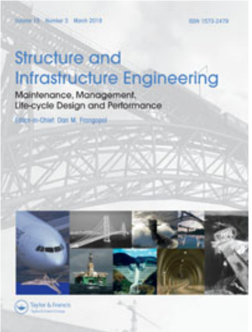

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Risk-based maintenance strategy for deteriorating bridges using a hybrid computational intelligence technique: a case study

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ABSTRACT
The current bridge inspection and maintenance protocol that is used in most countries focuses primarily on the visible aspects of bridge fitness and underestimates the invisible aspects, such as resistance to scouring and earthquake hazards. To help transportation authorities to better consider both aspects, the present study developed a new computational intelligence system, the so-called risk-based evaluation model for bridge life-cycle maintenance strategy (REMBMS). This model considers the three main risk factors of component deterioration, scouring and earthquakes in order to minimise the expected life-cycle cost of bridge maintenance. Monte Carlo simulation is used to estimate the probability of bridge maintenance. The evolutionary support vector machine inference model (ESIM) was applied to estimate the risk-related maintenance cost using historical data from the Taiwan Bridge Management System (TBMS) database. The time-influenced expected costs were obtained by multiplying each maintenance probability with its associated cost. Finally, the symbiotic organisms search (SOS) algorithm is used to identify the bridge maintenance schedule that optimises the life-cycle maintenance cost. The present study provides to bridge management authorities an effective approach for determining the optimal timing and budget for maintaining transportation bridges.

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Bridge maintenance strategy; artificial intelligence; optimisation; bridge risk evaluation; evolutionary support vector machine inference model; symbiotic organisms search

1. Introduction

Frequent earthquakes, typhoons and heavy rains regularly challenge the structural integrity of bridges and seriously deteriorate bridge components in Taiwan and the many other countries with similar climatic and tectonic conditions. In Taiwan, flooding and mudflows are particularly serious threats to bridges during the typhoon season, which typically lasts from summer through early autumn. Additionally, Taiwan's location in a complex tectonic area makes earthquakes fairly common. A particularly serious 7.3 magnitude earthquake that hit Taiwan in 1999 collapsed over 20 bridges. Furthermore, age-related deterioration is an issue that affects all bridges. Taiwan currently lists more than 4000 bridges that are over 30 years old, with 2500 of these dating from the 1970s, a period of heavy government investment in the national infrastructure (Liao & Yau, 2011).

The number of bridges that have deteriorated beyond their designed safety thresholds continues to increase worldwide. Furthermore, the expenditures that will be necessary to maintain, repair and rehabilitate these bridges greatly exceed the budgetary allocations for these purposes (Goyal, Whelan, & Cavalline, 2017). As daily traffic loads and natural stresses continue to deteriorate the conditions of bridges, proper bridge maintenance has become an increasingly crucial task for bridge-management agencies. Therefore, an updated approach to the management of bridges that optimises the available resources under conditions of uncertainty and of multiple, conflicting objectives is necessary to enhance bridge lifespans (Frangopol, Kong, & Gharaibeh, 2001; Hu, Daganzo, & Madanat, 2015).

Bridges may face serious multi-hazard risks such as natural ageing, scouring and earthquakes (seismic events) during the long-time operation. Researchers have studied the behaviour of bridges in dealing with the inevitable deterioration or natural hazards. Simon, Bracci, and Gardoni (2010) investigated the impact of corrosion on the seismic fragility and response of deteriorated bridges. Gardoni and Rosowsky (2011) proposed seismic fragility increment functions to estimate the deformation-shear fragility of deteriorating bridges, without requiring a traditional reliability analysis. Zanini, Pellegrino, Morbin, and Modena (2013) studied the effect of degradation phenomena on the seismic vulnerability of bridges. The seismic degradation of highway bridges was investigated by Kumar and Gardoni (2014) by using the nonlinear time history analysis. It was presented that the degradation in reinforced concrete columns may give a significant impact on the seismic vulnerability of the bridges. Similar to earthquakes, scouring can induce serious damage or even collapse to many bridges as reported by Zampieri, Zanini, Faleschini, Hofer, and Pellegrino (2017) in their failure analysis of masonry arch bridges. Therefore,

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there is a need for efficient maintenance strategy to reduce such crucial risks.

Significant research time and energy has invested in developing effective maintenance and restoration strategies for bridges (Frangopol & Bocchini, 2012; Furuta, Kameda, Nakahara, Takahashi, & Frangopol, 2006; Yadollahi, Abd Majid, & Mohamad Zin, 2015; Zanini, Faleschini, & Pellegrino, 2016). Roberts and Shepard (2001) developed the bridge health index (BHI), which relates to the ratio of the current element value and the proposed total element value (Frangopol et al., 2001; Roberts & Shepard, 2001). Huang (2003) used neural networks to model the deterioration of concrete bridge decks and came to conclusions that differed significantly from Roberts and Shepard using the Markov process in the bridge management system. Huang's study demonstrated that deterioration does not relate exclusively to the age of a bridge but also to its maintenance and history overlay. Huang and Mao (2010) used single-component deterioration to estimate the life-cycle cost of a bridge. However, his estimates focussed exclusively on the bridge deck slab. Tserng and Chung (2007) utilised Huang's approach in combination with the new performance index (NPI) to assess when preventive maintenance should be executed. However, this approach did not consider maintenance costs.

In addition, Bucher and Frangopol (2006) have developed lifetime maintenance strategies that cover time-based maintenance and performance-based maintenance. However, some invisible risks such as scour and earthquake were still not taken into account. Finally, the several studies that have analysed the effectiveness of various strategies in guiding bridge maintenance revealed that little offers a methodology to account for the maintenance costs over the life cycle of a bridge and that most of the visible and invisible risks related to this life cycle are not addressed.

The Taiwan Bridge Management System (TBMS) is a national bridge-management system that the transportation-related agencies of the Taiwan government use to direct visual inspections of more than a thousand bridges annually. TBMS provides the methodology to inspect the visible risk that is attributable to component deterioration using the bridge condition index (CI). Bridge CI values are calculated based on the visual inspection results, with these index values providing an indication of the overall condition of individual bridges, which is used to specify the relevant maintenance-service level of each bridge. Thus, the CI value helps decision makers in these agencies to perform a proper bridge maintenance. After a bridge is inspected, maintenance is scheduled only if the CI value falls below a specific threshold.

Nevertheless, using CI as a solely indicator for determining the maintenance decision may be misleading, as CI considers only component deterioration that is visible and detected during the inspection process (Liao & Yau, 2011). The invisible risks associated with natural hazards such as floods and earthquakes may also significantly deteriorate the bridge. Because the invisible risks attributable to scouring and earthquakes are not taken into consideration in the TBMS or in previous studies, the present research proposes an alternative bridge maintenance strategy: risk-based evaluation model for bridge life-cycle maintenance strategy (REMBMS). This strategy addresses both the visible and invisible risks in a more advanced bridge management system.

In the first stage, REMBMS uses Monte Carlo to simulate the probability of bridge maintenance using historical data. In the second stage, a hybrid artificial intelligence (AI) model called the evolutionary support vector machine inference model (ESIM) is used to estimate the impact of the various risk factors on costs. Next, the bridge maintenance probability is multiplied with the associated costs to calculate the expected cost. Finally, REMBMS utilises the symbiotic organisms search (SOS) algorithm to obtain an estimate of minimum cost. This advanced strategy is expected to yield a bridge maintenance strategy that generates optimal timing and budget estimates that bridge-maintenance planners may use to minimise life-cycle maintenance costs.

2. Literature review

2.1. Bridge inspection in Taiwan

Visual inspection is one of the common methods used to investigate the bridge condition (Quirk, Matos, Murphy, & Pakrashi, 2017; Yeum & Dyke, 2015). In Taiwan, the Taiwan Bridge Management System (TMBS) is used to manage the inventory and inspection data for thousands of domestic bridges. The TBMS, first developed in 2000 (Liao & Yau, 2011), is used by transportation-related government agencies to guide ongoing bridge inspection and maintenance efforts. Current regulations mandate that all bridges in the TMBS database be inspected visually at least once every two years and that special inspections are performed after extremely heavy rains and severe earthquakes. Special inspections are quick and simple inspections for obvious damage and regular inspections investigate a checklist of 20 bridge components. Trained inspectors perform the regular inspections using their eyes and portable tools only. These inspectors approach the target bridges on foot, by boat or in special vehicles.

In Taiwan, the methodology used to conduct these regular bridge inspections and evaluations is known as DER&U. DER&U mandates the inspection of 20 unique bridge components (Tserng & Chung, 2007), with four indices used to evaluate the conditions of these components: 'D' represents degree of deterioration; 'E' represents extent of the deterioration; 'R' represents the relationship between the deterioration and the safety of the bridge and 'U' represents the urgency of repair. All of these indexes are numerically rated on an integer scale from 0 to 4. An index value of 0 means either that the component does not exist or that the inspector was unable to make the inspection. Index values ranging from 1 to 4 correlate positively with deterioration status, with a 1 indicating good condition (no/minimal deterioration) and a 4 indicating extremely poor condition (serious deterioration).

Table 1. Bridge elements and their weighting values (w_i).

Index	Element	Weighting value w_i
1	Approach embankments	3
2	Approach quardrails	2
3	Waterway	4
4	Approach embankments protection works	3
5	Abutment foundation	7
6	Abutment	6
7	Wing/retaining wall	5
8	Surface/wearing coat	3
9	Superstructure drainage	4
10	Curb/sidewalk	2
11	Parapet	3
12	Pier protection work	6
13	Pier foundation	8
14	Pier and column	7
15	Bearing	5
16	Earthquake stopper/restrainer	5
17	Expansion joint	6
18	Girder	8
19	Diaphragm	6
20	Deck slab	7

The DER&U ratings are obtained for calculating the CI of a bridge. First, a component condition index Ic_{ij} is calculated based on the evaluated integers of D, E and R for each component. The calculation is based on a point-deduction mechanism, i.e. deficiencies in a component deduct points from a perfect score of 100. Equation (1) shows the formula for calculating an Ic_{ij} value for the 'j' item of component 'i'. Notably, the value of 'a', an integer in this equation usually set as 1, may be set by the user.

After the inspection is completed, the sub-item condition index (Ic_{ij}) for each sub-item of the 20 main items is calculated as follows:

$$\mathrm{Ic}_{ij} = 100 - 100 \times \frac{(D+E) \times R^a}{(4+4) \times 4^a} \tag{1}$$

where $I = 1 \sim 20$, $j = 1 \sim n$ (number of sub-items), and parameter 'a' relate to the importance of the bridge, with $a = 1$ for a highway bridge, $a = 2$ for a freeway bridge. Next, the condition index for each of the 20 main items is calculated as follows:

$$\mathrm{Ic}_i = \frac{\sum_{j=1}^{n} \mathrm{Ic}_{ij}}{n} \tag{2}$$

Finally, the CI of the bridge is calculated using Ic_i and its corresponding weighting w_i, as follows:

$$CI = \frac{\sum_{i=1}^{20} \mathrm{Ic}_i \times w_i}{\sum_{i=1}^{20} w_i} \tag{3}$$

The values of w_i are adopted from Tserng and Chung (2007) as reported in Table 1. The level of component deterioration of a bridge may be measured by its CI, which is calculated based on the DER&U inspection results.

The scouring stability index (SSI) may be used to measure the scouring stability of a bridge. The SSI of a bridge is calculated in a manner that is similar to CI, but uses only the several components in the DER&U inspection that are normally affected by scouring. These components include: Waterway (3), Abutment foundations (5), Abutments (6), Scouring protection of piers (12), Pier foundations (13) and Piers and columns (14). Equation (4) shows the formula used to calculate SSI:

$$SSI = \frac{Ic_3 \times w_3 + Ic_5 \times w_5 + Ic_6 \times w_6 + Ic_{12} \times w_{12} + Ic_{13} \times w_{13} + Ic_{14} \times w_{14}}{w_3 + w_5 + w_6 + w_{12} + w_{13} + w_{14}} \tag{4}$$

Regarding seismic risk, the pushover method is employed to carry out the assessment to obtain the yield acceleration (Ay) and collapse acceleration (Ac). To measure the damage state of bridges, this study adopts the seismic damage index from Chiu, Lyu, and Jean (2014). Due to the uncertainty in predicting the time at which an earthquake will occur, Monte Carlo Simulation is applied to simulate these two ground accelerations with seismic damage index to estimate the earthquake maintenance probability.

2.2. Evolutionary support vector machine inference model

Over the past years, many studies reveal that AI techniques have surpassed the traditional methods in terms of performance and accuracy as a result of their excellent learning features (Cheng & Prayogo, 2014; Cheng, Prayogo, & Wu, 2014; Cheng, Prayogo, Ju, Wu, & Sutanto, 2016; Cheng, Wibowo, Prayogo, & Roy, 2015). The ESIM is a hybrid AI method developed by Cheng and Wu (Cheng & Wu, 2009) that fuses two different AI techniques, namely support vector machine (SVM) and fast messy genetic algorithm (fmGA). In this complementary system, SVM acts as a supervised learning tool to handle input-output mapping and fmGA works to optimise SVM parameters.

SVM is a recent AI paradigm developed by Vapnik (1995) that has been used in a wide range of applications. This paradigm is a supervised learning tool that was designed to solve classification and regression problems. SVM works by mapping input vectors into a higher dimensional feature space. The optimal hyperplane is identified within this feature space with the help of a kernel function. This inner product in the feature space attempts to make training data linearly separable. Several admissible kernel functions that are used today include the polynomial kernel, the radial basis function (RBF) kernel, and the sigmoid kernel. However, the RBF kernel has been recommended for general users as a first choice due to its ability to analyse higher-dimension data, its ability to conduct searches using only one hyper parameter, and its relatively few numerical difficulties (Chang & Lin, 2011). Therefore, the generalisation ability and predictive accuracy of SVM are determined in the present study using the optimal penalty and kernel parameters (C and γ parameters).

Determining the SVM parameters C and γ is a complicated and problem-oriented process. Improper parameter settings lead to poor accuracy in the resultant prediction/classification model. It is noted that fmGA has previously been employed to simplify and increase the effectiveness of the SVM parameter-setting process. The version of fmGA that has been proposed by Goldberg, Deb, Kargupta, and Harik (1993) is a relatively recently developed optimisation

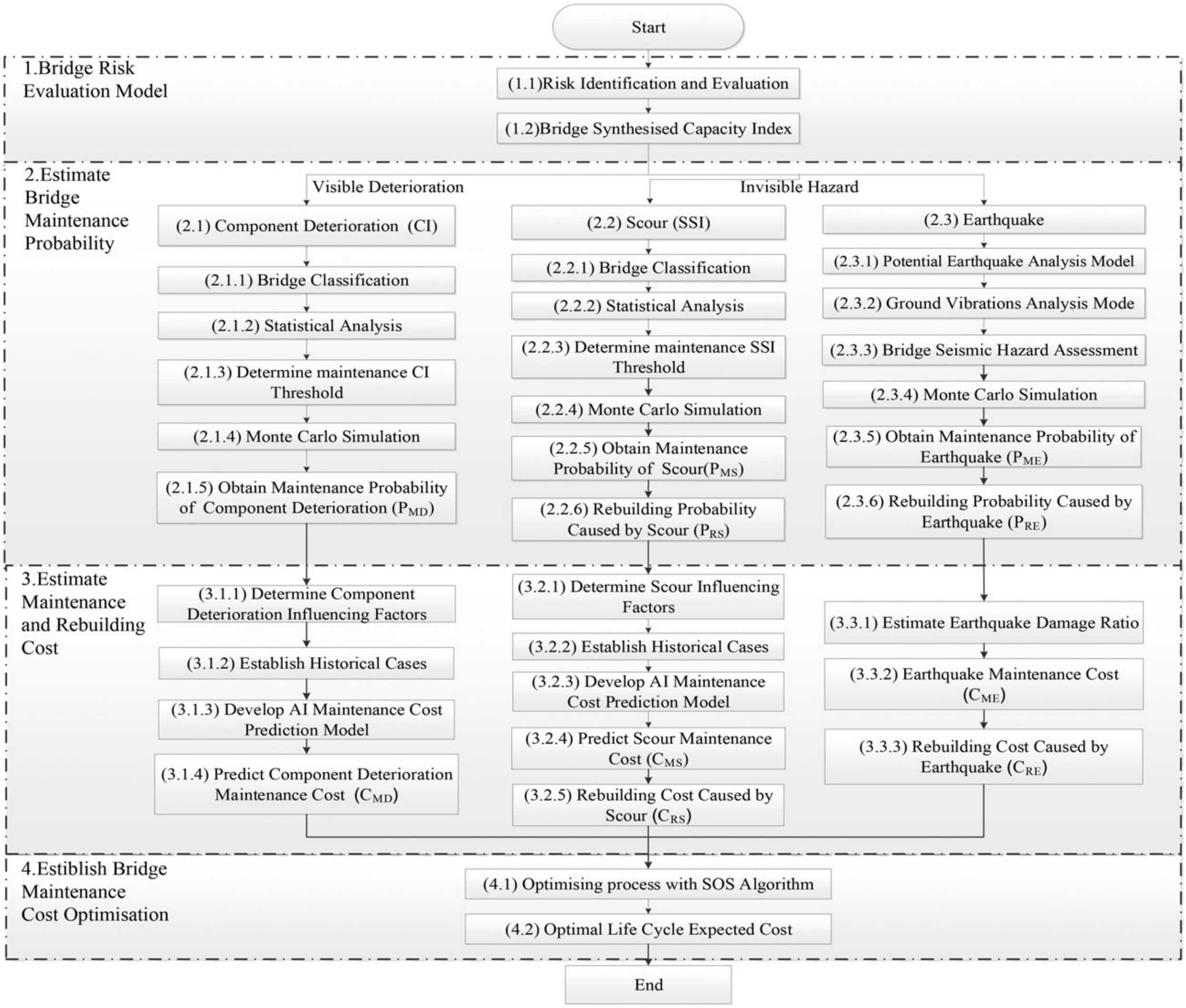

Figure 1. Flowchart of main research steps.

tool that is based on a genetic algorithm approach. Also, note that fmGA represents an improvement over the messy genetic algorithm (mGA), which was initially developed to overcome the simple genetic algorithm (sGA) linkage problem resulting from a parameter-coding problem that generated suboptimal solutions.

2.3. The SOS algorithm

The SOS algorithm is a new metaheuristic algorithm that was developed by Cheng and Prayogo (2014). It was inspired by the biological dependency-based interaction or symbiosis seen among organisms in nature. Similar to most population-based metaheuristic algorithms, SOS uses a population of organisms which contains candidate solutions to seek the global solution within a search space; has special operators that use the candidate solutions to guide the search process; uses a selection mechanism to preserve the better solutions; requires proper setting of common control parameters such as population size and maximum number of evaluations. Furthermore, SOS has been proven to successfully solve various problems in different fields of research (Cheng et al., 2014; Kamankesh, Agelidis, & Kavousi-Fard, 2016; Panda & Pani, 2016; Secui, 2016; Tran, Cheng, & Prayogo, 2016; Vincent, Redi, Yang, Ruskartina, & Santosa, 2017).

In the initial stage, a random ecosystem (population) matrix is created, with each row representing a candidate solution to the corresponding problem. The user predetermines the number of organisms in the ecosystem, which is the size of the ecosystem. As with other metaheuristic algorithms, the rows in the matrix are called organisms. Each virtual organism represents a candidate solution to the corresponding problem/objective. The search begins after the initial ecosystem has been generated. During the search process, each organism benefits from continuous interaction with others in three different ways:

1. *Mutualism Phase*: In this phase, an organism develops a mutually beneficial relationship with another organism. The relationship between bees and flowers is a classic example of mutualism.
2. *Commensalism Phase*: In this phase, an organism develops a relationship with another organism that benefits itself but does not impact upon the other organism. An example of commensalism is the relationship between remora fish and sharks.

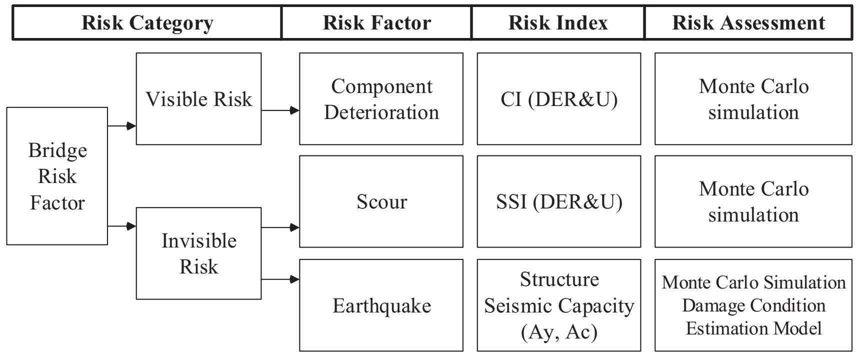

Figure 2. Bridge risk evaluation diagram.

3. *Parasitism Phase*: In this phase, an organism develops a relationship with another organism that benefits itself and harms the other organism. An example of parasitism is the plasmodium parasite, which uses its relationship with the anopheles mosquito to transfer between human hosts.

These three phases reflect the most common symbioses used by organisms to increase their fitness and survival advantage over the long term. During an interaction event, the one that receives a benefit will evolve into a fitter organism, while the one that is harmed will perish. The mechanisms for updating the best organism are conducted after an organism has completed its three phases. The phases are repeated until the stopping criterion is achieved.

3. Proposed risk-based evaluation model for bridge life-cycle maintenance strategy

This section describes the newly proposed REMBMS in detail. Risk-based approach presents an applicable strategy to determine the optimal design involving such uncertainties (Barone & Frangopol, 2014; Beaurepaire, Jensen, Schuëller, & Valdebenito, 2013; Beconcini, Croce, Marsili, Muzzi, & Rosso, 2016; Frangopol & Bocchini, 2012; Zhu & Frangopol, 2012). There are four main stages in the proposed model. The objective of the REMBMS is to minimise the total cost of maintenance related to both visible and invisible risk factors.

Three main AI techniques are involved in the last three stages. After completing the risk evaluation model in the first stage, a Monte Carlo Simulation is employed in the second stage to estimate the bridge maintenance and rebuilding probabilities, which will be used to calculate the expected future maintenance and rebuilding costs. In the third stage, ESIM is used to establish accurate bridge maintenance cost models that are based on historical data. In the final stage, SOS is used as the core optimiser in the REMBMS model to identify the lowest total-expected maintenance cost for the bridges. Figure 1 describes the overall operational architecture of the proposed algorithm.

The first stage of the proposed REMBMS identifies and categorised the risk involved in a bridge and to establish a bridge risk evaluation model by determining the bridge synthesised capacity index that will be used for further analysis

Table 2. Bridge classifications in Taiwan.

Type	Quantity
Truss bridge	63
Box bridge	1388
Cable-stayed bridge	62
Beam/Girder bridge	31,778
Simple supported beam	130
Strut-frame bridge	115
Slab beam	8319
Arch bridge	289
Frame bridge	243

in the subsequent stages. The present study adopted expectancy value theory (EVT) to address all of the three risk factors that were identified and evaluated in the previous stage (component deterioration, scour and earthquake). The objective was to estimate the total expected cost of maintenance by synthesising all of the risk factors involved in each bridge (see Figure 2). The expected cost considers the bridge maintenance and/or rebuilding strategy.

In the maintenance strategy, all three risks are considered to influence the expected maintenance cost. Alternatively, decision makers who do not perform necessary maintenance on bridges face much higher risks of bridge collapse due to scouring and earthquake damage and thus should consider the expected costs of rebuilding in their strategy. The following equations were used to represent the relationship between the expected cost and the risks factors:

$$\mathrm{E(Cost)} = \mathrm{E(MC)} + \mathrm{E(RC)} \tag{5}$$

$$\mathrm{E(MC)} = \left(\sum_{i=1}^{100} P_{MD_i} \times C_{MD_i} + \sum_{i=1}^{100} P_{MS_i} \times C_{MS_i} + \sum_{i=1}^{100} P_{ME_i} \times C_{ME_i} \right) \tag{6}$$

$$\mathrm{E(RC)} = \left(\sum_{i=1}^{100} P_{S_i} \times C_{RS_i} + \sum_{i=1}^{100} P_{E_i} \times C_{RE_i} \right) \tag{7}$$

where:

- E(Cost) is expected cost, E(MC) is expected maintenance cost and E(RC) is expected rebuilding cost.
- P_{MD} is the probability of deterioration-related maintenance, P_{MS} is the probability of scour-related maintenance and P_{ME} is the probability of earthquake-related maintenance.

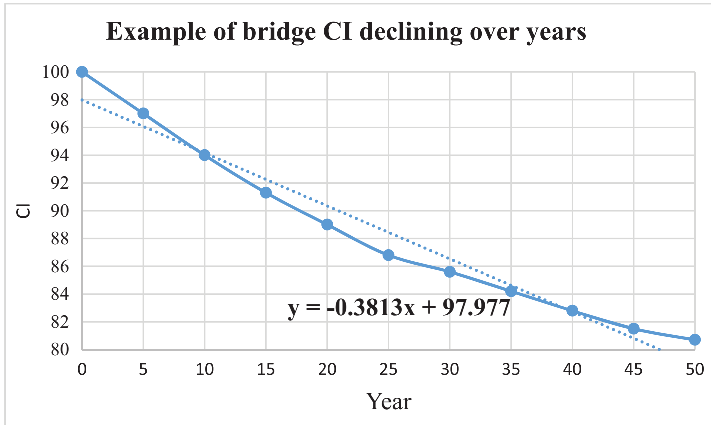

Figure 3. Decline in CI over time (beam/girder type bridges).

Table 3. The statistical analysis of the slope of beam/girder bridge.

Type	Distance from the sea (m)	Traffic loading (car/day)	Average of slope	Variance of the slope
Beam/girder	<300	<6000	−0.230	0.047
	<300	6000 ~ 12,000	−0.056	0.001
	<300	>12,000	−0.405	0.000
	300 ~ 1000	<6000	−0.229	0.094
	300 ~ 1000	6000 ~ 12,000	−0.060	0.001
	300 ~ 1000	>12,000	−0.405	0.000
	1000 ~ 3000	<6000	−0.201	0.096
	1000 ~ 3000	6000 ~ 12,000	−0.048	0.001
	1000 ~ 3000	>12,000	−0.405	0.000
	>3000	<6000	−0.275	0.552
	>3000	6000 ~ 12,000	−0.242	0.053
	>3000	>12,000	−0.284	0.048

Table 4. Bridge information.

Bridge number	Bridge name	Design year	Length (m)	Width (m)	Number of spans
B04-0030-217A	Jiaxin bridge	1973	15.6	18	2
B04-0030-217B	Maoluo river bridge	1995	950	17.25	23
B04-0030-217C	Xinjia bridge	1956	6.3	22.4	1
B04-0030-217D	Xinjie bridge	2002	90	22	3
B04-0030-220A	Huzaikeng bridge	1955	40.2	22.6	2

Figure 4. Photographic documentation for each bridge obtained from TBMS database.

Table 5. Annualised bridge maintenance probability attributable to component deterioration (P_{MD}), Bridges B04-0030-217A to B04-0030-220A (%).

	Years																			
Bridge number	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
B04-0030-217A	0	0	0	0	0	0	0	0	0	1.7	36.8	97	100	100	100	100	100	100	100	100
B04-0030-217B	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
B04-0030-217C	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
B04-0030-217D	0	0	0	0	0	0	0	0	0	2.3	39.1	97.1	100	100	100	100	100	100	100	100
B04-0030-220A	0	0	0	0	0	0	0	0	0	1.7	37.4	97.1	100	100	100	100	100	100	100	100

Table 6. Flood return period for Taiwan's main rivers, corresponding to the SSI slope index.

	Flood return period							
Main river	1-year	2-year	5-year	10-year	20-year	50-year	100-year	200-year
Tamsui	−1	−1	−2	−2	−3	−3	−3	−4
Fengshan	−1	−1	−7	−9	−11	−14	−17	−19
Touqian	−1	−1	−2	−3	−4	−5	−6	−7
Zhonggang	−2	−3	−4	−5	−6	−8	−9	−9
Houlong	−1	−1	−2	−2	−3	−3	−4	−5
Da-an	−1	−3	−5	−7	−10	−13	−16	−20
Dajia	−1	−3	−5	−7	−8	−10	−12	−13
Wu	−1	−1	−2	−2	−3	−3	−4	−5
Zhuoshui	−1	−7	−12	−15	−18	−22	−27	−30
Beigang	−1	−4	−6	−7	−9	−11	−12	−12
Puzi	−1	−2	−4	−5	−6	−7	−8	−9
Bazhang	−1	−2	−3	−4	−4	−5	−5	−6
Jishui	−1	−1	−2	−2	−3	−4	−5	−5
Cengwen	−1	−1	−2	−2	−2	−3	−3	−3
Yanshui	−1	−2	−4	−4	−5	−6	−6	−6
Erren	−1	−1	−1	−2	−3	−2	−2	−4
Gaoping	−1	−1	−2	−2	−3	−3	−3	−3
Donggang	−1	−3	−4	−5	−5	−6	−7	−8
Sicong	−1	−3	−4	−5	−6	−7	−7	−8
Beinan	−1	−1	−1	−2	−2	−2	−3	−3
Xiuguluan	−1	−2	−3	−4	−4	−5	−5	−6
Hualien	−1	−3	−4	−5	−5	−6	−7	−7
Heping	−1	−1	−2	−3	−3	−4	−5	−5
Lanyang	−1	−2	−2	−3	−3	−4	−5	−6

- C_{MD} is the maintenance cost attributable to deterioration, C_{MS} is the maintenance cost attributable to scouring and C_{ME} is the maintenance cost attributable to earthquake damage.
- P_S is the bridge collapse probability attributable to scouring, P_E is the bridge collapse probability attributable to earthquake, C_{RS} is the rebuilding cost attributable to scouring and C_{RE} is the rebuilding cost attributable to earthquake damage.

The following sections calculate the probabilities of bridge maintenance and rebuilding.

4. Estimating the bridge maintenance probability

This section describes the stepwise procedures that were used in the present study to calculate the bridge maintenance probability for all three identified risk factors. The bridge is composed of many different members, with each member having a distinct function. Conducting a risk assessment of an entire bridge structure is very difficult and prone to wide margins of error. However, using the previous identification and evaluation model, the risk factors that affect bridges may be distinguished into visible deterioration and invisible hazards.

Visible deterioration is represented by component deterioration, while invisible hazards are distinguished into two categories: scouring damage and earthquake damage. Thus, the aim of this stage is to obtain the bridge maintenance probability for each of the involved factors. The following subsection describes the steps used to achieve this goal.

4.1. Component deterioration (CI)

4.1.1. Step 1: Bridge classification

Bridges of the same type (design approach), similar traffic loading status, and similar distance from the sea are presumed to share similar deterioration conditions. The more than 40,000 bridges in Taiwan have been categorised into 10 types, summarised below in Table 2.

4.1.2. Step 2: Statistical analysis

In this step, the CI for each bridge was collected from the TBMS. The relationship between the age of a bridge and its CI was then plotted based on the historical data. Figure 3 shows an example plot, with the CI declining over time. Further, regression analysis was conducted to assess the relationship between bridge age and the CI. By obtaining the linear formula, the declining slope of the bridge CI may be determined for use in the next step. Figure 3 displays the slope of the bridge as −0.3813. Furthermore, applying regression analysis to all of the bridges of each type allowed the average and variance of the related slopes to be

Table 7. Probability of scour-related maintenance over time (P_{MS}), Bridges B04-0030-217A to B04-0030-220A (%).

	Years																			
Bridge number	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
B04-0030-217A	0	0	0	0	0	0	0	0	0.2	0.6	0.8	0.7	0.4	0.5	0.7	0.7	3	1.5	1.8	1.6
B04-0030-217B	0	0	0	0	0	0	0	0	0.4	0.4	0.6	0.3	0.4	0.7	0.3	1	1.8	1.6	1.6	2
B04-0030-217C	0	0	0	0	0	0	0	0	0.3	0.8	0.6	0.5	0.5	0.4	0.4	0.6	1.9	2.2	1.9	1.6
B04-0030-217D	6.3	5.7	5.7	5.5	5.6	5	18.5	16.8	19.6	20.5	20.4	20.4	18.5	19.6	20.5	21.1	20.2	22.6	19.4	21.5
B04-0030-220A	0	0	0	0	0	0	0	0	0.7	0.2	0.8	0.7	0.8	0.6	0.2	0.4	2.1	2.8	1.5	1.5

Table 8. Probability of earthquake-related bridge maintenance over time (P_{ME}), Bridges B04-0030-217A to B04-0030-220A (%).

	Years																			
Bridge number	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
B04-0030-217A	1	6.5	13	16.5	18.5	19.5	20	23.5	24.5	27.8	28.8	28.8	30.5	31.3	32	32.8	34.8	35.5	35.5	37.8
B04-0030-217B	1	1.25	2.25	2.75	3.75	4	5.25	6	6.5	7.5	8	9	9.75	11.3	11.8	13	14	14.5	15.5	18.8
B04-0030-217C	0.5	1.75	2	2.5	3.5	4.25	5.75	7	8.5	9.5	10.3	10.8	11.3	12.8	13	14	14.5	15	15.5	16.3
B04-0030-217D	9.5	16	28	32.8	34	35.5	39	40.5	44.5	49.3	50.5	50.8	53.3	55.8	59.3	62	63.3	65.8	67.8	71.5
B04-0030-220A	1.75	9.5	14.3	16.8	20.5	23.8	24.5	25.5	26.5	27.8	28.8	29.8	33.3	34.5	34.5	36.3	36.3	36.3	36.3	36.3

calculated. Table 3 shows the average and variance of the slope for the bridges of the beam/girder type.

4.1.3. Step 3: Determine CI threshold

The goal of this step was to identify the CI maintenance threshold. CI values below this threshold indicate that a bridge requires maintenance. After a review of relevant documents, interviews and historical information, the threshold was identified as varying between 75 and 85.

4.1.4. Step 4: Monte Carlo simulation

After obtaining the average and variance for each CI slope in step 3, statistical declining CI curves for each were established using the Monte Carlo Simulation. The maintenance probability was calculated by counting the number of times that the CI fell below the threshold during the simulation.

4.1.5. Step 5: Obtain maintenance probability attributable to component deterioration (P_{MD})

The annual probability of maintenance attributable to component deterioration (P_{MD}) may be calculated after completing the Monte Carlo Simulation. To illustrate the example of the proposed methodology, five bridges were included in this study. The information for each bridge is shown in Table 4. The photographic documentation for each bridge, which is obtained from TBMS database, is shown in Figure 4. Table 5 lists the annualised probability of maintenance for several of the bridges. For example, in bridge number B04-0030-217A, the P_{MD} value after 10 years is equal to 1.7%. It means that the 10-year CI fell below the threshold about 170 times out of every 10,000 simulations.

4.2. Scouring (SSI)

4.2.1. Step 1: Bridge classification

This step is similar to the approach used to classify bridges in the Component Deterioration section (see Section 4.1, Step 1). However, the bridges in the current section are classified by the river that they cross rather than by distance from the sea, traffic loading conditions, and structural type.

4.2.2. Step 2: Statistical analysis

Table 6 aligns the SSI slope index with the average flood return period for various main rivers in Taiwan. Statistical analysis may thus be used to obtain declining curve values for CI. As shown in Table 6, bridges that cross the Tamsui River have an expected average annual SSI decline of: $1{\cdot}(-1) + 0.5{\cdot}(-1) + 0.2{\cdot}(-2) + 0.1{\cdot}(-2) + 0.05{\cdot}(-3) + 0.02{\cdot}(-3) + 0.01{\cdot}(-3) + 0.005{\cdot}(-4) = -2.36$.

4.2.3. Step 3: Determine SSI threshold

The default SSI threshold value for maintenance was determined to be 75.

4.2.4. Step 4: Monte Carlo simulation

Based on the flood return period and the SSI slope index information obtained in Table 6, the Monte Carlo Simulation may be used to establish the statistically declining SSI curves for each bridge. Further, probability of maintenance values may be calculated by counting the number of times that the SSI fell below the threshold during the simulation. This step is similar to the Monte Carlo Simulation previously described in the Component Deterioration section (see Section 4.1, Step 4).

4.2.5. Step 5: Obtain the probability of scour-related maintenance (P_{MS})

An annualised estimate of P_{MS} may be obtained after completing the Monte Carlo Simulation. Table 7 illustrates several examples of bridge maintenance probability over time.

Table 9. Statistical description of historical data used to estimate the maintenance cost attributable to component deterioration (C_{MD}).

Influencing factors	Minimum	Maximum	Average	Standard deviation
X1: CI	68	100	95.92	5.21
X2: Construction cost index	77.52	124.25	105.16	11.86
X3: Last maintenance (year)	2002	2011	2007.21	2.41
X4: Bridge area (m^2)	40	72,682	5008.28	11,312.25
X5: Bridge height (m)	1.2	29	6.32	4.30
X6: Structural type	beam, arch, cantilever, box girder, truss			
X7: Distance from sea (m)	7.70	57,979.15	20,447.31	15,136.13
X8: Average daily traffic (ADT)	207.75	24,142.25	4001.61	5289.56
X9: Location (mountain or not mountain?)	0 = not mountain, 1 = mountain			
Y: Bridge maintenance cost (C_{MD}) (in NTD)	2590	23,289,363	1,845,238	3,541,901

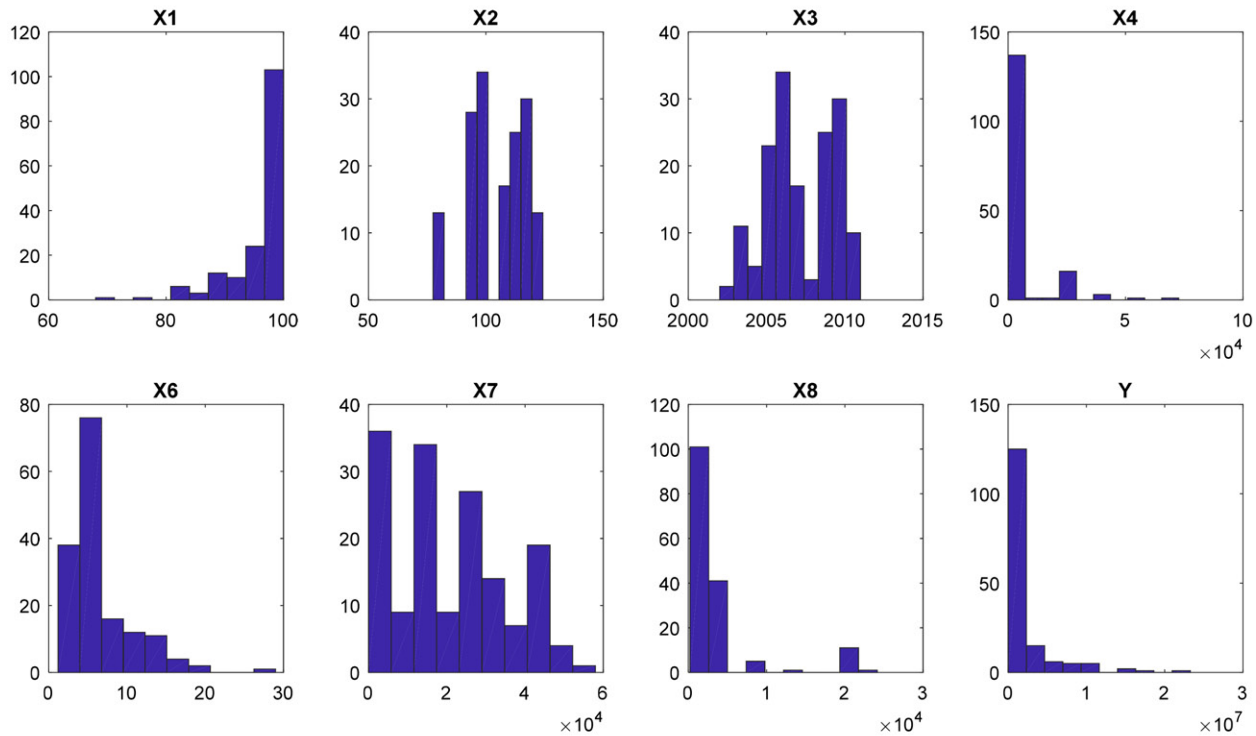

Figure 5. Distribution of influencing factors.

Table 10. ESIM training and testing results.

	Normalised RMSE		ESIM parameters	
Fold	Training	Testing	C	γ
1	0.0857	0.0976	192	0.6673
2	0.0712	0.1582	198	0.8821
3	0.1210	0.0934	66	0.1177
4	0.1220	0.0465	7	0.5356
5	0.1157	0.0630	50	0.2501
6	0.1404	0.1068	28	0.0358
7	0.1093	0.1728	24	0.2761
8	0.0845	0.0745	126	0.9991
9	0.0902	0.0827	140	0.5713
10	0.0798	0.1212	200	0.9501
Average	0.10198	0.10167		

4.2.6. Step 6: Obtain the probability of rebuilding due to scouring (P_{Rs})

Annualised estimate of the probability of rebuilding due to scouring (P_{Rs}) may be obtained after completing the Monte Carlo Simulation. This probability is calculated by counting the number of 100-year floods that occurred during the simulation period. The P_{Rs} should equal 1%, which is the equivalent of a 100-year probability.

4.3. Earthquake hazard

4.3.1. Step 1 – Step 3: Conduct the potential earthquake analysis model, the ground vibration analysis model, and the bridge seismic hazard assessment

These three steps were adopted from Chiu et al. (2014) and Das, Gupta, and Srimahavishnu (2007). The goal of these steps is to apply a ground vibrations analysis model in order to calculate two ground acceleration values for each bridge location: the yield acceleration (Ay) value and collapse acceleration (Ac) value.

To obtain Ay and Ac, the pushover method is employed. The purpose of the pushover analysis is to evaluate the expected performance of a structural system by estimating its strength and deformation demands in design earthquakes by means of a static-inelastic analysis, and comparing these demands to available capacities at the performance levels of interest. The 1999 Chi-Chi Earthquake and other ground motions are used to obtain the structural performance under peak ground acceleration (PGA). Furthermore, the seismic damage index is

Table 11. Bridge maintenance cost attributable to component deterioration (C_{MD}) by year, Bridges B04-0030-217A to B04-0030-220A (in New Taiwan Dollars/NTD).

	Years									
Bridge number	1	2	3	4	5	6	7	8	9	10
B04-0030-217A	769,327	769,327	769,327	769,327	769,327	769,327	769,327	769,327	769,327	769,327
B04-0030-217B	518,158	426,196	320,167	200,228	66,307	81,353	242,970	418,419	607,865	810,986
B04-0030-217C	751,985	652,901	539,671	412,192	270,438	114,565	55,610	239,671	437,862	649,824
B04-0030-217D	69,327	769,327	769,327	769,327	769,327	769,327	769,327	769,327	769,327	769,327
B04-0030-220A	47,688	286,148	568,542	889,987	1,268,394	1,690,465	2,155,155	2,684,238	3,231,054	3,815,305
	11	12	13	14	15	16	17	18	19	20
B04-0030-217A	769,327	769,327	769,327	769,327	769,327	769,327	769,327	769,327	769,327	769,327
B04-0030-217B	1,027,954	1,258,565	1,502,612	1,760,181	2,031,273	2,315,774	2,613,132	2,923,737	3,246,854	3,583,088
B04-0030-217C	876,045	1,116,318	1,370,070	1,637,835	1,919,359	2,214,250	2,522,517	2,843,734	3,178,572	3,526,268
B04-0030-217D	769,327	769,327	769,327	769,327	769,327	769,327	769,327	769,327	769,327	769,327
B04-0030-220A	4,448,906	5,128,277	5,854,979	6,621,112	7,429,297	8,267,156	9,135,507	10,022,185	10,964,802	11,912,463

Table 12. Historical data used to estimate the maintenance cost attributable to scouring (C_{MS}).

No	SSI	Construction cost index	Year of last maintenance	Bridge area (m^2)	Bridge height (m)	Structural type	Location (mountain or not mountain)	Bridge maintenance cost (C_{MS})
1	99	93.24	2005	9956	11.3	Beam	0	1502
2	99	116.86	2010	1200	4.2	Beam	0	1711
3	99	100.00	2006	1500	3.5	Beam	0	3000
4	99	100.00	2006	1500	3.5	Beam	0	3000
5	99	81.14	2003	6900	5.5	Beam	0	3697
6	98	113.24	2009	3979	8	Beam	0	3974
7	99	113.24	2009	3979	8	Beam	0	3974
…	…	…	…	…	…	…	…	…
222	50	93.24	2005	1188	6.5	Beam	0	9,750,107
223	81	124.25	2008	2530	25	Box Girder	0	10,068,410
224	77	92.60	2004	846	5.7	Beam	0	10,893,683
225	80	113.24	2009	11400	20	Beam	0	11,406,937
226	80	113.24	2009	11400	20	Beam	0	11,406,937
227	80	113.24	2009	39627	4.6	Beam	0	11,710,030
228	80	93.24	2005	34452	10.33	Beam	0	12,947,501

adopted from Chiu et al. (2014) to measure the damage state of bridges. The seismic damage index corresponding to each earthquake event can be estimated while considering the occurrence time and PGAs of earthquakes for a bridge within a specific period. The Monte Carlo Simulation will then be used to specify the exceedance probability of a specified damage state.

4.3.2. Step 4: Conduct the Monte Carlo simulation

In this step, the earthquake events that were obtained from local historical data are simulated using the Monte Carlo Simulation approach. The goal of these simulations is to estimate the earthquake maintenance probability (P_{ME}). P_{ME} may be calculated by counting the number of occurrences of earthquakes larger than the threshold values for Ay and Ac during the simulation period. The threshold values for Ay and Ac were set to 0.2 g and 0.24 g, respectively.

4.3.3. Step 5: Obtain the probability of earthquake-related maintenance (P_{ME})

An annualised estimate of P_{ME} may be obtained after completing the Monte Carlo Simulation. Table 8 illustrates several examples of bridge maintenance probability over time.

Table 13. ESIM training and testing results.

	Normalised RMSE		ESIM parameters	
Fold	Training	Testing	C	γ
1	0.0943	0.0989	200	0.4001
2	0.0955	0.0542	185	0.8705
3	0.0917	0.1013	120	0.6001
4	0.0875	0.1160	126	0.8881
5	0.0938	0.0819	192	0.5221
6	0.0993	0.0909	16	0.9592
7	0.1083	0.1434	0	0.7057
8	0.1158	0.1214	0	0.4705
9	0.0937	0.0675	189	0.8141
10	0.0898	0.0982	192	0.9571
Average	0.09697	0.09737		

4.3.4. Step 6: Obtain the probability of rebuilding due to earthquake damage (P_{RE})

The annual probability of rebuilding due to earthquake damage (P_{RE}) may be found using the results of the Monte Carlo Simulation by counting the number of earthquake incidents of peak ground acceleration magnitude greater than 0.24 g.

5. Estimating the maintenance and rebuilding cost

After acquiring all of the probability factors required for each risk factor in Section 4, this section explains the stepwise procedures that were used to calculate the maintenance and rebuilding costs for the three risk factors. The AI

Table 14. Bridge maintenance cost attributable to scouring (C_{MS}) by year, BridgesB04-0030-217A to B04-0030-220A (in NTD).

	Years									
Bridge number	1	2	3	4	5	6	7	8	9	10
B04-0030-217A	1,588,471	1,588,471	1,588,471	1,588,471	1,588,471	1,588,471	1,588,471	1,588,471	1,588,471	1,588,471
B04-0030-217B	223,618	115,391	43,521	40,759	153,388	259,237	357,112	444,700	594,138	700,062
B04-0030-217C	529,977	438,355	382,116	307,305	233,041	136,315	71,107	13,532	102,462	217,098
B04-0030-217D	1,588,471	1,588,471	1,588,471	1,588,471	1,588,471	1,588,471	1,588,471	1,588,471	1,588,471	1,588,471
B04-0030-220A	2728	152,986	259,548	425,425	568,759	729,117	889,111	1,006,588	1,181,400	1,372,786
	11	12	13	14	15	16	17	18	19	20
B04-0030-217A	1,588,471	1,588,471	1,588,471	1,588,471	1,588,471	1,588,471	1,588,471	1,588,471	1,588,471	1,588,471
B04-0030-217B	806,704	916,970	1,043,477	1,200,898	1,295,841	1,436,030	1,516,496	1,671,207	1,798,494	1,920,305
B04-0030-217C	280,433	370,874	501,534	618,916	696,968	819,749	939,350	1,062,485	1,143,094	1,241,048
B04-0030-217D	1,588,471	1,588,471	1,588,471	1,588,471	1,588,471	1,588,471	1,588,471	1,588,471	1,588,471	1,588,471
B04-0030-220A	1,538,706	1,672,951	1,877,533	2,068,785	2,203,953	2,391,232	2,597,531	2,846,115	2,967,085	3,131,235

Table 15. Bridge rebuilding cost attributable to scouring damage (C_{RS}), Bridges B04-0030-217A to B04-0030-220A (in NTD).

Bridge number	C_{RS}
B04-0030-217A	9,547,000
B04-0030-217B	737,438,000
B04-0030-217C	4,195,000
B04-0030-217D	67,320,000
B04-0030-220A	36,341,000

inference model ESIM is employed to build the prediction model to accurately estimate the costs. The datasets were obtained from the TBMS and the data were collected by the Directorate General of Highways (MOTC). The following subsection describes the stepwise procedures that were used.

5.1. Component deterioration

5.1.1. Step 1: Determine the factors that influence component deterioration

The factors that influence component deterioration include 9 inputs: CI, the Construction Cost Index, year of last maintenance, bridge area, bridge height, structural type, distance from sea and location. The output factor is bridge maintenance cost.

5.1.2. Step 2: Establish historical cases

A total of 160 cases were used to establish the dataset that was subsequently used to build the prediction model. Table 9 displays the statistical description of historical data that was used in the present study to estimate the cost of maintenance that is attributable to component deterioration. Additionaly, Figure 5 illustrates the distribution of each influencing factor.

5.1.3. Step 3: Develop AI-based prediction model for maintenance cost

ESIM was used to develop the prediction model. The iteration was set to 100 and the range for C and γ were set to 0–200 and 0.0001–1, respectively. Ten-fold cross validation was used in data partitioning in order to minimise the bias associated with the random sampling of training and testing data cases. Table 10 displays the training and testing results obtained using ESIM. Root mean square error (RMSE) was used to measure the performance. The data were normalised to range: 0–1. The graph shows that the average RMSE training and testing errors were minimal: 0.10198 and 0.10167, respectively. These errors were small enough to justify the model as good for predicting the new cases.

5.1.4. Step 4: Predict the maintenance cost attributable to component deterioration (C_{MD})

The maintenance cost attributable to component deterioration (C_{MD}) was predicted after all runs of the ESIM had been completed. Table 11 shows the final results of several examples of bridge maintenance costs over time.

5.2. Scouring

5.2.1. Step 1: Determine the factors that influence scouring

The factors that influence scouring include 9 inputs: SSI, the Construction Cost Index, year of last maintenance, bridge area, bridge height, structural type, distance from sea and location. The output factor is the cost of bridge maintenance attributable to scouring.

5.2.2. Step 2: Establish historical cases

A total of 228 cases were used to establish the dataset that was used to build the prediction model. Table 12 displays the historical data used in the present study to estimate the maintenance cost that is attributable to scouring.

5.2.3. Step 3: Develop AI-based prediction model for maintenance cost

This step is similar with the Section 5.1, Step 3. Table 13 depicts the training and testing results obtained by ESIM. The graphic shows that the average RMSE training and testing errors were minimal: 0.09697 and 0.09737, respectively. These errors were small enough to justify the model as good for predicting the new cases.

5.2.4. Step 4: Predict the maintenance cost attributable to scouring (C_{MS})

The maintenance cost attributable to scouring (C_{MS}) was predicted after all runs of the ESIM had been completed. Table 14 presents the final results of several examples of bridge maintenance costs over time.

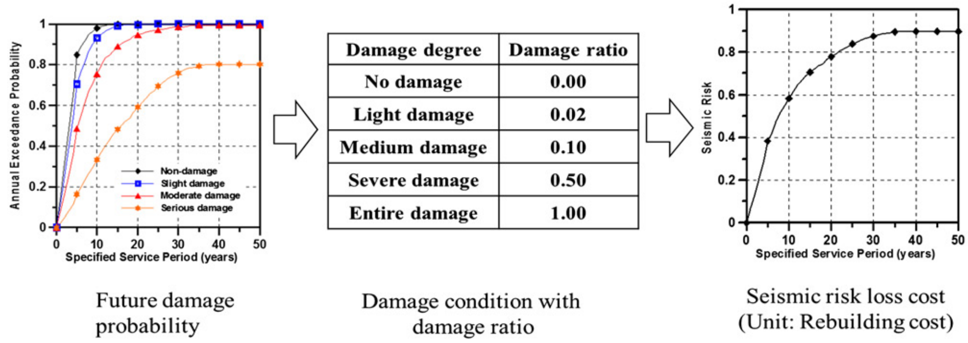

Figure 6. Method used to obtain the earthquake maintenance cost (C_{ME}).

Table 16. Earthquake maintenance cost (C_{ME}) for each damage ratio, Bridges B04-0030-217A to B04-0030-220A (in NTD).

		C_{ME}				
Bridges	Rebuilding cost	No damage	Light damage	Medium damage	Severe damage	Entire damage
B04-0030-217A	9,547,000	0	190,940	954,700	4,773,500	9,547,000
B04-0030-217B	737,438,000	0	14,748,760	73,743,800	368,719,000	737,438,000
B04-0030-217C	4,195,000	0	83,900	419,500	2,097,500	4,195,000
B04-0030-217D	67,320,000	0	1,346,400	6,732,000	33,660,000	67,320,000
B04-0030-220A	36,341,000	0	726,820	3,634,100	18,170,500	36,341,000

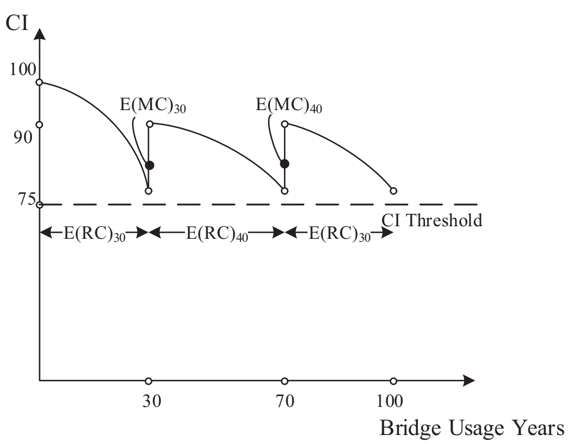

Figure 7. Example of maintenance strategy (30th and 70th).

5.2.5. Step 4: Rebuilding cost attributable to scouring (C_{RS})

In the absence of regular maintenance, bridges that are subject to scouring damage face a higher risk of bridge failure/collapse than those bridges that are not affected by scouring. Thus, the anticipated cost of rebuilding these bridges should be considered in long-term bridge budget strategies. The cost of rebuilding a bridge is the same regardless of the cause of failure (e.g. scouring, earthquake). Table 15 lists the estimated rebuilding costs for several bridges.

5.3. Earthquake risk

5.3.1. Step 1: Estimate the earthquake damage ratio

This research applies an estimation concept that utilises the damage ratio to estimate the probabilities of various maintenance costs. Figure 6 illustrates the methodology that was used to obtain the C_{ME}, as suggested by (Chiu et al., 2014). Each bridge has its own future damage probability, which is calculated during the earthquake events simulation.

5.3.2. Step 2: Earthquake maintenance cost (C_{ME})

Table 16 presents the final result of several examples of bridge maintenance costs for each damage ratio.

5.3.3. Step 3: Earthquake rebuilding cost (C_{RE})

Not performing regular maintenance on a bridge elevates the risk of bridge collapse during an earthquake. The cost of rebuilding is the same whether damage is attributable to an earthquake or to scouring. Thus, as described previously, the values of C_{RE} and C_{RS} are the same in the context of the same bridge (See Table 15).

6. Establishing the bridge maintenance cost optimisation model

This section integrates the maintenance probabilities, the rebuilding probabilities, and the associated costs in order to obtain the total expected cost E(Cost). Further, the SOS algorithm is used to identify the optimal E(Cost). The bridge maintenance and rebuilding probabilities (P_{MD}, P_{MS}, P_{RS}, P_{ME}, P_{RE}) were previously obtained using the Monte Carlo simulation in Section 4 and the bridge maintenance and rebuilding costs (C_{MD}, C_{MS}, C_{RS}, C_{ME}, C_{RE}) were previously estimated using ESIM in Section 5. The formula described in Section 3 is used to synthesise the obtained probabilities and costs in order to obtain the E(Cost).

Step 1: optimal search with SOS algorithm method

The SOS algorithm was used to simulate different maintenance strategies and to iteratively improve the best strategy using its unique searching mechanisms. After creating an initial group of random maintenance strategies, the so-called 'population', this population underwent three search phases: mutualism, commensalism and parasitism. Each of the three

Table 17. Expected maintenance costs attributable to component deterioration, scour, and earthquake, Bridges B04-0030-217A to B04-0030-220A (in NTD).

Maintenance costs	Bridge number	Years 1	2	3	4	5	6	7	8	9	10
$P_{MD}*C_{MD}$	B04-0030-217A	2434	2434	2434	2434	2434	2434	2434	2434	2434	2434
	B04-0030-217B	148,200	148,200	148,200	148,200	148,200	148,200	148,200	148,200	148,200	148,200
	B04-0030-217C	983	983	983	983	983	983	983	983	983	983
	B04-0030-217D	14,040	14,040	14,040	14,040	14,040	14,040	14,040	14,040	14,040	14,040
	B04-0030-220A	6271	6271	6271	6271	6271	6271	6271	6271	6271	6271
$P_{MS}*C_{MS}$	B04-0030-217A	0	0	0	0	0	0	0	0	3177	9531
	B04-0030-217B	0	0	0	0	0	0	0	0	2377	2800
	B04-0030-217C	0	0	0	0	0	0	0	0	307	1737
	B04-0030-217D	100,074	90,543	90,543	87,366	88,954	79,424	293,867	266,863	311,340	325,637
	B04-0030-220A	0	0	0	0	0	0	0	0	8270	2746
$P_{ME}*C_{ME}$	B04-0030-217A	95,470	620,555	1,241,110	1,575,255	1,766,195	1,861,665	1,909,400	2,243,545	2,339,015	2,649,293
	B04-0030-217B	7,374,380	9,217,975	16,592,355	20,279,545	27,653,925	29,497,520	38,715,495	44,246,280	47,933,470	55,307,850
	B04-0030-217C	20,975	73,413	83,900	104,875	146,825	178,288	241,213	293,650	356,575	398,525
	B04-0030-217D	6,395,400	10,771,200	18,849,600	22,047,300	22,888,800	23,898,600	26,254,800	27,264,600	29,957,400	33,155,100
	B04-0030-220A	635,968	3,452,395	5,178,593	6,087,118	7,449,905	8,630,988	8,903,545	9,266,955	9,630,365	10,084,628
		11	12	13	14	15	16	17	18	19	20
$P_{MD}*C_{MD}$	B04-0030-217A	285,546	748,681	771,761	771,761	771,761	771,761	771,761	771,761	771,761	771,761
	B04-0030-217B	148,200	148,200	148,200	148,200	148,200	148,200	148,200	148,200	148,200	148,200
	B04-0030-217C	983	983	983	983	983	983	983	983	983	983
	B04-0030-217D	314,847	761,057	783,367	783,367	783,367	783,367	783,367	783,367	783,367	783,367
	B04-0030-220A	1,670,162	4,985,829	5,861,251	6,627,383	7,435,568	8,273,427	9,141,778	10,028,456	10,971,074	11,918,735
$P_{MS}*C_{MS}$	B04-0030-217A	12,708	11,119	6,354	7,942	11,119	11,119	47,654	23,827	28,592	25,416
	B04-0030-217B	4840	2,751	4,174	8,406	3,888	14,360	27,297	26,739	28,776	38,406
	B04-0030-217C	1683	1854	2508	2476	2788	4918	17,848	23,375	21,719	19,857
	B04-0030-217D	324,048	324,048	293,867	311,340	325,637	335,167	320,871	358,994	308,163	341,521
	B04-0030-220A	12,310	11,711	15,020	12,413	4,408	9,565	54,548	79,691	44,506	46,969
$P_{ME}*C_{ME}$	B04-0030-217A	2,744,763	2,744,763	2,911,835	2,983,438	3,055,040	3,126,643	3,317,583	3,389,185	3,389,185	3,603,993
	B04-0030-217B	58,995,040	66,369,420	71,900,205	82,961,775	86,648,965	95,866,940	103,241,320	106,928,510	114,302,890	138,269,625
	B04-0030-217C	429,988	450,963	471,938	534,863	545,350	587,300	608,275	629,250	650,225	681,688
	B04-0030-217D	33,996,600	34,164,900	35,847,900	37,530,900	39,887,100	41,738,400	42,579,900	44,262,900	45,609,300	48,133,800
	B04-0030-220A	10,448,038	10,811,448	12,083,383	12,537,645	12,537,645	13,173,613	13,173,613	13,173,613	13,173,613	13,173,613

Table 18. Expected rebuilding costs attributable to component deterioration, scour and earthquake, Bridges B04-0030-217A to B04-0030-220A (in NTD).

Rebuilding costs	Bridge number	Years 1	2	3	4	5	6	7	8	9	10
P_S*C_{RS}	B04-0030-217A	0	0	0	0	0	0	0	0	571	1904
	B04-0030-217B	0	0	0	0	0	0	0	0	1142	1269
	B04-0030-217C	0	0	0	0	0	0	0	0	857	2539
	B04-0030-217D	1999	3618	5426	6981	8885	9520	41,095	42,650	55,978	65,053
	B04-0030-220A	0	0	0	0	0	0	0	0	1999	635
P_E*C_{RE}	B04-0030-217A	119,000	119,000	119,000	119,000	238,000	238,000	476,000	476,000	476,000	476,000
	B04-0030-217B	0	0	0	0	0	0	0	0	0	0
	B04-0030-217C	0	0	0	0	0	0	0	0	0	0
	B04-0030-217D	0	0	119,000	119,000	119,000	119,000	238,000	357,000	476,000	476,000
	B04-0030-220A	0	0	0	0	0	0	0	0	0	119,000
		11	12	13	14	15	16	17	18	19	20
P_S*C_{RS}	B04-0030-217A	2793	2666	1650	2221	3332	3554	16,184	8568	10,853	10,155
	B04-0030-217B	2094	1142	1650	3110	1428	5077	9710	9139	9647	12,693
	B04-0030-217C	2094	1904	2063	1777	1904	3046	10,250	12,566	11,456	10,155
	B04-0030-217D	71,210	77,683	76,319	87,076	97,580	107,132	108,972	129,091	116,969	136,453
	B04-0030-220A	2793	2666	3300	2666	952	2031	11,329	15,994	9044	9520
P_E*C_{RE}	B04-0030-217A	476,000	595,000	595,000	595,000	595,000	595,000	595,000	595,000	595,000	595,000
	B04-0030-217B	0	0	0	0	0	0	0	0	0	0
	B04-0030-217C	0	0	0	0	0	0	0	0	0	0
	B04-0030-217D	595,000	833,000	833,000	952,000	1,190,000	1,309,000	1,428,000	1,785,000	2,023,000	2,261,000
	B04-0030-220A	119,000	119,000	238,000	238,000	238,000	357,000	476,000	476,000	476,000	476,000

operators stochastically updated the strategy by improving and preserving the best strategy in population.

Figure 7 is an example of atypical maintenance strategy. In this example, the maintenance strategy implements maintenance activities at years 30 and 70. The chronological events of the strategy shown in Figure 7 are explained as follows:

1. The CI curve begins at the maximum value of 100 and declines along a path dictated by the corresponding CI slope. Maintenance should be conducted before the CI value drops below the CI threshold value.
2. The first maintenance was performed at year 30, after which the CI value rises to a higher level (90). In this event, maintenance cost $[E(MC)_{30}]$ and rebuilding cost $[E(RC)_{30}]$ are added into the total expected cost calculation. After year 30, the CI begins declining from 90.
3. The second maintenance was performed at year 70, after which the CI value again rises to 90. In this event,

Table 19. The best maintenance strategies for Bridge A02-0080-000B after SOS optimisation, using four CI threshold values between 75 and 85 (in NTD).

	Threshold: 75		Threshold: 76		…	Threshold: 84		Threshold: 85	
Maintenance year	CI value	Expected cost	CI value	Expected cost	…	CI value	Expected cost	CI value	Expected cost
0	100	0	100	0	…	100	0	100	0
5	–	–	–	–	…	–	–	–	–
10	–	–	–	–	…	–	–	–	–
15	–	–	–	–	…	–	–	–	–
20	–	–	–	–	…	–	–	–	–
25	–	–	–	–	…	–	–	–	–
30	–	–	–	–	…	–	–	–	–
35	–	–	89.92	65.333	…	89.92	65.333	89.92	65.333
40	88.53	74.316	–	–	…	–	–	–	–
45	–	–	86.97	14.086	…	86.97	14.086	86.97	14.086
50	86.97	14.086	–	–	…	–	–	–	–
55	–	–	86.97	14.086	…	86.97	14.086	86.97	14.086
60	–	–	–	–	…	–	–	–	–
65	–	–	–	–	…	86.97	14.086	86.97	14.086
70	–	–	–	–	…	–	–	–	–
75	–	–	–	–	…	86.97	14.086	86.97	14.086
80	–	–	–	–	…	–	–	–	–
85	–	–	–	–	…	86.97	14.086	86.97	14.086
90	–	–	–	–	…	–	–	–	–
95	–	–	–	–	…	–	–	–	–
100	75.52	0	76.84	0	…	85.65	0	85.65	0
Total Expected Cost		88.402		93.505	…		135.764		135.764

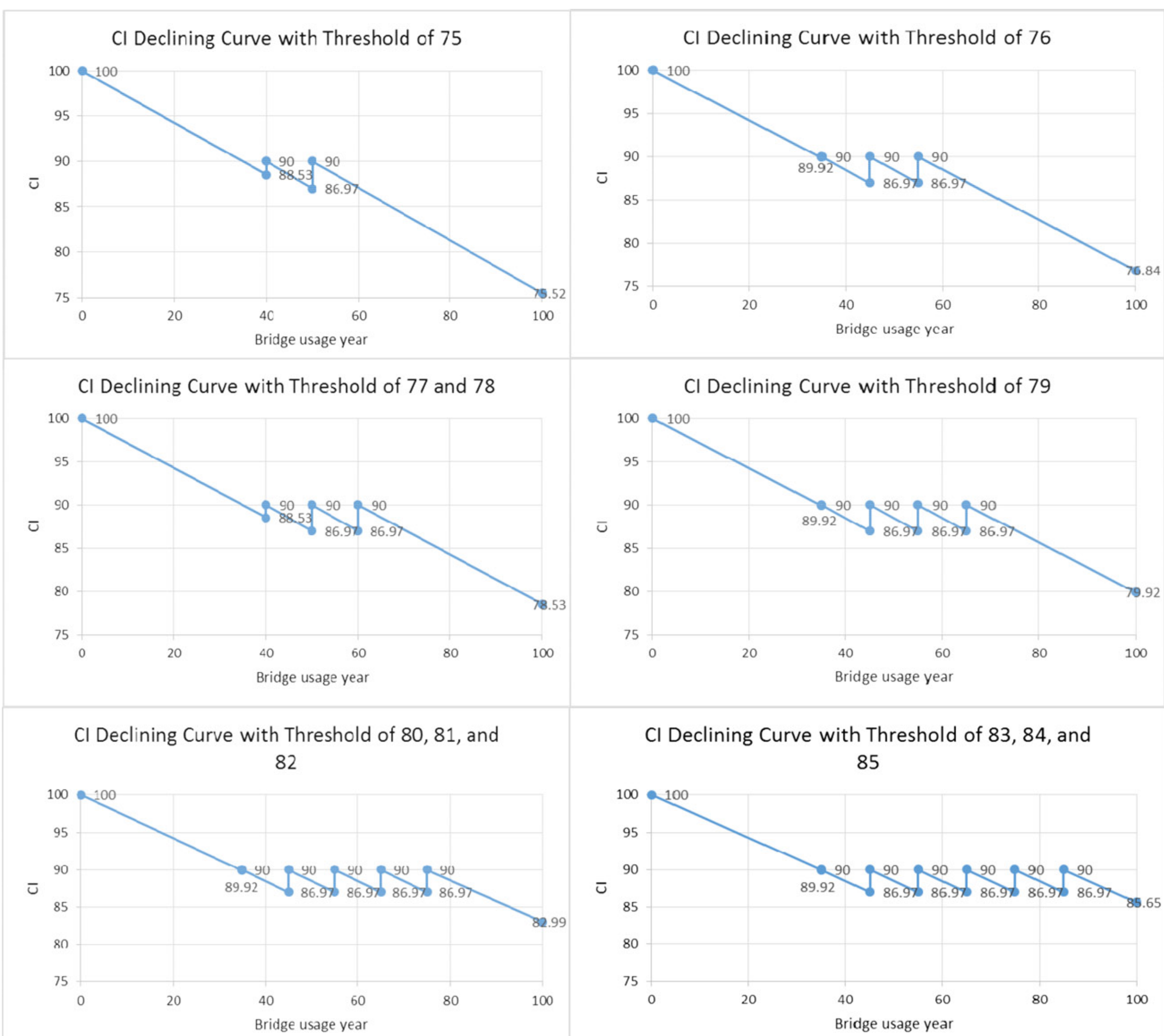

Figure 8. CI declining curves for CI threshold values ranging from 75 to 85.

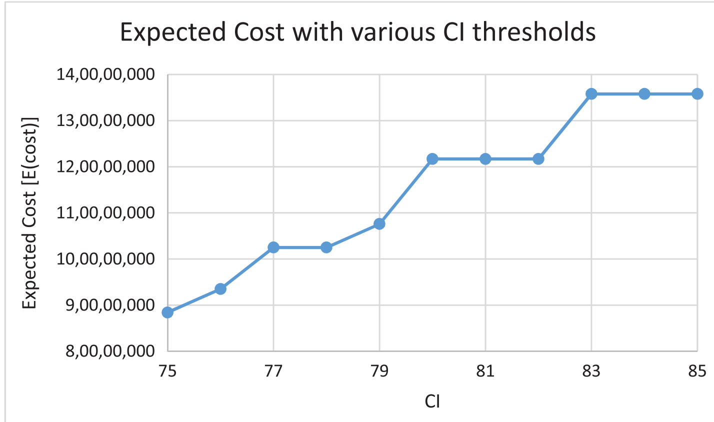

Figure 9. Expected costs at various CI thresholds.

maintenance cost $[E(MC)_{40}]$ and rebuilding cost $[E(RC)_{40}]$ are added to the total expected cost calculation.

4. At year 100 (the end of bridge life cycle), no maintenance is performed because the CI value remains above the CI threshold. Thus, only rebuilding cost $[E(RC)_{40}]$ was added into the total expected cost calculation.

Each E(MC) and E(RC) was calculated using Equations (5) and (6). The full E(Cost) calculation of this maintenance strategy is:

$E(Cost) = [E(MC)_{30} + E(MC)_{40}] + [E(RC)_{30} + E(RC)_{40} + E(RC)_{30}]$.

Step 2: Optimal life-cycle maintenance cost.

The SOS optimising procedure is repeated for different levels of the CI threshold. In the present study, the CI threshold is set between 75 and 85. The SOS preserves the best strategy until the end of the optimisation procedure.

7. Results from Taiwan Bridge Management System

The study uses the 3961 entries of historical bridge data that are included in the Taiwan Bridge Management System (TBMS). Most of the bridges included in the TBMS are reinforced concrete bridges and managed by Directorate General of Highways (MOTC). The life cycle of all of these bridges is assumed to be 100 years. REMBMS was performed in all four of the proposed stages.

After completing the third stage, all expected maintenance and rebuilding costs may be obtained by multiplying each probability with its associated cost. Tables 17 and 18 illustrate the expected maintenance and rebuilding costs that are attributable to component deterioration, scour and earthquake, respectively.

In the last stage, SOS used the corresponding maintenance and rebuilding costs to optimise the best strategy. The experiment was repeated using several threshold levels in the range of 75 to 85 to further elicit the relationship between CI threshold and expected cost. Table 19 displays the best result of the REMBMS strategy after the completion of the optimisation process in detail and Figure 8 depicts the CI declining curve for each period. Using a CI threshold of 85, maintenance on one of the bridges should be implemented during years 35, 45, 55, 65, 75, 85 and 100, with a total expected cost of NTD 135.764 million.

Figure 9 illustrates the relationship between CI threshold and expected cost. It is thus apparent that lower CI threshold values are associated with lower expected maintenance costs. However, it is important to remember that the model introduced in the present study does not consider traffic loading conditions or social costs. Therefore, the bridge management authority must consider these two factors in its ultimate determination of appropriate maintenance schedules and budgets. The REMBMS is designed to assist bridge management authorities by providing various strategic plan options for optimising the timing and budget for bridge maintenance.

8. Conclusions

The present research introduces a novel, integrated model called REMBMS. The solutions obtained using REMBMS provide significantly better maintenance timing and cost estimates than the bridge maintenance approach that is currently used by the transportation authorities in Taiwan. Reasons for the superiority of the REMBMS include: risk-factor identification considers scouring and earthquake damage as well as component deterioration as main risk factors. Monte Carlo simulation is used to determine risk probability; and ESIM is used to extrapolate estimates of bridge maintenance cost from historical data.

The total maintenance cost (E(Cost)) is calculated by multiplying each maintenance probability with its associated cost. Furthermore, the SOS optimises the given objective function to obtain the minimum E(Cost) for each bridge. The present study provides bridge management authorities with an effective approach for determining the optimal timing and budget for maintaining transportation bridges.

Disclosure statement

No potential conflict of interest was reported by the authors.

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