Reliability Assessment of Long-Span Cable-Stayed Bridges Based on Hybrid Algorithm

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Abstract: In order to evaluate the reliability of long-span cable-stayed bridges, a computational framework utilizing a hybrid algorithm is developed. The framework integrates the advantages of finite element analysis, radial basis function neural networks, genetic algorithms, and Monte-Carlo importance sampling method (MCIS) together. These approaches are combined intelligently with consideration of a platform. The feasibility of this framework is verified through a case study, where a prestressed concrete cable-stayed bridge is presented. The parametric study indicates that: a) the failure probability caused by displacement limit of mid-span is greater than that caused by the cable strength failure. b) the mean value and standard deviation of vehicle loads have a higher influence on reliability of the cable-stayed bridge.

Keywords: cable-stayed bridge, reliability, neural network, genetic algorithm, Monte Carlo simulation

1. Introduction

Cable-stayed bridges were widely used for long-span bridges because of their superior mechanical characteristics and reasonable economy. With consideration of increase of traffic flows and resistance deterioration, more attention should be taken more attention for the structural safety of these bridges. It is necessary to evaluate the reliability of these bridges using a high efficient algorithm.

The common used reliability evaluation method is the First-order Second-moment Method (FOSM), Monte Carlo sampling method (MCS), response surface method (RSM), random finite element method (RFEA). The RSM together with artificial neural network (ANN) was proposed to calculate structural failure probability and the method was proved to have a higher efficiency and precision compared with traditional FOSM method (Cheng et al., 2008). The FOSM method was utilized to evaluate reliability of RunYang Yangtze River Bridge and parameters were also carried out (Wang et al., 2010). A joint algorithm which combined RFEA and RSM, FEM, MCS methods was proposed to analysis the dynamic features of JiangYin Yangzte River Bridge where the joint algorithm was proved to be accurate and efficient (Cheng and Xiao, 2005).

There are three major problems in reliability assessment of long–span prestressed concrete (PC) cable-stayed bridge. First, structural nonlinearity during construction is getting more important with increase of the length of cable-stayed bridges. Second, there are many parameters for construction analysis and many random variables in the reliability analysis model. Finally, the structural response functions are implicit without a specific expression. With consideration of these reasons, the common reliability methods have some limits in evaluating reliability of cable-stayed bridges Thus, it is urgent to develop an effective and precise approach for reliability assessment of cable-stayed bridges.

In this paper, a hybrid approach will be developed for reliability assessment of long-span cable-stayed bridges. The hybrid approach will be verified through several numerical studies. Finally, the hybrid approach will be used for reliability assessment of a long-span suspension bridge. Parametric studies of the bridge will be discussed.

2. Mathematical Model

The structural system of cable-stayed bridges are highly statically indeterminate and geometric nonlinear. Therefore, the limit states functions of long-span cable-stayed bridge are complex and implicit with lots of random variables. It is important to establish an appropriate mathematical model for the cable-stayed bridge.

In actual, the reliability index of bridge under serviceability limit states is lower than the index under ultimate limit states (Wu and Zhao, 2006), so bridge reliability assessment is commonly analyzed to meet requirements under serviceability limit states instead of under ultimate limit states. In order to control stress, cracks and deformation under a certain limiting value under serviceability states and guarantee bridge structure in service, assessment of service performance for bridge is critically analyzed under serviceability limit states. Strength failure of a stay-cable and displacement transfinite failure of mid-span for main girder are taken into consideration in this paper. The limit state functions of cable-stayed bridges caused by strength failure of cables and displacement failure of girders can be written as

$$Z_1 = T_{\mathrm{u}}{}^i - T_{\mathrm{cab}}{}^i(x_1, ..., x_n) \tag{1}$$

$$Z_2 = u_{\max} - u_{\mathrm{mid}}(x_1, ..., x_n) \tag{2}$$

Where x is random variables, $T_{\mathrm{u}}{}^i$ is yield strength of the i th stay-cable, n is the number of strands in a stay-cable , A is cross-sectional area of single strands, σ_{b} is yield strength of single strands,

$T_{\mathrm{cab}}^{\ i}(x_1,...,x_n)$ is of the cable force of the ith cable. The maximum of vertical deflection $u_{\max}$ for concrete cable-stayed bridge is less than $L/500$（L is mid-span of main girder） under vehicle load according to the chinese national standard (JTJ027-96, 1996), $u_{\mathrm{mid}}(x_1,\ldots,x_n)$ is vertical displacement value of mid-span node for main girder under vehicle load. $T_{\mathrm{cab}}^{\ i}(x_1,\ldots,x_n)$ and $u_{\mathrm{mid}}(x_1,\ldots,x_n)$ both are high-order nonlinearity implicit performance function. All of the structural response functions can be calculated with the hybrid approach which will be illustrated below.

3. Proposed Hybrid Approach

The procedure of hybrid algorithm for structural reliability assessment is shown in Figure 1. As shown in Figure 1, the hybrid algorithm integrates the FEA, Neural networks, GA, and MCS together to computate the reliability index of cable-stayed bridges.

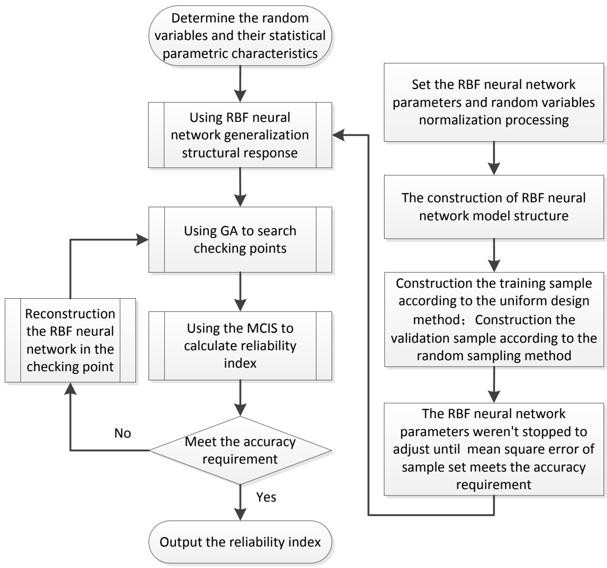


Figure 1. Flowchart of the Hybrid approach for Structural Reliability Analysis.

RBF neural networks in the hybrid algorithm is used to approximate the structural response function. RBF neural network is a feedforward neural network which is composed of input layer, hidden layer and output layer. The hidden layer of radial basis function is Gaussion function, while the out layer is linear functions. The kernel Gaussion is

$$G_i\left(x\right)=\exp\left[-\frac{(x-c_i)^T(x-c_i)}{2\sigma_i^2}\right] \tag{3}$$

Where x is m-dimensional vector of input data, c_i and σ_i are the mean and standard deviation of RBF neural network respectively, respectively. T is a transposed matrix.

For finite element analysis of the Long-span PC cable-stayed bridge, the high-order indetermination, strong nonlinearity, implicit performance function should be paid special attention. The RBF neural network is used to approximate the structural response instead of the FEA model. The advantage of RBF method is the computational efficiency and precision compared with the traditional BP neural networks. The RBF neural networks are especially efficient for structural high-order multivariate nonlinear functions. A RBF neural network is shown in Figure 2, where x and y are input data and output data of structural response, respectively.

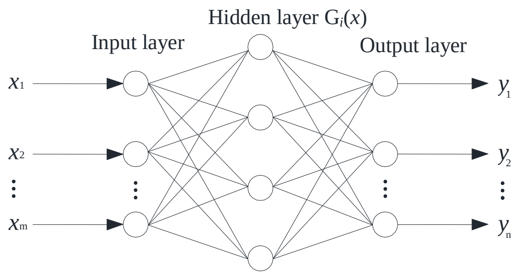


Figure 2. The Structural Diagram of RBF Neural Network.

Sample points are chosen according to the sample value range using a sample point formation method. In order to ensure design sample points are in an effective range, numerical value distributes betweenμ-3σ and μ+3σ) were used in this paper with consideration of the 3σ principle (Zhang et al., 2008). Uniform design (UD) method is used to simulate the experimental data, because the UD method has a supper performance in making the samples have a uniform distribution compared with the orthogonal design method. A data processing system (DPS) (Tang and Zhang, 2012) is used in this paper to simulate the uniform distribution samples, because of its multi-factors and multi-lever-figures by multi-iterations feature. After that the RBF neural network will be selected to conduct the response function approximation.

Genetic algorithm is used to search checking point in structural reliability index calculation. The search problem can be concluded in a constrained optimization models as follows.

$$\begin{cases} \min \quad \beta^2 = \sum_{i=1}^{n} \left[\dfrac{\left(x_i^* - \mu_{x_i}{}' \right)}{\sigma_{x_i}{}'} \right]^2 \\ \text{s.t.} \quad Z = Z_i(x_1, ..., x_n) = 0 \end{cases} \tag{4}$$

Where $x_1,\ldots,x_n$ are structural independent random variances, respectively. The structural limit state equation can be written as $Z_i(x_1,\ldots,x_n)=0$. Rosenblatt transformation or orthogonal transformation (Li and Hu, 2000) can be used to transform the relative random variables into linear independent standard normal distribution random variables. Afterwards, the equivalent normal distribution characteristic values, such as mean value $\mu_{x_i}{}'$ and standard deviation $\sigma_{x_i}{}'$, can be obtained. Reliability index β is defined as the shortest distance from origin to limit state plane in the standard normal coordinate system, where x_i^* is the most probability failure point.

On account of only existing one equality constraint in constraint optimization problem of calculating structural reliability, genetic algorithm is not suitable for the optimal solution. In addition, the constraint optimization should be transformed to unconstraint optimization, when using the genetic algorithm. In order to solve constraint optimization problem in Eq. (4), =a penalty function is used in this paper.

Failure probability P_f is usually quite small in actual engineering structures. When P_f is less than 10^{-3}, the sample number should be greater than 10^5 for the purpose of ensuring the computational accuracy. When the estimation $\hat{P}_f$ error of failure probability P_f is less than 20%, the probability is greater than 95%, where the relative error ε of $\hat{P}_f$ is 0.2 and significance level $u_{\alpha/2}$ is 1.96 (Gong et al, 2012). The sampling number N should satisfy the inequality.

$$N \geq \frac{100\left[\Phi(-2\beta)\exp(\beta^2) - \Phi^2(-\beta) \right]}{\Phi^2(-\beta) - \Phi^3(-\beta)} \tag{5}$$

Where β is an predicted reliability index, $\Phi()$ is an standard normal cumulative probability distribution function.

Importance sampling approach also known as variance reduction technique is adopted to reduce the sample size, the technique improves computational efficiency in conditions of guarantee of the same precision. Importance sampling method increases sample points in failure region appropriately to reduce variance through altering the sample center. This method is often applied in many areas because of its feasibility and efficiency.

According to the above mentioned computational framework of the hybrid algorithm, DPS uniform experimental design of data processing system, MATLAB neural network, genetic algorithm toolbox and APDL language platform are applied comprehensively. The calculation flowchart of these computer programs is shown in Figure 3.

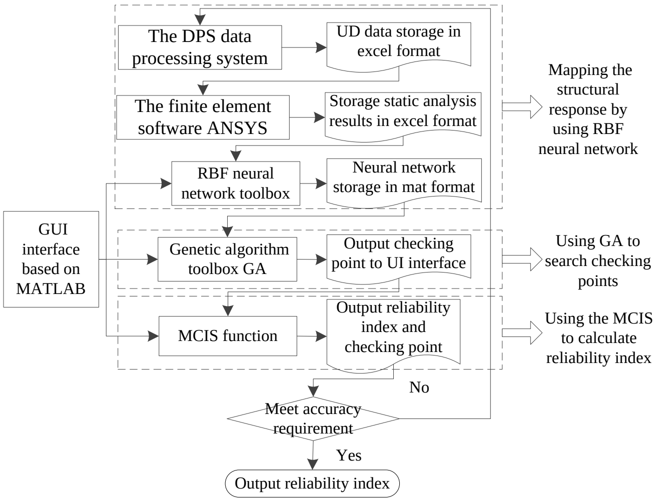


Figure 3. Framework of a software for Structural Reliability Assessment.

Firstly, uniform experimental data is obtained by DPS data processing system, and sample parameters are stored in this system. Secondly, ANSYS finite element analysis software is used to conduct structural static analysis. The results and sample parameters are imported in structural response of RBF neural network toolbox in order to get limit state equations. Thirdly, the GA genetic algorithm toolbox is used to search the design points. UD data is utilized to transform location of sample center. Finally, structural reliability index β gets in design point location by MCIS, while the precision requirement is satisfied. Otherwise, the above steps are repetition over and over again until meet precision requirement.

4. Validation Examples

Computational precision and reliability analysis of the hybrid algorithm will be verified systematically in this section. Two validation examples will be discussed. The first one is reliability analysis of performance function which has explicit analytic expression and higher nonlinearity degree. The other is reliability analysis of simplified bridge structure. In addition, compared with computational result of other methods is included.

4.1. NUMERICAL EXAMPLE ANALYSIS

Expression of performance function in case 1 is $Z=18.46-7.48X_1/X_2^3$, where X_1 and X_2 both are random variables, $X_1\sim N(10,2)$， $X_2\sim N(2.5,0.375)$.

Expression of performance function in case 2 is $Z=X_1 \cdot X_2-X_3$, where X_1 and X_2 are random variables, $X_1\sim N(0.5472,0.0274)$， $X_2\sim N(3.8,0.304)$， $X_3\sim N(1.3,0.91)$.

Table 1. Reliability calculation results of Case 1 and Case 2.

Case	Computational program	MC	FOSM	Reference(Gui J S, Kang H G, 2004)		Hybrid algorithm
				Partial RBF	Modified whole RBF	
Case 1	Reliability index	2.338	2.330	2.350	2.330	2.332
	Iterations	-	6	4	6	4
Case 2	Reliability index	3.806	3.795	3.799	3.798	3.801
	Iterations	-	6	5	9	4

As shown in Table 1, iterations of the hybrid algorithm is the least compared with other response surface methods mentioned in Table 1 and hybrid algorithm achieves the goal of improvement of computational efficiency. Hybrid algorithm can meet precision requirement as the same as other response surface methods, furthermore, its iterations reduce 20% and precision improves 25%.

4.2. RELIABILITY ANALYSIS OF BROTONNE CABLE-STAYED BRIDGE

A cable-stayed bridge named Brotonne bridge is selected herein as an additional verification example. More details regarding the limit state functions, description of the random variables and the statistical information can be found (Shen and Wang, 1996). As shown in Table 2, sampling times of MCS is 10^6 so that it is a precise value. Reliability index of hybrid algorithm has higher precision than reliability index of FOSM or RSM methods, and calculation result of hybrid algorithm is similar to the value that calculated by MCS method (Zhang et al., 2008; Zhang and Liu, 2001). Hence, hybrid algorithm proposed by this paper has better precision and can get corresponding checking point which is not list in Table 2 in reliability calculation of explicit performance function.

Table 2. Results of Static Reliability Analysis for Brotonne Cable-stayed Bridge.

Failure mode		Details	Methods					
			MCS	FOSM	RSM	Reference (Zhang J R, Liu Y, 2001)	Reference (Zhang Q H, Bu Y Z, Li Q, 2008)	Hybrid algorithm
Girders	static bending	Reliability index	3.6104	3.5658	3.5740	3.6193	3.6102	3.6153
	static torsion		-	6.0027	6.0027	6.6027	6.6027	6.0027
Cables and towers	Bulking along transverse bridge	Reliability index	-	9.7007	9.7397	9.7032	9.7042	9.7126
	Strength along longitudinal bridge		3.5128	3.4946	3.4973	3.5063	3.5146	3.5117

5. Case Study

5.1. Bridge Description

Kangbo bridge is located in Luyu highways in Sichuang province. It is a prestress concrete cable-stayed bridge with midspan of 420m as shown in Figure 4. The material of main girders is C60 concrete, that of towers is C50 concrete. Every tower contains 34 pairs of stay cables. The width of bridge deck is 30m, which is arranged in six-lanes.

5.2. Random variables

As the random variables is associated with materials, external load, and so on. Structural random variables in this paper are elasticity modulus E_i of main girder, towers and stay cables, cross-sectional area A_i, bending inertia moment I_i , material density γ_i, secondary dead load q_s and vehicle load q_k, statistical parameters of these basic random variables need the results of actual bridge detection.

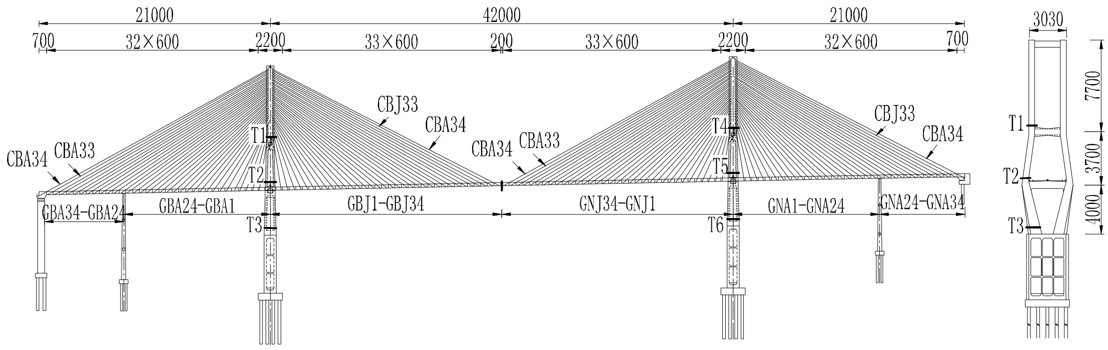


Figure 4. The General Arrangement Diagram of the Kangbo Bridge (unit: cm).

Bridge structure suffers many kinds of loads. In addition, the loading positions are complex under normal circumstance. As a result, structural reliability analysis mainly associates with dead load and live load for simplification. Live load on the deck regards as the shape of uniform distribution for calculating easily. Structural static reliability is lower only under consideration of uniform live load of mid-span for main girder of cable-stayed bridge when bridge has different distribution form of live load (Biondini et al., 2008). Therefore, vehicle load is simplified as uniform load of mid-span for main girder in the below static reliability analysis of cable-stayed bridge. Dead load and live load uniform distributed in mid-span of main girder is considered in this paper. Statistical parameters characteristics of random variables in this paper are shown in Table 3.

5.3. FINITE ELEMENT MODEL

Structure of long-span cable-stayed bridge is complex and its geometric nonlinear effects are important. Thus, structural reliability analysis should include their effects. Secondary sequence response surface method calculates reliability of main girder for Nanjing second bridge considering geometric nonlinear effect of cable-stayed bridge (Chen et al., 2000). It indicates that the reliability index of linear calculation is greater than that of nonlinear solution. RSM, FEM, FOSM and importance sampling method are used to analyze static reliability of main girder for Nanjing second bridge, the result shows that sag effect of stay cables cannot neglect in the field of geometric nonlinear effect and the beam-column effect and large displacement effect can neglect when static reliability of cable-stayed bridge is analyzed (Cheng and Xiao, 2004).

Table 3. Statistical Parameters of Random Variables of the Kangbo Bridge.

Type	Locations	Symbol	Distribution shape	Mean value	Standard variance
Elasticity modulus /(kN·m^{-2})	Main girder	E_1	Normal	3.64E7	3.64E6
	Towers	E_2	Normal	3.52E7	3.52E6
	Stay cables	E_3	Normal	1.95E8	1.95E7
Cross-sectional area /m^2	Main girder (standard beam section)	A_1	Lognormal	20.846	1.042
	Main girder (auxiliary pier)	A_2	Lognormal	24.694	1.235
	The body of towers	A_3	Lognormal	26.868	1.343
	The root of towers	A_4	Lognormal	22.280	1.114
	Single strand in stay cables	A_5	Lognormal	1.4E-4	7.0E-6
Density /(kN·m^{-3})	Main girder	γ_1	Normal	26.56	1.33
	Towers	γ_2	Normal	26.24	1.31
	Stay cables	γ_3	Normal	78.5	3.93
Second moment of area /m^4	Main girder (standard beam section)	I_1	Lognormal	18.598	0.930
	Main girder (auxiliary pier)	I_2	Lognormal	23.015	1.151
	The body of towers	I_3	Lognormal	120.864	6.043
	The root of towers	I_4	Lognormal	275.517	13.776
Secondary dead load /(kN·m^{-1})	Main girder	q_s	Normal	132	6.6
Vehicle load /(kN·m^{-1})	Main girder of the whole bridge	q_k	Extremum Type I	63.5	6.35

This paper is proposed parametric plane finite element model of the Kangbo bridge based on ANSYS, geometric nonlinear factors of sag effect for stay cables are considered by equivalent elastic modulus method. Main girder and towers are simulated by BEAM 44 units and the sum of units is 470, stay cables are simulated by LINK 10. Initial cable force is the measured force, the prestressed effect and the concrete shrinkage and creep effect are not considered in calculation.

5.4. LIMIT STATE FUNCTION

Long-span cable-stayed bridges are statically indeterminate. Since they consists lots of complicate elements, such as main girders, towers, stay cables, auxiliary piers, and so on. Nonlinear degree is higher so that the structural limit state functions are complex. As a result, the progress of searching the major failure mode is extremely complicated. In general, structural reliability analysis is associated with failure components, where serviceability is important under actual operation state.

The serviceability limit state is defined as the event that structural stress or crack exceeds a threshold. Hence, in this paper, two failure modes are considered as serviceability limit states including strength failure of a single stay-cable and vertical displacement failure of the girders.

The limit state function is shown in Eq.(1) and Eq.(2). The potential failure elements are shown in Figure 4. The serious number of stay-cables are CBA1~CBA34、CBJ1~CBJ34、CNJ1~CNJ34、CNA1~CNA34. The strength failure event is caused by four longest stay cables named as CBA34, CBJ34, CNJ34 and CNA34 on the north tower. The yield strength σ_b of cables is 1860MPa. The threshold of vertical deflection u_{max} for the main girders of cable-stayed concrete bridge is 0.84m under vehicle load without consideration of impact factor (JTJ027-96, 1996).

5.5. Network Parameters Selection and Reliability Analysis Result

For reliability analysis, several random variables are selected in this paper referred from calculation results about sensitivity factors of structural static reliability (Cheng and Xiao, 2004). A RBF neural network is designed and the network has 17 nodes of input layer. They are random variables considered in structural analysis progress primarily and 5 nodes of output layer which are displacement of mid-span for structural main girder, cable force of CBA34, CBJ34, CNJ34 and CNA34. Parameters in RBF neural network are shown in Table 4.

Table 4. Parameters of RBF Neural Network.

Items	Numerical value	Introductions
Nodes of the input layer	17	Random variables in Tab.3
Nodes of the output layer	5	u_{mid} 和 T_{cab}^{i}(i=CBA34, CBJ34, CNJ34,CNA34)
The class number of training data	200	Uniform design chart is ($U_{200}(200^{17})$)
The class number of test data	30	random drawing
Network control precision	1e-6	Precision of network training after data normalization
Precision testing requirements	1%	The error rate of mid-span displacement and #CNA34 cable force

Static reliability of cable-stayed bridge is calculated utilizing the hybrid approach. Under serviceability limit state, vehicle loads are distributed uniformly in mid-span of main girder. The corresponding static reliability β of displacement limit failure in mid-span for main girder is 7.394. The reliability indices of strength failure for #CBA34、#CBJ34、#CNJ34 and #CNA34 cables are β_{CBA34}=4.973, β_{CBJ34}=5.236, β_{CNJ34}=5.112 and β_{CNA34}=4.867. The five reliability indices are shown in Figure 5.

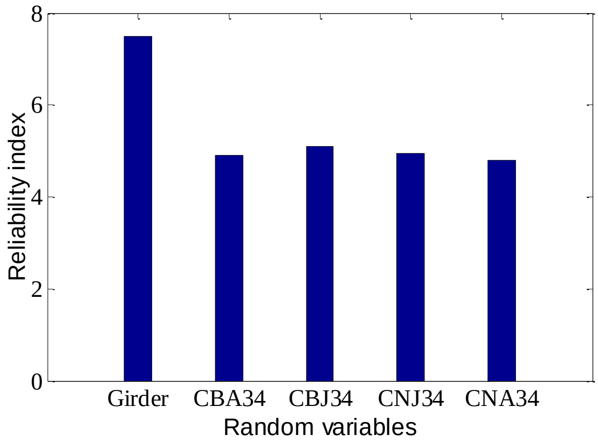
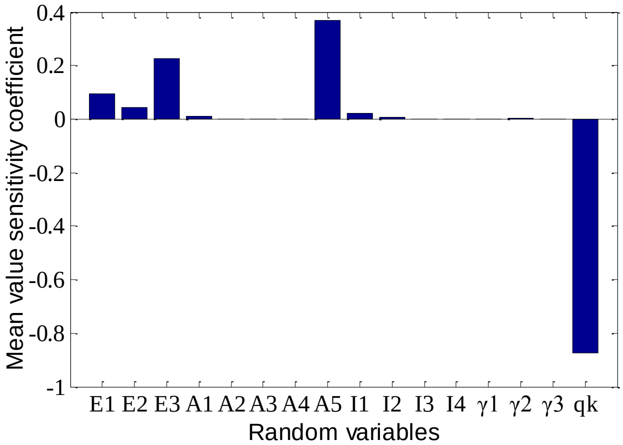


Figure 5. The Reliability Indices of the Critical Failure Location.

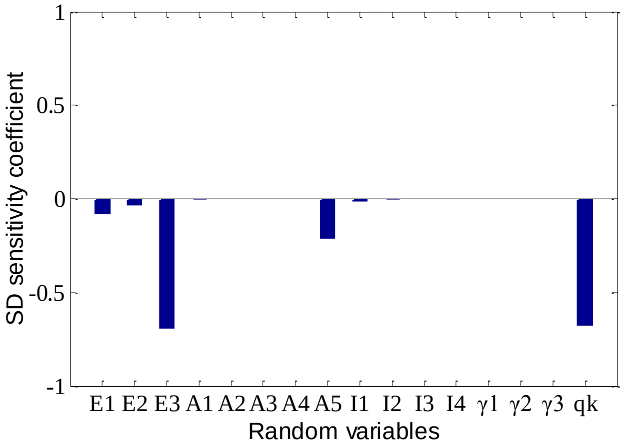
Structural reliability index β is calculated by mean value, standard deviation, of random variables. It is necessary to do research about influence on reliability index β by mean value, standard deviation, of random variables. It is sensitivity study of random variables (Cheng and Li, 2009). Reliability index β sensitivity on mean value μ_i, standard deviation σ_i of random variables is obtained by approximate formulae as follows (Hohenbichler and Rackwitz, 1986).

$$\begin{cases} \dfrac{\partial \beta}{\partial \mu_i} \approx -\alpha_i \\ \dfrac{\partial \beta}{\partial \sigma_i} = -\beta \alpha_i^{\;2} \end{cases} \tag{6}$$

Where α_i is direction of the *i*th random variable in standard normal distribution space, β is reliability index, μ_i and σ_i are mean value and standard deviation of the *i*th random variable. Sensitivity of reliability index on different mean value and standard deviation of random variable is observed under vehicle load distributed in whole main span in the point of mid-span of main span, as shown in Figure 6, reliability index is the most sensitive to mean value and standard deviation of vehicle load $q_{k.}$



(a) The mean of random variable.



(b) The standard deviation of random variable.

Figure 6. Sensitivity of the Reliability Index for the Random Variables of Mean, Standard Deviation.

The influence of vehicle load on reliability index is studied under different mean coefficient (Kong et al, 2012). The variation tendencies of reliability index β under displacement ultra-limit failure state in mid-span of main girder and strength failure state of the four longest stay cables are shown in Figure 7, where intervals of mean coefficient for vertical load q_k is 1~2.

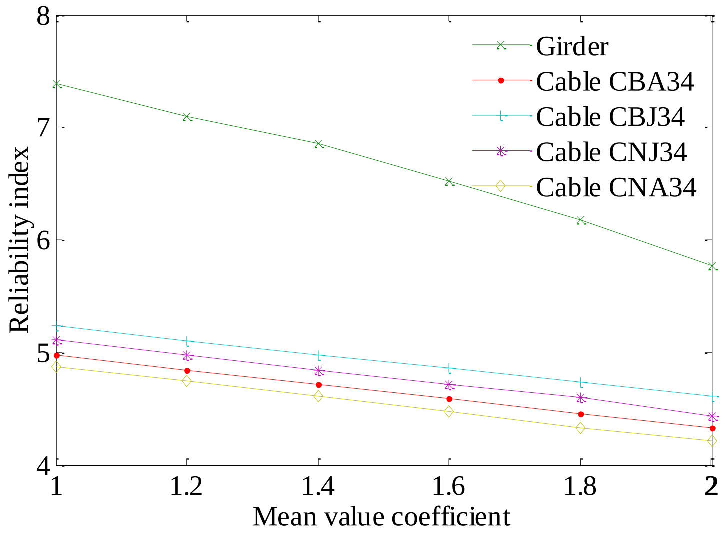


Figure 7. Reliability Index of Critical Failure Locations under Different Mean Coefficient of Vehicle Loads.

It can be found from Figure 7 that reliability indices β of displacement failure of mid-span for main girder and strength failure of that four longest stay cables are decrease with the increase of mean coefficient of vehicle load. When mean coefficient increase to 2.0, the displacement ultra-limit failure declines 30.786% and the strength failure declines 16.558%~18.923%. With gradually development of mean coefficient, downward trend of the displacement ultra-limit failure is more obvious. The reliability index of displacement ultra-limit failure for mid-span is greater than strength failure of four long stay cables.

6. Conclusions

This paper presented a hybrid algorithm method for reliability analysis of long-span PC cable-stayed bridge based on reliability theory. The hybrid algorithm method was used to analyze reliability index of a long-span PC cable-stayed bridge under vehicle load. Influence of random variables on structural reliability index has been conducted with a sensitivity analysis. The following conclusions can be obtained:

a) The hybrid approach integrates the advantage of RBF neural network, GA and Monte Carlo importance sampling method. Two numerical studies are utilized to verify the feasibility of the hybrid approach applied to reliability calculation of large complicated structures. The analysis results indicate that the hybrid approach has satisfactory accuracy and calculation efficiency.

b) In the case study, the reliability index for displacement failure of griders in mid-span is greater than reliability index for strength failure of the stay-cable.

c) Parametric sensitivity analysis indicates that reliability index of cable-stayed bridge is sensitive to mean and standard deviation of vehicle load. The other sensitive factors are cross section area of stay cable, mean and standard deviation of elasticity modulus.

d) Reliability indices of displacement failure of mid-span for main girder and strength failure of the four longest stay cables are decrease with the increase of mean coefficient of vehicle load. Besides, downward trend of the displacement ultra-limit failure is more obvious with gradually development of mean coefficient.

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