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Forecasting Repair Schedule for Building Components Based on Case-Based Reasoning and Fuzzy-AHP

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Abstract: Building maintenance is closely related to the performance and sustainability of buildings. However, existing approaches to maintenance are limited in terms of estimating required repairs. Therefore, this study proposes a case-based reasoning (CBR)-based model for estimating the time when the first repair will be needed after the completion of construction, even in phases where maintenance-related information is scarce. CBR and fuzzy-analytic hierarchy process (AHP) were employed as research methodologies. A database was established by collecting 257 cases related to maintenance of apartment buildings, and attributes were extracted through literature reviews and expert interviews. Then, attributes were weighted by fuzzy-AHP and case similarities were computed by measuring the Euclidean distance. Similar cases were retrieved based on similarity scores. The model was validated via a comparison of 20 randomly selected test cases with the output of retrieved cases. The results showed that the average case similarities of 3-, 5-, 7-, and 10-nearest neighbors (NN) were 98.05%, 97.86%, 97.73%, and 97.59%, respectively, and mean absolute percentage errors for 3-, 5-, 7-, and 10-NN were mostly lower than 20%, confirming the applicability of the proposed model. The proposed method will help in the preliminary estimation of the repair time of building components.

Keywords: building maintenance; proactive maintenance; apartment buildings; case-based reasoning; fuzzy-analytic hierarchy process

1. Introduction

As the number of aged buildings has increased, the importance of building maintenance has been recognized in recent years [1]. Building maintenance plays an essential role in ensuring the sustainability of buildings [2] because it affects their performance [1,3]. To ensure that buildings are in good condition for daily life and working, a specific maintenance plan ensuring the sustainability of the building is needed. Moreover, a systematic maintenance plan is required because the aging process affects repair costs for maintaining the function [4] and safety of buildings [5], especially in residential buildings. Aged buildings around the world account for a high proportion of all buildings. According to a report by the Ministry of Land, Infrastructure, and Transport [6], there are 2,666,732 buildings that are more than 30 years old, accounting for 37.08% of all the buildings (7,191,912 buildings) in South Korea. In particular, residential buildings account for 79.68% (2,129,727 buildings) of aged buildings over 30 years. Comparing the statistics for 2016, 2017, and 2018, the number of aged residential buildings that are more than 30 years old has been increasing steadily [6–8]. Moreover, residential buildings aged 20–30 years account for more than 20% of all residential buildings between 2016 and 2018. Particularly in South Korea, the number of apartment buildings is increasing [4], and as of 2018, apartments account for 33.9% (147,817 buildings) of apartment buildings (436,013 buildings) [6].

By 2005, residential buildings in Europe and private buildings in Hong Kong more than 30 years old accounted for about 70% [9] and 33.33% [10], respectively. As the performance level of buildings decreases over time [3], proper maintenance strategies are required to control the initial degradation [11] of residential buildings. In particular, it is difficult to establish proper maintenance plans for apartment buildings because they have co-owned areas such as entrance lobbies, access corridors, staircases, lifts, lighting, service ducts, and water pumps [12], unlike single-family dwellings. Thus, an appropriate maintenance plan is necessary to maintain their performance. However, estimating the specific time for repairing each building component is difficult in South Korea, where repair cycles are specified by the standard for long-term repair. It is difficult to identify when a building needs to be repaired using existing repair cycles. This is because long-term repair plans according to standards for establishing long-term repair in accordance with the Multi-Family Housing Management Act are only implemented in apartment buildings with more than 300 households, elevators, or central heating [13]. In addition, each apartment has different characteristics attributable to different heating systems or a different number of households. Therefore, the application of the repair cycle to all apartments is limited. The existing long-term repair plan or strategy reflects only the timing of repairs expected over time [14]. Moreover, in the existing long-term repair plan, historical data or estimation techniques required for calculating the repair cycle are not clearly specified [15]. The existing repair cycle does not conform to the concept of proactive maintenance, which involves the solving of a problem before its occurrence [16]. In addition, existing methods do not consider factors such as management area, maintenance cost per unit area, and level of maintenance. In such situations, existing data can be used to estimate the time for building maintenance as they include various information related to maintenance. However, the data or cases related to building maintenance are not systematically organized [1], and the extent to which relevant factors affect the maintenance plan has not been sufficiently investigated.

Accordingly, this study proposes a model for estimating the repair time of apartments by applying case-based reasoning (CBR). In this study, the repair time is defined as the duration of the first maintenance or repair after the completion of a building. The scope of this study is limited to examining the repair time of building components that play an important role in building operation, including the building exterior, building interior, outdoor facilities, electricity/fire safety/elevator, and home networks, water supply/sanitation/gas and ventilation, and heating and hot water. This study was conducted in the following order. First, preliminary research was conducted through a literature review related to building maintenance and limitations of existing research were then identified. To overcome the limitations identified in the literature review, a model was developed to predict the repair times through CBR, and fuzzy-analytic hierarchy process (fuzzy-AHP) approaches. A total of 712 cases from Korea Land and Housing Corporation (LH) were collected, including historical repair data of 22 building components, and a systematic database was established. Next, in order to implement CBR, attributes that affect building maintenance and repair times of building components were extracted through a literature review and expert interviews. Based on the extracted attributes, the weights of attributes were determined through fuzzy-AHP. Finally, case similarities for randomly selected test cases were calculated through the weighted Euclidean distance (WED) based on the weight of the attributes and the most similar cases were extracted from the database. In addition, the extracted cases were validated through a comparison with the actual repair time of test cases.

This study is expected to provide a method for estimating repair times of building components based on a database obtained from past data. The proposed model can contribute to extending the lifespan of buildings by reflecting repair times in the repair plan. Moreover, the model can help business entities involved in the construction of apartment buildings and supply of building components in establishing long-term repair plans by providing specific repair times.

2. Preliminary Research

2.1. Literature Review

Proper maintenance of buildings facilitates the optimal performance of buildings to residents throughout their life cycle because it is closely related to the safety of residents [17]. However, general difficulties are experienced in planning building maintenance because buildings consist of several components [1] and building components operate interdependently [5]. Moreover, the complexity of buildings is increasing and maintenance costs account for a large portion of life cycle cost [18]. If appropriate building maintenance is not implemented, the building performance may degrade. Thus, in order to prevent problems caused by performance degradation and ensure efficient building maintenance, various studies have been conducted in relation to service life pattern analysis, supporting maintenance planning and decisions, and optimal selection of building maintenance, repair, and renovation (MR&R) activities. The studies were carried out as presented in Table 1, which shows the factors considered in each study among nine factors. They used about three factors on average, and the most commonly used factors were period after completion, repair year, and the number of maintenance events. Furthermore, many factors that can be obtained from historical data were not considered when predicting cost or service life and envisioning models or systems. Therefore, they are insufficient for establishing an effective maintenance plan or supporting maintenance decisions.

Table 1. Contents of Previous Research.

Authors	Research Objective	Target	Methodology	Considered Factors for Maintenance Plan								
				F1	F2	F3	F4	F5	F6	F7	F8	F9
Lee and Ahn (2018)	To establish maintenance plan for analyzing service life pattern	Residential Building (MEP component)	Probabilistic, Monte-Carlo Simulation	×	×	×	–	–	–	–	–	–
Park et al. (2018)	To establish maintenance plan for analyzing service life pattern	Public Housing (Component of finishing work)	Probabilistic, Monte-Carlo Simulation	×	×	×	–	–	–	–	–	–
Kim et al. (2018)	To evaluate maintenance cost	Apartment building	Probabilistic, Monte-Carlo Simulation	×	×	×	×	×	–	×	–	–
Shohet and Lavy (2004)	To support the planning of FM activities	Healthcare Facilities	Statistical, Case-based reasoning	–	–	–	×	×	×	×	–	–
Motawa and Almarshad (2013)	To support preventive/corrective maintenance decision	Building	Qualitative, Case-based reasoning	–	–	–	–	–	×	–	–	×
Silva et al. (2011)	To establish a model for the service life prediction	Building (Natural stone wall claddings)	Mathematical (Index of the degradation severity)	–	–	–	–	–	–	–	×	–
Ghodoosi et al. (2017)	To develop framework that predicts the cost-effective intervention schedule	Infrastructure (Bridge)	Mathematical, Genetic algorithm	–	–	–	–	–	–	–	×	–
Grussing and Liu (2013)	To optimize the selection of building MR&R activities	Facility (Building)	Mathematical, Genetic algorithm	×	–	–	×	–	–	–	×	–

Note: F1 = period after completion, F2 = repair year, F3 = number of repairs occurred, F4 = maintenance cost, F5 = number of households/occupancy, F6 = building type, F7 = building area, F8 = degradation severity, F9 = structure type.

Lee and Ahn [19], Park et al. [17], and Kim et al. [4] applied the probabilistic method to reflect uncertainties in the building and building components. Lee and Ahn [19] and Park et al. [17] applied Monte-Carlo simulation (MCS) to produce a service life distribution of mechanical, electrical, and plumbing (MEP) components (12 items) and finishing work (eight items), respectively. These studies are meaningful in that they considered the uncertainty of building components beyond the existing deterministic repair cycle. However, since the probability distribution was performed considering only repair frequency identified through the repair time of building components, their method has limited applicability to building maintenance. In particular, a probabilistic approach to identifying service life is not helpful for maintenance managers who require specific repair time. Kim et al. [4] used historical data that include essential information for the building maintenance to predict the maintenance costs of apartment houses, and preliminarily analyzed the maintenance cost using the loss-distribution approach (LDA) technique, which can predict expected loss. This study is noteworthy because various factors related to building maintenance such as completion year, maintenance cost, year or repair, and number of households are utilized.

Some groups focused on utilizing CBR to support the planning of facility management (FM) activities and maintenance decisions. Motawa and Almarshad [20] developed a CBR-based integrated system to collect information regarding building maintenance operation and to assist decision-making related to building maintenance. They extracted case attributes (e.g., building type, structure type, category, section, subsection, topic, issue/problem, reaction/solution, keywords, affected elements) through interviews in order to execute the "Case Retrieval" phase, which retrieves similar cases in CBR, thereby providing maintenance-related solutions. However, appropriate management solutions could not be comprehensively provided because attributes directly related to maintenance were not considered prior to providing the maintenance-related solutions. In addition, they provided only the model concept, and its applicability was not reviewed. Shohet and Lavy [21] also proposed a facility management model for health care facilities by applying CBR. Their proposed model integrates the main operations (e.g., maintenance, performance, risk management, energy and operations, management, and development) in facility management (FM) to plan FM related activities. Their research is meaningful in that they considered various attributes related to the maintenance of healthcare facilities in order to increase the applicability of the model, and in particular, the geographical characteristics (e.g., coastal, desert, mountain) of the location of the healthcare facilities as an input attribute of CBR. However, the calculation of the weight of maintenance impact factors in executing CBR was not comprehensively described. Therefore, the accuracy of their proposed model is unclear if the weights of the attributes are not described because the results of CBR depend on the weight of attributes. Grussing and Liu [5] developed a model for selecting optimal MR&R (maintenance, repair, and renovation) activities for multiple years to minimize life cycle costs while maximizing the performance of facilities. They predicted the performance state of building components through the condition index and the capability index and estimated MR&R costs of building components utilizing the condition index (CI). In addition, they set goals to minimize life cycle costs and maximize the building's final performance state. They utilized the genetic algorithm to select optimal MR&R activities to meet each goal. Finally, each performance index and MR&R costs calculated from the selected activities were compared with the performance index and MR&R costs, which were determined by the existing MR&R work planning approach. Their study is meaningful in that the facility manager can plan MR&R activities simultaneously, considering performance and cost. However, the proposed model was validated through a case study for only one building, and additional applicability tests under actual similar circumstances are further required.

Other studies employed mathematical methods. Silva et al. [22] proposed a service life prediction model by applying a mathematical method. They focused on developing a service life prediction model of natural stone wall cladding using a numerical index called severity of degradation. They predicted service lives depending on the characteristics of cladding (e.g., types of stones, color of natural stone, type of finishing). Finally, they compared their result with the results of other studies using different methodologies to confirm the accuracy of the predicted service lives. However, their model has limited estimation accuracy because the sample sizes used in the two studies were different. Ghodoosi et al. [23] proposed a framework for predicting the most cost-effective intervention schedule to plan optimal maintenance activities. First, they identified degradation factors on a bridge. They developed a reliability-based model based on the reliability index considering the age of bridges in order to predict the time of the occurrence of potential intervention. Next, they constructed various intervention scenarios and then evaluated them. Finally, they selected optimal scenarios that considered the most cost-effective maintenance through the genetic algorithm. They presented the process of the proposed model through a case study, but the accuracy of their model is unclear because their case study did not consider various spans, and maintenance costs may vary depending on the span.

Previous studies can be summarized as follows. Some groups focused on estimating the service life and maintenance costs of buildings using Monte-Carlo simulations for long-term maintenance plans. However, they have a limitation in that they cannot estimate specific required repair times and maintenance costs because they analyzed only patterns for service life and maintenance costs using probabilistic approaches. Other groups developed a framework or model to support decision making and planning related to building maintenance. Motawa and Almarshad [20] developed an integrated system supporting maintenance-related decisions, and Shohet and Lavy [21] suggested a model for predicting annual maintenance expenditure and recommended maintenance policy using CBR. However, they did not consider factors directly related to building maintenance or assess relevant impact factors before implementing CBR. Grussing and Liu [5] developed a model that selects optimal MR&R activities and Ghodoossi et al. [23] proposed a framework that predicts a cost-effective intervention schedule. However, their actual applicability and accuracy could not be ensured because the model and framework were not validated with objects of varying criteria.

2.2. Case-Based Reasoning

In this study, CBR was applied to estimate the repair times of building components. CBR is an artificial intelligence method based on the work of cognitive scientists Schank and Abelson [24] that solves problems [1,25] based on data and knowledge obtained from past similar cases [1]. It has been applied to various fields, such as construction cost estimation, bid mark-up estimation, construction noise prediction, construction hazard identification, and building maintenance [1,26–29]. In particular, it is used as a decision tool in the construction industry [30] because it can identify required maintenance or construction-related problems through past cases and contribute to taking necessary actions in advance. CBR usually consists of four phases: Retrieving, reusing, revising, and retaining [31,32]. At the retrieving phase, the most similar cases to a given case are derived. The derived cases are then reused to solve the problem and the solution is revised if the estimated results are inappropriate [33]. Finally, the revised results are retained in the database as a new case [31]. This study focused on phases of retrieving and reusing because they are important phases of CBR [24,31]. The revising and retaining phases will be addressed in future studies. The advantages of CBR are as follows: (1) Solutions can be found even when relevant data are insufficient or limited [32,34], (2) Numerical data obtained from past cases may provide more objective results than decisions made according to an individual's experience [28], (3) CBR can consider various attributes, including numerical and nominal data [35], (4) CBR can be updated and maintained [36]. With these advantages, the limitations of existing studies can be overcome through CBR. Moreover, because CBR facilitates data accumulation, which is useful for building maintenance management and for predicting repair times in phases where information is scarce. In CBR, cases are retrieved based on similarity, which is determined by the distance measurement function and the weights of attributes [28]. Similar cases are expressed as a number of attributes [37] and it is important to determine the weights of attributes in CBR [38]. Therefore, a method for determining the optimal weight of an attribute is required. Weighting methods include feature counting (FC), gradient descent method (GDM), AHP, and multiple regression analysis (MRA) [38–40]. In this study, AHP was selected.

2.3. Fuzzy-Analytic Hierarchy Process (Fuzzy-AHP)

The term "case" refers to a previous case related to building maintenance, including the input attributes and output attributes. A case utilized in CBR can be expressed as attributes (e.g., maintenance cost, floor area ratio, number of floors, completion year, year of repair, number of households) associated with building maintenance and repair time. In order to retrieve similar cases for estimating repair times using CBR, the weights of attributes should be determined first. For this purpose, fuzzy-AHP was selected to compare relative importance between attributes. Analytic hierarchy process (AHP) was introduced by Saaty [41] to address complex problems in several aspects such as economic, technological and sociopolitical issues [42]. With AHP, each attribute is compared in pairs [28] assessing the relative importance ratio between attributes. In addition, the consistency ratio (CR) should be identified to evaluate whether the respondents are consistent in the pairwise comparison of AHP [28]. A CR lower than 0.1 is acceptable [37,43], but the comparison should be revised [42] if the CR exceeds 0.1. Fuzzy-AHP was applied because it can overcome the uncertainty of the existing AHP [44]. Furthermore, even in small matrix scales, there is a difference between fuzzy-AHP and traditional AHP from a quantitative perspective [45]. Fuzzy-AHP determines the attribute weights by pairwise comparisons [44], which is based on fuzzy numbers. The fuzzy number can be defined as various values, instead of a single value [46]. Based on this, fuzzy-AHP deals with uncertain or ambiguous expressions of the experts' judgment [46].

3. Model Development

A model was developed to estimate the repair time of building components based on previous data. The proposed model consists of four sub-modules as presented in Figure 1: (1) Database construction, (2) attribute selection, (3) attribute weight calculation based on fuzzy-AHP, and (4) case retrieval based on CBR. In the database construction module, the database was established from maintenance-related data, including repair history, to implement CBR. In the attribute selection module, attributes related to building maintenance and repair time were extracted through a literature review and expert interviews. The extracted attributes are called input attributes. Next, fuzzy-AHP was applied to compute the weight of input attributes. In the case retrieval module, cases similar to test cases were extracted by entering information about input attributes of the test case, where similarity scores are calculated by the weighted Euclidean distance and fuzzy-AHP. Finally, the proposed model was verified through (1) leave-one-out-validation (LOOCV) and (2) comparison of original repair times of test cases with the estimated value from retrieved cases.

3.1. Database Construction

Existing data provided by the Korea Land and Housing Corporation (LH) were utilized for the database construction of the proposed model. LH has been working on several projects related to building maintenance and repair cost and it has reliable data regarding repair times. The data obtained from LH include information on maintenance-related activities, which was utilized to estimate the repair time in this research. The collected data contain repair information for building components, which are presented in Table 2.

A total of 712 cases were collected to establish the database for the aforementioned building components. Each case in the database includes maintenance-related data obtained from previous cases. Incorrect data or missing values may reduce the reliability of the database and the accuracy of the estimated outcomes [46]. Therefore, case filtering was performed to exclude cases, including inappropriate data or missing values from the database. In this manner, a database consisting of 257 cases was established. Before implementing CBR, the raw data of these cases require standardization and normalization because attributes are represented at various scales [33]. Thus, ratio standardization was applied to represent raw data in different cases at an equal scale [24,31]. In addition, a normalization process was carried out to reduce the distortion in the similarity measurement that may occur with the use of data at different scales [24]. Raw data were normalized using the NORMDIST function in Microsoft Excel version 2016 with the following equation:

$$Normalization_i = \frac{x_i - x_{min}}{x_{max} - x_{min}} \quad (1)$$

where x_i is the value of attribute i, and x_{max} and x_{min} are the maximum and minimum values of each attribute in the cases utilized in CBR. Finally, normalized data were used for the similarity function to calculate case similarity.

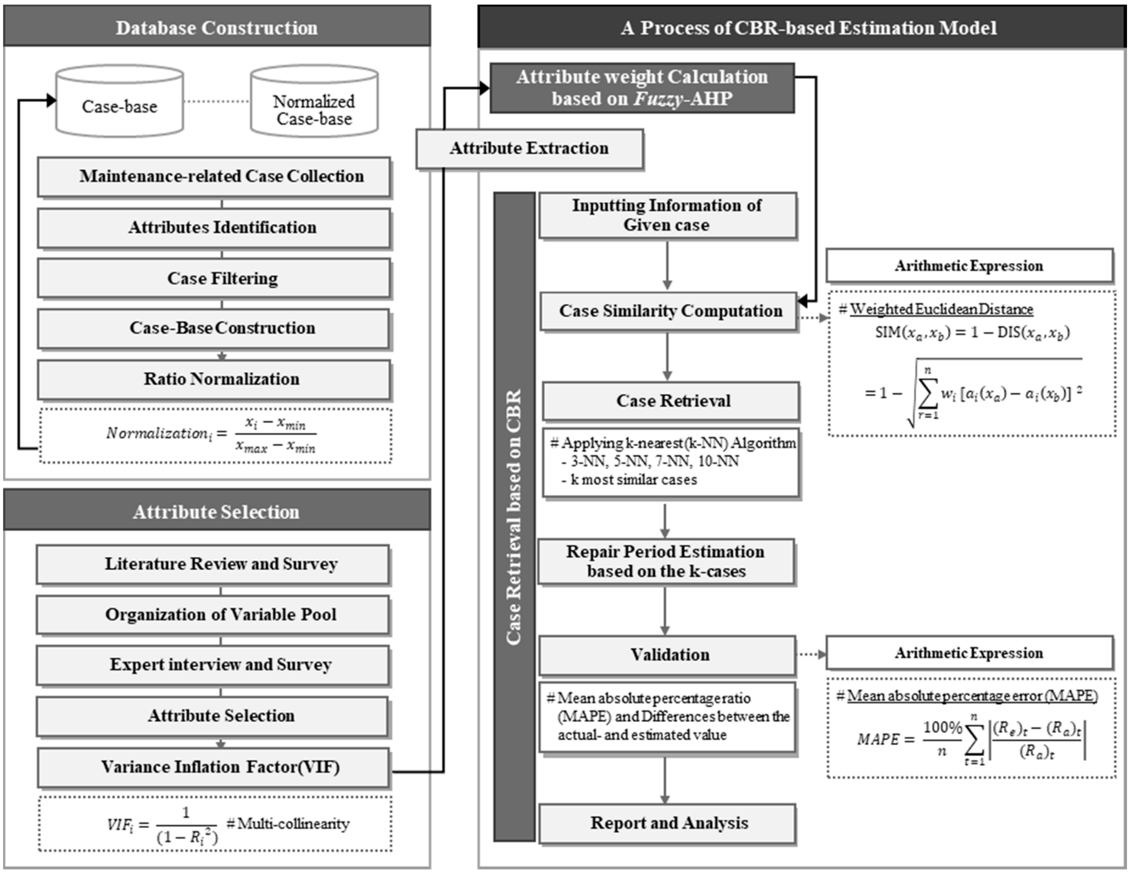

Figure 1. Repair time estimation model based on CBR.

Table 2. Building Components Contained in Data.

Maintenance Item	Building Component
Building exterior	roof, exterior, exterior windows and doors
Building interior	ceiling, interior wall, stair, floor
Outdoor facilities	outdoor facilities
Electricity, fire safety, elevator and home networks	elevator and lift, security/crime prevention facility, spare power facility, substation, lightning protection facility and outdoor lighting, communication and broadcast, extinguishment facility, fire detection facility
Water supply, sanitation, gas and ventilation	drainage facility, water supply facility, gas facility, ventilation facility
Heating and hot water	heating facility, hot water supply facility

3.2. Attribute Selection

In this module, major attributes associated with building maintenance and repair time were derived and then weighted by fuzzy-AHP. As described in Figure 2, 10 attributes were selected. First of all, the following variables extracted from Kwon et al. [1] were selected: Building coverage ratio, floor area ratio, number of building, number of floors, number of households, parking lots per household, heating system, management area, completion year, and maintenance cost per unit area. Next, studies and reports addressing building maintenance cost prediction [4,47], investigation of factors affecting building maintenance cost [48], service life pattern estimation [17,19], selection of optimal activities for building maintenance [5], and building maintenance [21,49] were reviewed to extract additional variables.

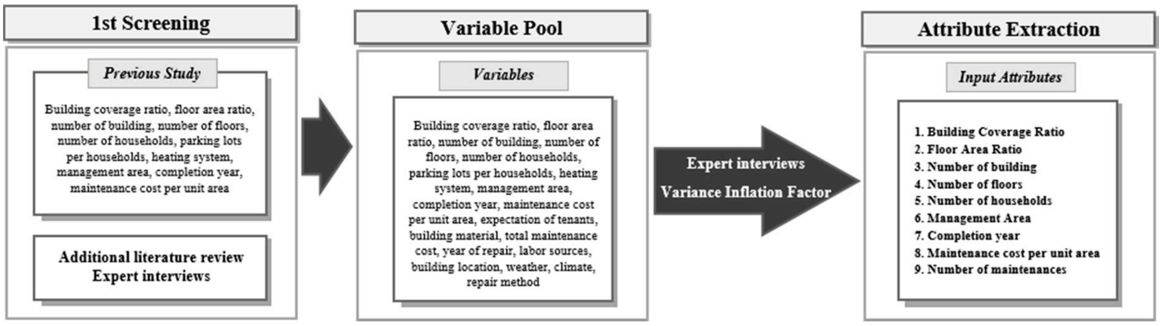

Figure 2. Process of Attribute Selection and Extraction

Accordingly, a total of 16 building maintenance-related factors were selected to establish Variable Pool, based on which expert interviews were conducted to extract key attributes. These experts had experienced careers in various fields of the construction industry, such as cost management (four persons), construction management (three persons), environment management (four persons), and maintenance management (eight persons). Therefore, they are suitable for determining the key attributes affecting building maintenance. Through expert interviews, 10 attributes were extracted and used to estimate repair times based on case similarity. Of these 10 attributes, nine (A_1, A_2, A_3, A_4, A_5, A_6, A_7, A_8, and A_9) were used as input attributes, and the repair time (A_{10}) was used as the output attribute. The extracted attributes were divided into building-related attributes and maintenance-related attributes. The building-related attributes included building coverage ratio (A_1), floor area ratio (A_2), number of buildings (A_3), number of floors (A_4), and number of households (A_5). The maintenance-related attributes included management area (A_6), completion year (A_7), maintenance cost per unit area (A_8), and the number of maintenances (A_9). The definitions of attributes are specified in Appendix A. Attributes belonging to building-related attributes should be considered in extracting similar cases as they contain information on the building itself, and the characteristics of the building affect the maintenance activities. Attributes belonging to maintenance-related attributes are also necessary in extracting similar cases because they are related to the degree of degradation of buildings or contain information that affects the repair time. Moreover, general details of the project are required to execute CBR, and the purpose of this research is to predict the repair time due to the aging of the building. Therefore, maintenance-related attributes were extracted. In addition, attributes composing the cases are likely to be covariance that reduces the accuracy and reliability of the results. Therefore, the multicollinearity of the main attributes was checked [33,50,51]. For this purpose, the variance inflation factor (VIF), which can be used to effectively evaluate multicollinearity [52], was calculated as follows:

$$VIF_i = \frac{1}{(1 - {R_i}^2)} \quad (2)$$

where ${R_i}^2$ is the coefficient of determination of the independent attributes (input attributes) obtained from regression analysis [1]. The VIF scores of A_1, A_2, A_3, A_4, A_5, A_6, A_7, A_8, and A_9 were 1.808, 3.327, 1.500, 2.922, 2.202, 1.487, 1.698, 1.080, and 1.047, respectively. Each VIF and tolerance for attributes was smaller than five and higher than 0.1, which indicates insufficient multicollinearity among attributes [53].

3.3. Attribute Weight Calculation Based on Fuzzy-AHP

As previously mentioned, fuzzy-AHP was used to compute the weights of the extracted attributes. After preparing surveys to determine the weights, they were sent to experts in various fields such as asset management, facility management, and leasing marketing. These experts are qualified for determining the weight of attributes considering that they have an average of 11.75 years of experience and are mostly in charge of building maintenance. Finally, 42 out of 70 questionnaires were returned, resulting in a response ratio of 60%. The consistency ratio (CR < 0.1) was checked and a total of 30 questionnaires were passed. The weights were then calculated using the triangular fuzzy number with the nine-point scale applied by Kaya and Kahraman [44], as described in Table 3. In this research, the geometric mean method was utilized to aggregate multiple opinions of the experts because it keeps the matrix consistent and reciprocal.

Table 3. Fuzzy Numbers with Nine-Point Scale

Linguistic Terms	Score
Absolute strong (AS)	(2, 2.5, 3)
Very strong (VS)	(1.5, 2, 2.5)
Fairly strong (FS)	(1, 1.5, 2)
Slightly strong (SS)	(1, 1, 1.5)
Equal	(1, 1, 1)
Slightly weak (SW)	(0.66, 1, 1)
Fairly weak (FW)	(0.5, 0.66, 1)
Very weak (VW)	(0.4, 0.5, 0.66)
Absolutely weak (AW)	(0.33, 0.4, 0.5)

Tables 4 and 5 show the final weights of the attributes. Among the building-related attributes and maintenance-related attributes, the number of maintenances (0.1895), maintenance cost per unit area (0.1567), and the number of households (0.0910) were confirmed as important attributes. Overall, the weights of the maintenance-related attributes were probably higher than those of building-related attributes. This shows that maintenance-related attributes should be considered more important for the estimation of the repair time of the buildings based on previous similar cases.

Table 4. Weights for Input Attributes Belonging to Building-Related Attributes.

Attribute	Building-Related Attributes (First Hierarchy: 0.3915)					Second Hierarchy Weights	Final Weights
	A_1	A_2	A_3	A_4	A_5		
A_1	(1, 1, 1)	(0.75, 1.01, 1.18)	(0.70, 0.94, 1.22)	(0.76, 0.99, 1.19)	(0.61, 0.84, 1.03)	0.1870	0.0732
A_2	(0.85, 0.99, 1.33)	(1, 1, 1)	(0.73, 1, 1.21)	(0.79, 0.99, 1.24)	(0.59, 0.79, 1)	0.1892	0.0741
A_3	(0.82, 1.07, 1.44)	(0.83, 1, 1.37)	(1, 1, 1)	(0.84, 0.98, 1.12)	(0.71, 0.82, 1.04)	0.1955	0.0765
A_4	(0.84, 1.01, 1.32)	(0.80, 1.01, 1.27)	(0.90, 1.02, 1.19)	(1, 1, 1)	(0.71, 0.87, 1.07)	0.1959	0.0767
A_5	(0.97, 1.19, 1.63)	(1, 1.27, 1.71)	(0.96, 1.21, 1.41)	(0.93, 1.15, 1.41)	(1, 1, 1)	0.2324	0.0910

Note: A_1 = building coverage ratio, A_2 = floor area ratio, A_3 = number of building, A_4 = number of floors, A_5 = number of households.

Table 5. Weights for Input Attributes Belonging to Maintenance-Related Attributes.

Attribute	Maintenance-Related Attributes (First Hierarchy: 0.6085)				Second Hierarchy Weights	Final Weights
	A_6	A_7	A_8	A_9		
A_6	(1, 1, 1)	(0.58, 0.73, 0.96)	(0.67, 0.84, 1.09)	(0.52, 0.68, 0.85)	0.1988	0.1210
A_7	(1.04, 1.37, 1.72)	(1, 1, 1)	(0.62, 0.81, 1.04)	(0.54, 0.72, 0.92)	0.2323	0.1414
A_8	(0.92, 1.20, 1.49)	(0.97, 1.23, 1.61)	(1, 1, 1)	(0.65, 0.81, 1.03)	0.2575	0.1567
A_9	(1.18, 1.47, 1.92)	(1.09, 1.39, 1.84)	(0.97, 1.23, 1.53)	(1, 1, 1)	0.3114	0.1895

Note: A_6 = management area, A_7 = completion year, A_8 = maintenance cost per unit area, A_9 = number of maintenances.

3.4. Case Retrieval Based on CBR

It is important to measure the similarity scores between cases [30,39] because cases that are similar to the given cases are retrieved using the similarity score [31,54], which is also called case similarity or similarity distance. There are similarity measurement methods such as Euclidean distance, arithmetic summation, and fractional function [50]. Among them, the Euclidean distance method is commonly used for measuring similarity distances [24,31]. Accordingly, the weighted Euclidean distance (WED), which calculates the distance between two independent cases, was used in this study. In the Case Retrieval module, the similarity scores were computed using the similarity function based on the weights of the attributes.

$$\mathrm{SIM}(x_a, x_b) = 1 - \mathrm{DIS}(x_a, x_b) = 1 - \sqrt{\sum_{i=1}^{n} w_i [a_i(x_a) - a_i(x_b)]^{\,2}} \tag{3}$$

where $\mathrm{SIM}(x_a, x_b)$ refers to the similarity score between cases x_a, x_b and $\mathrm{DIS}(x_a, x_b)$ refers to the relative distance between cases [1,55]. In addition, n means the total number of attributes and $a_i(x_a)$ is the value of the ith attribute of case x_a, which is normalized by Equation (1). w_i is the weight of ith attribute calculated from fuzzy-AHP. Based on Equation (3), the similarity distances between the previous and test cases were computed and the k-nearest near (NN) algorithm was applied. In CBR, the k-NN algorithm searches for k-similar cases based on case similarity measurement [28,56]. In this process, a limited number of NNs may reduce the accuracy of the estimated outcomes [1]. Therefore, the 3-NN, 5-NN, 7-NN, and 10-NN were used to estimate the repair time of the building components.

4. Experiment

4.1. Experimental Process

The applicability of the proposed model was validated in terms of two aspects: (1) LOOCV and (2) comparison of the original values with estimated results. The experimental process is illustrated in Figure 3. First, the weights of the attributes were determined through fuzzy-AHP. Then, the similarity scores between test cases and previous cases were calculated using the calculated weights of the attributes. From 20 test cases, 3-, 5-, 7-, and 10- nearest cases were extracted through the k-NN algorithm. Finally, the proposed model was validated. For this purpose, mean absolute percentage errors (MAPEs) based on LOOCV were checked. In addition, estimated values for 20 test cases were compared and analyzed with the original repair times. LOOCV is a type of k-fold cross validation where a single case is used for validation and the remaining cases are used for training [33]. MAPE was utilized because it is a commonly used measure for forecast accuracy [57]. MAPE is calculated as follows:

$$\mathrm{MAPE} = \frac{100\%}{n} \sum_{t=1}^{n} \left| \frac{(R_e)_t - (R_a)_t}{(R_a)_t} \right| \tag{4}$$

where n is the number of cases, $(R_a)_t$ and $(R_e)_t$ are the actual repair time and estimated value, respectively.

4.2. Results and Discussion

As mentioned earlier, the actual repair times of the test cases were compared with the estimated repair time to verify the applicability of the model. In this research, "actual repair time" represents the times when maintenances or repairs were actually performed owing to the deterioration of the building. LOOCV was applied to identify the overall estimation accuracy of the proposed model [33] before the comparison between the actual and estimated repair time. Table 6 presents error rates of 3-, 5-, 7-, and 10-NN, calculated at 8.48%, 9.35%, 9.84%, and 10.52%, respectively. The distance measurement method appeared to be effective in estimating the value of the repair time. However, the error rate increased with the increasing number of cases retrieved. This can be attributed to the increased probability of retrieving cases with an outlier.

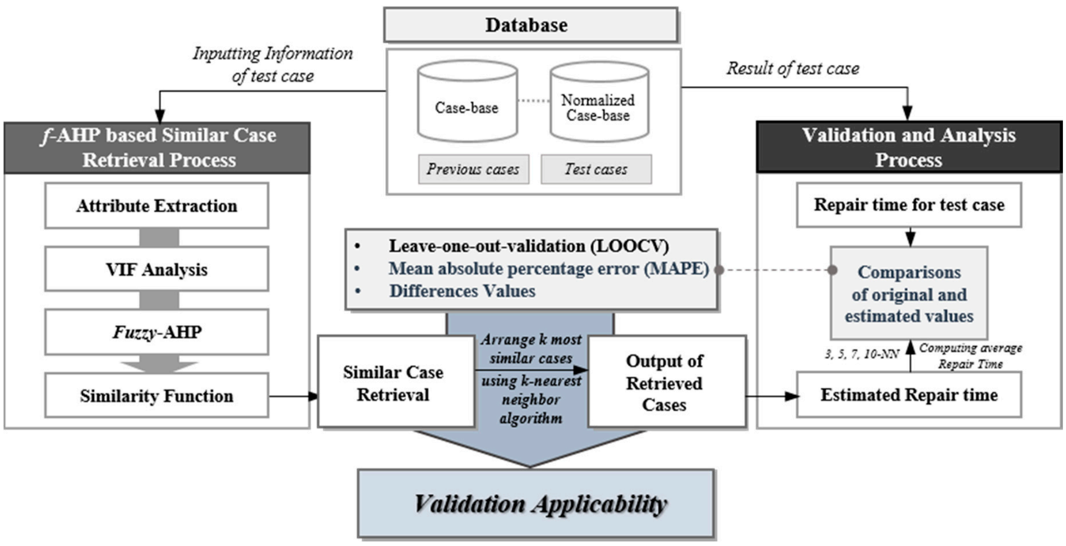

Figure 3. Experimental Process of Validating the Applicability of the Proposed Model.

Table 6. Error Rates of 3-, 5-, 7-, 10-NNs.

	k-Nearest Neighbors			
Error rate	3-NN	5-NN	7-NN	10-NN
MAPE (%)	8.48	9.35	9.84	10.52

Next, to determine the applicability of the developed model, 20 test cases were selected randomly, and information about test cases is given in Table 7. The average completion year of the cases was around 1993, with an average number of 10.9 maintenances. In addition, the number of floors in all cases was more than 12 stories.

Table 7. Profiles and Information about Input Attributes for 20 Test Cases.

Case Number	Input Attributes								
	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8	A_9
1	21.09%	262.23%	2	15	427	39,674.82 m^2	1992	0.7385	6
2	15.99%	179.89%	8	14	541	66,648.68 m^2	1984	6313.257	17
3	15.02%	143.25%	3	15	210	21,360.9 m^2	1986	2.7912	13
4	24.34%	284.68%	3	18	249	28,323.93 m^2	1993	8.5871	6
5	17.38%	249.85%	10	21	1056	108,460 m^2	1990	14.7886	4
6	19.62%	194.86%	6	13	364	38,506 m^2	1992	3.3399	8
7	22.38%	269.36%	5	15	336	34,805.77 m^2	1991	2.0974	8
8	31.79%	378.54%	1	20	232	24,629.49 m^2	1995	1.0576	11
9	39.94%	559.69%	1	22	199	23,140 m^2	1995	7.1305	1
10	20.16%	297.47%	2	23	437	48,556.27 m^2	1997	2.2563	26
11	22.67%	359.02%	6	23	538	44,020.28 m^2	1999	0.7586	3
12	22.79%	278%	3	15	397	38,663.01 m^2	1998	7.8253	6
13	21.51%	190.79%	12	12	1070	71,411.89 m^2	1996	2.6526	9
14	27.48%	310.71%	5	25	876	92,645.76 m^2	1994	4.5306	18
15	25.24%	210%	17	12	818	113,198 m^2	1995	2.5301	2
16	20.22%	234.58%	6	13	824	52,241.71 m^2	1987	2.1694	20
17	14.45%	143.37%	5	13	296	119,739.7 m^2	1978	2.8229	17
18	18.02%	242.78%	6	15	742	73,398.42 m^2	1991	4.2581	2
19	17.37%	191.71%	25	15	3481	2,374,050 m^2	1990	0.5972	2
20	21.01%	198.22%	10	15	700	62,776.43 m^2	1998	3.2524	3

Note: A_1 = building coverage ratio, A_2 = floor area ratio, A_3 = number of building, A_4 = number of floors, A_5 = number of households, A_6 = management area, A_7 = completion year, A_8 = maintenance cost per unit area, A_9 = number of maintenances.

Table 8 presents the average case similarities obtained from the 3-, 5-, 7-, and 10-NN approaches. The case similarities ranged from 88.71% to 99.47%. The case similarities from 10-NN were over 97% for 18 test cases, but case similarities of T2 and T19 were 88.71% and 89.40%, respectively, where similarities were relatively low. This is attributable to the lack of cases similar to the test case in the database [28,46]. In particular, for T2, the case similarity was lower compared to other cases regarding 3- and 10-NN. Similar cases appear to be insufficient for T2. It seems that there are not a sufficient number of cases similar to T2 in the case database.

Table 8. Case Similarities of 3-, 5-, 7-, 10-NNs.

Case Number	Case Similarity			
	3-NN	5-NN	7-NN	10-NN
T1	99.47	99.42	99.38	99.31
T2	92.50	90.65	89.55	88.71
T3	99.15	99.04	98.95	98.75
T4	99.29	99.20	99.12	99.06
T5	98.44	98.44	98.40	98.34
T6	99.14	99.1	99.07	99.01
T7	99.35	99.28	99.24	99.19
T8	99.16	98.90	98.76	98.62
T9	97.62	97.56	97.49	97.39
T10	97.94	97.77	97.66	97.52
T11	99.06	98.99	98.94	98.87
T12	99.27	99.19	99.13	99.07
T13	98.71	98.62	98.57	98.50
T14	98.22	98.08	97.98	97.85
T15	98.88	98.75	98.64	98.55
T16	98.51	98.33	98.21	98.04
T17	98.07	97.76	97.58	97.39
T18	99.00	98.98	98.96	98.91
T19	89.89	89.72	89.58	89.40
T20	99.43	99.40	99.37	99.31
Average	98.05	97.86	97.73	97.59

Table 9 presents a comparison of the actual repair time with the estimated repair time for 3-, 5-, and 10-NN according to the difference and mean absolute percentage error. The overall MAPEs for 3-, 5-, 7-, and 10-NN were 8.07%, 9.21%, 9.64%, and 9.51%, and the overall average error rate was 9.11%, indicating the reliability of the model. However, the MAPEs of 10-NN in T2, T10, and T19 were 16.67%, 17.86%, and 22.38%, respectively, which were significantly higher than those of the other cases. In addition, the case similarities were similar for 10-NN of T6 and T7, but the MAPE of 10-NN differed by 4.21% (Tables 8 and 9). This appears to be because outcomes are sensitive to cases, which means that estimated outcomes may vary depending on the output of the retrieved cases [28,33]. In other words, even if the similarity score between the retrieved and test cases is high, the output may vary depending on the characteristics and weights of attributes. This implies that reliable cases should be collected. According to Lewis [58], the MAPE results <10%, 10–20%, 20–50%, and 50%> indicate highly accurate forecasting, good forecasting, reasonable forecasting, inaccurate forecasting, respectively. MAPEs for 3-NN, 5-NN, and 10-NN (Table 9) were generally lower than 20%, which indicates good forecasting. Although these criteria may be arbitrary, the errors are allowable because the model can support decision-making based on the repair time of the building estimated in advance. Therefore, the developed model is applicable to the estimation of the repair time of building components.

Table 9. MAPE and Differences between Test Case and Previous Cases.

Case Number	Actual Repair Time	Repair Time (Year)				Differences				Mean Absolute Percentage Error (MAPE, %)			
		Predicted Repair Time				Predicted Repair Time				Predicted Repair Time			
		3-NN	5-NN	7-NN	10-NN	3-NN	5-NN	7-NN	10-NN	3-NN	5-NN	7-NN	10-NN
T1	19	19.33	19.8	19.86	19.5	−0.33	−0.8	−0.86	−0.5	5.26	6.32	7.52	7.89
T2	27	17.67	19.4	21.57	22.9	9.33	7.6	5.43	4.1	34.57	28.15	21.16	16.67
T3	25	25.33	25.6	26.14	25.9	−0.33	−0.6	−1.14	−0.9	1.33	2.4	4.57	5.2
T4	19	17.67	18.4	18.57	18.5	1.33	0.6	0.43	0.5	7.02	5.26	5.26	4.74
T5	21	23	22.2	22	22	−2	−1.2	−1.00	−1	9.52	7.62	7.48	7.62
T6	19	18.67	19.4	19.43	19.5	0.33	−0.4	−0.43	−0.5	5.26	6.32	6.77	5.79
T7	22	20	20.2	20	19.8	2	1.8	2.00	2.2	9.09	8.18	9.09	10
T8	17	16	15.4	15.57	15.4	1	1.6	1.43	1.6	5.88	9.41	8.40	10.59
T9	17	15.33	15.6	15.57	15.2	1.67	1.4	1.43	1.8	9.80	8.24	8.40	10.59
T10	14	13.33	14.6	14.43	15.3	0.67	−0.6	−0.43	−1.3	9.52	12.86	15.31	17.86
T11	13	12.67	12.6	12.29	12.7	0.33	0.4	0.71	0.3	2.56	3.08	5.49	5.38
T12	23	22.67	23.6	23.29	22.9	0.33	−0.6	−0.29	0.1	1.45	4.35	3.73	3.91
T13	15	14.67	15.8	15.29	15.1	0.33	−0.8	−0.29	−0.1	6.67	10.67	9.52	10
T14	17	15.67	15.2	14.71	14.8	1.33	1.8	2.29	2.2	7.84	10.59	13.45	12.94
T15	17	16.33	16	16.43	16.6	0.67	1	0.57	0.4	7.84	8.24	8.40	8.24
T16	24	23.67	24	24.71	24.6	0.33	0	−0.71	−0.6	4.17	5	6.55	6.67
T17	33	29.33	28.6	28.29	28.1	3.67	4.4	4.71	4.9	11.11	13.33	14.29	14.85
T18	20	21	21	20.71	20.5	−1	1	−0.71	−0.5	5.50	5.00	6.43	5.50
T19	21	22	24.8	22.57	22.7	−1	−3.8	−1.57	−1.7	17.46	25.71	27.89	22.38
T20	23	23	23.4	23.14	23.2	0	−0.4	−0.14	−0.2	0.00	3.48	3.11	3.48
		Mean absolute percentage error (MAPE)								8.07	9.21	9.64	9.51

Table 10 presents reference information derived from 10 cases similar to T20, which shows that components such as C1 (16.13%), C4 (32.26%), and C8 (16.13%) account for the majority of the repair or maintenance. Therefore, it allows building managers to obtain useful maintenance-related information for specific components in advance. Furthermore, Figure 4 presents the probability distributions of the repair times, based on the Monte-Carlo simulation (MCS). A beta-PERT distribution was utilized because it can consider various types of skewness and also estimate values from insufficient information [46].

Table 10. Reference Information for Retrieved Test Case (T20).

NN	Building Components								Repair Frequency
	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	
1	1	0	1	2	0	0	0	0	4
2	0	0	0	2	0	1	0	0	3
3	1	1	0	0	0	0	0	1	3
4	0	1	0	0	2	0	0	0	3
5	0	1	0	0	0	1	0	0	2
6	1	0	0	0	0	0	0	1	2
7	0	0	0	1	0	0	1	2	4
8	1	0	0	1	0	0	0	0	2
9	0	0	0	1	2	0	0	0	3
10	1	0	0	3	0	0	0	1	5
%	16.13%	9.68%	3.23%	32.26%	12.90%	6.45%	3.22%	16.13%	

Note: C_1 = drainage facility, C_2 = water supply facility, C_3 = hot water supply facility, C_4 = heating facility, C_5 = elevator and lift, C_6 = roof, C_7 = exterior, C_8 = outdoor facilities.

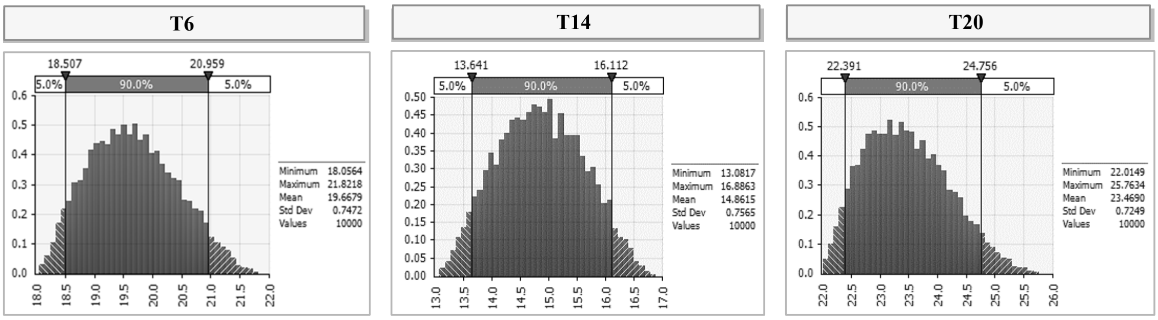

Figure 4. Repair Time Distribution for T6, T14, T20.

5. Conclusions

There has been a worldwide increase in the number of buildings that are more than 30 years old. Numerous problems have arisen regarding building maintenance. To preserve the performance of the buildings and provide a sustainable environment to residents, proper maintenance should be carried out. Moreover, it is important to estimate the time when building maintenance, especially repair, should be conducted. To cope with this issue, various studies on building maintenance have been conducted. Despite such efforts, there is still a lack of accuracy in repair time prediction.

In this research, a model was developed on the basis of CBR and fuzzy-AHP to estimate repair times for phases where information regarding the buildings is insufficient. Based on the weights of the input attributes, similarity scores between the existing cases and test cases were computed. The retrieved cases were compared with the test case in terms of MAPE to verify the applicability of the model. The overall MAPEs for 3-, 5-, 7-, and 10-NN were 8.07%, 9.21%, 9.64%, and 9.51%, respectively, and average case similarities for 3-, 5-, 7-, and 10-NN were 98.05%, 97.86%, 97.73%, and 97.59%, respectively. Furthermore, MAPEs between the test case and previous cases were generally lower than 20%, which indicates a reliable estimation performance according to the criteria suggested by Lewis [58]. The error rates seem to be permissible for estimating the repair time or maintenance cost because the model will provide building managers with essential information regarding building maintenance during the preconstruction or early construction phase. The developed model will be useful for managers in estimating specific repair times even when related information about buildings is insufficient. In addition, the model is expected to be used as a basis for decision making and budget allocation. The model presented in this study could have limited applicability to specific maintenance items because the estimation was performed from the overall perspective of building maintenance. However, if a database is organized by specific components, more reliable and accurate repair times for each component can be estimated. In addition, there are other limitations in that building materials and specifications of the components are not considered. This is attributable to the existence of a large number of building components and the lack of a unified system to organize maintenance-related information. Therefore, reliable cases need to be collected to enhance the accuracy and applicability of the model. Nevertheless, this research will provide meaningful results for estimating the repair time because maintenance-related attributes (e.g., management area, completion year, maintenance cost per unit area, number of maintenance) were considered. Furthermore, future research should address additional environmental factors, such as weather, climate, and degree of air pollution because air pollution can damage buildings [59], and the weather also affects the deterioration of buildings [9]. Despite these constraints, this research provides meaningful results for estimating the repair times of residential buildings in advance. This research contributes to the literature and knowledge of building maintenance by suggesting a method for estimating the repair time based on existing similar cases.

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Appendix A. Definitions of Attributes

1. Building coverage ratio: The ratio of the building area divided by site area
2. Floor area ratio: The ratio of total floor area divided by site area
3. Number of building: Total number of buildings in apartment buildings
4. Number of floors: Average floors of buildings
5. Number of households: The number of people who live in a dwelling.
6. Management area: area That is required for building maintenance
7. Completion year: The year the building was completed
8. Maintenance cost per area: Cost per unit area for building maintenance
9. Number of maintenances: The number of times maintenance after completion

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