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Reliability-based Evaluation of River-bridge Flood Resistance Ability Via a Visual Inspection Table

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Abstract

This research establishes a reliability-based preliminary evaluation table for assessing river-bridge flood resistance. Flood resistance for a river-bridge is affected by numerous factors, including bridge structure, river environment, hydrology, and riverbank protection infrastructure. Flood resistance assessment is a complex issue that involves multiple areas of expertise. A comprehensive assessment process is extremely time-consuming and difficult to implement in practice, especially given the limited time and resources. Many bridges require risk evaluations. A preliminary visual inspection is often conducted in response to these problems. The primary issue with visual inspection is the high subjectivity regarding the understanding and standards for the various indicators. To solve this issue, a Bayesian Network (BN) is proposed to combine the contributions from experts and reliability analyses. Eight bridges are selected for performing FOSM-based reliability calculations using a parameterized ABAQUS model. An ideal preliminary inspection table enables a close relationship with the failure probability that is calculated from an advance analysis. Thus, PSO is employed to maximize the correlation between the scores obtained from the visual inspection table and the failure probability calculated from the BN to establish a reliability-based visual inspection table that provides a strong foundation for a bridge risk analysis.

Keywords: *bayesian network, PSO, reliability, preliminary visual inspection, flood risk*

1. Introduction

Bridges are considered critical and essential structures because of their fundamental functions such as requirements during an emergency. There are thousands of bridges in Taiwan. Many of these bridges were built several decades ago and need to be examined to ensure operational safety. Thus, bridge management must review various bridges that are under their jurisdiction and identify bridges that require prioritized bridge retrofitting. Because detailed evaluations are time-consuming, preliminary evaluation via visual inspection, which is the focus of this study, will be necessary despite imperfections. Taiwan's earliest Preliminary Risk Evaluation Table (PRET) for flood resistance was proposed by Tang *et al*. (2002). This version was treated as the fundamental basis of other PRETs that were subsequently proposed (Chen *et al.,* 2007; DGH, 2006; DGH, 2011; Liao *et al.*, 2015). These PRETs, similar to the preliminary flood risk assessment in the European Union (Muller, 2013), are constructed to provide pilot bridge safety information via a visual inspection. If the total assessment score does not satisfy a predefined standard, the evaluation should proceed to an advanced investigation, such as a finite element analysis (Rajabalinejad *et al*., 2010), to ensure the bridge safety. The evaluation of these PRETs includes several items, which are potential threats for bridge safety. Each evaluated item is allocated a weight to indicate its relative importance. The sum of all weights is 100. The items in the PRET proposed by Tang *et al.* (2002) include the scouring depth, the foundation type, the attack angle of the river flow, the presence of protective facilities at the river bank and bed and the presence of a dam upstream. Similarly, the Japanese Railway Technical Research Institute (RTRI) established a "Scouring Evaluation Table" for use in Japan (2007). The University of Washington in the US proposed a CAESAR evaluation form (1997). The American Federal Highway Administration (FHWA) also released three manuals (HEC-18 2012; HEC-20 2001; HEC-23 2001) that offered methods for evaluating bridge scour and stream stability. It is seen that there is a need to develop an efficient and accurate bridge preliminary evaluation table against floods.

This study determines the score distribution for the items in the evaluation form via a reliability analysis and optimization method. To fulfill this target, the risk evaluation for a bridge is divided into two parts: 1. Analysis using a visual inspection table and 2. Calculating failure probability using a Bayesian Network (BN). The second part on a BN may be subdivided into five

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portions: 1. Using the item relationship in the current PRET to build the structure of the Bayesian network; 2. Using the item weights suggested in the current PRET to establish conditional probability of various nodes in the first part of the Bayesian network; 3. Integrating the method of a First-order Second Moment (FOSM) with ABAQUS to compute reliability; 4. Using outcomes of the reliability analysis to determine the conditional probability at various nodes in the second part of the Bayesian network; 5. Using historical events to update the failure probability of the Bayesian Network. Results of PRET and the Bayesian network were used to adjust the set of weights in the PRET to improve the correlation between Bayesian failure probability and the PRET scores via Particle Swarm Optimization (PSO). Adjustments to the set of weights will enable the evaluation tables to better reflect actual safety conditions of river-bridges. Eight bridges with pile foundations across Taiwan are selected as representative samples: Lanyang Bridge, Dongshi Bridge, Taichung-Changhua Bridge, Jishui River Bridge, Qianniao Bridge, Puzi River Bridge, Shuangyuan Bridge, and Wanda Bridge.

The design variable in PSO is the set of weights of the items in the evaluation table (set as the particle in PSO). Fig. 1 shows the detailed PSO evaluation process. For a given set of particles, the optimization process simultaneously computes both the Bayesian reliability and the preliminary evaluation results to acquire the correlation coefficient. The pbest and gbest scores that are determined by PSO (details to be provided in section 2.0) are employed to identify the optimal set of weights. The calculation process requires rebuilding the ABAQUS finite element model and Bayesian network as shown in Fig. 2. Thus, parameterized models for both procedures are constructed to fulfill this need.

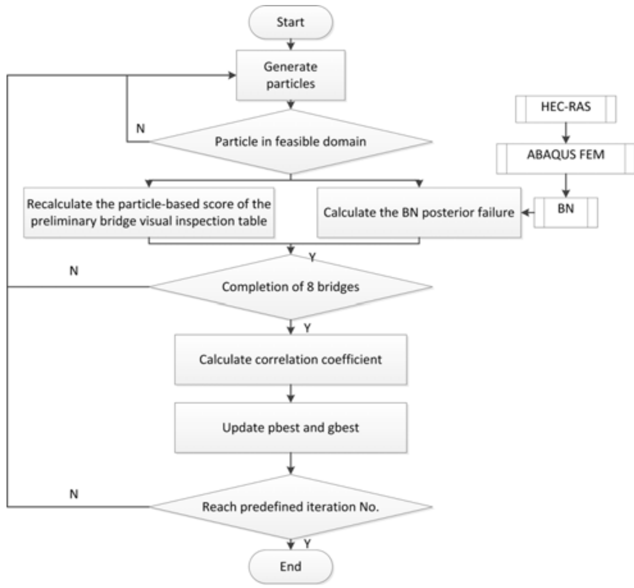

Fig. 1. Process Flow for the Particle Swarm Optimization (PSO) Algorithm Used in This Study

The objective of this study is to use a reliability analysis and optimization method to determine a PRET for bridges in Taiwan, as indicated in Figs. 1 and 2. Three additional analysis modules (i.e., the HEC-RAS hydraulic analysis, the ABAQUS finite element analysis and the Bayesian Network) are built to support the evaluation process and to achieve the research goal. Results of the HEC-RAS hydraulic analysis are used to build the scour risk of the investigated bridges. Finite element analysis, a general structural analysis tool, is adopted and served as the deterministic model. The Bayesian Network is used to calculate reliability for a complicated system. The details of the proposed evaluation process are described in the following section.

2. Particle Swarm Optimization

PSO, a gradient-free approach, was proposed by Eberhart and Kennedy (1995). PSO is a heuristic algorithm that operates on the basis of a large population of solutions. Gradient-based optimization approach such as Sequential Quadratic Programming (SQP) is another popular method. SQP is efficient at finding local minima when an optimization problem is high-dimensional, nonlinearly constrained, and with convex behavior. On the other hand, similar to most gradient-based optimizers, SQP is unable to find global minima and handle an optimization problem with noisy and discontinuous functions. PSO, similar to Genetic Algorithm (GA), is a population-based search method. Both approaches are often considered as an unfeasible approach due to their high cost. The enhancement of computer speed has enabled PSO and GA to become a feasible approach. The advantage of PSO is it is more computationally efficient (uses less number of function evaluations) than the GA (Hassan *et al*., 2005). In addition, compared to GA, PSO is popular due to its simplicity. Therefore, PSO is adopted in this study to optimize the correlation between the methods of the preliminary visual inspection table and the Bayesian network. That is, the optimization target is to find a set

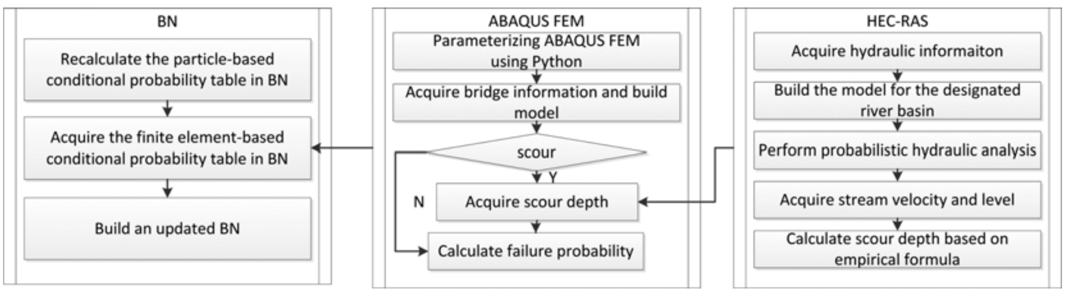

Fig. 2. Supplementary Calculation Modules Used During the Optimization Process

Table 1. Assessment Items in Preliminary Inspection Table

No.		Name
1	Indoor items	Upstream river dam or reservoir facilities
2		Foundation type
3		Bending or narrowing of the river
4		Eroded riverbed
5		Material on the riverbed
6		Location of the main channel
7	On-site items	Hydraulic drop effect
8		Attack angle of flow
9		Area ratio of bridge to cross-section
10		Foundation scouring depth
11		Effective pier diameter
12		Protection for riverbank
13		Protection for riverbed

of weights in the preliminary visual inspection table that maximize the correlation. To execute PSO, random variables were first generated to initialize a population which is a set of individual particles. Often, a population includes 20 to 30 particles. A particle is the design variable in optimization and is the 13 weights indicated in Table 1. Particle movements were influenced by the optimal experience of an individual particle and the population. Weighted values were employed to determine the degree of influence between the two values. Thus, the physical definition of PSO may be regarded as similar to the "mating" step of a GA. Random elements were also considered when determining the direction of a particle movement, which gives particles a chance to leave local trends and prevent them from being trapped within local optimums. Additionally, every particle that is used in PSO algorithms may be a potential solution that carries memory. These features were not provided in a GA. Many variations have been proposed for PSO. The following equation briefly describes the PSO that is used in this study. A new particle, which represents a set of weights in this study, is generated using Eq. (1) as

$$\vec{x}_i(t+1) = \vec{v}_i(t+1) + \vec{x}_i(t) \tag{1}$$

where $\vec{x}_i(t+1)$ denotes the position of the i^{th} particle in the next iteration, $\vec{x}_i(t)$ denotes the position of the i^{th} particle in the current iteration and $\vec{v}_i(t+1)$ denotes the velocity of the i^{th} particle in the current iteration. The position of a particle represents the values of this particle. The velocity of the i^{th} particle is determined by Eq. (2) as

$$\vec{v}_i(t+1) = w \times \vec{v}_i(t) + r_1 c_1(\vec{x}_{pBest} - \vec{x}_i(t)) + r_2 c_2(\vec{x}_{gBest} - \vec{x}_i(t)) \tag{2}$$

where w is the inertia factor; $\vec{v}_i(t)$ is the velocity at the previous iteration; r_i (i = 1–2) are random numbers between 0 and 1; c_1 and c_2 are the cognition factor and the social factor, respectively; $\vec{x}_{pBest}$ is the particle position with the minimum objective value in the i^{th} population; and $\vec{x}_{gBest}$ is the particle position with the minimum objective value among all populations. Detailed information about the PSO parameter setting is provided in Table 2. Please note that PSO in this study is used to optimize the correlation between the methods of the preliminary visual inspection table and the Bayesian network. Thus, each particle represents a set of weights in the preliminary visual inspection table. A particle is a vector with a length of 13, as indicated in Table 1.

Table 2. Parameters in PSO

No. of particles	20
Length of particle	13
Iteration No.	300
Upper bound for the particle	30
Lower bound for the particle	1
Max (w)	0.9
Min (w)	0.2
c_1	2
c_2	2

3. Establishing Parameterized ABAQUS Finite Element Model

The conditional probability in the second part of the Bayesian network is dependent on the reliability analysis results that are conducted by the FOSM (Wu *et al*., 2011). The accuracy of the FOSM is dependent on a precise deterministic analysis. Finite element simulation is considered to be a reliable tool for structural analysis. In addition to FOSM, several reliability analyses such as First Order Reliability Method (FORM), Second Order Reliability Method (SORM), Monte Carlo Simulation (MCS), Importance Sampling (IS) and subset simulation, are available and may be used in this study. FOSM, FORM and SORM are considered as moment-based reliability analysis. MCS, IS and subset simulation are categorized as simulation-based reliability analysis. In general, the computational cost of simulation-based approaches is higher than that of moment-based approaches but with better accuracy if the system is highly nonlinear. As mentioned, in addition to nonlinearity, the accuracy of reliability analysis also depends on the precision of the deterministic model. This is a typical trade-off problem. Earlier researches (Liao *et al.,* 2015; Liao *et al.,* 2016) used a simplified deterministic model with a simulation-based reliability analysis. This study proposes a different approach to complete the reliability analysis. That is, a more precise deterministic model with a moment-based reliability analysis is proposed to evaluate the reliability for a given system. Because the execution of ABAQUS is time consuming, among many available moment-based methods, the most efficient approach (i.e., FOSM) is selected to perform the reliability analysis. Therefore, this study integrates FOSM with ABAQUS to compute bridge reliability. The deterministic model (ABAQUS model) is divided into two parts: the bridge and the soil structure. The bridge foundations that are being investigated in this study have a single pier with a pile group. For the soil model, cylinders that are similar to the pier and piles are employed in the analysis to

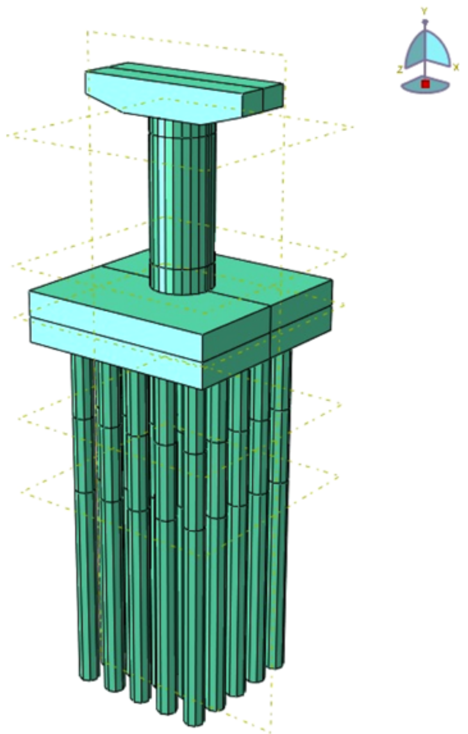

Fig. 3. 3D Model of the Analyzed Bridge

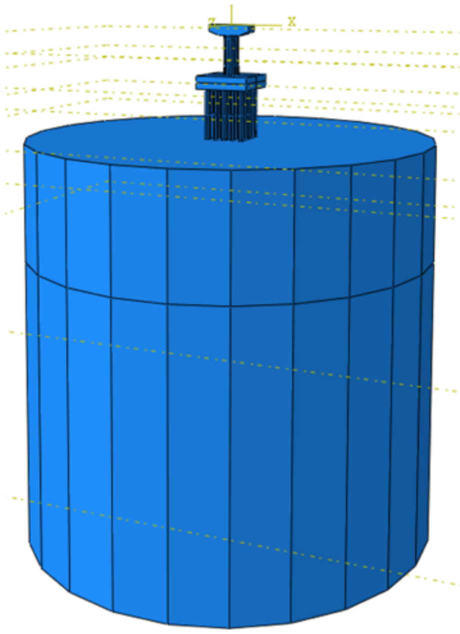

Fig. 4. The Complete 3D Model of the Analyzed Bridge (soil included)

reduce the element distortion in the meshing process, which may affect the precision of the analysis. Figs. 3 and 4 show the 3D model of the analyzed bridges. A mesh convergence analysis is performed to determine the element size in the built ABAQUS model.

A reliability analysis, such as the FOSM adopted in this study, is an optimization process that is aimed at finding the minimum

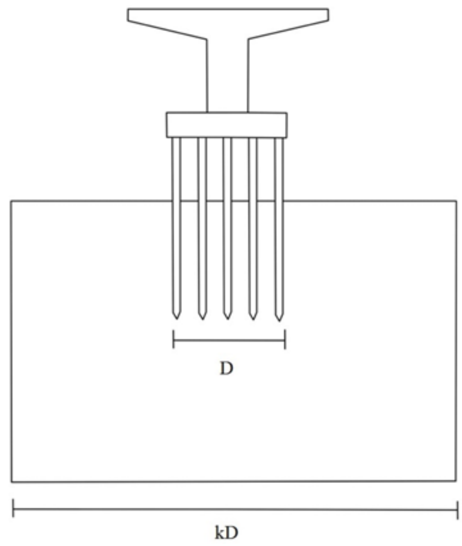

Fig. 5. Concept Diagram for the 3D Soil Diagram

distance between the failure point and the origin (i.e., the location of mean value) in the standard random variable space. That is, the ABAQUS model needs to be reanalyzed in each optimization iteration. To fulfill this need, Python is adopted to generate a parameterized finite element model that automates the previously mentioned reanalyzed procedure from the model building (e.g., meshing), analysis to data acquisition (postprocessing). The pile diameter, number of piles, material properties, number of soil layers, or grid settings, are considered to be variables in our ABAQUS model. Soil property exerts critical influences to the analytical results. The setting methods are described as follows:

(1) Horizontal dimensions of the soil: This dimension is often expressed using kD (Fu, 2012), where D is the distance between the outermost piles (as shown in Fig. 5) and k is a multiplier that is larger than 1. The primary factors for determining the value of k include computing cost and desired precision. By trial and error, the value of k in this study is 10. Because this study only considers the horizontal force that is induced by floods and disregards the settlement effect caused by vertical loads, a solid support is assumed on the pile bottom and the embedded depth of a pile is directly employed as the vertical dimension of the soil.

(2) Number of soil layers: Drilling reports that are provided in the design drawing are used to determine the soil property and number of soil layers. Based on the survey, the maximum number of layers of soils that can be accommodated within the parameterized ABAQUS model is 6.

Table 3. Poisson Ratios Used in This Study

Soil category	Poisson ratio
Clay	0.35
Sand	0.3
Gravel	0.25

(3) Elastic modulus is (E_D) calculated using Eq. (3)

$$E_D = 2(1+\mu_D)G_D \tag{3}$$

where G_D is the soil dynamic shear modulus and m_D is the Poisson ratio, as shown in Table 3.

(4) Typical material properties used in Taiwan are provided below. The concrete strengths are 28 MPa and 21 MPa for the bridge pier and caisson, respectively. The SD280 steel bar is used for diameters less than or equal to 16 mm whereas SD420W is used for diameters greater than 16 mm. Soil property of each bridge is described in its design drawing and is used in our ABAQUS model.

4. Reliability Analysis and Random Variables

This study considers five limit state functions that correspond to the performances of the pile shear stress, the pile axial stress, the bridge serviceability (the horizontal displacement on the pile head), the soil bearing and the soil pulling force. Detailed descriptions of these functions are provided in Liao *et al.* (2016).

The FOSM is selected for the reliability analysis. The FOSM converts a reliability problem into an optimization formulation by minimizing the distance between the limit state function to the origin in standard space. The minimum distance is referred to as the reliability index (β). Because the deterministic analysis (e.g., ABAQUS analysis) in this paper induces an implicit limit state function, a first-order Taylor series is used to approximate the limit state function, in which the mean values of random variables are the expansion point. The Taylor series (e.g., g(***X***)) is used to acquire both μ_g and σ_g (indicated in Eqs. (4) and (5)), which are necessary parameters for calculating the FOSM-based reliability index (b), as described in Eq. (6):

$$\mu_g = -\sum_{i=1}^{n} \mu_{X_i'} \left(\frac{\partial g}{\partial X_i'} \right) \tag{4}$$

$$\sigma_g^2 = \sum_{i=1}^{n} \sigma_{X_i}^2 \left(\frac{\partial g}{\partial X_i} \right) = \sum_{i=1}^{n} \left(\frac{\partial g}{\partial X_i'} \right) \tag{5}$$

$$\beta = \frac{\mu_g}{\sigma_g} \tag{6}$$

where ***X'*** represents a random variable in standard space and $\mu_{X_i'}$ is the mean value for each random variable. The resulting β can be converted to the corresponding reliability (r; the survival probability which is 1- P_f), as shown in Eq. (7)

$$\rho = \Phi(\beta) \tag{7}$$

where F is the cumulative probability density function of standard normal distribution. As shown, the greater distance (β) will yield a higher reliability (r), and vice versa. The calculated reliability is used as the conditional probability for the failure probability node in the proposed Bayesian network. Details are provided in section 5. A total of three random variables are considered during the reliability analysis. Two of these random variables, namely, water level and stream velocity, are calculated using the Hydrologic Engineering Center's River Analysis System (HEC-RAS), which is developed by the US Army Corps of Engineers. Input information for HEC-RAS, such as the hydrological data, are primarily collected from the Geographical Information Center of the Water Resources Agency of the Ministry of Economic Affairs (MOEA) and the reports of regulation planning for various river basins. Using this information, a probabilistic HEC-RAS is conducted to capture the uncertainty in the water level and stream velocity. Their probability density function (pdf) is determined using chi-squared tests. The third random variable—scouring depth—is calculated using various empirical scouring depth equations. Among many empirical equations, this study selects seven equations, as recommended by Liao *et al*. (2015), for use in this study. Detailed information about the random variables is described in the next section.

4.1 Stream Velocity and Water Level

Currently, the mean values of stream velocity and water levels

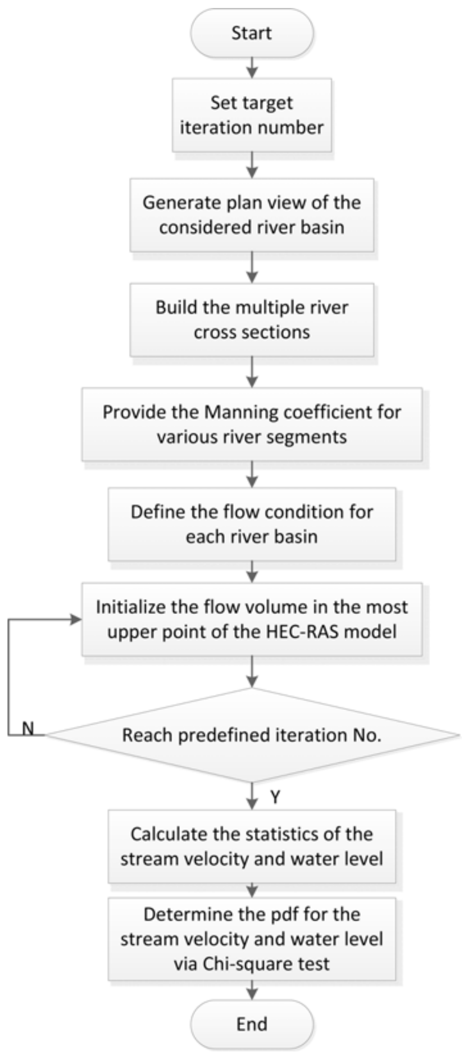

Fig. 6. Procedure of Monte-Carlo for Acquiring Stream Velocity and Water Level Used in This Study

that correspond to a 100-year returning period are used for bridge design in Taiwan. This helps engineers simplify the design procedure. However, reliability analysis requires additional information, such as the variation in stream velocity and the corresponding pdf. This study utilizes HEC-RAS with relevant hydrological data (such as the upstream flow volume and Manning's coefficient) to establish a probabilistic-based hydraulic model. Fig. 6 shows the detailed analytical process. As shown, this study utilizes a Monte Carlo simulation to collect data for the stream velocity and water level. Once the execution number reaches the predefined target value, the coefficient of variation and pdf for the stream velocity and water level are readily computed. The bridge basic information and the statistics of random variables are summarized in Tables 4 and 5, respectively. Note that the Manning coefficient in the HEC-RAS model is a random variable; its values vary depending on the bridge location.

4.2 Calculating Local Scouring Depths

Hong and Abid (2016) showed that live-bed local scour in the field can be reproduced in the laboratory model if an appropriate sediment size is selected. Several laboratory-based formulae are available, in which seven of them suggested by Liao *et al.* (2015) are adopted to compute the local scouring depth for each bridge. The required information about scouring depth in the reliability analysis is the mean value, standard deviation and pdf of the water level and stream velocity. The average of the results of each prediction equation is the mean value for the scouring depth; 1/6 of the difference between the minimum values and maximum values obtained from each prediction equation is the standard deviation for the scouring depth. The pdf is determined by a chi-square test using the results of the prediction formulae. Note that the stream velocity, water level, and local scouring depth in this study are either directly or indirectly acquired from the hydraulic analysis. These three variables are highly correlated (with a minimum correlation coefficient of 0.9). Table 5 shows the calculation results of these three random variables for the eight selected bridges. The scouring depth exhibited relatively high variance (with a CV range of 0.2 to 0.74). Because the selection of a single prediction formula for a specific bridge is challenging, seven different prediction equations are used for each bridge. This decision introduces the epistemic uncertainty in the calculated scouring depth and explains the reason for a significant variance. If an applicable scouring depth formula can be identified, the uncertainty of scouring depth may be significantly reduced.

Table 4. The Basic Information of the Investigated Bridges

Name	Type*	Length	Time built
Lanyang Bridge	Type A	~800 m (34 span)	1991
Dongshi Bridge	Type B	~564 m (12 span)	2002
Taichung-Changhua Bridge	Type C	~2320 m (64 span)	2007
Jishui River Bridge	Type A	~250 m (8 span)	1986
Qianniao Bridge	Type A	~200 m (5 span)	1996
Puzi River Bridge	Type C	~260 m (8 span)	2005
Shuangyuan Bridge	Type C	~2800 m (68 span)	2011
Wanda Bridge	Type A	~2400 m (65 span)	2014

*Type A: Prestressed concrete girder with pile foundation
Type B: Steel I girder with pile foundation
Type C: Steel box girder with pile foundation

5. Establishment of the Bayesian Network

The Bayes Net Toolbox (BNT), which is an open-source Matlab package for directed graphical models that was developed by Murphy (2001), is adopted in this paper to establish the Bayesian network. A Bayesian network is a graphical structure that represents an interested variable with uncertainty. The nodes, which are the most basic elements in a Bayesian network, represents a set of random variables. To complete a Bayesian network, a set of directed links connects pairs of nodes, which represents the direct dependencies between variables. The relationship between variables is described by conditional probability distributions that are associated with each node. Note that a directed cycle is not allowed in a Bayesian network.

To perform a bridge reliability analysis using Bayesian network, definitions of nodes, the structure of a network and dependence between nodes are needed. The nodes in our BN are the assessment items in the previous PRET. The structure is based on the PRET that was suggested by Liao *et al.* (2015). The conditional probability distributions between nodes are calculated based on the item weights in the PRET. Based on the collected evidence in the selected bridge sites, the parameters in the BN is updated

Table 5. Statistics of Random Variable foR Each Bridge in This Study

Randomized variable / Bridge name	Mean stream velocity (m/s)		Water level (m)		Scouring depth (m)	
	Avg.	Std Dev.	Avg.	Std Dev.	Avg.	Std Dev.
Lanyang Bridge	2.7	0.6	8.5	2.1	8.0	3.6
Dongshi Bridge	6.5	1.8	4.9	1.6	7.6	5.6
Taichung-Changhua Bridge	4.0	0.9	7.2	4.9	4.9	2.2
Jishui River Bridge	3.8	0.5	5.5	0.8	3.8	2.0
Qianniao Bridge	3.6	0.4	2.5	0.6	2.7	1.5
Puzi River Bridge	2.6	0.4	6.0	1.1	3.2	1.9
Shuangyuan Bridge	10.5	2.1	10.5	0.7	7.8	1.6
Wanda Bridge	9.5	1.9	3.0	0.6	7.2	1.4

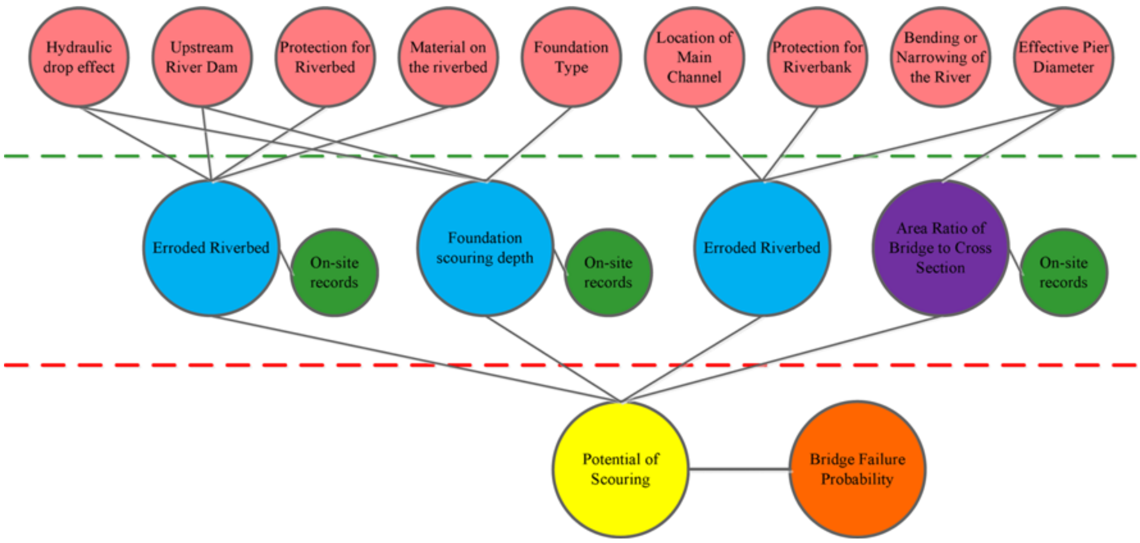

Fig. 7. Concept Diagram of the Bayesian Network

according to Bayesian theory. Details of constructing a BN are provided in the next section.

The existing PRET includes 13 items. Based on the evaluation location, these items are subdivided into two groups: indoor and onsite evaluation items (as shown in Table 1). In the proposed BN, these 13 items are categorized into four groups based on their influencing effect on bridge scouring, namely, (1) eroded river bed; (2) river bank erosion; (3) area ratio of bridge to cross-section; and (4) foundation scouring depth. These four groups serve as the basis for determining the scouring potential, that is, these four nodes represent the parent nodes and child nodes of the potential of a scouring node and the 13 PRET items, respectively, as shown in Fig. 7. For example, four parent nodes exist for the node of an eroded river bed, namely, upstream river dam or reservoir facilities, material on the river bed, hydraulic drop effect, and protection of the river bed. The node of river bank erosion is provided with three parent nodes, namely, bending or narrowing of the river, location of the main channel, and protection of the river bank. The node of the bridge failure probability has one parent node of scouring potential. To evaluate the failure probability of a bridge, two more conditional probabilities must be provided for the network, namely, bridge failure probability with or without scouring potential. These two conditional probabilities can be acquired using the reliability analysis described in Section 4.

The advantages of using the existing PRET to create the network structure are as follows: (1) conditional probabilities between nodes can be defined using the scoring weights between various nodes; (2) the network structure can be maintained within a reasonable dimension to prevent excessive difficulties during calculation. The 13 items in the PRET can serve as the parent nodes for scouring potential node. However, the use of too many parent nodes of the interested node can require a long computing time when revising the Bayesian network. Because nodes of the eroded river bed, river bank erosion, area ratio of bridge to cross-section and foundation scouring depth are relatively more important compared with the remaining 13 items, they are used to divide the BN from two levels to three levels, as shown in Fig. 7. This arrangement can significantly reduce computation time and enable the total Bayesian network to reflect the mutual influences between the parent nodes and children nodes.

6. Conclusions

The primary objective of this study is to re-adjust the set of weights that are used in the evaluation table for scouring potential and to deliver a more reliable PRET. The design variables in PSO are designated as the weights of the evaluation items in the PRET, as shown in Table 1. Based on the comprehensiveness of the collected hydraulic data and the construction design drawing, this study selects eight bridges in Taiwan to demonstrate the proposed approach. Both the PRET and BN methods are conducted for each bridge; the results are displayed in Table 6. The correlation coefficient between the PRET scores and the souring potential is 0.88, which proves that the Bayesian network can accurately reflect the principle of the evaluation tables. The correlation coefficient between the PRET scores and the Bayesian failure probability is only 0.75, which indicates a limited correlation between these two values and additional improvement in the evaluation tables is needed. For example, the Taichung-Changhua Bridge and Qianniao Bridge exhibited similar failure probabilities, as calculated by the Bayesian network despite the different evaluation scores for the two bridges. The following chapters primarily investigate the use of the PSO algorithm to identify the optimal set of weights, investigate the resulting impact on the scouring potential and failure probability, and discuss additional improvements.

6.1 Evaluation Results using the PRET (prior to optimization)

The evaluation results of the eight bridges using the PRET demonstrated that the Wanda Bridge had the highest score (20.0,

Table 6. Correlation between Preliminary Evaluation scores and Bayesian Failure Probabilities of Each Bridge (using original set of weights)

Bridge name	Preliminary evaluation score (A)	Scouring potential (B)	Correlation coefficient (A & B)	Bayesian failure probability (C)	Correlation coefficient (A & C)
Lanyang Bridge	6.2	4.16×10^{-2}	0.88	3.19×10^{-5}	0.75
Dongshi Bridge	1.5	3.97×10^{-2}		3.06×10^{-5}	
Taichung-Changhua Bridge	3.9	4.16×10^{-2}		2.59×10^{-5}	
Jishui River Bridge	4.8	4.16×10^{-2}		2.58×10^{-5}	
Qianniao Bridge	12.1	8.18×10^{-2}		5.78×10^{-5}	
Puzi River Bridge	7.7	4.83×10^{-2}		7.09×10^{-5}	
Shuangyuan Bridge	12.0	5.18×10^{-2}		2.20×10^{-2}	
Wanda Bridge	20.0	2.20×10^{-1}		1.53×10^{-1}	

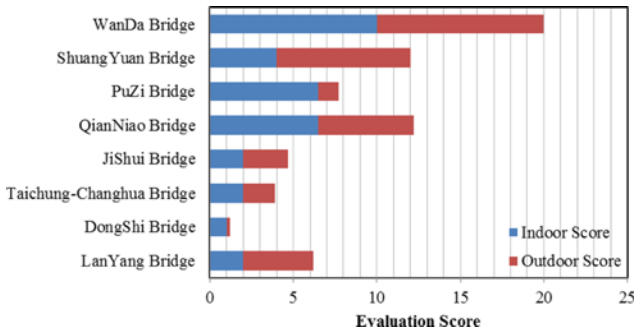

Fig. 8. Bar Chart for the Cumulative Scores of Indoor and Outdoor Item

as shown in Table 6). According to the PRET standards, this bridge has a low scouring potential (< 25). The Dongshi Bridge had the lowest score (1.5) and was also cauterized as a bridge with low scouring potential. The influence of bridge location on the indoor and onsite scores warrants investigation. The bridge locations are as follows: Upstream - Qianniao Bridge; midstream: Dongshi Bridge, Jishui River Bridge, and Puzi River Bridge; downstream: Lanyang Bridge, Taichung-Changhua Bridge, Shuangyuan Bridge, and Wanda Bridge. As shown in Fig. 8, the Qianniao Bridge, Puzi River Bridge, and Wanda Bridge were significantly affected by indoor evaluation items. However, as these bridges belonged to different sections of the river basin, indoor or onsite evaluation items do not significantly influence the evaluation results. The Puzi River Bridge was given a total score of 7.7, of which the main contributing evaluation item was the *location of the main channel,* as the distance between the main channel to the bridge abutment was within 5 meters, which yielded a score of five points. Although the Puzi River Bridge had a reasonable correlation with a scouring potential probability (4.8%), a single evaluation item (*location of the main channel*) was the major contributor that is not appropriate. Similarly, the set of weights in the PRET implies that piers with greater size produced less space for water flow, which should produce higher scouring potential. However, large-sized piers also provided satisfactory structural performance; thus, the weight provided to the pier diameter should be re-examined with greater caution. Additional improvements to the PRET would be required.

6.2 Optimized Set of Weights for the PRET

Although high levels of correlation were observed between the PRET scores and scouring potential of the bridges, the correlation coefficient for the Bayesian failure probability was only 0.75. To improve the correlations between the scores of the preliminary evaluation and the Bayesian failure probability, this study attempted to adjust the set of weights, which should be converted to conditional probabilities between the parent nodes and children nodes in the Bayesian network. To verify the stability of the optimal solution that was identified by the optimization process, this study also repeated the optimization ten times using the same search space and iteration number. The results were displayed in Table 7, and the following discussion is provided:

(1) The three items of the *upstream river dam or reservoir facilities* (No. 1 in Table 1), *foundation scouring depth* (No. 10 in Table 1) and *protection for riverbank* (No. 12 in Table 1) exhibited decreasing trends during the ten rounds of optimization. The possible reason for this phenomenon was that foundation scouring did not occur, dam facilities and river bank protection were available for all eight bridges. Thus, the bridges exhibited minimal difference in the evaluation results. During the optimization process, these evaluation items exhibited low sensitivity, which decreased their importance. Their set of weights was lowered to reduce their degree of influence in the Bayesian network.

(2) For indoor evaluation items, the majority of the weights were increased after optimization. *Material on the river bed* (No. 5 in Table 1) was given the highest level of increase because the original set of weights was only assigned two points, which was considered extremely low compared with other items; this score was significantly increased during the optimization process. In addition, the existing PRET included "special rules". For example, if the score of the *Eroded riverbed* (No. 4 in Table 1) was significant, the bridge was assumed to have high scouring potential disregarding the total evaluation score is greater than the threshold value or not. The optimization process assigned a higher weight to this item, which is reasonable.

(3) The optimization results indicated that the correlation between the PRET scores and the bridge failure probability was improved from 0.75 to 0.92 (as shown in Table 7). The results were extremely stable. However, the coefficient of variation (cov)

Table 7. Results of Ten Optimizations

	Design variable (evaluation item)	Original weight	Results of each round of optimization											
			No.1	No.2	No.3	No.4	No.5	No.6	No.7	No.8	No.9	No.10	Mean	Cov
Indoor items	1	7	3	3	3	3	3	3	2	2	2	3	3.1	0.44
	2	7	4	9	10	12	12	10	12	11	9	6	9.3	0.29
	3	6	9	12	9	10	10	10	11	9	10	13	9.9	0.18
	4	8	13	12	12	12	12	11	13	11	12	14	11.8	0.13
	5	2	9	12	12	12	13	10	13	11	10	14	10.7	0.30
	6	5	2	3	2	4	4	2	3	2	4	3	3.1	0.34
Outdoor items	7	5	2	2	3	5	5	6	2	4	7	5	4.2	0.41
	8	7	15	4	9	3	3	10	9	10	8	3	7.4	0.52
	9	5	3	3	4	3	3	3	2	2	2	4	3.1	0.31
	10	20	12	15	14	13	14	11	13	15	13	15	14.1	0.17
	11	13	12	10	10	11	12	11	7	10	10	9	10.4	0.16
	12	5	3	5	2	3	3	2	3	2	3	2	3.0	0.37
	13	10	13	10	10	9	9	11	10	11	10	9	10.2	0.12
	Total weight	100	100	100	100	100	103	100	100	100	100	100		
	R*		0.93	0.92	0.93	0.92	0.92	0.93	0.92	0.93	0.92	0.92	0.92	

*Correlation coefficient between the Bayesian failure probability and evaluation table score in this round of optimization

Table 8. Set of Weights of Evaluation Tables Recommended by Various Experts

Set of weights of evaluation tables recommended by various experts					
(evaluation item)	Set of weights of the NTU version	Set of weights of the NCHU version	Set of weights of the CECI version	Avg	Std Dev
Upstream river dam or reservoir facilities	5	3	7	5.00	2.00
Foundation type	10	3	7	6.67	3.51
Bending or narrowing of the river	5	10	6	7.00	2.65
Eroded riverbed	5	10	8	7.67	2.52
Material on the riverbed		5	2	3.50	2.12
Location of the main channel	5	10	5	6.67	2.89
Hydraulic drop effect	5	4	5	4.67	0.58
Attack angle of flow	5	4	7	5.33	1.53
Area ratio of bridge to cross section	5	8	5	6.00	1.73
Foundation scouring depth	15	13	20	16.00	3.61
Effective pier diameter	7.5	12	13	10.83	2.93
Protection for riverbank	5	4	5	4.67	0.58
Protection for riverbed	5	4	10	6.33	3.22

for the set of weights exhibited a large range from 0.12 to 0.52 (as shown in Table 7). Despite significant improvements in the correlation coefficient, the variance was too large for the set of weights. To reduce the variance in the weights among different optimizations, this study proposed integration of expert opinions into the set of weights to better reflect the actual status. Expert opinions, which were extracted from several existing PRETs, were regarded as prior probability, and Bayesian theory was used to revise the optimized set of weights, as described in section 6.3.

6.3 Updating Optimal Set of Weights Using Bayes' Theorem

Three different PRETs (Tang *et al.*, 2002; Chen *et al.*, 2007; DGH, 2011) were used to obtain the prior information, and the statistics of the PRETs were displayed in Table 8. To apply the Bayes' theorem, the values of the evaluated items were assumed to be a normal distribution and expressed as follows. To follow the procedure described below, a non-normal data must be transformed to normal (e.g., using Box-Cox power transformation, Box and Cox (1964)). If transformation is not conducted, the Markov-Chain Monte Carlo simulation may be used in applying the Bayes' theorem. However, the application of non-normal data is beyond the scope of the current study.

$$N_{\mu}(\mu', \sigma') \tag{8}$$

where μ' and σ' were the mean value and the standard deviation described in Table 8. The probability of the Bayesian Network analysis results, as described in section 6.2, can be expressed using Eq. (9).

$$\prod_{i=1}^{n} \frac{1}{\sqrt{2\pi}\sigma} \exp[\frac{-1}{2}(\frac{x_i - \mu}{\sigma})^2] = \prod_{i=1}^{n} N_{\mu}(x_i, \sigma) \tag{9}$$

where n is the number of observations (i.e., the results of ten rounds of optimization); x_i is the observed value in each round (i.e., set of weights in PRET); m is an unknown parameter (the target set of weights for each evaluation item); s is assumed to be the known value and equal to the standard deviation of the sample. Eq. (9) is a series of multiplication of n normal distribution equations; its result can be described in Eq. (10).

$$N_\mu(\bar{x}, \sigma/\sqrt{n}) \tag{10}$$

where $\bar{x}$ is the sample mean. According to Bayes' Theorem, the posterior probability of the mean weight for each evaluation item ($f''(\mu)$) was

$$f''(\mu) = kL(\mu)f'(\mu) = kN_\mu(\bar{x}, \sigma/\sqrt{n})N_\mu(\mu', \sigma') \tag{11}$$

Equation (11) is the product of two normal equations. The mean posterior probability can be calculated using Eq. (12).

$$\mu'' = \frac{\bar{x}(\sigma')^2 + \mu'(\sigma^2/n)}{(\sigma')^2 + (\sigma^2/n)} \tag{12}$$

After obtaining the mean weight of each evaluation item, normalization was conducted to achieve a total weight of 100 points, as shown in Table 9. After revising the evaluation items using Bayes' Theorem and expert opinions, the weight for the item *material on the riverbed* was reduced from 11 points to nine points. The main reason for this reduction was the fact that the majority of expert opinions indicated a smaller weight for *material on the riverbed* compared with the optimized results (shown in section 6.2). Thus, the weight for this item was reduced after using Bayes' Theorem. Table 9 shows that most items that gained additional weight after revising using Bayes' Theorem were onsite items because most expert opinions regarded onsite items as major control factors; thus, the weights of these items were increased.

Table 10 shows the relationships among the revised preliminary evaluation scores, scouring potential, and Bayesian failure probabilities, which demonstrates that the Bayesian weights (section 6.3), compared with the optimization weights (section 6.2), would not increase the correlation between the preliminary evaluation scores and the scouring potential. For example, the evaluation scores for the Qianniao Bridge and Puzi River Bridge increased (from 12.1 to 15.97 and 7.7 to 10.8, respectively), whereas the corresponding scouring potentials decreased (from 8.18×10^{-2} to 3.33×10^{-2} and 4.83×10^{-2} to 1.24×10^{-2}, respectively). Generally, Bayesian weights produced a slight reduction to correlations between the PRET score and the scouring potential. For example, the correlation decreased from 0.88 to 0.83, whereas the correlation between the PIEF score and the bridge failure probability increased from 0.75 to 0.88. The evaluation scores that were revised using Bayes' Theorem, which are shown in

Table 9. Normalized Set of Weights

	(evaluation item)	Original set of weights	Optimized set of weights	Optimized using Bayes' Theorem
Indoor items	Upstream river dam or reservoir facilities	7	3	3
	Foundation type	7	9	9
	Bending or narrowing of the river	6	10	10
	Eroded riverbed	8	12	12
	Material on the riverbed	2	11	9
	Location of the main channel	5	3	3
Outdoor items	Hydraulic drop effect	5	4	5
	Attack angle of flow	7	7	7
	Area ratio of bridge to cross section	5	3	3
	Foundation scouring depth	20	14	14
	Effective pier diameter	13	11	11
	Protection for riverbank	5	3	4
	Protection for riverbed	10	10	10

Table 10. Correlation between the Preliminary Evaluation Score and Optimized Failure Probability Revised Using Bayes' Theorem

Bridge name	Preliminary evaluation score (A)	Scouring potential (B)	Correlation coefficient (A & B)	Bayesian failure probability (C)	Correlation coefficient (A & C)
Lanyang Bridge	12.73	7.39×10^{-2}	0.83	8.28×10^{-5}	0.88
Dongshi Bridge	5.13	6.97×10^{-2}		6.92×10^{-5}	
Taichung-Changhua Bridge	10.60	7.39×10^{-2}		2.63×10^{-5}	
Jishui River Bridge	11.33	7.39×10^{-2}		2.50×10^{-5}	
Qianniao Bridge	15.97	3.33×10^{-2}		2.37×10^{-3}	
Puzi River Bridge	10.80	1.24×10^{-2}		4.41×10^{-5}	
Shuangyuan Bridge	18.97	8.69×10^{-2}		2.58×10^{-2}	
Wanda Bridge	29.87	4.34×10^{-1}		1.78×10^{-1}	

Table 9 (section 6.3), were optimized and included expert opinions and should be regarded as a more appropriate choice for evaluation purposes.

7. Conclusions

Preliminary evaluation using visual inspection is a necessary method that is employed by bridge management when prioritizing bridge reinforcement projects. This research used PSO to optimize the set of weights in evaluation tables to maximize the correlation between preliminary visual inspection scores and Bayesian network failure probabilities and create a reliable evaluation table that can be provided to bridge management as a reference for preforming future preliminary evaluations. When revising the preliminary visual inspection scores, various information and probability distributions of random variables obtained from hydraulic analysis were utilized to address the importance of uncertainty in FOSM-based reliability analysis. To automatically perform the reliability analysis and PSO optimization, Python was used to establish a parameterized ABAQUS model for the deterministic analysis of a bridge. Because the eight bridges that were analyzed did not exhibit differences in certain evaluated items, such as *protection for river bank*, the weights of these items were unable to demonstrate their importance, and their weights were reduced during the optimization process. To compensate for these inadequacies, this study used Bayes' Theorem to integrate three different evaluation tables and the PSO results to obtain the finalized evaluation form. The correlation coefficient between the original evaluation form and the results of the Bayesian network analysis was only 0.75. The finalized evaluation form, however, improved the correlation coefficient to 0.88. The following restrictions apply to this revised evaluation form:

1. The target bridge that was analyzed in Taiwan had a pile foundation. The appropriateness of this finalized evaluation table must be reviewed when used for other types of bridges or regions.
2. Although the influence of the driftwood has been recognized as a significant factor for bridge safety against floods, this factor was not considered in this study.

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