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Remaining Service Life Evaluation of Reinforced Concrete Buildings Considering Failure Probability of Members

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Abstract

The durability and structural performance of reinforced concrete (RC) structures decrease over time owing to various factors such as environmental deterioration and increased service loads. Therefore, as the service life of RC structures increases, it is important to derive objective and quantitative evaluation results on their durability and structural performance. However, most previous studies have analyzed only the individual impacts of multiple factors that reduce the durability of RC structures and have not considered the combined effects of these factors. In addition, the durability and structural performance evaluation methods for RC structures proposed by domestic and international institutions are based on the subjective judgments of experts in structural diagnostics, and the evaluation results are generally expressed as grades, posing significant limitations on the effective maintenance of RC structures. Therefore, this study conducted a detailed field investigation on the factors that reduce the durability of 21 RC structures. Based on field investigation data, a remaining service life evaluation model reflecting combined deterioration was developed using an adaptive neuro-fuzzy inference system. In addition, the structural reliability theory was introduced into the proposed model to reflect the failure probability of structural members and the importance of each member, block, and floor. An evaluation procedure was developed to objectively evaluate the safety level of RC structures by comprehensively considering both the durability and structural performance. The procedure is expected to be widely utilized in the field of structural safety diagnostics as it provides a quantitative estimate of the remaining service life.

Keywords Remaining service life, Combined deterioration, Adaptive neuro-fuzzy inference system, Structural reliability, Failure probability

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1 Introduction

The service life of a reinforced concrete (RC) structure is defined as the period during which its durability and structural performance are maintained above the minimum allowable values required by standards or specifications (Cho et al., 2015; KCI, 2009; KALIS, 2009). In Korea, the Concrete Institute (KCI, 2009) Standard Concrete Specification, a limit state in durability, is defined concerning the depth of concrete carbonation and the concentration of chlorine ions at the location of reinforcement. The limit state of structural performance is defined as a state in which the external force acting on the concrete member exceeds the resistive force.

Accordingly, the durability and structural performance of an RC structure should not exceed the limit state during its service life. When the durability and structural performance deteriorate over the service life and exceed the limit state, maintenance plans such as structural repair, reinforcement, or reconstruction may be necessary (Coppola et al., 2022; Croce et al., 2020; Lei et al., 2022).

The maintenance of RC structures is conducted in accordance with standards for structural safety diagnosis specified by countries (ACI 201.2R-08, 2008; ACI 365.1R-00, 2000; JSCE, 2007; BS 7543:2015, 2015; KCI, 2009). The American Concrete Institute (ACI) classifies safety diagnosis procedures as visual examination, field testing, and laboratory testing and then presents diagnostic methods for each procedure. The Japan Society of Civil Engineers (JSCE) categorizes various deterioration mechanisms and diagnostic equipment suitable for deterioration measurement. It provides information to be obtained and major investigation methods according to investigation items. However, in most safety diagnosis methods for RC structures, the evaluation results are determined by the subjective judgments of experts in structural diagnostics (KCI, 2009; KCSC, 2016). In South Korea, safety diagnosis is conducted in accordance with the Detailed Guidelines for Safety Inspections and Precise Safety Diagnosis presented by the Korea Authority of Land & Infrastructure Safety (KALIS, 2009), based on which the level of structural safety and durability can be graded (A, B, C, D, or E). However, it is not capable of estimating the remaining service life (RSL) of RC structures. In contrast to other national diagnostic methodologies, fuzzy theory was introduced as a diagnosis technology to minimize the subjective judgements of experts in structural diagnostics (Klir & Folger, 1988; Sahu & Jena, 2023; Zadeh, 1965; Zimmermann, 2001). In this safety diagnosis evaluation method, the safety diagnosis evaluation results of RC structures are provided as grades (A, B, C, D, or E). However, it is difficult to utilize such simple grade evaluation results to determine the optimal timing for repair and reinforcement, and there can be significant differences in performances between structures with the same grades. Therefore, if it is possible to estimate the time remaining to reach the limit state, it will be advantageous in terms of structural maintenance, such as in determining the optimal time for repair or reinforcement. The time remaining until reaching the limit state is defined as the RSL, and it is calculated by excluding the elapsed time (in years) from the target service life of the structure.

However, it is difficult to evaluate the remaining service life of RC structures because the durability deteriorates over time owing to various environmental factors (Qu et al., 2021; Yi et al., 2020). In the authors' previous research (Cho et al., 2016), the effects of concrete compressive strength, water-binder ratio, crack width, chloride ion concentration, chloride ion diffusion coefficient, and concrete carbonation depth on concrete deterioration were analyzed. A model capable of estimating the concrete carbonation depth was developed considering combined deterioration using an adaptive neuro-fuzzy inference system (ANFIS) (Jang & Sun, 1995; Jang et al., 1997). The carbonation depth is a key factor in determining the durability of ground structures in RC structures. Unlike structures located in coastal environments, those located in inland environments suffer minimal damage from chloride penetration; thus, corrosion is mainly dominated by concrete carbonation. In this study, a detailed field investigation was conducted on the factors that reduce the durability of 21 RC structures, and an RSL evaluation model reflecting the combined deterioration of RC structures was developed based on the field investigation data. In the proposed model, the time required for the concrete carbonation depth to exceed the cover thickness of the member was used to estimate the RSL of the structure. In addition, because the service life of a member is directly related to the safety of the occupants, it is desirable to consider a conservative approach towards the calculation of service life. In this study, the service life of a member was limited such that it did not exceed the target service life. Structural reliability theory (Hassoun & Al-Manaseer, 2020; Breneman et al., 2022) was also taken to account into assess the failure probability of structural members, and the importance modification coefficients of members, blocks, and floors developed by Cho et al. (2023) were applied in the proposed model. Based on this approach, the durability and structural performance of RC structures were objectively evaluated, and their RSLs were estimated quantitatively. This approach not only facilitates a quantitative estimate of the RSL but also enables determining the optimal timing for repair and reinforcement. The evaluation procedure is expected to be widely utilized in the field of structural safety diagnostics.

2 RSL at the Member Level

The RSL of RC members can be evaluated using the concrete carbonation depth estimation model, which reflects the combined deterioration proposed by Cho et al. (2016). Although RC members ensure safety against design loads, their durability deteriorates owing to various environmental factors, such as chloride penetration, concrete carbonation, frost damage, alkali-aggregate reactions, and chemical erosion. Chloride penetration and concrete carbonation are frequent problems in RC structures, and it is relatively easy to measure the degree of deterioration. However, durability degradation caused by deterioration factors such as frost damage, alkali-aggregate reactions, and chemical erosion is less severe in general environments, making the measurement of the degree of deterioration difficult. This study used the concrete surface chloride ion concentration, chloride ion diffusion coefficient, and concrete carbonation, which are durability deterioration factors measured via safety diagnosis, to evaluate the RSL. The crack width, concrete compressive strength, and water-binder ratio were also considered.

2.1 Concrete Carbonation Depth Considering Multiple Degradation Factors

Concrete carbonation, which occurs most frequently in inland environments, is a phenomenon in which the alkalinity of concrete decreases as calcium hydroxide in concrete changes into calcium carbonate when it comes into contact with carbon dioxide in the air (Neville, 1996). The depth of concrete carbonation varies depending on the types of cement, water, aggregate, and curing conditions. The water-binder ratio has a particularly significant impact on the depth of carbonation. The concrete carbonation depth is generally known to be proportional to the square root of time (Neville, 1996), and the carbonation rate coefficient (A) can be calculated as follows:

$$A = C_a/\sqrt{t} \tag{1}$$

where C_a is the concrete carbonation depth and t is the time (year). The concrete-carbonation rate coefficient in Eq. (1) is a constant coefficient that considers the effects of various environmental factors simultaneously. In the Standard Specification for Reinforced Concrete (KCSC, 2016), the carbonation rate coefficient (A_p) in a state where no combined deterioration occurs is calculated as the function of a water-binder ratio (W/B) as follows.

$$A_p = -3.57 + 9.0(W/B) \tag{2}$$

In this study, the carbonation rate coefficient in the state with no combined deterioration in Eq. (2) was applied as the input variable, and the combined action and the other input variables were considered.

Chloride ion penetration in concrete significantly impacts the durability due to reinforcement corrosion. Chloride penetration also accelerates the decline in durability owing to other factors. Therefore, to better reflect combined deterioration, chloride penetration should be considered an influencing factor. Andrade et al. (1997) experimentally determined the difference in the chloride ion diffusion coefficient between carbonated and non-carbonated concrete sections. They reported that the initiation period of reinforcement corrosion could be accelerated owing to concentrations at the interface between carbonated and non-carbonated sections. Therefore, in this study, the surface salinity and chloride ion content at each depth were measured in a field investigation to reflect the effects of chloride penetration. The chloride ion diffusion coefficient (D_a) was calculated using a diffusion model based on Fick's second law (Crank, 1975; Porter & Easterling, 1992) and used as an input variable, together with the surface salinity.

$$C_d - C_i = (C_0 - C_i)\left(1 + erf\left(\frac{x}{2\sqrt{D_a t}}\right)\right) \tag{3}$$

Here, C_d is the chloride ion concentration at a distance x from the surface to the inside of the concrete; C_i is the initial chloride ion concentration; and C_0 is the surface chloride ion concentration.

Cracks in RC structures can be divided into structural and nonstructural cracks. In general, structural cracks are considered a major factor affecting the durability and structural performance in safety and precision safety diagnoses. Although structural cracks have a significantly higher impact on durability and structural performance degradation, non-structural cracks also have a significant impact. In most cases, non-structural cracks are finishing cracks, where the concrete surface is directly exposed to air, facilitating concrete carbonation and chloride ion penetration. Song et al. (2006) reported that carbon dioxide penetration occurs faster in cracked sections than that in uncracked sections, which has been experimentally proven.

Cho (2014) reported that the rate of carbonation in high-strength concrete was significantly lower than that in low-strength concrete. Microscopic and void analyses found that as the compressive strength of concrete increased, the structure became denser, resulting in approximately no voids.

2.2 RSL at the Member Level Based on ANFIS

In this study, a model for predicting the carbonation depth with combined deteriorations was adopted from a previous study (Cho et al., 2016) and utilized to estimate the RSL of RC members using ANFIS. In ANFIS, a learning system is introduced to correct errors in fuzzy theory. It is widely applied in various academic fields to solve problems in which it is difficult to determine the correlation between variables owing to the influence of different variables or unclear boundaries. (Anoop et al., 2002; Anoop & Rao, 2007; Cho et al., 2015, 2016, 2017a, 2017b; Choi et al., 2007; Kim et al., 2002, 2007; Nehdi & Bassuoni, 2009; Unal et al., 2005) ANFIS is an evaluation method based on a database, similar to an artificial neutral network or genetic algorithm (Jang et al., 1997). In general, the prediction model's performance improves as the database size increases. Cho et al. (2016) used safety diagnosis data from nine RC structures to predict the carbonation depth, reflecting the combined deterioration. This study attempted to predict the carbonation depth of concrete members reflecting combined deterioration and to evaluate the RSL of the members based on the field investigation results of nine RC structures and 12 RC structures used in the research conducted by Cho et al. (2016), as shown in Table 1.

The ANFIS structure comprises five layers. In Layer 1, the membership function is calculated; that is, fuzzification of the input parameters is conducted. As shown in Fig. 1, the fuzzy set used in this study was constructed using bell-shaped membership functions that resemble Gaussian distributions. Gaussian distributions are often employed to model natural phenomena because of their ability to effectively represent central tendencies and variations. The membership function can be represented as follows:

$$bell\left(x; x_c, x_w, x_q\right) = \frac{1}{1 + \left|\frac{x - x_c}{x_w}\right|^{2x_q}} \tag{4}$$

where x is the input parameter, x_c is the median of the fuzzy set, x_w is the fuzzy set width, and x_q is the fuzzy set shape factor. x_c, x_w, and x_q were used as the premise parameters, and three fuzzy sets were created for each input parameter.

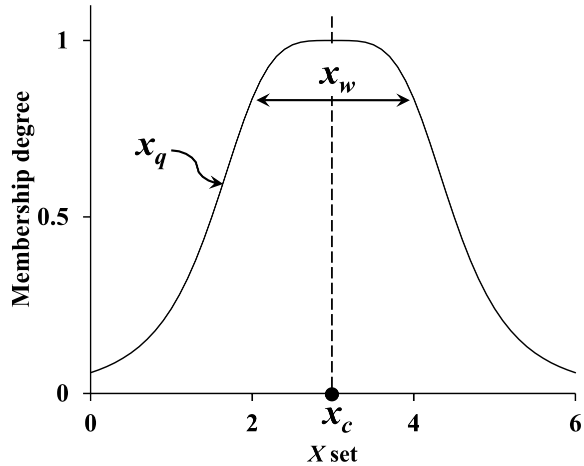

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Fig. 1 Bell-shaped fuzzy set

Table 1 Field investigation data

Building name	Elapsed time (years)	Concrete compressive strength (MPa)	Concrete carbonation depth (mm)	Cover depth (mm)	Crack width (mm)	Chloride ion concentration (kg/m^3)		Chloride ion diffusion coefficient (m^2/year)
						Inside	Outside	
B1	35	17.7 ~ 37.7	5.0 ~ 54.5	26 ~ 86	SC[a] ~ 0.1	0.27	0.63	3.2×10^{-6}
B2	35	20.7 ~ 33.2	4.6 ~ 36.9	35 ~ 85	SC ~ 0.1	0.15	0.18	46.6×10^{-6}
B3	35	19.3 ~ 32.8	7.1 ~ 42.2	25 ~ 75	SC	0.47	0.47	11.2×10^{-6}
B4	32	18.6 ~ 34.9	11.8 ~ 71.1	20 ~ 72	SC ~ 0.5	0.40	0.63	73.9×10^{-6}
B5	33	23.2 ~ 37.7	5.5 ~ 40.2	25 ~ 100	SC	0.24	0.42	10.0×10^{-6}
B6	35	20.2 ~ 30.3	11.1 ~ 25.8	20 ~ 90	SC ~ 0.1	0.13	0.38	42.7×10^{-6}
B7	33	18.6 ~ 32.1	7.4 ~ 21.3	25 ~ 70	0.1	1.38	1.58	10.6×10^{-6}
B8	34	16 ~ 35.7	9.2 ~ 57.8	20 ~ 95	SC ~ 0.2	0.15	0.22	13.3×10^{-6}
B9	40	19.6 ~ 27.3	14.6 ~ 49.9	20 ~ 75	SC ~ 0.1	0.22	0.27	27.6×10^{-6}
B10	32	20.1 ~ 33.7	8.3 ~ 50.9	20 ~ 85	0.1	0.13	0.20	6.4×10^{-5}
B11	40	18.3 ~ 27.7	12.1 ~ 41.7	30 ~ 90	SC ~ 0.1	0.19	0.34	3.7×10^{-6}
B12	33	20.8 ~ 30.7	14.3 ~ 57.9	20 ~ 100	SC ~ 0.1	0.16	0.21	1.5×10^{-5}
B13	33	20.2 ~ 27.6	15.7 ~ 57.4	25 ~ 80	0.1	0.69	1.78	3.6×10^{-6}
B14	35	21.4 ~ 31.5	12.0 ~ 27.8	25 ~ 70	SC ~ 0.1	1.25	1.18	3.7×10^{-6}
B15	34	20.5 ~ 26.1	17.1 ~ 54.7	20 ~ 100	SC ~ 0.1	0.67	1.84	8.9×10^{-6}
B16	35	20.7 ~ 27.3	12.2 ~ 41.4	15 ~ 60	0.1	0.33	1.07	4.3×10^{-5}
B17	33	20.7 ~ 23.5	15.9 ~ 53.0	30 ~ 100	SC ~ 0.2	0.16	0.28	2.0×10^{-5}
B18	29	20.9 ~ 28.9	14.6 ~ 39.1	25 ~ 75	SC ~ 0.3	0.41	0.69	5.7×10^{-6}
B19	30	20.0 ~ 30.7	8.5 ~ 37.2	20 ~ 70	0.1	0.28	0.31	7.8×10^{-5}
B20	39	20.7 ~ 44.4	12.1 ~ 23.1	10 ~ 80	0.1 ~ 0.5	0.33	0.33	1.3×10^{-5}
B21	13	21.1 ~ 33.4	7.1 ~ 15.4	20 ~ 75	0.1	0.40	0.44	1.9×10^{-4}

[a] *SC* surface finishing crack

In Layer 2, a fuzzy rule is defined, and the rule set contains 729 linear functions as follows:

$$\begin{aligned} fr_1 &= a_1x_1^1 + b_1x_1^2 + c_1x_1^3 + d_1x_1^4 + e_1x_1^5 + f_1x_1^6 + g_1 \\ fr_2 &= a_2x_2^1 + b_2x_2^2 + c_2x_2^3 + d_2x_2^4 + e_2x_2^5 + f_2x_2^6 + g_2 \\ &\vdots \\ fr_{729} &= a_{729}x_{729}^1 + b_{729}x_{729}^2 + c_{729}x_{729}^3 + d_{729}x_{729}^4 + \\ &\quad e_{729}x_{729}^5 + f_{729}x_{729}^6 + g_{729} \end{aligned} \tag{5}$$

where x_i^1 is the water-binder ratio, x_i^2 is the concrete compressive strength, x_i^3 is the crack width, x_i^4 is the concrete surface chloride ion concentration, x_i^5 is the chloride ion diffusion coefficient, x_i^6 is the time (year), and a, b, c, d, e, f, and g are the constants that can be calculated using the method of least squares. In Layer 3, the membership degree of the rule is calculated. Every fuzzy value has a membership degree, and the membership degree (w_i) of each rule is calculated using the T-norm method as follows:

$$\begin{aligned} & w_i = T\left(\mu_{Ca_j}, \mu_{fc_j}, \mu_{Cr_j}, \mu_{Cs_j}, \mu_{Da_j}, \mu_{t_j}\right) \\ & i = 1, 2, 3, \cdots, 729 \\ & j = 1, 2, 3 \end{aligned} \tag{6}$$

where $w_i$is the membership degree of the i-th rule, $\mu_{Ca_j}$is the membership degree of the Ca_j fuzzy set for the water-binder ratio, μ_{fc_j} is membership degree of the fc_j fuzzy set for the concrete compressive strength, μ_{Cs_j} is the membership degree of the Cs_j fuzzy set for the surface salinity content, μ_{Da_j} is the membership degree of the Da_j fuzzy set for the chloride ion diffusion coefficient, and μ_{t_j} is the membership of the t_j fuzzy set for the time. As the result of the rule established in Layer 2 is a fuzzified value, defuzzification must be performed. Defuzzification is a method for deriving crisp values from inferred fuzzy values, and the centroid method is generally used. The centroid method calculates the expected value using the normalized membership degree of the rule as a weight. Layers 3–5 represent the defuzzification processes. In Layer 3, the membership degrees were normalized. Specifically, the normalized membership degree ($\overline{w}_i$) of a rule is calculated as follows:

$$\overline{w}_i = \frac{w_i}{\sum w_i} \tag{7}$$

In Layer 4, the normalized fuzzy rule (y_i) is calculated using the normalized membership degree and fuzzy set determined in Layers 2 and 3 as follows:

$$y_i = \overline{w}_i fr_i = \overline{w}_i\left(a_ix_i^1 + b_ix_i^2 + c_ix_i^3 + d_ix_i^4 + e_ix_i^5 + f_ix_i^6 + g_i\right) \tag{8}$$

In Layer 5, the crisp value (y) is calculated as follows:

$$y = \sum_{i=1}^{729} y_i = \sum_{i=1}^{729} \overline{w}_i fr_i \tag{9}$$

As described previously, a_i, b_i, c_i, d_i, e_i, f_i and g_i, which are constants in Eq. (8), are determined through the least squares method using the sum of squares error between the measured and predicted values. The least squares ($E(\theta)$) of the measured and predicted value errors can be represented as follows:

$$\begin{aligned} & E(\theta) = \sum_{i=1}^{m}\left(y_{t_i} - a_i^T\theta\right)^2 = e^2e = (Y_t - A\Theta)^T(Y_t - A\Theta) \\ & Y_t = \left[y_{t_1}, y_{t_2}, \ldots, y_{t_{729}}\right]^T \\ & A = \begin{bmatrix} \overline{w}_1x_1^1 & \overline{w}_1x_1^2 & \ldots & \overline{w}_1x_1^7 & \overline{w}_1 & \ldots & \overline{w}_2x_1^1 & \ldots & \overline{w}_{2187} \\ \overline{w}_1x_2^1 & \overline{w}_1x_2^2 & \ldots & \overline{w}_1x_2^7 & \overline{w}_1 & \ldots & \overline{w}_2x_2^1 & \ldots & \overline{w}_{2187} \\ \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ \overline{w}_1x_{729}^1 & \overline{w}_1x_{729}^2 & \ldots & \overline{w}_1x_{729}^7 & \overline{w}_1 & \ldots & \overline{w}_2x_{729}^1 & \ldots & \overline{w}_{729} \end{bmatrix} \\ & \Theta = \left[\, a_1 \;\; b_1 \;\ldots\; h_1 \;\; a_2 \;\ldots\; a_{729} \;\ldots\; h_{729} \,\right] \end{aligned} \tag{10}$$

where Y_t is the measured value, or the concrete carbonation depth reflecting combined deterioration; A is the input parameter; Θ is a constant; and m is the number of data points. If the left-hand term is expressed as a derivative representing the slope of the function, Eq. (10) can be expressed as follows:

$$\frac{E(\theta)}{\partial\theta} = 2A^TA\Theta - 2A^TY_t \tag{11}$$

When the slope is zero, Eq. (10), the number of errors can be minimized; therefore, the constant (Θ) is calculated as follows:

$$\Theta = \left(A^TA\right)^{-1}A^TY_t \tag{12}$$

When one cycle of operations from layers 1 to 5 is completed, the error is recalculated, and the input argument is updated using a backpropagation algorithm in ANFIS. The error was calculated as follows:

$$E = \left(y - y_t\right)^2/2 \tag{13}$$

The error increment (Δx_{cwq}) for updating the input argument is calculated as follows:

$$\Delta x_{cwq} = \frac{\partial E}{\partial x_{cwq}}$$
$$x_{cwq} = \{x_c, x_w, x_q\} \tag{14}$$

The updated premise parameter ($x_{cwq}(t'+1)$) is calculated using the learning rate (η_a) and error increment as follows:

$$x_{cwq}(t'+1) = x_{cwq}(t') - \frac{\eta_a}{p}\frac{\partial E}{\partial x_{cwq}} \tag{15}$$

where $x_{cwq}(t')$ is the premise parameter before updating and p is the size of the database as the amount of data. The error-modification process is repeated until the number of errors shown in Eq. (13) is minimized. The RSL of a member refers to the time until the carbonation depth derived from the ANFIS algorithm, trained to minimize the number of errors, reaches its limit state.

3 RSL Evaluation Method for RC Structures

The RSL of the members derived using the previous RSL evaluation method for each member does not represent the RSL of the RC structures. If the entire structure and floor's remaining service life is used as each member's minimum RSL, an excessively low RSL evaluation result is obtained. However, if the average value is used, an RSL that does not reflect the importance of the member is derived. Therefore, in this study, the building plan was divided into several blocks made of columns, girders, beams, and slabs, as shown in Fig. 2, and the RSL of the block, with the importance and RSL of members considered appropriately, was evaluated using a fuzzy measure.

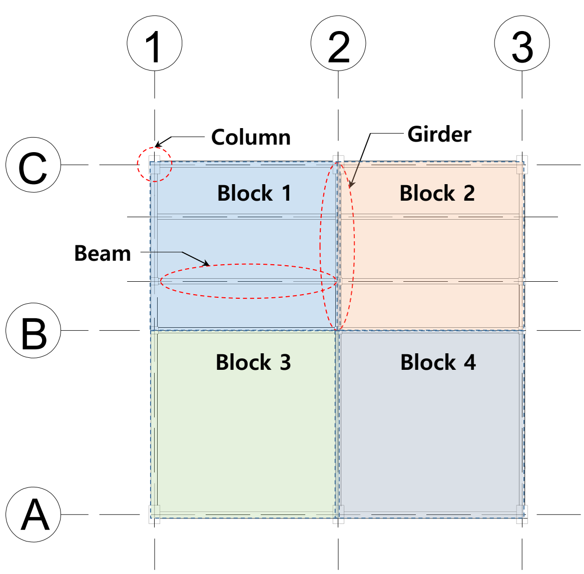

Fig. 2 Classification of blocks in a building floor plan

A method for determining the importance of each member considering the failure probability of the member was proposed based on reliability theory, and it was ultimately confirmed that the RSL of the structure was evaluated reasonably. The RSL evaluation from the member stage to the structural stage was performed sequentially in the block, floor, and structural stages, as shown in Fig. 3. As in the block stage evaluation, the remaining service lives of the floor and structural stages were evaluated using a fuzzy measure.

3.1 Importance Factor of a Member

In the Detailed Guidelines for Safety Inspections and Precise Safety Diagnosis presented by the Korea Authority of Land & Infrastructure Safety (KALIS, 2011), the comprehensive safety evaluation grades of members are determined by calculating the expected values based on the importance and safety diagnosis evaluation results of each member, where the Sugeno fuzzy measure (Grabisch et al., 2007) and Choquet fuzzy integral (Choquet, 1954) are used as methods to calculate the expected value. In contrast to probability measures, fuzzy measures are used when additivity is not satisfied in the measure space. The probability weight mean can be calculated with probability measures because the sum of all importance factors or weights is unity. However, the Detailed Guidelines

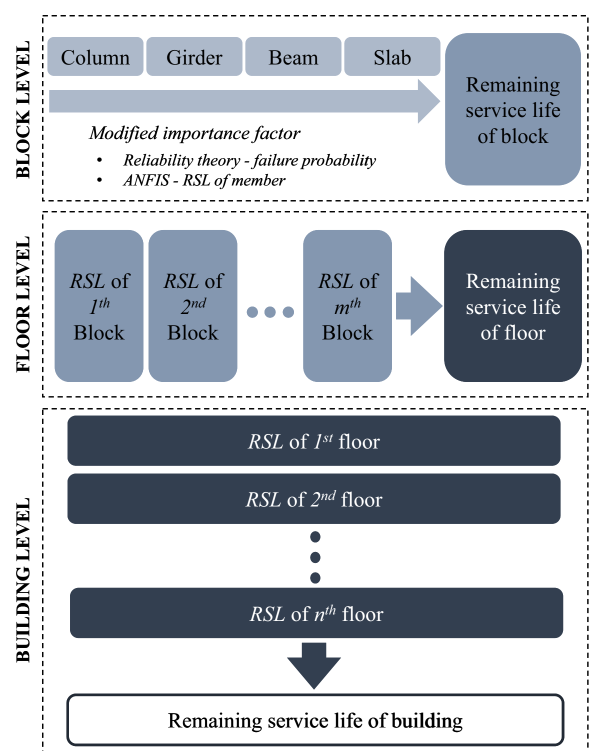

Fig. 3 Flowchart of the evaluation method

for Safety Inspections and Precise Safety Diagnosis presented by the Korea Authority of Land & Infrastructure Safety (KALIS, 2011) require that when safety diagnosis grades are set for a floor, the importance of a member is set to 0.9 for columns and load-bearing walls, and 0.7, 0.5, and 0.3 for girders, small beams, and slabs, respectively. In this case, the arithmetic sum of the importance of a member exceeds 1, which is displayed in the measure space as shown in Fig. 4. $f(x_i)$ is the evaluation value for x_i, that is, if x_1 is assumed to be a column, $f(x_1)$ is the safety diagnosis result or RSL of the column. Moreover, $g(x_i)$ is the measure value, that is, if x_1 is assumed to be a column, $g(x_1)$ is the importance of the column. If x_2 is a girder, the probability weight mean cannot be calculated because $g(x_1) + g(x_2)$, the sum of the importance of the column and the girder is 1.6, which exceeds 1. Accordingly, Sugeno (Sugeno, 1974) proposed the Sugeno fuzzy measure capable of artificially making the sum of measures equal 1 via a normalized parameter λ. For example, the sum of importance $(g(x_1, x_2, x_3, x_4))$ for the evaluation results that combine the safety diagnosis grades of

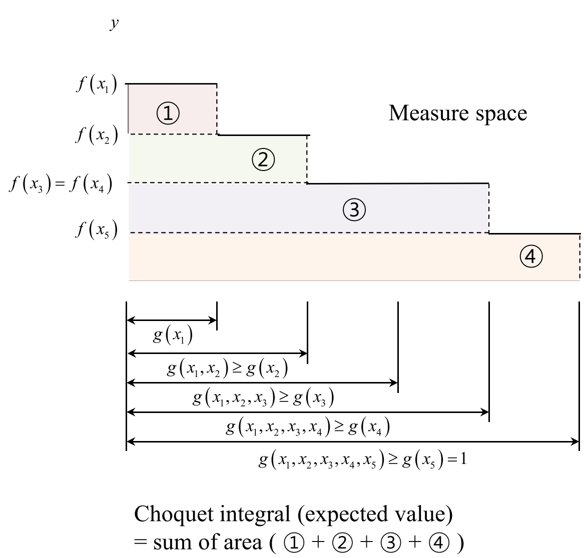

Fig. 4 Fuzzy measure and integral

columns (x_1), girders (x_2), small beams (x_3) and slabs (x_4) can be calculated as follows:

$$\begin{aligned} g(x_1, x_2, x_3, x_4) = 1 = g(x_1) + g(x_2) + g(x_3) + g(x_4) \\ + \lambda\big(g(x_1)g(x_2) + g(x_1)g(x_3) + g(x_1)g(x_4) \\ + g(x_2)g(x_3) + g(x_2)g(S) + g(x_3)g(x_4)\big) \\ + \lambda^2\big(g(x_1)g(x_2)g(x_3) + g(x_1)g(x_2)g(x_4) \\ + g(x_1)g(x_3)g(x_4) + g(x_2)g(x_3)g(x_4)\big) \\ + \lambda^3\big(g(x_1)g(x_2)g(x_3)g(x_4)\big) \end{aligned} \tag{16}$$

when the importance of the column, girder, small beam, and slab were 0.9, 0.7, 0.5, and 0.3, respectively, with $\lambda = -0.988$. In the measurement space, the expected value is calculated using integrals. In the probability measure, additivity is satisfied, the sum of all the important factors satisfies 1, and the expected value can be calculated using a Lebesgue integral. However, the Lebesgue integral cannot be obtained because the fuzzy measure does not satisfy this condition. Accordingly, Choquet modified the Lebesgue integral to develop the Choquet integral, which is integrable under conditions where additivity is not satisfied. The Choquet integral is also used to calculate the expected value in the Detailed Guidelines for Safety Inspections and Precise Safety Diagnosis presented by the Korea Authority of Land & Infrastructure Safety (KALIS, 2011). The Choquet integral is a method of calculating the sum of areas ①, ②, ③ and ④ in the measure space as shown in Fig. 4, and the domain in which additivity is not satisfied can be calculated using λ. Specifically, $g(x_1, x_2)$ was calculated as follows:

$$g(x_1, x_2) = g(x_1) + g(x_2) + \lambda\big(g(x_1)g(x_2)\big) \tag{17}$$

However, in relation to the evaluation scores for the grades of members provided by the Korea Authority of Land and Infrastructure Safety (KALIS, 2011), the higher the grade, the lower the evaluation score, as summarized in Table 2. In other words, the score decreases as the evaluation result deviates toward the safe side. However, the higher the value of the remaining service life, the closer

Table 2 Evaluation score according to safety grade at the structural member

Safety grade	Evaluation score range	Representative value before change (KALIS)	Representative value after change (proposed method)
A	$0 \leq m \leq 2$	1	9
B	$2 \leq m \leq 4$	3	7
C	$4 \leq m \leq 6$	5	5
D	$6 \leq m \leq 8$	7	3
E	$8 \leq m \leq 10$	9	1

the result is to the safe side; thus, the same λ cannot be applied to the RSL. In this regard, this study aimed to estimate λ through which the floor evaluation grade can be calculated based on the inverse substitution of evaluation scores shown in Table 2. This is aimed at ensuring the evaluation scores according to the evaluation grade provided by the Korea Authority of Land and Infrastructure Safety are on the safe side and can be calculated similarly to the evaluation grade before substitution.

3.2 Modified Lambda

Sugeno defined λ in the fuzzy measure as shown in Fig. 5. (Grabisch et al., 2007; Sugeno, 1974). The RSL of RC structures to be derived in this study is an arithmetic measure indicating the structure's safety. It therefore should be evaluated conservatively, and the risk should also be low. As shown in Fig. 5, if λ is negative, the risk increases because the expected value increases. Conversely, the risk decreases if it is positive because the expected value decreases. As described previously, if the arithmetic sum of measures is greater than 1, λ becomes negative to satisfy Eq. (16). However, if the arithmetic sum is less than 1, λ become positive. Therefore, to have a positive λ, the arithmetic sum of importance factors should be set to less than 1.

In this study, the normalized importance of members ($\overline{g}_m$) were recalculated using Eq. (16) and the importance of the member provided by the Korea Land and Infrastructure Safety and Technology Agency, adjusting the sum of the importance ($\sum g_m$) to 1.0, 0.75, 0.5, and 0.3. As shown in Fig. 6 and Table 2, a block-level evaluation applied with the evaluation grades of members according to the safety grade proposed in this study was conducted, and the results were compared with the evaluation results of the method presented by the Korea Authority of Land & Infrastructure Safety.

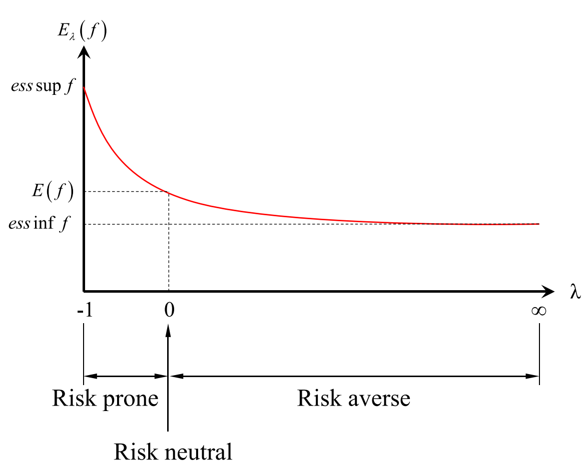

Fig. 5 Interpretation of the parameter λ (Grabisch et al., 2007)

As shown in Fig. 6, the sum of importance factors ($\sum g_m$) suggested in the KALIS (2011) guidelines was normalized to 1.0, 0.75, 0.5, and 0.3, λ was calculated at 0, 1.10, 4.15, and 12.82, respectively. When the sum of importance factors was normalized to 1 or 0.75, the evaluation grades of blocks using the proposed method were significantly higher than the KALIS grades. When the sum of member factors was normalized to 0.3, the coefficient of variation (COV) of block grades using the proposed method and KALIS was most similar at 0.061. However, there were cases in which the proposed method evaluated the block as unsound compared to the existing KALIS evaluation method. In addition, as indicated by the dotted line in Fig. 6, there were many inappropriate cases in which the block grades by the proposed method were significantly higher than those by KALIS. This is because in the proposed method, the impact of members with low evaluation grades is not properly reflected in block evaluation. As shown in Table 3, even when the evaluation grade of the column, girder, or slab was E, which was very low (that is, significantly defected), the block grade was C or D. Therefore, to compensate for this inadequate evaluation, a method of increasing the importance of members with high failure probability was introduced based on structural reliability theory (Ang & Tang, 1990).

3.3 Structural Reliability Theory

Structural reliability theory is a common method used to approximate the probability of failure of structural members using a reliability index (β) (Ang & Tang, 1990; Chetchotisak et al., 2014; Cho et al., 2017a, 2017b; Macgregor, 1983; Nowak & Szerszen, 2003; Szerszen & Nowak, 2003) and is used to determine the safety factor in the Eurocode (Standard, 2002) and KCI (KCI, 2012) concrete structural design standards. Cho et al. (2023) proposed an importance modification coefficient (α_1) and modified importance ($\overline{g}'_m$) based on structural reliability theory to supplement the KALIS evaluation method that does not reflect the influence of high-probability failure members, as follows:

$$\alpha_1 = 1 - \frac{\beta}{\beta_t} \tag{18}$$

$$\overline{g}'_m = \overline{g}_m \times (1 + \alpha_1) \tag{19}$$

where β is the reliability index of the member, which is inversely related to the failure probability of the member, and β_t is the target reliability index. In this study, a target reliability index of 3.0 was used for the flexure-controlled

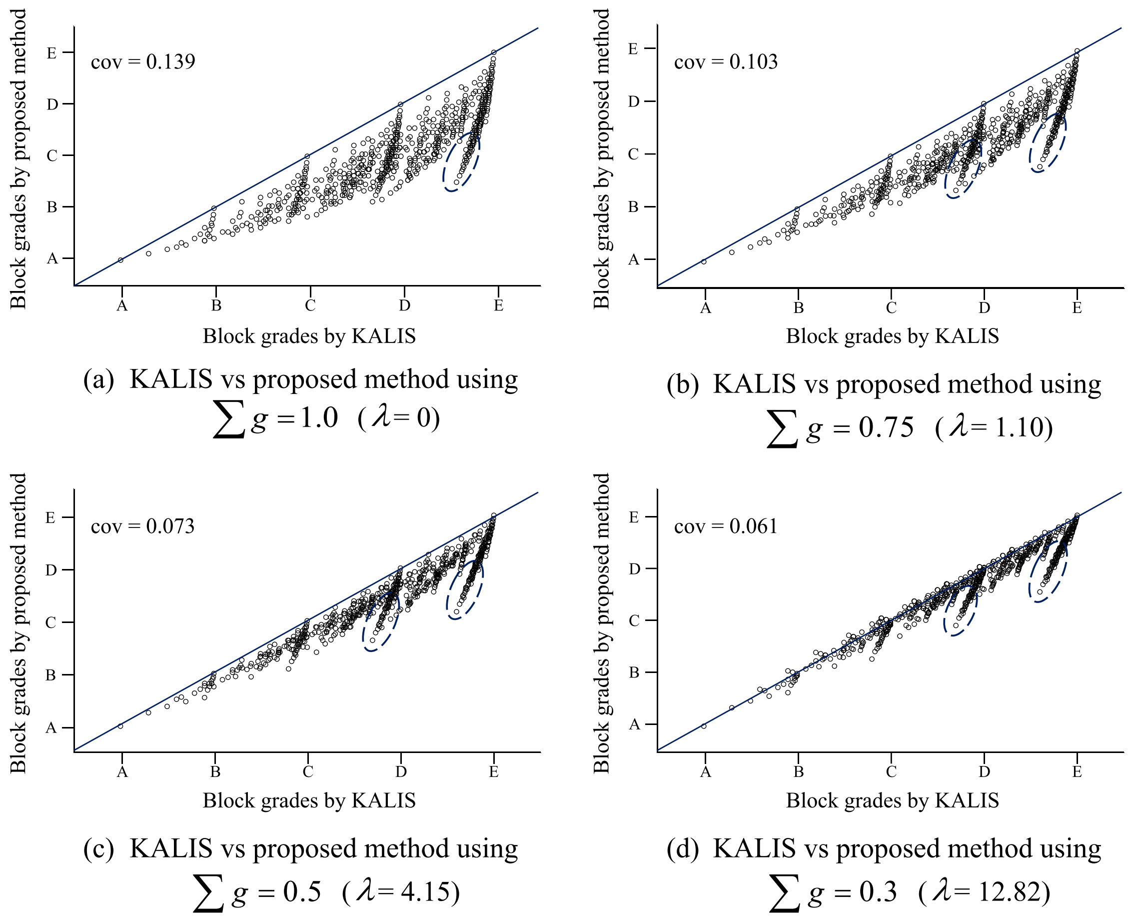

Fig. 6 Block grades according to the sum of important factors. **a** KALIS vs proposed method using $\sum g = 1.0$ ($\lambda = 0$), **b** KALIS vs proposed method using $\sum g = 0.75$ ($\lambda = 1.10$), **c** KALIS vs proposed method using $\sum g = 0.5$ ($\lambda = 4.15$), **d** KALIS vs proposed method using $\sum g = 0.3$ ($\lambda = 12.82$)

Table 3 Grades and scores of blocks according to structural members

NO	Column	Girder	Beam	Slab	Block
1	E (9)	E (9)	A (1)	A (1)	D (7)
2	E (9)	A (1)	B (3)	B (3)	C (5)
3	E (9)	A (1)	A (1)	C (5)	C (5)
4	E (9)	A (1)	A (1)	D (7)	C (5)
5	E (9)	A (1)	A (1)	E (9)	C (5)

section and 3.5 for the shear-controlled section, as suggested by Nowak and Szerszen (2003) and Szerszen and Nowak (2003). Moreover, $\overline{g}'_m$ is the modified member importance and $\overline{g}_m$ is the importance of each member when the sum of importance factors ($\sum g_m$) is normalized to 1.0, 0.75, 0.5, and 0.3, respectively. The limit state equation (G) of the member used to calculate the reliability index (β) is configured as follows:

$$G = R - Q \tag{20}$$

where R is the resistance of the member and Q is the applied loads. If the limit state function is linear, as in Eq. (20), the reliability index can be calculated using the mean value and standard deviation of each random variable. The reliability index (β) is calculated as follows:

$$\beta = \frac{\mu_{R_n} - \mu_{Q_u}}{\sqrt{\sigma_{R_n}^2 + \sigma_{Q_u}^2}} \tag{21}$$

where μ_{R_n} is the average resistive force, μ_{Q_u} is the average action force, σ_{R_n} is the standard deviation of the resistive force, and $\sigma_{Q_u}$is the standard deviation of the action force. Then, the failure probability (P_f) is calculated as follows:

$$P_f = \Phi(-\beta) \tag{22}$$

where the $\Phi(x)$ is cumulative distribution function.

In this study, the importance of the members is modified using Eqs. (18) and (19), and the statistical data presented by Nowak and Szerszen (2003) were used to calculate the average and standard deviation of the load and member resistance, which are random variables. The modified importance is limited to an increase of up to two times, and even when all importance factors double, λ is calculated as zero and does not fall into the risk-prone section. In addition, because the importance of the member increases with increasing failure probability, and its impact on block evaluation increases. It can compensate for cases in which the impact of members with low evaluation grades is not properly reflected in the evaluation results, as shown in Fig. 6 and Table 3. In the KALIS (2011) guidelines, the evaluation grade and score are divided into five levels according to the strength ratio of the member to the applied load (that is, strength ratio, *SR*), as listed in Table 4, and commentaries are provided for each grade. Members with an *SR* of less than 90% were assigned grades D and E, indicating a significant decline in structural safety. To select the sum of the importance factors ($\sum g_m$) suitable for the RSL evaluation model, the block evaluation results (score$_{cor.}$, marked by red circles) using the modified importance ($\overline{g}'_m$) were compared with the KALIS evaluation results, as shown in Fig. 7. The modified importance ($\overline{g}'_m$) of members corresponding to grades D and E was calculated (80 and 60%, respectively) and applied as the *SR* of the members with reference to KALIS (2011). Block evaluation results: (score$_{cor.}$) applied with the modified importance ($\overline{g}'_m$) showed high similarity to the KALIS (2011) evaluation results than those of the block evaluation results without considering the failure probability of the member (score$_{org.}$, marked as black circles). When the sum of the importance factors ($\sum g_m$) was normalized to 1.0, 0.75, and 0.5, the COV decreased as the modified importance ($\overline{g}'_m$) was used. When the sum of the importance factors was 0.5, the COV was 0.064, showing the highest similarity with the modified importance ($\overline{g}'_m$). However, if the sum of the importance factors was normalized to 0.3, the COV increased to 0.068 with modified importance ($\overline{g}'_m$). Therefore, in this study, the sum of the importance factors ($\sum g_m$) was normalized to 0.5, which had the closest similarity to the KALIS evaluation results, and was applied to the RSL evaluation model.

3.4 Evaluation of RSL of Buildings

The RSL evaluation model proposed in this study was used to evaluate the RSLs of the block by combining the RSL evaluation results of the members, estimating the RSL of the floor by combining the evaluation results of the remaining service life of the blocks, and deriving the RSL of the RC structures by combining the RSL of the floors. The RSL of the block was calculated based on the importance and RSL of members included in the block, and the RSL of members was calculated using ANFIS. To consider the failure probability of a member along with the impact of the member's durability deterioration, the RSL of the member was also reflected in the calculation of the importance of the member, and the modified importance ($\overline{g}^*_m$) reflecting the failure probability of the member and the impact of the remaining service life was calculated as follows:

$$\overline{g}^*_m = \overline{g}_m \times (1 + \alpha_1 + \alpha_2) \tag{23}$$

where $\overline{g}_m$ is the normalized importance of the member so that the sum of the member importances given in KALIS becomes 0.5. The normalized importance of the column, girder, beam, and slab are 0.188, 0.146, 0.104, and 0.062, respectively. Moreover, α_1 is the importance modification coefficient of a member that can be calculated using Eq. (18). In Eq. (23), α_2 is calculated as follows:

Table 4 Evaluation grades based on the ratio of member's strength to applied load (KALIS 2011)

Grade	Evaluation score	Ranges of grades	Commentary
A	1	SR ≥ 100% (in perfect condition)	Structural integrity meets design objectives, with minimal issues observed both locally and overall, in an optimal condition
B	3	SR ≥ 100% (with slight damage)	The structural integrity meets design objectives, with minor damage observed, overall in a generally satisfactory condition
C	5	90% ≤ SR < 100%	The overall safety of the structure is generally ensured, despite a partial deficiency in structural integrity
D	7	75% ≤ SR < 90%	The overall structural integrity is insufficient, making it difficult to ensure the safety of the structure, and it is in a deteriorated condition
E	9	SR < 75%	The overall deficiency in structural integrity is significant, raising serious concerns about the potential collapse of the structure

Strength ratio (SR): the ratio of member's strength to applied load

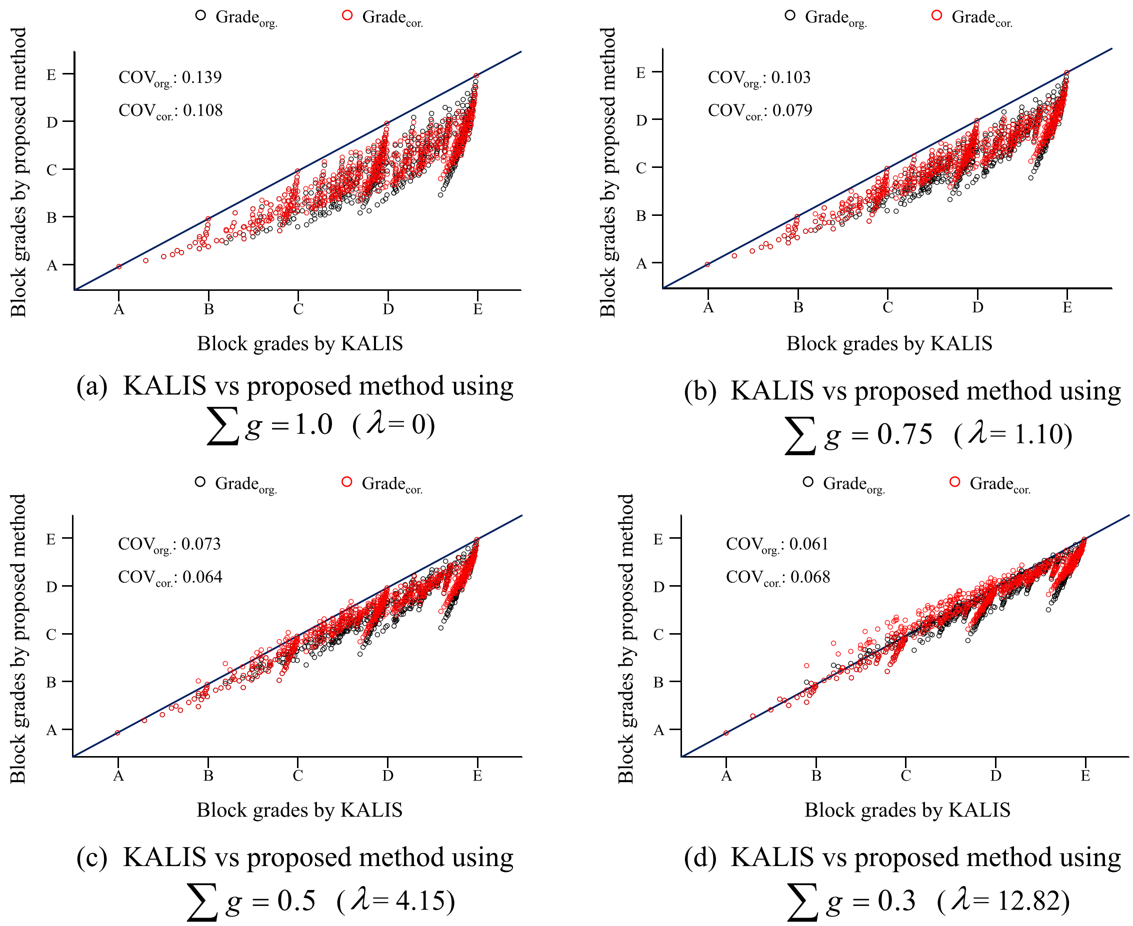

Fig. 7 Block grades according to the sum of important factors (failure probability considered). **a** KALIS vs. proposed method using $\sum g = 1.0$ (λ = 0), **b** KALIS vs. proposed method using $\sum g = 0.75$ (λ = 1.10), **c** KALIS vs. proposed method using $\sum g = 0.5$ (λ = 4.15), **d** KALIS vs. proposed method using $\sum g = 0.3$ (λ = 12.82)

$$\alpha_2 = 1 - \frac{RSL_m}{(SL_t - EL)} \tag{24}$$

where RSL_m is the RSL of the member, SL_t is the target service life, and EL is the elapsed time. The RSL of the member and the modified importance can be expressed in the measurement space in the same manner as that shown in Fig. 4, and the RSL of the block can be calculated by obtaining the sum of the total area using the fuzzy integral. The RSL of the floor was calculated using the RSL of the blocks included on the floor and the importance of the blocks. The modified importance ($\overline{g}_b^*$) of a block is calculated as follows:

$$\overline{g}_b^* = \frac{A_c}{2} \times \left(1 + \alpha_{1,b\,\max} + \alpha_3\right) \tag{25}$$

where A_c is the area ratio of the block to the total area of the corresponding floor and $\alpha_{1,b\,\max}$ is the maximum value of the importance modification coefficient (α_1) of the members located in the corresponding block.

In Eq. (25), α_3 is calculated as follows:

$$\alpha_3 = 1 - \frac{RSL_b}{(SL_t - EL)} \tag{26}$$

where RSL_b is the RSL of the block, SL_t is the target service life, and EL is the elapsed time.

The RSL of the floor was calculated using the Sugeno and Choquet integral in Fig. 4 in the same manner as that for the RSL of the block. The RSL of the block is substituted into $f(x)$ and its importance into $g(x)$ when evaluating the remaining service life of the floor. The sum of the total area is the estimated RSL of the floor. Similarly, the RSL and importance of the floor are substituted into $f(x)$ and $g(x)$, respectively, to evaluate the RSL of the entire structure. The sum of the total area is the estimated RSL of the entire structure. The modified importance of the floor ($\overline{g}_f^*$) is calculated as follows:

$$\overline{g}_f^* = \overline{g}_f \times \left(1 + \alpha_{1,f\,\max} + \alpha_4\right) \tag{27}$$

where $\overline{g}_f$ is the floor importance normalized such that the sum of the importance factors is 0.5, $\alpha_{1,f\,\max}$ is the maximum value of the importance modification coefficient of the members located on the floor, and α_4 is the ratio of the remaining service life of the floor (RSL_f) to the expected service life of the structure. Accordingly, the importance of the normalized floor $\overline{g}_f$ is represented as follows:

$$\overline{g}_f = \frac{\frac{[N-(n-1)]/N}{\sum [N-(n-1)]/N}}{2} \tag{28}$$

where N is the total number of floors, including the basement, and n is the number of corresponding floors, including the basement. Additionally, α_4 can be calculated as follows:

$$\alpha_4 = 1 - \frac{RSL_f}{(SL_t - EL)} \tag{29}$$

Table 5 Safety score and remaining service life for RC structures

Building name	Safety score (grade) by KALIS	Elapsed time	Remaining service life
B1	3.68 (B)	35.0	29.1
B2	4.85 (C)	35.0	26.7
B3	4.68 (C)	35.0	22.3
B4	5.67 (C)	32.0	29.6
B5	2.92 (B)	33.0	28.7
B6	5.03 (C)	35.0	28.3
B7	7.70 (D)	33.0	21.6
B8	4.88 (C)	34.0	17.0
B9	4.65 (C)	40.0	17.3
B10	5.74 (C)	32.0	30.4
B11	4.55 (C)	40.0	23.5
B12	5.19 (C)	33.0	15.3
B13	6.50 (D)	33.0	14.3
B14	6.58 (D)	35.0	22.3
B15	6.42 (D)	34.0	7.7
B16	6.18 (D)	35.0	19.9
B17	5.17 (C)	33.0	25.5
B18	5.58 (C)	29.0	26.6
B19	5.82 (C)	30.0	22.7
B20	5.77 (C)	39.0	10.1
B21	5.31 (C)	13.0	40.3

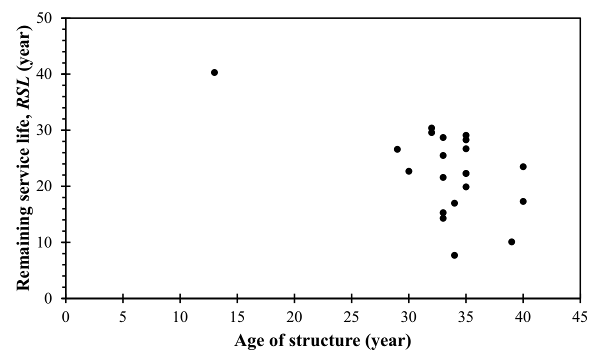

Fig. 8 RSL Evaluation results of RC structures

4 Evaluation Results and Verification

This study evaluated the RSLs of 21 RC structures using the proposed RSL evaluation model shown in Table 5 and Fig. 8. The elapsed time of most RC structures was approximately 30–40 years, as shown in Table 1. The RSL in the member, block, floor, and structural stages of each RC structure was sequentially evaluated according to the evaluation procedures of the proposed model. The number of blocks was 5–10 per floor, depending on the plan configuration of the RC structure. The evaluation results indicated that the B15 structure, with an elapsed time of 34 years, had significantly higher values of both carbonation depth and chloride ion concentration compared to other structures with similar elapsed times, as shown in Table 1. As a result, the RSL of the B15 structure was estimated to be only 7.7 years, which is considerably lower than those of other comparable structures. It was difficult to verify the proposed RSL evaluation model experimentally. Therefore, in this study, the proposed evaluation model was indirectly verified by comparing the results of the KALIS evaluation method (KALIS, 2011) with those of the proposed evaluation model, as listed in Table 5. The target service life of the structures evaluated in this study was 65 years, which corresponds to the service life of 'structures requiring high durability' according to the durability classifications in the Standard Concrete Specification (KCSC, 2004). Among the structures listed in Table 5, most structures evaluated as grade C according to the KALIS guidelines (KALIS, 2011) were estimated to have an RSL of more than 20 years by the RSL evaluation method. According to the KALIS guidelines, C grade is defined as a state in which minor defects occur in major members but do not harm the structural safety, which implies that they are likely to be sufficiently used during the target service life. Based on this, the proposed evaluation method is considered to show reasonable results that are consistent with the evaluation grade of the KALIS guidelines. The RSL of the B15 structure evaluated as D grade according to the KALIS guidelines was estimated to be 7.7 years by the RSL evaluation method. According to the KALIS guidelines, D grade is defined as a state in which the overall structural integrity is insufficient, making it difficult to ensure the safety of the structure. This is reflected well in the RSL evaluation method, exhibiting significant drops in the RSL of the B15 structure to 7.7 years. The B20 structure was assigned grade C, and not grade D, in the evaluation based on the KALIS guidelines, although the remaining service life was estimated to be low (10.1 years). As shown in the table, the evaluation score of the B20 structure based on the KALIS guidelines was 5.77, which is close to the score range (6–8) of grade D. Therefore, in this case, grade C was assigned to the B20 structure, ensuring a certain degree of similarity between the evaluation results. The B2, B4, B6, B10, and B21 structures were found to have RSLs of 26.7 to 40.3 years, but the evaluation grade of each structure was estimated to be as low as grade C in the KALIS evaluation method (KALIS, 2011). This is because the evaluation result on the floor is excessively conservative in the KALIS evaluation method, where the member with the most severe defects owing to deterioration among the members comprising each floor is reflected as a representative member of the floor (Cho et al., 2023). However, in the service life evaluation model proposed in this study, the member evaluation results are reflected sequentially according to the evaluation process of the block, floor, and structural stages, in which the importance of each member is increased according to the failure probability of each member so that the impact of defects that occur in all members can be properly reflected in the structural evaluation.

5 Conclusion

This study proposes a model for evaluating the RSL of RC structures that reflects combined deterioration. Based on the results of a field investigation conducted on 21 structures, ANFIS was implemented for each member, and the RSL of each structure was evaluated. In addition, structural reliability theory was introduced to calculate the importance of each member, block, and floor based on the structural analysis results, and the RSL of the RC structure was evaluated using the calculated importance factor. The following conclusions were drawn from this study:

(1) This study developed a service life evaluation model for RC structures based on the measured safety diagnosis data that reflects the effects of various factors affecting durability, such as the water-binder ratio, concrete compressive strength, crack width, chloride ion concentration, chloride ion diffusion coefficient, and concrete surface condition.
(2) In addition, the developed RSL evaluation model applied with structural reliability theory is capable of deriving evaluation results that consider not only the durability of members but also the impact of structural performance degradation. The calculated importance coefficient and RSL of each member enable evaluating the RSL of the blocks, floors, and structures in serial order.
(3) The evaluation results of the developed RSL evaluation model were compared with those of the KALIS evaluation method, and the comparison confirmed that similar evaluation results were derived for most RC structures.
(4) The proposed model presents the RSL of RC structures in a quantitative manner, while KALIS can provide the evaluation results as grades with respect to the level of safety and durability of RC structures.
(5) The developed model enables quantitative estimation of the RSL of RC structures, enhancing its applicability in structural health monitoring and the scheduling of repair and reinforcement. Additionally, as a pivotal technology in this research domain, the model is expected to foster significant advancements across a broad spectrum of research and practical applications.

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Availability of data and materials
The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

Declarations

Competing interests
The authors declare that they have no competing interests.

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