

## A Robust Fuzzy Model for Evaluating Defects in Building Elements

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### Abstract:

This study addresses the critical issue of building element defect management, focusing on prevalent concerns like cracks, dampness, and surface degradation. Recognizing the limitations introduced by human subjectivity in defect classification, the research proposes a novel, data-driven approach to automate the process. The methodology leverages extensive field data collection, encompassing 500 painted walls from 24 geographically dispersed buildings, to develop a robust fuzzy logic-based building element condition assessment model. The model categorizes element conditions (C1-C5) and classifies damage severity into five groups: no damage, slight damage, moderate damage, extensive damage, and complete damage, with nuanced precision. The efficacy of the fuzzy C-Means clustering is rigorously validated through the application of the silhouette index and Davis-Bouldin index, ensuring optimal cluster formation and enhanced model accuracy. A real-world case study involving an office building exemplifies the model's practical application, showcasing its effectiveness in minimizing human error during defect identification and classification. This research contributes a sophisticated defect management framework informed by extensive field data and validated fuzzy logic, ultimately leading to demonstrably improved building quality and reduced operational costs within the construction industry.

## 1. Introduction

The deterioration of building elements is an unavoidable occurrence resulting from improper utilization, external influences like weather conditions, physical deterioration, and insufficient upkeep. Building condition assessment (BCA) [1] is a process used to evaluate the state, performance, and overall condition of a building or its components. BCAs are essential for upholding the safety, operational efficiency, and overall worth of property[2]. These assessments are typically carried out by building owners, facility managers, engineers, and inspectors to verify that buildings are well-maintained and adhere to safety and regulatory requirements. The evaluation of building elements' condition usually involves physical inspection to determine their health status[3]. Building

Condition Assessment (BCA) is commonly carried out to evaluate a building's current condition and predict the level of deterioration it may have undergone[4]. Examining different parts of a building is an essential aspect of maintaining and evaluating its condition. This process includes assessing the state of various elements and systems to identify any problems or shortcomings and confirm that they are operating properly. When conducting a building condition assessment, walls are one of the components that are taken into consideration. The relationship between the severity of degradation of walls and Facility Management (FM) is crucial in ensuring the proper maintenance and upkeep of a building or facility[5]. Building occupants, maintenance personnel, or facility management teams typically detect wall imperfections like cracks or moisture problems. Facility management professionals are tasked with organizing and carrying out maintenance and repair tasks. When anomalies in wall structures are detected, facilities management (FM) teams evaluate their extent and strategize the required repairs or upkeep to promptly resolve the matter. FM systems can amalgamate information from diverse origins, such as Building Information Modeling

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(BIM) and maintenance documentation[6]. Maintenance records allow FM teams to access historical data on wall damage, repairs, and maintenance activities, helping them make informed decisions. In instances of wall damage, information on the damage, including its location, nature, and extent, can be incorporated into the inspection documentation. This process results in the establishment of a thorough documentation of the structural state of the building. The identification and management of defects in building elements present notable challenges within the construction and maintenance sectors, primarily attributed to issues like cracks, dampness, and surface deterioration. These problems not only compromise the structural stability and visual appeal of structures but also have implications on operational effectiveness and maintenance expenditures. Conventional methods of categorizing defects frequently encounter issues of subjectivity and inconsistency, largely due to human interpretation. Despite significant advancements in building maintenance and defect management, several critical gaps persist in current methodologies. Traditional approaches to defect classification are heavily reliant on human expertise, which introduces subjectivity and inconsistency. This reliance on manual inspection and assessment often leads to variability in the identification and categorization of defects, impacting the reliability and accuracy of maintenance strategies. Moreover, existing models and frameworks for building defect management frequently lack the integration of comprehensive data-driven techniques. While some studies have explored automated methods, they often fall short effectively handling the inherent uncertainties and complexities associated with real-world defect data. This limitation is particularly evident in the context of nuanced defect patterns, where traditional algorithms struggle to provide precise and consistent classifications. Additionally, the application of fuzzy logic in building defect management remains underexplored, particularly in the context of large-scale, field data-driven models. Although fuzzy logic offers a robust framework for dealing with uncertainty and imprecision, its potential has not been fully realized in the construction industry. Current research often overlooks the integration of advanced fuzzy clustering techniques, such as fuzzy C-Means, which can enhance the precision of defect classification and condition assessment. Furthermore, there is a notable scarcity of comprehensive validation studies that rigorously test the effectiveness of proposed models in real-world scenarios. Many existing approaches lack empirical validation through extensive field data and fail to demonstrate practical applicability in diverse building environments. This gap underscores the need for robust validation methodologies that can ensure the reliability and accuracy of automated defect management systems. In addressing these research gaps, this study aims to develop

and validate a fuzzy logic-based model for building element condition assessment, leveraging extensive field data and advanced clustering techniques. By focusing on the precise categorization of element conditions and damage severity, this research seeks to minimize human subjectivity and improve the accuracy of defect management processes. The integration of rigorous validation metrics further aims to establish the model's practical applicability and reliability in real-world scenarios, thereby contributing to enhanced building quality and reduced operational costs within the construction industry.

## 2. Research background and related works

### 2.1 Building condition assessment

Building condition assessment is a critical process used to evaluate the physical state of a building. This process is optimized based on different criteria corresponding to owners' objectives under existing constraints [7]. The assessment involves systematic approaches based on condition state and life cycle cost of building components to optimize maintenance and renovation scheduling in multifamily buildings [7]. This approach allows for a comprehensive evaluation of the building's components, providing insights into the condition of the building and aiding in the decision-making process for maintenance and renovation activities. In situ assessment of superficial moisture conditions in facades of historic buildings using non-destructive techniques is crucial for building condition assessment [8]. This type of assessment allows for the evaluation of moisture levels in building exteriors, providing valuable information for the preservation and maintenance of historic structures. The integration of Building Information Modelling (BIM) in building condition assessment has been explored as a means to support and enhance the assessment process [9]. BIM provides a platform for creating and managing digital representations of the physical and functional characteristics of buildings, offering opportunities to streamline the assessment process and improve the accuracy of condition evaluations. Moreover, various numerical methods have been employed for modeling the building condition to assess the technical condition of structures [10]. These methods contribute to the development of advanced tools for evaluating the structural integrity and overall condition of buildings. Machine-learning-based approaches have also been leveraged for post-event assessment of damage in building structures, contributing to the advancement of building condition assessment techniques [11]. These approaches offer the potential to automate and improve the accuracy of damage assessment, particularly in the aftermath of natural events or unforeseen incidents.

Furthermore, the utilization of phase change materials for building cooling load abatement in composite climatic conditions has been explored as a means to assess and enhance building conditions [12]. This indicates the potential for integrating energy-efficient and sustainable solutions within the building condition assessment process to address environmental concerns and improve building performance. Despite the advancements in building condition assessment, there are still knowledge gaps that warrant further research. For instance, there is a need to explore the integration of emerging technologies, such as the Internet of Things (IoT) and remote sensing, in building condition assessment to enhance the accuracy and efficiency of evaluations. Additionally, further research is required to develop standardized frameworks and guidelines for building condition assessment, particularly in the context of historic and heritage buildings where preservation and maintenance are of utmost importance. Asset management systems are tools that support owner organizations to better manage their assets [13]. According to multiple sources in scholarly literature, the evaluation of condition (CA) holds significant importance within the asset management system, as the outcomes of this phase serve as the foundational basis for subsequent functions. BCA is part of the asset management system, defined in ISO 55000:2013[14] and so, should be conducted in combination with other important activities, like inspections and maintenance operations. A decision support system (DSS) can aid in decision-making processes both in the initial stages of design development and throughout the operation and maintenance (O&M) phase. To support decision-making on building condition assessment, Matos, R., [9] prioritized maintenance actions, using Key Performance Indicators (KPI) and a support tool. Frederik et al[15] created a probabilistic model that learns from user feedback and adapts to the users' specific preferences over time to analyze building conditions. Yang et al[16] developed a probabilistic model based on a comprehensive survey of air handling unit (AHU) fault detection and diagnosis methods. Lee et al.[17] developed a Bayesian method for probabilistic occupant thermal preference categorization and prediction in office buildings, to provide predictions for personalized thermal preference profiles. Bortolini, R. [18] developed a model for assessing the condition of a building using a Bayesian network (BN) method. Artificial intelligence (AI) and machine learning have become pivotal in automating the condition assessment processes and enhancing the accuracy of evaluations. Himeur et al. [19] provide a comprehensive survey of AI and big data analytics in building automation and management systems, identifying challenges and future perspectives. The integration of AI can lead to more efficient condition assessments by processing vast amounts of data and identifying patterns that human inspectors might overlook.

Recent advancements in digital twin (DT) technology have shown promise in improving building condition assessments. Kaewunruen et al.[20] propose a comprehensive condition assessment framework utilizing DTs for managing railway bridge maintenance and climate change adaptation. This framework emphasizes the importance of real-time data integration and analytics to enhance decision-making processes related to asset management. Additionally, a data-driven approach for regional bridge condition assessment was presented by Xia et al.[21], highlighting the necessity for efficient data collection methods to accurately gauge the as-is status of assets. This study underscores the role of inspection reports in creating an asset inventory, which is crucial for maintaining infrastructure health. During the O&M phase, existing studies utilized probabilistic models to make decisions on improving building conditions but in this study, we used fuzzy models for building components inspection.

## 2.2 Building Component Rating Systems

Buildings consist of numerous interconnected elements. Evaluating the components of a building provides a standard for comparison when assessing its condition. Various rating systems for building components have been created, each designed with distinct objectives and methodologies. Abbott et al. [2] proposed a five-point color-coded rating system for hospital building rating in South Africa for evaluation of maintenance budget. Pedro et al. [22] explain the method for assessing the condition of buildings in Portugal which is evaluated by dividing the entire building into elements and building defects detected in an element are assessed on a scale based on pre-defined criteria. Eweda et al.[23] proposed integrated condition assessment model that considers both the physical and the environmental aspects for rating educational buildings in Canada. Straub[24] explains the use of condition assessment of buildings using Dutch. The evaluation process relies on identifying flaws in operational components and determining their significance, scope, and severity. The scholarly sources examined in this investigation demonstrate that conducting thorough examinations of structures is a technically intricate endeavor that demands substantial resources and a workforce. Cheng et al. [25] conducted a comprehensive assessment of the embodied environmental impacts of buildings, utilizing normalized environmental impact factors. This methodological approach offers a standardized basis for evaluating the sustainability of different building components, setting a precedent for future BCRS development. The integration of these factors into BCRS can enhance their relevance in promoting environmentally friendly construction practices. The work by Meng et al[26] outlined key performance indicators distributed across five categories: energy and power performance, GHG emissions,

indoor environmental quality, smartness, and life cycle costs. This classification is instrumental for BCRS as it provides a structured approach for evaluating building components across multiple performance dimensions, ensuring a comprehensive assessment. Research by Salom et al. [27] discussed the application of the Internet of Things (IoT) in the construction industry, providing insights into how technology can enhance building performance evaluations. The integration of IoT data into BCRS could facilitate real-time monitoring and assessment, allowing for more dynamic and responsive rating systems. This paper introduces a novel approach for assessing building elements to reduce the impact of human fallibility on the precision of component ratings.

### 2.3 Defect Detection

The evaluation of defects in building elements, such as concrete columns, is critical for ensuring the safety and integrity of structures. The development of a system that can identify defects in these elements before responders enter a structure has the potential to save lives. In this context, several researchers have proposed innovative methods for defect detection and localization in building elements. Wang, Tian, Chen, Qiao, and Snoussi [28] proposed a system centered around an image-based three-dimensional (3D) reconstruction method and a new 3D crack detection algorithm. They aimed to evaluate the application of convolutional neural networks (CNN) for automated detection and localization of key building defects, such as mould, deterioration, and stain, from images. Similarly, Torok, Fard, and Kochersberger [29] focused on image-based automated 3D crack detection for post-disaster building assessment. Their work also highlights the potential of CNN in detecting critical defects in building elements. Furthermore, Perez, Tah, and Mosavi [30] conducted research on deep learning for detecting building defects using convolutional neural networks. Their study aimed to evaluate the effectiveness of CNN in identifying various building defects, providing further evidence of the potential of this approach in the context of defect evaluation. While the existing research has made significant strides in proposing innovative methods for building defect evaluation, there are still some knowledge gaps that need to be addressed. One of the potential future research directions in this field could be the development of a robust fuzzy model for evaluating defects in building elements. This model could build upon the advancements in CNN-based defect detection and integrate fuzzy logic to enhance the accuracy and robustness of defect evaluation systems. Additionally, further research could focus on the integration of differential evolution techniques, as proposed by Bui, Nguyen, Hoang, and Klempe [31], to improve the spatial prediction of building defects, particularly in challenging

environmental conditions. In conclusion, the existing literature has demonstrated the potential of CNN-based methods for defect detection in building elements. The integration of innovative technologies in defect detection is further illustrated by the work of Mishra et al. [32], who developed an artificial intelligence-based visual inspection system aimed at monitoring the structural health of cultural heritage buildings. Their approach not only identifies cracks and cavities but also provides a comprehensive assessment of overall structural integrity. This highlights the potential for AI to enhance traditional inspection methods. Moreover, the development of Building Information Modeling (BIM) systems has been a significant advancement in defect management. May et al. [33] introduced a BIM-based Augmented Reality Defect Management (BIM-ARDM) system, which facilitates the identification and management of defects during construction inspections. This innovative approach provides a visual context that enhances understanding and communication among stakeholders. Cracks are among the most common defects observed in concrete structures, often serving as indicators of underlying structural issues. Golding et al. [34] explored the application of deep learning techniques for crack detection in concrete, highlighting the advantages of automated systems in enhancing the accuracy and efficiency of inspections. Their findings suggest a potential shift towards more advanced, data-driven methodologies for assessing structural health. However, there is a need for further research to develop a comprehensive and robust fuzzy model that integrates advanced techniques to enhance the accuracy and reliability of defect evaluation systems in the built environment.

## 3. Materials and Methods

This study introduces a fuzzy model designed to evaluate the state of building components with imperfections, with a particular emphasis on painted walls. The research employed a fuzzy algorithm to replicate the deterioration of painted walls. The data collection process entailed the inspection of 500 interior painted walls across 24 buildings in Tehran province, Iran, with statistical field data serving as the principal methodological framework. Information on crack dimensions, dampness extent, and surface irregularities in building walls was collected during the field investigation. This data will be examined using the Supervised Center Classification (SCC) technique [35, 36], which will act as the primary centroid for the clustering procedure utilizing fuzzy C-Means algorithms. The next step in evaluating results using the SCC technique will entail employing a unique methodology, namely the fuzzy C-Means clustering technique. Subsequently, the resultant clusters will be assessed for validation utilizing the Davies Bouldin index and Silhouette coefficient techniques, to

derive definitive cluster centroids. The severity of the degradation index ( $S_d$ ) for the walls will be estimated using the Fuzzy Inference System. The final severity of the degradation index is represented as a precise value obtained through the defuzzification process. A research investigation was carried out on an office building to assess the effectiveness of the proposed model. The information employed in this research was obtained from building inspection documents collected during fieldwork. The schematic representation of the study can be observed in Figure 1. The practical implications of our fuzzy model and clustering algorithms in building condition assessment and decision-making are significant:

- 1- Precision in Defect Identification: The model enhances accuracy in classifying building defects, minimizing human error and subjectivity.
- 2- Optimized Maintenance Strategies: By categorizing defects and damage severity, building managers can prioritize maintenance actions based on data-driven insights, leading to cost-efficient and timely interventions.
- 3- Predictive Maintenance: The model's predictive capabilities allow for early detection of potential issues, enabling proactive maintenance that extends the building's lifespan and reduces costly repairs.
- 4- Resource Allocation: Decision-makers can use the model to allocate resources more effectively, focusing on critical areas that require immediate attention

### 3.1 Creation of a fuzzy model for assessing the condition of building elements based on defects

#### 3.1.1 Pathology

To determine the current frequency of maintenance protocols and identify significant structural anomalies in the building, a set of 12-hour interviews were carried out with departmental partners, comprising technicians possessing previous building maintenance expertise, alongside licensed building engineers. A compilation of possible imperfections that could manifest in each nonstructural component was presented to participants, drawing from prior research sources[37-39]. Respondents were requested to identify a maximum of three primary flaws associated with painted walls, with the opportunity to include any additional defects they deemed pertinent. The defects identified by experts as having a significant impact on the performance of interior partitions are cracking, water issues (dampness), and surface problems. The presence of these imperfections carries significant consequences for the safety, functionality, and visual attractiveness of architectural elements, particularly interior partitions. By employing this framework, each designated area within a structure can be evaluated in terms of its visual appeal and state of repair, taking into account

the extent of any defects present. These individual evaluations can subsequently be combined to ascertain the general condition of the entire building.

#### 3.1.2 Gathering data on defective samples

To establish a fuzzy model for assessing building element conditions based on defects, a specialized inspection plan was devised for structures exhibiting wall imperfections. A series of standardized inspections were carried out between September 2022 and December 2022 during fieldwork activities, with observations recorded using designated inspection forms. The fieldwork encompassed the evaluation of 500 painted walls displaying defects within 24 buildings situated in Tehran province, predominantly serving residential, office, and educational purposes. The selected structures ranged in construction dates from 1955 to 2012. The visual inspection protocol commenced by meticulously surveying wall surfaces and meticulously examining each wall for surface irregularities such as horizontal and vertical cracks, watermarks, paint deterioration, discoloration, as well as any anomalies or inconsistencies in the plaster coating. The width of cracks at different locations along their length was measured using a digital caliper, while the length of each crack on the wall was determined with a Digital Rolling Ruler. These instruments provided precise measurements for further examination and assessment of wall degradation. The sqftAR application was utilized to quantify the extent of dampness and surface problems on the walls, enabling a detailed evaluation of the affected surface area. The collected measurements supported thorough documentation and analysis of identified issues to inform decisions on maintenance, repair, and restoration. Figure 2 illustrates instances of these imperfections. All defect data was documented in inspection forms. Three certified judicial experts actively participated in data collection alongside the researchers. To establish a comprehensive framework for evaluating degradation severity, a structured classification system consisting of five distinct categories (E1 to E5) was initially developed. This system delineated varying levels of degradation severity, ranging from E1 indicating no visible damage to E5 denoting complete deterioration, with E2 representing minor damage, E3 moderate damage, and E4 significant damage. However, in the practical context of fieldwork, the process was more fluid. The judicial experts, drawing on their combined expertise and engaging in collaborative discussions, individually assessed and categorized each wall based on observed defects. This collaborative approach facilitated a nuanced and thorough evaluation, ensuring accurate classification of each wall's degradation severity within the predefined categories, and enhancing the evaluation methodology (Table 1 offers examples of the collected data).

### 3.1.3 Developing a fuzzy model via fieldwork

Information gathered during fieldwork is utilized for the evaluation of a fuzzy model for assessing the condition of building elements based on defects. Five linguistic fuzzy sets have been created for the input parameters of Crack, Dampness, and Surface problems area, denoted as bad (B), relatively bad (RB), medium (M), relatively good (RG), and good (G). In the context of classification output parameters,

damage (ED), and complete damage (CD). A triangular-shaped membership function is employed for each of the input and output parameters. The ranges of membership functions for both input and output parameters are determined through the supervised center classification method. Initially, the defect data is segmented based on the corresponding wall area and represented as a percentage to achieve standardized information. Subsequently, the normalized defects are subjected to a set of guidelines to establish the membership functions of the standardized input variables using the SCC-FCM methodology.

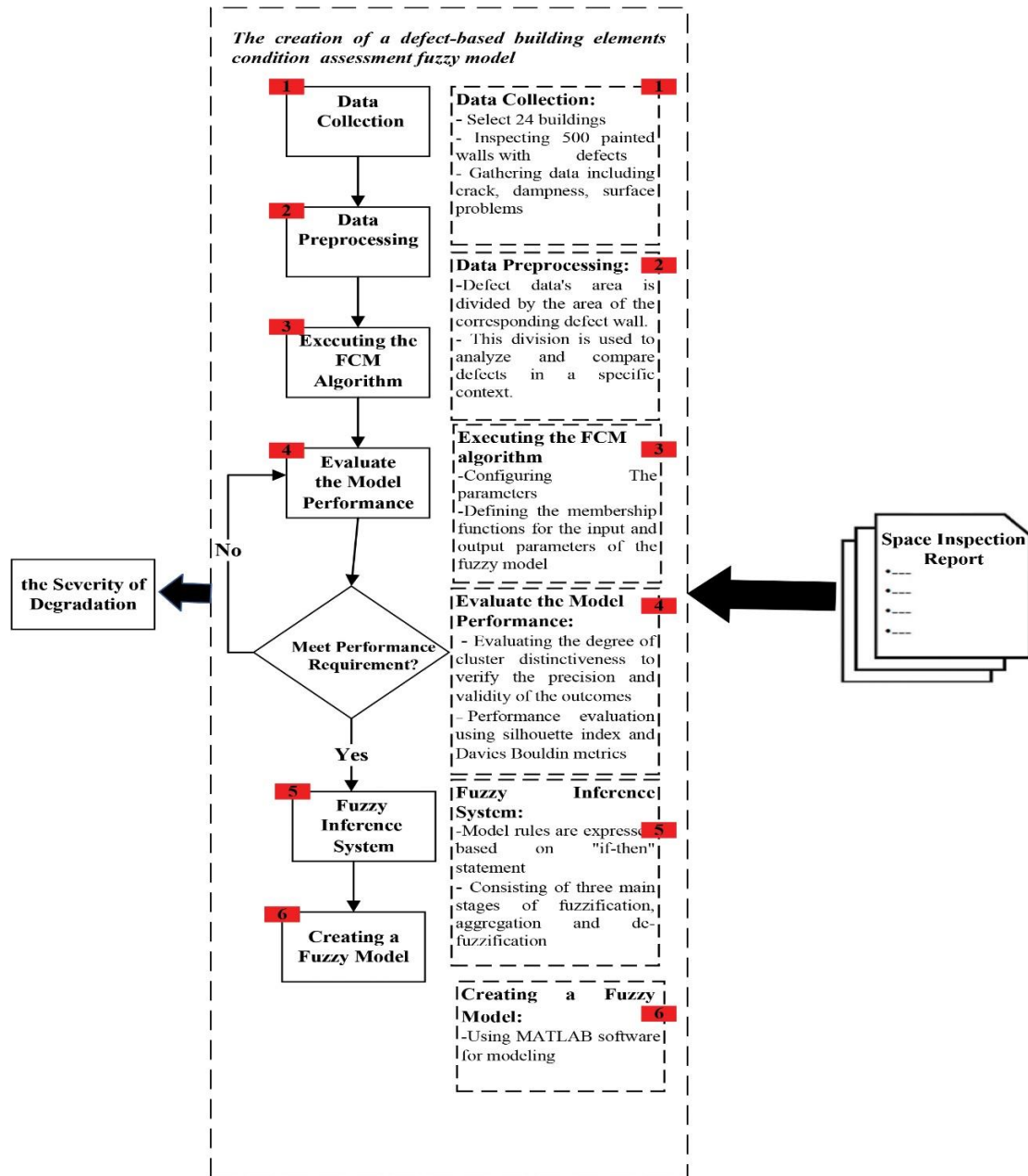


Fig. 1: The diagrammatic illustration of the research

- Minimum measured values in fieldwork for parameters with desirable lower values fall in the G range, while those with desirable higher values fall in the B range. An example is the parameter of crack, where lower values are desirable.
- Maximum values for parameters with lower desirable values are in the B range, while for higher desirable values, they are in the G range.
- Average values for all parameters, whether lower or higher values are desirable, are in the M range.
- The average of minimum value and mean for parameters with lower desirable values is in the RG range, and for higher desirable values is in the RB range.
- The average of maximum value and mean for parameters with lower desirable values is in the RB range, and for higher desirable values is in the RG range.

According to these rules, Table 2 was obtained for normalized primitive membership functions, which were the criteria for the ranges of membership functions in the normalized input parameters of the model.

### 3.1.3.1 The implementation of the Fuzzy C-Means (FCM) algorithm using fieldwork

In fuzzy clustering, each data point is assigned a degree of membership to every cluster, making it suitable for scenarios where cluster boundaries are ambiguous. The Fuzzy c-means (FCM) algorithm is an unsupervised clustering technique that has been effectively utilized in various applications involving feature analysis, clustering, and classifier design. The iterative process of the FCM algorithm involves utilizing the MATLAB programming language to execute the necessary steps for deriving the normalized final membership function for input and output parameters.

**The initial step:** involves setting the cluster centers (c) as Bad (B), relatively bad (RB), medium (M), relatively good (RG), and good (G) based on the SCC method.

**Second step:** Initializing the membership matrix  $u^{(0)}$ : By using the function (1) membership degrees of every 500 samples were calculated for crack, dampness, and surface problem areas. So that we have a membership degree matrix  $[u]_{500 \times 5}$ . Membership degree matrix “U” shows every defect belongs to 5 clusters with a degree of membership. The membership degree of  $i^{th}$  sample to the  $j^{th}$  cluster is represented as  $u_{ij}$ , which denotes the similarity between the sample i and the certain cluster j.

$$u_{ij} = \frac{1}{\sum_{k=1}^c \left( \frac{\|x_i - c_j\|}{\|x_i - c_k\|} \right)^{\frac{2}{m-1}}} \quad (1)$$

$$i = 1, \dots, N \quad j, k = 1, \dots, c$$

Where  $\|x_i - c_j\|^2$  is the distance from the sample i to the cluster center j, and m is the weighting fuzziness parameter. The fuzziness parameter, denoted by m, controls how much overlap there is between clusters. It determines how the membership degrees are calculated for each data point and cluster that is considered constrained by (1).

**Third step:** Computing the new cluster centers matrix  $c^{(new)}$ : By using the function (2) the new cluster centers matrix for 5 clusters was calculated and replaced with initial cluster centers derived from minimum, maximum, and average of fieldwork data.

$$c_j = \frac{\sum_{i=1}^N u_{ij}^m \cdot x_i}{\sum_{i=1}^N u_{ij}^m} \quad j = 1, \dots, c \quad (2)$$

**Fourth step:** Compute the new membership matrix  $u^{(1)}$ : By using functions (2) and with  $c^{(new)}$  new membership degree matrix was obtained.

**Fifth step:** The algorithm completion condition is checked to terminate the iteration when it reaches a stable condition. Termination can be based on changes in cluster centers or membership values being smaller than a predefined threshold ( $\|u^{(l)} - u^{(l-1)}\| < .01$ ). In the case of the crack area, the process stopped at the first iteration due to the centroid position being the same as the previous iteration. For dampness and surface problem areas, the iterations stopped at the thirteenth and eighth iteration respectively. The final centroid value for the input parameters of crack, dampness, and surface problem areas was obtained, as depicted in Figure 3 and Table 3.

### 3.1.4 Evaluation criteria for clustering algorithms

After the application of the Fuzzy C-Means (FCM) algorithm, there is a notable question concerning the evaluation of its effectiveness. While supervised algorithms provide metrics like accuracy, R-squared value, sensitivity, and specificity for performance assessment, evaluating the accuracy or efficacy of a clustering method poses a unique difficulty. In this regard, the Silhouette Coefficient and Davies Bouldin index are recognized as significant indicators for measuring the quality of clustering results.

#### 3.1.4.1 The Silhouette score

One potential method for examining the spatial distribution of clusters generated by the algorithm is through the application of silhouette analysis to determine the separation distance between these clusters.



Fig. 2: Examples of some defects during inspection

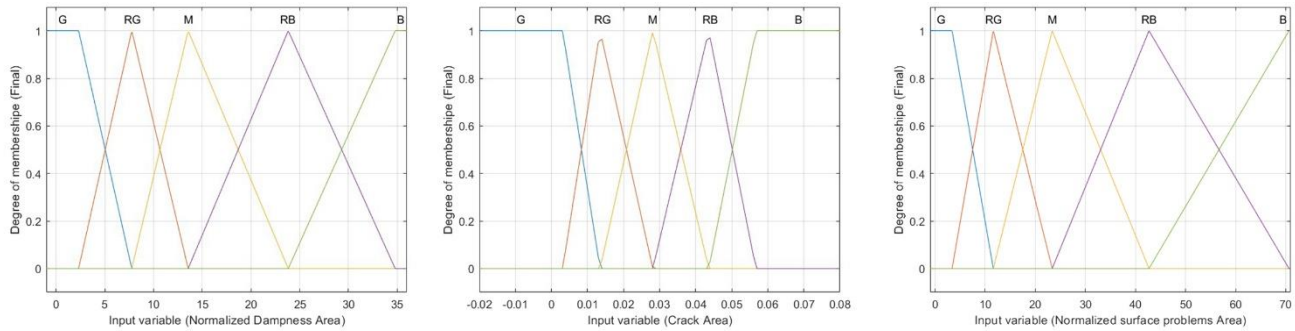


Fig. 3: Final Membership functions of the input parameters of the fuzzy model

Table 1: A sample of fieldwork

Building	Crack Width(mm)	Crack Length(m)	Dampness(m <sup>2</sup> )	Surface problems(m <sup>2</sup> )
A1	1.358	2.444	1.338	1.237
A2	3.807	2.717	0.000	0.000
A3	3.681	0.381	0.531	1.872
A4	0.211	2.740	0.000	0.000
B1	2.951	1.897	0.992	1.461
B2	1.077	0.293	2.695	0.000
B3	1.691	0.835	0.354	1.666
C1	2.192	1.641	0.000	0.797
C2	3.771	2.873	1.620	1.500

A indicates office buildings, B indicates educational buildings, and C indicates residential buildings

Table 2: Input variable values with primitive membership degree equal to 1.

	Crack Area	Dampness	Surface problems
G	0.101	0.031	0.015
RG	1.035	0.733	0.517
M	1.968	1.436	1.02
RB	2.983	2.217	1.507
B	3.998	2.998	1.995

Table 3: Input variable values with final membership degree equal to 1.

	Crack Width	Dampness	Surface problems
G	0.419	0.267	0.187
RG	1.164	0.800	0.625
M	1.984	1.442	1.015
RB	2.787	2.152	1.411
B	3.622	2.774	1.812

The Silhouette Coefficient is calculated using the mean intra-cluster distance (a) and the mean nearest cluster distance (b) for each sample. The expression of the individual silhouette coefficient is as follows[40]:

$$a(i) = \frac{1}{n_c - 1} \sum_{i,j \in C_c} d(i,j) \quad (3)$$

$$b(i) = \min \frac{1}{n_p} \sum_{j \in C_p} d(i,j) \quad (4)$$

$$S(i) = \frac{b(i) - a(i)}{\max(b(i), a(i))} \quad (5)$$

$$SC = \frac{1}{N} \sum_{i=1}^N S(i) \quad (6)$$

Where  $n_c$  is the number of points belonging to the cluster  $C_c$ ,  $d(i,j)$  is the distance between data points  $i$  and  $j$  in the cluster  $C_c$ ,  $b(i)$  is the average distance to all data points in the nearest neighboring cluster,  $S(i)$  is the silhouette coefficient for each data, and  $SC$  is the average silhouette coefficient across all data points for the clustering result. Cluster validation was conducted on field data consisting of three distinct categories - crack, dampness, and surface problem areas - using the silhouette algorithm (Equation 3-6). The data within these categories were segmented into five clusters through the FCM algorithm. A custom MATLAB script was developed to execute the silhouette algorithm for evaluating the quality of clustering. The Silhouette Index measures how similar an object is to its cluster (cohesion) compared to other clusters (separation). The index ranges from -1 to 1, where values close to 1 indicate that the objects are well-clustered, meaning they are highly cohesive within their clusters and well-separated from other clusters. The findings of the Silhouette Evaluation are detailed in Table 4. Notably, a value of 0.730 assigned to the normalized surface area signifies successful clustering of field data points, demonstrating distinct separation between clusters. This outcome indicates well-defined and separated clusters within the dataset.

### 3.1.4.2 Davies-Bouldin index

Like the silhouette score, the Davies-Bouldin Index (DBI) helps assess the separation and compactness of clusters. The stages of calculating the Davies Bouldin Index are as follows[41]:

$$SSW_i = \frac{1}{m_i} \sum_{j=1}^{m_i} d(x_j, c_i) \quad (7)$$

$$SSB_{i,j} = d(c_i, c_j) \quad (8)$$

$$R_{i,j} = \frac{SSW_i + SSW_j}{SSB_{i,j}} \quad (9)$$

$$DBI = \frac{1}{k} \sum_{i=1}^k \max(R_{i,j}) \quad (10)$$

Where (SSW) is the Sum of the Square Within-cluster, (SSB) is the Sum of the Square Between-cluster,  $R_{i,j}$  is the comparison value between cluster  $i$  and cluster  $j$ , and DBI is the Davies-Bouldin Index.

The Davis-Bouldin Index assesses the average similarity ratio of each cluster with its most similar cluster. The index is calculated based on the ratio of within-cluster scatter to between-cluster separation, with lower values indicating better clustering performance. A MATLAB algorithm was developed to calculate the Davies-Bouldin Index, and the results of its validation are detailed in Tables 5-7. Notably, the computation yielded a DBI score of 0.468 for the normalized surface area concerns, indicating a relatively modest value that implies the presence of distinct and tightly packed clusters. This finding implies that the data points within each cluster exhibit similarity and coherence. The DBI value of 0.468 suggests that the clustering results are advantageous for understanding patterns or aiding decision-making within the scope of our research or practical application.

### 3.1.5 The membership functions linked to the output parameter

To determine the extent of the membership function range for the normalized output parameter obtained through fieldwork utilizing the SCC-FCM methodology, it is essential to calculate the distances between the defect degrees of the various components of the building using the prescribed equation (11) [35, 36]. Subsequently, the collective sum of these distances needs to be ascertained. The membership function for the normalized output parameter was then calculated based on the outcomes obtained from equation (11), as depicted in Figure 4. Table 8 presents an overview of the spectrum of the membership function associated with the normalized output parameter.

$$D_{i,i-1} = \sqrt{\sum_{k=1}^3 (M_{ki} - M_{k(i-1)})^2} \quad (11)$$

**Table 4:** Silhouette Evaluation

	Crack Width	Dampness	Surface problems
<b>Num of Observations</b>	500	430	460
<b>Criterion Values</b>	0.719	0.71	0.726

**Table 5:** Validation results with DBI for Crack

Clusters	SSW	SSB	Ratio	DBI
1	0.171	0.745	0.4859	
2	0.19	0.82	0.486	
3	0.208	0.803	0.505	0.49
4	0.198	0.803	0.505	
5	0.207	0.835	0.484	

**Table 6:** Validation results with DBI for Dampness

Clusters	SSW	SSB	Ratio	DBI
1	0.105	0.532	0.501	
2	0.161	0.642	0.537	
3	0.184	0.642	0.537	0.5
4	0.16	0.71	0.484	
5	0.122	0.622	0.454	

**Table 7:** Validation results with DBI for Surface Problems

Clusters	SSW	SSB	Ratio	DBI
1	0.097	0.438	0.467	
2	0.108	0.39	0.529	
3	0.099	0.39	0.529	0.49
4	0.091	0.396	0.48	
5	0.092	0.4	0.458	

**Table 8:** The range of membership function for the output parameter

	Percent distance Centers	Percent Cum distance Centers
<b>ND</b> No Damage	0.147	0.147
<b>SD</b> Slight Damage	0.206	0.353
<b>MD</b> Moderate Damage	0.214	0.568
<b>ED</b> Extensive Damage	0.218	0.785
<b>CD</b> Complete Damage	0.215	1.000

#### 4. The outcomes of the fuzzy clustering analysis, as well as the evaluation of these findings

One essential element of a fuzzy model is its rule segment, which plays a crucial role in facilitating the inference process and attaining the intended outcomes. Fuzzy inference entails establishing the connection between a given input and output through the application of fuzzy logic principles. A Fuzzy Inference System (FIS) is a type of fuzzy model that utilizes fuzzy logic to make decisions or perform reasoning tasks based on imprecise or uncertain information[42]. FIS methods use fuzzification, inference, and defuzzification processes. Fuzzy rules are a fundamental component of fuzzy logic and fuzzy inference systems (FIS) [42]. Figure 5 illustrates the structure of the Fuzzy Inference System (FIS) developed for assessing the condition of building elements based on defect data. The FIS is designed to process inputs related to defect characteristics and produce an output that indicates the condition and severity of the damage. As shown in the figure Input Layer receives the raw data related to defect characteristics. In this study, the inputs are derived from extensive field data collection of 500 painted walls. Input Variables represent the measurable features of the defects, such as the size of cracks, extent of dampness, and area of surface problems. Each input variable is mapped to fuzzy sets that represent different levels of the variable, such as "G," "RG," "M," "RB," and "B". A set of if-then rules that define how the input variables are combined to determine the output. These rules capture expert knowledge and are used to infer the condition and severity levels. The fuzzy inference engine applies a set of predefined rules to the fuzzified inputs. These rules are constructed based on expert knowledge and field data insights. A select number of rules, typically numbering in the tens, are employed in research applications, representing a subset of dependable and coherent rules. In adherence to established criteria, a total of 58 rules were incorporated into the fuzzy model for this study. The implementation of the Fuzzy Inference System (FIS) was carried out using the Fuzzy Logic Toolbox within the MATLAB environment. A fuzzy model was developed in MATLAB software by establishing membership functions for the three input parameters using fuzzy C-mean, along with defining the membership function for the severity of degradation ( $S_d$ ) of painted walls as the output, and specifying the model rules. The fuzzy C-Means algorithm is utilized to enhance the precision of categorization. The next stage is defuzzification where the fuzzy outputs are converted back into crisp values to provide a clear assessment of the building element's condition and the severity of the defects. The outputs of the FIS indicate the condition of the building elements (C1-C5) and the severity of the damage which facilitate accurate and

objective defect classification. By acquiring ( $S_d$ ), it is categorized as a fuzzy concept alongside complete damage (CD), extensive damage (ED), moderate damage (MD), slight damage (SD), and no damage (ND). In this investigation, the Mamdani Fuzzy Inference System, introduced by Ebrahim Mamdani in 1975, was utilized. While there exists a considerable array of potential rules governing the relationship between input and output parameters, a substantial portion of these rules lack reliability. These classifications aid in offering practical insights derived from the output of the Fuzzy Inference System (FIS). Consequently, through the utilization of input parameters such as crack area, dampness level, and surface issues about building walls, the extent of degradation can be quantified utilizing a qualitative model in conjunction with field data. For instance, a hypothetical scenario was constructed where a wall exhibited a crack area of 0.03, a dampness level of 17.5, and a surface problems rating of 35.5. This model yielded a degradation severity value of 0.643 as the output parameter. The degradation severity of the new wall is determined by assessing the impact of each input parameter and applying the rules of the fuzzy model. Based on the depicted ranges of degradation severity output parameters in Figure 4, this model, exhibiting a degradation severity value of 0.643, falls within the 29% moderate degradation (MD) and 71% extensive degradation (ED) ranges. Furthermore, it is possible to explore the alterations in model behavior resulting from variations in input parameters. In our research, we conducted a thorough examination of building walls in collaboration with three experienced inspectors. Each identified imperfection was sorted into one of five pre-established categories based on its severity and nature (spanning from E1, which signifies no observable harm, to E5, which denotes total damage, with E2 indicating slight damage, E3 denoting moderate damage, and E4 indicating substantial damage). Subsequently, we utilized a fuzzy model to independently analyze the same group of building walls. To evaluate the effectiveness of the fuzzy model in defect classification, we compared its results with those determined by the human inspectors on specific walls. Interestingly, our investigation revealed a significant level of agreement between the classifications produced by the fuzzy model and those provided by the human inspectors. Across the examined walls, the classifications assigned by both the fuzzy model and the human inspectors exhibited a notable degree of similarity, indicating a strong correlation between computational and human-based evaluations. The decision to use the Mamdani FIS was driven by its strengths in interpretability, handling linguistic variables, and suitability for complex decision-making in environments characterized by uncertainty—such as building defect assessments.

Comparison:

- Mamdani FIS: The Mamdani FIS is known for its intuitive and interpretable rule-based system, which uses fuzzy sets and if-then rules to model complex systems. It is particularly effective in situations where human expert knowledge needs to be incorporated into the decision-making process. The output is a fuzzy set, which is then defuzzified to obtain a crisp value, making it well-suited for qualitative analysis and building condition assessments. In the context of our study, Mamdani FIS's ability to translate expert knowledge into fuzzy rules allows for a more accurate and explainable classification of building defects.

- Sugeno FIS: The Sugeno model is often favored for its computational efficiency and ability to handle optimization problems. Unlike Mamdani, it uses linear or constant output functions, which simplifies the defuzzification process. While this is advantageous in control systems and real-time applications, it is less effective in scenarios requiring interpretability and linguistic reasoning, such as building assessments. The focus on mathematical optimization rather than qualitative interpretation makes Sugeno less appropriate for the nuanced decisions required in building defect management.

- Tsukamoto FIS: Similar to Mamdani, Tsukamoto FIS also employs fuzzy sets and rules, but it handles defuzzification differently by producing crisp outputs for each rule. While Tsukamoto FIS provides clarity in output, it is more complex to implement and is not as widely used in applications like building condition assessment, where the interpretability of the rules and outputs is crucial.

The choice of Mamdani FIS in our study is based on its balance between interpretability, flexibility, and effectiveness in handling uncertain and imprecise data—key factors in building defect classification. Its ability to model expert knowledge through linguistic variables makes it particularly well-suited for practical applications like those in The Tehran Construction Engineering Organization (TCEO), where understanding and explaining the decision-making process is as important as the outcomes themselves. Figures 6 and 7 depict various scenarios showcasing alterations in the input parameters and the corresponding levels of degradation observed in the painted walls. Figure 6(a) illustrates the variations in the crack area and ( $S_d$ ). Analysis of this graph reveals that the crack area experiences a sharp increase up to 0.035, followed by a period of stability between 0.035 and 0.05, and subsequently undergoes another sharp increase beyond 0.05. Figure 6(b) and 6(c) illustrate the variations in ( $S_d$ ) concerning dampness and surface issues. Figure 6(b) delineates the dampness region into four distinct categories. Given constant values for all other parameters, ( $S_d$ ) will remain constant when the dampness area is less than 3. If the dampness area falls between 3 and 15, ( $S_d$ ) will increase at a steep rate. In contrast, in areas with dampness levels ranging from 15 to

25, no notable alteration in ( $S_d$ ) is noted. However, in regions where the dampness area exceeds 25, a steep incline in ( $S_d$ ) is observed. In Figure 6(c), the segment of surface issues can be categorized into three distinct groups. Holding other variables constant, when the surface problems area measures less than 25, ( $S_d$ ) will exhibit a sharp incline. Conversely, within the range of 25 to 50, a gradual increase in ( $S_d$ ) is noted, and beyond 50, a steep rise in the severity of degradation to painted walls is observed. Figure 7 assesses the combined impact of two input parameters on the extent of degradation within the model. The analysis reveals that for walls exhibiting a crack area exceeding 0.02 and a dampness area surpassing 15, there is a notable escalation in the severity of degradation, as depicted in Figure 7(a). Similarly, in instances where walls display a crack area exceeding 0.02 alongside a surface problems area exceeding 60, the severity of degradation is observed to be significantly elevated, as illustrated in Figure 7(b). Furthermore, as depicted in Figure 7(c), the extent of degradation is significantly reduced in walls exhibiting dampness levels below 20 and surface issues below 20.

### 5. Case study description

The Tehran Construction Engineering Organization (TCEO) was selected as the subject of study due to its status as a professional, nonpartisan, nonprofit, and autonomous institution (see Figure 8). The structure being examined is an office building that was constructed in the 1990s and originally served as a medical facility. It comprises five above-ground stories and three partially underground levels. The primary structural components are constructed from reinforced concrete, while the internal partitions are composed of clay bricks and medium-density fiberboard (MDF).

#### 5.1 Implementation proposed defect-based building elements condition assessment fuzzy model within a specific case study structure

In this section, we demonstrate the practical application of the fuzzy model, as derived in the previous sections, within a specific case study. The selected case study is an office building, with a focus on the third floor, to illustrate the model's capability in assessing building element defects accurately.

##### 5.1.1 Data Collection Process

Initially, an asset inspection data entry form was designed. This form was created to facilitate data entry and populate external databases, to increase the efficiency and accuracy of the inspection process. The fields included in this form are as follows:

- **Type of Building Element:** The type of walls was determined as the inspected element.
- **Location ID (unique identifier for each room):** The unique identifier for each room was entered for more precise localization of the walls.
- **Floor Number:** The third floor was specified as the inspected floor.
- **Inspection Date:** The date of the inspection, i.e., the first half of 2021, was recorded.
- **Crack Length (mm):** The length of the cracks in each wall was measured and entered into the form. Crack size was measured using a combination of digital calipers and a Digital Rolling Ruler to ensure precise and comprehensive data.
- **Crack Width (mm):** The width of the cracks was also accurately measured and recorded.
- **Damp Area Size (m<sup>2</sup>):** The size of the damp areas on the walls was determined and entered into the form.
- **Surface Damage Area (m<sup>2</sup>):** The area of surface damage, such as peeling or dirt, was measured and recorded. The sqftAR application was utilized to quantify the extent of surface problems and dampness area.

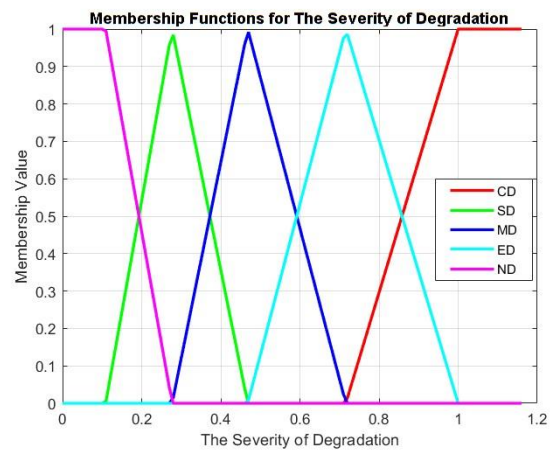


Fig. 4: The membership function of the severity of degradation

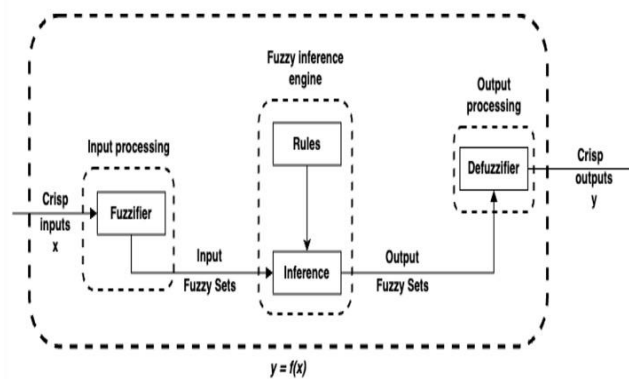


Fig. 5: Framework for fuzzy inference system

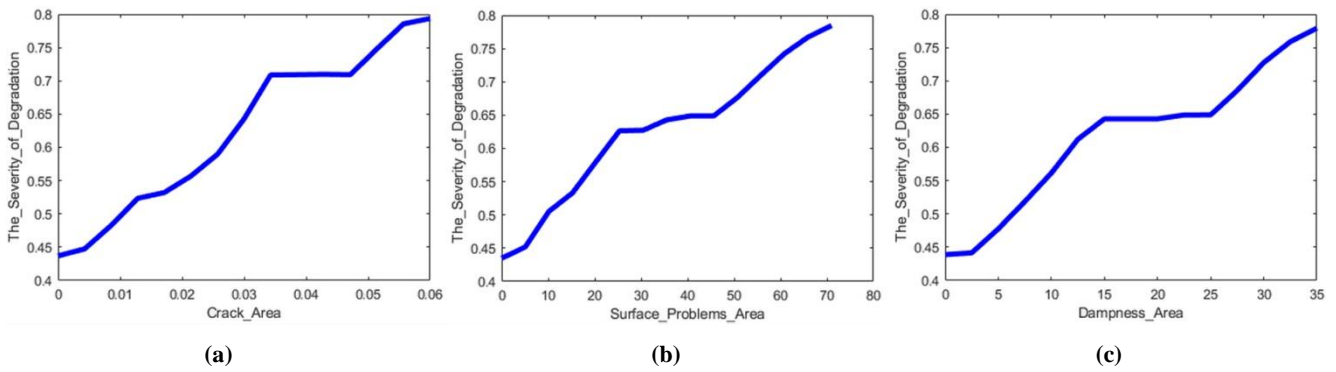


Fig. 6: Curves of changes in the input parameters and severity of degradation of wall

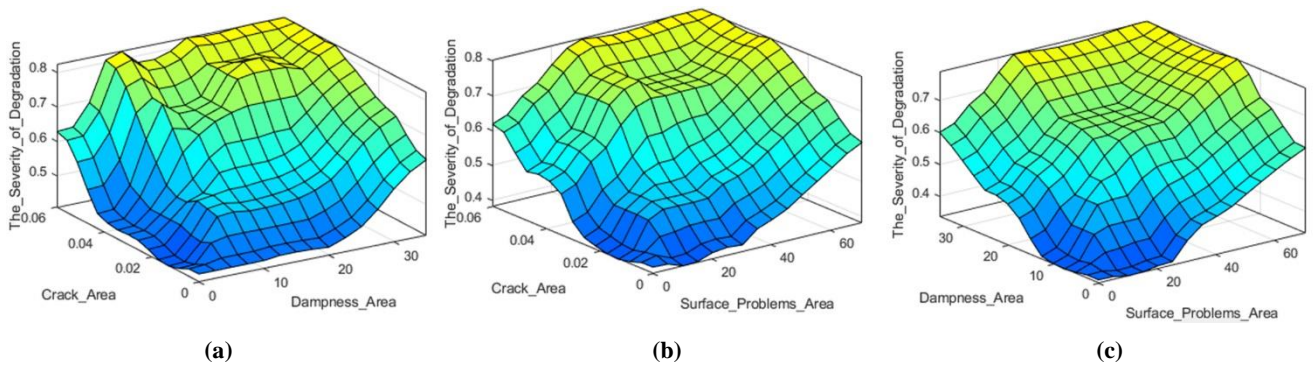


Fig. 7: 3D curves of changes in the input parameters and severity of degradation of wall

This augmented reality tool allowed inspectors to capture and measure areas of degradation accurately. At this stage, a system was designed and implemented to assign a unique identifier to each building element to facilitate the organization and management of information. This system provides an easy mechanism for coding each room and space within the building. The proposed coding scheme can identify all processes and tasks of a construction project, leading to greater transparency and accuracy in building information management.

For example, in Figure 9, a room or enclosed space labeled with the letter D and shown in red contains a wall with the unique identifier "T3DW10." This identifier indicates the tenth wall in room D, which is located on the third floor. The structure of the identifier is explained as follows:

- T3: Indicates the third floor of the building.
- D: Represents a specific room or space (here, room D).
- W: Abbreviation for "Wall."
- 10: The element number within the room (the tenth wall).

This identification system helps project managers and engineers easily and accurately identify and manage information related to each building element. Additionally, during building maintenance and repair phases, this coding can expedite processes and reduce errors. To test the proposed fuzzy defect-based building elements condition assessment model for this research, an entire floor of the TCEO building was selected. The chosen floor is located on

level 3. This floor comprises 16 rooms, which are used for office purposes. Additionally, there are 2 staircases, 2 elevator shafts, and 5 restroom facilities on this floor. In the first half of 2021, a thorough inspection of the walls on the third floor of the TCEO building was conducted. After performing these inspections, the collected data were meticulously entered into the asset inspection data entry form. This process was carried out with high accuracy and detail to ensure that all information regarding the defects and damages of the third-floor walls was correctly collected and recorded. is shown in Table 9. This form includes all the necessary fields for collecting and recording defect information on the third-floor walls.

### 5.1.2 Inspection data analysis with defect-based fuzzy model

For the evaluation of the inspection data, the fuzzy defect-based building elements condition assessment model obtained in Section 3.1.3.1 was utilized. The severity of degradation of the painted walls in TCEO was calculated by inputting three parameters derived from the inspection data of each wall into the MATLAB software. The results obtained from the fuzzy model were considered as a performance index for the element. This index represents a value between 0 and 1, indicating the condition of the wall from (no damage) to (collapse). Table 10 presents the detailed results of the wall degradation assessment for the third floor using the fuzzy model. The table includes the

calculated performance indices for each wall, offering a comprehensive view of their condition. These results demonstrate the model's effectiveness in identifying and categorizing the severity of wall defects, ultimately aiding in better maintenance planning and resource allocation.

5.1.3 Building Element Performance Index (EPI)

The defect data were measured, and a report on the condition assessment of building elements was prepared. Then, the fuzzy defect-based building elements condition assessment model obtained was used to evaluate the inspection data. The severity of degradation of the painted walls in TCEO was calculated using MATLAB software by inputting three parameters derived from the inspection data of each building element. The results obtained were considered as a performance index for the element. This index, ranging from 0 to 1, indicates the condition of the wall. Specifically:

- 0.86 ≤ EPI ≤ 1: Indicates complete damage.
- 0.60 ≤ EPI ≤ 0.85: Indicates severe damage.
- 0.38 ≤ EPI ≤ 0.59: Indicates moderate damage.
- 0.20 ≤ EPI ≤ 0.37: Indicates minor damage.

0 ≤ EPI ≤ 0.19: Indicates the best condition (no damage).

Table 9: The Asset Data Entry Form

General Information	
Field	Value
Building element type	Wall/ceiling/floor/door / window / other
Element Id	
Floor Number	1 / 2 / 3 / 4 / Other
Date of Inspection	
Defect Information	
Field	Value
Carack Length(mm)	
Carack Width(mm)	
Dampness Area(m <sup>2</sup> )	
Surface Problems Area(m <sup>2</sup> )	

Table 10: displays the comprehensive findings of the wall degradation evaluation conducted on the third level utilizing the fuzzy model

Element Id	Crack Width	Crack_Length	Dampness Area	Surface_Pr_Area	EPI	Severity_degradation
T3CW 9	0	0	0	0	0	ND
T3DW	0	0	0	0.4	0.0995	ND
T3DW 10	0	0	0	0	0	ND
T3DW 11	0	0	0	0	0	ND
T3DW 12	0.0007	0.28	0	2	0.269	SD
T3DW 2	0	0	0	0	0	ND
T3DW 3	0	0	0	0	0	ND
T3DW 4	0	0	0	0	0	ND
T3DW 5	0	0	0	0	0	ND
T3DW 6	0	0	0	0.03	0.0995	ND
T3DW 7	0	0	0	0	0	ND
T3DW 8	0	0	0	0	0	ND
T3DW 9	0.0001	0.3	0	0.1	0.0995	ND
T3EW	0.0005	0.45	0	0	0.0995	ND
T3EW 2	0.00032	1.87	0.02	0	0.0995	ND
T3EW 3	0	0	0	0	0	ND
T3EW 4	0	0	0	0	0	ND
T3FW	0	0	0	0	0	ND
T3FW 2	0.00035	0.24	0	0	0.0995	ND
T3FW 3	0	0	0	0.8	0.289	SD
T3FW 4	0	0	0	0	0	ND
T3FW 5	0	0	0	0	0	ND



Fig.8: Case study



Fig. 9: Unique ID for each building elements

## 6. Model Limitations:

While the proposed fuzzy logic model offers significant advantages in building condition assessment, it is important to acknowledge certain limitations:

1-Dependence on Expert Knowledge: The model relies on expert-defined rules, which can introduce subjectivity and potential biases.

2-Scalability Challenges: The model may face difficulties in handling large-scale projects or complex datasets, particularly in diverse building environments.

3-Sensitivity to Data Quality: The performance of the model is closely tied to the quality and completeness of the input data. Poor-quality data may lead to less accurate results.

4-Limited Generalization: The current model is tailored to specific scenarios and may require adaptation for different building types or conditions, limiting its broad applicability.

## 7. Conclusion and Discussion

This study presents a significant advancement in the management of building element defects by developing a fuzzy logic-based condition assessment model. The research focused on common issues such as cracks, dampness, and surface degradation, aiming to mitigate the limitations associated with human subjectivity in defect classification.

By utilizing extensive field data collected from 500 painted walls across 24 geographically dispersed buildings, the study successfully developed a robust and automated approach for evaluating building conditions. The implementation of the fuzzy C-Means algorithm within the model facilitated a precise categorization of element condition (C1-C5) and damage severity into five distinct groups: no damage, slight damage, moderate damage, extensive damage, and complete damage. This nuanced classification process demonstrated significant improvements over traditional methods, providing a more accurate and reliable assessment of building defects.

The validation of the fuzzy C-Means clustering through the silhouette index and Davis-Bouldin index further ensured optimal cluster formation and enhanced model accuracy. A real-world case study involving an office building on the third floor highlighted the practical application and effectiveness of the developed model. The case study demonstrated how the model could minimize human error during defect identification and classification, leading to more accurate and consistent evaluations. By incorporating parameters such as crack size, dampness, and surface degradation, the model generated a performance index for each wall, indicating its condition on a scale from 0 (no damage) to 1 (complete collapse). The findings of this research underline the importance of integrating data-driven approaches in building defect management. The fuzzy logic-based model not only improves the accuracy and reliability of defect assessments but also contributes to enhanced building quality and reduced operational costs within the construction industry. The automated nature of the model ensures that assessments are less prone to human error, providing a more objective and consistent evaluation of building conditions.

The innovative approach presented in this study addresses several key challenges in the field of building defect management. Traditional methods often rely heavily on subjective judgments, leading to inconsistencies and inaccuracies in defect classification. By leveraging a data-driven methodology, this research offers a solution that reduces the influence of human bias and enhances the precision of defect assessments. The use of extensive field data collected from a diverse set of buildings ensures that the model is robust and generalizable across different contexts. The fuzzy C-Means algorithm's ability to handle the inherent uncertainty and vagueness in defect data makes it particularly well-suited for this application. The validation metrics employed in the study, including the silhouette index and Davis-Bouldin index, provide strong evidence of the model's reliability and effectiveness.

One of the notable contributions of this research is the practical applicability of the developed model. The real-world case study demonstrates how the model can be

seamlessly integrated into existing building management practices, providing actionable insights and facilitating timely maintenance and repair actions. The ability to quantify the severity of defects and prioritize interventions based on objective criteria is a significant advantage for building managers and maintenance teams.

Future research could explore the integration of this fuzzy logic-based model with other advanced technologies such as Building Information Modeling (BIM) and Internet of Things (IoT) sensors. By incorporating the fuzzy model within a BIM platform, facility managers can visualize the condition of building elements in a 3D environment. This visualization allows for more informed decision-making regarding maintenance and renovation projects. For example, the model could highlight areas at high risk of damage based on the data, helping managers prioritize repairs in the most critical areas, optimizing resource allocation, and extending the building's lifecycle. Moreover, IoT sensors could continuously provide real-time data on critical parameters such as humidity, temperature, and structural integrity. This real-time data would feed directly into the model, enhancing the accuracy and timeliness of defect assessments. Such integration could further enhance the accuracy and efficiency of defect assessments by providing real-time data and enabling predictive maintenance strategies. Additionally, expanding the model to include other types of building elements and defects could broaden its applicability and utility.

In conclusion, this study contributes a sophisticated and effective framework for building defect management, offering a valuable tool for improving building quality and operational efficiency. The fuzzy logic-based model's ability to automate and enhance defect assessments marks a significant step forward in the field, paving the way for more reliable and data-driven building management practices.

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