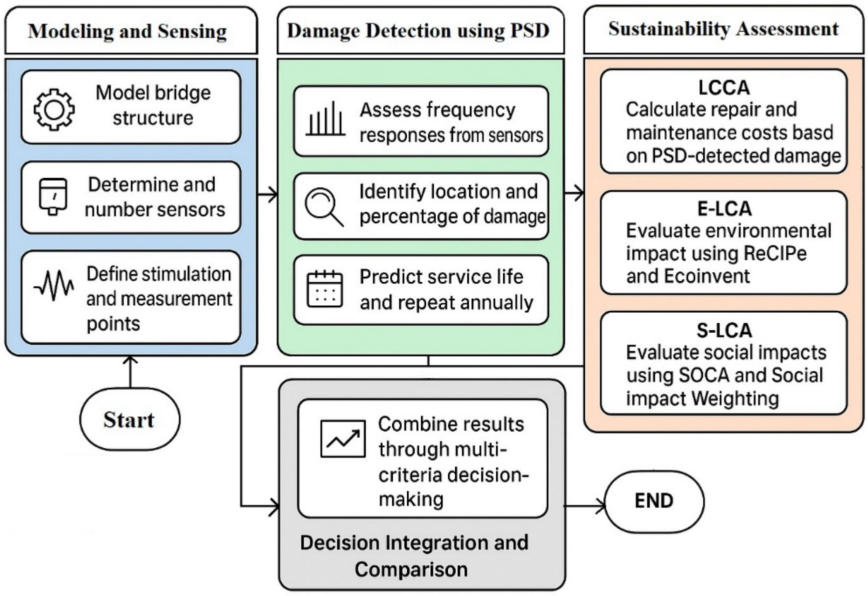

Figure 1. Concise overview of the sustainability assessment stage of an RC bridge using the PSD approach.

This figure illustrates a comprehensive framework for evaluating the sustainability of a coastal concrete bridge for maintenance and repair, utilizing the PSD method. The process begins with selecting and modeling the bridge, considering and numbering sensors, and analyzing their frequency responses to identify the location and extent of structural damage, as well as the percentage of damage. The bridge's remaining service life is updated annually.

LCCA is used for cost estimation, E-LCA for environmental impacts using ReCiPe and Ecoinvent, and S-LCA for social impacts using SOCA. Finally, the results are integrated using the MCDM method through the TOPSIS approach, which compares and ranks the sustainability of PSD-based maintenance against conventional methods, considering factors such as cost, environmental quality, human health, resource efficiency, and social impact. The study employs PSD as a non-destructive method to predict bridge damage over time, outlining the assessment model and associated methods.

The proposed method integrates and improves the structural health monitoring of a concrete coastal bridge, from corrosion modeling to life-cycle stability assessment, into a single framework. The process involves sequential steps, starting with modeling the bridge structure and progressing to damage detection and prediction, damage quantification and location, and stability assessment.

To improve the clarity and repeatability of the overall workflow, a proposed framework is shown in Figure 2.

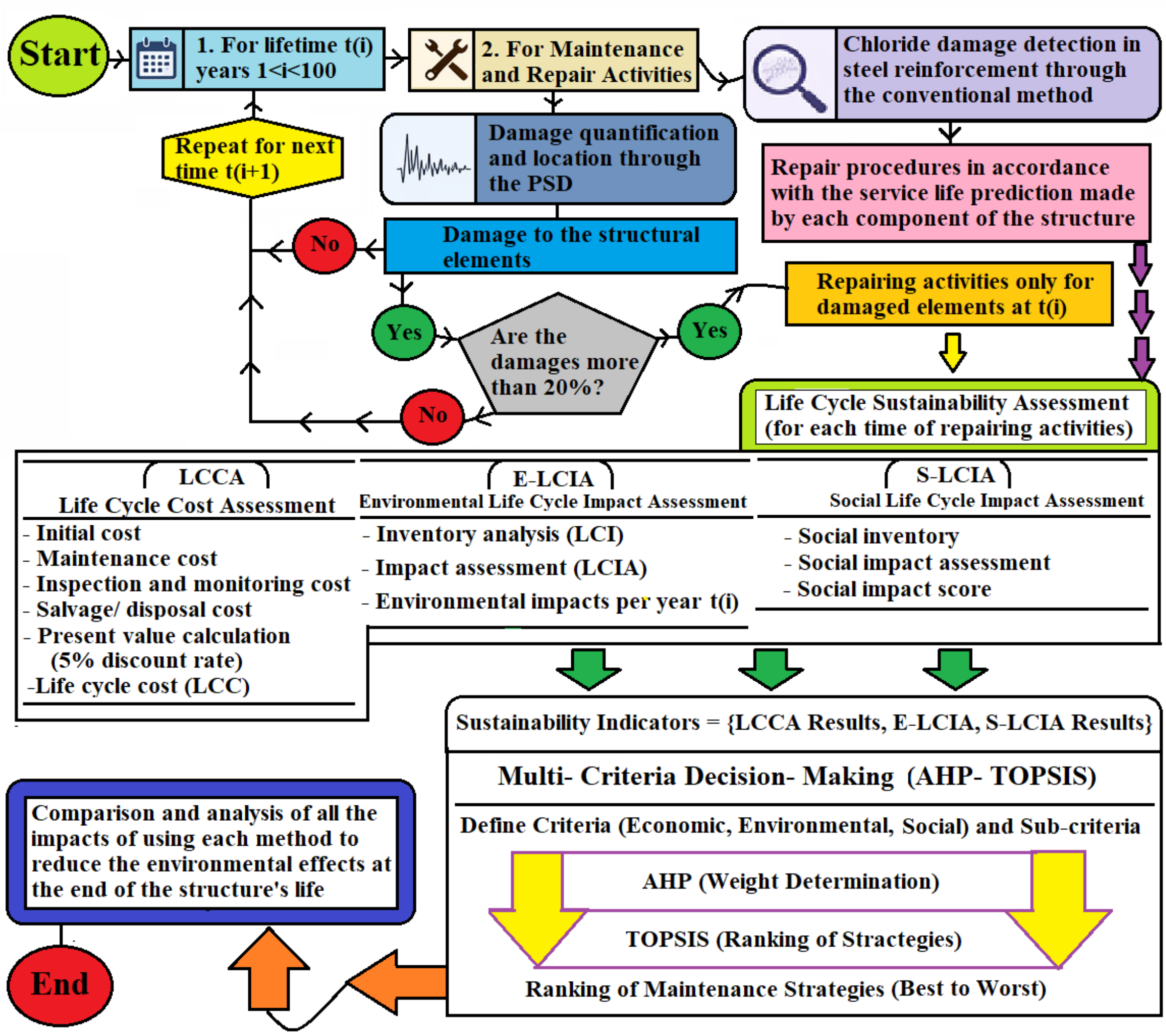

Figure 2. Flowchart of the proposed methodology integrating PSD-based damage detection with life-cycle sustainability assessment (E-LCIA, S-LCIA, and LCCA) and decision-making for a coastal RC bridge.

As shown in Figure 2, the methods considered in this study follow a structured, step-by-step process. First, a coastal reinforced concrete bridge exposed to chloride corrosion is modeled to simulate the structural behavior over the lifetime of the structure (100 years). Then, PSD-based dynamic non-destructive identification analysis is applied to detect changes in dynamic properties in structural elements to identify and locate damage. In the next step, the identified damage is quantified by location and severity. Then, based on the output information and data, maintenance actions are determined depending on predefined damage thresholds.

The quantified damage is subsequently used as input for a life-cycle sustainability assessment, including environmental (E-LCIA), economic (LCCA), and social (S-LCIA) assessments, while considering the activities required to repair and maintain each element over time.

Finally, the results from each part are integrated and refined into a decision-making framework for comparing and evaluating maintenance strategies, enabling researchers and practitioners to select the most sustainable option over the bridge's useful life. The proposed framework, by linking structural performance in structural health monitoring to sustainability indicators, can enable a comprehensive evaluation of repair and maintenance activity strategies.

To assess the robustness of the proposed framework, a sensitivity analysis is used on key parameters, including the weighting factors in the AHP and TOPSIS methods, as well as the discount rate used in the LCCA (3-7%) and the noise level considered in the PSD analysis (5-15%). These parameters are selected based on the commonly reported and most widely considered ranges in the literature and are intended primarily to reflect uncertainty in economic conditions and measurement variability in the analyses.

2.1 Bridge model description

The analysis in this study focused on a concrete bridge in Galicia, Spain, with a single-box girder deck. The bridge is 1980 meters long and comprises 40 separate spans (González et al., 2013; Pérez-Fadón Martínez, 1985; Pérez-Fadón Martínez, 1986).

The bridge's box-girder deck is positioned 9.6 meters above sea level, constantly exposed to airborne saltwater chlorides. According to Figure 3, the deck is 13 meters wide and 2.3 meters high. The bridge piers measure 5.26 meters across and 1.80 meters along their length (Pérez-Fadón Martínez, 1985; Pérez-Fadón Martínez, 1986).

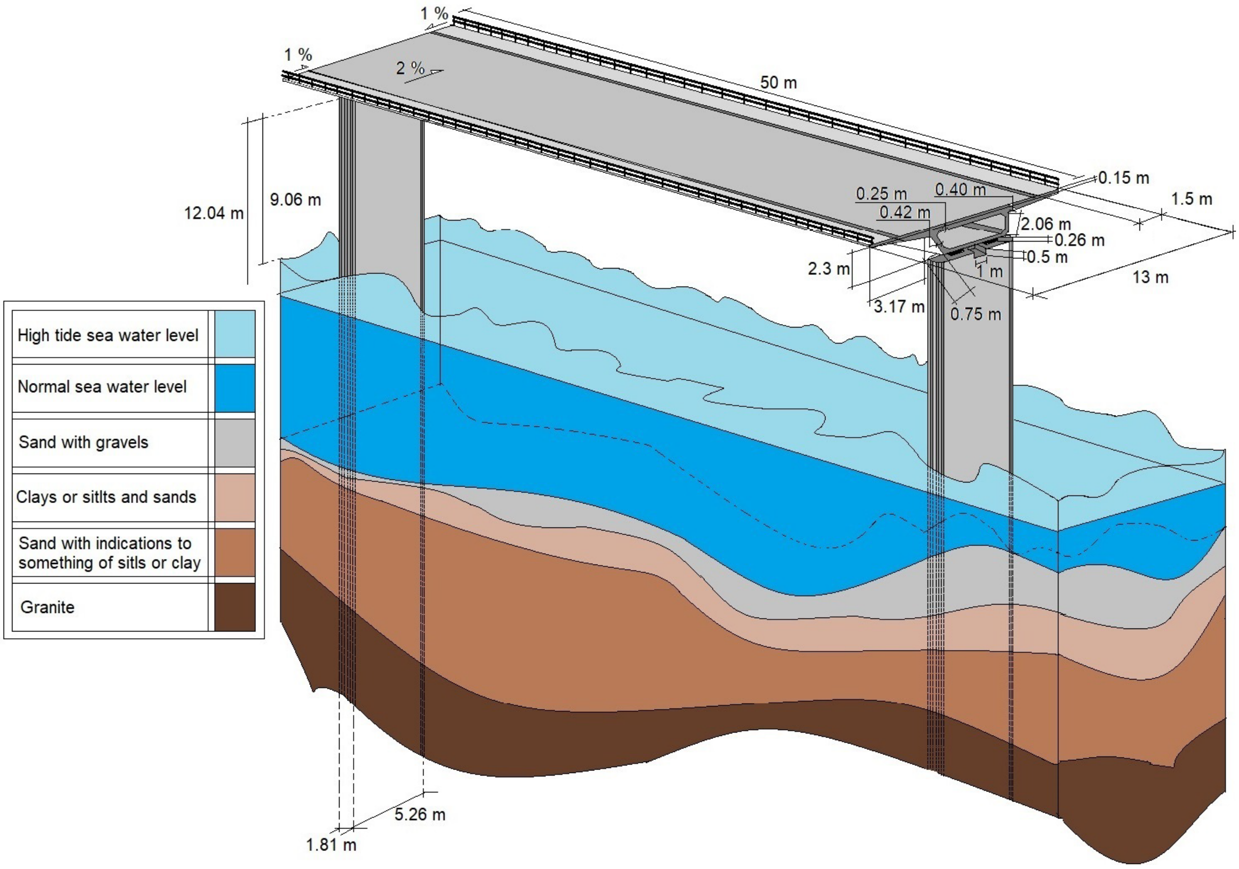

Figure 3. The measurements of the deck and columns of the bridge's central section.

The bridge utilizes cement and 100 kg/m³ of steel (González et al., 2013), with concrete designed to resist chloride and sulfate damage through a specific mix and a water-to-cement (w/c) ratio of 0.45. The concrete cover is 35 mm on the deck and 45 mm on the piers. The concrete mix has a water-to-cement ratio of 0.45 and contains the following quantities: 218.5 L/m³ of water, 485.6 kg/m³ of cement, 926.7 kg/m³ of gravel, and 827.9 kg/m³ of sand. The concrete's modulus of elasticity (Ec) is 29 GPa, and its compressive strength (fcm) is 40 MPa.

2.2 Service life prediction techniques

The PSD method is a non-destructive dynamic method for structural health monitoring (SHM) and detecting damage in bridges. According to this method, the vibrational response of the structure to stimulation is recorded at measurement points and transformed into the frequency domain using the Fourier transform. The peaks in the PSD spectrum indicate the structure's natural frequencies, which are directly related to its stiffness. In marine concrete structures, chloride-ion corrosion reduces the cross-section of reinforcing bars, increases cracking, and consequently decreases local stiffness. This conclusion is drawn from comparing dynamic parameter data, such as stiffness, mass, and damping, between corroded rebars and undamaged ones on the first day, prior to establishing that corrosion will be monitored annually throughout the bridge's lifespan. It evaluates the accuracy of this method, its impact on LCA, and its effect on the structure's environmental footprint. Based on a transfer function, the PSD equation is given below (Hadizadeh-Bazaz et al., 2022; Zheng et al., 2015; Luo et al., 2022).

$$H(\omega) = (K - \omega^2 M + i\omega C)^{-1} \quad (1)$$

The matrices K, M, and C denote stiffness, mass, and damping, respectively. The matrix 'i' is the identity matrix with a value of -1. Equation (2) represents the structural response equation that can be formulated based on the power spectral density.

$$S_{XX}(\omega) = H^*(\omega) S_{FF}(\omega) H^T(\omega) \quad (2)$$

S_{FF} represents the matrix of PSD inputs across all active Degrees of Freedom (DOF), while $H^*(\omega)$ is the complex conjugate of a transfer function. Equation (2) illustrates that the power spectral density is a second-order function of the Frequency Response Function (FRF), signifying its highly nonlinear response to structural parameters. Corrosion is a common problem in reinforced concrete bridges. Figure 43 illustrates a model proposed by Tuutti, which links the bridge's service life to corrosion caused by chloride damage to rebars (Tuutti, 1982).

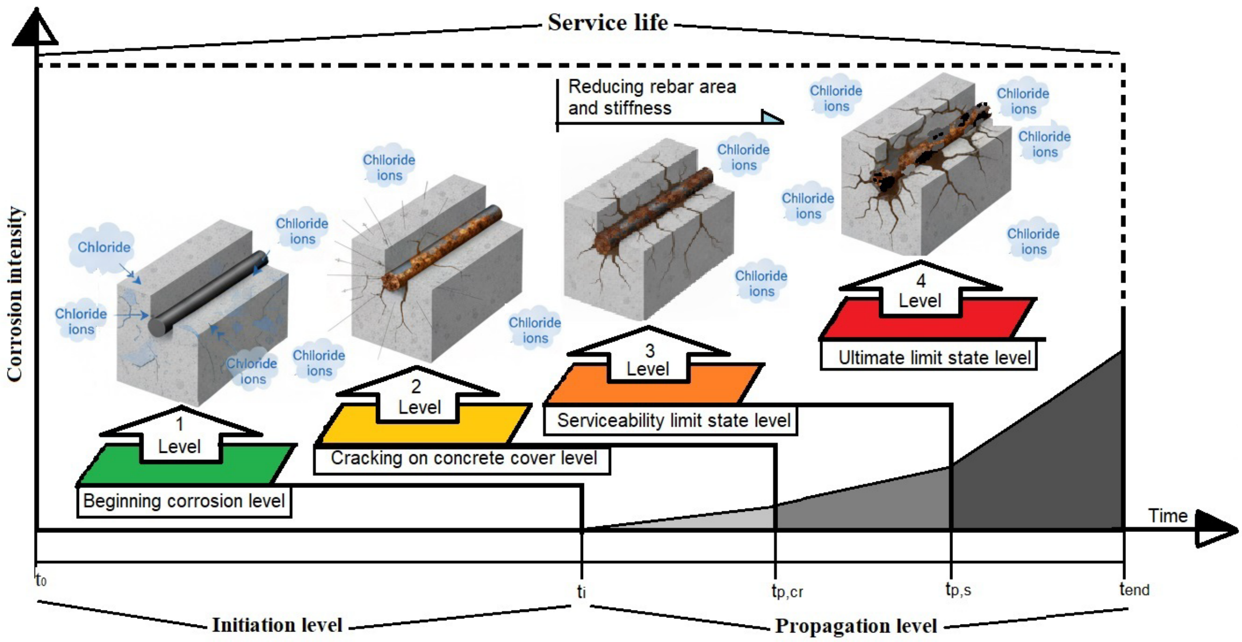

Figure 4. Service Life Prediction for Rebars in an RC Structure using Tuutti's Model (Tuutti, 1982).

Figure 4 shows how chloride corrosion begins, with chloride levels below a harmful threshold. Combined with Fick's second law, the Totti corrosion model can provide a more accurate estimate of chloride infiltration and the initiation time of corrosion in steel rebars in coastal and marine concrete structures. On the other hand, the accuracy of this model decreases for long-term predictions and during the corrosion propagation stage, because it ignores time-dependent propagation, chloride binding, cracking, and variable boundary conditions. It can predict initiation times with an approximate accuracy of 20%-50%. However, propagation and service-life estimates require more advanced or calibrated models, which can be compensated for and strengthened by structural health monitoring methods and damage prediction and detection.

Chloride ions initiate a process that progresses through several stages: corrosion begins, cracks appear in the concrete cover, the usable life of the structure shortens, and eventually, the structure reaches its final failure (Zhang et al., 2019). The total time for chloride corrosion to occur (t_l), which represents the service life of the bridge's reinforcement, is estimated by the following Equation (Spanish Ministry of Public Works, 2008). This time includes the initial stage before corrosion begins and the later stage when it spreads.

$$t_l = t_i + t_p \tag{3}$$

The corrosion initiation period (t_i) is when sufficient chlorides accumulate and begin damaging the steel rebars. The exact level of chlorides needed depends on the properties of both the steel and the concrete.

After initiation, the propagation period (t_p) begins, where corrosion spreads through the structure until it causes severe damage. This study uses Fick's Equation to predict how chlorides move (diffuse) through the concrete. According to Fib Bulletin 34 (Code, C.F.F.M., 2006), the surface chloride level is assumed to stay constant over time. The start of chloride diffusion can be calculated using certain equations (Spanish Ministry of Public Works, 2008).

$$t_i = \frac{x^2}{4D}\left[erf^{-1}\left(\frac{C_s - C(x.t)}{C(x.t)}\right)\right]^{-2} \tag{4}$$

D is the chloride diffusion coefficient for each concrete age, calculated as:

$$D = D(t_0).\left(\frac{t_0}{t}\right) \tag{5}$$

According to Fick's second law of diffusion, the diffusion coefficient and a critical chloride threshold are the primary factors influencing the progression of chlorides through the concrete cover. These parameters are contingent upon the composition of the concrete mixture (Code, C.F.F.M., 2006).

$$C(x,t) = C_s \cdot \left(1 - erf\frac{x}{2\sqrt{D_0 \cdot t \cdot \left(\frac{t_0}{t}\right)^{\alpha}}}\right) \quad (6)$$

Where $C(x,t)$ represents the chloride concentration in the water at a specific depth x below the surface at a given time t (measured in years) D_0 is the coefficient of chloride diffusion, C_s is the concentration of chloride on the surface, t_0 is the initial time, typically assumed to be $t_0 = 0.0767$ (equivalent to 28 days), and $\alpha = 0.5$ is a factor that represents the age of the chloride.

Alonso and Sanchez (2009) found that chloride thresholds vary from 0.4% to 4%. The critical chloride level in Spain is typically around 0.6% of the cement's weight. Corrosion begins when the chloride level in rebars reaches this threshold; below it, no damage occurs. After chlorides reach the rebars, the corrosion spreading phase (t_p) starts. During this time, chloride ions damage the steel reinforcement, gradually weakening it by reducing its stiffness and thickness.

$$t_p = \frac{80}{\phi}\frac{d}{V_{corr}} \quad (7)$$

Here, d is the concrete cover thickness, V_{corr} the corrosion rate, and ϕ the rebar diameter. Table 2 from the Spanish Ministry of Public Works helps analyze the condition of the marine bridge.

Table 2. Parameters of durability in a bridge located in a coastal area (Spanish Ministry of Public Works, 2008).

Marine exposure classification	C_s (% of concrete weight)	V_{corr} (µm/year)	D_0 ($\times 10^{-12} m^2/s$)
Aerial	0.14	20	
Submerged	0.72	4	10.0
In tide zone	0.50	50	

The following Equation estimates the damage caused by chloride corrosion in coastal bridge reinforcements, showing the damage as a percentage (Hadizadeh-Bazaz et al., 2023b).

$$Dam_{st\ rebar}(t) = \frac{t-t_i}{t_p} \times 100 \quad (8)$$

D_{amst} rebar refers to the proportion of reinforcement influenced by chloride ions over a given period (t) starting from the initiation of propagation (t_p).

The updating process can be modeled using equations based on the sensitivity equation.

$$\Delta Z(\omega) = \Delta K - \omega^2 \Delta M + i\omega \Delta C \quad (9)$$

$$H_D(\omega) = [Z(\omega) + \Delta Z(\omega)]^{-1} \quad (10)$$

The frequency response of the corroded bridge, denoted as $H_D(\omega)$, is determined by Eq. (8). The impedance matrix is represented by $Z(\omega)$, corresponding to the inverse transfer function. The potential sources of harm in the PSD equation can include the following:

$$S_{XX}(\omega) = H_D^*(\omega)S_{FF}(\omega)\Delta H(\omega) - H_D^*(\omega)\Delta Z^*(\omega)S_{XX}(\omega) \quad (11)$$

The transfer function for the failure of a complicated conjugate bridge due to reinforced chloride corrosion is denoted as H^*_D, and its value depends on the chosen approach for predicting the failure. The exact ΔH value as reported by Liu (2013) using the following Equation:

$$\Delta H(\omega) = -H_D(\omega)(\Delta K - \omega^2 \Delta M + i\omega C)H(\omega) \quad (12)$$

Equation (10) can be reformulated by utilizing Equation (11) and Equation (13) as follows:

$$\Delta S_{XX}(\omega) = -H_D^*(\omega)S_{FF}(\omega)H_D(\omega)\big(\Delta Z(\omega)\big)H(\omega) - H_D^*(\omega)\big(\Delta Z^*(\omega)\big)H^*(\omega)S_{FF}(\omega)H(\omega) \quad (13)$$

Changes in each element's dynamic properties are assessed to assess how corrosion impacts the structure. Corrosion of rebar in concrete coastal structures by chloride ions causes a decrease in stiffness (due to a decrease in the cross-sectional area of the steel, cracking, and loss of concrete-steel bond), an increase in damping (due to friction and slip in the cracked areas), and usually a slight change in the effective mass of the structure. Changes in dynamic characteristics reduce natural frequencies and alter the shapes of the bridge's vibration modes. To identify and quantify these effects, methods based on PSD, such as frequency domain decomposition of the frequency response function, are used, which extract the shape of the modes by analyzing vibrations at the excitation points and measuring the frequencies, and by comparing them with the baseline values, the degree of stiffness loss or corrosion progression is determined.

The structural stiffness, mass, and damping were represented using matrix equations.

$$\begin{cases} \Delta K = \sum_{n=1}^{ne} K_n \Delta P_n^K \\ \Delta M = \sum_{n=1}^{ne} M_n \Delta P_n^M \\ \Delta C = \sum_{n=1}^{ne} C_n \Delta P_n^C \end{cases} \quad (14)$$

Structural parts' stiffness, mass, and damping are shown as K_n, M_n, and C_n. Changes in these properties (ΔP_n^K, ΔP_n^M, ΔP_n^C) range between -1 and 1. Sensitivity matrices (from Equation 13) help calculate the effect of chloride corrosion on the stiffness of the RC bridge.

$$\begin{cases} S^K = -H_D^*(\omega)S_{FF}(\omega)H_D(\omega)K_n H^T(\omega) - H_D^*(\omega)K_n H(w)S_{FF}(\omega)H^T(\omega) \\ S^M = \omega^2(H_D^*(\omega)S_{FF}(\omega)H_D(\omega)M_n H^T(\omega) + H_D^*(\omega)M_n H(w)S_{FF}(\omega)H^T(\omega) \\ S^C = i\omega(-H_D^*(\omega)S_{FF}(\omega)H_D(\omega)C_n H^T(\omega) + H_D^*(\omega)C_n H(w)S_{FF}(\omega)H^T(\omega) \end{cases} \quad (15)$$

The PSD equation calculates changes in dynamic parameters for expected damages.

$$\Delta S_{xx} = S^K \Delta p_K + S^M \Delta p_M + S^C \Delta p_C \quad (16)$$

Using the PSD method and reinforcement corrosion equations, Δp_k, Δp_M, and Δp_C indicate changes in structural stiffness due to degradation over time in concrete bridge elements.

The parameters considered in this analysis, including the 10% noise level in the PSD analysis in identifying the extent and location of damage and the corrosion progression models, were selected based on commonly reported ranges in the literature to reflect realistic measurement uncertainty and environmental conditions. Similarly, a 5% discount rate is used in LCCA, which is widely accepted and commonly considered in economic analysis of infrastructure.

2.3 Sustainability life cycle assessment

The life cycle concept is widely accepted and standardized worldwide (ISO 14040, 2006; ISO 14044, 2006). Using LCA involves examining the economic, environmental, and social impacts of a product or process (Soust-Verdaguer et al., 2022). The accuracy and speed of structural health monitoring methods significantly influence the timely completion of repair and strengthening activities in structures like bridges; thus, better performance in identifying damage and predicting its extent and location can lead to cost reductions, minimize unnecessary assessments of the structure's condition, and help prevent sudden collapses or extensive damage that could have environmental and social consequences.

2.3.1 LCCA through PSD method

According to ISO 15686-5 (2017), the Life Cycle Cost method considers all expenditures associated with a building from its inception to its end, including maintenance, repair, and demolition at the end of its life. It also accounts for inflation and adjusts future costs to their current value. Maintenance costs refer to all expenses incurred to keep the building in good condition. Although the method provides a general framework, it can become complicated because many factors affect the costs.

Life-cycle cost assessment helps evaluate a bridge’s performance by estimating costs based on its location and the yearly damage it incurs. It covers manufacturing, construction, use, maintenance, and disposal. The formulas below show the total expected cost (Hadizadeh-Bazaz et al., 2023a; Frangopol et al., 2019; Dong and Frangopol, 2016).

$$C_T = C_I + C_M + C_{INS} + C_R + C_{Dam} \quad (17)$$

Eq. (17) represents the various costs associated with a system. C_I denotes the starting cost, C_M represents the maintenance cost, C_{INS} signifies the cost of inspections, C_R denotes the total repairing cost, and C_{Dam} represents the expected damage cost.

The total repair cost for the concrete bridge comes from the following:

$$C_R(t_V) = C_{DNRC}(t_V) + C_{DRC}(t_V) + C_{SM}(t_V) + C_{PE}(t_V) + C_S(t_V) + C_C(t_V) \quad (18)$$

Where the t_v represents the time under study; C_{DNRC} the cost of demolishing non-reinforced concrete components such as the structure's cover; C_{DRC} the cost of demolishing reinforced concrete components such as the bridge's structural parts; C_{SM} the cost of sorting and recycling demolition debris; C_{PE} the cost of preparing equipment for repairing the bridge's concrete and rebars; and C_S the total cost including all these components; The C_C refers to the overall cost associated with repairing the concrete section of the bridge that has deteriorated over time.

Damage from chloride ions and other risks, such as earthquakes and floods, following a Poisson process can be included in the total life-cycle impact for each bridge part over time. The Poisson process models the likelihood of random events like these occurring during the bridge's lifespan, based on their typical frequency (Chiu et al., 2014).

$$C_{Dam}(t_v) = \sum_{K}^{N(t_v)} D_{dam}(t_k).\, e^{-rt_k} \quad (19)$$

In Equation (19), $N(t_v)$ represents the quantity and magnitude of detrimental variables affecting a structure within a specific time. D_{dam} is the proportion of the yearly damages created by chloride ions and predicted by the PSD method at the time t_v. The discount rate, denoted as r, is 5%. According to the Poisson model, the time t_k follows a uniform interval distribution $[0, t_v]$ with a mean rate of λ_f. The annual damage percentage in items exposed to hazard effects is expressed as ($N(t_v) = \lambda_f \times t_v$).

$$E[C_D(t_v)] = \frac{\lambda_f \,.\, E(D)}{r} \,.\, (1 - e^{-rt_k}) \quad (20)$$

In Equation (20), $E[C_D(t_v)]$ represents the monetary worth of bridge components that have been affected by both damage and corrosion.

Ultimately, as the LCCA, the total expenses for bridge repairs are determined based on the projected proportion of damage for the entire bridge section, as per the following Equation.

$$E[C_T\ (\bar{x}.t_v)] = C_I + C_M + \sum_{t=1}^{t_v} \left[\frac{\left(\sum_{t=1}^{N(t_v)} E[C_{DNRC}\ (\bar{x}.t)] + \sum_{t=1}^{N(t_v)} E[C_{DRC}\ (\bar{x}.t)] + \sum_{t=1}^{N(t_v)} E[C_{SM}\ (\bar{x}.t)] + \sum_{t=1}^{N(t_v)} E[C_{PE}\ (\bar{x}.t)] + \sum_{t=1}^{N(t_v)} E[C_S\ (\bar{x}.t)] + \sum_{t=1}^{N(t_v)} E[C_C\ (\bar{x}.t)]\right)}{(1+r)^t} \right] + C_D \quad (21)$$

The LCCA evaluates the total cost of maintenance and repair for characteristics over the lifetime of the bridge structure, as evidenced by the expected value of the cumulative total cost

($E[C_{Total}\ (\bar{x}.t_{int})]$). $\sum_{t=1}^{N(t_v)} E[C_{DNRC}\ (\bar{x}.t)]$, $\sum_{t=1}^{N(t_v)} E[C_{DRC}\ (\bar{x}.t)]$, $\sum_{t=1}^{N(t_v)} E[C_{SM}\ (\bar{x}.t)]$, $\sum_{t=1}^{N(t_v)} E[C_{PE}\ (\bar{x}.t)]$, $\sum_{t=1}^{N(t_v)} E[C_S\ (\bar{x}.t)]$, and $\sum_{t=1}^{N(t_v)} E[C_C\ (\bar{x}.t)]$ are respectively the total costs of demolishing the unreinforced concrete parts, the reinforced concrete parts demolition, management, separation, and categorization of debris resulting from destruction, installation, and subsequent removal of formwork for repair concrete activity, repair, and replacement of damaged bar steel with corrugated bar steel with improved ductility characteristics, and preparing and pouring concrete costs during and until the end of bridge life.

This study analyzed the repair costs of the coastal bridge using Spanish national construction data (MITMA, 2022). The PSD method predicted the bridge's deterioration over time. The study evaluated how accurately it detects where and when damage happens, and how it reduces maintenance costs.

2.3.2 E-LCA through the PSD method

Bridge infrastructure harms the environment by disrupting ecosystems and contaminating water. E-LCA assesses these impacts using two methods: the midpoint approach (which focuses on specific impacts) and the endpoint approach (which shows overall consequences) (Penadés-Plà et al., 2018). Generally, the approaches can be analyzed using CML, ReCiPe 2016, IMPACT 2002+, and TRACI, as well as databases such as SimaPro and Ecoinvent (Barahmand and Eikeland, 2022). This investigation utilizes the Ecoinvent database and the ReCiPe method, illustrated in Figure 5.

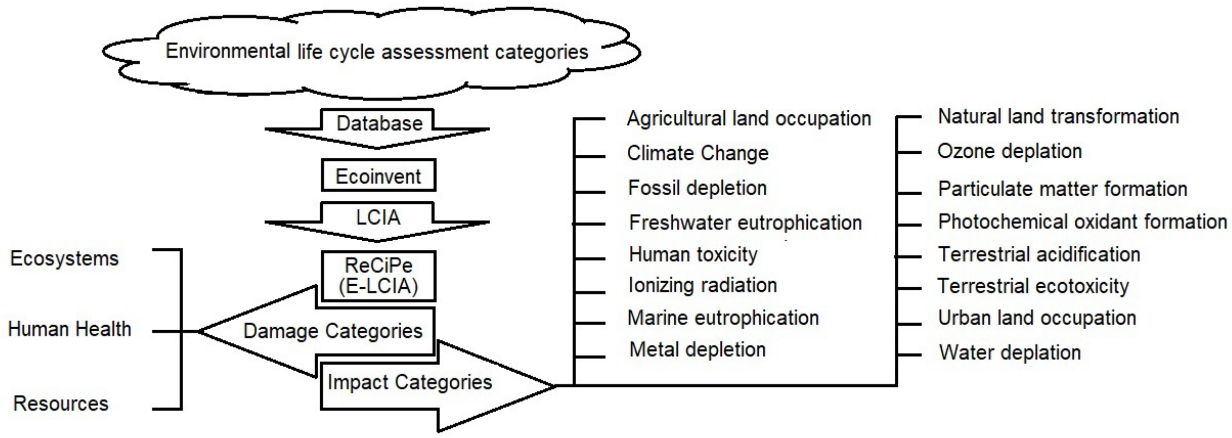

Figure 5. Environmental Life Cycle Assessment Indicators and Methods Used

Figure 4 shows that the ReCiPe midpoint method evaluates factors such as toxicity, land use, and resource depletion. These feed into endpoint categories: human health, ecosystems, and resources. This study used the PSD method with Ecoinvent and ReCiPe to assess corrosion damage on a coastal RC bridge, focusing on the maintenance stage (Association, 2023).

2.3.3 S-LCA through the PSD method

S-LCA, first introduced by UNEP in 2009 (Benoît et al., 2010), has evolved from an academic tool into a practical framework now used by researchers, industries, and policymakers to assess the social impacts of products throughout their life cycle (Benoît Norris et al., 2020). S-LCA follows four main steps: goal and scope definition, inventory analysis, impact assessment, and interpretation. It offers critical insights for improving social performance and stakeholder well-being (Meng et al., 2025). Figure 6 illustrates how S-LCA impact categories and subcategories can positively or negatively affect the life cycle (UNEP, 2020; UNEP, 2021).

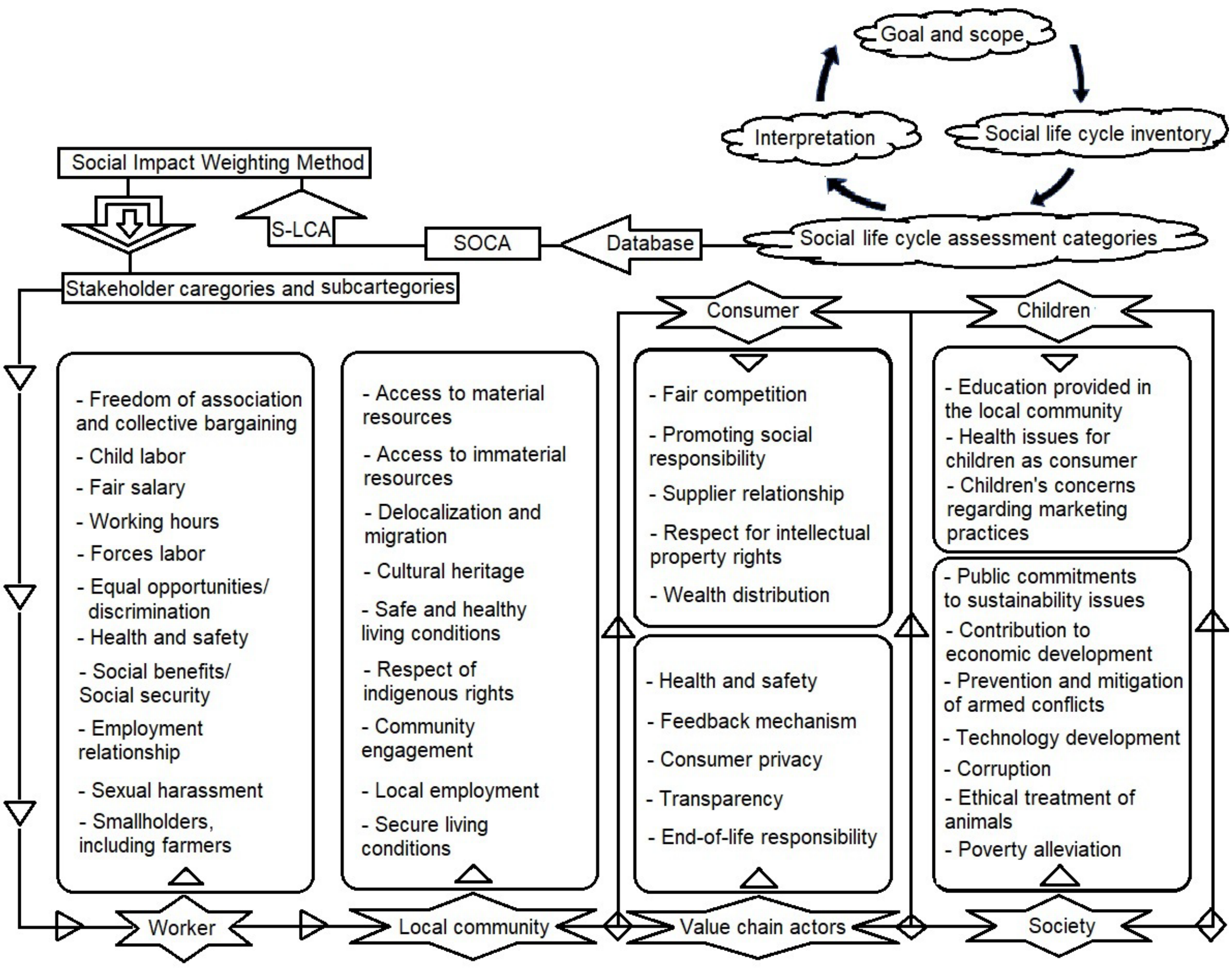

Figure 6. S-LCA phases, stakeholder groups, and subcategories per UNEP 2020 Guidelines.

Simply, assessing social impacts across S-LCA ensures that social sustainability is considered alongside environmental and economic factors. This study utilized the SOCA database (based on Ecoinvent v3.3) and OpenLCA software to assess social risks using a 6-level ordinal risk scale (Eisfeldt, 2017; Kovačič Lukman et al., 2021). Because social indicators vary in units, the risk levels help standardize the data. Stakeholders, including workers, communities, society, and supply chain actors, were included, and the Social Impacts Weighting Method was employed to prioritize categories (Sánchez-Garrido et al., 2024; Kovačič Lukman et al., 2021).

2.4 MCDM model through the PSD method

MCDM methods help evaluate and choose the best economic, environmental, and social options by analyzing multiple, often conflicting factors (Navarro et al., 2020b). In construction and civil engineering, common MCDM tools include SAW, COPRAS, TOPSIS, VIKOR, and MIVES, each offering distinct methods for scoring or ranking alternatives. Researchers often use a mix since there's no universal agreement on a single best method. To enhance decision-making in this study, the Global Structural Sustainability Index (GSSI) was introduced to evaluate the overall sustainability of each option across its entire life cycle (Zavadskas et al., 2015).

The Analytic Hierarchy Process (AHP) simplifies complex decision-making by structuring decisions into a hierarchy and using pairwise comparisons to rank criteria and alternatives by importance. Instead of generating a single index, AHP prioritizes options by their relative dominance.

The weighting factors in the AHP method are selected based on a balanced sustainability perspective, in which economic, environmental, and social criteria are given significant importance. This approach is commonly adopted in infrastructure sustainability to avoid bias towards a single dimension.

This study employs the TOPSIS method to assess the service life of a concrete coastal bridge, with a focus on maintenance and repair planning. Figure 7 illustrates eight life-cycle impact criteria and damage detection, with the calculation process structured using the TOPSIS flowchart.

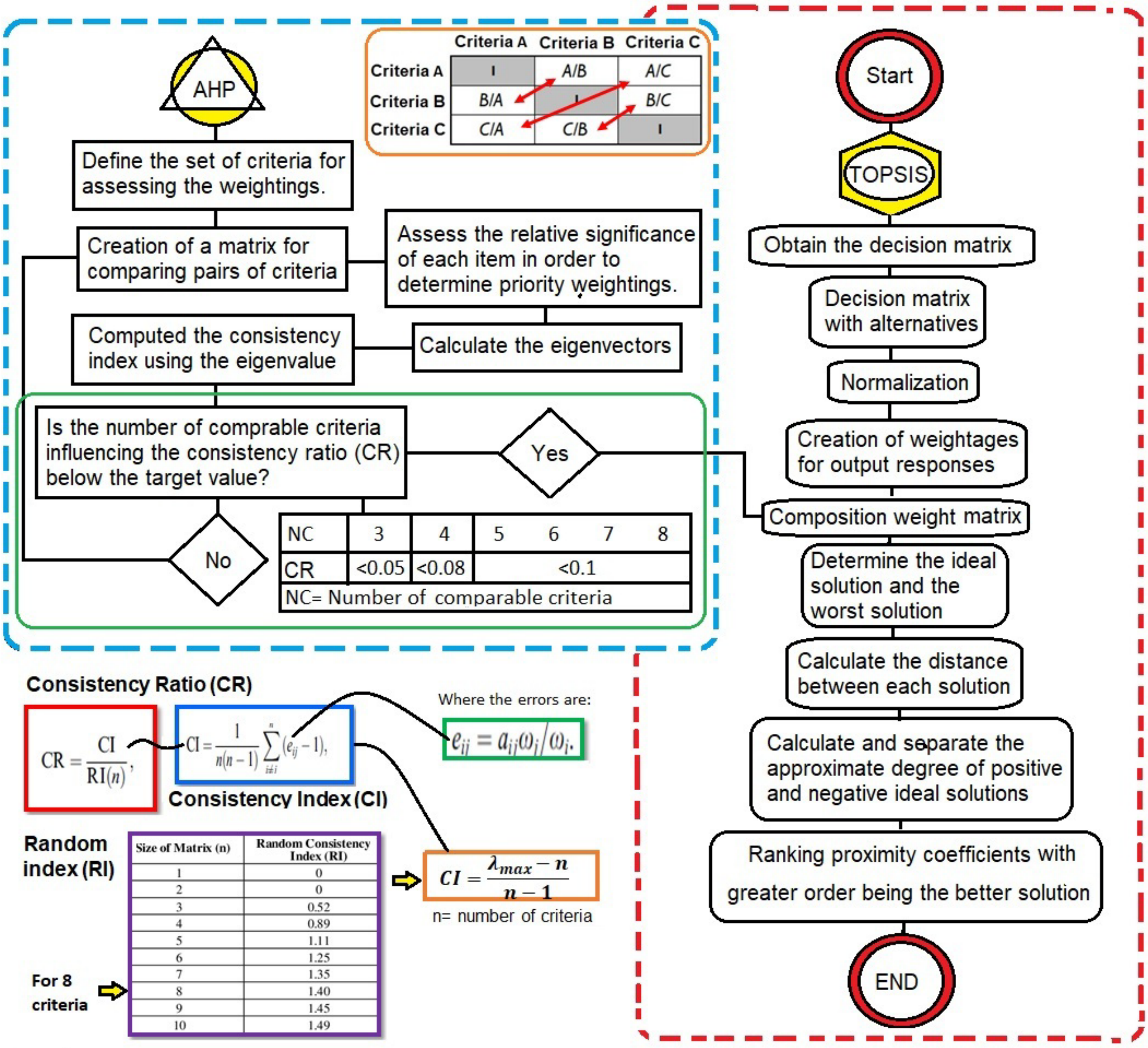

Figure 7. TOPSIS-based MCDM flowchart for evaluating comprehensive bridge maintenance.

The figure illustrates a hybrid decision-making process that combines the AHP and TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) methods. First, the AHP phase, shown in the blue-dashed box, determines the criterion weights. This involves defining the criteria, creating a comparison matrix, computing the consistency index (CR) using the eigenvalue, calculating priority weight eigenvectors, and validating the CR against a target value based on the number of criteria. If the consistency is good, the process moves to the TOPSIS phase in the red-dashed box to rank the alternatives. This phase uses AHP weights to create a decision matrix, normalize it, generate a composition weight matrix, identify the ideal and worst solutions, calculate distances, and rank alternatives based on proximity to the ideal solution.

TOPSIS ranks solutions based on their proximity to the optimal and worst possible choices. The best alternatives are intermediate between the perfect option and the worst one. The TOPSIS method is characterized by its proximity to the positive ideal solution (PIS) and its distance from the negative ideal solution (NIS). The first stage involves standardizing the scores (r_{ij}) for each alternative i and criteria j in the following manner (Sánchez-Garrido et al., 2024; Sánchez-Garrido et al., 2022):

$$\acute{r}_{ij} = \frac{r_{ij}}{\sqrt{\sum_{j=1}^{m} r_{ij}^2}} \tag{22}$$

In Eq. (22), the number of criteria in the decision problem is denoted by m. The standardized scores $\acute{r}_{ij}$ are multiplied by the appropriate criterion weights wi to get the standardized, weighted score v_{ij}. The distances to the positive ideal solution (D_i^+) and negative ideal solution (D_i^-) are calculated as follows:

$$D_i^+ = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^+)^2} \tag{23}$$

$$D_i^- = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^-)^2} \tag{24}$$

The variables v_j^+ and v_j^- represent the highest and lowest scores, respectively, for criterion j across all possible alternatives i. Ultimately, an index C_i^* is established to quantify the ultimate performance of each option i, considering its relative position to the positive and negative ideal solutions.

$$C_i^* = \frac{D_i^-}{(D_i^+ + D_i^-)} \tag{25}$$

According to the TOPSIS, the optimal solution will have the highest proximity index C_i^*.

2.5 Numerical model analysis

Structural damage detection using numerical models has become a key focus in engineering research. This study employed the PSD method to analyze chloride-induced corrosion in a simulated coastal concrete bridge, with a focus on vibration and signal analysis. Monitoring points were strategically placed on the model to assess annual damage. As shown in Figure 8, the bridge deck and columns were renumbered from 1 to 189 for easier tracking.

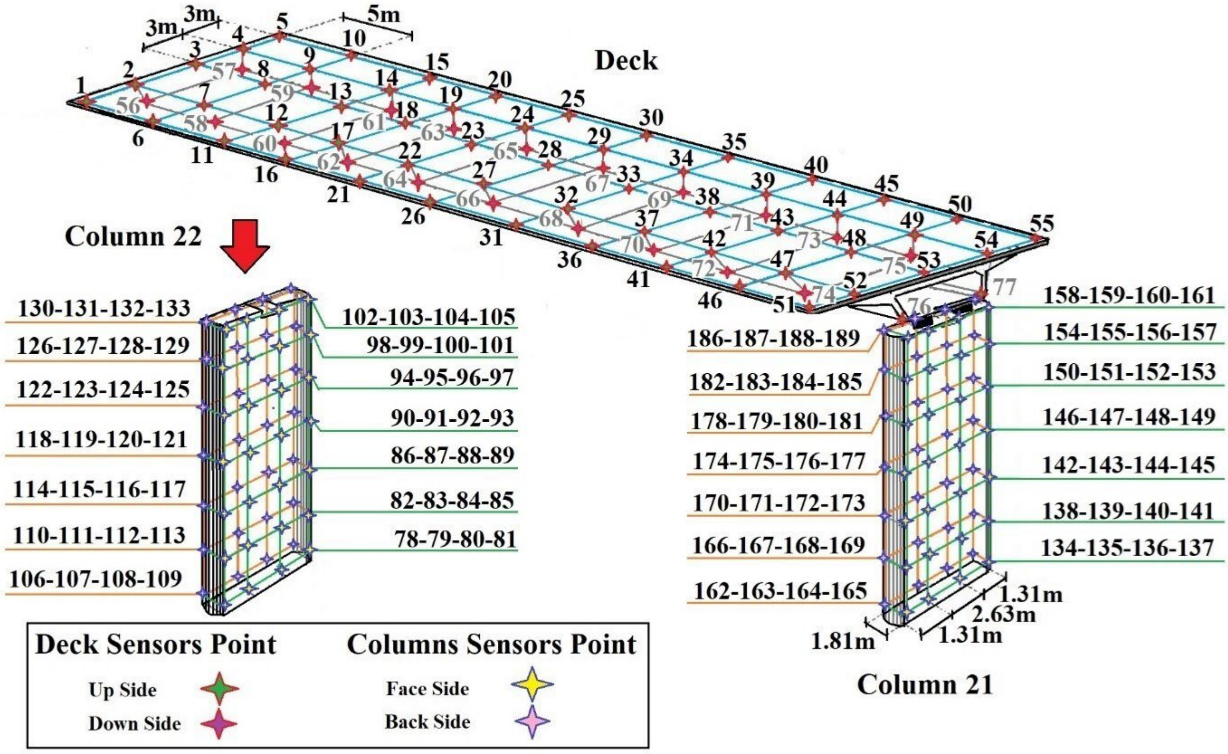

Figure 8. Situation and numbering of sensor points on one middle span of the concrete bridge.

Figure 8 shows the sensor points used for analysis, numbered from 1 to 77 on the bridge deck, spaced 5 meters apart lengthwise and 3 meters apart widthwise. Pier points are numbered from 78 to 189, with distances of 2.63 meters between points along the columns, 2 meters in height, and about 1.8 meters across the pier width. Some points serve as simulation spots, and others are measurement spots to monitor yearly chloride damage across the bridge. These points remain fixed each year to ensure consistent monitoring, as detailed in Table 3.

Table 3. Simulation and measuring point numbers on a span of the bridge.

Location	Stimulation points	Measuring points
Deck	3, 18, 33, 48, 58, 59, 64, 65, 70, 71, 76, 77.	remaining points (Between 1 to 77)
Pier 20	86, 89, 98, 101, 115, 116, 127, 128.	remaining points (Between 78 to 133)
Pier 21	135, 136, 147, 148, 159, 160, 162, 165, 174, 177.	remaining points (Between 134 to 189)

The locations listed in Table 2 were evaluated annually throughout the bridge's life, keeping their positions constant. This assumption allowed tracking changes over time. A 10% error and noise were considered in the analysis of damage detection due to chloride ions on the bridge. The PSD method effectively detects this damage using MATLAB and OpenSees software.

3. Repair Activities Description

Repair methods, as outlined in the European standard EN 1504-9:2008, are employed to extend the service life of structures, such as bridges. These include patch repairs, regular maintenance, sacrificial anodes, galvanic cathodic protection (GCP), impressed current cathodic protection (ICCP), and full replacement of damaged parts (Wittocx et al., 2022; Navarro et al., 2019b).

The six main goals are: (1) blocking harmful substances, (2) controlling moisture, (3) repairing concrete, (4) strengthening structures, (5) improving durability, and (6) resisting chemicals (Renne et al., 2022). Concrete repair follows these steps after addressing rebar damage. Additional methods to tackle corrosion damage include: (7) restoring passivity, (8) increasing resistivity, (9) cathodic control, (10) cathodic protection, and (11) anodic area control. In this study, repairs were carried out on damaged parts identified using the PSD non-destructive method, as shown in Figure 9.

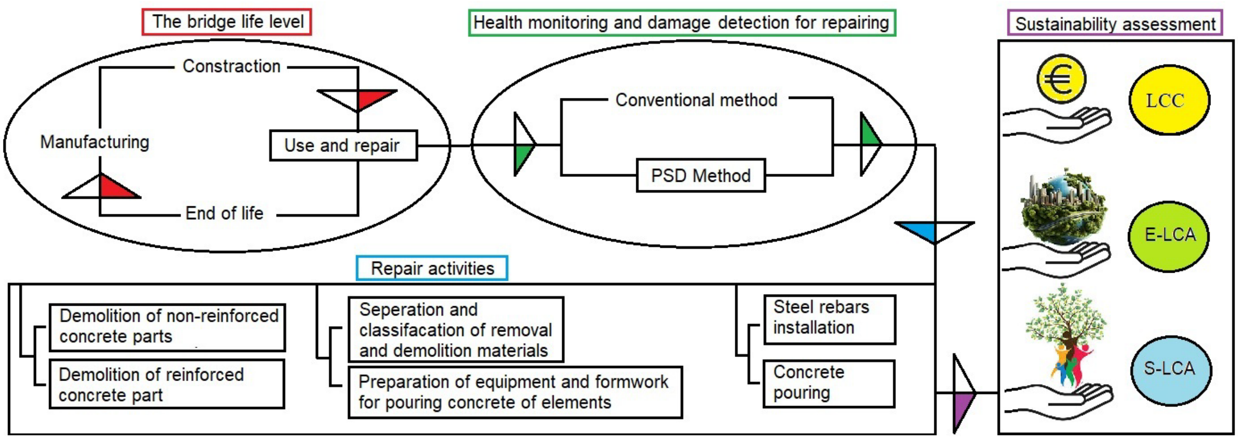

Figure 9. Total repair activities to assess sustainability by the PSD method.

As shown in Figure 9, the PSD method was used to predict damage progression over time and assess maintenance needs. Repair activities included demolishing both reinforced and non-reinforced concrete parts, sorting and disposing of debris, preparing equipment and formwork, installing steel rebars, and finally pouring new concrete.

4. Results and discussion

4.1 Service Life Prediction Methods: Performance results

In the first step, a non-destructive dynamic damage detection method was used to estimate the lifespan of the concrete bridge during repair and maintenance. It was crucial to evaluate how effectively this method could identify the location and severity of damage over the bridge's 100-year lifespan. The PSD method's predictions were compared with a traditional approach for estimating chloride-induced corrosion in coastal reinforced concrete bridges (Hadizadeh-Bazaz et al., 2023b). Table 4 presents the repair timelines for different parts of the Arosa bridge, based on measured and simulated data. Using PSD, repair times were calculated for damages exceeding a 20% damage threshold, aligned with the conventional method's estimated service life. The aim was to determine the optimal repair timing for rebars affected by chloride corrosion.

Table 4. The coastal bridge location, time, damage, and service lifetime for repairing activities.

Section No.	Location and situation of each section	Damage prediction techniques			
		PSD		Conventional	
		Damage (%)	Repair time (year)	Damage (%)	Repair time (year)
Section 1	Deck	20.06	60	26.67	6
Section 2		20.08	50	26.67	6
Section 3		20.15	29	26.67	6
Section 4		20.64	19	26.67	6
Section 5		22.04	18	26.67	6
Section 6		21.5	18	26.67	6
Section 7		20.14	27	26.67	6
Section 8		20.08	54	26.67	6
Section 9		20.31	51	26.67	6

Section 10		20.34	56	26.67	6
Section 11	Column 20	21.1	14	20	17
Section 12		24.23	15	50	14
Section 13		26.63	16	20	18
Section 14		21.48	17	20	18
Section 15		26.45	19	20	18
Section 16		22.11	19	20	18
Section 17	Column 21	21.1	14	20	17
Section 18		24.23	15	50	14
Section 19		26.63	16	20	18
Section 20		21.48	17	20	18
Section 21		26.45	19	20	18
Section 22		22.11	19	20	18

As shown in Table 4, the Arosa bridge deck was divided into 10 segments, each 5 meters long, to enhance the assessment's accuracy. Similarly, each bridge column was split into six segments spaced 2 meters apart. The conventional method predicts the exact repair time for entire deck spans. In contrast, the PSD method provides varied repair times for different segments, offering a more detailed and precise view of the service life of bridge components.

4.2 Life cycle impacts assessment results

Examining LCA results across economic, environmental, and social aspects is essential. This study, focused on the bridge, highlights differences in repair assessments between the PSD method and conventional service-life predictions. The goal is to reduce both environmental harm and maintenance costs. The analysis focuses on the economic aspects of bridge repair and maintenance (Navarro et al., 2020a). Figure 10 presents a comparative LCCA between the conventional and PSD approaches for predicting damage.

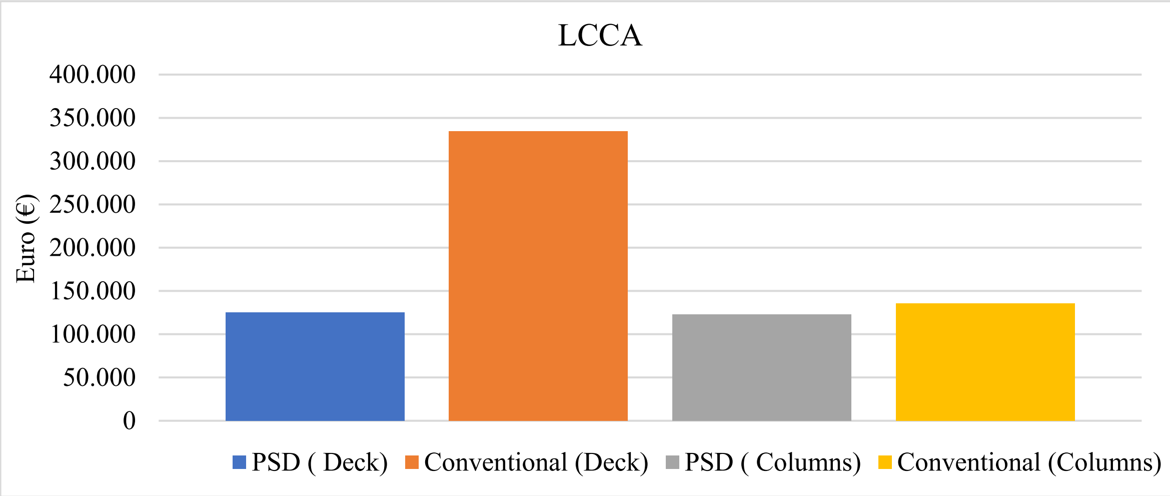

Figure 10. Total LCC for the deck and columns of a bridge span through each method.

Figure 10 shows that the life cycle cost (LCC) for one bridge span is about 248,001.19 euros using the PSD method, compared to 470,113.12 euros with conventional methods. This means the PSD approach could save roughly 222,111.92 euros in maintenance and repair costs over 100 years for the coastal bridge. All repair and maintenance costs were considered, and a 5% discount rate was applied to provide more accurate savings estimates. The results show that the proposed approach to maintenance and repair activities has the potential to reduce the life cycle costs of a coastal concrete bridge by up to 40% under the assumptions considered.

Following this economic analysis, Figure 11 highlights the environmental benefits of the PSD method for the bridge's deck and columns in a corrosive environment, compared to the traditional approach, and illustrates how different prediction methods affect environmental impact.

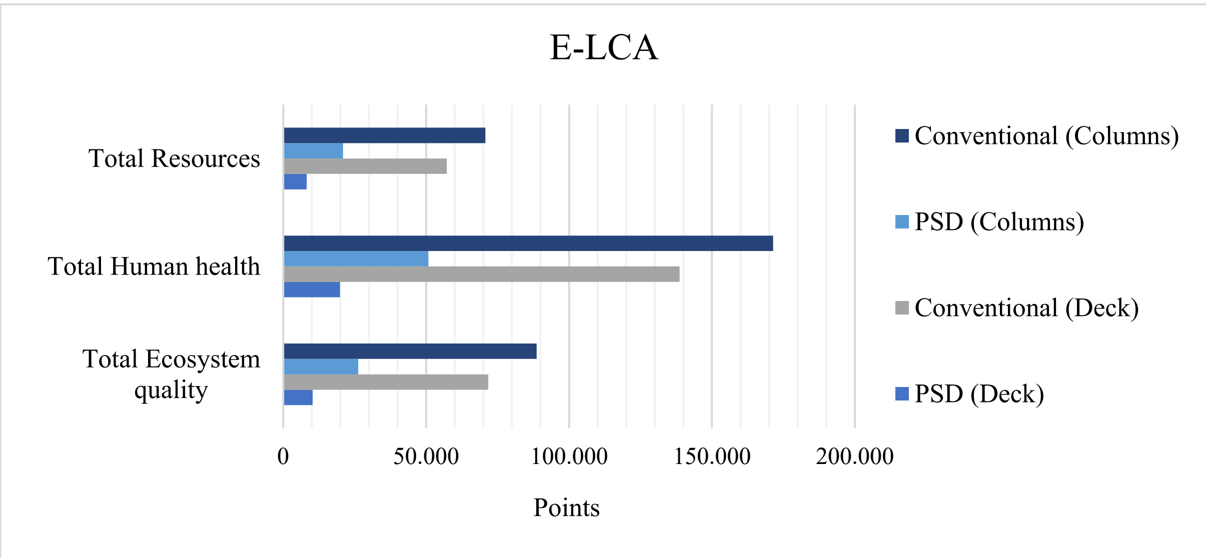

Figure 11. Total E-LCA for the deck and columns of a bridge span through each method.

As shown in Figure 11, using the PSD method for E-LCA instead of traditional maintenance significantly reduces environmental impacts. It lowers ecosystem damage by 61,449.68 points and human health impacts by 118,802.69 points for the bridge deck. 49,028.9 points also reduce resource use on the deck. For the coastal bridge columns, PSD cuts environmental damage by 62,363.55 (ecosystem quality), 120,608.15 (human health), and 49,774 points (resources). Overall, PSD causes less harm to ecosystem quality, human health, and resources compared to conventional methods.

This study also uses PSD, a non-destructive damage detection method, to evaluate the social impact of maintaining a corrosion-prone coastal concrete bridge. Figure 12 illustrates the S-LCA results, highlighting key groups, including the local community, society, value chain actors, and workers. The PSD method offers valuable insights into the social impacts of repair and maintenance throughout the bridge's lifetime.

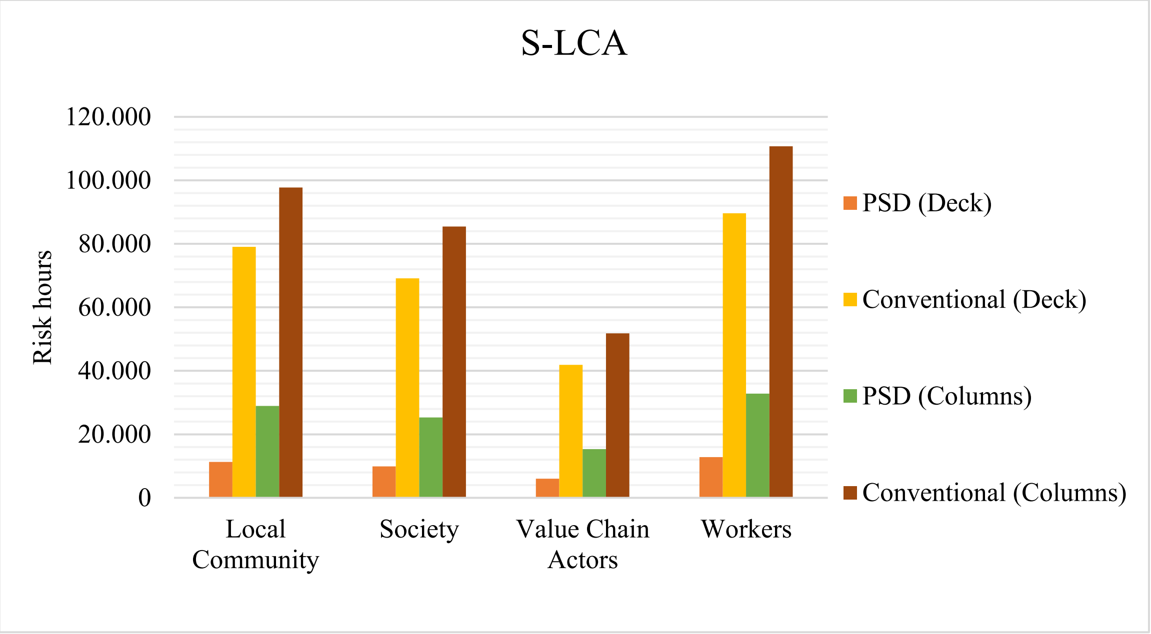

Figure 12. Total S-LCA for the deck and columns of a bridge span through each method.

Figure 12 presents the social impact assessment results for four main stakeholder groups, each further divided into subgroups as shown in Figure 6. The PSD method was applied to evaluate these subcategories for a mid-span section of the Arosa bridge, which includes two columns and a 50-meter deck, and the results were compared with those from the conventional corrosion prediction approach.

Using the PSD method, the total S-LCA risk hours for the deck and two columns are 40,283.37 for the local community, 35,226.05 for society, 21,346.03 for value chain actors, and 45,650.65 for workers. In contrast, the conventional method shows much higher risk hours: 176,807.60, 154,610.55, 93,689.80, and 200,365.10, respectively, for these groups.

4.3 Sustainability and MCDM Analysis Results

Although it may seem that economic (LCCA), environmental (E-LCA), and social (S-LCA) assessments are assessed separately, they are inherently interconnected. For example, the use of innovative maintenance strategies that can reduce the number of repairs can reduce economic costs and significantly reduce environmental impacts and social disruptions by predicting the time, location, and extent of damage. In this context, the framework proposed in this study integrates these dimensions using the AHP-TOPSIS method and enables a comprehensive assessment by analyzing trade-offs among different sustainability criteria.

This study evaluated the sustainability of maintenance and repair activities using the PSD method based on eight criteria: total cost (C1), ecosystem quality (C2), human health (C3), resources (C4), workers (C5), local community (C6), society (C7), and value chain actors (C8).

Weights for each criterion were determined using the AHP, and these scores were applied in the TOPSIS method. Table 5 details the weights assigned to each criterion for the bridge.

Table 5. Criteria and weights pairwise comparison matrix for the bridge by AHP.

Criteria	C1	C2	C3	C4	C5	C6	C7	C8	Weights	CR
Costs (C1)	1	0.5	0.33	1	0.2	7	1	2	0.08	
Ecosystem quality – total (C2)		1	0.5	2	0.33	3	0.5	3	0.11	
Human health – total (C3)			1	4	1	8	4	7	0.27	
Resources – total (C4)				1	0.5	1	0.5	1	0.06	0.07
Workers (C5)					1	9	9	9	0.32	
Local Community (C6)						1	0.5	1	0.03	
Society (C7)							1	5	0.09	
Value Chain Actors (C8)								1	0.04	

Table 5 presents the pairwise weights assigned to the bridge using the AHP method. Furthermore, it was verified that the number of criteria meeting the consistency ratio (CR) threshold is below the desired threshold. If there are more than five criteria, it should be less than 0.1. Therefore, the value for these eight criteria is 0.07, less than 0.1. To assess the performance of the PSD method for sustainability assessment, the TOPSIS method is compared with the conventional method for predicting service life, as shown in Table 6.

Table 6. The score for each damage-preparation method is determined using the TOPSIS method.

LCA	Criteria	Optimization direction	Alternatives		Distances				Score	
			$\acute{r}_{ij}$		D_i^+		D_i^-		C_i^*	
			Conv	PSD	Conv	PSD	Conv	PSD	Conv	PSD
LCCA	C1	min	0.074	0.039						
E-LCA	C2	min	0.103	0.023						
	C3	min	0.265	0.043						
	C4	min	0.058	0.013	0.35	0.00	0.00	0.35	0.00	1.00
S-LCA	C5	min	0.312	0.071						
	C6	min	0.033	0.007						
	C7	min	0.091	0.021						
	C8	min	0.035	0.008						

Notes: Conventional method = Conv

According to the TOPSIS results shown in Table 6, the minimum optimization value (min) plays a key role. To compare the sustainability of two methods, results from LCC (€), E-LCA (points), and S-LCA (risk hours) were normalized into comparable units. The distances to the positive ideal solution (Di+) and negative ideal solution (Di-) indicate that a higher score corresponds to better performance (i.e., being farther from the negative ideal). Thus, the optimal solution has the highest closeness index ($Ci*$). For the PSD method, this value is 1.00, significantly outperforming the conventional method, which scored 0.00.

For more detailed investigations, a sensitivity analysis was conducted to assess the robustness of the proposed framework with respect to key parameters, including AHP weighting coefficients, the discount rate, and the noise level in the PSD analysis.

Table 7. Sensitivity analysis of key parameters on decision-making results

Case	Parameter Variation	Description	Best Strategy (TOPSIS Ranking)
Base Case	—	Reference scenario (AHP weights: 0.4–0.3–0.3, discount rate = 5%, noise = 10%)	PSD-based
Case 1	Economic weight ↑	Economic = 0.5, Environmental = 0.25, Social = 0.25	PSD-based
Case 2	Environmental weight ↑	Economic = 0.3, Environmental = 0.4, Social = 0.3	PSD-based
Case 3	Social weight ↑	Economic = 0.3, Environmental = 0.3, Social = 0.4	PSD-based
Case 4	Discount rate ↓	Discount rate = 3%	PSD-based
Case 5	Discount rate ↑	Discount rate = 7%	PSD-based
Case 6	Noise level ↓	Noise = 5%	PSD-based
Case 7	Noise level ↑	Noise = 15%	PSD-based

As shown in Table 7, the ranking of repair and maintenance methods using a damage identification method in terms of stability remains constant across all the scenarios examined. Although minor changes in parameter values may affect intermediate results, the PSD-based damage location and extent prediction strategy can remain one of the most desirable options. These findings demonstrate the stability and robustness of the proposed integrated framework under reasonable changes in key parameters and assumptions.

Although the present study is based on a numerical simulation framework and does not include validation using real-world monitoring data, we plan to validate the proposed PSD-based method using experimental or long-term monitoring data from real bridge structures in future research to increase its practical applicability. We will then evaluate it on other damage factors in different environments and on other types of structures.

Despite the promising results, some limitations and uncertainties remain. It should be noted that uncertainties in the detection of damage extent and location throughout the structure's life, as well as model assumptions, may affect the sustainability assessment results. For example, changes in the levels of damage detected can affect the timing of maintenance and repair activities, thereby significantly affecting economic costs, environmental impacts, and social consequences. This interaction highlights the importance of considering uncertainty in future developments of repair and maintenance in the proposed framework.

5. Conclusions

The investigation showed the integrated framework of PSD-based damage detection with life-cycle sustainability assessment and multi-criteria decision-making for identifying the extent and location of corrosion damage and supporting the maintenance of coastal reinforced concrete bridges.

By predicting the location and amount of corrosion damage each year of a bridge's life, PSD through LCC can reduce maintenance and repair costs by 40% compared to the conventional method. In addition, the E-LCA for the PSD method can reduce environmental impact by 14.33% for the deck and 29.62% for the columns compared to traditional methods. The S-LCA results further demonstrate notable social benefits, reducing negative impacts on society, including the local community (28.27%), society as a whole (24.72%), value chain actors (14.98%), and workers (32.03%). Using TOPSIS for multi-criteria evaluation, the PSD method (scored = 1) outperforms the conventional method (score = 0), confirming its strong sustainability performance throughout the bridge's life cycle.

The results suggest that the developed approach to maintenance has the potential to improve maintenance planning by enabling early detection of corrosion damage and supporting better decision-making than the conventional approach. This inclusion in the analysis performed well in reducing adverse economic, environmental, and social repercussions, providing a more thorough assessment than typical maintenance procedures.

Overall, this study introduces the PSD method as a robust, stable, and data-driven framework for long-term structural health monitoring and corrosion assessment in reinforced concrete coastal bridges, facilitating repair and maintenance. The PSD-based method goes beyond its diagnostic capabilities, offering a path toward predictive, preventive, and resource-efficient maintenance practices that significantly contribute to the sustainability and resilience of corroding, deteriorating coastal civil infrastructure.

From a practical point of view, the results of this study also suggest that engineers, infrastructure asset managers, and transportation authorities will benefit from adopting adaptive vibration-based monitoring of chloride corrosion damage to bridge internal flange rebars and from evaluating the sustainability of this approach in maintenance planning. This technique can potentially result in more efficient resource use, lower maintenance costs, and reduced environmental and social impacts, as well as increased long-term performance of bridge systems. Future research should focus on validating the framework using monitoring data from actual-world bridges and extending the technique to other bridge types and environmental conditions. More research on the transmission of uncertainty and improved decision-making models could enhance the resilience of the process.

Overall, the suggested methodology is a promising step towards integrating structural health monitoring and sustainability evaluation to achieve more resilient, sustainable infrastructure management.

Declaration of competing interest

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

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Ethics statement

The authors confirm that this study did not involve any human participants or animals. Therefore, ethical approval from an institutional review board was not required for this research.

AI

During the submission of this work, the authors carefully used Grammarly and ChatGPT as AI editing assistants to correct grammar and improve sentence Structure, as well as to revise and correct the manuscript in small sections, including the Abstract, Introduction, Methodology, Results, and Conclusion. After using these tools, the authors reviewed and edited the content as needed and took full responsibility for the publication's content.

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