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Reliability analysis of structure with random parameters based on multivariate power polynomial expansion

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Abstract: A new method for calculating the failure probability of structures with random parameters is proposed based on multivariate power polynomial expansion, in which the uncertain quantities include material properties, structural geometric characteristics and static loads. The structural response is first expressed as a multivariable power polynomial expansion, of which the coefficients are then determined by utilizing the higher-order perturbation technique and Galerkin projection scheme. Then, the final performance function of the structure is determined. Due to the explicitness of the performance function, a multifold integral of the structural failure probability can be calculated directly by the Monte Carlo simulation, which only requires a small amount of computation time. Two numerical examples are presented to illustrate the accuracy and efficiency of the proposed method. It is shown that compared with the widely used first-order reliability method (FORM) and second-order reliability method (SORM), the results of the proposed method are closer to that of the direct Monte Carlo method, and it requires much less computational time.

Key words: reliability; random parameters; multivariable power polynomial expansion; perturbation technique; Galerkin projection

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Structural reliability analysis is in general an important and computationally demanding task, which arouses the interest of many scholars. Methods to compute the failure probability is a basic research concern in structural reliability analyses. According to the definition of failure probability, estimating an integral equation is needed. However, it is quite difficult or even impossible when the dimension of multifold integral is large, or the performance function is highly non-linear and so on. Thus, in the past decades, many methods have been presented to solve the integral equation, such as the first-order reliability method (FORM) and the second-order reliability method (SORM)[1-4], simulation methods[5-10], etc.

Among the above mentioned methods, the FORM and SORM are the most common approaches for structural reliability analysis. However, they will be ineffective when the limit state function is highly nonlinear or multiple most probable points exist. As the most basic and direct one of the simulation methods, the direct Monte Carlo method (DMC) is accurate and commonly used to verify newly proposed methods, but it is very time-consuming. Thus, several improved methods, such as the importance sampling method[8-10] have been developed. Even so, they generally require considerable computations.

For more complex reliability problems, stochastic finite element methods have consequently been developed to estimate the response surface functions, e.g., the traditional perturbation stochastic finite element methods (PSFEM)[11-12], the spectral stochastic finite element methods (SSFEM)[13-14], and the stochastic reduced basis methods (SRBM)[15-16].

The PSFEM methods are widely used for stochastic series expansion. However, the random responses of structures may not be obtained if the uncertainty of random parameters changes from small to large or the relationship between inputs and output gradually becomes nonlinear. The SSFEM methods are highly accurate, but they often require too much time on large problems[17]. The SRBM methods have comparable accuracy and need less time compared with the SSFEM methods, but the selection of the basic vectors needs more exploration.

Different from the existing methods, a novel method for calculating the failure probability of structures is proposed based on the improved recursive stochastic finite element method (IRSFEM). The IRSFEM was originally developed for statistical moment analysis[18-19], in which the high-order perturbation technique is used to determine the initial coefficients of the multivariate power polynomial expansion of the structural response. Subsequently, the initial coefficients are modified by the Galerkin projection scheme. After the structural response or performance function is determined by means of the IRSFEM, the failure probability of the structures can be calculated by the Monte Carlo simulation in accordance with the definition of structural reliability. To evaluate the accuracy and efficiency of the proposed method, two numerical examples are investigated using the proposed method, as well as the widely used FORM and SORM. Comparison results show that the proposed method is the most accurate and has al-

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most the same accuracy as the DMC. Furthermore, the proposed method is revealed to be far more efficient than the DMC method.

1 Multivariable Polynomial Expansion Approach

1.1 Multivariable power polynomial expansion

To solve a static problem involved in a random vector $\boldsymbol{\theta}$ where the elements are $\theta_i(i=1,2,\ldots,n)$, an unknown random response, $\boldsymbol{Y}(\boldsymbol{P},\boldsymbol{\theta})$, can be defined as the multivariable power series expansion, and it can be written as

$$\boldsymbol{Y}(\boldsymbol{P},\boldsymbol{\theta}) = \boldsymbol{C}_0(\boldsymbol{P})\Gamma_0(\boldsymbol{\theta}) + \sum_{i=1}^{n}\boldsymbol{C}_i(\boldsymbol{P})\Gamma_1(\boldsymbol{\theta}) + \sum_{i=1}^{n}\sum_{j=1}^{i}\boldsymbol{C}_{ij}(\boldsymbol{P})\Gamma_2(\boldsymbol{\theta}) + \sum_{i=1}^{n}\sum_{j=1}^{i}\sum_{k=1}^{j}\boldsymbol{C}_{ijk}(\boldsymbol{P})\Gamma_3(\boldsymbol{\theta}) + \ldots \tag{1}$$

where $\boldsymbol{P}$ is a coordinate vector of space position; $\boldsymbol{C}_0(\boldsymbol{P})$, $\boldsymbol{C}_i(\boldsymbol{P})$, $\boldsymbol{C}_{ij}(\boldsymbol{P})$, … are the coefficients of the corresponding expanded terms; $\Gamma_0(\boldsymbol{\theta})$, $\Gamma_1(\boldsymbol{\theta})$, $\Gamma_2(\boldsymbol{\theta})$, … denote the expanded power polynomial terms, and the first four terms are shown as

$$\Gamma_0(\boldsymbol{\theta})=1, \quad \Gamma_1(\boldsymbol{\theta})=\theta_i$$
$$\Gamma_2(\boldsymbol{\theta})=\theta_i\theta_j, \quad \Gamma_3(\boldsymbol{\theta})=\theta_i\theta_j\theta_k \tag{2}$$

1.2 Recursive approach of static problem

The finite element equation of a structural system subjected to static load can be written as

$$\boldsymbol{KY}=\boldsymbol{F} \tag{3}$$

where $\boldsymbol{K}$ is an $N\times N$ dimensional structural stiffness matrix including l_1 random variables; $\boldsymbol{Y}$ is an $N\times 1$ dimensional nodal displacement vector, as mentioned in Eq. (1); $\boldsymbol{F}$ denotes an $N\times 1$ dimensional equivalent nodal load vector including l_2 random variables.

If the random field of elasticity modulus is defined as the Karhunen-Loève expansion, the stiffness matrix of the random structure can be written as

$$\boldsymbol{K} = \sum_{i=0}^{l_1+l_2}\theta_i\boldsymbol{K}_i$$
$$\boldsymbol{K}_i = \boldsymbol{0} \qquad i = l_1+1, l_2+2, \ldots, l_1+l_2 \tag{4}$$

where $\boldsymbol{K}_0$ is an $N\times N$ dimensional deterministic matrix with respect to the deterministic mean of the structural matrix; $\boldsymbol{K}_i$ refer to $N\times N$ dimensional matrices; $\theta_0=1$.

The nodal load vector of the random structure can be expressed as

$$\boldsymbol{F} = \sum_{i=0}^{l_1+l_2}\theta_i\boldsymbol{F}_i$$
$$\boldsymbol{F}_i = \boldsymbol{0} \qquad i = 0, 1, \ldots, l_1 \tag{5}$$

where $\boldsymbol{F}_0$ refers to an $N\times 1$ dimensional deterministic matrix with respect to the deterministic mean of external load; $\boldsymbol{F}_i$ denotes $N\times 1$ dimensional vectors.

Considering the first $l+1$ terms of Eq. (1), and substituting Eqs. (1), (4) and (5) into Eq. (3), we obtain

$$\left(\sum_{i=0}^{l_1+l_2}\theta_i\boldsymbol{K}_i\right)\boldsymbol{Y}(\boldsymbol{P},\boldsymbol{\theta}) = \sum_{i=0}^{l_1+l_2}\theta_i\boldsymbol{F}_i \tag{6}$$

Since each term of the random vector $\boldsymbol{\theta}$ should satisfy Eq. (6), the sum of coefficients of the same order terms based on multivariable polynomial expansion should be equal to zero. Then, a series of deterministic recursive equations can be determined by the high-order perturbation technique. Following the above steps, the initial coefficients, $\boldsymbol{C}_0(\boldsymbol{P})$, $\boldsymbol{C}_i(\boldsymbol{P})$, $\boldsymbol{C}_{ij}(\boldsymbol{P})$, …, of the displacement vector can be obtained recursively.

1.3 Galerkin projection scheme

As the convergent rate of unknown random output can be improved by the Galerkin projection scheme, the displacement vector $\boldsymbol{Y}(\boldsymbol{P},\boldsymbol{\theta})$ is reassumed to be

$$\boldsymbol{Y}(\boldsymbol{P},\boldsymbol{\theta}) = \sum_{i=0}^{l}\gamma_i T_i \tag{7}$$

where $\gamma_i(i=0,1,2,\ldots,l)$ are unknown modification coefficients; T_0, T_1, T_2, …, respectively, denote $\boldsymbol{C}_0(\boldsymbol{P})\Gamma_0(\boldsymbol{\theta})$, $\sum_{i=1}^{n}\boldsymbol{C}_i(\boldsymbol{P})\Gamma_1(\boldsymbol{\theta})$, $\sum_{i=1}^{n}\sum_{j=1}^{i}\boldsymbol{C}_{ij}(\boldsymbol{P})\Gamma_2(\boldsymbol{\theta})$, ….

Then, using the Galerkin projection, the following equation can be obtained:

$$\sum_{j=0}^{l}\sum_{i=0}^{l_1+l_2}\langle\theta_i T_q^T\boldsymbol{K}_i T_j\rangle\gamma_j = \sum_{i=0}^{l_1+l_2}\langle\theta_i T_q^T\boldsymbol{F}_i\rangle$$
$$q = 0, 1, \ldots, l \tag{8}$$

From Eq. (8), the unknown coefficients γ_0, γ_1, …, γ_l can be obtained easily.

2 Reliability Analysis of Random Structures

2.1 Definition of failure probability

Structural reliability is defined as the probability that a structure or structural system performs its intended function during a specified period of time under stated conditions. To assess the reliability of a structure, a limit state function or performance function $\Delta(\boldsymbol{\theta})$ should be established as follows:

$$\Delta(\boldsymbol{\theta}) = \Theta(\boldsymbol{P}) - \boldsymbol{Y}(\boldsymbol{P},\boldsymbol{\theta}) \tag{9}$$

where $\Theta(\boldsymbol{P})$ is the capacity at failure at point $\boldsymbol{P}$ of the structural system.

The failure probability P_{f} can be estimated by a multifold integral, as

$$P_{\mathrm{f}} = \int_{\Delta(\boldsymbol{\theta})<0} f(\theta_1,\theta_2,\ldots,\theta_n)\,\mathrm{d}\theta_1\mathrm{d}\theta_2\ldots\mathrm{d}\theta_n \tag{10}$$

where $f(\theta_1,\theta_2,\ldots,\theta_n)$ is the joint probability distribution function of the random variables.

2.2 Calculation of multifold integral

Once $\Delta(\boldsymbol{\theta})$ is determined, the failure probability can be obtained through the Monte Carlo simulation, and the proposed method is named IRSFEM-P.

With the explicit performance function $\Delta(\boldsymbol{\theta})$, the failure probability of the structure can be estimated directly as

$$P_{\mathrm{f}} = \frac{1}{N_{\mathrm{f}}}\sum_{i=1}^{N_{\mathrm{f}}} \Omega[\Delta(\boldsymbol{\theta}^{(i)}) < 0] \tag{11}$$

where N_{f} is the number of samples; $\boldsymbol{\theta}^{(i)}$ denotes the i-th sample of the random vector $\boldsymbol{\theta}$; $\Omega[\cdot]$ is defined as a counting function such that when $\Delta(\boldsymbol{\theta}^{(i)})$ is in the failure domain, $\Omega[\cdot]=1$, otherwise $\Omega[\cdot]=0$.

In order to illustrate the accuracy of the proposed method IRSFEM-P, the DMC method is carried out to verify the proposed method. In the following, two numerical examples are taken to check the effectiveness of the proposed method.

3 Numerical Examples

Example 1 Consider a one-dimensional cantilever beam subjected to two concentrated forces. One force is located in the middle of beam, and the other is at the free end, as shown in Fig. 1. The whole length L of the beam is 6 m, and the beam is divided into 12 elements. It is assumed here that the bending rigidity, EI, of the beams F_1 and F_2 are all random. The means of EI, F_1, and F_2 are 4×10^4 kN m^2, 4 kN and 4 kN, respectively.

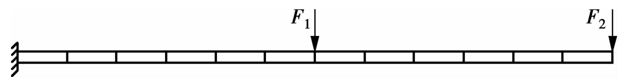


Fig. 1 Random cantilever beam

Assuming that EI, F_1, F_2 are all of Beta distribution, thus we have

$$EI = EI_0(1+\sqrt{5}\theta_1\delta_1), \qquad F_1 = F_{01}(1+\sqrt{5}\theta_2\delta_2)$$
$$F_2 = F_{02}(1+\sqrt{5}\theta_3\delta_3) \tag{12}$$

where EI_0 and F_{01}, F_{02} denote the means of EI, F_1, F_2, respectively; δ_1, δ_2 and δ_3 are the coefficients of variation (COVs) of EI, F_1, F_2, respectively. In addition, $\theta_i(i=1,2,3)$ are independent random variables with Beta distributions, of which the probability density function is written as

$$f(\theta) = \frac{3}{4}(1-\theta^2) \qquad \theta\in(-1,1) \tag{13}$$

The failure probability of the random beam is computed by four methods, i. e., FORM, SORM (Breitung), IRSFEM-P, and DMC. The results of the failure probability calculated by these four methods are listed in Tab. 1.

Tab. 1 The failure probability of the beam from different methods with $\delta_1=0.1$, $\delta_2=0.2$

Methods	δ_3							
	0.05	0.1	0.15	0.2	0.25	0.3	0.35	0.4
FORM	8.734×10^{-4}	6.531×10^{-3}	1.613×10^{-2}	3.408×10^{-2}	5.722×10^{-2}	8.335×10^{-2}	1.104×10^{-1}	1.370×10^{-1}
SORM(Breitung)	4.442×10^{-4}	3.948×10^{-3}	1.026×10^{-2}	2.443×10^{-2}	4.477×10^{-2}	6.969×10^{-2}	9.707×10^{-2}	1.249×10^{-1}
IRSFEM-P	2.500×10^{-4}	2.545×10^{-3}	9.680×10^{-3}	2.275×10^{-2}	4.193×10^{-2}	6.525×10^{-2}	9.203×10^{-2}	1.199×10^{-1}
DMC	2.500×10^{-4}	2.540×10^{-3}	9.690×10^{-3}	2.275×10^{-2}	4.192×10^{-2}	6.525×10^{-2}	9.202×10^{-2}	1.199×10^{-1}

Here it is assumed that δ_1 (the coefficient of variation of EI) is equal to 0.1 and δ_2 (the coefficient of variation of F_1) is equal to 0.2, respectively, and δ_3 (the coefficient of variation of F_2) is supposed to be 0.05, 0.1, 0.15, 0.2, 0.25, 0.3, 0.35 and 0.4, respectively. The threshold value, $\Theta(\theta_1,\theta_2,\theta_3)$, of the vertical displacement at the end of the beam is assigned as 1.34×10^{-2} m. It can be seen from Tab. 1 that the results of the IRSFEM-P are the closest to that of the DMC, and SORM (Breitung) is more precise than FORM. To fully illustrate the effects of the random inputs on the statistical properties of the random response, the curves of probability density function (PDF) of the response with the proposed method are shown in Fig. 2. It can be seen that the PDF curves of the vertical displacement at the end of beam vary with different δ_3 while $\delta_1=0.1$ and $\delta_2=0.2$. It is also found that the increment of δ_3 will result in the large fluctuation of the vertical displacement, and therefore the failure probability increases as shown in Tab. 1.

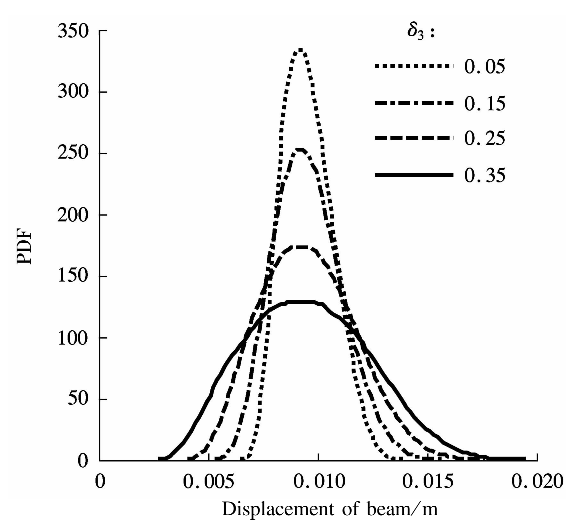


Fig. 2 PDF curves of the displacement at the end of beam with various δ_3 while $\delta_1=0.1$ and $\delta_2=0.2$

Example 2 A random wedge under gravity and hydraulic pressure and its boundary conditions are shown in Fig. 3. The height, bottom width, thickness, Poisson ratio and specific gravity of the wedge are 10, 8 and 1 m, 0.167 and 24 kN/m^3, respectively. The density of water is 10^3 kg/m^3. The mean of elastic modulus, E, of the wedge is 2.2×10^7 kN/m^2, and the wedge is divided into 100 finite elements. The proposed IRSFEM-P is used in this example.

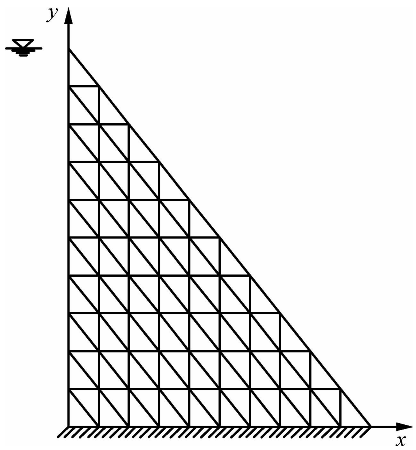


Fig. 3 Random wedge

The exponential covariance kernel function of the wedge is given as

$$C((x_1, y_1), (x_2, y_2)) = \sigma^2 e^{-|y_1 - y_2|/l} \tag{14}$$

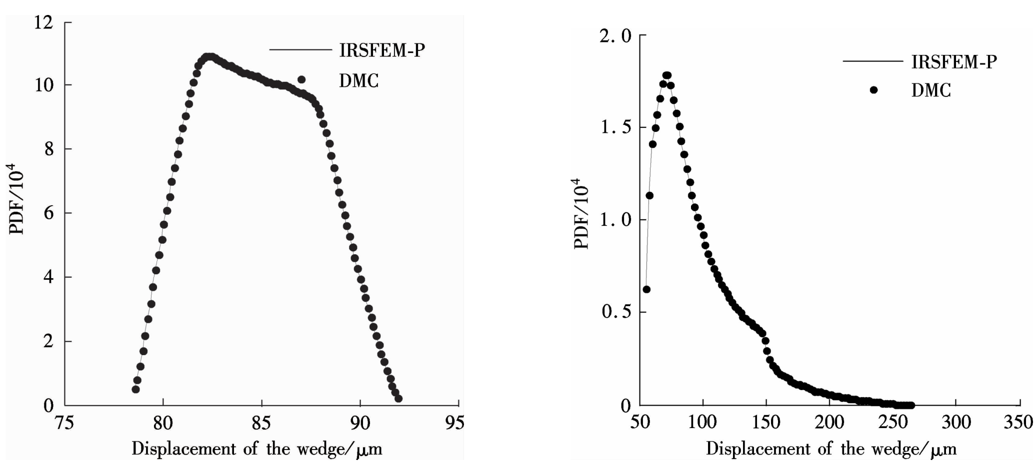
where σ is the mean square deviation of the elastic modulus of the wedge. The variance of elastic modulus changes along with the height of the wedge and $l = 3$ m.

Here, the first two terms of the Karhunen-Loève expansion of elastic modulus of the wedge are taken. All independent random variables are considered to be of uniform distribution, and their probability density functions can be expressed as $f(\theta) = 1/2$, $\theta \in (-1, 1)$.

When the threshold value $\Theta(\theta_1, \theta_2)$ of the horizontal displacement at the top of the wedge is assigned as 9.15×10^{-5} m, the failure probability of the wedge can be obtained (see Tab. 2). It can be seen that the proposed IRSFEM-P also has almost the same accuracy as the DMC method. In order to explain some more detailed aspects herein, some cases are chosen, as shown in Fig. 4.

Tab. 2 The failure probability of the wedge from different methods

Methods	δ							
	0.05	0.1	0.15	0.2	0.25	0.3	0.35	0.4
IRSFEM-P	0.001 6	0.178 8	0.291 9	0.350 5	0.386 7	0.412 0	0.429 8	0.443 0
DMC	0.001 6	0.178 9	0.292 0	0.350 8	0.387 3	0.413 1	0.432 1	0.447 5



(a) (b)

Fig. 4 PDF curves of the displacement of the wedge with different δ. (a) $\delta = 0.05$; (b) $\delta = 0.4$

Fig. 4 shows the PDF curves of the displacement of the wedge with different δ calculated by the proposed IRSFEM-P and the DMC. It can be seen that the output horizontal displacements at the top of the wedge are not of uniform distribution, and differ from each other for different coefficients of variation. Meanwhile, it is also observed that the failure probability curves of IRSFEM-P are very close to that of DMC whether the Cov δ is small or large, which illustrates that the accuracy of the proposed IRSFEM-P is very high.

Furthermore, the CPU time cost by the proposed IRSFEM-P (3.93 s) is only 1/600 of that of the DMC method (2 428.63 s), which proves that the proposed IRSFEM-P is more efficient than DMC.

4 Conclusions

1) Compared with the widely used FORM and SORM, the results of the proposed method are closer to that of the direct Monte Carlo method.

2) Considering that the DMC is time-consuming, the efficiency of the proposed IRSFEM-P is high.

3) The proposed IRSFEM-P is competitive for use in the reliability analysis of structures.

References

[1] Breitung K. Asymptotic approximations for multinormal

integrals[J]. *Journal of Engineering Mechanics*, 1984, **110**(3): 357 − 366. DOI: 10.1061/(asce)0733-9399(1984)110:3(357).

[2] Cai G Q, Elishakoff I. Refined second-order reliability analysis[J]. *Structural Safety*, 1994, **14**(4): 267 − 276. DOI: 10.1016/0167-4730(94)90015-9.

[3] Low B K, Einstein H H. Reliability analysis of roof wedges and rockbolt forces in tunnels[J]. *Tunnelling and Underground Space Technology*, 2013, **38**: 1 − 10. DOI: 10.1016/j.tust.2013.04.006.

[4] Chan C L, Low B K. Practical second-order reliability analysis applied to foundation engineering[J]. *International Journal for Numerical and Analytical Methods in Geomechanics*, 2012, **36**(11): 1387 − 1409. DOI: 10.1002/nag.1057.

[5] Plotnikov M Y, Shkarupa E V. Estimating the statistical error in calculating velocity and temperature components by the direct simulation Monte Carlo method[J]. *Numerical Analysis &Applications*, 2016, **9**(3): 246 − 256. DOI: 10.1134/s199542391603006x.

[6] Guo T, Li A Q, Miao C Q. Monte Carlo numerical simulation and its application in probability analysis of long span bridges[J]. *Journal of Southeast University* (*English Edition*), 2005, **21**(4): 469 − 473.

[7] Zhang H, Dai H, Beer M, et al. Structural reliability analysis on the basis of small samples: An interval quasi-Monte Carlo method[J]. *Mechanical Systems and Signal Processing*, 2013, **37**(1/2): 137 − 151. DOI: 10.1016/j.ymssp.2012.03.001.

[8] Echard B, Gayton N, Lemaire M, et al. A combined importance sampling and Kriging reliability method for small failure probabilities with time-demanding numerical models[J]. *Reliability Engineering & System Safety*, 2013, **111**(2): 232 − 240. DOI: 10.1016/j.ress.2012.10.008.

[9] Kuznetsov N Y, Homyak O N. Evaluation of the probability of functional failure of a redundant system by importance sampling method[J]. *Cybernetics and Systems Analysis*, 2014, **50**(4): 538 − 547. DOI: 10.1007/s10559-014-9642-4.

[10] Dubourg V, Sudret B. Meta-model-based importance sampling for reliability sensitivity analysis[J]. *Structural Safety*, 2014, **49**(10): 27 − 36. DOI: 10.1016/j.strusafe.2013.08.010.

[11] Wang X Y, Cen S, Li C F, et al. A priori, error estimation for the stochastic perturbation method[J]. *Computer Methods in Applied Mechanics and Engineering*, 2015, **286**(3): 1 − 21. DOI: 10.1016/j.cma.2014.11.044.

[12] Huang B, Li Q S, Shi W H, et al. Eigenvalues of structures with uncertain elastic boundary restraints[J]. *Applied Acoustics*, 2007, **68**(3): 350 − 363. DOI: 10.1016/j.apacoust.2006.01.012.

[13] Beddek K, Clenet S, Moreau O, et al. Spectral stochastic finite element method for solving 3D stochastic eddy current problems[J]. *International Journal of Applied Electromagnetics &Mechanics*, 2012, **39**(1): 753 − 760.

[14] Ghosh D. Probabilistic interpretation of conjugate gradient iterations in spectral stochastic finite element method[J]. *AIAA Journal*, 2014, **52**(6): 1313 − 1316. DOI: 10.2514/1.j052769.

[15] Nair P B, Keane A J. Stochastic reduced basis methods [J]. *AIAA Journal*, 2012, **40**(8): 1653 − 1664. DOI: 10.2514/3.15243.

[16] Sachdeva S K, Nair P B, Keane A J. Comparative study of projection schemes for stochastic finite element analysis [J]. *Computer Methods in Applied Mechanics &Engineering*, 2006, **195**(19/20/21/22): 2371 − 2392. DOI: 10.1016/j.cma.2005.05.010.

[17] Huang B, Li Q S, Tuan A Y, et al. Recursive approach for random response analysis using non-orthogonal polynomial expansion[J]. *Computational Mechanics*, 2009, **44**(3): 309 − 320. DOI: 10.1007/s00466-009-0375-6.

[18] Huang B, Liu W, Qu W. Recursive stochastic finite element method[C]//*Proceedings of the* 8*th International Symposium on Structural Engineering for Young Experts*. Xi'an, China, 2004: 155 − 160.

[19] Huang B, Zhu L P, Seresh R F. Statistical analysis of dynamic characteristics of large span cable-stayed bridge based on the recursive stochastic finite element method [C]// *Proceedings of the* 12*th International Symposium on Structural Engineering*. Wuhan, China, 2012: 440 − 448.

基于多变量幂多项式展开的含随机参数结构可靠性分析

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摘要: 基于多变量幂多项式展开,提出了一种计算带有随机参数的结构失效概率的新方法,随机参数包括材料性能、结构几何特征和静力荷载. 首先,将结构响应展开为一个系数未知的多变量幂多项式展开式,然后结合高阶摄动技术和伽辽金投影方法确定多变量幂多项式展开式的待定系数,从而最终获得结构的功能函数. 由于得到的功能函数是一种显式表达,可通过蒙特卡洛模拟直接进行结构失效概率的多维积分计算,且只需少量的计算时间. 2 个数值算例证明了所提出方法的精确性和高效性. 将该方法与被广泛应用的一次二阶矩可靠性方法(FORM)和二次二阶矩可靠性方法(SORM)进行了比较,结果表明该方法的计算结果最接近直接蒙特卡洛方法,且比直接蒙特卡洛方法耗时低很多.

关键词: 可靠度;随机参数;多变量幂多项式展开;摄动技术;伽辽金投影

中图分类号: O343; TU313