Journal of Marine Science and Technology

Volume 24 | Issue 5 Article 13

A RISK ASSESSMENT MODEL FOR BUILDINGS OF REINFORCED CONCRETE CONTAINING HIGH CONCENTRATIONS OF CHLORIDE IONS

Tsai-Lung Weng
Physics Division, Tatung University, Taipei, Taiwan, R.O.C. Institute of Engineering Management, College of Engineering, Tatung University, Taipei, Taiwan, R.O.C., wengabc@ttu.edu.tw

Journal of Marine Science and Technology, Vol. 24, No. 5 pp. 1016-1025 (2016)
DOI: 10.6119/JMST-016-0913-2

A RISK ASSESSMENT MODEL FOR BUILDINGS OF REINFORCED CONCRETE CONTAINING HIGH CONCENTRATIONS OF CHLORIDE IONS

Tsai-Lung Weng[1, 2]

Key words: chloride ion content, grey statistical clustering, multi-phase fuzzy, risk assessment.

ABSTRACT

Risk assessment is crucial to the safety and durability of buildings constructed using concrete with high concentrations of chloride ions. This study adopted grey statistical clustering and multi-phase fuzzy statistics in the development of a risk assessment model for existing reinforced concrete buildings. In the proposed model, evaluative indicators are divided into two categories: strength category included compressive strength and corrosion category included carbonation depth, chloride ion content, and steel corrosion current. Overall, the risk to the building can be divided into three levels (low, medium, and high) based on critical values in risk evaluation strategies, parameter weights, and grey statistical clustering coefficients. A case study is presented to demonstrate the applicability and effectiveness of the proposed model.

I. INTRODUCTION

Despite considerable advances in construction techniques, the upkeep of existing buildings via repair, maintenance, alteration and addition (RMAA) remains an important topic of research. The influence of chloride ions is particularly important in evaluating the safety and durability of reinforced concrete (RC). This study defined indicators for the evaluation of RC with high concentrations of chloride ions in order to characterize symptoms of decay. Grey statistical clustering and multi-phase fuzzy statistics were then used to develop a risk assessment model, in which three levels of risk (low, medium, and high) were defined. The fuzzy membership function of each indicator with respect to every level (level membership functions) represents the core of grey statistical clustering. This study combined multi-phase fuzzy statistics with the results of a questionnaire distributed to experts to calculate the critical values and weights in risk evaluation strategies of the level membership functions. We then applied the proposed model to a case study to demonstrate its applicability and effectiveness.

Paper submitted 06/30/16; revised 07/26/16; accepted 09/13/16. Author for correspondence: Tsai-Lung Weng (e-mail: wengabc@ttu.edu.tw).
[1] *Physics Division, Tatung University, Taipei, Taiwan, R.O.C.*
[2] *Institute of Engineering Management, College of Engineering, Tatung University, Taipei, Taiwan, R.O.C.*

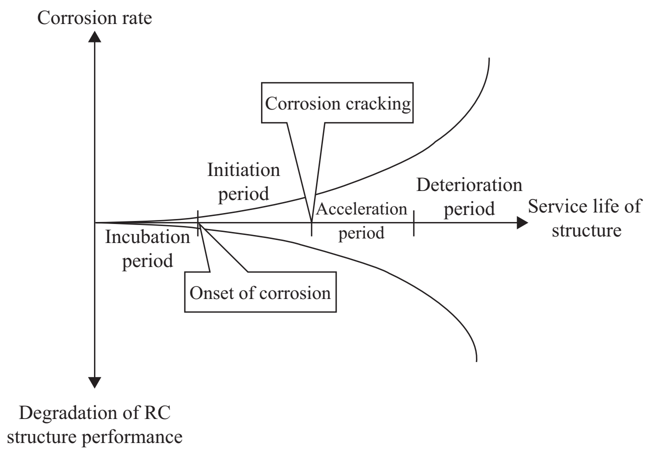


Fig. 1. Relationship between rate of rebar corrosion and service life of structure (Ohtsu, 2003).

II. LITERATURE REVIEW

In this chapter, we outline grey statistical clustering and multi-phase fuzzy statistics.

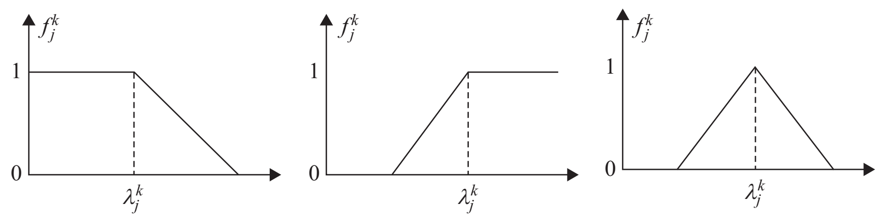
1. RC Durability

Concrete is a durable construction material which lasts for a long time as long as it is carefully proportioned and placed. However, incipient damage can occur when concrete is exposed to a severe environment without adequate protection. The causes of concrete degradation can be divided into chemical and physical attacks (Dhir et al., 1993; Young et al., 1998; Mamlouk et al., 1999; Secco et al., 2015; Wu et al., 2016), as shown in Table 1. Rebar corrosion is the major cause of premature degradation and the subsequent failure of reinforced concrete structures. Rebar corrosion can be induced by carbonation and/or chloride ingress, resulting in cracking due to chemical attack or physical degradation. Fig. 1 illustrates the relationship between deterioration and the service life of re-

Table 1. Causes and symptoms of concrete degradation.

Type	Description	Causes	Symptoms
Chemical	Alkali-aggregate	reaction of siliceous aggregates by alkali ions	coarse “map-cracking” with eruption of viscous fluids
	Sulfate attack	reaction of paste components with sulfates	general cracking and softening
	Acid attack	dissolution by acids	general etching of surfaces
	Rebar corrosion	rusting of steel	cracks with rust stains above location of reinforcement
Physical	Frost attack	freezing of water in pores	general scaling and spalling at surface
	D-cracking	freezing of water in pores	fine crack pattern roughly parallel to joint in pavements
	Fire damage	decomposition of hydration products	cracking and spalling
	Thermal cracking shrinkage	internal stress from restrained contractions	local cracking

*summarized from studies by Dhir et al., 1993; Young et al., 1998; Mamlouk et al., 1999; Secco et al., 2015; Wu et al., 2016



(a) Lower limit (b) Upper limit (c) Middle

Fig. 2. Level membership functions used in grey statistical clustering.

inforced concrete structures (Ohtsu, 2003).

Concrete degradation due to rebar corrosion can be divided into four periods: incubation, initiation, acceleration and deterioration. The incubation time is governed by the penetration and concentration of chloride ions, the onset of corrosion, and the thickness of concrete covering the rebar. When the concentration of chloride ions at the surface of the rebar exceeds a critical value, the passive film is destroyed. When oxygen and water are supplied by the environment, rebar corrosion is initiated. The reaction of iron and oxygen leads to the formation of iron oxide (rust), which increases the volume of area taken up by the rebar. This expansion process undermines the tensile strength on the surrounding concrete, resulting in cracking, spalling, or fracturing. One survey of collapsed buildings reported that the failure of most reinforced concrete structures can be attributed to the corrosion of rebar. Rebar corrosion shortens the service life of concrete structures and necessitates costly repairs (Kramar et al., 2016; Mangat et al., 2016; Zhou et al., 2016). The influence of chloride ions is particularly important when evaluating the safety and durability of existing RC structures.

2. Grey Statistical Clustering

Grey statistical clustering for risk assessment is an integration of grey system theory with fuzzy theory. This approach results in reliable decisions, even when limited by the availability of data. It also maintains compatibility with fuzzy linguistic scales, which can help to overcome many of the disputes involved in real-world applications (Lin et al., 2008). The algorithm used in the grey statistical clustering method is outlined in the following (Wen, 2008; Lin et al., 2009; Hsu, 2011). Assume that a decision problem comprises *n* objects, m evaluation indicators, and *s* levels. Grey statistical clustering is used to identify the level to which the i^{th} object belongs, according to calculations based on the *m* evaluation indicators.

The core of grey statistical clustering is the level membership function, denoted as f_i^k(i). Level membership functions can be divided into three types: upper, medium, and lower, as shown in Fig. 2.

In Fig. 2, λ_i^k indicates the critical value of the j^{th} indicator on the k^{th} level. After the level membership function and the critical value are defined, the weight of the j^{th} indicator on the kth level (η_i^k) can be calculated using Eq. (1).

$$\eta_j^k = \frac{\lambda_j^k}{\sum_{j=1}^{m} \lambda_j^k} \tag{1}$$

Thus, the grey statistical clustering coefficient σ_j^k can be defined as follows:

$$\sigma_i^k = \sum_{j=1}^{m} f_j^k(x_{ij}) \cdot \eta_j^k \tag{2}$$

Table 2. Level membership functions for compressive strength of concrete.

Level	Level membership function	R^2	
Low risk	$\begin{cases} 0.95 \le x,\ f(x)=1 \\ 0.61 \le x \le 0.95,\ f(x)=3x-1.82 \\ others,\ f(x)=0 \end{cases}$	Left Right	0.96 --
Medium risk	$\begin{cases} 0.75 \le x \le 0.92,\ f(x)=-6x+5.5 \\ 0.55 \le x \le 0.75,\ f(x)=1 \\ 0.38 \le x \le 0.55,\ f(x)=6x-2.3 \\ others,\ f(x)=0 \end{cases}$	Left Right	1 1
High risk	$\begin{cases} 0.45 \le x \le 0.59,\ f(x)=-7x+4.15 \\ x \le 0.45,\ f(x)=1 \\ others,\ f(x)=0 \end{cases}$	Left Right	-- 1

where x_{ij} refers to the measurement of the i^{th} object on the j^{th} indicator. Coefficient vector σ_i comprises s grey statistical clustering coefficients and indicates the level to which the i^{th} object belongs:

$$\sigma_i = (\sigma_i^1, \sigma_i^2, \ldots, \sigma_i^s) = \left[\sum_{j=1}^{m} f_j^1\left(x_{ij}\right)\cdot\eta_j^1, \sum_{j=1}^{m} f_j^2\left(x_{ij}\right)\cdot\eta_j^2, \ldots, \sum_{j=1}^{m} f_j^s\left(x_{ij}\right)\cdot\eta_j^s\right] \quad (3)$$

The level to which the i^{th} object belongs can be identified according to the maximum value of the grey statistical clustering vector:

$$\sigma_i^{k*} = \max_{1\le k\le s}\left\{\sigma_i^k\right\} \quad (4)$$

3. Multi-Phase Fuzzy Statistics

The level membership function is defined by the researcher based on the results of previous studies or experience; however, this process can be daunting. To overcome these difficulties, we employed multi-phase fuzzy statistics (Chen, 2009; Choi et al., 2009) in the integration of the knowledge of experts (obtained from questionnaires) in the definition of the level membership functions.

We first sought to establish the frequency distribution in order to identify the membership degree with the highest frequency, as follows: $u_A(x) = 1$. We then calculated the relative frequency ratios by dividing the highest frequency into a frequency at each point and drawing a draft level membership function curve to connect them. We employed the least square method for curve fitting to avoid the difficulties involved in using an irregular membership function curve. Explanation capability (R^2) was used to identify a curve suitable for curve fitting. Higher order curves are sometimes required; however, a linear function is sufficient to explain most situations.

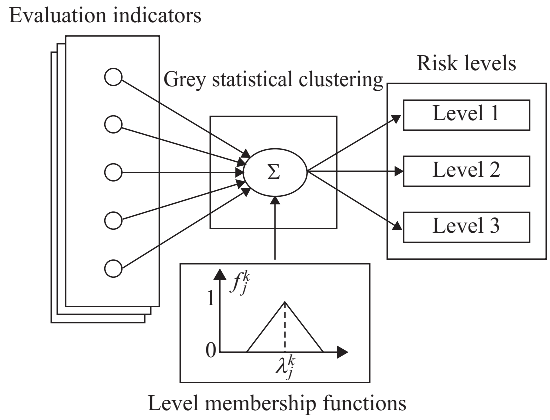


Fig. 3. Structure of proposed risk assessment model.

III. RISK ASSESSMENT MODEL FOR CONCRETE WITH HIGH CONCENTRATIONS OF CHLORIDE IONS

The structure of the proposed risk assessment model is outlined in Fig. 3. Evaluative indicators were used to measure symptoms of decay in the floors of the selected building. Level membership functions derived from experts were then used to implement grey statistical clustering in order to determine the level of risk associated with each floor.

1. Risk Evaluation Indicators in RC Buildings with High Concentrations of Chloride Ions

This study divided into two categories the indicators used to evaluate the risk of RC buildings: compressive strength and corrosion, including carbonation depth, chloride ion content, and steel corrosion current (Angst et al., 2009; Carvajal et al., 2012; Shi et al., 2012). These are both important indicators of the durability of RC buildings, particularly those with high concentrations of chloride ions.

2. Level Membership Functions

A questionnaire was used to define the level membership

Table 3. Level membership functions for carbonation depth in concrete.

Level	Level membership function	R^2	
Low risk	$\begin{cases} x \le 1.2,\ f(x)=1 \\ 1.2 \le x \le 1.45,\ f(x)=-4x+5.8 \\ others,\ f(x)=0 \end{cases}$	Left Right	-- 1
Medium risk	$\begin{cases} 0.82 \le x \le 1.4,\ f(x)=1.75x-1.43 \\ 1.4 \le x \le 1.6,\ f(x)=1 \\ 1.6 \le x \le 2.1,\ f(x)=-2x+4.2 \\ others,\ f(x)=0 \end{cases}$	Left Right	0.99 1
High risk	$\begin{cases} 1.71 \le x \le 2.0,\ f(x)=-3.5x-6 \\ 2.0 \le x,\ f(x)=1 \\ others,\ f(x)=0 \end{cases}$	Left Right	1 --

Table 4. Level membership functions for concentration of chloride ions in concrete.

Level	Level membership function	R^2	
Low risk	$\begin{cases} x \le 0.3,\ f(x)=1 \\ 0.3 \le x \le 0.425,\ f(x)=-8x+3.4 \\ others,\ f(x)=0 \end{cases}$	Left Right	-- 1
Medium risk	$\begin{cases} 0.167 \le x \le 0.5,\ f(x)=3x-0.5 \\ 0.5 \le x \le 0.78,\ f(x)=-3.5x+2.74 \\ others,\ f(x)=0 \end{cases}$	Left Right	1 0.99
High risk	$\begin{cases} 0.475 \le x \le 0.6,\ f(x)=8x-3.8 \\ 0.6 \le x,\ f(x)=1 \\ others,\ f(x)=0 \end{cases}$	Left Right	1 --

Table 5. Level membership functions for corrosion current of steel.

Level	Level membership function	R^2	
Low risk	$\begin{cases} x \le 0.5,\ f(x)=1 \\ 0.5 \le x \le 1.125,\ f(x)=-1.6x+1.8 \\ others,\ f(x)=0 \end{cases}$	Left Right	-- 1
Medium risk	$\begin{cases} 0.80 \le x \le 2.0,\ f(x)=0.9x-0.7167 \\ 2.0 \le x \le 4.0,\ f(x)=1 \\ 4.0 \le x \le 5.54,\ f(x)=-0.7x+3.8167 \\ others,\ f(x)=0 \end{cases}$	Left Right	0.9067 0.9932
High risk	$\begin{cases} 4.29 \le x \le 5.0,\ f(x)=1.4x-6 \\ 5.0 \le x,\ f(x)=1 \\ others,\ f(x)=0 \end{cases}$	Left Right	1 --

functions. For reliability, it is recommended that no fewer than ten experts be recruited from a variety of fields or fifteen to thirty experts from the same field (Dallkeyrt al., 1963; Delbecq et al., 1975). We invited ten experts to participate in this investigation, including professors, technicians, and engineers in the field of RC buildings. The average range of experience dealing with high concentrations of chloride ions exceeded fifteen years.

Based on multi-phase fuzzy statistics, we used the results of the questionnaire (Tables 1 to 4) to draw up draft membership

Table 6. Critical values and weights of indicators.

Indicators	Low risk		Medium risk		High risk	
	Critical	Weight	Critical	Weight	Critical	Weight
Compressive strength	0.95	1	0.65	1	0.45	1
Carbonation depth	1.2	0.48	1.5	0.31	2.0	0.30
Chloride ion content	0.3	0.41	0.5	0.35	0.6	0.30
Corrosion current	0.5	0.11	3.0	0.34	5.0	0.41

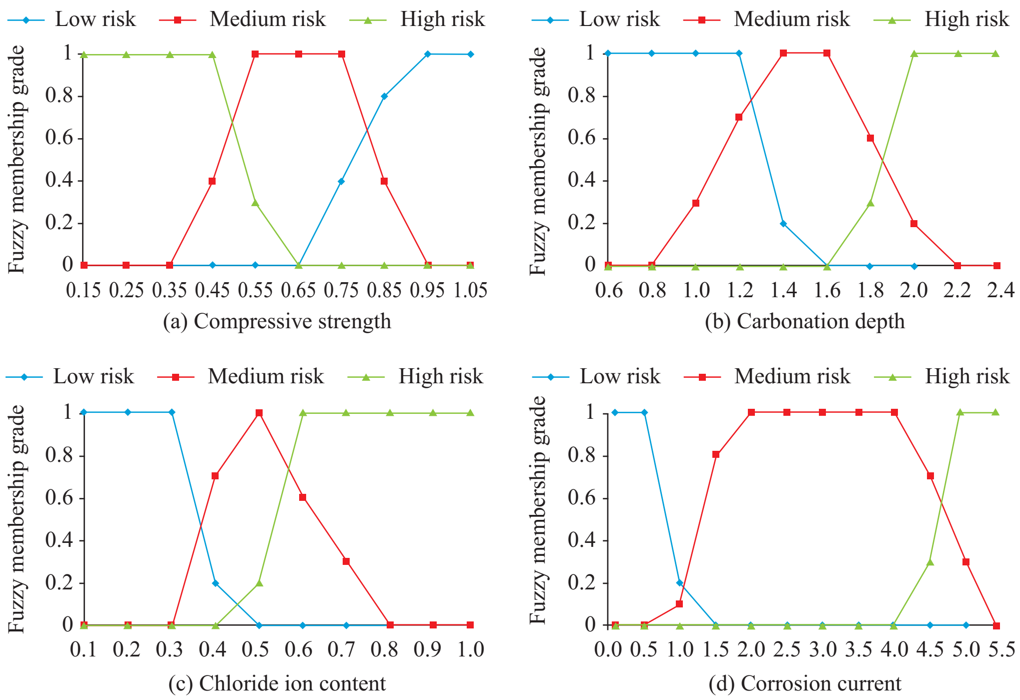


Fig. 4. Level membership functions of indicators.

functions of indicators, as shown in Fig. 4. We then used the linear least square method to fit the level membership functions, as shown in Tables 2 to 5. The R^2 of the level membership functions indicates that the explanatory power provided by the curve fitting is acceptable.

3. Risk Evaluation and Maintenance Strategies

The next step involved calculating the critical values and weights of the level membership functions, as shown in Table 6. The critical value can be defined as the mean of the two end points in the upper side of the trapezoid. For example, in the medium level membership function for the compressive strength of concrete, the critical value is defined as follows:

$$\lambda_{Compressive\ strength}^{Middle\ risk} = \frac{0.55 + 0.75}{2} = 0.65 \tag{5}$$

This includes only one indicator related to strength risk. Therefore, the weight of each level membership function is the same and calculated as follows:

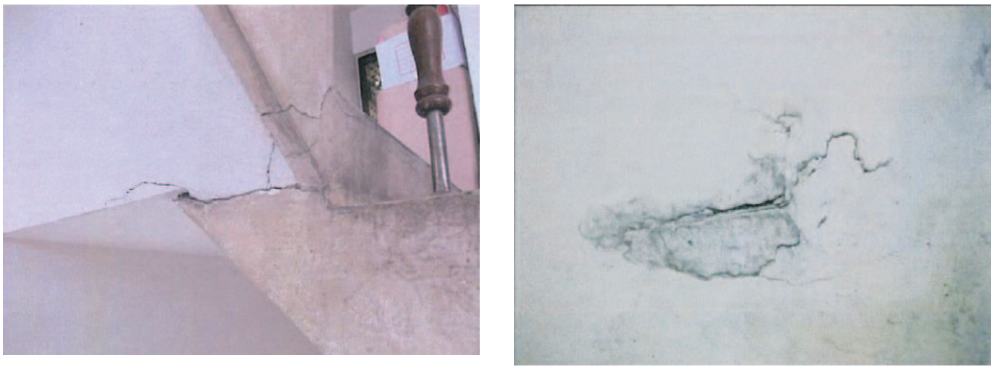
$$\eta_1^k = \frac{\lambda_1^k}{\sum_{j=1}^{1} \lambda_j^k = \lambda_1^k} = 1 \tag{6}$$

The weights of the level membership function for corrosion risk are calculated using Eq. (1), the results of which are presented in Table 6. However, grey statistical clustering does not allow for a comparison of indicators with critical values of different scales. Indicators with critical values of larger scales are allocated greater weights, which results in an unfair comparison. This study used preprocessing to overcome this problem.

Generally, preprocessing can be conducted using the initial value, the mean value, or the maximum or minimum value (Hsia et al., 2004; Pan et al., 2004). In the initial pre-processing stage, the first value is used as a base for dividing the critical value. However, this can lead to considerable error. The maximum value and minimum value preprocessing methods both introduce directionality, which may distort the relative relationship with the original critical values. Thus, we adopted mean

Table 7. Maintenance strategies.

	Low risk (Strength)	Medium risk (Strength)	High risk (Strength)
Low risk (Corrosion)	MS1: Paint concrete surfaces	MS2: Repair concrete spalling and cracks Apply antirust paint or epoxy to steel.	MS3: Repair cracks in concrete and apply carbon fiber mesh, steel beams, or steel plating. Apply antirust paint or epoxy to steel.
Medium risk (Corrosion)	MS4: Repair cracks in concrete. Apply antirust paint or epoxy to steel.	MS5: Repair cracks in concrete. Apply current cathodic protection.	MS6: Repair cracks in concrete and apply carbon fiber mesh, steel beams, or steel plating. Apply antirust paint or epoxy to steel. Apply current cathodic protection.
High risk (Corrosion)	MS7: Repair cracks in concrete. Apply current cathodic protection.	MS8: Repair cracks in concrete. Apply current cathodic protection. Partially demolish and rebuild beams and plates.	MS9: Partially demolish and rebuild beams and plates.



(a) cracking (b) spalling

Fig. 5. Deterioration of reinforced concrete structure: twelve-story residential building.

value preprocessing in this study.

As shown in Table 6, the weights related to corrosion risk were calculated using critical values that underwent preprocessing. Under high corrosion risk, the weight of steel corrosion current (0.41) was the largest. Under medium corrosion risk, the weights of the three indicators (carbonation depth, chloride ion content, corrosion current) were similar. Under low corrosion risk, the weight of concrete carbonation depth (0.48) was the largest.

After obtaining values for the indicators (x_{ij}), we calculated the grey statistical clustering coefficient (σ_i^k) using Eq. (2). The level membership functions, ($f_j(i)$) are listed in Tables 2 to 5, and the weights (η_j) are listed in Table 5. This makes it possible to formulate maintenance strategies according to the assessment of risk pertaining to strength and corrosion. To determine a suitable maintenance strategy, we assembled a matrix based on the levels of risk, as shown in Table 7.

IV. ILLUSTRATIVE EXAMPLE

This study applied the proposed model to the case of a building in Taiwan to demonstrate its applicability and effectiveness. The case study was an RC building with twelve floors and one basement level. The building showed symptoms of high concentrations of chloride ions, including concrete spalling, efflorescence, and steel corrosion. The average risk indicator values from six samples are presented in Table 8. The reinforced concrete structure was designed to function as a twelve-story residential building for 25 years. The initial compressive strength exceeded 210 kg/cm^2; however, cracks and spalling appeared in several locations, as illustrated in Fig. 5.

Table 8. Measurements of evaluative indicators.

Floor	Compressive strength (kgf/cm^2)	Carbonation depth (cm)	Chloride ion content (kg/m^3)	Corrosion current ($\mu A/cm^2$)
B1F	136.0	3.50	1.202	5.00
1F	139.7	0.76	1.647	0.25
2F	166.0	3.70	1.188	5.00
3F	166.0	2.93	1.499	0.50
4F	192.0	3.63	1.488	0.25
5F	93.7	1.83	1.242	5.00
6F	190.0	3.73	1.264	5.00
7F	183.7	1.63	1.430	4.50
8F	195.7	0.80	0.573	3.50
9F	260.0	0.36	1.082	0.50
10F	205.7	2.23	0.525	0.25
11F	269.7	1.83	1.654	5.00
12F	205.3	2.13	1.850	1.00

Table 9. Strength risk: $f_j^k(x_{ij})$.

Floor	Low risk	Medium risk	High risk
B1F	0.12	1.00	0.00
1F	0.18	1.00	0.00
2F	0.55	0.76	0.00
3F	0.47	0.93	0.00
4F	0.92	0.01	0.00
5F	0.00	0.38	1.00
6F	0.89	0.07	0.00
7F	0.80	0.25	0.00
8F	0.98	0.00	0.00
9F	1.00	0.00	0.00
10F	1.00	0.00	0.00
11F	1.00	0.00	0.00
12F	1.00	0.00	0.00

Table 10. Strength risk: σ_i^k values.

Floor	Low risk	Medium risk	High risk
B1F	0.12	1.00	0.00
1F	0.18	1.00	0.00
2F	0.55	0.76	0.00
3F	0.47	0.93	0.00
4F	0.92	0.01	0.00
5F	0.00	0.38	1.00
6F	0.89	0.07	0.00
7F	0.80	0.25	0.00
8F	0.98	0.00	0.00
9F	1.00	0.00	0.00
10F	1.00	0.00	0.00
11F	1.00	0.00	0.00
12F	1.00	0.00	0.00

Table 11. Corrosion risk: $f_j^k(x_{ij})$ values.

Floor	Indicator	Low risk	Medium risk	High risk
	Carbonation depth	0.00	0.00	1.00
B1F	chloride ion content	0.00	0.00	1.00
	corrosion current	0.00	0.42	1.00
	Carbonation depth	1.00	0.00	0.00
1F	chloride ion content	0.00	0.00	1.00
	corrosion current	1.00	0.00	0.00
	Carbonation depth	0.00	0.00	1.00
2F	chloride ion content	0.00	0.00	1.00
	corrosion current	0.00	0.42	1.00
	Carbonation depth	0.00	0.00	1.00
3F	chloride ion content	0.00	0.00	1.00
	corrosion current	1.00	0.00	0.00
	Carbonation depth	0.00	0.00	1.00
4F	chloride ion content	0.00	0.00	1.00
	corrosion current	1.00	0.00	0.00
	Carbonation depth	0.00	0.54	0.41
5F	chloride ion content	0.00	0.00	1.00
	corrosion current	0.00	0.42	1.00
	Carbonation depth	0.00	0.00	1.00
6F	chloride ion content	0.00	0.00	1.00
	corrosion current	0.00	0.42	1.00
	Carbonation depth	0.00	0.94	0.00
7F	chloride ion content	0.00	0.00	1.00
	corrosion current	0.00	0.77	0.30
	Carbonation depth	1.00	0.00	0.00
8F	chloride ion content	0.00	0.72	0.78
	corrosion current	0.00	1.00	0.00
	Carbonation depth	1.00	0.00	0.00
9F	chloride ion content	0.00	0.00	1.00
	corrosion current	1.00	0.00	0.00
	Carbonation depth	0.00	0.00	1.00
10F	chloride ion content	0.00	0.89	0.40
	corrosion current	1.00	0.00	0.00
	Carbonation depth	0.00	0.54	0.41
11F	chloride ion content	0.00	0.00	1.00
	corrosion current	0.00	0.42	1.00
	Carbonation depth	0.00	0.00	1.00
12F	chloride ion content	0.00	0.00	1.00
	corrosion current	0.20	0.18	0.00

1. Strength Risk Assessment

In the assessment of strength risk, the values of $f_i^k(x_{ij})$ were calculated by substituting data (Table 8) into the level membership functions of strength risk to obtain the results shown in Table 9. Grey statistical clustering coefficients (σ_i^k) were then calculated using Eq. (2) and the previously determined weights. As shown in Table 10, the fifth floor was within the range of high risk, while the others were within the ranges of medium risk or low risk.

2. Corrosion Risk Assessment

In the assessment of corrosion risk, the values of $f_i^k(x_{ij})$ were calculated by substituting the measurements of concrete carbonation depth, concrete chloride ion content, and steel corrosion current into the level membership functions of corrosion risk, as shown in Table 11. Grey statistical clustering coefficients (σ_i^k) were then calculated using Eq. (2) and their

Table 12. Corrosion risk: σ_i^k values.

Floor	Low risk	Medium risk	High risk
B1F	0.00	0.14	1.00
1F	0.59	0.00	0.30
2F	0.00	0.14	1.00
3F	0.11	0.00	0.59
4F	0.11	0.00	0.59
5F	0.00	0.31	0.82
6F	0.00	0.14	1.00
7F	0.00	0.55	0.42
8F	0.48	0.59	0.23
9F	0.59	0.00	0.30
10F	0.11	0.31	0.41
11F	0.00	0.31	0.82
12F	0.02	0.06	0.59

pre-determined weights. As shown in Table 12, the first and ninth floors were at low risk, while the others were at medium or high risk.

Finally, we drew up a maintenance strategy based on these results. For example, the chloride ion content of the concrete on the ninth floor was not high enough to cause damage (low risk for strength as well as corrosion). The maintenance recommended for this case is painting of the surface.

V. CONCLUSIONS

Three conclusions can be drawn from the results of this study:

1. The risk assessment indicators for buildings with high concentrations of chloride ions can be divided into: those associated with compressive strength and those associated with corrosion, including carbonation depth, chloride ion content, and steel corrosion current. Overall, risk can be divided into three levels: low, medium, and high.
2. We employed multi-phase fuzzy statistics and the results of a questionnaire distributed to experts to define effective level membership functions. The least squares method and explanatory power were used to direct curve fitting. Grey statistical clustering was used to develop a risk assessment model for RC buildings. The level membership functions, critical values, and weights were used to determine the risk level of the building through evaluative indicators. We also presented a maintenance strategy matrix based on the assessment of risk pertaining to the compressive strength of the concrete and observed corrosion.
3. A case study was used to demonstrate the applicability of the proposed model in assessing risk and identifying an appropriate maintenance strategy for the evaluation of existing RC structures with high concentrations of chloride ions. The proposed model could easily be extended to other cases in civil engineering with similar problems, such as existing RC bridges, RC dams, or RC pump houses.

REFERENCE

Angst, U., B. Elsener, C. K. Larsen and O. Vennesland (2009). Critical chloride content in reinforced concrete - A review. Cement and Concrete Research 39, 1122-1138.

Carvajal, A. M., R. Vera, F. Corvo and A. Castaneda (2012). Diagnosis and rehabilitation of real reinforced concrete structures in coastal areas. Corrosion Engineering, Science and Technology 47, 70-77.

Chen, L. H. (2009). Fuzzy Regression Models Using the Least-Squares Method Based on the Concept of Distance. Fuzzy Systems 17, 1259-1272.

Choi, B. I. and C. H. Rhee (2009). Interval type-2 fuzzy membership function generation methods for pattern recognition. Information Sciences 179, 2102-2122.

Dallkey, N. and O. Helmer (1963). An experimental application of the Delphi method to use of experts. Management Science 9, 458-467.

Delbecq, A. L., A. H. Van de Ven and D. H. Gustafson (1975). Group techniques for program planning: A guide to nominal group and Delphi processes. Glenview, IL: Scott, Foresman, 40-66.

Dhir, R. K. and M. R. Jones (1993). Concrete repair, rehabilitation and protection, Chapman & Hall, London.

Hsia, K. H., M. Y. Chen and M. C. Chang (2004). Comments on Data Preprocessing for Grey Relational Analysis. Journal of System 7, 15-20.

Hsu, K. T. (2011). Using a back propagation network combined with grey clustering to forecast policyholder decision to purchase investment-inked insurance. Expert Systems with Applications 38, 6736-6747.

Kramar, S., A. Šajna and V. Ducman (2016). Assessment of alkali activated mortars based on different precursors with regard to their suitability for concrete repair. Construction and Building Materials 124, 937-944.

Lin, Y. H. and P. C. Lee (2008). Effective evaluation model under the condition of insufficient and uncertain information. Expert Systems with Applications 36, 5600-5604.

Lin, C. H., C. H. Wu and P. Z. Huang (2009). Grey clustering analysis for incipient fault diagnosis in oil-immersed transformers. Expert Systems with Applications 36, 1371-1379.

Mamlouk, M. S. and J. P. Zaniewski (1999). Materials for civil and construction engineers, Addison Wesley Longman, California.

Mangat, P. S., K. Grigoriadis and S. Abubakri (2016). Microwave curing parameters of in-situ concrete repairs. Construction and Building Materials 112, 856-866.

Ohtsu, M. (2003). Detection and identification of concrete cracking in reinforced concrete by AE. Review of Progress in Quantitative NDE, AIP conference, 1455-1462.

Pan, C. L., Y. F. Huang and G. Lin (2004). Evaluation and Comparison of Data Preprocessing Transformer for Grey Relational analysis. Journal of Grey

System 7, 65-74.

Secco, M., G. I. Lampronti, M. Schlegel, L. Maritan and F. Zorzi (2015). Degradation processes of reinforced concretes by combined sulfate-phosphate attack. Cement and Concrete Research 68, 49-63.

Shi, X., N. Xie, K. Fortune and J. Gong (2012). Durability of steel reinforced concrete in chloride environments: An overview. Construction and Building Materials 30, 125-138.

Wen, K. L. (2008). A Matlab toolbox for grey clustering and fuzzy comprehensive evaluation. Advances in Engineering Software 39, 137-145.

Wu, Y. Z., H. L. Lv, S. C. Zhou and Z. N. Fang (2016). Degradation model of bond performance between deteriorated concrete and corroded deformed steel bars. Construction and Building Materials 119, 89-95.

Young, J. F., S. Mindess, A. Bentur and R. J. Gray (1998). The science and technology of civil engineering materials, Prentice Hall, New Jersey.

Zhou, J., G. Ye and K. V. Breugel (2016). Cement hydration and microstructure in concrete repairs with cementitious repair materials. Construction and Building Materials 112, 765-772.