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Research Article

Multiple repair scenario of life cycle cost of RCC girder bridge using Markov chain model

Md. Shafiqul Islam [a], Shayla Sharmin [b,*], Jebunnesa Islam [a]

[a] *Department of Civil Engineering, Rajshahi University of Engineering & Technology, Kazla 6204, Rajshahi, Bangladesh*

[b] *Department of Building Engineering and Construction Management, Rajshahi University of Engineering & Technology, Kazla 6204, Rajshahi, Bangladesh*

ABSTRACT

At present, many road authorities in the world face challenges in condition monitoring diagnosis of distress and forecasting deterioration, strengthening and convalescence of aging bridge structures. The accurate prediction of the future condition is crucial for optimizing the maintenance activities. It is very tough to predict the actual performance scenario or actual in–situ structures without carrying out inspection. Limited availability of detailed inspection data is considered as one of the major drawbacks in developing deterioration models. In State Based Markov deterioration (SNMD) modelling, the main job is to estimate transition probability matrixes (TPMs). In this paper, Markov Chain Monte Carlo (MCMC) is used to estimate TPMs. In Markov Chain Model, future conditions depend on only present bridge inspection data. Multiple repair options are adopted in order to optimize life cycle cost. Repairs are needed when the critical chloride concentration exceeds 0.2. Three distinct types of cost corresponding to each repair option is considered. The objective of this paper is to minimize the life cycle cost considering appropriate repair timings of mixed repair methods. Variation of life cycle cost of five different concretes (stronger to weaker) using three different repair option is shown in this paper. For specific normalized condition of concrete's failure probability (0.3) and specific type of concrete, variation of life cycle cost using multiple repair options is also shown in this paper.

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1. Introduction

Various random impact factors can initiate time dependent deterioration in RCC Girder Bridge. They can vary in loading and environmental conditions. In Girder Bridge, girders are used to support the deck. Girders are made of concrete which is deteriorated by increasing chloride concentration. It is an important factor for bridge deterioration. Chloride can come into water from various wastes, which causes corrosion in reinforced concrete structure. The corrosion occurred when the ion chloride has reached the steel reinforcement and the corrosion has begun to spread which caused spalling on concrete cover. As a result chloride penetration often causes failure of structure before the lifetime service of structure. It also reduces the compressive strength and accelerates the corrosion of reinforcement bars in recycled aggregate concrete. Nowadays, it is essential to establish an effective maintenance and repair strategy to keep bridges sufficiently safe and serviceable throughout their service lives. To prevent shortened structure lifetime the initiation time of chloride penetration must be delayed.

2. Modelling of Bridge Deterioration

Bridge deterioration is the process of declining in the condition of bridge resulting from normal operating conditions. The deterioration process exhibits the complex phenomena of physical and chemical changes that occur in different bridge components. Generally, deterioration models can be categorized into three categories. They are: deterministic models, stochastic models, and artificial intelligence models. These categories are discussed below.

* *Corresponding author.* Tel.: +880-17-5447-2244 ; E-mail address: shaylasharmin.100016@gmail.com (S. Sharmin)
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a) Deterministic Models

These models calculate the predicted conditions deterministically by ignoring the random error in prediction. These models can be used for analysis of networks with a large population. However, they are considered to have some drawbacks:

i) The current condition and the condition history of individual facilities are not considered while predicting the average condition of a family of facilities (Shahin et al., 1987; Jiang and Sinha, 1989)

ii) They estimate facility deterioration for the "no maintenance" strategy only because of the difficulty of estimating the impacts of various maintenance strategies (Sanders and Zhang, 1994)

iii) Updating these models with new data is very tough

b) Stochastic Models

The uncertainty and randomness of facility deterioration process are considered as one or more random variables in stochastic models. Among the stochastic techniques Markovian models has been used extensively in modelling the deterioration of infrastructure facilities (Butt et al., 1987; Jiang et al., 1988). These models use the Markov Decision Process (MDP) to determine the expected failure condition of facility based on previous condition. The uncertainty of the deterioration process and considering the current facility condition in predicting future one, these two problems of deterministic models have been covered by Markovian models. In this study, stochastic models are used to predict future condition.

c) Artificial Intelligence (AI) Models

These models make use of computer techniques that aim to automate intelligent behaviors. Artificial neural networks (ANN), genetic algorithm (GA), and case based monitoring (CBR) are used to optimize the future prediction conditions. Sobanjo (1997) has performed detailed investigation to use the ANN in modelling bridge deterioration. Even though ANN has automated the process of finding the polynomial that best fits a set of data points, it still shares the problems of the deterministic model.

3. Prediction of Performance by Markov Chain Models

3.1. Markov chain

A Markov chain is a mathematical model of a random phenomenon evolving with time in a way that the past affects the future only through the present. The "time" can be discrete (i.e. the integers), continuous (i.e. the real numbers), or, more generally, a totally ordered set. Markov chain is the distinctive case of the Markov process whose development can be treated as a series of transitions between certain states. Markov process describes the probability of attaining a future state in the process which is dependent only on the present state not on the previous state.

3.2. Transition probability matrix formation

A Markov transition matrix is a square matrix describing the probabilities of moving from one state to another in a dynamic system. The rows of Markov transition matrix are valued as one. Transition probability matrix is also the matrix form of probabilities where each element denotes the transition probabilities of system having in the same state or to the higher states with time. While developing performance prediction models for bridge components Markov chains are used, which includes defining discrete condition states and accumulating the probability of transition from one condition state to another over multiple discrete time intervals. Transition probabilities are represented by a matrix of order $n \times n$ called the transition probability matrix (P), where n is the number of possible condition states. Each element (P_{ij}) in this matrix represents the probability that the condition of a bridge component will change from state (i) to state (j) during a certain time interval called the transition period, where the following relation is valid $0 \le P_{ij} \le 1$.

It is assumed that the transition probabilities are not time dependent (t_n, t_{n+1}). Two more conditions apply to the process when it is used to predict deterioration. Firstly, $P_{ij}=0$ for $i>j$, signifying the belief that bridges cannot improve in condition without first receiving treatment. Secondly, $P_{nn}=1$, signifying a holding state where by bridges that have reached their worst condition cannot deteriorate further. If the initial condition vector $P(0)$ that describes the present condition of a bridge component is known, the future condition vector $P(t)$ at any number of transition periods (t) can be obtained as follows (Collins, 1975):

$$P(t) = P(0) \cdot P(t) \tag{1}$$

where

$$P = \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1n} \\ p_{21} & p_{22} & \cdots & p_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ \cdots & \cdots & \cdots & \cdots \\ \cdots & \cdots & \cdots & \cdots \\ p_{n1} & p_{n2} & \cdots & p_{nn} \end{bmatrix} \tag{2}$$

The values composing the TPM matrix must be nonnegative and lie between 0 and 1. The addition of the entrance of each line must be equal to 1. The probabilities of the initial state of the system $P(0)$ may be represented by a line matrix.

$$P(0) = [P1\ (0),\ P2\ (0), \ldots, Pn\ (0)] \tag{3}$$

4. Methodology

4.1. Condition rating

The decision to employ Markov chains to predict service life, together with reliability theory, aims to consider uncertainties of degradation process until the structure reach the durability limit state. The condition rate may be classified based on the critical chloride concentration (C_{cr}) on the surface of the steel bar to define durability limit state.

4.2. Transition probability matrix

Markov process can be described through the following formula (Ross, 2000).

$$S_t = r(P)^t \tag{4}$$

S_t = State vector at time step t.
P = Transition probability matrix, P_{ij} represents the probability of process going from state i to state j.
r = Initial state vector.

The random variable vectors $x = [C_{cr}, C_o, x, D_c]$, where C_{cr} is the critical chloride concentration to initiate corrosion, C_o is the surface chloride concentration, x is the cover depth to reinforcement, and D_c is the diffusion coefficient of chloride ion, Fick's second law can be written in the simple form:

$$\frac{\partial c}{\partial t} = D_0 \frac{\partial^2}{\partial x^2} \tag{5}$$

in which D_0 is the constant coefficient of diffusion. The solution of the differential equation is presented above, for a semi-infinite domain with a uniform concentration at the structural surface, is given by:

$$C(x,t) \;=\; C_0\, erfc\, [x/(2\sqrt{D_0 t}] \tag{6}$$

where C_0 is the chloride concentration at the structural surface supposed constant in the time; *erfc* is the complementary error function. Here, Eq. (6) is used to evaluate the chloride concentration, $C(x, t)$, at a given depth and time into reinforced concrete structures.

The random variables C_{cr}, C_0, x, D_c can be generated by Monte Carlo Simulation and thus reliability index and probability of failure are calculated according to the following formulas.

$$\beta = \frac{\mu_{C_{cr}} - \mu_{C(x,t)}}{\sqrt{SD^2_{C_{cr}} + SD^2_{C(x,t)}}} \tag{7}$$

$$P_{(f)} = \varphi(-\beta) \tag{8}$$

φ = Standard normal distribution, β = Reliability index.

The probability of failure for a particular damage level will indicate the condition rating for a specific age of structure while the inspection is done. This probability of failure is used in transition probability matrix (TPM).

If five states of transition is considered, TPM matrix takes the following form:

$$P = \begin{bmatrix} p_{11} & p_{12} & 0 & 0 & 0 \\ 0 & p_{22} & p_{23} & 0 & 0 \\ 0 & 0 & p_{33} & p_{34} & 0 \\ 0 & 0 & 0 & p_{44} & p_{45} \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \tag{9}$$

where P_{11}, P_{22}, P_{33}, P_{44} probability that the process will remain in the existing condition state. P_{12}, P_{23}, P_{34}, P_{45} probability that the process will pass into a higher condition state P_{55}=1 because the element cannot pass from condition state 5 to any other condition state.

Table 1. Condition rating of concrete.

Failure Extent	Condition Rating	Damage Level	Action Required
Safe	0	C_{cr} <0.2	No Maintenance
Fair	1	0.3 > C_{cr} ≥ 0.2	Repair
Poor	2	0.4 > C_{cr} ≥ 0.3	Repair
Critical	3	0.8 > C_{cr} ≥ 0.4	Repair
Failure	4	C_{cr} ≥ 0.8	Replacement

4.3. Repairing option

The maintenance policy can be described as "when the system hits state *i*, recovers it back to state *j*".

$$S_t = r(RP)^t \tag{10}$$

R=Repair matrix.

Repair action against deterioration of bridge can be represented by matrix form. However, the repair matrix is also a square matrix like TPM with same number of rows and columns as number of condition states are considered. In case of repair matrix, the elements above the diagonal are zero because repair action means the improvement of condition from deteriorating condition to good condition e.g. improvement from

3 → 1, 3 → 2, 2 → 1

So, in repair matrix, there will be elements corresponding to those state transition only and other value will be equal to zero. Three types of repair matrix are used for improvement of bridge deterioration which are shown below:

Repair Matrix 3:

	1	2	3	4	5
1	1	0	0	0	0
2	0	1	0	0	0
3	0	0	1	0	0
4	0	0	1	0	0
5	0	0	1	0	0

In this matrix, the value of elements 1-1, 2-2, 3-3 is 1 which means there will not be any change in this repair. Bridge element condition in state 4, 5 will be improved to state 3.

Repair Matrix 5:

	1	2	3	4	5
1	1	0	0	0	0
2	0	1	0	0	0
3	0	0.95	0.05	0	0
4	0	1	0	0	0
5	0	1	0	0	0

In this matrix, probability of elements 1-1 and 2-2 is 1 which means there will be no change in state. There is a probability that the 95% of bridge will be improved to state 2 from state 3 and all the bridges from states 4 and 5 will be improved to state 2. It is costlier than the previous repair matrix.

Repair Matrix 7:

	1	2	3	4	5
1	1	0	0	0	0
2	0.95	0.05	0	0	0
3	0.9	0.05	0.05	0	0
4	0	0	0	0	0
5	0	0	0	0	0

In this matrix, bridges in state 1 will remain in the same state as the probability is 1. 95% of bridges in state 2 will be improved to state 1. Bridges in state 3, there are 5% of bridges remain in the same state, 5% will be improved to state 2 and the remaining 90% will be improved to state 1. Bridges in state 4 and 5 will directly improve to state 1 as the probability is 1. It is costlier than the other two repair options.

If there is no maintenance, then system will deteriorate towards the "fail" state eventually. However, with appropriate maintenance interventions the system behaves periodically in the long run. Following is an example of maintenance policy (Fig. 1).

There are various state improvements of the structure in the above chart according to the consideration of different types of repairing. The structure has to be replaced when only it reaches to state 4 to come back to state 0 (Fig. 2).

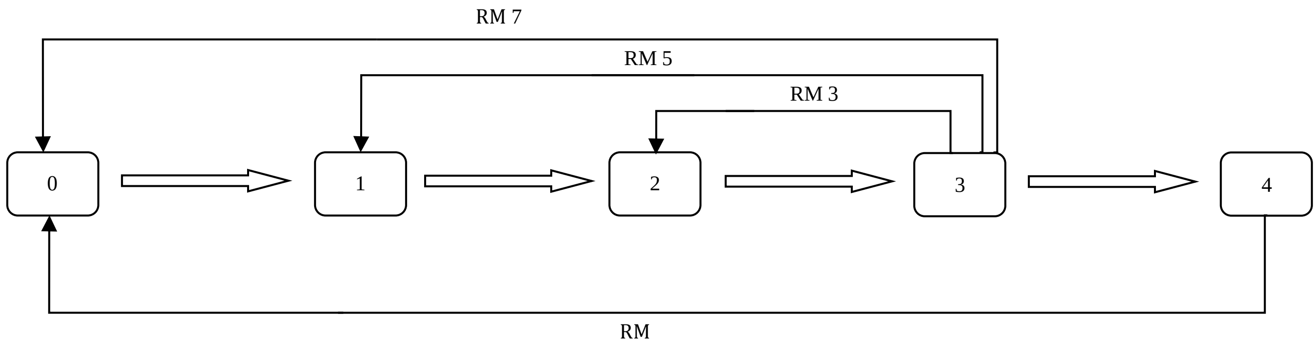

Fig. 1. Improvement capacity of RM 3, RM 5, RM 7 repair options.

5. Results and Discussions

In this paper, five types of concrete of different failure probabilities are used. The concrete of less failure probability is considered as stronger concrete. Repair options 3, 5, 7 are used to satisfy the dynamic expected condition.

Assuming, the costs for repair matrix 3, 5, 7 are 200 units, 500 units & 800 units respectively.

For C1 type concrete (0.98-0.02)

Here, 0.02 is the critical chloride concentration. The more the critical concentration, the less the stronger concrete.

Fig 3. shows bridge deterioration probability for C1 type concrete. It is stronger concrete and its remaining rate in its present state is 98%. Its rate going to next higher state is 2%. Fig. 3 shows that, C1 type concrete requires two of RM 3, one of RM 5 and one of RM 7 to satisfy the expected critical failure probability 0.3.

For C2 type concrete (0.90-0.10)

Here, 0.10 is the critical chloride concentration. As the value is small, so C2 type concrete is stronger concrete.

Fig. 4 shows bridge deterioration probability for C2 type concrete. It is stronger concrete and its remaining rate in its present state is 90%. Its rate going to next higher state is 10%. Fig. 4 shows that, C2 type concrete requires three of RM 3, two of RM 5 and one of RM 7 to satisfy the expected critical failure probability 0.3.

For C3 type concrete (0.80-0.20)

Here, 0.20 is the critical chloride concentration. As the value is average, so C3 type concrete is average concrete.

Fig. 5 shows bridge deterioration probability for C3 type concrete. It is average concrete and its remaining rate in its present state is 80%. Its rate going to next higher state is 20%. Fig. 5 shows that, C3 type concrete requires four of RM 3, four of RM 5 and two of RM 7 to satisfy the expected critical failure probability 0.3.

For C4 type concrete (0.70-0.30)

Here, 0.30 is the critical chloride concentration. As the value is large, so C4 type concrete is weakest concrete.

Fig. 6 shows bridge deterioration probability for C4 type concrete. It is weaker concrete and its remaining rate in its present state is 70%. Its rate going to next higher state is 30%. Fig. 6 shows that, C4 type concrete requires nine of RM 3, four of RM 5 and two of RM 7 to satisfy the expected critical failure probability 0.3.

For C5 type concrete (0.60-0.40)

Here, 0.40 is the critical chloride concentration. As the value is largest, so C5 type concrete is weakest concrete.

Fig. 7 shows bridge deterioration probability for C5 type concrete. It is weakest concrete and its remaining rate in its present state is 60%. Its rate going to next higher state is 40%. Fig. 7 shows that, C5 type concrete requires nine of RM 3, six of RM 5 and four of RM 7 to satisfy the expected critical failure probability.

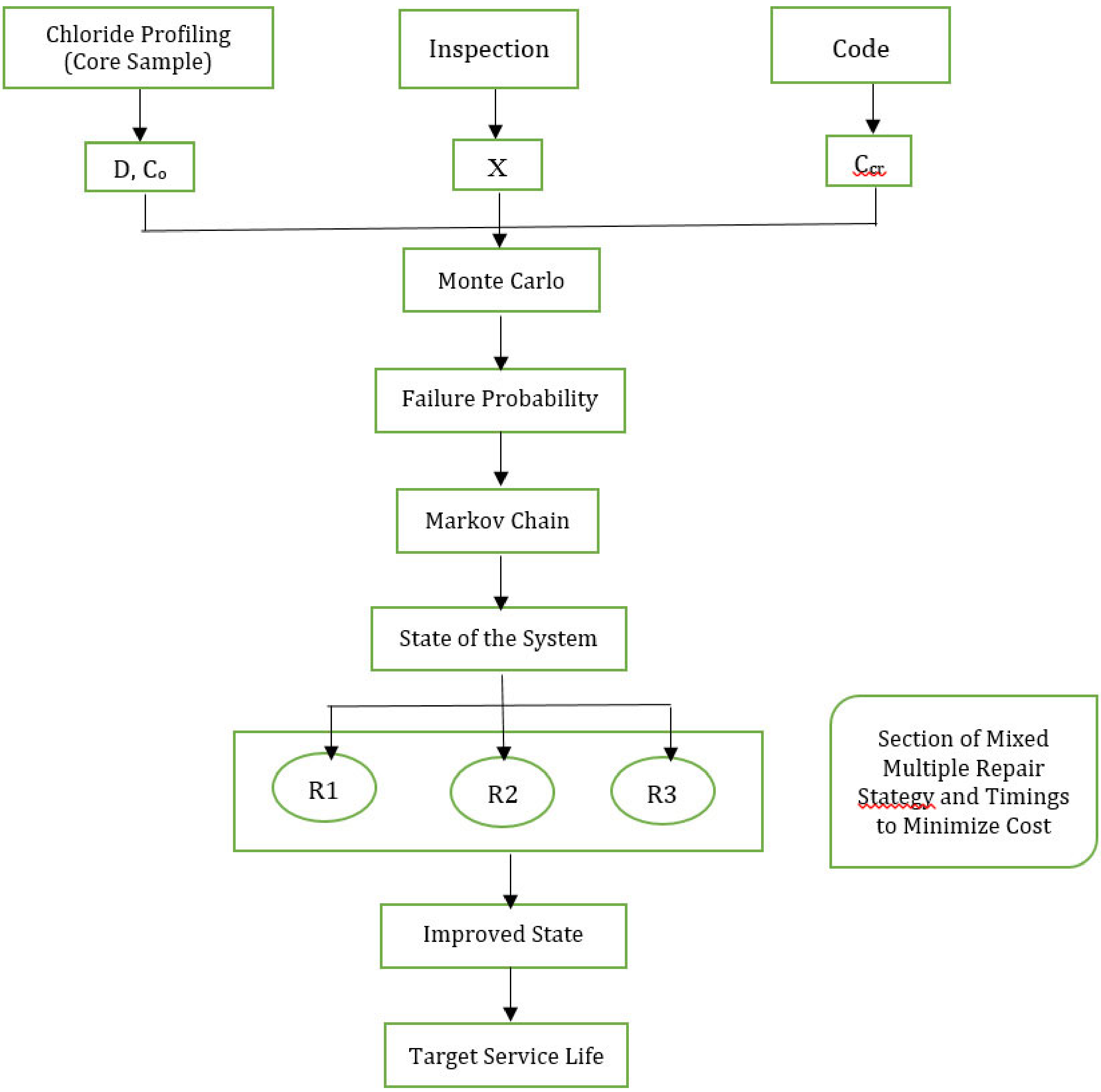

Fig. 2. Work flow of Simulation process of degradation of concrete.

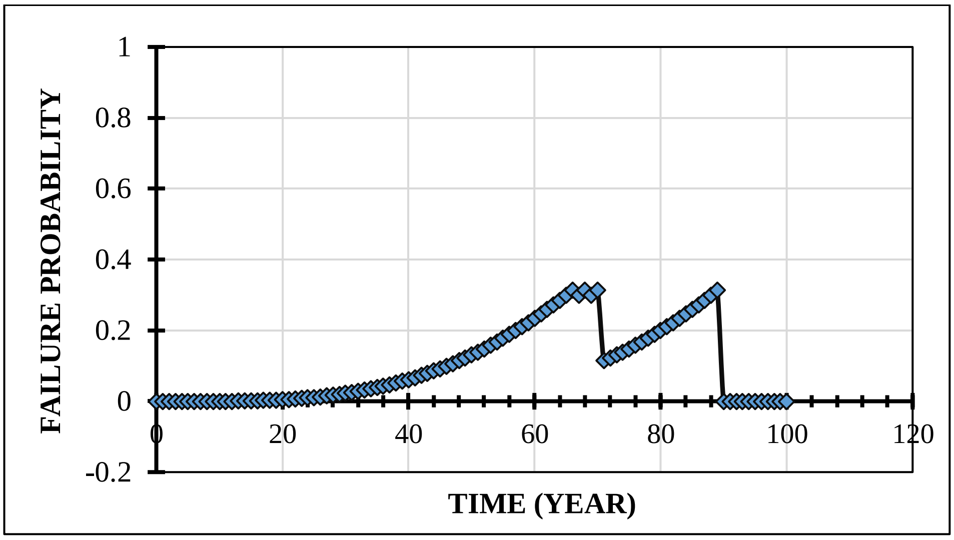

Fig. 3. Bridge deterioration probability for C1 type concrete.

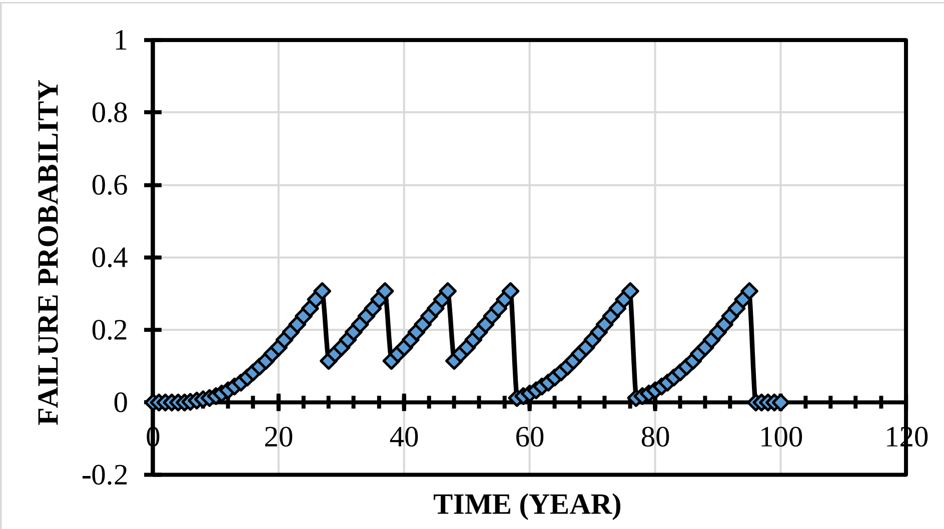

Fig. 4. Bridge deterioration probability for C2 type concrete.

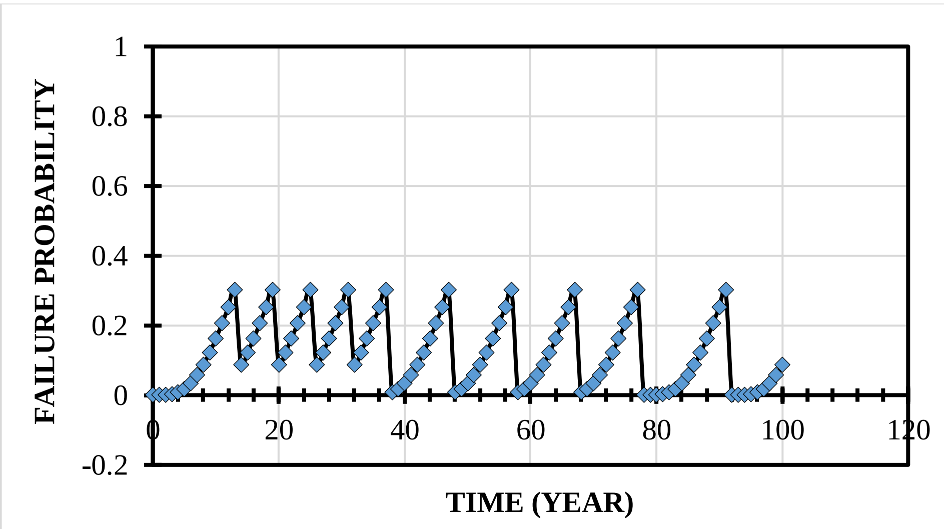

Fig. 5. Bridge deterioration probability for C3 type concrete.

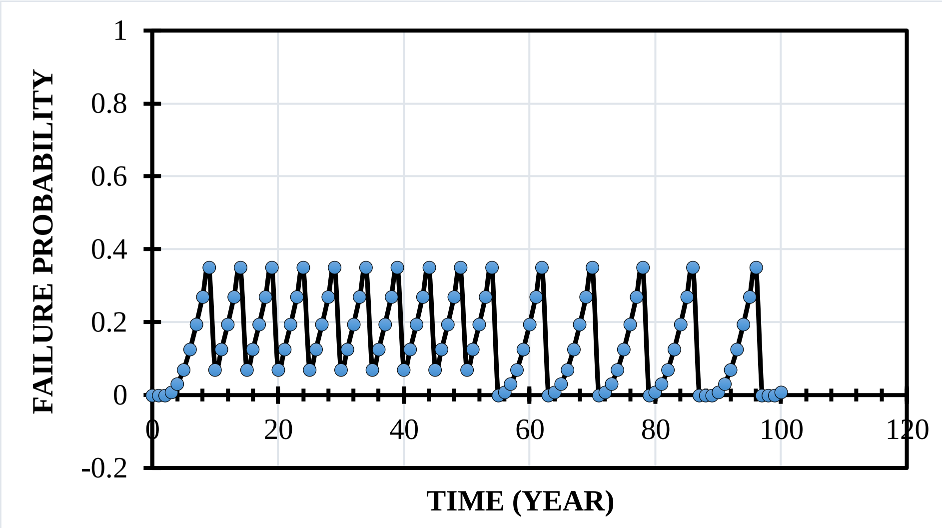

Fig. 6. Bridge deterioration probability for C4 type concrete.

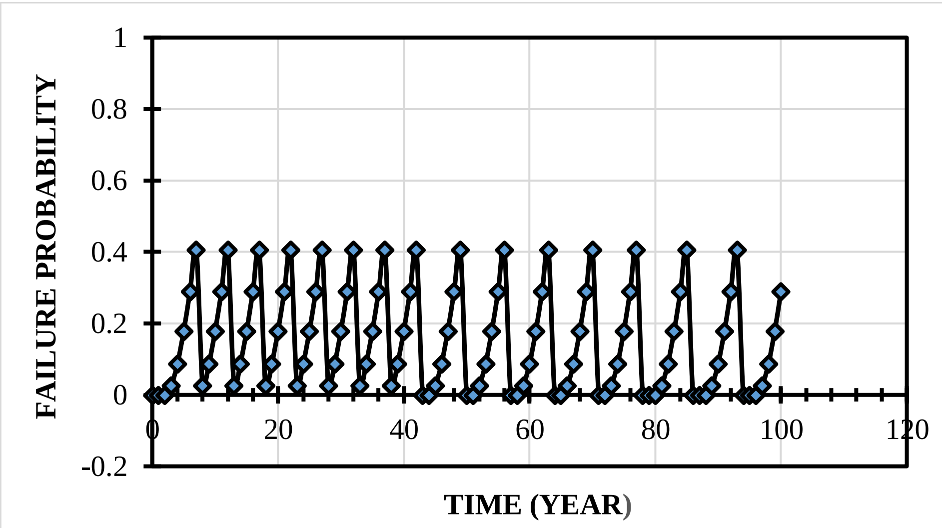

Fig. 7. Bridge deterioration probability for C5 type concrete.

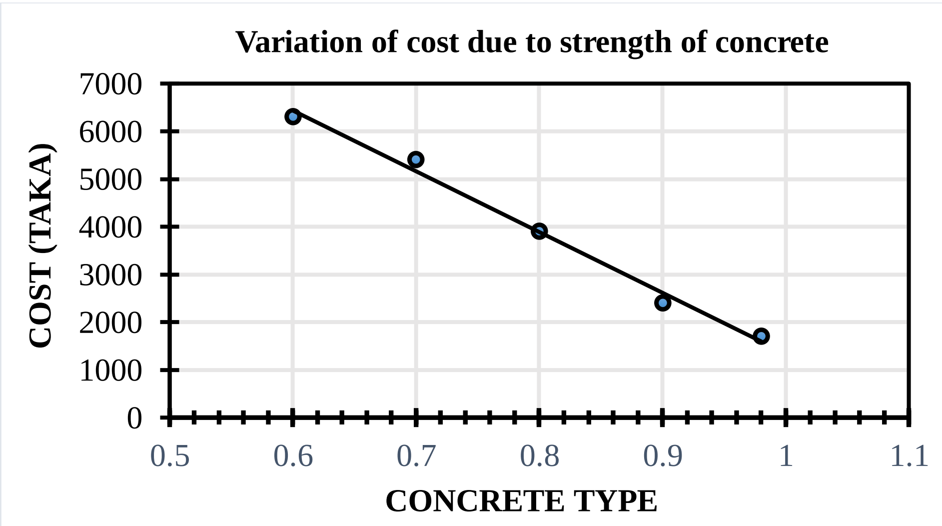

Fig. 8. Variation of life cycle cost according to strength of concrete.

6. Conclusions

The objective of this paper is to create multiple repair scenario from mix repair options and to optimize the life cycle cost. A deterministic prediction method will not be appropriate for deterioration modelling of bridge component. The Markov chain approach appears to offer a superior solution by using the percentage prediction method to develop the transition matrix. Using the developed transition matrices, some preliminary conclusions about deterioration of the bridge components can be made.

Fig. 8 shows variation of life cycle cost of five types of concrete (stronger to weaker) with specific critical failure probability with combination of mix repair. Here, we can see the life cycle cost for strongest concrete is less comparatively weakest concrete. As a result, weakest concrete will need a huge amount of cost applying repair options to satisfy the dynamic expected critical failure probability 0.3. Also for weakest concrete, large numbers of repair options are required and for stronger concrete, small numbers of repair options are required to satisfy the critical failure probability.

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References

Elbehairy H (2007). Bridge Management System with Integrated Life Cycle Cost Optimization. *Ph.D thesis*, University of Waterloo, Waterloo, Ontario, Canada.

Hegazy T, Elbeltagi E, El-Behairy H (2007). Bridge Deck Management System with integrated life cycle cost optimization. Transportation Research Record: *Journal of the Transportation Research Board*, 1866(1), 44-50.

Hrvatske R (2013). Bridge condition forecasting for maintenance optimization. *Journal of the Croatian Association of Civil Engineers*, 65(12), 1079-1088.

Li L, Sun L, Ning G (2014). Deterioration prediction of urban bridges on network level using Markov chain model. *Mathematical Problems in Engineering*, 2014, 728107.

Nogueira CG, Leonel ED, Coda HB (2012). Probabilistic failure modelling of reinforced concrete structures subjected to chloride penetration. *Journal of Advanced Structural Engineering*, 4(1), 1-14.

Possan E, Andrade J (2014). Markov Chain and reliability analysis for reinforced concrete structure service life. *Materials Research*, *17(3),* 593-602.

Saeed Hasan Md, Setunge S, Law DW, Koay Y (2014). Forcasting deterioration of bridge components from visual inspection data. *International Journal of Engineering and Technology*, 7(1), 40-44.

Setunge S, Saeed Hasan Md (2011). Concrete bridge deterioration prediction using Markov-chain model. *Digital Library*, 17(3), 593-602.

Shafiqul Islam Md, Kanti Baul P, Haque O (2018). Observation of chloride permeability between normal aggregates concrete and recycled aggregates concrete containing fly ash and clay. *Challenge Journal of Concrete Research Letters,* 9(4), 103-109.