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Automatic Calibration of Structural Damage in Building Information Modeling Models with Robotic Process Automation

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ABSTRACT

Building information modeling (BIM) enables the integration of multidisciplinary data into detailed three-dimensional structural models. However, accurately capturing the mechanical behavior of real-world structures requires the calibration of these virtual models with *in situ* measurements, particularly to reflect damage-induced changes that influence safety and structural integrity. Traditional calibration workflows rely heavily on the manual updating of structural databases and parameter assignments, which are time-consuming, prone to human error, and lack scalability. This study presents, for the first time, a robotic process automation (RPA)-based workflow for automating the integration of corrosion-related damage into structural BIM models. A bridge structure serves as a demonstrative case. However, the proposed methodology is not confined to bridge engineering. The underlying framework is broadly applicable to a wide range of civil infrastructural assets including buildings, tunnels, retaining walls, and industrial facilities. Beyond damage integration, the proposed RPA-based approach can be extended to automate various repetitive and error-prone tasks related to design, maintenance, and operation, such as model updating, inspection data extraction, documentation management, and multidisciplinary workflow coordination, thereby enhancing the efficiency and reliability throughout the lifecycle of infrastructure. Steel bridges affected by corrosion damage were selected as representative case studies because of their vulnerability to environmental exposure, labor-intensive nature of frequent inspections, and digital model updates. The structural and geometric complexities of bridges, combined with available on-site inspection data, provide a challenging yet realistic scenario for validating the performance and robustness of the proposed automation strategy. A case study involving a real footbridge validated the effectiveness of the RPA tool and demonstrated significant improvements in efficiency, accuracy, and repeatability compared with conventional manual methods. This study presents a novel and scalable application of RPA in structural BIM calibration, offering a practical, low-risk solution to enhance digital twin fidelity and structural health monitoring across diverse civil infrastructure sectors.

1. Introduction

Building information modeling (BIM) has emerged as a transformative methodology in the architectural, engineering, and construction (AEC) sector [1]. BIM enhances the coordination among stakeholders by integrating three-dimensional (3D) models that capture geometric and spatial data related to buildings and civil infrastructure, along with multidisciplinary information stored in databases. By integrating a 3D virtual model with databases, BIM is a comprehensive information repository, enabling enhanced data-driven analysis and decision-making. This integration enables the association of specific attributes and properties with elements within the 3D model. The main benefits of the BIM methodology are detailed in Ref. [2] and include enhanced scheduling, improved sequence coordination, enhanced visualization capabilities, increased productivity, and reductions in both error and cost.

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BIM is based on a federated approach that integrates multiple discipline-specific models into a single, cohesive, virtual, and holistic representation of a construction project [3]. Federated models serve as a central hub for all project stakeholders, including owners, architects, engineers, contractors, subcontractors, and suppliers, to collectively contribute to a synchronized environment. This ensures that all components of a construction project are properly integrated and coordinated, resulting in more successful project outcomes. This integration fosters improved communication, reduces errors, streamlines workflow, enhances the overall efficiency of a project, and facilitates sustainability assessment [4]. During the design phase, this integration enables stakeholders to work with interdisciplinary information, improve error detection, and enhance the design quality. During the construction phase, project management involves tracking resources, schedules, and progress. When the project transitions to the operation and maintenance phases, a connected BIM provides detailed information on systems and components, such as material properties, cost estimates, maintenance records, and performance data, facilitating informed decision-making. For example, a bridge model linked to a structural analysis database, as proposed in this study, can automatically update its structural response based on simulations, thereby enhancing its structural safety. Furthermore, Atencio et al. [5] expanded BIM databases by incorporating weather data specific to the physical location of a building to improve maintenance decisions. In renovation projects, connecting BIM models with multidisciplinary databases enables the analysis of historical data along with current models, thereby supporting the planning of effective upgrades. Bertin et al. [6] developed a databank linked to BIM models to facilitate the reuse of load-bearing structural elements. Finally, in asset management and disaster response, this integration is invaluable for prioritizing repairs. For example, Xu et al. [7] utilized the level of development (LOD) in BIM models to assess seismic losses in buildings. However, as highlighted by Bellido-Montesinos et al. [8] and Muller et al. [9], challenges related to interoperability have frequently emerged in various disciplines. For example, Shoieb et al. [10] developed a web-based converter to enable connectivity among structural analysis applications, Hu et al. [11] enhanced the interoperability between architectural and structural design models, and Lee et al. [12] proposed validation methods to ensure the interoperability of data exchange in BIM models.

To simulate the response of a real-world structure accurately, its BIM structural model must account for the impacts of on-site pathologies. Among the most prevalent pathologies encountered in structures, two noteworthy examples are the corrosion of metal elements and cracks in concrete. Corrosion results in mass reduction [13] and alters both the mechanical and material properties of the structural elements [14]. Numerous studies have been conducted on corrosion, including those by Komary et al. [15], who reviewed corrosion monitoring technologies; Fernandez et al. [16], who investigated the structural effects of corrosion on reinforced concrete members; François et al. [17], who analyzed the impact of corrosion on reinforced concrete beams; and Hou et al. [18], who examined the effects of corrosion on the mechanical properties of buried pipes. Excessive cracks in concrete also diminish the flexural stiffness of load-bearing elements. Mohd et al. [19] explored the effects of cracking on the lateral response of concrete buildings, Li [20] studied the serviceability performance of corrosion-affected concrete structures, and Chen et al. [21] examined crack detection in wading-concrete structures using water irrigation and electric heating. These and other studies illustrate the need for ongoing research and practical solutions to mitigate the adverse effects of structural pathologies and ensure the safety and durability of infrastructures.

The structural properties of a BIM model must be calibrated to accurately replicate the true behavior of a civil infrastructural asset. This calibration ensures that the mechanical properties, such as cross-sectional areas and moments of inertia, are adjusted to reflect the diminished values resulting from damage or deterioration observed on-site.

The calibration of structural parameters, such as axial or flexural stiffnesses, is traditionally performed using structural system identification (SSI) techniques based on the static [22,23] or dynamic [24] structural responses measured on-site. SSI methods play a crucial role in the field of civil engineering because they enable the early detection, localization, and/or quantification of structural damage [25] to prevent potential failures and ensure the long-term safety of structures. SSI tools are widely used to assist in the maintenance of decision-making processes. Overviews of some of the most common SSI methods and future trends in the field are presented in Refs. [26,27], respectively.

Most existing SSI methods operate with their own independent structural models, which are seldom integrated with the BIM methodology. Such studies have primarily focused on calibrating the mechanical and material properties of a structural model exported from a BIM model. For example, Bouzas et al. [28] addressed the calibration of the stiffness degradation resulting from corrosion in a steel bridge. In their study, Bouzas et al. [28] began by exporting the BIM model to ANSYS, a dedicated structural software program. Subsequently, they utilized an optimization algorithm to update the steel plate thicknesses within the structural model, aiming to minimize the discrepancy between the predicted dynamic response and observed behavior.

Osadcha et al. [29] presented a comprehensive literature review of studies proposing geometric parameter updating in virtual models and indicated that the three prominent research directions in these fields are bridge inspection [30], monitoring of structures in seismically active regions [31], and industrial facility monitoring [32]. Other studies focused on other aspects. For example, Mahami et al. [33] developed structural models from point cloud data with the "scan to finite element model (FEM)" approach. Li et al. [34] introduced pictures of cracks identified using machine learning processes into BIM software. Ritto and Rochinha [35] explored the integration of physics-based models with a machine learning classifier. Jeon et al. [36] developed digital twins for the maintenance of prestressed concrete bridges, and Loverdos and Sarhosis [37] used digital twins to document and structurally assess masonry structures.

Despite its importance, the calibration of BIM structural parameters has not yet been addressed in the literature. Furthermore, the interoperability challenges among BIM software necessary for this calibration process have not been studied. The calibration process typically involves manual operations, such as modifying predefined structural databases and updating the properties of damaged elements. However, this manual approach introduces complexities and potential inaccuracies. Consequently, automated solutions that streamline and enhance the calibration process, ensuring the efficient and accurate integration of calibrated properties into BIM models, are urgently required. Visual programming tools, such as Dynamo, an extension of Autodesk's design, are commonly used to enhance interoperability, introduce information into the BIM model, and update the BIM database. The state-of-the-art use of Dynamo in civil engineering applications is presented in Ref. [38]. Atencio et al. [39] proposed the use of Dynamo to address the interoperability challenges in the BIM-based design of domestic drinking-water and sewerage systems. Sanseverino [40] employed Dynamo to calibrate damage indexes obtained from visual inspections of bridge elements, and Kensek [41] integrated environmental measurements from low-cost sensors into BIM models using Dynamo. Alothaimeen et al. [42] connected BIM models with multi-objective optimization tools, Lozano et al. [43] used Dynamo to link BIM models with the sustainability assessment of bridges, Liu et al. [44] used Dynamo to connect BIM models with steel fabrication machine codes, Wang et al. [45] developed a BIM platform to automate the assembly of steel structures, and Elghaish et al. [46] automated the management of BIM data using an artificial intelligence (AI) voice assistant. The state-of-the-art of interoperability problems between BIM models is reviewed in Ref. [47]. Specific tools for automating the calibration of BIM structural models are not available in the literature.

Robotic process automation (RPA) is a promising alternative to visual programming tools for calibrating BIM model properties. RPA is a software technology that uses robots or "bots" to automate repetitive, rule-based tasks by mimicking human interactions with digital interfaces. It operates through a series of predefined logical instructions, enabling bots to execute actions, such as clicking, typing, searching, and transferring data across software platforms without human intervention. This technology is based on the following principles: ① user interface (UI) integration: RPA bots are engineered to function at the UI level, enabling them to interact with existing software application interfaces. This interaction does not necessitate altering the underlying software code, making it a noninvasive automation solution. ② Instruction-based operations: RPA models can be programmed to execute a predefined set of instructions that mimic the actions that a human would perform, such as clicking, typing, searching, and transferring data from one place to another. ③ Scripting and configuration: RPA bots include scripting and configuration capabilities that empower users to outline a series of steps and apply logical rules. This structured framework supports the automation of specific tasks, thereby streamlining the processes and improving efficiency. RPA utilizes rules and activity structures to automate tasks traditionally performed by humans, replicating the same UI interactions as a human operator [48]. By emulating these activities, RPA offers enhanced efficiency, reduced errors, and increased productivity [49]. The key benefits of RPA lie in its ability to automate repetitive rule-based tasks using low-complexity programming techniques [50,51]. A detailed comparison of RPA with alternative automation tools is presented in Section 4.1.

RPA technology is well established in several sectors, such as banking, healthcare, and manufacturing. The inherent characteristics of AEC workflows—complex information exchange, reliance on multiple software platforms, and frequent manual data manipulation—make this sector particularly well-suited to benefit from RPA integration. However, the integration of these protocols into the AEC industry remains limited. To date, only three studies have explored the use of the RPA in this field. Atencio et al. [52] employed RPA tools to automate the data management processes associated with low-cost sensor systems, demonstrating the potential of RPA for efficiently handling repetitive data-transfer tasks in structural monitoring. Jiang and Ling [53] proposed the use of RPA for remote and automated operation and maintenance of smart building equipment rooms, illustrating its capacity to optimize digital workflows in facility management. Recently, Atencio et al. [3] developed an RPA-based framework to integrate real-time weather data into BIM environments, enabling automatic hazard alerts and decision-support functionalities. This limited number of studies in the AEC field suggests not a lack of relevance but rather an unexplored research opportunity.

The aforementioned studies share with the present work the common objective of using RPA tools to automate digital processes by interfacing with multiple software platforms, thereby reducing the need for complex programming or direct application programming interface (API) integration. In contrast, this study introduces the first application of RPA to update the mechanical properties of structural elements directly within a BIM-structural analysis environment. This implementation extends beyond the automation of data management or environmental monitoring tasks by addressing the more advanced process of automated calibration of structural stiffness within a structural analysis platform while maintaining full compatibility with the BIM environment. The results demonstrate the potential of RPA to enhance the efficiency and reliability of BIM-based structural workflows while also raising awareness and fostering the adoption of RPA technologies in AEC applications.

The principal contribution of this study lies in extending RPA to the automation of structural model calibration within BIM-based environments, a field that has not yet been explored. The developed RPA tools automate the generation of new sections in the structural database and assignment of updated stiffness properties to damaged elements, enabling a seamless and repeatable calibration workflow. This automation significantly enhances the accuracy, efficiency, and reliability of processes that are typically labor-intensive and prone to human error. Although demonstrated on a steel bridge affected by corrosion-induced stiffness reduction, the proposed methodology is scalable and adaptable to a wide range of architectural and civil infrastructure assets. Furthermore, its modular design enables the protocol to be readily extended to other structural pathologies that involve reductions in the cross-sectional stiffness or mechanical properties (such as concrete cracking).

Beyond its practical implementation, this study also provides a conceptual contribution by positioning RPA as a low-code automation bridge between BIM and structural analysis tools, thereby improving the interoperability across digital platforms. This establishes a new paradigm for integrating automated data-driven calibration processes into digital twins, with significant potential for addressing diverse challenges in structural assessment, monitoring, and maintenance within civil engineering applications.

The proposed tool also demonstrates the potential of integrating SSI results into BIM models, improving interoperability, and supporting data-driven decision-making in maintenance and asset management. To validate the developed tool, we present a case study involving the calibration of the mechanical properties of a real steel bridge. In addition, the underlying RPA-based approach can be extended to automate a range of BIM-related tasks, such as model updating, inspection data integration, documentation management, and the coordination of multidisciplinary workflows. These capabilities align with emerging trends, such as BIM bots [54], which leverage AI and automation to enhance lifecycle management in civil infrastructure. Given the absence of equivalent methods to automate corrosion damage integration in the literature, conducting a direct comparative study was not feasible within the scope of this study.

The proposed workflow integrates three software platforms: two commercial software platforms, Autodesk Revit and Robot Structural Analysis (Autodesk, Inc., USA), hereinafter referred to as Revit and Robot, and one freely available RPA tool (UiPath Inc., USA). The selection of commercial software was deliberate, as both Revit and Robot are among the most widely adopted platforms for architectural and structural BIM workflows in professional practice and academic research. Their inclusion ensures that the proposed methodology is compatible with current industry standards and relevant to the workflows commonly employed in the AEC sector.

Despite belonging to the same Autodesk ecosystem, Revit and Robot offer limited native capabilities for automating structural calibration tasks, particularly when incorporating stiffness reductions derived from *in situ* inspection or monitoring data. This limitation motivated us to integrate RPA into the proposed framework. In this study, the implementation of the RPA tool constituted the core contribution and generalizable component of the methodology. Hence, the freely available software UiPath was selected.

The developed RPA-based protocol can be readily adapted to other software environments or structural analysis platforms, enabling the application of the same automation principles to a wide range of tasks involving the calibration or updating of BIM-based structural models. Therefore, although the case study employed commercial Autodesk products for demonstration purposes, the methodology itself is platform-independent and can be extended to open-source or alternative commercial software with only minor adaptations depending on the UI.

The remainder of this study is organized as follows: Section 2 presents the research methodology adopted in this study. Section 3 provides a comprehensive explanation of the identified problems associated with calibrating structural parameters in BIM models. Section 4 presents the utilization of RPAs for automatic calibration of structural damage in BIM structural models. This process involves modifying structural databases to incorporate new steel elements with updated mechanical properties and changing the element types of the BIM structural model to align its mechanical response with that observed in the physical asset. Section 5 presents a case study involving the calibration of structural parameters in a BIM model through *in situ* inspections. Finally, Section 6 presents the main conclusions of this study.

2. Research design and methodology

The research design of this study follows the design science research method (DSRM) outlined in Ref. [55], incorporating modifications recommended by Wieringa [56] and Peffers et al. [57]. This methodology is delineated according to the stages, goals, activities, and deliverables presented in Fig. 1.

As shown in Fig. 1, the research method is structured into four sequential stages:

(1) **Stage 1: state-of-the-art review.** This stage aims to identify gaps in existing literature and justify the need for an automated approach to calibrate structural BIM models. It begins with a systematic review of the calibration methods for BIM models and the prevalent automation tools. Following a comparative analysis, RPA is selected as the preferred automation tool, and its applications in civil engineering are examined. This stage also reports on interoperability challenges between the selected architectural and structural BIM software. Literature reviews at this stage were conducted using Scopus and Web of Science following the systematic approach proposed by Navarro et al. [58] and applied in subsequent studies, including those by Collao et al. [38] and Mobaraki et al. [59]. The findings from this stage were incorporated into the Introduction and Section 3: "interoperability problems between architectural and structural BIM software."

(2) **Stage 2: solution design.** The objective of this stage is to develop a solution design to solve the identified problems and automate the calibration of structural BIM models. This solution is addressed by defining an automation protocol that enables interoperability among selected BIM software programs. This process is then automated using an RPA-based protocol. The results of this stage are included in Section 4: "automatic calibration of BIM models using RPA." This stage can be repeated because of the evaluation stage (Fig. 1), as the evaluation results can indicate a requirement for the improvement of the solution proposal. This iterative process is expected in both technological and RPA projects

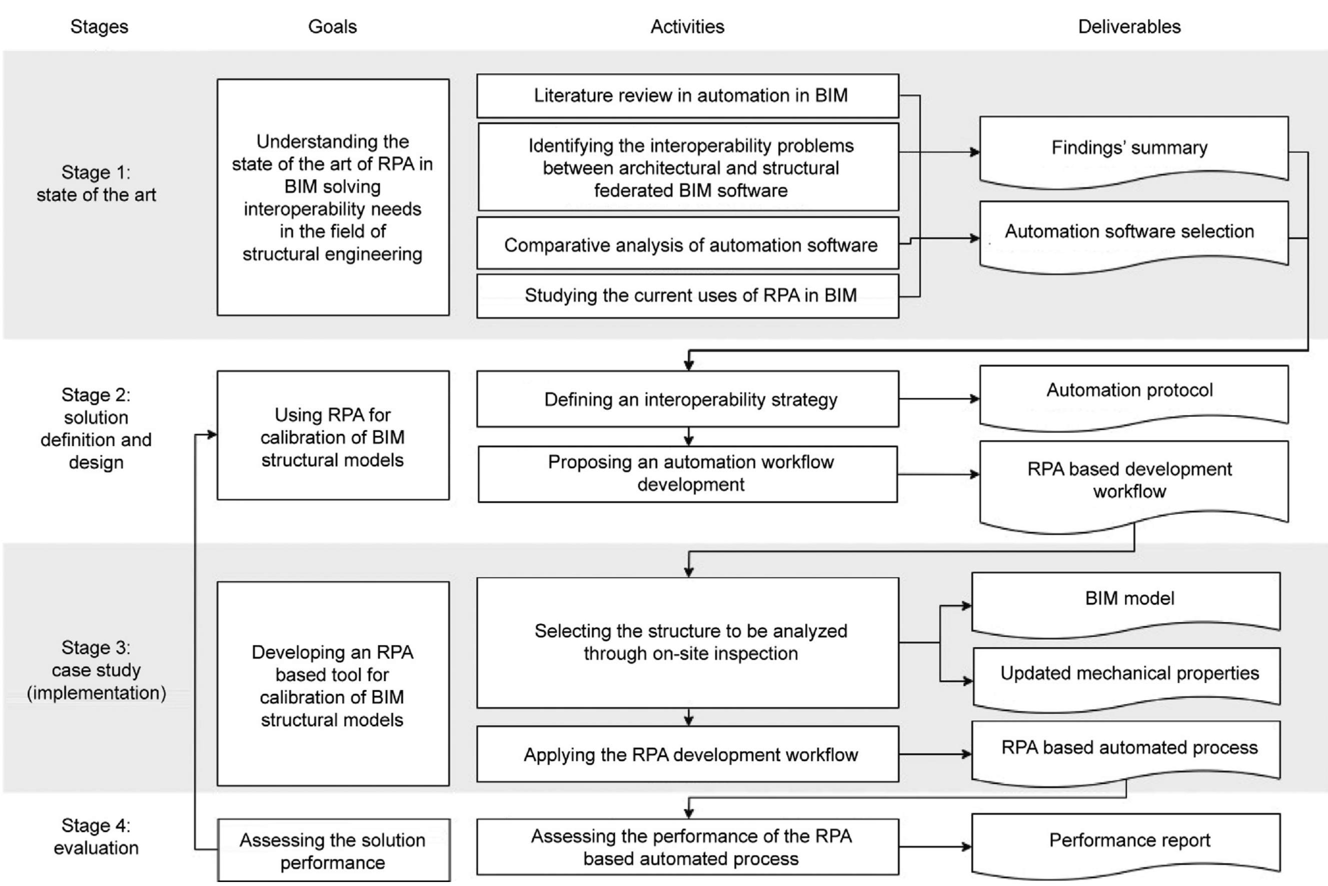


Fig. 1. Research methodology based on the DSRM.

[60], and allows the solution requirements to be achieved gradually.

(3) **Stage 3: case study.** This stage validates the application of the proposed automation tool using a real case study. The structure to be analyzed was selected, and its BIM model was created using an on-site cloud of points. The structural pathologies of this structure were then located and quantified based on on-site inspection. Subsequently, the RPA tool required for the calibration of the damaged mechanical properties in the BIM structural model was developed. The results of this stage are presented in Section 5: "case study."

(4) **Stage 4: evaluation.** This stage is designed to assess the efficacy and performance of the automated calibration methodology by examining the scalability, limitations, and future research. The performance report and discussion at this stage are included in Section 5: "case study," and Section 6: "conclusions."

In the following section, the interoperability challenges between architectural and structural BIM software are discussed.

3. Interoperability problems between architectural and structural BIM software

Achieving the interoperability of customized structural parameters between architectural and structural BIM software is challenging. When these elements are connected between different software packages, either geometric or structural attributes may be lost. To illustrate these challenges, this section analyzes the interoperability of architectural and structural BIM software. Initially, a comparative analysis is provided to select the BIM software for the interoperability study. Subsequently, the specific interoperability challenges between the two selected software examples are detailed. Problems occur in two information flows: from Revit to Robot, and from Robot to Revit. Furthermore, this section addresses the challenges associated with the manual updating of damaged elements.

3.1. BIM software selection

To select the most appropriate BIM software, we conducted a comparative analysis among commonly used solutions in infrastructure projects, paying particular attention to those suited for bridge modeling and analysis. The analyzed software included the following: ① architecture: Revit [61], OpenBridge Modeler (Bentley Systems, Inc., USA) [62], and Allplan Bridge (ALLPLAN GmbH, Germany) [63]; ② for structural analysis: Autodesk Robot Structural Analysis (Autodesk, Inc., USA) [64], CSiBridge (Computers and Structures, Inc., USA) [65], and midas Civil (MIDAS IT Co., Ltd., Republic of Korea) [66].

Based on the authors' experience, Revit lacks some of the advanced bridge-modeling tools available in specialized software such as OpenBridge Modeler or Allplan Bridge. Nevertheless, the program is sufficiently versatile, enabling the modeling of any bridge element with relative ease. Compared with software specialized in bridge design, Revit provides distinctive features, including superior integration within the Autodesk BIM suite, widespread acceptance among technical professionals, and a user-friendly learning curve. Furthermore, Revit's adaptability to various structural modeling endeavors extends its scope of application, enriching the relevance of the proposed calibration protocols for assorted structural types. Based on these benefits, Revit was selected as the architectural modeling software for this study.

The authors' experience also reveals that, unlike midas Civil and CSiBridge, Robot Structural Analysis is not tailored exclusively for bridge design and potentially lacks some of the more advanced analytical tools required. However, the application of these advanced tools is beyond the scope of this study, which focuses on calibrating mechanical properties. Robot offers several advantages over bridge-specific structural analysis software, including enhanced compatibility with Autodesk's architectural BIM platforms and superior handling of rebar and steel detailing within the BIM environment. These advantages motivated the selection of Robot for structural analysis in this study.

In the following sections, the interoperability problems between Revit and Robot, and between Robot and Revit, are presented.

3.2. Lack of visibility of structural parameters in Revit

The structural elements in the BIM modeling software Revit, such as beams or columns, are clustered in families. The attributes of the analytical model of these families are linked with predefined structural databases, such as "EuroPro.xml" for steel profiles [67]. Every time a structural element is introduced into the BIM model, its structural attributes, such as area and inertia, are automatically imported from the corresponding database. The "EuroPro.xml" database is organized as follows: ① definition of the name, section, and shape parameters for various steel shape families; ② mathematical equations to establish the steel profile boundary based on the defined geometry; and ③ values of the dimensions and mechanical properties of the different steel profiles. A fragment of the database focusing on the European I-beam (IPE) series is provided in Fig. S1 in Appendix A for additional reference, following standard European steel profile designations (EN 10365).

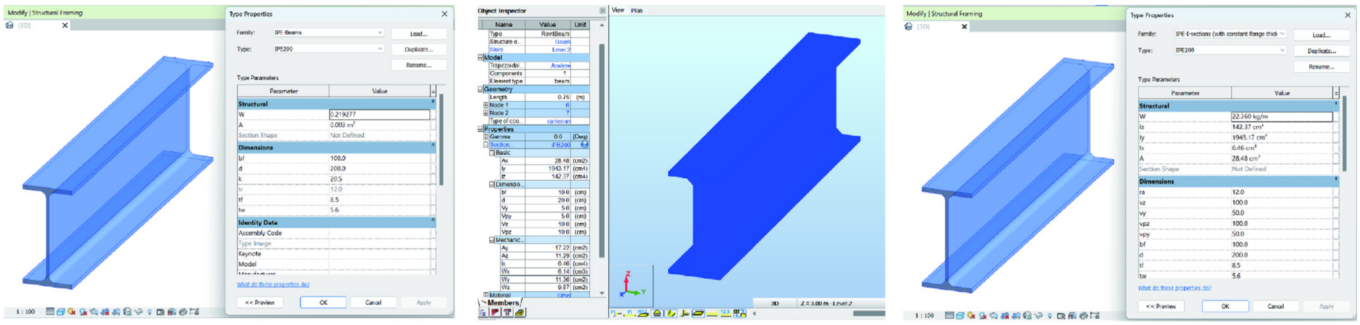
Not all mechanical parameters defined in the databases are visible within the corresponding "Type Properties" in Revit. Notably, this applies to flexural inertia (I). This is illustrated in Fig. 2(a), which shows both the geometry and type properties for an IPE 200 beam in Revit. Fig. 2(a) shows that this information contains only two structural parameters, area (A) and self-weight (W). This lack of accessibility to structural parameters prevents direct customization within Revit.

Any structural parameters not displayed in Revit became visible upon exporting the structure to Robot Structural Analysis using the Revit structure integration dialog box. The visibility of these structural parameters is shown in Fig. 2(b), with an example of exporting an IPE 200 beam from Revit to Robot. This figure effectively demonstrates the newfound visibility of inertias (I_y, I_z) in the "Object Inspector" of Robot.

The structural models from Robot can be re-imported into Revit. However, the inertias will not be visible in the "Type Properties" unless the pre-existing families in Revit are removed, allowing the structural families to be directly imported from Robot. This problem is outlined in Fig. 2(c), which shows the geometry and type properties of an IPE 200 profile imported into Revit from Robot after removing the steel profile families in Revit. Note that, without removing these families, the parameters within the attributes window would remain limited to those shown in Fig. 2(a).

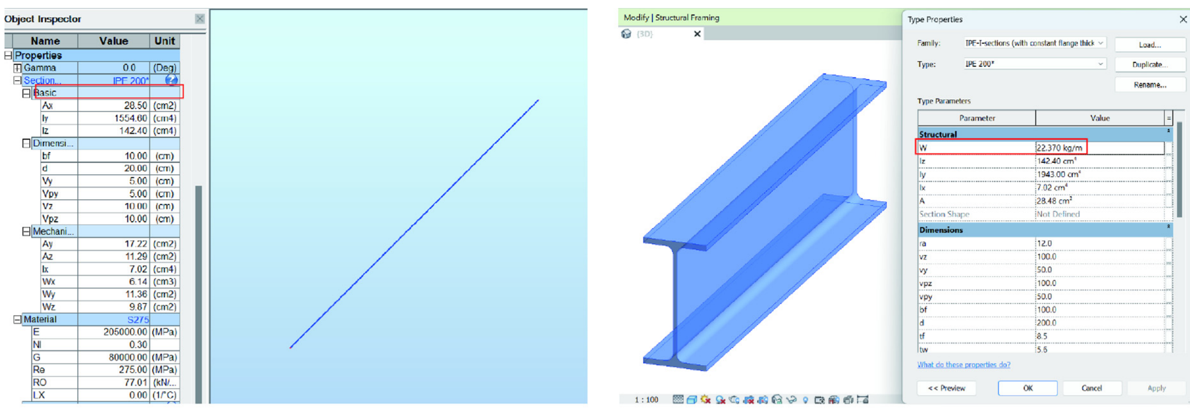
3.3. Interoperability problem of customized structural elements between Robot and Revit

The mechanical properties of predefined structural elements can be manually adjusted in Robot and factored into structural analyses. This capability is illustrated in Fig. 3(a), which shows a modified steel profile designated as IPE 200*. The customized profile considered in this figure includes a 20% reduction in inertia along the y-axis (I_y), modifying its reference value from 1943.2 to 1554.6 cm^4. Notably, this figure demonstrates that the 3D geometry of the updated profile is no longer visible in Robot. However, the structural attributes of the customized profiles in Robot are not properly imported into Revit. This problem is outlined in



(a) (b) (c)

Fig. 2. Geometry and type properties of (a) IPE 200 profile in Revit, (b) IPE 200 profile exported from Revit to Robot, and (c) IPE 200 in Revit imported from Robot after removing the steel profile families.



(a) (b)

Fig. 3. Geometry and type properties of (a) IPE 200* with a modified inertia I_y in Robot and (b) IPE 200* imported in Revit.

Fig. 3(b), where both the geometry and type properties of the imported IPE 200* in Revit are shown. An analysis of this figure shows that although the geometry of the element is accurately imported, the same cannot be said for the customized inertia (I_y), which reverts to its original value. This interoperability problem occurs because the name of the customized element is absent from the steel profile database ("EuroPro.xml") employed by Revit. Consequently, regardless of the database used, the customized element cannot be properly imported as a BIM object.

3.4. Manual calibration of the profile databases

For interoperability of customized structural sections, the structural databases should be modified. Manual updating of the profiles database can pose several challenges and limitations. First, the process is time-consuming and labor-intensive and requires significant effort to manually modify and update the model parameters and attributes. Second, manual calibration is prone to human error as it relies on individual judgment and interpretation, which can result in inaccuracies and inconsistencies in the model. Additionally, manual calibration lacks a systematic and standardized approach, making the calibration process difficult to update in other projects. Finally, as the model evolves over time, manual calibration becomes cumbersome for maintenance and updating, potentially resulting in outdated or inaccurate information. However, note that automation of the calibration process can offer significant benefits in terms of efficiency, accuracy, and scalability. To automate the solutions to these three problems, we propose an innovative RPA protocol in the following section.

In the following section, a methodology for automating the calibration of the mechanical properties in BIM structural models is presented. To automate manual operations, this methodology relies on the use of RPAs.

4. Automatic calibration of BIM models using RPA

This section delves into three critical components of RPA: automation method selection, development of RPA protocols, and limitations. By examining these factors, this section provides valuable insights essential for effective RPA implementation and optimization within organizational frameworks.

4.1. Automation method selection

The most traditional tools for automating the manual input of information into software applications documented in the existing literature are RPA [68], API [69], custom scripts [70], and enterprise application integration (EAI) tools [71]. A comparison of the main strengths and weaknesses of each method is presented in Table 1 [72 79].

The selection of automation tools depends on the nature of the task to be automated, the type of data entry required, the level of integration required, and the technical capabilities of the organization or individual implementing the automation. Notably, the existing literature emphasizes the widespread adoption of RPA because of its capability to streamline manual data entry over a broad range of software systems and sectors. The main advantages of using RPA technology for the automation of manual data entry

Table 1
Comparison of existing automation tools.

Automation tool	Tool example	Strengths	Weaknesses
RPA	UiPath (UiPath, Inc., USA) [72] Automation Anywhere (Automation Anywhere, Inc., USA) [73]	User friendly Efficient and lightweight programming Reduced development time Noninvasiveness Scalability and flexibility	Limited to UI interaction Limited adaptation to changes Complexity limitation
API	RESTful [74] Simple object access protocol (SOAP) [75]	Direct system integration User friendly Real-time data access	Requires API access and customization May not cover all integration needs
Custom Scripts	Python (Python Software Foundation, USA) [76] PowerShell (Microsoft Corporation, USA) [77]	Highly customizable Can be optimized for performance	Requires programming expertise Maintenance and scalability can be challenging
EAI	MuleSoft (Salesforce, Inc., USA) [78] Oracle Integration Cloud (Oracle Corporation, USA) [79]	Cohesive system environment Comprehensive integration Streamlines data flow	Complex setup and maintenance Requires substantial initial investment

across various software systems summarized in Table 1 are as follows:

(1) User-friendly interface: RPA offers an intuitive and user-friendly interface that enables users with various technical backgrounds to create automation processes without extensive programming knowledge. This ease of use simplifies the automation process and makes it accessible to a wide range of users.

(2) Efficient and lightweight programming: RPA enables faster and more lightweight programming than traditional custom scripts. When using RPA, the process of creating automated processes is more streamlined and requires less technical expertise because it is based on direct interactions on the software UI. This efficiency results in quicker development and implementation of automation solutions.

(3) Reduced development time: RPA typically reduces the time required to develop automation solutions by providing pre-built modules and templates that can be customized easily. This accelerates the deployment of automation and saves time and resources.

(4) Noninvasiveness: The noninvasive nature of RPA, coupled with its ability to operate on top of existing information technology (IT) infrastructures, makes it a versatile solution that fits into many organizational IT strategies without the need for significant overhauls.

(5) Scalability and flexibility: RPA is particularly scalable and flexible for tasks that involve frequent user interaction patterns, such as updating databases, transferring data between platforms, and processing repetitive tasks. Its rule-based logic and preconfigured workflows enable rapid deployment even in environments with minimal programming expertise, making it a practical choice for real-world applications.

RPA protocols have a significant potential for transforming the field of bridge engineering by enhancing the efficiency, accuracy, and productivity of various tasks. RPA can also automatically generate maintenance schedules and alert engineers to areas requiring attention based on predefined criteria, thereby reducing the need for manual oversight. Another application involves automating the compliance checks for regulations and standards to ensure that bridge designs and maintenance practices conform to local or international codes. Additionally, RPA can streamline the procurement process by automating material requisitions and inventory management, ensuring that all necessary resources are available when required, thereby minimizing delays in bridge construction and maintenance projects.

4.2. Development of RPA protocols

The process for calibrating BIM models is illustrated in Fig. 4 and consists of the following steps:

(1) Step 1: generation of the analytical model. The BIM model of the structure is initially created in Revit based on point clouds or drawings with the required LOD and level of information (LOI). In this model, the structural elements are assumed to be undamaged, and their properties are extracted from a predefined database. For example, for normalized steel profiles, the "EuroPro.xml" database case be used. Subsequently, an analytical model of the structural elements is generated in Revit.

(2) Step 2: exporting the analytical model. The analytical model is exported from Revit to Robot Structural Analysis through integration with the Revit structure dialog box.

(3) Step 3: introduction of damages in Robot. The effects of different types of damage on the mechanical properties and their assignment to the structural elements are defined in a Microsoft Excel spreadsheet. This information is then used to create new damaged sections and assign them to the corresponding elements, thereby updating the structural model. This updated model can be used to investigate the effects of damages on structural reliability.

(4) Step 4: calibrated structure in Revit. The updated Robot model is imported back into Revit through integration with the Revit structure dialog box.

The process outlined in Fig. 4 requires the manual definition of the data in Steps 1 and 2. This includes defining the geometry and elements of the BIM model, geometry, and mechanical properties of the undamaged elements in the structure, creating an analytical model, specifying the properties of the undamaged sections, and assigning these properties to the corresponding structural elements in the BIM model. The required information includes ① an analytical model in Robot with undamaged elements, and ② an Excel spreadsheet containing the identification of the damaged elements, their names, and the corresponding effects on their mechanical properties.

In the proposed application, the manual definition of this information remains necessary to ensure accuracy and enable expert validation, because fully automating the input of damage identification and characterization involves complex data acquisition and interpretation processes that often require human expertise. Nonetheless, future research aims to explore the integration of sensor data, image processing, and machine learning techniques

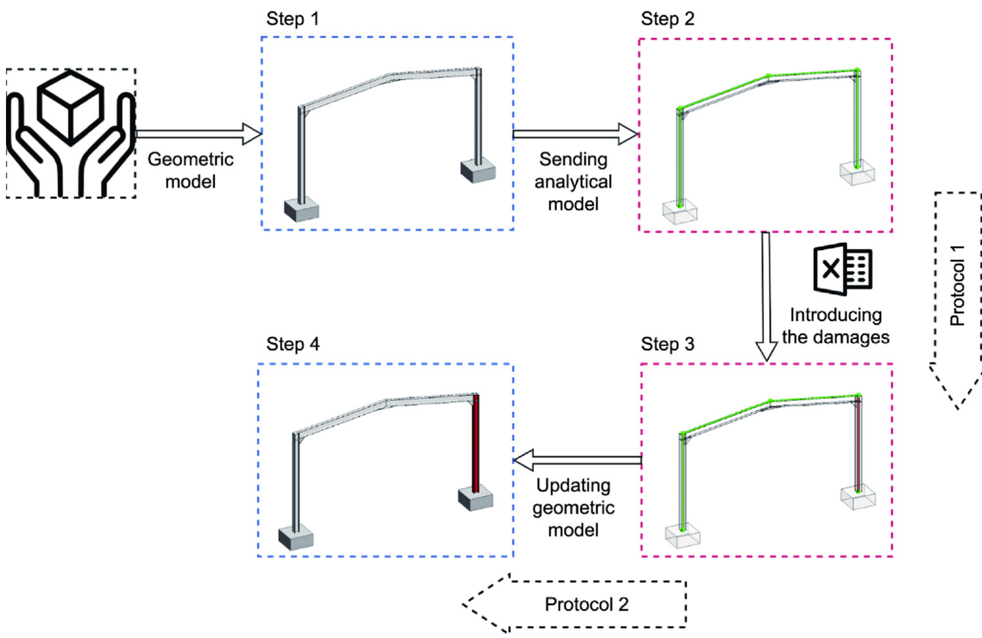


Fig. 4. Steps to automate the introduction of damages into BIM models.

to enable automatic detection and characterization of damaged elements, thereby reducing or eliminating the need for manual input.

After the required information is manually defined, Steps 3 and 4 are automated to calibrate the defined structural damages in the analytical model using Robot. This automated process involves creating new sections for each damaged element in the structural database, uploading the damaged sections from the structural database, updating the sections of the damaged elements in Robot, and updating the model in Revit. This process is automated using an RPA based on the following two protocols: ① automatically updating the structural databases to facilitate the transfer of analytical models between Revit and Robot, and ② automatically updating structural damages in the BIM structural models. The steps of this RPA are summarized in Fig. 5 and described as follows:

(1) Step 1: reading damaged information. The RPA opens the Excel spreadsheet input data, reads and stores information about the damages, including their name, the values of their mechanical properties, and their allocation to the structural element identification (ID). The Excel spreadsheet was then closed.

(2) Step 2: updating the database with the damaged sections. The RPA opens the .xml database of mechanical properties and creates a new section for each of the damaged properties detailed in the Excel spreadsheet. The database is then saved and closed.

(3) Step 3: loading the damaged sections in Robot. The RPA opens Robot and loads the damaged sections introduced into the structural database in Step 2.

(4) Step 4: updating the cross-sections of the damaged elements. The damaged elements are assigned according to the definition in the Excel spreadsheet. The proposed RPA protocol addresses both interoperability challenges and manual calibration challenges (between Revit and Robot Structural Analysis) identified in the study. In this regard, the RPA bot automates the alignment of customized mechanical properties, such as reduced inertias or cross-sectional areas, which are often lost during data transfers between platforms because of the differences in how each software handles structural databases. This is achieved by creating new damaged element profiles directly within the structural database (e.g., "EuroPro.xml") with unique identifiers and modified parameters. Additionally, the protocol ensures that these updated profiles are recognized and correctly applied when reintegrated into Revit while maintaining consistency across platforms without requiring manual adjustments.

The RPA bot automatically updates structural databases, eliminating the limitations of manual updates, such as human errors and scalability problems. By automatically extracting damage parameters from an Excel spreadsheet, the RPA generates updated profiles in the database and validates these changes to prevent inconsistencies. This accelerates the calibration process and ensures systematic and uniform updates.

Regarding the assignment of updated properties, the RPA simplifies the process by automatically mapping damaged elements to their corresponding updated profiles using unique identifiers from the Excel spreadsheet. This mapping ensures that each

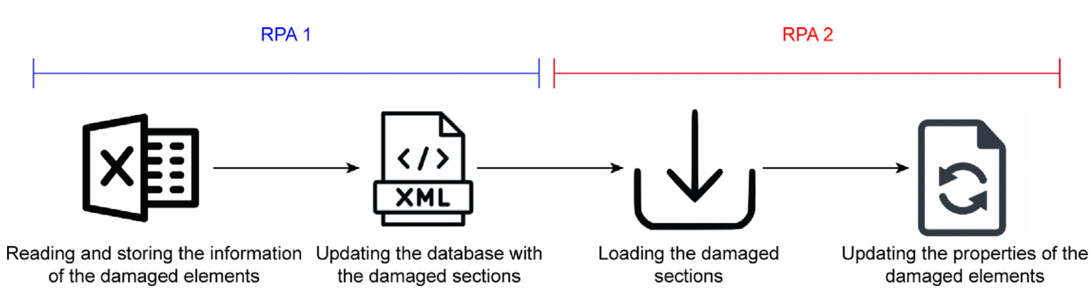


Fig. 5. Steps followed by the developed RPA process.

damaged element in Robot is accurately updated to reflect its actual condition, even in large models. The automated approach also significantly improves efficiency and scalability, reducing the time required to process complex models.

Overall, the designed protocol avoids the typical inconsistencies of manual calibration, such as incoherent data, lack of standardization, and scalability challenges. By automating repetitive and complex tasks, the RPA reduces errors and ensures uniformity and reliability throughout the calibration process. These capabilities demonstrate that the RPA provides a useful solution, reinforcing its applicability in BIM structural models and its success in the presented case study.

4.3. Limitations

The main limitations of the proposed calibration protocol are as follows:

(1) **Scope of work.** This study specifically focuses on calibrating BIM structural models and does not explore the development of digital twins. Future research should employ the proposed protocols to create dynamic digital twins, continually updated using real-time data from physical assets. This enables ongoing analyses and adjustments during the operational phase. To extend the proposed protocol to include digital twin development, future RPA workflows should incorporate real-time information from on-site sensors into the BIM model. For example, Syed et al. [50] demonstrated the application of RPA for processing monitoring data from low-cost Internet-of-Things (IoT) sensors.

(2) **Software dependance.** The designed RPA was developed to automate the calibration of mechanical properties within BIM software Revit and Robot. Adapting this protocol to other BIM software requires a comprehensive investigation of interoperability challenges and structural databases to define the necessary information flow. Consequently, addressing other BIM software will require the development of a new customized RPA. To address this, future research could aim to create modular RPA workflows that support interoperability through common exchange formats, such as industry foundation classes (IFC) or construction operations building information exchange (COBie), facilitating smoother transitions between BIM software applications.

(3) **Limited adaptation to changes.** RPA systems are programmed to perform specific tasks according to predetermined rules, which constrains their flexibility in adapting to dynamic changes. For example, scenarios such as software interface updates pose challenges for RPA adaptation, necessitating an understanding of the new graphical elements with which to interact. Similarly, alterations in a computer's processing capacity would demand adjustments in the pause intervals between RPA tasks. Addressing these changes would require manual modifications to the RPA's automated tasks and logic rules. To enhance adaptability, future research could integrate AI or machine learning components into the RPA. For example, RPA protocols can be trained to recognize and adapt to new graphical elements in updated software interfaces.

(4) **Complexity limitation.** RPA may not be suitable for all automation tasks. In scenarios requiring complex data transformations, large-scale integrations, or advanced logic, either traditional programming or specific tools in data integration platforms may offer more robust and efficient solutions. To address this limitation, RPA algorithms can be used for front-end task automation while relying on more advanced programming frameworks (e.g., Python) for backend data processing and logic.

(5) **Manual supervision required.** Similar to programming languages, errors in input data, programming, and logic can result in inaccuracies in automated tasks. Periodic human supervision and verification throughout all stages of automation are imperative to ensure the precision and reliability of the tool. To mitigate this problem, future developments can incorporate a layered verification system within the RPA workflow, automatically checking for anomalies or discrepancies in the data inputs and outputs.

(6) **Computer performance.** The RPA bot is programmed to update the entire model element-by-element. If a step of the process fails (because of any of the challenges presented above), the process is rebooted. The parameter fixed by the user limits the number of reboot repetitions. Another computational performance problem could occur if the size of the BIM model is particularly large. The slow response time of the software when manipulating the model was described above. In this regard, the RPA bot comprises a set of delay boxes that impose a waiting time between tasks such that they can be effectively completed. These delay boxes are also user adjustable. Therefore, this time parameter would require to be updated while processing a new model using the developed RPA bot.

5. Case study

This section describes the application of the proposed methodology to automate the calibration of structural damage in BIM models in a real case study. First, the geometry and BIM model of the structure are described. Subsequently, detailed information about the pathologies identified during the on-site inspection of the structure is provided. Finally, the application of RPA to the automated calibration of the structural parameters in the BIM model is presented.

5.1. Description of the structure and BIM model

The analyzed structure was the Pajareles footbridge, a suspension bridge located in Albacete, Spain, which was constructed in 1935. The bridge includes two steel pylons and has a span of 85 m. The steel deck, 2.35 m wide, is connected to the main suspension cables using vertical hangers. A photography of this structure is shown in Fig. 6(a). Because no drawings of the structural elements were available, a point cloud was generated on-site using a drone for aerial flights and a Leica BLK2GO Scan Laser [80]. The resulting point cloud was processed and cleaned using Autodesk, ReCap (Autodesk, Inc., USA) obtaining the visualization shown in Fig. 6(b).

The point cloud data were used to create in Revit the BIM structural models shown in Fig. 7. The structure in this figure is composed of normalized steel profiles, and each family is indicated by a different color. The geometry and mechanical properties of the sections of the structure (FL 4 × 30, FL 5 × 60, HEB 160, IPN 100, CAE 30 × 3, CAE 50 × 5, CAE 120 × 15, ROND 10, ROND 30, UPN 80, UPN 140, and UPN 160) were obtained from the "Euro-Pro.xml" database, where FL refers to flat bars, HEB to European wide flange beams, IPN to European standard I-beams, CAE to equal angle sections, ROND to round bars, and UPN to European U-shaped channels, in accordance with standard European steel profile designations (EN 10365 and EN 10056).

The LOI in this case study encompassed the parametric data automatically associated with specific beam elements, including geometry (dimensions, material, and section profile) and data attributes (e.g., load-bearing capacity and material properties such as steel strength and concrete grade). The mechanical properties of the corroded steel elements were updated to reflect the corresponding damage, ensuring that the model accurately represented the current conditions of the structure. An analytical model of the structure was then created in Revit, which simplified the lacing system of the railing diagonals into a unified structural element. The mechanical properties of these unified elements were

(a) (b)

Fig. 6. Pajareles footbridge. (a) Photograph of the structure; (b) point cloud visualization.

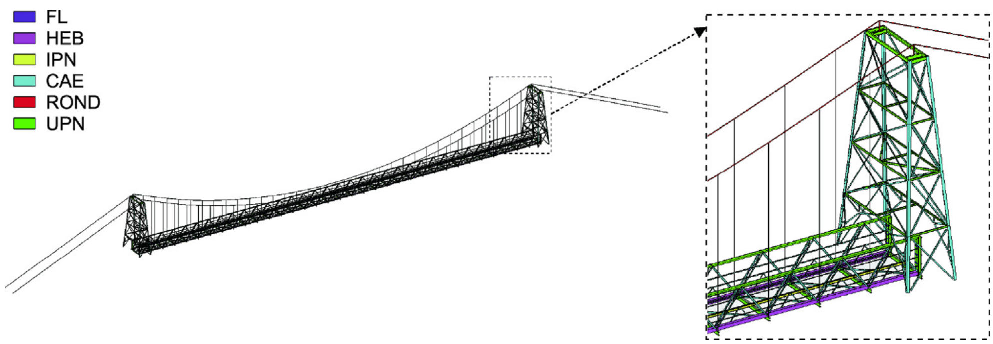


Fig. 7. Revit model of the Pajareles footbridge in which the steel profiles are distinguished by different colors.

manually calculated following the specifications of Eurocode 3 [67] for laced compression members and incorporated into the "Euro-Pro.xml" database. The resulting analytical model in Revit, which included 747 analytical bar elements, is shown in Fig. 8.

5.2. Inspection on-site

An on-site inspection of the Pajareles footbridge was conducted in 2022 to assess the condition of its structural elements. Spanish protocols [81] were followed to identify the pathologies and quantify their severity. The inspection results revealed that the majority of the steel elements exhibited significant corrosion, as exemplified by the deck elements shown in Fig. 9. To accurately quantify the reduction in structural parameters caused by corrosion in each individual member, we would need to complement the on-site inspection with sensor data and SSI tools; however, the estimation of the actual mechanical properties of the corroded elements was beyond the scope of this study.

The percentage of corrosion that can reduce the stiffness of a steel specimen can vary depending on several factors, such as the exposure environment, duration of exposure, type of corrosion, and initial condition of the steel. Generally, localized corrosion processes, such as pitting corrosion, can cause significant reductions in the cross-sectional area of steel at specific points, whereas more uniform corrosion may cause a more gradual reduction across the entire surface. In severe cases, corrosion can cause area and yield strength reductions exceeding 37.5% [82] or even lead to the complete failure of the steel structure. An investigation of the experimental effects of corrosion in cable-supported structures was conducted by Feng et al. [83], who assessed the in-service performance of such structures, focusing on the impact of corroded cables resulting from fire.

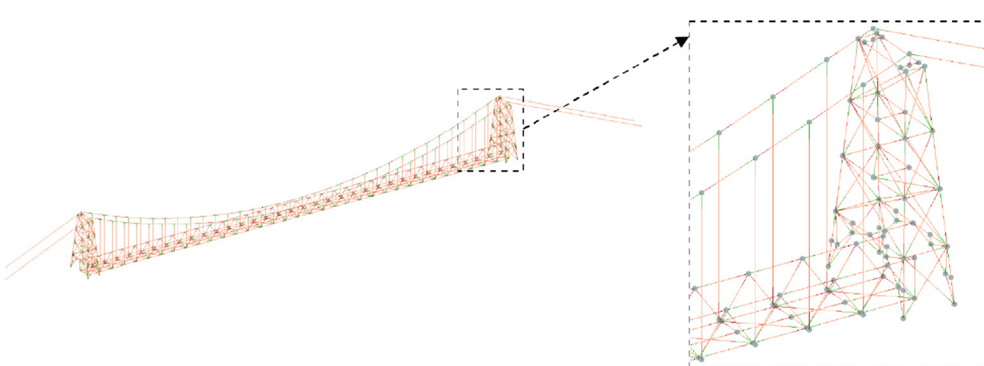


Fig. 8. Analytical model of the Pajareles footbridge in Revit.

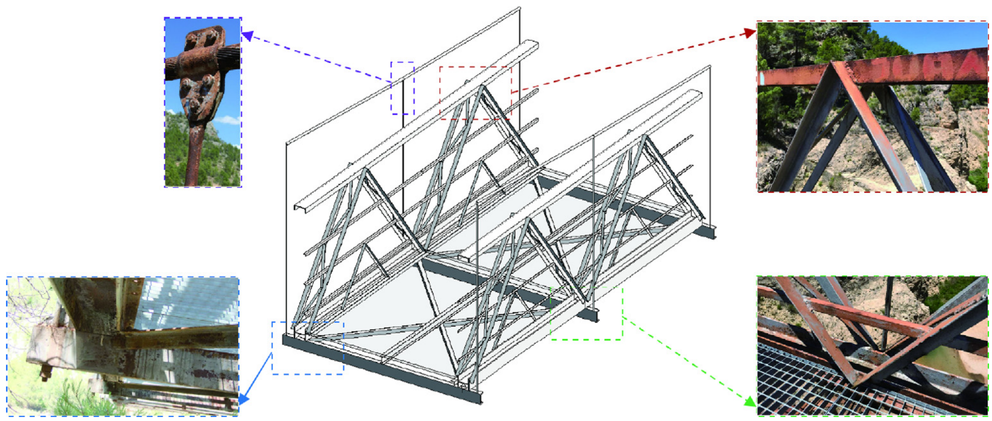


Fig. 9. Examples of corrosion pathologies in the deck of the Pajareles footbridge.

A damage scenario affecting all structural members was considered to validate the application of the proposed calibration methodology. In this scenario, the corrosion pathologies were assumed to cause noticeable reductions in the mechanical properties, particularly in terms of area and inertia, compared with the normalized values of the corresponding steel profiles. However, determining the exact percentage reduction without specific information regarding the conditions of the steel and its corrosion process is challenging. Hence, to model the reduction in corrosion strength, we used a random percentage ranging between 0% and 15% as the average value for the entire bar. This percentage was based on previous tests reported in the literature (e.g., Dacuan et al. [84]). Experimental data or corrosion models based on specific environmental and material conditions are required for more precise estimation of the percentage reduction in a specific case.

An Excel spreadsheet with element IDs exported from the BIM model in Robot was created to incorporate the perceptual effects of corrosion into the BIM. Perceptual corrosion damage was then introduced randomly for each element in the sheet, influencing both the area and inertia. A segment of the Excel spreadsheet for 15 of the 747 elements is provided in Fig. S2 in Appendix A. The figure includes the following information: bar ID in Robot, corresponding steel profile, ID in Revit, assumed random damage percentage, strength percentage, and names of the updated steel profiles in Robot.

The corrosion effects introduced into the BIM model are limited to a reduction in its mechanical properties, specifically the area and inertia of the respective structural elements. Future research will build on these developments by incorporating a more realistic representation of pathologies, including reduced cross-sections, customized materials (e.g., with rust textures), and real images from *in situ* inspections. For example, Hattori et al. [85] integrated corrosion inspection images of bridges into BIM models, and Lozano [86] incorporated pictures of georeferenced pathologies, including cracks and corrosion, from *in situ* bridge inspections into BIM models.

Shared parameters were dynamically generated using a Dynamo code to automate the incorporation of perceptual corrosion damage into Revit. The step-by-step process of the developed code is outlined in Fig. 10 and can be summarized as follows:

(1) Step 1: importing and extracting damage information from the Excel spreadsheet where specific damage is specified.

(2) Step 2: defining the precise type of shared parameter, such as a numerical value, and associating it with appropriate categories, such as "Analytical Beams" and "Structural Framing."

(3) Step 3: filtering relevant details from the Excel file and extracting perceptual damage values from the "percent random damage" column.

(4) Step 4: executing the combined operations from Steps 2 and 3 by first mapping the manually identified damaged elements (Step 2) to their corresponding Revit components and then applying automated procedures (Step 3) to create, upload, and assign new damaged sections within the structural database to the appropriate categories in the Revit model.

The perceptual corrosion damage imported into Revit through the Dynamo code is graphically represented in Fig. 11. This illustration incorporates a color-coded filter to categorize the perceptual corrosion damage into three ranges: less than 5%, between 5% and 10%, and between 10% and 15%. Note that the precise values of the damage percentages for each element aligned with those specified in the Excel spreadsheet, as shown in Fig. S2.

5.3. Automatic calibration of the BIM model

UiPath was used to develop the two RPA routines described in Section 3. UiPath has been widely adopted in different applications (e.g., Refs. [87,88]) and was selected for this study owing to its accessibility, including the availability of most features under an unlimited trial license. Note that the development of the proposed RPA routines involved assembling a sequence of simple, rule-based operations that replicate repetitive user actions within BIM environments, such as navigating the interface, selecting structural elements, and modifying cross-section attributes. Although the resulting workflow consists of numerous steps, each is logically defined and constructed using UiPath's visual drag-and-drop interface, requiring minimal programming expertise. In contrast to complex algorithmic coding, the process involves configuring predefined action blocks, which significantly lowers the technical barrier for implementation. Although moderate technical knowledge was necessary during the initial setup, particularly to structure the workflows and integrate external data sources, the routines were developed entirely from scratch by the authors. When configured, these can be reused or adapted with minimal effort by users with limited coding experience. This approach ensures that the proposed methodology facilitates automation without demanding advanced software development skills.

The steps outlined in Section 4 for automating the calibration of the mechanical properties owing to corrosion effects were tailored for this specific case study. Following the definition of the BIM and damage information (Step 1), RPA 1 was designed to automatically

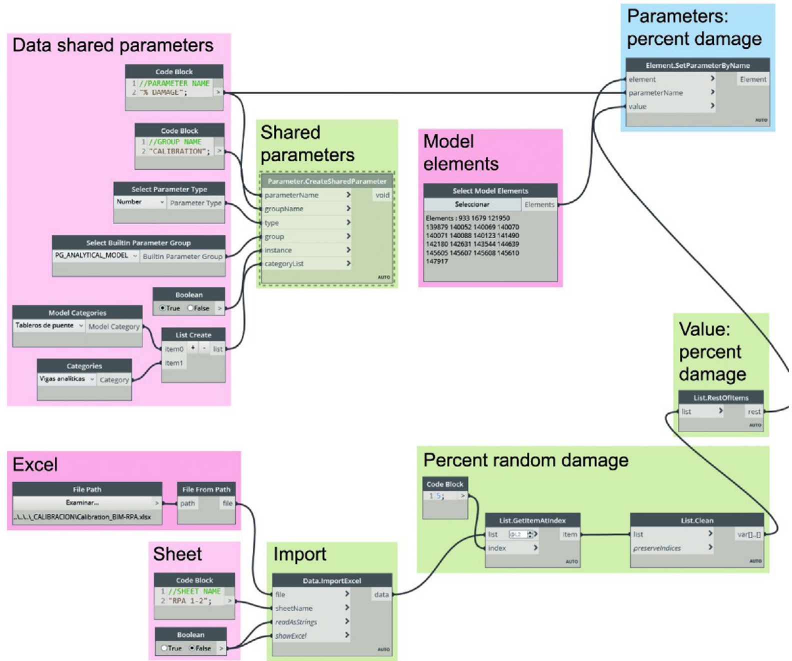


Fig. 10. Dynamo script used to read the perceptual corrosion damages from Excel spreadsheet including references to the steps followed.

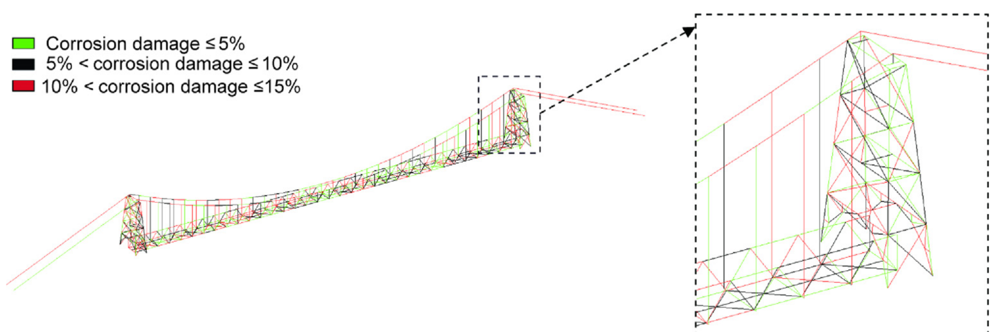


Fig. 11. Assumed reductions in mechanical properties due to corrosion effects in the BIM model (distinguished by different colors).

update the structural databases, streamlining the transfer of analytical models between BIM models (Step 2). The input data for this process were derived from the Excel spreadsheet delineated in Fig. S2, and the resulting output encompassed the updated profile database, in this case, the "EuroPro-mod.xml" database. The activities followed by RPA 1 in UiPath are presented in Fig. 12 and are summarized as follows:

(1) The "EuroPro.xml" database is uploaded in .txt format (Fig. 12(a)).

(2) The length of the .txt file is retrieved and stored in a new variable (Fig. 12(b)).

(3) The list of corrosion damages is imported from the Excel spreadsheet (Fig. 12(c)).

(4) The .txt file is copied into a string variable (Fig. 12(d)).

(5) The .txt file undergoes a comprehensive editing process involving the analysis and updating of the steel profile family information based on the damaged elements defined in Fig. 12 (e). This process is executed through the following sub-activities: First, the UiPath command regular expression (RegEx) is employed to pinpoint the ID, name, position, geometry, and mechanical properties of the reference steel profile families specified in the Excel spreadsheet. This command, which is widely employed in existing literature for data validation, text search and replacement, and data extraction [91,92], serves as the foundation for accurate data identification. Second, a new damaged steel profile was generated for each damaged section, as outlined in the Excel spreadsheet. This is achieved by customizing the information of the original undamaged steel profile and altering the parameters influenced by corrosion. These affected parameters include reductions in mechanical properties, such as area and inertia, stemming from the corrosion section loss. Furthermore, the IDs and names of the damaged steel profiles are adjusted to ensure the uniqueness of each steel profile. The damaged steel profiles are written sequentially at the end of the .txt document.

(6) The modified .txt file is exported to .xml format to ensure compatibility with Revit and Robot (Fig. 12(f)).

A fragment of the updated database obtained by RPA 1 is shown in Fig. S3 in Appendix A, where the definition of a damaged UPN 160 labeled as "UPN_1 160" in Robot is indicated. The modified parameters include the name of the software (NAME, NAME1, and NAME_REVIT), area, and inertias.

RPA 2 was customized to enable an automated update of the structural damage within the BIM model of the case study. The input data for this process encompassed both the updated profile database and the analytical model in Robot, whereas the resulting output corresponded to the analytical model updated with the

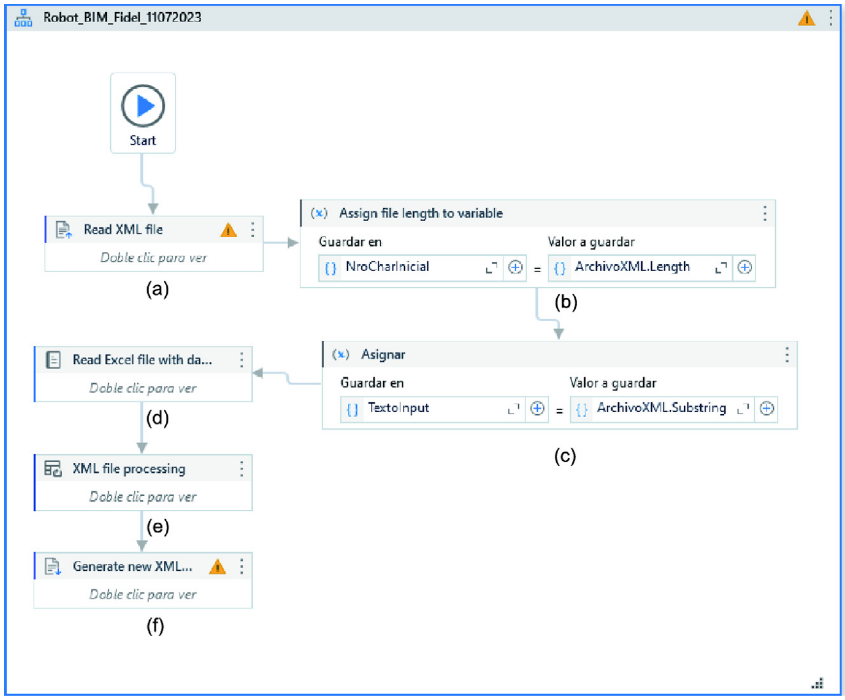


Fig. 12. RPA 1 for updating the profile database with the damaged sections: (a) read extensible markup language (XML) file; (b) assign file length to variable; (c) assign variables; (d) read Excel file with data; (e) XML file processing; and (f) generate new XML data.

specified corrosion damage. As shown in Fig. 13(a), RPA 2 is structured around two distinct modules: one operating within Revit and the other within Robot. The activities undertaken by each module are summarized in Fig. 13(b) and described as follows: The BIM model is accessed through its Revit file; the analytical model of the case study is exported from Revit to Robot using integration with the Revit structure dialog box. The updated database containing the damaged sections is imported into Robot; the list of families for the damaged sections is extracted from the Excel spreadsheet, as shown in Fig. S2; each damaged family is loaded into Robot; the list of damages is imported from the Excel spreadsheet; and the updated properties are attributed to the damaged elements.

This process involves modifying the section type of the damaged elements from their original designation (e.g. UPN 160) to the corresponding damaged designation (such as UPN_1 160) in the table of properties of the beam elements within Robot. This task can be automated by pasting the section name specified in the Excel spreadsheet into a section-type column for the respective beam elements. The steps followed by the Revit and Robot modules in RPA 2 of UiPath are shown in Figs. S4 and S5 in Appendix A, respectively.

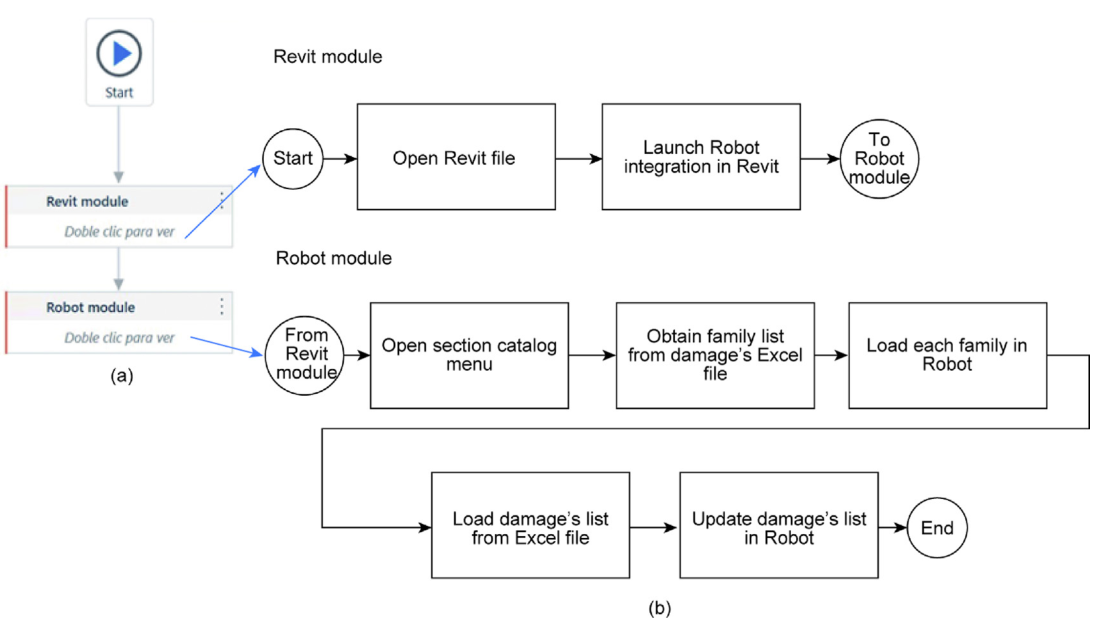


Fig. 13. RPA 2 automating the update of the structural damages within the BIM model: (a) Revit and Robot modules, and (b) activities within each module.

Following the implementation of the two RPAs, the mechanical properties of the structural parameters in Robot were updated based on the specifications outlined in Fig. S2. A segment of the acquired data in Robot is shown in Fig. S6 in Appendix A, providing the following information: the bar ID (member), node connectivity (nodes 1 and 2), and section for the distinct structural elements in Robot. Note that a distinct profile was employed for each instance of structural damage. These profiles were designated with a specific profile type (UPN, HEB, IPN, FL, ROND, or CAE) and their respective bar ID and dimensions. For example, UPN_1 160 denotes the damaged UPN 160 profile employed for Bar 1.

The analytical model was ultimately transferred from the Robot to Revit by integrating it with the Revit structure dialog box. The resulting model is shown in Fig. 14. Note that both the nomenclature and attributes of the elements correspond to the updated mechanical sections. To demonstrate this characteristic, the properties of five damaged sections (UPN_1 160, UPN_2 160, HEB_3 160, HEB_4 160, and IPN_5 100) are shown in Fig. 14.

5.4. Time comparison analyses

Various time-based comparisons were conducted to assess the advantages of the proposed RPAs using this case study. The initial computation time required to process a single element using RPA 1 was measured as 0.109 s. This duration was then dissected into its six process activities, as shown in Fig. 15(a). However, when this process was extended to analyze all elements within the case study (a total of 747 elements), the cumulative computation time for RPA 1 increased to 81.350 s (1 min 21.35 s), as shown in Fig. 15(b).

In contrast, RPA 2 required a total of 37.194 s to process a single damaged element. This time span was divided into seven individual process activities specific to RPA 2, as shown in Fig. 16(a). Nevertheless, considering all structural elements within the case study resulted in a significant increase of the RPA 2 computation time to 27 783.918 s (7 h 43 min 3.918 s), as shown in Fig. 16(b).

The calculated time intervals distinctly exemplify how the benefits from the utilization of RPAs become more pronounced as the number of required elements increases. Indeed, the total computation time increased from 37.303 to 27 865.268 s (7 h 44 m 25.268 s), whereas the number of elements in the model increased from 1 to 747. Note that the proposed procedure for updating mechanical properties cannot be executed manually at a faster pace.

5.5. Discussion

The results presented in Section 5.4 demonstrate that the RPA-based workflow accomplishes the calibration task with significantly less human effort than the corresponding manual procedure, while simultaneously reducing potential inaccuracies associated with manual data entry. The application demonstrates the following key practical advantages:

(1) **Repeatability and scalability.** Because the RPA bot executes a deterministic sequence of UI interactions and logs every transaction, the process can be rerun unattended overnight using much larger models—capabilities that manual workflows cannot match.

(2) **Maintainability.** Although RPA requires occasional updates to its software graphical components, this maintenance is relatively lightweight compared to the extensive refactoring or recompiling required when the native code must be updated for major version changes in Revit or Robot.

(3) **Accessibility for non-programmers.** The low-code UiPath interface enables domain engineers, rather than specialist developers, to prototype, test, and refine automation routines. This reduces

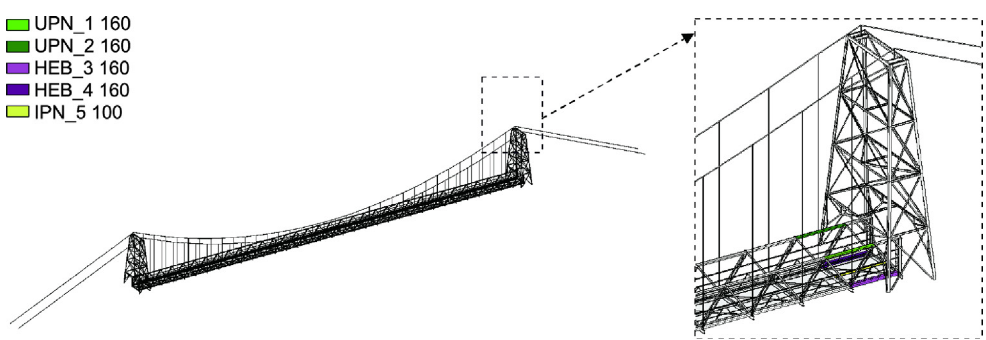


Fig. 14. BIM model with updated structural parameters in Revit, highlighting the properties of five damaged elements.

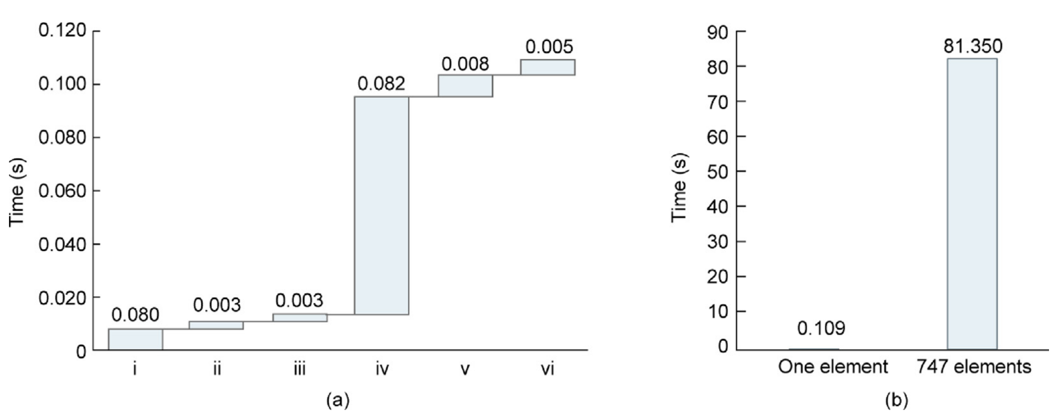


Fig. 15. Computation time of RPA 1. (a) Breakdown for the different process activities (i–vi) for one element; (b) total time for one and 747 elements.

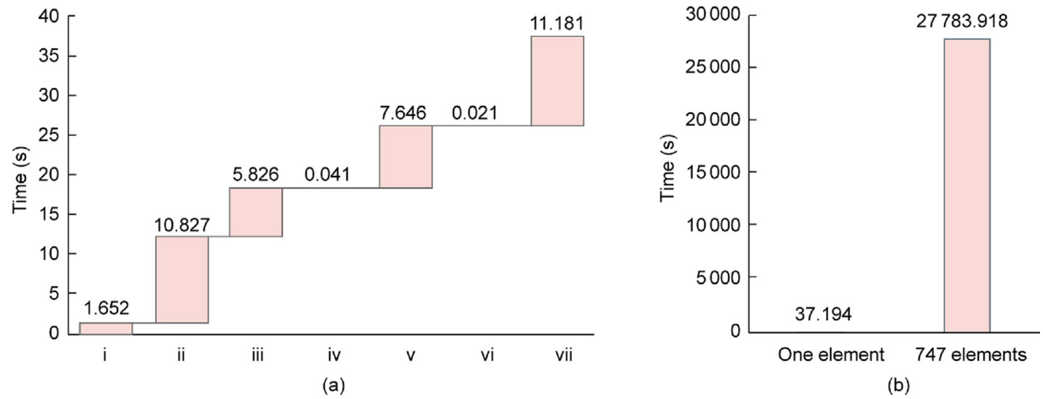


Fig. 16. Computation time of RPA 2. (a) Different process activities (i–vii) for one element; (b) total time for one and 747 elements.

the learning curve and fosters greater ownership within the operational team.

Alternative automation strategies were considered during the planning phase but were ultimately selected against. Fully implementing the calibration using native C#/Python add-ins would bypass the graphical user interface (GUI), offering superior runtime performance; however, it also demands sustained programming expertise, is vulnerable to API-level breaking changes, and provides limited transparency to users unfamiliar with coding. Another possibility involves linking Dynamo graphs within Revit to pyRevit macros, which could automate parameter propagation inside Revit. However, this approach still requires partial manual intervention when transferring data to Robot and necessitates user interaction during software context switches.

In contrast, the adopted RPA tool successfully integrates both applications, delivering immediate productivity gains using the infrastructure commonly available in design offices. Furthermore, it supports staged evolution: Once the calibration protocol stabilizes and the internal coding capabilities increase, isolated workflow segments can be refactored into robust API scripts, whereas the RPA wrapper continues to manage cross-platform handoffs and exception handling.

Beyond this specific use case, the proposed RPA methodology is fundamentally designed with a modular and flexible architecture, enabling straightforward adaptation across a wide range of bridge engineering applications. Its modular framework allows individual components—such as data management, processing rules, classification logic, and BIM interaction scripts—to be independently modified or extended without requiring a complete redesign of the workflow. For example, the framework can be adapted to automate the processing and integration of various inspection data types, including surface cracks, spalling, delamination, fatigue damage, or deformation patterns detected using techniques such as visual surveys, infrared thermography, acoustic emission, or ultrasonic testing. By tailoring data parsing and model update rules, the same automation logic can be repurposed for different structural pathologies with minimal effort. Moreover, the methodology supports broader lifecycle management activities in bridge engineering, such as automated updating of BIM models with as-built or retrofitted geometries, integration of monitoring data for asset management, and automation of load-rating workflows.

The proposed RPA-based workflow also exhibits a high degree of scalability and adaptability, making it suitable for applications in larger and/or more geometrically complex structures. The workflow is driven by iterative loops and structured data inputs that are not inherently limited by the number of elements or instances of damage. This feature makes the methodology particularly advantageous for structural models with numerous elements and/or pathologies. Additionally, the RPA framework can be extended beyond damage modeling to support the automated creation of entire structural systems based on predefined rules, taxonomies, or data-import routines. Thus, it offers an effective and efficient tool for automating complex modeling tasks across various phases of the asset lifecycle, from design and construction to inspection and maintenance.

The capabilities of the RPA become particularly effective when situated within the digital twin paradigm. In this context, the RPA serves as a crucial intermediary layer that automates the flow of raw inspection data—from visual assessments, sensor outputs, or semi-structured reports—into the digital twin environment. In addition, by handling repetitive and rule-based tasks, such as data classification, damage localization and quantification, and model updating, RPA ensures a structured, reliable, and timely transfer of information from the field to the BIM model. This continuous data processing pipeline helps maintain an accurate and up-to-date digital twin, which is particularly important for infrastructures subject to frequent inspections owing to environmental exposure or aging. Furthermore, the RPA framework can be extended to integrate real-time data streams from IoT devices or scheduled condition assessments, thereby enabling the autonomous updating of structural parameters within the BIM model. As an orchestration layer, RPA can periodically query sensor networks or inspection databases, process incoming data, and update digital twins. For example, based on predefined threshold conditions derived from periodic inspections or continuous sensor monitoring, the RPA tool can automatically generate alerts to prioritize maintenance interventions or trigger advanced computational processes—such as finite element method (FEM) recalibration or residual life estimations—for structural components affected by pathologies. These capabilities enable proactive asset management strategies to optimize maintenance scheduling, prioritize critical interventions, and ultimately extend the service life of infrastructural assets.

More importantly, the application of RPA in structural modeling is not limited to the integration of inspection data into BIM environments. Future developments should aim to enhance intelligence and responsiveness through integration with AI techniques and structural health-monitoring (SHM) sensor networks. In terms of AI, combining RPA with computer vision (CV) and natural language processing (NLP) enables the automated interpretation of unstructured data from inspections. CV can identify and classify pathologies using images and videos, whereas NLP can extract the relevant descriptors from reports and maintenance logs. These outputs can be automatically incorporated into the BIM via the RPA pipeline. In parallel, coupling RPA with SHM sensor networks facilitates continuous synchronization between the physical structure and its digital counterpart. Thus, the system can automate full data flow by querying sensors, validating inputs, updating BIM annotations, and triggering alerts or simulations based on predefined rules. This integration positions the BIM model as a responsive, data-driven digital twin capable of supporting predictive maintenance and real-time decision making.

Altogether, these considerations demonstrate the distinct advantages of the RPA over conventional methods in terms of efficiency gains, improved accuracy, and workflow optimization. The adaptability, modularity, and low-code nature of the framework make it a pragmatic and scalable solution for organizations seeking to enhance data consistency and process efficiency without initially committing to full-scale software development.

Although this study focused exclusively on corrosion-induced stiffness loss in steel members, the proposed methodology is general and can be readily extended to other types of structural damage that modify the mechanical properties of the model, such as cracking in reinforced concrete elements. In such cases, the stiffness reduction associated with each damage mechanism must first be quantified using suitable damage detection or model-updating techniques (e.g., the observability-based approach proposed by Lozano-Galant et al. [23]) or through laboratory calibration tests. The resulting stiffness values can then be incorporated into an external Excel file that lists the damaged elements and their updated mechanical properties.

The RPA subsequently reads this information and updates the analytical model within Autodesk Robot Structural Analysis. For the steel elements, the methodology remained essentially the same as that presented in this study. For standard steel profiles (e.g., IPE and HEB), Robot retrieves the geometric and inertial properties from section catalog XML databases (e.g., "EuroPro.xml"). Therefore, RPA can apply the stiffness reductions directly by creating new "damaged" elements within the XML file and automatically substituting the corresponding modified section or inertia values in Robot.

However, its application to concrete elements requires certain adaptations. Because concrete cross-sections are parametrically defined within Revit families rather than through XML catalogs, the same procedure cannot be applied. In this case, the RPA must update the stiffness modification factors available in the bar property dialog of Robot. These factors, derived from the damage information contained in the Excel file, would adjust the effective stiffness of each concrete member to accurately reflect the degree of cracking or degradation detected *in situ*.

6. Conclusions

This study proposes a novel tool for automating the calibration of BIM structural models. This methodology is based on the innovative use of RPA tools that automate, from a user-friendly and intuitive approach, both the generation of new sections in the structural database and the assignment of updated mechanical properties to damaged elements. State of the art BIM, including Revit and Robot Structural Analysis, and RPA and UiPath, was used in this study to ensure robust and reliable results. This study contributes to the automation of calibration and updating of structural attributes within BIM structural models.

To evaluate the effectiveness of the proposed tool, we present a comprehensive case study, focusing on the calibration of the mechanical properties in a real suspension bridge with corrosion pathologies. By demonstrating a successful implementation in a real-world scenario, this study reinforced the practical value and applicability of the proposed RPAs for automating the calibration process in BIM structural models. Moreover, the computation time across varying element quantities was assessed.

The acquired computation times underscore that the proposed procedure for updating the mechanical properties can be time-consuming for extensive structures, such as the example considered in the case study presented herein. This factor acts as a deterrent to manual execution. Additionally, unlike RPA, manual interventions would inherently amplify the likelihood of modeling errors.

Beyond the specific application of automating the calibration of mechanical properties in damaged elements, the proposed RPA-based methodology offers a versatile and extensible framework that can be customized to address a wide range of challenges in infrastructural projects in general and for bridges in particular. For example, it can be adapted to automate the integration of inspection data into digital models, facilitating more efficient and accurate condition assessments, while reducing reliance on manual data entry. In the context of bridges, this is particularly relevant for the management of inspection and maintenance tasks. This methodology can also support automated compliance checks with evolving design standards, generate maintenance reports, and schedule interventions based on performance thresholds embedded within the BIM environment. Furthermore, it enhances the coordination among structural, geotechnical, and construction disciplines, contributing to more integrated and reliable workflows. In summary, the proposed RPA approach provides a scalable solution for advancing the digitalization and automation of lifecycle processes and improving decision-making and operational efficiency.

CRediT authorship contribution statement

Fidel Lozano Galant: Writing – original draft, Validation, Software, Resources, Methodology, Formal analysis, Data curation, Conceptualization. **Edison Atencio:** Writing – review & editing, Validation, Supervision, Resources, Investigation, Conceptualization. **Nikola Tošić:** Resources, Methodology, Data curation. **Jesús González-Arteaga:** Supervision, Project administration, Funding acquisition. **Ye Xia:** Writing – review & editing, Validation, Supervision, Conceptualization.

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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Appendix A. Supplementary data

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