Journal of
Engineering Sciences
Faculty of Engineering
Assiut University

مجلة
العلوم الهندسية
كلية الهندسة
جامعة أسيوط

journal homepage: http://jesaun.journals.ekb.eg

Applying Fuzzy Decision-Making and Markov Chain Modelling for Detecting Life Cycle of RC Bridges

Received 31 May 2025; Revised 2 August 2025; Accepted 2 August 2025

Ahmed Mohammed Abdelalim *1
Yasmin Shalaby *2
Gamal A. Ebrahim 3
Mohamed Badawy4

Keywords

Reinforced concrete bridges; assessment; AI; Fuzzy logic; Markov Chain

Abstract: Bridge inspection become essential for ensuring structural safety and longevity. Recently, Artificial Intelligence (AI) has become significant in improving bridge assessment by supporting different approaches that enhance maintenance planning and minimize associated costs. Objective of this study is to investigate the more accurate and applicable AI-driven technique for assessing reinforced concrete bridges. Therefore, the presented study proposed two different techniques to estimate the current Bridge Condition Rating (BCR) of reinforced concrete (R.C.) bridges: 1) fuzzy decision-making and 2) Markov chain modelling. This paper focused on a corrosion attack as the main defect utilized to assess the bridge condition. The dual methods depend on visual inspection, applying field and laboratory tests, and reviewing the historical data of the inspected bridge to estimate its condition rating. The fuzzy decision model is used to find a correlation between corrosion degree and concrete surface condition to estimate the Bridge Condition Rating (BCR). The Markov chain model is applied to predict the current and the future Bridge Condition Rating (BCR) and when the bridge will reach the critical condition. The service life for each bridge element is evaluated due to the total time required for corrosion based on carbonation and chloride attack. The proposed models are validated through a real case study of R.C. bridge, and the results demonstrate that the fuzzy model is less accurate compared to the Markov chain. The introduced models provide valuable insights to provide proper Maintenance, Repair, and Replacement (MRR) decisions for the bridges.

1. Introduction

Civil infrastructure systems could be classified into roadways, bridges, buildings, and water and sewer networks. Meanwhile, statistics show that 98% of its domestic cargo depends on this road network and bridges, demonstrating their significant role in the country's economy and people’s daily activities [1]. Deterioration and degradation are the most popular issues

*1 Professor, Project Management and Sustainable Construction Program, PMSC Founder, Civil Engineering Department, Faculty of Engineering at Mataria, Helwan University, Cairo, Egypt. Dr.Ahmedabdelalim@m-eng.helwan.edu.eg
*2 PhD Candidate, Structural Engineering Department, Ain Shams University, Cairo, Egypt. eng.yasmeen.s@hotmail.com
3 Professor, Computer and Systems Engineering Department, Ain Shams University, Cairo, Egypt. gamal.ebrahim@eng.asu.edu.eg
4 Professor, Structural Engineering Department, Ain Shams University, Cairo, Egypt. Mohamed_badawy@eng.asu.edu.eg

https://doi.org/10.21608/jesaun.2025.390430.1534

for the bridges, which are essential components of infrastructure systems. In the United States, 22.7% of the bridges are either structurally deficient or functionally obsolete, according to the American Society of Civil Engineers (2017). In 2006, the cost of eliminating all existing bridge deficiencies was estimated at $850 billion [2,3]. The average age of 607,380 bridges in the US was 42 years old in 2013 [4]. Numerous factors affect RC bridges; deterioration leads to different defects, which reflect the main challenge in bridge inspection programs. Some of them belong to design, techniques used for construction, materials, aging, excessive loads, environmental exposure, and maintenance of the structure in service [5]. Bridge inspection and performance assessment are important in many countries.

It's worth mentioning that there are several categories of bridge inspection that reflect the intensity of the inspection [6,7]. Mainly, visual inspection is used to evaluate the service statuary of the bridges, which can be applied for condition assessment [8]. The diagnosis and evaluation of current conditions are the main tools for concrete structure management [9]. The authorities around the world have a desire to develop solutions to periodically inspect their bridges and to support maintenance activities. They used the bridge management system (BMS), which is a visual inspection-based decision support tool, to analyze engineering and economic factors and to assist the authorities in taking the decisions regarding maintenance, repair, and rehabilitation of bridge structures at a suitable time. In order to take the best decision, it is necessary to measure the deterioration of bridges using several Bridge Condition Rating (BCR) scales [10,11,12,13]. Generally, it is rare to find an effective, clear, and practical system to assess the bridge condition and predict its future deterioration to make a decision between three strategies: (a) maintenance, (b) repair, or (c) rehabilitation.

Over the past years, a lot of studies were competing to integrate a comprehensive study for structural safety assessment. Abdelalim [14] suggested an approach for rehabilitated reinforced concrete buildings based on a probabilistic deterioration model. The model took into account the effects of various maintenance options because of the annual maintenance cost. Abdelalim et al. [15] applied a Markov chain model to predict the future building condition throughout its life cycle. Ali Mohamed et al. [9] introduced a framework for building condition assessment based on building information modelling (BIM). The system was divided into two models: the condition assessment model and the deterioration predictive model. Nevertheless, the previous models have been designated for RC buildings without considering other types of structures. Alsharqawi et al. [16] developed a condition rating index utilizing visual inspection in conjunction with ground-penetrating radar (GPR) technology to assess subsurface defects. The quality function deployment (QFD) methodology was applied for evaluating bridge conditions, while the k-means clustering technique was employed to determine the thresholds among various ratings. Their assessment depended only on a single nondestructive assessment technique and one clustering algorithm, which decreased its accuracy. Rhee et al. [17] proposed a dielectric constant curve that can be applied to the assessment of asphalt condition-covered concrete bridge decks, considering the concrete's age. Ground penetrating radar (GPR) technology was used in the field survey to obtain a condition assessment. Rogulj et al. [18] applied fuzzy analysis to estimate the bridge condition. They depended only on visual inspection for bridge condition assessment. The bridge components are divided into three elements: superstructure, substructure, and equipment. Each element rating evaluated by experts was defuzzied according to defined fuzzy sets, membership functions, and linguistic values. Additionally, ratings for every element are assigned a fuzzy structural importance. Finally, the centroid method was applied for defuzzifying the component rating. Xia et al. [19] established an approach based on inspection reports to estimate the Bridge Condition Rating (BCR). Three levels were combined to analyze the bridge condition assessment: component, unit, and system levels. The subjective condition rating was divided into five categories: excellent, good, fair, serious, and failed. Information from inspection reports was read using an LSTM neural network to extract the necessary feature for estimating the Bridge Condition Rating (BCR). The main limitation is related to the requirement of a large amount of data for training the neural networks. Bertagnoli et al. [20] assessed the safety level of several damage scenarios for bridge decks using 3D global non-linear numerical analysis. The ultimate limit state due to the safety loss of the damage level was used to evaluate the safety level of the deck. The damage threshold was defined in terms of measurable static parameters. Shivam [21] assessed the bridge using an inventory of bridges that contains the number and measurement of each type of component. At the last stage, the condition of each component was assessed based on its percentage of distress in order to observe its severity.

Although there are different techniques employed for bridge condition assessment, it is still a challenge to determine the most effective method because there aren't enough studies that compare different approaches. Also, most of the literature studies applied their assessment methods on the bridge deck only and ignored the other parts of the bridge. On the other hand, deep learning algorithms are suffering from limited transparency and require high computational cost during training. Additionally, the previous studies are focusing on the visual inspection and inventory data to assess the current condition of the structure. They ignored that the inspectors may be required to carry out non-destructive and destructive tests, followed by laboratory tests to diagnose the structural condition to get an accurate Bridge Condition Rating (BCR).

Thus, the presented study has a desire to compare different techniques to assess the reinforced concrete bridges. Among the two methods compared in this paper, dual AI-based methods are selected in recognition of the significance of Artificial Intelligence (AI) in the evaluation of reinforced concrete bridges. The current research adopted fuzzy decision-making and Markov chain modelling to estimate the overall Bridge Condition Rating (BCR). Fuzzy theory is applied because of its ability to deal with uncertainty, flexibility, and generality in how problems are formulated and resolved. Also, it gives an opportunity to incorporate all input facts to make well-informed decisions. It is useful for membership measures and rule-based modelling. Furthermore, it doesn't require high computational cost resources for training compared with other AI techniques [22]. For simpler systems, fuzzy logic has proven to be very successful and flexible enough to be understood by humans. For more complicated systems, it has been demonstrated to be more demanding. Thus, fuzzy logic is widely used in complicated systems where it is difficult to identify the interdependencies between individual variables using other approaches [18]. On the other hand, the Markov chain is a stochastic process applied to capture parameter dependency and uncertainty variables such as load and resistance. It is distinguished by its wide range of applications and its practical applicability.

This model has been commonly used in the last decade for predicting the deterioration state of different infrastructure systems. It was applied based on the concept of predicting the deterioration of each element by accumulating its probability of transferring from one condition state to another at a given time. The model depends on the transition probability matrix [TPM] that is used to express the chance of changing from one condition state to another [23]. Once transition probabilities are established, the model is computationally efficient for deterioration prediction.

The established techniques depend not only on visual inspection by bridge inspectors but also on applying field and laboratory tests and reviewing the historical data of the inspected bridge to estimate the Bridge Condition Rating (BCR). The first technique relied on applying a fuzzy decision model to find a correlation between the corrosion degree and concrete surface condition to estimate the condition rating for each bridge element to find the overall bridge rating. The second technique adopted the Markov Chain model to predict the future condition for each bridge element and to determine when the inspected bridge will reach the critical condition. Also, it was taken into consideration to generate the transition probability matrix [TPM] of the Markov chain and customise it to specific conditions by optimization. Additionally, this paper estimates the bridge service life based on laboratory and field tests. The service life for the RC bridge is calculated due to carbonation attack and chloride-induced corrosion of the embedded steel bars. The proposed system aims to investigate the more applicable and accurate technique to diagnose the bridge condition state to take the proper decision.

1.2 Novelty and Contribution of the Presented Research

This study does not merely apply existing models but presents a comparison between fuzzy decision-making and Markov chain modeling in the context of reinforced concrete bridge condition assessment. Key contributions include:

- Development of dual decision-support system tools includes real-time diagnosis (fuzzy logic) with future deterioration forecasting (MCM).
- Application to real-world case data, including field inspection, laboratory tests, and historical records.
- The calculation of the service life for the RC bridge due to carbonation based on the carbonation depth equation and chloride induced by applying the Life-365 software.
- Optimization of [TPM] values through nonlinear programming based on actual inspection trends, providing a dynamic and accurate prediction approach.
- Use of expert-informed weighting schemes to improve the relevance of condition scores across bridge components.
- This study offers adaptive tool for infrastructure management.

2. Methods and Tools

The introduced research is applied to compare the Bridge Condition Rating (BCR) for R.C. bridges due to fuzzy decision model and Markov chain modelling. The data from the condition assessment contributes to create deterioration model to predict the state of the whole bridge to decide the best strategy reaction. Corrosion of the embedded steel bars is considered in this paper as the main defect to estimate the Bridge Condition Rating (BCR) and its service life. The research procedure followed in this study is illustrated in Fig 1.

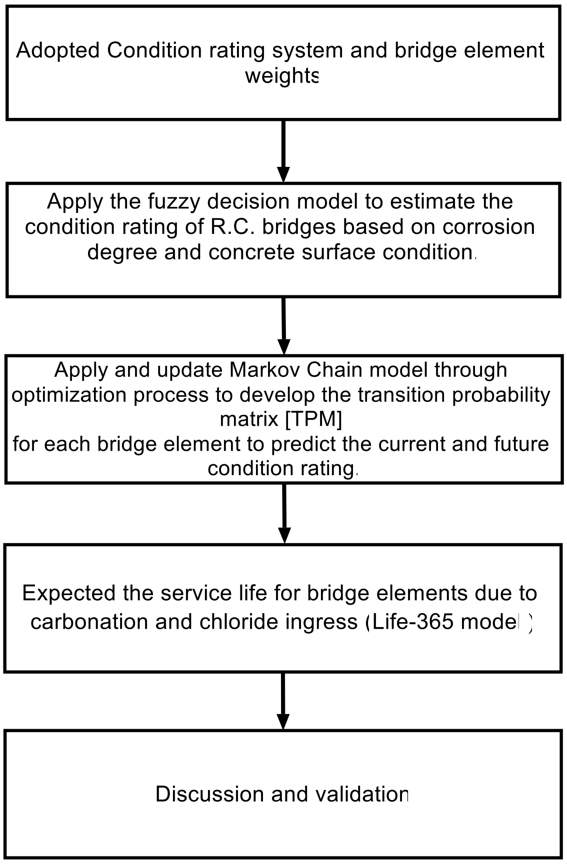


Fig. 1: Research procedure to apply dual techniques for detecting the life cycle of RC bridges

2.1. Adopted Condition Rating System and Bridge Element Weights

The National Bridge Inventory has the most common condition rating scale, which has been developed by the Federal Highway Administration (FHWA, 2012). It is used to evaluate three main components of bridges: deck, superstructure, and substructure. The scale ranged from 9, which presents excellent condition, to zero, which refers to failed condition, as shown in Table 1 [24]. The Federal Highway Administration classification system (FHWA, 2012) is adopted in this approach system to categorise the deterioration of reinforced concrete bridges.

Table 1: Scaling Deterioration as per FHWA, 2012 [24]

Rating	Description
10-N	Not applicable (Just Constructed)
9	Excellent Condition, new Condition, not worthy deficiency.
8	Very Good Condition, no repair is needed
7	Good Condition, Some minor Problems for Minor maintenance.
6	Satisfactory Condition, some minor deterioration for major maintenance.
5	Fair Condition, Minor Section Loss, Cracking or Scouring for minor Rehabilitation, Minor Rehabilitation is needed
4	Poor Condition, Advanced section loss, deterioration, Spalling or Scouring for major Rehabilitation, Major Rehabilitation is needed.

Rating	Description
3	Serious Condition, Section Loss, Deterioration, Spalling or Scouring have seriously affected primary Structural components, Immediate Rehabilitation is needed.
2	Critical Condition, advanced deterioration of Primary Structural elements, Urgent Rehabilitation, the Structure may be closed until Corrective Actions taken.
1	Imminent Failure Condition, Major Deterioration or Section loss, Structure may be closed until Corrective actions which may put it back into light service.
0	Failed Condition, Beyond Corrective action, Out-of Service

On the other hand, the NY ranking system assigned relative weights for thirteen bridge elements as listed in Table 2. The current study used the Weighted Evaluation Method (WEM ASTM1957) to justify the weight importance of bridge elements. Weighted evaluation is a useful tool that helps decision-makers make suitable decisions.

Table 2: Element weights in the NY rating system [24,25]

	Component	Weight
1	Primary members	10
2	Deck	8
3	Abutment	8
4	Piers	8
5	Bearings	6
6	Bridge Seats	6
7	Wing walls	5
8	Back Wall	5
9	Secondary members	5
10	Joints	4
11	Wearing Surface	4
12	Sidewalks	2
13	Curb	1

A question of which component element is more important than others based on the thirteen elements mentioned in the NY ranking system was discussed with experts with rich knowledge in the bridge industry in Egypt, Saudi Arabia, and the United Arab Emirates. The aim of the question is to be used in WEM to capture the opinion of experts regarding the important elements affecting the Bridge Condition Rating (BCR), especially for R.C. bridges, as shown in Table 3.

Table 3: Proposed element weights

	Component	Weight
1	Primary members	15
2	Deck	12
3	Abutment	12
4	Piers	12
5	Bearings	9
6	Bridge Seats	9
7	Wing walls	7

	Component	Weight
8	Back Wall	7
9	Secondary members	6.5
10	Joints	4.5
11	Wearing Surface	4.5
12	Sidewalks	1
13	Curb	0.5

The weight of each element is compensated in equation (1) to evaluate the overall Bridge Condition Rating (BCR) [24].

$$BCR = \frac{\sum(component\ rating \times Weight}{\sum Weights} \tag{1}$$

2.2 Predicting the Bridge Condition Rating (BCR) of Reinforced Concrete Bridges by Fuzzy Decision Model

In this technique, the corrosion is considered the common symptom of distress and bridge deterioration. The article adopted a fuzzy decision model to find a correlation between concrete surface condition and corrosion degree. Abdelalim, A. M. [26] defined four degrees of corrosion as shown in Table 4.

Table 4: **Degrees of corrosion and how they affect surface condition of concrete** [26]

Corrosion Degree	Steel Bars Condition
Condition-1	Mill scale remains on the surface of steel bars, rust forms on the surface of reinforcing bars, but it is "thin", and the bar is "solid" throughout; rust is not formed on the surface of concrete.
Condition-2	Small region covered by the "partly floating rust" and the rust is spotty too
Condition-3	"Floating rust" is seen across the entire circumstance or length of the reinforcement bars, although there is no observable loss of cross section area.
Condition-4	"Loss of cross-sectional area" is observed in reinforcing bars.

To create a correlation between corrosion degree and concrete surface condition, logic approach has been adopted with applying Mamdani's Inference system. Concrete surface condition can be categorized into four conditions as shown in Table 5.

Table 5: Degrees of corrosion /surface conditions

Corrosion Degree	Concrete Surface Condition	Subjective Assessment of Concrete Surface
Condition-1	Unchanged	6
Condition-2	Slight	5
Condition-3	Obvious	4
Condition-4	Deteriorated	3

Trapezoidal and triangular shapes of membership functions are the most common [27]. Some experts preferred the triangular membership and other preferred trapezoidal [28]. Thus, the current study applies both trapezoidal and triangular shapes to compare the results between them.

2.2.1 The Membership Functions

The numerical value for corrosion degree is determined by the rate of corrosion based on the pH value. The corrosion degree is the first linguistic variable and takes linguistic values (low, moderate, significant, and critical) based on equations (2), (3), and (4) to be shown in Table 6.

Let's X=pH, Y=f(x) where f(x) is the rate of corrosion (mm/year) [26]

$$f(x) = -0.5155 + (7.318/X) \qquad 9.6< pH \le 14 \qquad (2)$$

$$f(x) = 0.25 \qquad 3.6<pH\le 9.6 \qquad (3)$$

$$f(x) = 1.484 - (5.016/X) + (4.541/X^{2}) \qquad -\infty< pH \le 3.6 \qquad (4)$$

Table 6: The numerical value of the corrosion rate based on pH values

pH value	f(x): Corrosion rate (mm/year)	Corrosion degree
14	0.007214286	Low
13.6	0.022588235	
13.2	0.038893939	
12.8	0.05621875	
12.4	0.07466129	
12	0.094333333	
11.6	0.115362069	Moderate
11.2	0.137892857	
10.8	0.162092593	
10.4	0.188153846	
10	0.2163	
9.6	0.25	Significant
9.2	0.25	
8.8	0.25	
8.4	0.25	
8	0.25	
7.6	0.25	
7.2	0.25	
6.8	0.25	
6.4	0.25	
6	0.25	
5.6	0.25	
5.2	0.25	
4.8	0.25	
4.4	0.25	
4	0.25	
3.6	0.441052469	Critical
-∞		

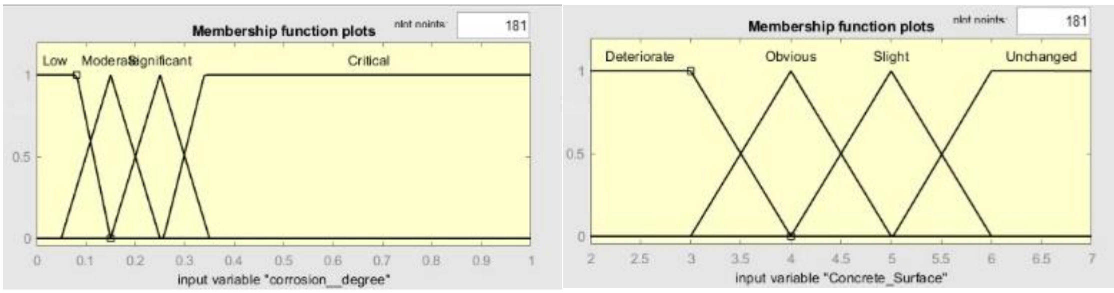
The second linguistic variable is the concrete surface condition, which takes linguistic values (unchanged, slight, obvious, and deteriorated) based on bridge experts' opinions and takes a value from 3 to 6 as shown in table 5. Both variables are applied to create a correlation between corrosion degree and concrete surface condition to get the semi-quantitative condition for the bridge element. On the other hand, the output linguistic variables are related to FWHA (2012) [24] from rate 3 to 6, as shown in Table 7.

Table 7: Semi quantitative condition rating score based on FHWA, 2012 [24]

6	Satisfactory Condition
5	Fair Condition
4	Poor Condition
3	Serious Condition.

- <u>First case:</u>

In the first case trapezoidal and triangular membership are applied for both inputs and output, as shown in the Fig.2 and Fig.3.



(a) (b)

Fig. 2: Fuzzy sets of the input variables (first case) by MATLAB (R2021a): (a) Corrosion degree, (b) Concrete surface condition

To determine the membership value correctly for a specific quantity in a linguistic term is a challenge and requires an experiment in order to define it properly. Furthermore, it is possible to subjectively determine the membership functions: the closer an element is to meeting a set's conditions, the closer its membership grade is to 1, and vice versa [29]. It's worth mentioning that the shapes of the corrosion degree values of the membership function are narrow compared with the concrete surface condition membership function. The explanation can be related to the fact that the range values of the corrosion degree are determined by applying the equations of the rate of corrosion based on the pH values. Whereas the concrete surface range values are uncertainties and determined based on expert judgements. Fig. 3 shows the range values of the membership function of the output variable in the semi-quantitative condition.

- <u>Second case:</u>

The triangular shape is only applied in the second case for both input and output membership variables, and the range values for both inputs and output are shown in Fig. 4.

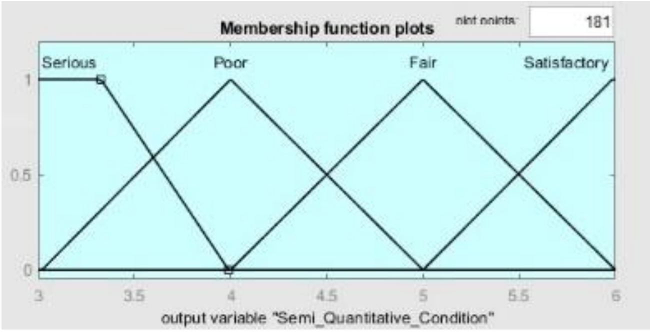
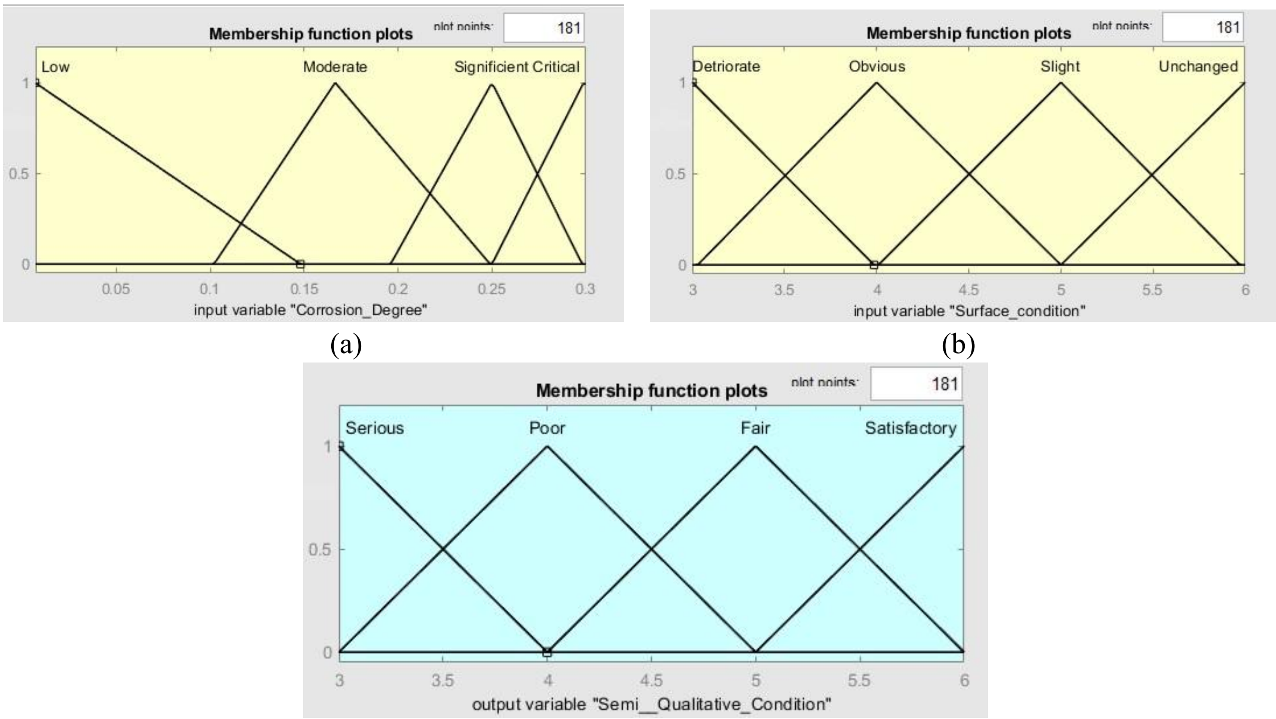


Fig. 3: Fuzzy sets of the output variables (first case) by MATLAB (R2021a)



(a) (b)

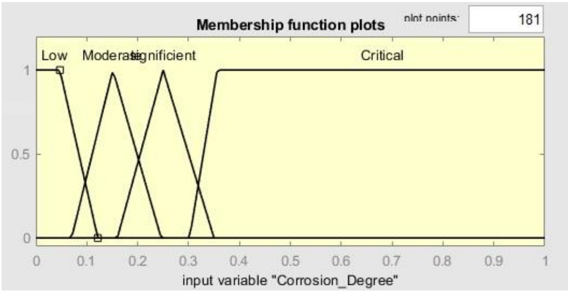
(c)

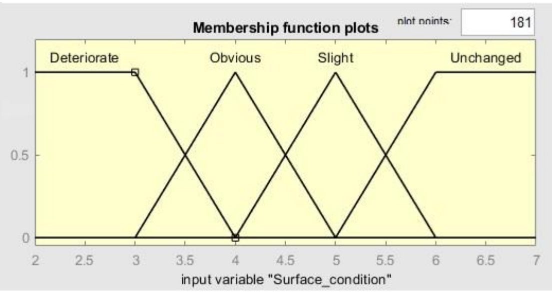
Fig. 4: Fuzzy set for both input and output variables (second case) by MATLAB (R2021a): (a) The first input variable is corrosion degree; (b) the second input variable is concrete surface condition; and (c) the output is semi-quantitative condition rating.

• Third case:
Triangular and trapezoidal shapes are applied for input membership, while the output is only a triangular shape. The value ranges are shown in Fig. 5.

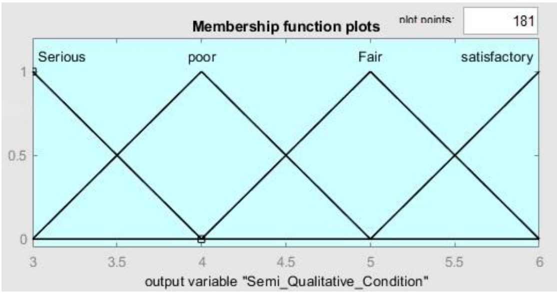
2.2.2 Applying Fuzzy Decision Rules

The semi-quantitative condition rating is determined by two fuzzy variables: corrosion degree and concrete surface condition. Because each of these variables has four membership functions, there could be a total of 4^2 (16) precondition combinations that influence the condition rating. These preconditions are formed by a set of fuzzy if-then rules, as shown in Table 8.





(a) (b)



(c)

Fig. 5: Fuzzy set for both input and output variables (third case) by MATLAB (R2021a): (a) The first input variable is corrosion degree; (b) the second input variable is concrete surface condition; and (c) the output semi-quantitative condition rating.

Table 8: Fuzzy decision rule

Rule no	Corrosion degree	Concrete surface condition	Semi-quantitative condition rating
1	Low (L)	Unchanged (UC)	Satisfactory (ST)
2	Low (L)	Slight (SL)	Fair (F)
3	Low (L)	Obvious (O)	Poor (P)
4	Low (L)	Deteriorate (D)	Serious (S)
5	Moderate (M)	Unchanged (UC)	Satisfactory (ST)
6	Moderate (M)	Slight (SL)	Fair (F)
7	Moderate (M)	Obvious (O)	Poor (P)
8	Moderate (M)	Deteriorate (D)	Serious (S)
9	Significant (SI)	Unchanged (UC)	Fair (F)
10	Significant (SI)	Slight (SL)	Poor (P)
11	Significant (SI)	Obvious (O)	Poor (P)
12	Significant (SI)	Deteriorate (D)	Serious (S)
13	Critical (C)	Unchanged (UC)	Poor (P)
14	Critical (C)	Slight (SL)	Poor (P)
15	Critical (C)	Obvious (O)	Serious (S)
16	Critical (C)	Deteriorate (D)	Serious (S)

2.2.3 Defuzzification Stage

Defuzzification is the last step in a fuzzy process that converts the fuzzy results into real-world values by applying several methods. The current study applied the centre of gravity method, which is defined by equation (5) [29]. Tables (9), (10), and (11) show the fuzzy process output after the defuzzification, which shows how the current proposed technique is working effectively.

$$u = \frac{\sum_{n=1}^{N} I_n \, \mu_n}{\sum_{n=1}^{N} \mu_n} \tag{5}$$

Where:

U: control action, I_n: value of interval, n: total no. of intervals.

Table 9: Defuzzification of the fuzzy set for the first case

Corrosion Degree	Semi Quantitative Condition Rating Score									
0.5	4.01	4.01	4.01	4.01	4.01	3.87	3.35	3.41	3.35	3.35
0.45	4.01	4.01	4.01	4.01	4.01	3.87	3.35	3.41	3.35	3.35
0.4	4.01	4.01	4.01	4.01	4.01	3.87	3.35	3.41	3.35	3.35
0.35	4.01	4.01	4.01	4.01	4.01	3.87	3.35	3.41	3.35	3.35
0.3	4.5	4.5	4 .5	4.5	4.01	3.87	3.86	3.87	3.41	3.41
0.25	5	5	5	4.5	4.01	4.01	4.01	3.87	3.35	3.35
0.2	5.13	5.13	5.13	4.51	4.5	4.51	4.01	3.87	3.41	3.41
0.15	5.68	5.68	5.68	5.12	5	4.51	4.01	3.87	3.35	3.35
0.1	5.65	5.65	5.65	5.12	5	4.51	4.01	3.87	3.38	3.38
0.05	5.68	5.68	5.68	5.12	5	4.51	4.01	3.87	3.35	3.35
Concrete Surface Condition	7	6.5	6	5.5	5	4.5	4	3.5	3	2.5

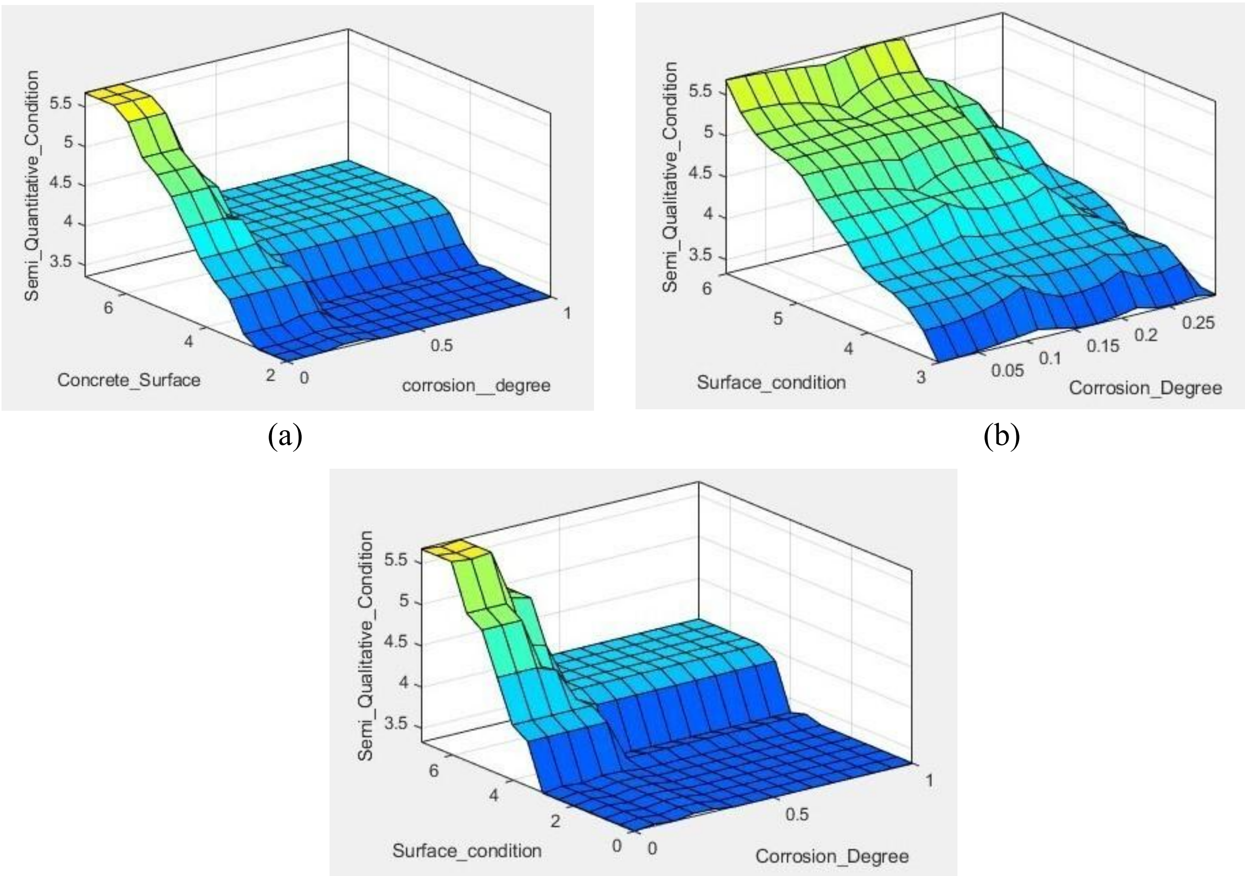
Table 10: Defuzzification of the fuzzy set for the second case

Corrosion Degree	Semi Quantitative Condition Rating Score						
0.3	4	4	4	3.87	3.32	3.38	3.32
0.28	4.4	4.44	4	3.87	3.8	3.85	3.36
0.23	5.03	4.54	4.29	4.33	4	3.87	3.36
0.18	5.67	5.13	5	4.5	4	3.87	3.33
0.13	5.61	5.11	5	4.5	4	3.89	3.39
0.08	5.62	5.12	5	4.5	4	3.88	3.38
0.03	5.67	5.13	5	4.5	4	3.87	3.33
Concrete Surface Condition	6	5.5	5	4.5	4	3.5	3

Table 11: Defuzzification of the fuzzy set for the third case

Corrosion Degree	Semi Quantitative Condition Rating Score									
0.48	4	4	4	4	4	3.87	3.32	3.38	3.32	3.32
0.43	4	4	4	4	4	3.87	3.32	3.38	3.32	3.32
0.38	4	4	4	4	4	3.87	3.32	3.38	3.32	3.32
0.33	4.29	4.29	4.29	4.29	4	3.87	3.72	3.73	3.38	3.38
0.28	5	5	5	4.5	4	4	4	3.87	3.35	3.35
0.23	5.02	5.02	5.02	4.52	4.21	4.26	4	3.87	3..34	3.34
0.18	5.31	5.31	5.31	4.82	4.73	4.5	4	3.87	3.35	3.35
0.13	5.66	5.66	5.66	5.13	5	4.5	4	3.87	3.34	3.34
0.08	5.68	5.68	5.68	5.13	5	4.5	4	3.87	3.37	3.37
0.03	5.68	5.68	5.68	5.13	5	4.5	4	3.87	3.32	3.32
Concrete Surface Condition	7	6.5	6	5.5	5	4.5	4	3.5	3	2.5

As illustrated in Fig. 6, the fuzzy model produces the result output of each pair (corrosion degree, concrete surface condition) by applying rules. The three cases got approximately the same result.



(a) (b)

(c)

Fig. 6: Surface viewer by MATLAB (R2021a) for: (a) first case, (b) second case, and (c) third case

2.3 Predicting the Bridge Condition Rating (BCR) Of Reinforced Concrete Bridges by Markov Chain Model

The Markov chain is a stochastic process has been commonly for predicting the deterioration state of different infrastructure systems. The model depends on the transition probability matrix [TPM] that is used to express the chance of changing from one condition state to another [23, 30]. There are no [TPMs] in the literature that can be generalised to all bridges all over the world. However, the biggest challenge in the Markov chain is how to create a transition probability matrix for each component in the bridge and update it in case of the availability of new data. Therefore, it is important to generate this matrix and customise it to specific conditions by optimization. This study assumed that the condition rating would not decrease by more than one state in a single year. The maximum rating of bridge components (deck, superstructure, substructure) at age zero is 9 on the FHWA rating scale, which represents a perfect condition of the bridge. Therefore, the initial state vector $IP_{(0)}$ for any component of a new bridge is [1, 0, 0, …. 0]. The lowest condition rating to be considered is 3, because if it is less than that, the structure may be closed immediately. R is a vector of condition ratings [9 8 7 6 5 4 3], and R ̀is a transform of R'. The following sections will illustrate more details about the Markov chain model and its components:

2.3.1 Spreadsheet Modelling for Markov Chains

A spreadsheet model for Markov chains has been structured, including all formulations required in cells of Excel 2013. The [TPM] is multiplied sequentially to raise it to the different powers from 1 to A as shown in equation (8). The initial condition state [IP_0] is multiplied by [TPM] to calculate the future condition state [FP_t] at any age (t). Finally, the single value of the predicted condition rating is calculated by multiplying [FP_t] by the column vector [R̀].

2.3.2 Optimizing [TPM] Probabilities

Due to the initial [TPMs] arbitrary character, it is likely to produce an inaccurate condition rating. Thus, the objective of the optimization model is to find suitable values of the [TPM] in order to coincide the Markov predicted condition rating curve with the actual curve.

2.3.3 Objective Function

To achieve the optimized model the objective function is to minimize the error between the Markov predicted condition rating (PC_t) and the actual rating (AC_t) from, summed among the age (A) of the instance being considered as shown in equation (6) [23,31].

$$Min \sum_{t=1}^{t=A} |PC_t - AC_t| \tag{6}$$

Subject to:

$$PC_t = [\mathrm{IP0}]x \begin{bmatrix} p11 & q1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & p22 & q2 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & p33 & q3 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & p44 & q4 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & p55 & q5 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & p66 & q6 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}^t x\ [\grave{R}]\ \forall\ t; = 1,2,3, \dots. A \tag{7}$$

Where; $0 \leq P_{i,i} \leq 1$ (8)

$$[IP_0] = |1\ 0\ 0\ 0\ 0\ 0\ 0| \tag{9}$$

Additionally, some constraints can be used to optimise the [TPM] for a specific instance with a known condition rating (AC_t) from historical data. Thus, the error between the predicted condition rating and the actual rating should equal zero, as shown in equation (10) [23,31].

$$|PC_t - AC_t| = 0 \tag{10}$$

2.3.4 Variables

The diagonal probability values are the $P_{i,i}$ values in the [TPM], as shown in equation (7). After optimisation was completed, the TPM reached the optimum values, and the Markov prediction became very close to the actual measure, as shown in Figs. 7 and 8 respectively.

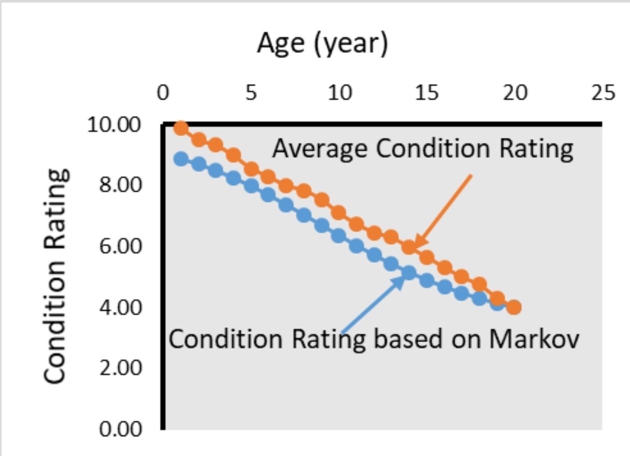


Fig. 7: Markov chain model before optimization

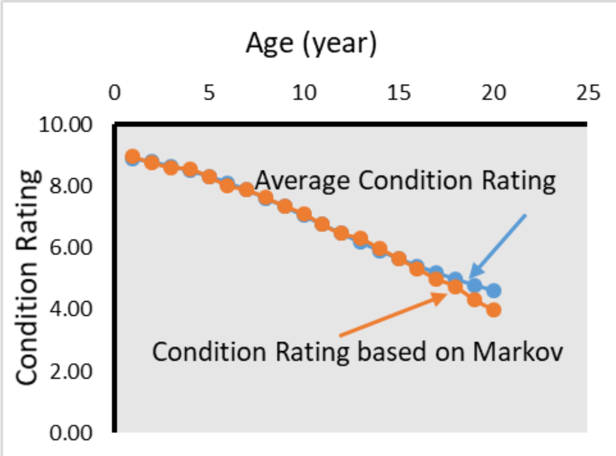


Fig. 8: Markov chain model after optimization

The formula in the spreadsheet is non-linear; that is called a non-linear programming (NLP) problem and was solved by (SOLVER) which comes with the Excel software. For Non-Linear Programming (NLP), SOLVER uses the Generalised Reduced Gradient method [32].

2.4 Expected the Service Life for the Reinforced Concrete Bridge Elements

The main cause of bridge deterioration could be related to steel corrosion. Carbonation, chloride-induced, and sulphate attacks are the main causes of reinforcement corrosion [33]. This article considers both carbonation and chloride-induced corrosion to estimate the corrosion rate and to predict the bridge service life as shown in the following sections:

2.4.1 Service Life Prediction based on Carbonation Attack

The corrosion process of embedded steel in concrete is a function of time. The corrosion operation can be divided into three stages as shown in equations (11), (14), and (19) [26,34,35,36]. Carbonation models typically show a relationship between carbonation depth and structure age. The depth of carbonation depends on many factors, such as water-cement ratio, cement type, and time. Equation (11) is used to determine the depth of carbonation in (mm) [9].

$$D = C\sqrt{T_1} \tag{11}$$

Where;

D: depth of carbonation which is less than maximum carbonation depth with (5 mm-10 mm)

T: time for carbonation till reach embedded steel bars, C: coefficient of carbonation

The coefficient of carbonation can be found by the following equation (12) [26,35]:

$$C = \frac{46*\left(\frac{w}{c}\right)-17.6}{2.7} * C_1 * C_2 \tag{12}$$

Where;

w/c: water cement ratio, C_1: constant based on type of cement as shown in Table 12

C_2: constant based on the atmospheric condition of concrete as shown in Table 13

Table 12: Values of constant C_1 due to type of cement [26]

Type of cement	**C_1**
Ordinary Portland cement (type I)	1
Ordinary Portland cement (type II)	0.6
Ferrous cement (ferrous slag 30% - 40%)	1.4
Ferrous cement (ferrous slag 60%)	2.2

Table 13: Values of C_2 due to concrete atmospheric condition [26]

Concrete atmospheric condition	**C_2**
wet concrete	0.3
Externally exposed concrete members	0.5
Internally exposed members.	1

The time required for developing corrosion rate based on carbonation depth can be calculated using the following equation (13) [26,35]:

$$T_2 = \frac{0.08 * c.c}{\emptyset * f(x)} \tag{13}$$

Where;
T_2: the amount of time needed for corrosion to occur and for concrete to begin to spall.
c.c: thickness of concrete cover
φ: steel bar diameter
f(x): rate of corrosion (mm/year) that is estimated based on equations (2), (3), and (4).

T_1 and T_2 can be calculated as following [26,35];

$$T_1 = \left(\frac{D}{C}\right)^2 \tag{14}$$

Let' assume

$$\boldsymbol{K_1} = \frac{\mathbf{1}}{\boldsymbol{C^2}} \tag{15}$$

$$\boldsymbol{K_2} = \frac{\mathbf{0.08} * \boldsymbol{c.c}}{\emptyset} \tag{16}$$

Thus;

$$T_1 = K_2 D^2 \tag{17}$$

$$T_2 = \frac{K_1}{f(x)} \tag{18}$$

$$The\ total\ time\ for\ corrosion\ or\ spalling = \mathrm{K}_1 D^2 + \frac{\mathrm{K}_2}{f(x)} \tag{19}$$

2.4.2 Life-365 Model for Service Life Prediction due to Chloride-Induced

The Life 365 model is used to predict the service life for concrete structures exposed to chloride environments and not cover corrosion due to carbonation. The main parameters needed for the service life prediction are the concrete cover, the properties of concrete (mainly diffusion coefficient), chloride threshold, and surface chloride and surface chloride [37,38, 39,40,41,42].

3. Discussion & Validation

The proposed approach to diagnosis and maintenance decision-making applies to a real bridge. The gathering data was taken from the General Authority for Roads and Bridges (GARB) and the Ministry of Transportation (MOT). The bridge is a reinforced concrete located near the Suez Gulf in Egypt. It was built in 2004, and after 20 years, it shows several types of damage (cracks, spalling, etc.). In 2024, a special committee was formed to assess the bridge's performance and take appropriate action regarding its situation. The data gathering, visual inspection reports, and tests of this committee were studied carefully to apply the proposed method. The inspectors add the rate for each bridge element based on visual inspection, their expertise, measuring instruments such as callipers, and some tests. The experts found that after twenty years, the Bridge Condition Rating (BCR) dropped from 9 to 4.36. It should be mentioned here that the rehabilitation decision was taken by the revising committee, and the bridge has been in service since then. Investigating and estimating the Bridge Condition Rating (BCR) of the R.C. bridge due to the dual proposed models is shown in the following sections:

3.1 Data Gathering, Historical Data, Inventory of R.C. Bridge Elements

All the inventory, including bridge geometry, was collected from the General Authority for Roads and Bridges (GARB). Numerous photos are taken to reflect the bridge's general conditions from different elements (girders, abutments, deck, and wing walls). The images in Fig.9 show that bridge elements are suffering from several defects, such as cracks, spalling, rebar exposure, and rust staining due to rebar corrosion. The images of any defects found in the bridge elements are collected and classified, such as cracks, spalling, etc. The photos are important to identify any defects found in the bridge elements to be an accurate documentation of defects. They should be added to the condition inspection form. It can be used in determining the required field investigation. Also, they help the inspectors and engineers to track any changes that occur over time through the comparison of historical and new photos. The required tests were applied and the results were reported, such as ground penetrating radar, ultrasonic pulse velocity, half-cell potential, compressive strength, chloride content, etc., to investigate and evaluate the damage for each defected element in the reinforced concrete bridge. For durability assessment tests, there should be combinations between destructive and nondestructive tests. The next step is to estimate the bridge service life.

3.2 Expected the Service Life for Bridge Elements due to Carbonation and Chloride-Induced

Carbonation, chloride ingress, and sulphate attack are the main causes of reinforcement corrosion. According to laboratory testing, the average sulphate content was lower than the allowable limits, therefore the sulphate attack will not have a significant effect on concrete.

The R.C. bridge service life will be estimated due to carbonation and chloride induced as shown in the following sections:

3.2.1 Corrosion due to Carbonation for Bridge Elements

A carbonation test was applied for samples taken from the bridge to find the maximum carbonation depth to be applied in equation (11). Compensating with a parameter extracted from historical data to get the value of “C” and substitute in equation (11) to calculate T_1. Also, T_2 (propagation time), the time required for corrosion to cause spalling of concrete cover, can be calculated by equation (13). Hence, the total time of corrosion, T, must equal the sum of T_1 and T_2; refer to equation (19) and the summary in Appendix Table A1.

3.2.2 Chloride Induced Corrosion of Reinforcing Steel

The Life 365 v2.2.3.1 service life software, which was explained by Ehlen and others [43] was applied to predict the service life of the concrete for the chloride-induced corrosion. Table A1 in Appendix shows the service life for each element of the inspected bridge by Life-365 software.

(a) (b) (c)

Fig.9: Photos taken during inspection. (a) corrosion steel bar (b) spalling, and (c) cracks and exposed rebar

3.3 Condition Assessment for R.C Bridges due to dual Approach, 1) Fuzzy Decision Model, 2) Markov Chain Model

The condition assessment for each bridge element and for whole bridge is estimated due to both fuzzy analysis and Markoc chain as shown in the following sections:

3.3.1 Fuzzy Decision Model

In this stage, a fuzzy analysis technique is implemented by MATLAB (R2021a) to estimate the Bridge Condition Rating (BCR) based on the relationship between concrete surface condition and corrosion degree, as discussed in the previous section. The triangular membership function is applied for both inputs and outputs, as shown in Figure. 5, because of the narrow peak of its absolute membership compared to the trapezoidal membership function, where the peak (absolute membership) is shown through the interval. Triangular shape introduces fuzzy numbers, while fuzzy intervals are represented by trapezoidal shape.

For G1L1 :

The first input corrosion rate = 0.065 mm/yr → The corrosion degree is Condition 1 (low)

The second input is Concrete surface condition (Obvious) → Subjective assessment is 4.

Then the semi-quantitative condition rate = 4 as shown in in rule viewer Fig.10.

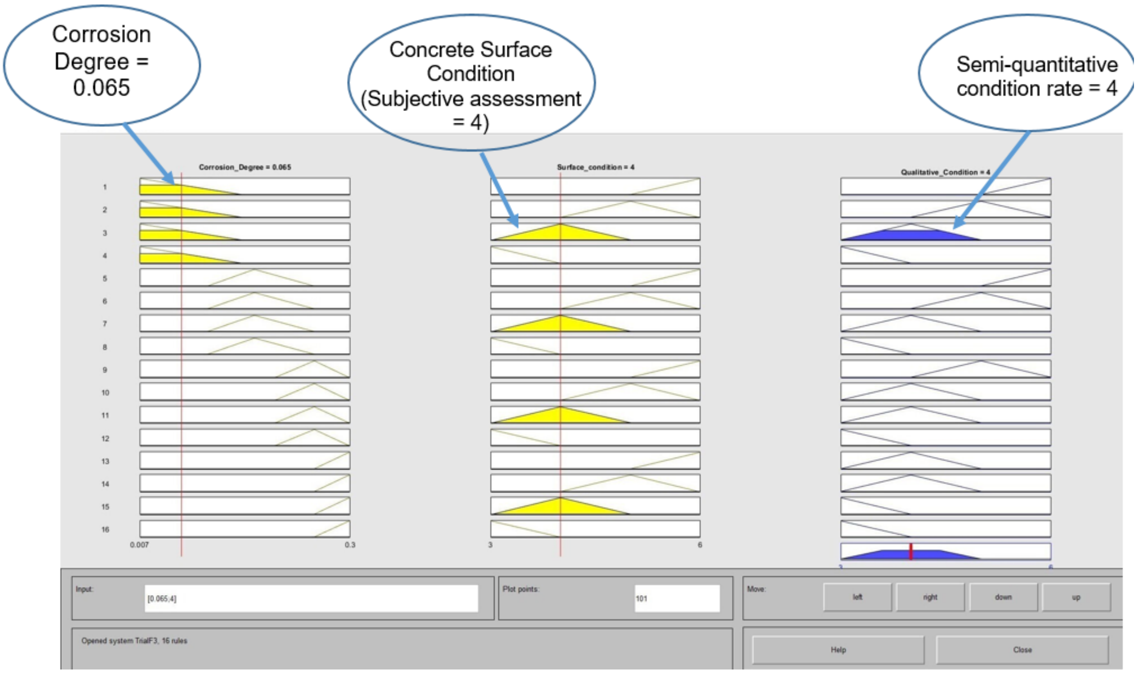


Fig. 10: The set of all rules with its output values for specified two inputs. MATLAB (R2021a)

The condition rating result for each bridge element from fuzzy analysis, as illustrated in the previous example of the girder (G1L1) is shown in Table 14. The estimation for each bridge element gives an indication of which element is suffering from a critical condition and could impact the whole bridge. This makes it easier to prioritize repairs and prevents minor problems from developing into major structural issues. Also, the whole bridge elements contribute to estimate the overall Bridge Condition Rating (BCR_1), as shown in Table 14.

3.3.2 Markov Chain Model

Markov chain analysis will be applied to estimate the future conditions of the current bridge. The bridge was built in 2004. In 2024, there is an evaluation and rehabilitation work. The service life of the bridge at the time of rehabilitation is 20 years. Also, due to laboratory tests for carbonation and chloride profiles, the service life is calculated for each element and found that the girder (G3L1) has the shortest service life of 20 years as shown in Appendix Table A1. The transition probability matrix for the deck, superstructure, and substructure of the three bridge parts was created in this model. Based on equation (7), the predicted condition rating (PC_t), the initial condition state [IP0], the column vector [R̀], and the age (t) which is equal 20 years, are known. The transition probability matrix [TPM] is only the unknown where $0 \leq Pi_{,i} \leq 1$. To find the [TPM], MATLAB R2021a is applied to solve the equation (7), as shown in Fig. 11.

Table 14: Summary of the Bridge Condition Rating (BCR_1) based on Fuzzy analysis technique

Elements	Component No	Corrosion rate based on PH value (mm/yr)	Corrosion Degree	Concrete Surface Condition	Subjective assessment of concrete surface	Semi-quantitative condition Semi-quantitative condition	Average rate	Component rate* Weight
Deck	S1L1	0.13	2	3	4	4	4.5	54
	S6L1	0.08	1	2	5	5		
Girders	G1L1	0.065	1	3	4	4	4.2	63
	G2L1	0.03	1	3	4	4		
	G3L1	0.042	1	2	5	5		
	G4L1	0.25	3	3	4	4		
	G5L1	0.02	1	3	4	4		
Abutments	AB1	0.01	1	3	4	4	4	48
	AB2	0.095	1	3	4	4		
Wing Walls	W21	0.06	1	3	4	4	4.5	31.5
	W22	0.042	1	2	5	5		
Diaphragm	D1L1	0.25	3	3	4	4	4	60
$BCR_1 = 4.01$								

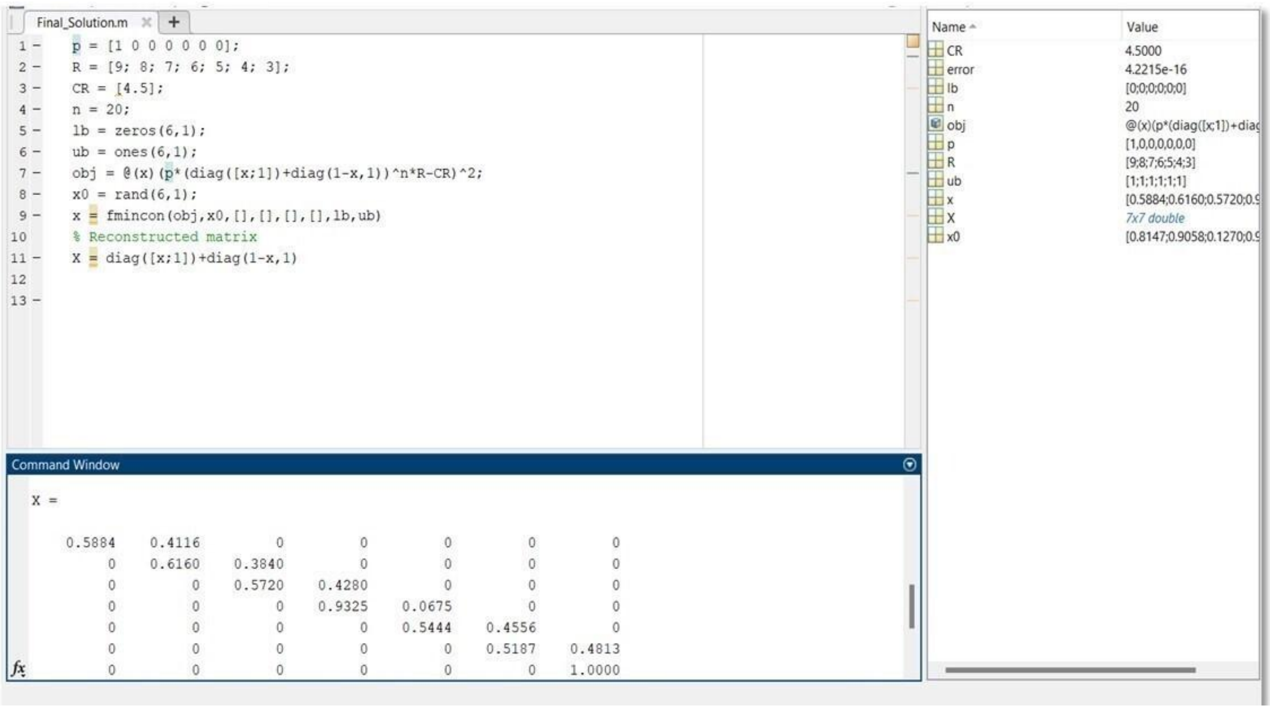


Fig. 11: Screenshot of MATLAB (R2021a) code to find unknown [TPM]

SOLVER, which comes with the Excel software that has been discussed in section 2.3.4 is applied for optimization of the generated [TPM] for each bridge element in order to bring the Markov prediction very close to the actual measure from the historical data based on equations (6) and (10) for the past 20 years, as shown in tables (A2), (A3), (A4), (A5), and (A6) in the Appendix and illustrated in Figs. 12, 13, 14, 15, and 16.

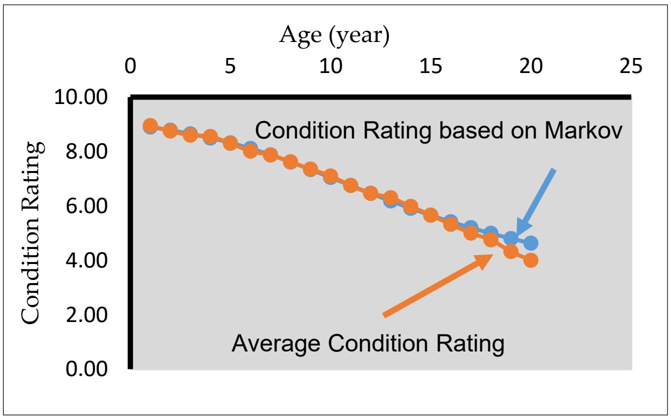


Fig. 12: Deterioration curve for diaphragm

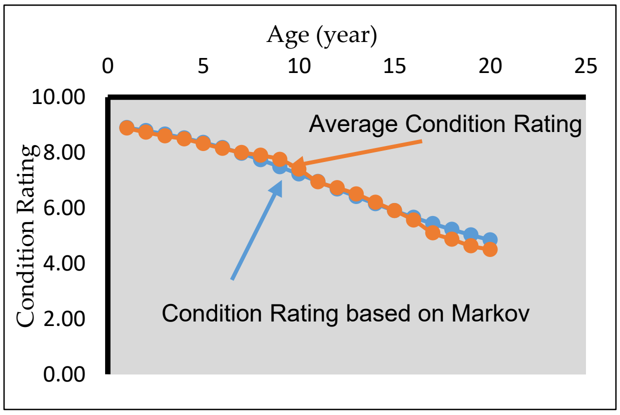


Fig. 13: Deterioration curve for wing wall

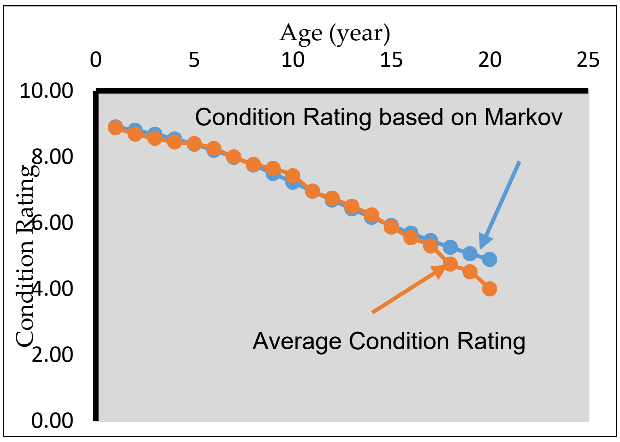


Fig. 14: Deterioration curve for abutment

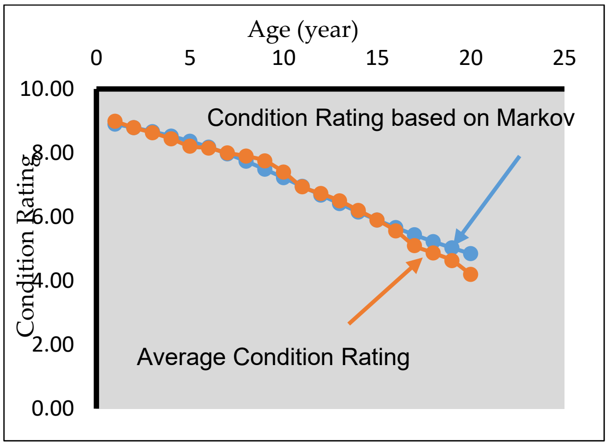


Fig. 15: Deterioration curve for girders

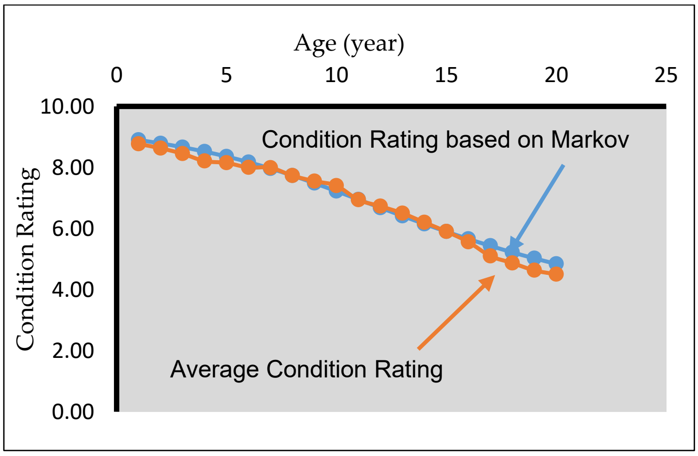


Fig. 16: Deterioration curve for deck

The summary of the condition rating for each element and the overall Bridge Condition Rating (BCR_2) based on FHWA (2012) are shown in Table 15 and calculated based on each element weight as shown in Table 3 and equation (1).

Table 15: Summary of the Bridge Condition Rating (BCR_2) based on MCM

Element	Predicted condition rating	CR*Wt
Deck	4.84	58.08
Girder	4.85	72.75
abutment	4.89	58.68
wing wall	4.84	33.88
Diaphragm	4.63	69.45
BCR_2= 4.576		

Predicting the future Bridge Condition Rating (BCR) based on the Markov Chain Model (MCM) has been discussed previously. The model predicted the deterioration of the deck, girders, diaphragm, abutment, and wing wall of the current bridge study. The Tables (A2), (A3), (A4), (A5), and (A6) in the Appendix show when each element will reach a condition rating of 3, which is the critical condition rating. The Bridge Condition Rating (BCR) will reach 3 after 78 years.

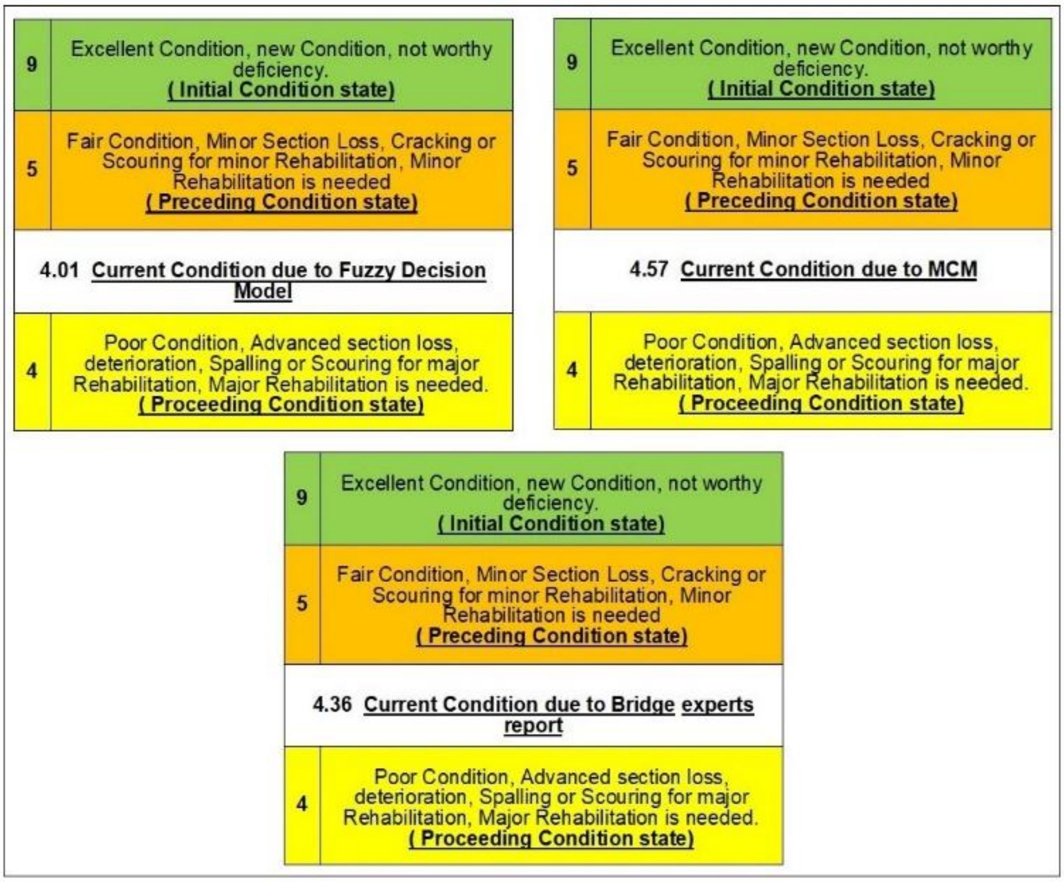


Fig. 17: Comparison of ranking the current Bridge Condition Rating (BCR) by fuzzy decision model , MCM, and bridge inspection experts report (actual Bridge Condition Rating (BCR))

The results from the dual artificial intelligence techniques differ from the result reported from the bridge expert report of the validated case, as shown in Fig. 17. The fuzzy decision model and the Markov Chain model required both field and laboratory tests to find and calculate essential parameters such as carbonation depth, diffusion coefficient, surface chloride, and others. Nevertheless, fuzzy analysis is communicated with ranges that make it less accurate than other methods. Additionally, fuzzy is suffering from the redundancy, which is one of the problems of linguistic fuzzy IF-THEN rules. While MCM depends on field tests, laboratory tests, and historical data, which is required in optimization process to coincide the Markov predicted condition rating curve with the actual curve. Selection of the proper decision regarding the estimated Bridge Condition Rating (BCR) of the inspected bridges relies on strategy maintenance options as per FHWA, 2012, as shown in Table 1. The two different results of the current Bridge Condition Rating (BCR) show that the inspected bridge required major rehabilitation as shown in Fig.17.

4. Conclusions

This research has aimed to apply artificial intelligence in assessing reinforced concrete bridges. The study compares two different methods that relied on visual inspection, historical data, bridge inventory and field and laboratory tests to diagnose the bridge reinforcement concrete diseases. The dual techniques applied in the study are fuzzy decision-making and Markov chain modelling to estimate the overall Bridge Condition Rating (BCR). The corrosion is considered the main reason for bridge deterioration. Therefore, the service life for the bridge is calculated due to carbonation and chloride attack. The current method established a fuzzy decision-making model to find a correlation between concrete surface condition and corrosion degree to estimate the current rating for each bridge element. Then, the Markov chain model has been used for predicting the deterioration state for each element and the whole bridge. Finally, the inspector is able to estimate when the bridge will achieve the critical condition based on the FHWA, 2012 rating to take the proper decision.

The different results obtained make both models applicable. Although the fuzzy decision model depends on both field and laboratory tests, the technique is communicated with ranges that make it less accurate and is suffering from redundancy. In contrast, MCM depends on field tests, laboratory tests, and historical data, which is necessary for the optimization process in order to minimize the error between the Markov predicted condition rating and the actual rating. Therefore, the assessment derived from MCM is the closest to that obtained by bridge inspector experts of the validated case.

From the obtained results, the suggested models would assist the bridge inspector experts and decision-makers in the bridge management sector to achieve appropriate assessment to create a systematic plan for the bridge's eventual maintenance, repair, or rehabilitation in accordance with their condition and the available budget. The introduced techniques enhance both diagnostic and predictive capabilities and are adaptable for broader infrastructure assessment scenarios. The presented study considered only the effects of carbonation and chloride on steel corrosion, without accounting for the impact of sulfate attack. Therefore, it is recommended that future research incorporate the effect of sulfate exposure to assess the condition of bridges using various estimation methods. The future workers are encouraged to apply other types of AI in bridge assessment and make a comparison between them to select the more applicable technique. Also, it is recommended to concentrate on selecting the proper action based on the cost, duration, efficiency, and urgency of the most deteriorated areas. The proposed techniques can be developed to be carried out on the other types of bridges, such as steel bridges, precast concrete, etc.

Data Availability Statement

Any data used during the study can be accessed when requested.

Competing Interests

The authors declare no competing interests.

Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
MRR	Maintenance, Repair, and Replacement
RC	Reinforced concrete
BMS	Bridge Management System
GPR	Ground Penetrating Radar
AASHTO	*American Association of State Highway and Transportation Officials*
GARB	General Authority for Roads and Bridges
MCM	Markov Chain Modelling
PC_t	Markov predicted condition rating
AC_t	actual condition rating
WEM	Weight Evaluation Method
BCR	Bridge Condition Rating
TPM	Transition Probability Matrix
FHWA	Federal Highway Administration classification system
NY	New York ranking system

References

[1] General authority for roads and bridges (GARB), Arab Republic of Egypt (July 2015). The project for improvement of bridge management capacity. Project completion report.

[2] Figueiredo, E., Moldovan, I., & Marques, M. B. (2013). Condition Assessment of Bridges: Past, Present, and Future. A Complementary Approach. Universidade Católica Editora.

[3] AASHTO — American Association of State Highway and Transportation Officials (2008). Bridging the Gap: Restoring and Rebuilding the Nation's Bridges. July.

[4] Herrmann AW. ASCE 2013 report card for America's infrastructure. International Association for Bridge and Structural Engineering; 2013:9-10

[5] Omar, T., & Nehdi, M. L. (2018). Condition assessment of reinforced concrete bridges: Current practice and research challenges. Infrastructures, 3(3), 36.

[6] Abdelalim, A. M., Shalaby, Y., Ebrahim, G. A., & Badawy, M. (2024). An Article Review on Vision-Based Defect Detection Technologies for Reinforced Concrete Bridges. Ann Civ Eng. Manag, 1(1), 01-17.

[7] Transportation Officials. Subcommittee on Bridges. (2018). *The manual for bridge evaluation*. AASHTO.

[8] Kim, H., Ahn, E., Shin, M., & Sim, S. H. (2019). Crack and noncrack classification from concrete surface images using machine learning. Structural Health Monitoring, 18(3), 725-738

[9] Ali Mohamed, N., Mohammed Abdel-Alim, A., Hamdy Ghith, H., & Gamal Sherif, A. (2020). Assessment and Prediction Planning of RC Structures Using BIM Technology. Engineering Research Journal, 167, 394-403.

[10] Abdelalim, A.M. and Said, S.O.M., 2021. "Dynamic labor tracking system in construction project using BIM technology", International Journal of Civil and Structural Engineering Research ISSN 2348-7607 (Online), Vol. 9, Issue 1, pp: (10-20), Month: April 2021 - September 2021.

[11] Shawky, K. A., Abdelalim, A. M., & Sherif, A. G. (2024). Standardization of BIM Execution Plans (BEP's) for Mega Construction Projects: A Comparative and Scientometric Study.

[12] Shehab, A., & Abdelalim, A. M. Utilization BIM for Integrating Cost Estimation and Cost Control Using BIM in Construction Projects, 2023.

[13] Abdelalim, A. M., & Abo. elsaud, Y. (2018, October). Integrating BIM-based simulation technique for sustainable building design. In *International Congress and Exhibition" Sustainable Civil Infrastructures: Innovative Infrastructure Geotechnology"* (pp. 209-238). Cham: Springer International Publishing.

[14] Abdelalim, A. M. (2019). A novel diagnostic prognostic approach for rehabilitated RC structures based on integrated probabilistic deterioration models. International Journal of Decision Sciences, Risk and Management, 8(3), 119-134.

[15] Abdelalim,A.M., Nahla Ali Mohamed Fahmy, Hatem Hamdy Ghith, Alaa Gamal sheriff (2020). Condition Assessment and Deterioration Prediction of RC Structures, International Journal of Civil and Structural Engineering Research, 8(1), 173-181, available at: https://www.researchpublish.com/papers/condition-assessment-and-deterioration-prediction-of-rc-structures.

[16] Alsharqawi, M., Zayed, T., & Abu Dabous, S. (2020). Integrated condition-based rating model for sustainable bridge management. *Journal of Performance of Constructed Facilities*, *34*(5), 04020091.

[17] Rhee, J. Y., Park, K. E., Lee, K. H., & Kee, S. H. (2020). A practical approach to condition assessment of asphalt-covered concrete bridge decks on Korean expressways by dielectric constant measurements using air-coupled GPR. *Sensors*, *20*(9), 2497.

[18] Rogulj, K., Kilić Pamuković, J., & Jajac, N. (2021). Knowledge-based fuzzy expert system to the condition assessment of historic road bridges. *Applied Sciences*, *11*(3), 1021.

[19] Xia, Y., Lei, X., Wang, P., & Sun, L. (2022). A data-driven approach for regional bridge condition assessment using inspection reports. *Structural Control and Health Monitoring*, *29*(4), e2915.

[20] Bertagnoli, G., Ferrara, M., Miceli, E., Castaldo, P., & Giordano, L. (2024). Safety assessment of an existing bridge deck subject to different damage scenarios through the global safety format ECOV. *Engineering Structures*, *306*, 117859.

[21] Shivam, S. (2024). Efficient Bridge Management System: A Comprehensive Approach for Sustainability of Bridge. *Chemical Health Risks*, *JCHR (2024) 14(3), 1831-1845*(2251–6727).

[22] Bajpai, A., & Kushwah, V. S. (2019). Importance of fuzzy logic and application areas in engineering research. *International Journal of Recent Technology and Engineering (IJRTE)*, *7*(6), 1467- 1471.

[23] Yeo, G. L., & Cornell, C. A. (2009). Building life-cycle cost analysis due to mainshock and aftershock occurrences. *Structural safety*, *31*(5), 396-408.31.

[24] FHWA, N. (2012). Bridge inspector's reference manual.

[25] Egyptian standard code for planning, designing, and constructing bridges and intersections (2015), No. (207/10).

[26] Abdelalim, A. M. (2010) ' Safety Assessment in The Rehabilitation of RC Structures' (Doctoral dissertation) Ain Shams University.

[27] Lin, S. S., Shen, S. L., Zhou, A., & Xu, Y. S. (2021). Risk assessment and management of excavation system based on fuzzy set theory and machine learning methods. *Automation in Construction*, *122*, 103490.28.

[28] Hachani, D., & Ounelli, H. (2008). Membership functions generation based on density function. *Computational Intelligence and Security*.

[29] Elbeltagi, E., Hosny, O. A., Elhakeem, A., Abd-Elrazek, M. E., & Abdullah, A. (2011). Selection of slab formwork system using fuzzy logic. *Construction Management and Economics*, *29*(7), 659-670.

[30] Jiang, Y., Sinha, K. C., Saito, M., Murthy, S., Tee, A. B., & Bowman, M. D. (1990). The developmentof optimal strategies for maintenance, rehabilitation and replacement of highway bridges, Vol. 1: The elements of the Indiana bridge management system (IBMS).

[31] Bowman, M. D. (1988). The development of optimal strategies for maintenance, rehabilitation and replacement of highway bridges, Vol. 1: The elements of the Indiana bridge management system (IBMS).

[32] Elhakeem, A. A. (2005). *An asset management framework for educational buildings with life-cycle cost analysis*. Waterloo: University of Waterloo.

[33] Hu, J. Y., Zhang, S. S., Chen, E., & Li, W. G. (2022). A review on corrosion detection and protection of existing reinforced concrete (RC) structures. *Construction and Building Materials*, *325*, 126718.

[34] Ahmad, S. (2003). Reinforcement corrosion in concrete structures, its monitoring and service life prediction—a review. *Cement and concrete . composites*, *25*(4-5), 459-471.

[35] Abdelalim, A. M. (2012, May). Quantitive assessment of deteriorated RC structures due to reinforcing steel corrosion. In *The International Conference on Civil and Architecture Engineering* (Vol. 9, No. 9th International Conference on Civil and Architecture Engineering, pp. 1-12). Military Technical College.

[36] Abdelalim, A. M. (2012, May). A NEW APPROACH TO INTRPRET DISINTEGRATION, COMPRESSIVE STRENGTH, AND WATER ABSORBTION OF CONCRETE UNDER THE APPLICATION OF ADMIXTURES. In *The International Conference on Civil and Architecture Engineering* (Vol. 9, No. 9th International Conference on Civil and Architecture Engineering, pp. 1-13). Military Technical College.

[37] ASTM C 1556 – 04 (2009) ASTM C 1556: Standard Test Method for Determining the Apparent Chloride Diffusion Coefficient of Cementitious Mixtures by Bulk Diffusion

[38] Riding, K. A., Thomas, M. D., & Folliard, K. J. (2013). Apparent diffusivity model for concrete containing supplementary cementitious materials. *ACI Materials Journal*, *110*(6), 705-714.

[39] Mangat, P. S., and Molloy, B. T., "Prediction of Long Term Chloride Concentrations in Concrete," Materials and Structures, V. 27, 1994, pp. 338-346.

[40] Kirkpatrick, T. J., Weyers, R. E., Anderson-Cook, C. M., & Sprinkel, M. M. (2002). Probabilistic model for the chloride-induced corrosion service life of bridge decks. *Cement and concrete research*, *32*(12), 1943-1960.

[41] Weyers, R.E., Fitch, M.G., Larsen, E.P., Al-Quadi, I.L., Chamberlin, W.P., and Hoffman, P.C., 1993. Concrete Bridge Protection and Rehabilitation: Chemical Physical Techniques, Service Life Estimates, SHRP-S-668, Strategic Highway Research Program, National Research Council, Washington, D.C., 357 p.

[42] Weyers, R.E. 1998. "Service life model for concrete structures in chloride laden environments." ACI Materials Journal, Vol. 95 (4), pp. 445-453.

[43] Ehlen, Mark A., Michael DA Thomas, and Evan C. Bentz. "Life-365 Service Life Prediction Model™ Version 2.2.3 " *Concrete international* 31, no. 5 (2020).

Appendix

Table A1: Summary of corrosion characteristics for bridge elements

Parameter \ Element	S1L1	S6L1	G1L1	G2L1	G3L1	G4L1	G5L1	D1L1	AB1	AB2	W21	W22
Primary Evaluation	4	5	4	4	5	4	4	4	4	4	4	5
pH-value	7.38	12.28	7.28	13.41	13.12	7.18	13.66	8	13.99	11.98	12.71	13.12
Rate of corrosion due to pH (mm/yr.)	0.13	0.08	0.25	0.03	0.042	0.25	0.02	0.25	0.01	0.095	0.06	0.042
Concrete resistivity (ohm.cm)	8000	11500	8000	11800	11800	8000	11800	8500	11800	11200	11500	11800
C.C (mm)	15	15	15	18	15	15	18	12	18	18	15	15
Measured carbonation test (mm) (Laboratory test)	5	5	5	5	5	5	5	2	5	5	5	5
Uncarbonated depth (dc)=min cover-carbonation depth	10	10	10	13	10	10	13	10	13	13	10	10
Steel Diameter	14	14	22	22	22	22	22	22	25	25	18	18
T1: initiation period (years)	25	25	25	42.25	25	25	42.25	25	42.25	42.25	25	25
T2: Propagation Period (years)	0.659	1.071	0.218	2.182	1.299	0.218	3.273	0.175	5.760	0.606	1.111	1.587
$T_t = T_1 + T_2$ (Due to carbonation)	25.66	26.07	25.22	44.43	26.30	25.22	45.52	25.17	48.01	42.86	26.11	26.59
Service life due to Chloride Induced (Life -365)	26.80	28.10	23.50	23.60	20.30	21.30	26.30	24.50	39.60	38.40	23.80	27.70

Journal of
Engineering Sciences
Faculty of Engineering
Assiut University
مجلة
العلوم الهندسية
كلية الهندسة
جامعة أسيوط
journal homepage: http://jesaun.journals.ekb.eg

Table A2: Actual and predicted condition rating for diaphragm

Time	PC_t	AC_t	Error
1	8.90	8.95	0.05
2	8.78	8.75	0.03
3	8.65	8.6	0.05
4	8.49	8.55	0.06
5	8.32	8.3	0.02
6	8.11	8.01	0.10
7	7.87	7.87	0.00
8	7.61	7.62	0.01
9	7.33	7.35	0.02
10	7.04	7.1	0.06
11	6.75	6.75	0.00
12	6.46	6.46	0.00
13	6.18	6.3	0.12
14	5.91	5.98	0.07
15	5.66	5.66	0.00
16	5.42	5.32	0.10
17	5.20	5	0.20
18	4.99	4.75	0.24
19	4.80	4.32	0.48
20	4.63	4	0.63
21	4.47		
22	4.32		
23	4.19		
24	4.07		
25	3.97		
26	3.87		
27	3.78		
28	3.70		
29	3.63		
30	3.57		
31	3.51		
32	3.46		
33	3.41		
34	3.37		
35	3.33		
36	3.30		
37	3.27		
38	3.24		
39	3.21		
40	3.19		
41	3.17		
42	3.15		
43	3.14		
44	3.12		
45	3.11		
46	3.10		

https://doi.org/10.21608/jesaun.2025.390430.1534

Time	PC_t	AC_t	Error
47	3.09		
48	3.08		
49	3.07		
50	3.06		
51	3.06		
52	3.05		
53	3.05		
54	3.04		
55	3.04		
56	3.03		
57	3.03		
58	3.03		
59	3.02		
60	3.02		
61	3.02		
62	3.02		
63	3.02		
64	3.01		
65	3.01		
66	3.01		
67	3.01		
68	3.01		
69	3.01		
70	3.01		
71	3.01		
72	3.01		
73	3.01		
74	3.00		

Table A3: Actual and predicted condition rating for wing wall

Time	PC_t	AC_t	Error
1	8.90	8.88	0.02
2	8.79	8.73	0.06
3	8.66	8.6	0.06
4	8.52	8.49	0.03
5	8.36	8.32	0.04
6	8.18	8.15	0.03
7	7.97	8	0.03
8	7.74	7.9	0.16
9	7.49	7.75	0.26
10	7.22	7.4	0.18
11	6.95	6.94	0.01
12	6.68	6.73	0.05
13	6.41	6.5	0.09
14	6.15	6.2	0.05
15	5.90	5.9	0.00
16	5.66	5.56	0.10
17	5.44	5.1	0.34
18	5.22	4.87	0.35
19	5.03	4.63	0.40
20	4.84	4.5	0.34
21	4.67		
22	4.52		

Time	PC_t	AC_t	Error
23	4.38		
24	4.25		
25	4.13		
26	4.02		
27	3.92		
28	3.83		
29	3.75		
30	3.68		
31	3.61		
32	3.55		
33	3.49		
34	3.45		
35	3.40		
36	3.36		
37	3.32		
38	3.29		
39	3.26		
40	3.24		
41	3.21		
42	3.19		
43	3.17		
44	3.16		
45	3.14		
46	3.13		
47	3.11		
48	3.10		
49	3.09		
50	3.08		
51	3.07		
52	3.07		
53	3.06		
54	3.05		
55	3.05		
56	3.04		
57	3.04		
58	3.04		
59	3.03		
60	3.03		
61	3.03		
62	3.02		
63	3.02		
64	3.02		
65	3.02		
66	3.02		
67	3.01		
68	3.01		
69	3.01		
70	3.01		
71	3.01		
72	3.01		
73	3.01		
74	3.01		

75	3.01		
76	3.01		
77	3.00		

Table A4: Actual and predicted condition rating for abutment

Time	PC_t	AC_t	Error
1	8.91	8.88	0.03
2	8.80	8.69	0.11
3	8.68	8.56	0.12
4	8.54	8.45	0.09
5	8.38	8.4	0.02
6	8.20	8.25	0.05
7	7.99	8	0.01
8	7.75	7.77	0.02
9	7.50	7.65	0.15
10	7.23	7.43	0.20
11	6.96	6.96	0.00
12	6.69	6.75	0.06
13	6.42	6.5	0.08
14	6.17	6.24	0.07
15	5.92	5.87	0.05
16	5.69	5.55	0.14
17	5.47	5.3	0.17
18	5.26	4.75	0.51
19	5.07	4.52	0.55
20	4.89	4	0.89
21	4.73		
22	4.58		
23	4.44		
24	4.31		
25	4.19		
26	4.09		
27	3.99		
28	3.90		
29	3.82		
30	3.82		
31	3.68		
32	3.62		
33	3.56		
34	3.51		
35	3.46		
36	3.42		
37	3.38		
38	3.35		
39	3.32		
40	3.29		
41	3.26		
42	3.24		
43	3.21		
44	3.20		
45	3.18		
46	3.16		
47	3.15		
48	3.13		

Time	PC_t	AC_t	Error
49	3.12		
50	3.11		
51	3.10		
52	3.09		
53	3.08		
54	3.07		
55	3.07		
56	3.06		
57	3.06		
58	3.05		
59	3.05		
60	3.04		
61	3.04		
62	3.03		
63	3.03		
64	3.03		
65	3.03		
66	3.02		
67	3.02		
68	3.02		
69	3.02		
70	3.02		
71	3.01		
72	3.01		
73	3.01		
74	3.01		
75	3.01		
76	3.01		
77	3.01		
78	3.01		
79	3.01		
80	3.01		
81	3.01		
82	3.01		
83	3.01		
84	3.00		

Table A5: Actual and predicted condition rating for abutment rating for girders

Time	PC_t	AC_t	Error
1	8.90	8.99	0.09
2	8.79	8.79	0.00
3	8.67	8.63	0.04
4	8.52	8.44	0.08
5	8.36	8.21	0.15
6	8.18	8.15	0.03
7	7.97	8	0.03
8	7.74	7.9	0.16
9	7.49	7.75	0.26
10	7.22	7.4	0.18
11	6.95	6.94	0.01
12	6.68	6.73	0.05
13	6.41	6.5	0.09
14	6.15	6.2	0.05
15	5.90	5.9	0.00

Time	**PC_t**	**AC_t**	**Error**
16	5.66	5.56	0.10
17	5.44	5.1	0.34
18	5.23	4.87	0.36
19	5.03	4.63	0.40
20	4.85	4.2	0.65
21	4.68		
22	4.52		
23	4.38		
24	4.25		
25	4.13		
26	4.02		
27	3.93		
28	3.84		
29	3.76		
30	3.68		
31	3.62		
32	3.56		
33	3.50		
34	3.45		
35	3.41		
36	3.37		
37	3.33		
38	3.30		
39	3.27		
40	3.24		
41	3.22		
42	3.20		
43	3.18		
44	3.16		
45	3.14		
46	3.13		
47	3.12		
48	3.11		
49	3.10		
50	3.09		
51	3.08		
52	3.07		
53	3.06		
54	3.06		
55	3.05		
56	3.05		
57	3.04		
58	3.04		
59	3.03		
60	3.03		
61	3.03		
62	3.02		
63	3.02		
64	3.02		
65	3.02		
66	3.02		
67	3.01		
68	3.01		
69	3.01		

Time	PC_t	AC_t	Error
70	3.01		
71	3.01		
72	3.01		
73	3.01		
74	3.01		
75	3.01		
76	3.01		
77	3.01		
78	3.00		

Table A6: Actual and predicted condition rating for deck

Time	PC_t	AC_t	Error
1	8.90	8.77	0.13
2	8.79	8.63	0.16
3	8.66	8.45	0.21
4	8.52	8.21	0.31
5	8.36	8.15	0.21
6	8.17	8	0.17
7	7.96	7.99	0.03
8	7.73	7.73	0.00
9	7.48	7.55	0.07
10	7.22	7.4	0.18
11	6.95	6.94	0.01
12	6.68	6.73	0.05
13	6.41	6.5	0.09
14	6.15	6.2	0.05
15	5.90	5.9	0.00
16	5.66	5.56	0.10
17	5.43	5.1	0.33
18	5.22	4.87	0.35
19	5.02	4.63	0.39
20	4.84	4.5	0.34
21	4.67		
22	4.52		
23	4.37		
24	4.24		
25	4.13		
26	4.02		
27	3.92		
28	3.83		
29	3.75		
30	3.68		
31	3.61		
32	3.55		
33	3.50		
34	3.45		
35	3.40		
36	3.36		
37	3.33		
38	3.27		
39	3.27		
40	3.24		
41	3.22		
42	3.19		

Time	PC_t	AC_t	Error
43	3.18		
44	3.16		
45	3.14		
46	3.13		
47	3.12		
48	3.10		
49	3.09		
50	3.08		
51	3.08		
52	3.07		
53	3.06		
54	3.06		
55	3.05		
56	3.04		
57	3.04		
58	3.04		
59	3.03		
60	3.03		
61	3.03		
62	3.02		
63	3.02		
64	3.02		
65	3.02		
66	3.02		
67	3.01		
68	3.01		
69	3.01		
70	3.01		
71	3.01		
72	3.01		
73	3.01		
74	3.01		
75	3.01		
76	3.01		
77	3.00		

تطبيق منهجية اتخاذ القرار الضبابي ونموذج سلسلة ماركوف لتحديد دورة حياة الجسور الخرسانية المسلحة

احمد محمد عبد العليم *[١] ، ياسمين شلبي *[٢] ، جمال ابراهيم[٣]، محمد بدوي[٤]

الملخص

ان فحص الجسور الخرسانية المسلحة ضروريًا لضمان السلامة الإنشائية وطول العمر الافتراضي. وفي الآونة الأخيرة، أصبح الذكاء الاصطناعي مهمًا في تحسين عملية تقييم الجسور من خلال دعم مناهج مختلفة تعزز خطط الصيانة وتقلل من التكاليف اللازمة لها. إن هذه الدراسة تهدف إلى استكشاف تقنية أكثر دقة وقابلة للتطبيق تعتمد على الذكاء الاصطناعي لتقييم الجسور الخرسانية المسلحة. لذلك، اقترحت الدراسة المقدمة طريقتين مختلفتين لتقييم حالة الجسور الخرسانية المسلحة: ١) منهجية اتخاذ القرار الضبابي و٢) نمذجة سلسلة ماركوف. ركزت هذه الورقة على تآكل حديد التسليح باعتباره أحد العيوب الرئيسية المستخدمة في تقييم حالة الجسر. تعتمد الطريقتان على الفحص البصري، وتطبيق الاختبارات الميدانية والمعملية، ومراجعة البيانات التاريخية المسبقة للجسر الذي يتم فحصه لتقييم حالته. لقد استخدم نموذج القرار الضبابي لإيجاد علاقة بين درجة التآكل وحالة سطح الخرسانة لتصنيف حالة الجسر. ويُطبق نموذج سلسلة ماركوف للتنبؤ بالحالة الحالية و المستقبلية للجسر بأكمله ومتى سيصل إلى الحالة الحرجة. ان العمر الافتراضي لكل عنصر من عناصر الجسر قدر بناء حساب الزمن المستغرق لحدوث صدأ الحديد الناتج عن الكربنة وتسرب الكلوريد. لقد تم التحقق من فاعلية النماذج المقترحة من خلال دراسة حالة واقعية لجسر خرساني مسلح، وأظهرت النتائج أن النموذج الضبابي أقل دقة مقارنةً بسلسلة ماركوف. وبناء عليه يتضح ان النماذج المقترحة توفر رؤى قيّمة لاتخاذ القرارات المناسبة من صيانة أو إصلاح أو استبدال للجسور محل الفحص.

الكلمات المفتاحية: جسور خرسانية مسلحة ،تقييم ، طرق اتخاذ القرار، الذكاء الاصطناعي، المنطق الضبابي، سلسلة ماركوف