

EXTENDING BUILDING LIFESPAN: INTEGRATING BIM AND MCDM FOR STRATEGIC REHABILITATION

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SUMMARY: Building renovation is essential to reduce environmental impacts and address social demands, yet structural rehabilitation planning remains uncertain and disruptive. This paper presents Endurify 2.0, a BIM-based automated scheduling system for structural maintenance that estimates the Remaining Useful Life (RUL) of reinforced concrete beams and automatically generates multi-phase rehabilitation plans. By minimizing manual planning input and integrating maintenance data into the BIM model, the system serves as a decision-support tool that enhances the efficiency and accuracy of rehabilitation planning. The tool combines analytical models for four damage indicators to define element-level intervention thresholds. These outputs feed a multi-criteria decision-making framework, economic cost, and two social criteria are weighted, and TOPSIS selects the optimal rehabilitation schedule. The method is validated on a residential building with 191 beams, 139 exhibiting damage. Compared to expert-based planning, the automated approach reduces total cost by 15% and proximity impact by 10%, while maintaining structural safety.

KEYWORDS: BIM, structural performance, MCDM, rehabilitation planning, data-driven decision-making, lifecycle analysis.

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1. INTRODUCTION

The Architecture Engineering and Construction (AEC) Industry is responsible for 35 % of the greenhouse gas emissions, 42 % of the total energy consumption, 50 % of extracted resources, and 30 % of water consumption (IEA, 2024). These numbers highlight the sector's importance for a sustainable transition. The United Nations' Sustainable Development Goals (SDGs) present a call for action, establishing guidelines for this change to come while addressing social and economic inequalities (Griggs et al., 2014). Building renovation directly addresses these goals, and this paper presents a new approach to enhance a building's lifespan by using BIM environments.

To achieve these goals, national and regional strategies have been implemented to enable a sustainable transition to a net-zero emission society. The EU's efforts to achieve the transition are defined in the European Green Deal ("European Green Deal," 2024), which aims for all new buildings to have zero emissions by 2030. In Spain, this goal is specified in the 'Agenda 2030' ("Ministerio de Derechos Sociales y Agenda 2030" 2023), which points the country to a cleaner future.

The focus of measures is primarily on reducing carbon emissions during the operation phase of a building, which is achieved in two distinct ways. On the one hand, using Building Performance Simulation tools enables better and more optimized solutions to reduce energy and resource consumption (Abdalla & Eltayeb, 2018; Azhar et al., 2015; Chong et al., 2017). Conversely, improving techniques and materials to achieve higher requirements reduces their energy consumption or improves their performance (Pachla et al., 2021; Rodríguez-Álvaro et al., 2021).

Unfortunately, climatic emergencies are not the only challenges endangering our society. Poverty and inequality are pressing trends that need to be addressed in the coming years and are also discussed in the SDGs. The different policies, laws, and regulations implemented by governments aim to adopt a holistic approach and achieve a better society. The AEC industry must also overview these demands. Building renovation also contributes to a more equal society by providing access to better housing for everyone, reducing the poverty index, and creating new opportunities for disadvantaged sectors.

Building renovation is a direct response from the Industry to the necessities and demands of the current society. Extending the lifespan of an existing building and improving its performance contribute to both problems. It reduces the need for new constructions and the energy consumption of existing ones (Alba-Rodríguez et al., 2017; Volk et al., 2014). Proactive rehabilitation is only one aspect of sustainable structural lifecycle management; on the other hand, researchers are devising circular economy strategies for end-of-life management. For example, developing an automated planning tool for the robotic deconstruction of concrete structures optimizes the sequence of dismantling, allowing components can be efficiently salvaged and their service life effectively extended through reuse (Ostapska et al., 2025).

The Spanish approach to achieving the European Green Deal's renovation strategies. The policies aim to renovate most buildings to meet a minimum energy requirement or remove them from the market, unable to sell or rent (EU, 2022). Currently, 57.42% of houses in Spain were built before 1980 (MITMA, 2022), and only 2.54% have been built in the last ten years (Fernández-Mora et al., 2023). This is a trend in other European countries, where most buildings are older than the expected life span of 50 years. Older buildings have a higher energy consumption (Kylili & Fokaidis, 2015) and have lost performance over the years due to natural degradation. Moreover, housing access has become increasingly complicated in recent years (MITMA, 2021). We are leaving new buildings unoccupied and in need of maintenance, which requires inspection and renovation to improve energy efficiency and ensure security and integrity.

Maintenance strategies are mandatory for building renovation to be successful. These strategies provide a structured approach to implementing maintenance measures and extending the service life of a building before degradation impairs it. Predictive maintenance is a proactive maintenance strategy that predicts the building's behavior (Flores-Colen & de Brito, 2010). Despite its importance, building renovation remains one of the most uncertain and complex domains in project management (Liang et al., 2016). Decisions between renovation and replacement are rarely straightforward; although new construction typically offers higher efficiency, renovation often proves more cost-effective when considering full lifecycle costs and social impacts. (Dominguez et al., 2024). Digital tools are increasingly necessary to navigate this complexity.

1.1 Use of BIM for refurbishment projects

Building Information Modelling (BIM) offers a robust framework for addressing these challenges (Eastman et al., 2011). As a multidimensional, database-driven environment, BIM enables the integration of geometric, semantic, and operational workflows. Its capacity to coordinate Building Performance Simulation (BPS) tools, sustainability assessments, and structural evaluations makes it a prime candidate for managing rehabilitation processes.

It is a widely adopted technology in the AEC Industry. A powerful tool has revolutionized the Industry recently. BIM technology is based on sharing and relating, and it is database-driven software that can create and link properties and variables. It provides a geometrically accurate space where the building's data can be represented in a 3D model, showing data and its relations in several ways. BIM is

BIM is leading and changing the industry, and receiving much attention from professionals adopting it (Yang & Chou, 2019). Taking advantage of BIM standardization is vital, as it provides a way to extend functionalities across multiple projects (Azhar et al., 2015). Building Performance Simulation (BPS) tools can profit from BIM advantages as a database. BIM provides a highly accurate digital model for performing any kind of analysis. Several tools have been presented over the years to aid professionals in sustainability assessment (Carvalho et al., 2021; Eleftheriadis et al., 2017; S. Liu et al., 2015). There are also tools to aid in the design or as support for building renovation in energy matters (Fenz et al., 2023).

The use of BIM on existing buildings has received relatively little research attention (Fernández-Mora et al., 2022), with a primary focus on heritage buildings (HBIM). Research in this field has focused on using point-cloud technologies to accurately represent historical buildings (Jiang et al., 2020), with notable case studies such as the example of Seville's cathedral (Angulo & Castellano-Román, 2020). The other research line is based on taking advantage of these digital models to study building decay (Chiabrando et al., 2017) or health (Di Re et al., 2021) to properly define the actions to preserve the building (Dore et al., 2015). Research interest in existing buildings has focused on building performance and refurbishment (Alnaser et al., 2024; Bellos et al., 2022). This lack of research effort in BIM for existing buildings is due to the difficulties identified by various authors (Pavlovskis et al., 2017; Peeraya Inyim et al., 2015). One of the main barriers to implementing BIM for existing buildings is standardisation [5], as most developed solutions are tailored to each specific case study. Recognizing the challenge that many older buildings lack digital models, recent work has introduced automated scan-to-BIM solutions (Duan et al., 2025), developing a UAV- and GIS-based workflow to rapidly generate BIM models of existing buildings, specifically to facilitate downstream tasks like infrastructure maintenance and retrofit planning

Despite the lack of research, BIM implementation has been proven helpful in building refurbishment (Ilter & Ergen, 2015). Durability analysis has been a topic of great interest, with works on using BIM for housing refurbishment (Kim & Park, 2016). This research has led to further research on structural durability with other damage indicators presented in this paper. The use of BIM to create digital twins that replicate building performance over time has been studied and highlighted (Chinesta et al., 2019), as well as its application in structural rehabilitation (Xu et al., 2023).

BIM's inherent advantages provide an ideal platform for developing and utilizing BPS tools. While significant research has focused on leveraging BIM for design purposes, further exploration of its application in existing buildings presents untapped potential to positively impact society by enhancing renovation projects and extending building lifespan. Embedding decision support into BIM has proven beneficial in various contexts. For example, integrating a natural language-derived knowledge base with BIM, accessible via an AR interface, provides inspectors with on-site, component-specific guidance drawn from construction standards (H. Liu et al., 2025).

The potential of using BIM for predictive maintenance can significantly help in building refurbishment projects (Okakpu et al., 2018). Research has proven useful, but some aspects could be improved due to the need for additional information and effective stakeholder coordination. Successful research has used BIM to plan façade maintenance (Ferreira et al., 2023) and perform simulation analysis to reduce energy consumption.

Using BIM analysis tools to describe and diagnose the current state of preservation of buildings has received little attention. This application can help perform predictive maintenance, as it displays the degradation state of the building and plans the various interventions before they become critical.

The potential of Building Information Modeling (BIM) as a platform for developing Building Performance Simulation (BPS) tools to facilitate design is unprecedented (Azhar et al., 2015). Literature reviews have identified

a gap in research regarding the utilization of BIM for building renovation (Chong et al., 2017; Joblot et al., 2017; Lu et al., 2017; Volk et al., 2014). Uncertainties and inaccuracies exacerbate the risks associated with rehabilitation projects, presenting challenges in implementation within the inherently standardized environment of BIM. However, despite these challenges, the robust data management and computational capabilities of BIM position it as a valuable tool for building renovation endeavors.

A comprehensive solution to building refurbishment and renovation can be achieved by incorporating both BIM approaches. This method involves analyzing and enhancing the building's performance to diminish its environmental impact and prolong its lifespan through predictive maintenance. The outcome of this approach is a systematic and scientific building rehabilitation.

1.2 MCDM and TOPSIS

Multicriteria decision-making (MCDM) has been employed by the AEC industry in various situations to address complex problems, particularly in sustainability assessments (Sánchez-Garrido et al., 2022). These algorithms are used to select among different criteria, find a compromise solution, and coordinate the interests of all stakeholders. They have been widely adopted and used by the AEC industry for sustainable design (Navarro et al., 2019) and have been successfully integrated into BIM environments (Tan et al., 2021). The use of these algorithms deals with the complexity of the problem, tailoring for each situation. In this research, the algorithm will be used to coordinate the interests and affection of the neighbors to minimize the structural rehabilitation impact in their lives by employing social criteria (Navarro et al., 2024).

1.3 Aim of the research

This paper presents a practical solution to address social needs, grounded in prior research. Specifically, it presents a planning tool that analyzes and optimizes a building's remaining lifespan by identifying critical points in its structural elements. By adopting this tool, stakeholders can make more cost-effective investments and minimize any adverse impact on neighboring communities. Furthermore, this tool seamlessly integrates into BIM environments, leveraging advanced data management capabilities. Unlike a Digital Twin, which requires real-time sensor synchronization and bidirectional cyber-physical feedback, Endurify 2.0 operates as a predictive BIM-embedded decision-support tool based on analytical degradation modeling.

2. METHODOLOGY

2.1 A general approach to the problem

Structural materials deteriorate over time, leading to progressive losses in safety, serviceability, and performance. While modern building codes increasingly incorporate durability-based design, most existing buildings were constructed without such provisions and now operate under uncertain degradation states. The lifetime increases depending on the degree and type of degradation and the actions taken. Theoretically, this process can be repeated to ensure a building's safety (Yepes et al., 2016). Rehabilitation thus becomes a strategic necessity to extend structural lifespan and mitigate societal and economic disruption.

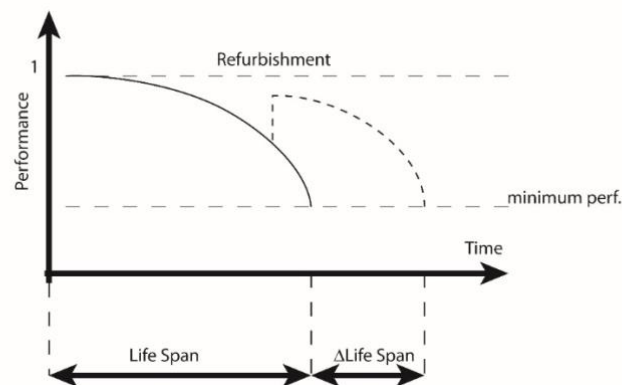


Figure 1: Refurbishment effects on lifetime.

This research adopts a performance-based approach to building lifecycle management. Rather than viewing rehabilitation as a one-time response to failure, the methodology models degradation as a continuous process across structural elements. For each element, a set of physical indicators is used to estimate its Remaining Useful Life (RUL), defined as the time interval until performance thresholds are exceeded. Once the RUL for each element is known, a plan to rehabilitate them is developed, extending their lifespan (Figure 1).

The decision-making framework operates at the element level, aggregating RUL values to inform whole-building intervention planning. Planning is optimized based on two real-world constraints: (i) the need to minimize the number and invasiveness of interventions for occupants (Rohe et al., 2010), and (ii) the need to reduce economic costs under limited information, where original construction records and lab testing are often unavailable. The methodology assumes high uncertainty and is designed for integration into Building Information Modelling (BIM) environments for replicability and lifecycle traceability.

2.2 Indicators of degradation

Several co-occurring physical mechanisms govern the progressive loss of structural performance in reinforced concrete. To assess the Remaining Useful Life (RUL) of each structural element, this methodology evaluates four degradation indicators: transversal cracking, carbonation, creep, and deflection. These were selected based on their regulatory relevance, physical observability, and structural implications.

2.2.1 Transversal cracking

Cracking is among the earliest symptoms of degradation and acts as an accelerator for subsequent damage mechanisms. This study focuses on transversal cracks, which compromise the rebar's protective concrete layer and reduce durability. Crack width, influenced by loading history and environmental conditions, is considered a trigger for inspection. Regulatory limits are adopted to ensure compliance with serviceability and exposure requirements.

2.2.2 Carbonation

Carbonation reduces the alkalinity of concrete, allowing rebar corrosion to occur when it reaches the reinforcement layer. The process is modeled in two phases: initiation (t_{inic}) and propagation (t_{prop}), based on concrete strength (f_{ck}), exposure class (c_{env}), porosity (c_{air}), and corrosion velocity (v_{corr}). The analytical model follows Tutti's approach, with carbonation front progression and steel corrosion depth estimated via Equations (1) and (2), as shown in Figure 2. Equation (1) shows time to initiate the process, (2) propagation time.

$$t_{inic} = \left(\frac{c}{k_{ap,carb}} \right)^2 \rightarrow k_{ap,carb} = c_{env} \cdot c_{air} \cdot a(f_{ck} + 8)^b \quad (1)$$

$$t_{prop} = \frac{80 \cdot c}{\emptyset \cdot v_{corr}} \quad (2)$$

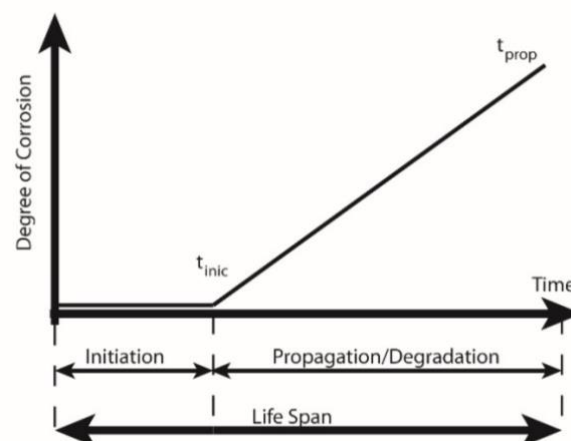


Figure 2: Tutti's corrosion model.

2.2.3 Creep and deflection

Creep refers to time-dependent deformation that occurs due to sustained loading, while deflection represents the visible outcome of stiffness loss. Both affect serviceability and user perception. Creep is assumed to follow a quasi-linear behavior beyond 400 days, a valid assumption for the existing buildings targeted in this study. Deflection is interpolated between uncracked and fully cracked stiffness states.

Figure 3 provide the deflection formulation and limit states, following standard analytical codes. Equation (3) show deflection interpolation, (4,5 and 6) interpolation ration and (7) bending moment.

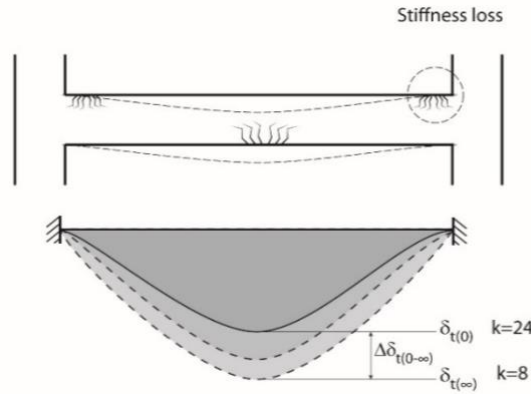


Figure 3: Deflection evolution.

$$\delta_T = \zeta \delta_{11} + (1 - \zeta) \delta_{12} \quad (3)$$

$$\delta_{11} = \frac{Q_{qp} \cdot L^4}{8 \cdot E_{cm} \cdot I_b} \quad (4)$$

$$\delta_{12} = \frac{Q_{qp} \cdot L^4}{8 \cdot E_{ceff} \cdot I_f} \quad (5)$$

$$\zeta = 1 - \beta \left(\frac{M_{fis}}{M_{Ed}} \right)^2 \quad (6)$$

$$M_{Ed} = \frac{Q \cdot L^2}{k} \quad (7)$$

2.2.4 Indicator independence and limitations

Although these indicators are interrelated in physical behavior, each is treated independently in the model to maintain analytical tractability and enhance replicability. This avoids redundancy in failure flags and ensures consistent thresholds. Due to the variability of environmental exposure and limited data availability in existing buildings, these models provide a bounded approximation of degradation, which is sufficient for preliminary RUL estimation under uncertainty (EN 1990: Basis of Structural Design, 2010; Zhang et al., 2023).

2.3 Predictions over reality

Every damage indicator in this paper has received research attention, and different analytical models exist to predict their development. These models form the basis of the regulations in various countries and limit them during the design phase. The predictive models enable professionals to ensure safety and durability throughout a lifespan. They are built upon experimental data to ensure their safety, but they do not represent the actual state of a structure after a specific period.

Damage evolution in existing building structures is a complex topic with many variables that cannot be controlled. As has been explained for each indicator, they evolve. If analytical models were accurate, the evolution would be

the same, and there would be no difference between theoretical and actual behavior. However, that is not the case; due to various uncontrolled variables, the degradation mechanisms can act faster or slower.

For example, creep development depends on factors such as the amount of load over a long period, the concrete's strength at the time it receives the charge, humidity, size, exposure of the structural element, and age, among others (EN 1990: Basis of Structural Design, 2010; Zhang et al., 2023). While the analytical model keeps track of every factor, it can vary significantly throughout its lifetime.

The previous statement does not invalidate the models. They serve their purpose: to ensure durability during the design phase and to guarantee a lifespan for the buildings. However, to perform a durability analysis of an existing building structure and ensure its safety, professionals need to be able to determine the remaining lifespan.

The utilization of analytical models allows for the prediction of the current and future state of degradation. The authors have utilized building data to compare the actual degradation behavior with the theoretical state of degradation. This compares the theoretical age of the element at a specific stage of degradation and the actual age of the element from the day of its construction. To determine if the structural element requires maintenance, the degradation must have been higher and sooner than the design premises. Even then, its progression from the given point can decrease the element's performance sooner than intended, or a preventive treatment can be performed to avoid the damage.

2.4 Intervention threshold

To enable predictive and optimized rehabilitation, each structural element is evaluated against predefined intervention thresholds derived from its degradation indicators. These thresholds represent the boundary between acceptable performance and the onset of serviceability or durability risk, and are selected based on regulatory limits, physical interpretation, and empirical validation.

Each indicator operates independently and is assigned a limit state beyond which intervention is flagged. For crack width, thresholds correspond to the maximum allowable values defined by exposure class under Eurocode standards. Carbonation depth thresholds are defined as the point at which the carbonation front reaches or exceeds rebar depth, triggering concern for passive layer breakdown. For creep and deflection, thresholds are based on normalized deformation ratios that reflect stiffness loss and perceptible displacement under long-term loads.

The methodology defines the Remaining Useful Life (RUL) of an element as the time remaining before any of its indicators surpasses its associated threshold. A worst-case logic is adopted: the earliest threshold crossing among the four indicators determines the RUL (Figure 4). This conservative approach ensures intervention planning is robust to the most vulnerable degradation mechanism, especially under uncertain input data. All thresholds are applied independently to avoid bias caused by correlated indicators or imbalanced weighting.

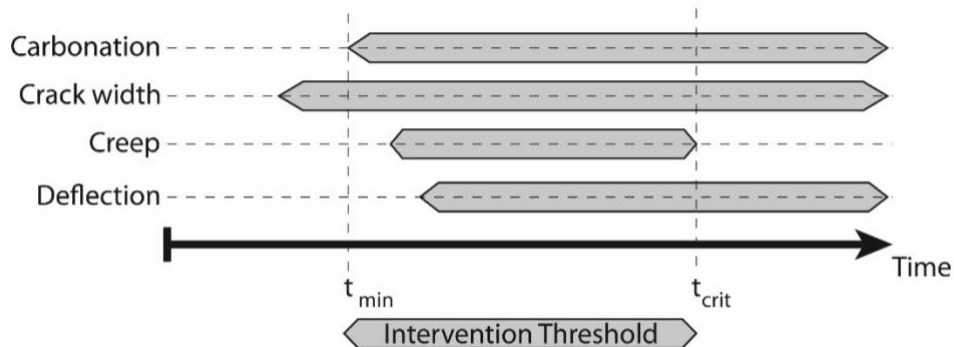


Figure 4: Intervention threshold.

Threshold values and their interpretations are summarized in Table 1, with associated equations and boundary conditions established in previous work (Fernández-Mora et al., 2025). Once thresholds are exceeded, the affected elements are queued for rehabilitation planning, which proceeds through multicriteria optimization detailed in the following sections.

Table 1: Intervention threshold values.

	MINIMUM DEGRADATION TIME (T _{MIN})	CRITICAL DEGRADATION TIME (T _{CRIT})
CARBONATION	Carbonation reaches rebar	$\Delta\phi_{max} > 5 \%$
CRACK WIDTH	0	-
CREEP	0.95 df (age)	df (age)
DEFLECTION	0.95 dL/500	L/500

2.5 Optimization functions

To generate efficient and stakeholder-sensitive rehabilitation schedules, this study combines structural deterioration modeling with a two-tier optimization approach. The first layer formulates a set of candidate intervention plans based on technical urgency, cost, and spatial clustering, performing a Cost-effective analysis (CEA). The second layer applies a multi-criteria decision-making (MCDM) method to select the most appropriate plan among the candidates.

Three optimization criteria were defined:

2.5.1 Economic cost function (C1)

The total cost (C_{Total}) includes structural rehabilitation costs (C_{rehab}) and indirect costs (C_{ind}), discounted over time using a standard factor. Indirect costs include expected loss of use, disruption, and social compensation.

2.5.2 Number of intervention phase (C2)

$$C_{tot} = \sum_1^{i=n_{phase}} \left[\sum_{i=1}^{i=n_{ele}} (C_{rehab} + C_{ind}) \right] \cdot \left(\frac{1}{(1+d)^t} \right) \rightarrow d: \text{discount rate } 3\% \quad (8)$$

The total number of intervention phases (n_{phase}) defined along the rehabilitation planning measures the disturbance to the neighbors. As every intervention will disrupt the lives of the building's inhabitants, it is preferable to minimize the number of interventions.

$$N = \sum n_{phase} \quad (9)$$

2.5.3 Proximity criteria (C3)

A secondary social criterion has been delineated to mitigate the impact on neighboring residents. The proximity criterion is assessed based on the aggregate distance (D) between the centroid of each elements (X_e, Y_e, Z_e) within each phase and the "critical element" ($X_{crit}, Y_{crit}, Z_{crit}$) of that phase. The critical element denotes the structural component that reaches a critical state during the specified phase. A shorter distance indicates closer proximity among elements and to the critical element, enhancing the efficacy of the criterion. This approach ensures that interventions are strategically planned to minimize inconvenience to residents while optimizing the effectiveness of the rehabilitation process.

$$D = \sum_1^{n_{phase}} \left(\sum \sqrt{(x_{crit} - x_e)^2 + (y_{crit} - y_e)^2 + (z_{crit} - z_e)^2} \right) \quad (10)$$

2.6 Definition of interventions

Once a structural element surpasses its degradation threshold, the methodology assigns one of three predefined intervention strategies based on the severity of the degradation, the degree of performance loss, and the cost-

effectiveness. These strategies are designed to reflect typical structural rehabilitation measures while aligning with real-world resource constraints and refurbishment practices.

2.6.1 Solution A – Surface sealing and protection

This is the least invasive option and is considered a temporary intervention. It is applied when degradation is identified early (e.g., visible cracking without significant corrosion or deformation). The primary objective is to slow the progression of deterioration by limiting exposure to aggressive agents. It includes surface sealants, protective coatings, and crack injection, and is appropriate for short-term stabilization pending full rehabilitation (Figure 5).

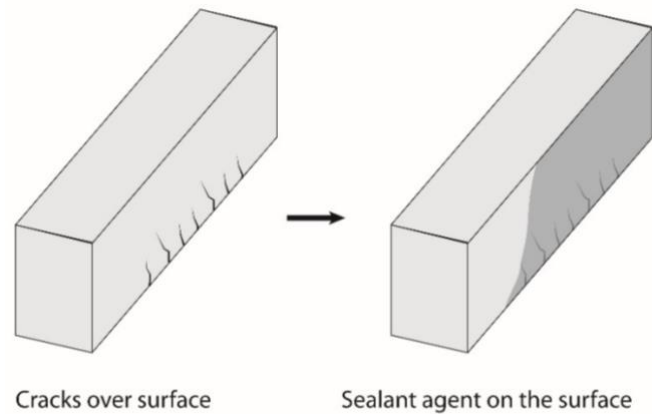


Figure 5: Solution for cracking.

2.6.2 Solution B – Localized rebar treatment and repassivation

This is a semi-permanent intervention designed to halt corrosion once it has initiated, but before significant section loss occurs. It includes the removal of concrete, cleaning or replacement of corroded reinforcement, and the application of corrosion inhibitors or repassivation agents. This solution addresses moderate degradation with targeted, mid-lifespan restoration (Figure 6).

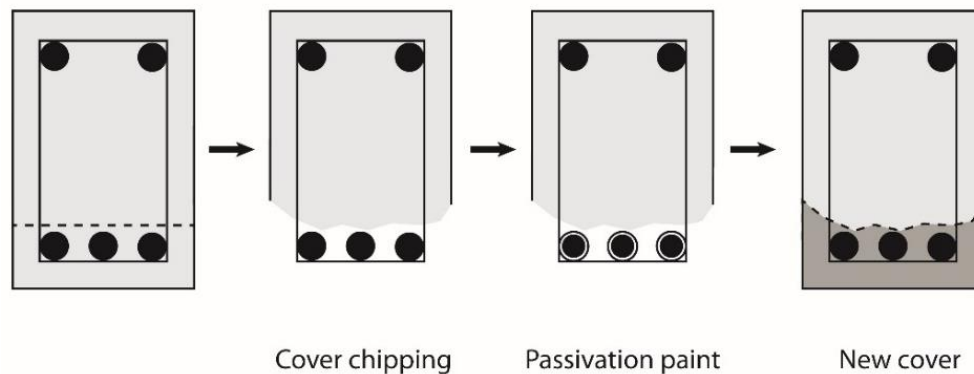


Figure 6: Building process for corrosion assessment.

2.6.3 Solution C – Structural strengthening

The most invasive and permanent intervention is applied when elements approach or exceed serviceability or ultimate limit states. It includes cross-sectional enlargement, external reinforcement, fiber-reinforced polymer (FRP) applications, or complete element replacement. This strategy restores both capacity and durability, extending life significantly but at a higher economic and operational cost.

The intervention selection is based on the indicator(s) triggering the RUL threshold, the severity of the predicted damage, and historical performance data (Figure 7).

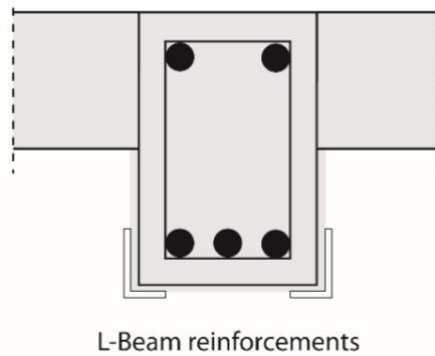


Figure 7: L-beam reinforcements for excessive deflection or creep.

Cost estimations are derived from the *Instituto Valenciano de la Edificación (IVE)* regional pricing database [IVE 2023], which provides unitary costs for refurbishment tasks commonly used in Spain. Each solution is assigned a base cost. Increased by 3% applied later during the multicriteria planning phase.

2.7 MCDM optimization

To support optimal decision-making in structural rehabilitation planning, the methodology incorporates a Multi-Criteria Decision-Making (MCDM) framework based on the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS). This allows candidate rehabilitation schedules to be evaluated against multiple, potentially conflicting criteria in a structured and repeatable way. Weights are found in Table 2.

TOPSIS was selected for its simplicity, transparency, and ability to handle normalized, weighted criteria without requiring extensive domain-specific tuning. Each intervention schedule is scored based on its Euclidean distance from the ideal and nadir solutions in the normalized criteria space, with stakeholder-defined weights applied to reflect project priorities.

Table 2: AHP scale weights for each criterion.

	Cost	Intervention	Proximity		w
Cost	1	1	5	1.71	0.48
Intervention	1	1	3.00	1.44	0.41
Proximity	0.2	0.33	1	0.41	0.11

3. DEVELOPMENT

3.1 BIM integration

The integration of the proposed tool into a Building Information Modeling (BIM) environment was carried out using Autodesk Revit®, which was selected due to its widespread adoption among project stakeholders and its dominance in the Spanish AEC market. Revit offers a robust application programming interface (API) that enables the development of customized workflows, making it suitable for integrating structural performance analysis and rehabilitation planning.

A key requirement for this tool is the ability to extract structural data from the BIM model, process it externally, and then reinsert the computed information in a usable and persistent format. To achieve this, the plugin relies on Revit's data infrastructure, specifically its parameter system and transactional capabilities.

In Revit, parameters serve as data containers associated with building elements. These can store various data types (e.g., numerical, Boolean, text) and are referenced using a unique element ID. Two types of parameters are used in this workflow:

- Built-in parameters: Native to Revit families and used to define intrinsic properties such as dimensions and material.
- Shared parameters: User-defined and project-wide, these allow the plugin to store and propagate analysis results across multiple models and disciplines. Shared parameters enable seamless access by other tools or project participants, supporting consistent BIM interoperability.

Transactions in Revit represent atomic operations in which data is read from or written to the model. Due to API restrictions, the tool is designed to perform only one data export and one data import per session. During execution, the plugin scans all structural elements, records their Unique IDs, and extracts relevant durability and performance information. After analysis, the results are written back into the model using the duplicate IDs, ensuring accurate element-level mapping and traceability.

This Revit-based implementation enables automated performance tracking and decision-support integration directly within the BIM workflow, facilitating scalable application across real-world building models.

3.2 Development of the algorithm

The developed plugin, Endurify 2.0, implements the complete structural degradation analysis and rehabilitation planning workflow within a BIM-integrated environment. The algorithm is structured into three main stages (Figure 8): (1) data extraction, (2) degradation assessment, and (3) planning and reintegration.

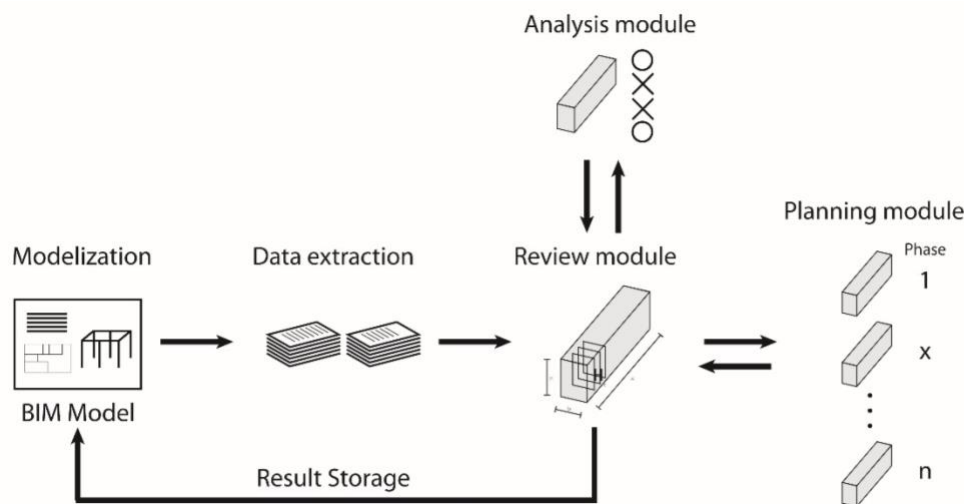


Figure 8: General Endurify 2.0 workflow for durability analysis and intervention plan.

In the first stage, the plugin initiates by extracting relevant data from all structural elements within the Revit model. Each element is identified by its unique ID, and its geometric and parametric attributes are retrieved for further analysis. This process requires the BIM model to reach a minimum Level of Development (LoD) of 250–300, which ensures that structural components are sufficiently defined and annotated with degradation-related information. Although this is lower than typical final LoD standards (400–450), it is sufficient for initiating predictive assessments.

The second stage involves per-element evaluation. Each structural component is analyzed individually to ensure traceability and user oversight. The plugin provides a structured interface where the degradation indicators (cracking, carbonation, creep, and deflection) are introduced or verified, and where users can confirm or adjust imported data. This ensures transparency and mitigates the “black-box effect” commonly associated with Building Performance Simulation (BPS) tools. For each indicator, the tool computes three outputs: (1) current preservation

state, (2) time to reach the predefined threshold, and (3) time to reach a critical condition. Elements that have not yet reached the intervention threshold are retained for comparison in a centralized planning matrix.

The final stage of the algorithm involves generating rehabilitation plans. Based on the temporal degradation forecasts, Endurify 2.0 partitions interventions into discrete phases aligned with predicted failure timelines. A pool of alternative rehabilitation schedules is generated by varying execution timing and grouping strategies. Each schedule is evaluated against three optimization criteria: economic cost, the number of intervention phases, and social impact (defined by proximity to residential units). The multicriteria decision-making (MCDM) algorithm is then applied to select the optimal rehabilitation strategy.

Once the optimal plan is identified, the tool writes the results back into the BIM model. Output values include the assigned intervention phase, estimated repair cost, and Boolean indicators for each degradation state. This structured reintegration ensures that the rehabilitation data is preserved in the digital model and accessible for downstream decision-making, stakeholder review, or facility management.

4. DISCUSSION

4.1 Case study

To evaluate the practical functionality and methodological consistency of the developed tool, a representative BIM model of a reinforced concrete residential building was constructed in Autodesk Revit® (Figure 9). The model is not based on an existing structure but was digitally designed to reflect common mid-rise residential typologies in the Spanish built environment. The design criteria are presented in Table 3. Its purpose is to serve as a controlled testbed for validating the plugin’s end-to-end automation — from degradation indexing and analysis to planning and BIM-level reintegration.

Table 3: Structural elements in the model.

	Width (<i>w</i>) mm	Height (<i>h</i>) mm	Cover (<i>c</i>) mm	Superior rebars	Inferior rebars
Beam 1	500	300	35	4Ø12	7Ø20
Beam 2	300	300	35	2Ø12	3Ø16
Beam 3	200	300	35	2Ø12	3Ø12

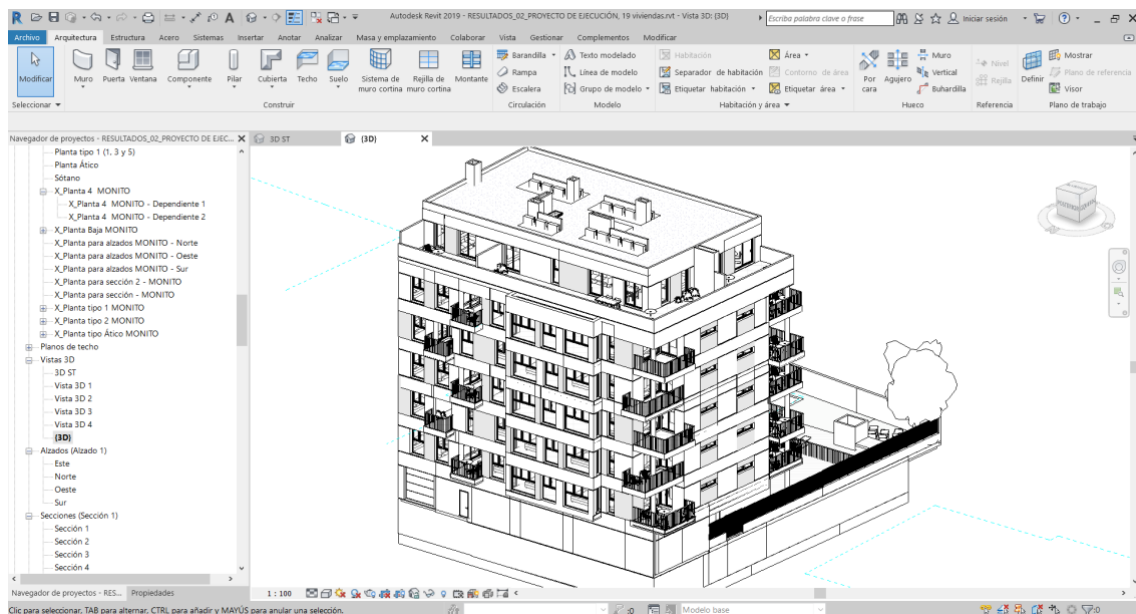


Figure 9: Case study building inside Autodesk Revit® interface.

The structural system consists of 191 beams. Degradation indicators were synthetically assigned to each element to emulate realistic deterioration scenarios. These values were not derived from field inspection. However, they were instead manually input using Revit shared parameters, based on degradation patterns established in the authors' prior research on damage indicators and RUL estimation. The objective was to ensure a consistent, diverse dataset that could be used to rigorously test the plugin's logic across a wide range of degradation states.

The analysis workflow proceeded as follows:

- Each element was individually assessed by Endurify 2.0, computing its degradation state across four indicators (cracking, carbonation, creep, and deflection).
- For each indicator, the tool calculated three outputs: current condition, time to threshold, and time to critical failure (Figure 11).
- Elements exceeding thresholds were automatically queued for intervention planning.

Of the 191 elements, 72 required some form of rehabilitation (Figure 10). The plugin assigned interventions based on damage severity and temporal priority, grouping them into phased action plans. A total of 3,715 valid intervention schedules were generated using combinatorial planning logic. Each schedule was evaluated using three criteria: total cost, number of interventions, and estimated disruption based on proximity to the site.

Add	GUID	Carbonatacion	Fisuracion	Fluencia	Deformación	Coste	Tiempo	Carbonatacion Int	Fisuración Int
+	2075784	Si	Si	No	No	€		0	0
+	2076646	Si	Si	No	No	€		0	0
+	2076683	Si	Si	No	No	€		0	0
+	2076715	No	No	No	No	€		4.12	0
+	2076747					€			
+	2076773					€			
+	2076834					€			
+	2076851					€			
+	2076868	No	No	No	No	€		10.98	0
+	2076885					€			
+	2076925					€			

Figure 10: GUI Durability analysis tool after data extraction.

The MCDM framework ranked all candidate plans using the AHP-derived weights and the TOPSIS decision method. The top-ranked plan reduced intervention cost by 15.16% and proximity impact by 10.46% compared to a conventional manual scheduling approach defined by a domain expert.

All results were written back into the BIM model through shared parameters. Element views were filtered and color-coded by intervention phase and damage state, allowing professionals to visualize and review the recommended strategy within the Revit environment.

This case study demonstrates the feasibility of embedding structural lifecycle analytics, predictive degradation modeling, and multicriteria planning into a single BIM-integrated toolchain. While based on a simulated degradation dataset, the workflow is fully replicable on real building models using the same plugin structure.

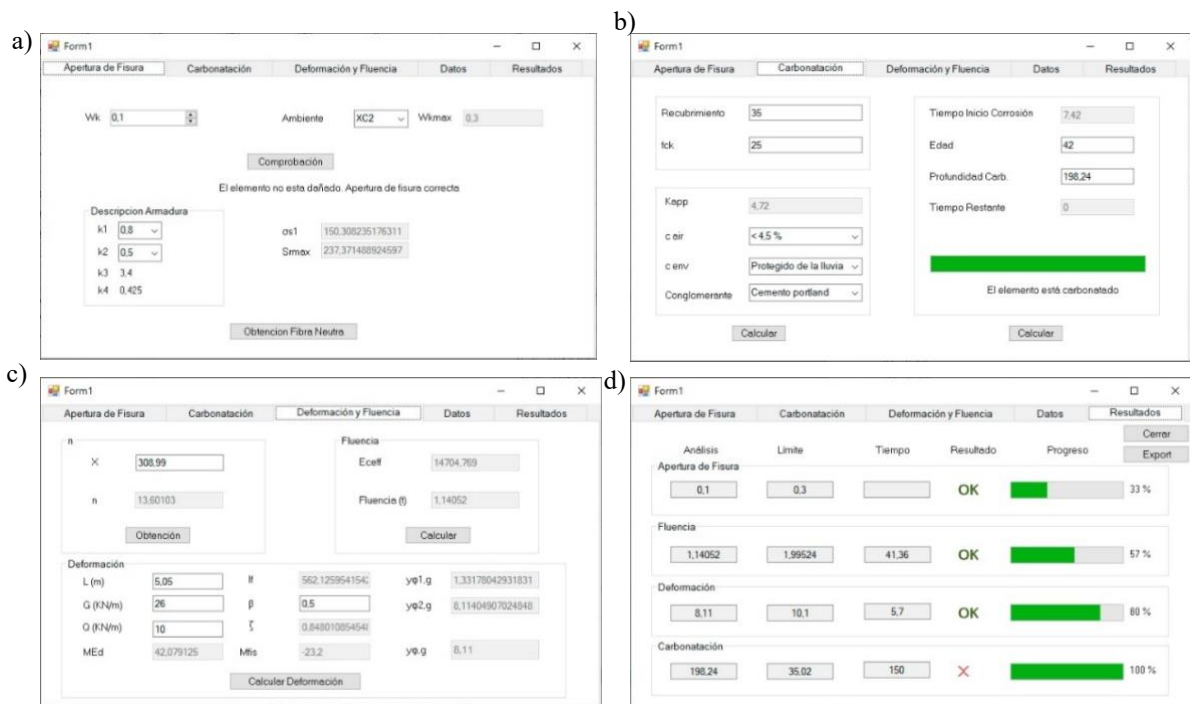


Figure 11: Individual analysis window a) Longitudinal crack b) Carbonation c) Creep and deflection d) Results.

4.2 Comparison with professional evaluation

To assess the added value of the proposed methodology, the plan generated by Endurify 2.0 was compared against a rehabilitation strategy manually developed by a structural engineering professional. The professional was instructed to group the 72 critical elements into logical intervention phases, using only visual inspection of the BIM model and degradation metadata provided via shared parameters. No access was granted to the automated tool, ensuring an unbiased baseline reflective of expert practice. The criteria followed by the professional in developing the strategy are summarized in Table 4.

Table 4: Criteria used to determine the need of intervention in the structural elements.

PHASE	CRITERIA	TIME SPAN
Phase 1 (P1)	<ul style="list-style-type: none"> Crack width ≥ 0.3 mm. Deflection $\geq L/500$ 	Immediate
Phase 2 (P2)	<ul style="list-style-type: none"> Crack width ≥ 0.3 mm. Exposure to the exterior environment (carbonation depth ≥ 99.08 mm.) 	20 years
Phase 3 (P3)	<ul style="list-style-type: none"> Other elements 	Not in need of intervention

Both plans were evaluated using the same three decision criteria: total cost, number of intervention events, and proximity-based social impact. The cost model was standardized using unit values from the *Instituto Valenciano de la Edificación (IVE 2023)*, while proximity impact was measured using the same centroid-based metric employed in the automated optimization.

Table 5 presents a comparative analysis of the two rehabilitation planning strategies. While the professional plan involved fewer intervention phases by default, it lacked analytical support to determine the optimal scheduling of those interventions. In contrast, the MCDM-based approach employed by Endurify 2.0 integrates both structural urgency and spatial-social considerations, enabling a more balanced and data-driven outcome. The optimization process yielded improvements across all criteria, reinforcing the value of computational support in complex planning scenarios. Specifically, the automated plan achieved:

- A 15.16% reduction in total rehabilitation cost
- A 10.46% reduction in cumulative spatial impact on households

These improvements stem from the tool’s capacity to identify latent optimization opportunities in the degradation timelines—grouping interventions not only by severity, but also by projected urgency and cumulative disruption metrics.

GUID	Coste	T. Mínimo	T. Crítico	Fase
2075784	724.68	0	41,41	1
2076646	1268,27	0	0	0
2076683	2002,91	0	41,41	2
2076715	960,73	0	0	0
2076747	1674,8	0	41,41	2
2076773	154,43	0	0	0
2076834	96,63	0	0	0
2076851	79,39	0	0	0
2076868	498,04	0	0	0
2076885	26,85	0	0	0
2076925	431,7	0	41,41	1
2076955	476,85	0	41,41	0
2076981	476,58	0	41,41	1
2077010	428,26	0	41,41	3
2077082	136,99	9,07	41,41	1

Figure 12: Intervention plan window.

Table 5: Results from the optimization criteria comparison.

Endurify 2.0 MCDM results							
Phase 0		Phase 1		Phase 2		Total	
Cost	Proximity	Cost	Proximity	Cost	Proximity	Cost	Proximity
31.653,31 €	4645,09 m.	5.124,65 €	1488,46 m.	1.445,17 €	351,17 m.	38.223,13 €	6133,55 m.

Professional planing results							
Phase 0		Phase 1		Phase 2		Total	
Cost	Proximity	Cost	Proximity	Cost	Proximity	Cost	Proximity
34.003,26 €	5029,55 m.	10.013,68 €	1469,51 m.	- €	0,00 m.	44.016,94 €	6850,22 m.

Comparison							
Phase 0		Phase 1		Phase 2		Total	
Cost	Proximity	Cost	Proximity	Cost	Proximity	Cost	Proximity
-7,42 %	-7,64 %	-95,40 %	-1,29 %	-100,00 %	-100,00 %	-15,16 %	-10,46 %

As shown in Figure 12, the plugin-selected plan features fewer, better-timed clusters of repairs, reducing both mobilization requirements and tenant disturbance. The expert-defined plan, although technically feasible, resulted in a higher cost and social impact due to a more reactive grouping strategy, which was primarily based on observed damage levels.

This comparison highlights the tool’s potential to help professionals develop more cost-effective and socially responsible strategies, particularly when managing large portfolios or operating under resource constraints.

4.3 Designing for durability

To investigate the impact of design-phase decisions on long-term structural durability, a parametric analysis was conducted on a set of 250 synthetically generated beam elements. These elements were configured to meet the same service load requirements as the building used in the case study and were fully compliant with applicable structural codes. The software could also work under new load demands in all or part of the elements to adapt the building to a different use. Each beam varied across several geometric and reinforcement-related parameters, as summarized in Table 6.

Table 6: Design parameters for the random set.

Parameter	Minimum value	Maximum value
Span length (m)	4.5	6.5
Width (m)	0.3	0.75
Height (m)	0.3	0.65
Cover (mm)	5	55
Number of inferior rebars	2	7
Ø inferior rebars	8	25
Number of superior rebars	2	7
Ø superior rebars	8	25

All generated elements were assigned plausible degradation profiles, and Boolean damage outcomes (presence or absence) were computed for four indicators: carbonation, crack width, creep, and deflection. A Pearson correlation analysis was then performed to assess associations between design parameters and damage occurrence. Results are shown in Table 7.

Table 7: Pearson correlation among design parameters and damage index. (*) indicates correlation.

	Carbonation	Crack Width	Creep	Deflection
Span length (L)	-0.022	0.06	-0.013	0.21*
Width (w)	-0.017	-0.002	-0.107	-0.086
Height (h)	0.073	0.036	0.021	-0.382*
Cover (c)	0.241*	-0.023	-0.321*	0.065
Span/height ratio (L/h)	-0.078	0.011	-0.018	0.436*

The analysis highlights several design-sensitive trends:

- Concrete cover is positively correlated with protection against carbonation and negatively correlated with creep, suggesting its dual role in durability performance.
- Deflection behavior is highly sensitive to geometric configuration, particularly the span-to-height ratio and absolute element height.
- Crack width, by contrast, showed minimal correlation with any individual design parameter, implying a stronger dependency on service conditions or material properties.

While specific correlations are statistically meaningful, the absence of strong predictive relationships for several indicators reinforces the importance of environmental exposure and maintenance regimes in determining long-term performance. Design alone appears insufficient to halt degradation once it has been initiated.

In this preliminary study, damage indicators were modeled as Boolean variables (i.e., present or absent). Future work should consider developing continuous severity scales to enable finer-grained analysis and potentially inform prescriptive design guidelines. Such extensions could also enhance the potential for integration into early-stage design decision-support tools within BIM environments.

4.4 Advantages of BIM implementation

The integration of the proposed methodology within a Building Information Modeling (BIM) environment yields several notable advantages in the context of structural durability analysis and rehabilitation planning.

4.4.1 Data reuse and process efficiency

By operating entirely within the BIM environment, Endurify 2.0 eliminates the need for redundant data transfer between software platforms. All relevant structural data—geometrical properties, degradation indicators, and material attributes—are extracted directly from the existing model and re-integrated after analysis. This reduces manual input errors and significantly shortens processing time, especially in large-scale or legacy projects where re-modeling can be prohibitive.

4.4.2 Centralized coordination and error minimization

BIM acts as a unified data source that synchronizes multiple analyses and stakeholders. Rehabilitation planning often involves diverse disciplines, structural engineers, sustainability consultants, and building managers, and requires consistency across tools. By embedding the plugin directly within Revit, the analysis draws from a single verified model, ensuring data coherence and reducing inconsistencies between separate tools or phases.

4.4.3 Lifecycle integration and multi-domain compatibility

While the focus of this study is on structural rehabilitation, BIM provides a natural platform for integrating additional performance domains such as energy efficiency, acoustic comfort, or indoor air quality. This interoperability supports the development of holistic refurbishment strategies aligned with long-term lifecycle and sustainability goals. The tool's results—intervention phases, RUL predictions, and cost parameters—can coexist alongside other analysis layers, enhancing decision-making transparency.

4.4.4 Visualization and stakeholder communication

The 3D nature of BIM facilitates visual tracking of structural condition and intervention schedules. By encoding the results as shared parameters, professionals can use standard view filters, legends, and color mapping to visualize deterioration states and repair timing within the model. This enhances communication with non-technical stakeholders, such as building owners or residents, who benefit from intuitive graphical outputs rather than technical reports alone.

In sum, BIM not only supports the execution of structural analysis but also enhances the interpretability, transparency, and replicability of rehabilitation workflows. The embedding of Endurify 2.0 into the BIM environment positions it as a practical and scalable solution for real-world refurbishment projects.

The combined implementation of structural degradation modeling, intervention prioritization, and multicriteria planning within a BIM-integrated environment demonstrates the potential of Endurify 2.0 to bridge the gap between predictive diagnostics and actionable rehabilitation strategies. Each component—damage indicator analysis, RUL estimation, stakeholder-sensitive optimization, and 3D reintegration—contributes to a comprehensive workflow that extends beyond technical performance to support transparent, data-driven decision-making. The case study confirms the tool's capacity to generate cost-effective and socially considerate plans while reducing manual coordination effort. Moreover, the durability simulations and plugin architecture highlight the value of early-stage design feedback loops and standardized parameterization. This work positions BIM not merely as a modeling tool, but as a decision-support ecosystem capable of guiding refurbishment across the full lifecycle of existing buildings. Future adaptations could extend the tool's reach by integrating uncertainty modeling, broader performance domains (e.g., energy, comfort), or stakeholder feedback systems.

5. CONCLUSIONS

This work presents a practical, replicable methodology for assessing and extending the structural lifespan of existing buildings by developing the Endurify 2.0 plugin. By automating structural damage assessment, Remaining Useful Life (RUL) estimation, and multicriteria planning within a BIM-based workflow, the tool supports a transparent, automated decision-making process for building refurbishment. This research shows that structural maintenance scheduling can be automated and enhanced using BIM-based tools.



The proposed methodology contributes to both scientific and professional practice. Technically, it demonstrates how degradation indicators can be extracted and modeled within a standardized Revit environment. The planning component provides an optimized intervention schedule based on predefined social, economic, and operational criteria using MCDM techniques. These results are embedded directly into the BIM model, enabling professionals to visualize and communicate planning outcomes to all stakeholders and making it compatible with Digital Twins technology.

Practically, the tool offers an approach aligned with current needs in sustainable construction: promoting building reuse, enabling early detection of deterioration, and facilitating maintenance strategies that consider technical, economic, and social impacts. Its alignment with BIM best practices ensures compatibility with existing AEC workflows, while its modular design enables future extension and expansion.

Future developments may include automating visual inspection using computer vision or sensor data, as well as enhancing decision-making algorithms to account for uncertainty, regulatory constraints, and broader lifecycle objectives. These improvements could further align the tool with circular economy principles and long-term building resilience planning.

5.1 Towards scientific rehabilitation

The rehabilitation of existing structures remains one of the most technically and socially complex challenges in the Architecture, Engineering, and Construction (AEC) sector. Unlike new construction, refurbishment projects often lack reliable data, suffer from inconsistent planning methods, and rely heavily on expert intuition. As the built environment continues to age, there is a growing need to move beyond ad hoc interventions toward a framework of scientific rehabilitation—defined as the integration of standardized diagnostics, performance-based decision models, and digital traceability into building maintenance and recovery workflows.

This work contributes to that vision by operationalizing and automating structural degradation indicators, embedding decision-support logic within BIM environments, and enabling automated, criteria-driven scheduling of interventions. By structuring rehabilitation as a repeatable and traceable process—rooted in data, coordinated through interoperable models, and optimized using formal multicriteria methods—Endurify 2.0 takes a tangible step toward a standardized, scalable approach to building lifecycle extension.

Scientific rehabilitation implies more than computational efficiency; it requires the convergence of digital modeling, automation, engineering heuristics, stakeholder negotiation, and long-term performance forecasting. It calls for a shift in mindset—from isolated repairs to strategic preservation of buildings. Future work should extend this paradigm to other domains, including energy retrofitting, accessibility upgrades, and resilience planning, ensuring that refurbishment is not only reactive but also anticipatory and evidence-based.

CONFLICT OF INTERESE

On behalf of all authors, the corresponding author states that there is no conflict of interest.

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