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Effect of uncertain system properties on the reliability of dynamic jacket structures

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ABSTRACT: System uncertainties in offshore structures in general have been found to be small but some measurements and some more or less sophisticated structural analyses indicate that they can be significant both with respect to extreme value failure and with respect to fatigue in some cases. A rigorous analysis by stochastic finite element codes in conjunction with modern reliability methods such as FORM/SORM, however, is not yet feasible for realistic structures. This is primarily due to the fact that rigorous FORM/SORM methods require numerical or analytical gradients involving considerable computational effort. Even if this problem can be overcome the existence of multiple β-points especially in the dynamic case and/or the necessity to investigate many "hot spots" makes such an analysis difficult. As an alternative simulation methods have been proposed among which so-called adaptive conditional expectation methods appear most suitable as they can overcome some of the more important disadvantages of the more rigorous methods and retain the advantages of FORM/SORM. In the paper, a two dynamic structures exposed to random wave loading with/without current is investigated with emphasis on the methodological aspects. Apart from the loading environment the coefficients in the Morison equation, the stiffnesses of the structural members, the stress concentration factors and the deck load are assumed uncertain. In agreement with earlier studies it is found that adaptive and non-adaptive conditional expectation procedures are in fact appropriate means to investigate the influence of system uncertainties. However, adaptive schemes can be suboptimal whenever several "hot spots" need to be investigated simultaneously. Their convergence behaviour also depends strongly on the starting conditions for the simulations. In any case the coefficient of variation of the probability estimates must not be used as a convergence criterion. Furthermore the system uncertainties should be small relative to other uncertainties and not too high dimensional. The numerical effort required for real large structures may still be excessive and schemes should be designed which use more information from sample points than incorporated in the implemented procedure.

Introduction

The reliability methodology for failure due to fatigue damage accumulation or to extreme loading is well known and has been used in many offshore applications. FORM/SORM approaches have been shown to be especially efficient. In most of these studies uncertainties in the loading and the resistance parameters were considered whereas uncertainties in structural data were neglected or simplified (see, e.g., Flint and Baker (1977), Olufsen et al. (1989), Karadeniz and Haritos (1993)). Structural uncertainties, however, may have a great influence on reliability results for dynamic structures. Due to larger water depth, offshore structures now become increasingly more flexible and dynamically sensitive. Hence it seems interesting to improve the reliability tools to allow handling of uncertain system properties in the assessment of reliability.

This goal may be achieved in different ways. Firstly, the theory may be rigorously extended in the frame work of FORM/SORM requiring primarily schemes for the calculation of gradients of the state function. This was already done for linear static problems and lead to combinations of stochastic finite element codes and extended FORM/SORM tools with numerical or analytical gradients (see, e.g. Hisada and Nakagiri (1985), Igusa and Der Kiureghian (1988)). These theoretical derivations can be easily extended for linear dynamic problems but it is found that these extensions result in excessively large and time consuming programmes. This is especially the case for multimodal failure criteria as each of those requires a separate analysis. This can be shown by counting the necessary state function calls and the associate calls of a structural analysis program. Furthermore, it is not clear whether the gradient based methods yield accurate results in the case of multiple β-points or strong non-linearities in the failure surface. In fact, the authors believe that classical FORM/SORM analysis including system uncertainties are just impractical for realistic dynamic structures.

Simulation based techniques may have the potential to solve the problems. These techniques, no doubt, are less elegant than gradient based techniques but they are easy to implement and they provide estimates of the failure probability together with accuracy measures if properly implemented. Crude Monte Carlo simulation, on the one hand, cannot be used for practical purposes because low failure probabilities cannot be estimated sufficiently accurate in few iterations with this technique. Conditional expectation, on the other hand, does not suffer from any of the aforementioned shortcomings if it is properly used (see, e.g., Melchers (1987), Ayyub and Chia (1992)) as it can combine rigorous FORM/SORM with simulation. It may, however, be slow in convergence in some cases but this may be improved by using the fact that the knowledge of the failure region increases during simulation. This improvement can for instance be achieved with so-called adaptive schemes. Those proved to be effective in simple non-linear cases (see, e.g., Karamchandani and Cornell (1991)). These different points make of conditional sampling the most attractive practical method.

Conditional sampling is thus used to quantify the influence of system and loading uncertainties on the reliability of tubular sections of an offshore jacket subjected to irregular long crested sea waves. To simplify, problems related to non-linearities in the loading, in wave kinematics, in material behaviour, in fatigue phenomena etc. are neglected in this study. Linear wave theory is used and wave forcing is estimated with a linearized form of Morison's equation. The nominal stress is linearly interpolated on any cross section using so-called stress concentration factors (SCF's). Uncertainties in structural data, hydrodynamic coefficients in Morison's equation, SCF's and resistance parameters are taken into account in the reliability assessment of a single cross section against fatigue and yielding failures. The statistical modelling of structural uncertainties is shortly discussed in the following. Furthermore, it is explained how conditional sampling may be used for the considered problem. Two representative examples illustrate the theoretical development.

1. Modelling of system uncertainties

Consideration of uncertain system properties must be performed with great care and due regard must be given to the nature of these uncertainties. On the one hand, there are uncertainties which have to be modelled by random fields, for example the stiffness properties in the structure or the fluctuating part of marine growth. Those may be assumed as nearly ergodic. Experience shows that their effect on reliability generally is not large. On the other hand, there are distinctly non-ergodic quantities and most of them have to be considered as model uncertainties. The latter will be discussed in more detail below.

1.1 *Structural data*

Structural data is quite accurately known, i.e. the coefficient of variation of structural variables exceeds rarely 5%. With this small variability little influence is expected on reliability if, for example, a normal or lognormal distribution is assumed. It also makes very little difference whether these variabilities are fully or partly assumed non-ergodic.

1.2 *Hydrodynamic coefficients*

The Morison equation was experimentally derived from measurements of forces induced by regular waves on a vertically fixed member (Morison et al. (1950)). It consists of a drag term and of a mass term linearly combined with factors C_d and C_m, respectively. Morison's equation was later extended for inclined and/or moving members and for random waves. For each extension, hydrodynamic coefficients C_d and C_m should be measured but this can rarely be done in practice. Constant values are then usually used which are supposed to yield conservative estimates of the wave loading.

However, Sarpkaya (1976,1977,1978) reported that C_d and C_m do not take constant values in a sinusoidal oscillating flow but depend, and not in a simple way, on flow characteristics, such as Reynolds *Re* and Keulegan Carpenter *KC* parameters. When results of spectral analyses are used in reliability calculations, dependencies of C_d and C_m on flow conditions should therefore be taken into account. Modelling, however, is difficult because published results exhibit a considerable degree of scatter, even for similar flow conditions and similar experimental settings. Further, some numerical studies showed that a part of the observed scatter may in fact be attributed to the different methods of estimating the coefficients (see Dean (1976) and Isaacson et al. (1991)). Finally, and this is probably the most worrying point, only few published results correspond to realistic sea conditions. Consequently,

it is rather tempting to use simple statistical modelling to account for the variability in the forcing coefficients and this until deeper knowledge of hydrodynamics is acquired. In the following, we conservatively consider C_d and C_m as uniformly distributed in the intervals [0.7, 1.8] and [1.0, 2.0] in following published results (see, e.g., Chakrabarti (1987) or Clauss et al. (1992)). The strong negative correlation between these two values is neglected as would be done in practice to avoid wave forcing underestimation.

1.3 *Stress concentration factors*

It is equally difficult to estimate the probability distribution of the SCF's because here also model uncertainty exists together with parameter uncertainty. Indeed, the linear interpolation of the hot spot stress is questionable in itself because large discrepancies exist between SCF's estimated from parametric equations or from finite element calculations for a given joint configuration. The problem is that these coefficients are not robust enough and, consequently, a better interpolation scheme of the hot spot stress should be worked out. This is not the aim of this paper and, therefore, a statistical modelling is used which reproduces the large scatter exhibited by the SCF's. These quantities are modelled as independent normally distributed random variables with high coefficients of variation (10%).

2. Conditional expectation

Let $\boldsymbol{X}$ denote a set of random variables, $f_{\boldsymbol{X}}(.)$ its probability density and $D = \{\boldsymbol{x} \;/\; g_{\boldsymbol{X}}(\boldsymbol{x}) \le 0\}$ the failure domain. The failure probability is calculated as

$$P_f = \int_D f_X(x)\,dx \tag{1}$$

It can also be calculated in the standard space if there exists a transformation T: $\boldsymbol{U} \rightarrow \boldsymbol{X}$ where $\boldsymbol{U}$ is a standard independent vector. Let us divide the set $\boldsymbol{X}$ into two subsets $\boldsymbol{Y}$ and $\boldsymbol{Z}$. Then the failure probability can be calculated as

$$P_f = \int_y P_{f|Y=y}\, f_Y(y)\,dy \tag{2}$$

In the following the subsets $\boldsymbol{Y}$ and $\boldsymbol{Z}$ are respectively termed the generated and the controlling sets. If N sample outcomes y_i of $\boldsymbol{Y}$ are generated and the corresponding conditional probabilities are calculated, an unbiased estimate of the failure probability is

$$\bar{P}_f = \frac{1}{N}\sum_{i=1}^{N} P_{f|Y=y_i}\, f_Y(y_i) \tag{3}$$

Its variance is

$$\operatorname{var}(\bar{P}_f) = \frac{1}{N(N-1)}\sum_{i=1}^{N}\left(P_{f|Y=y_i}\, f_Y(y_i) - \bar{P}_f\right)^2 \tag{4}$$

It can be shown that the variance (4) of the estimate is unbiased, too. Then accuracy of the failure probability estimate can be judged from its coefficient of variation. In practice, samples are generated until this coefficient of variation reaches a target value, say 30% for practical purposes.

Conditional sampling is particularly effective if the conditional probability of failure given $\boldsymbol{Y}$=$\boldsymbol{y}$ can easily and accurately be calculated. This is for instance the case when the subset $\boldsymbol{Z}$ is chosen such that the failure surface possesses a unique most likely failure point (β-point) in the *z*-space. Any conditional failure probability may then be calculated by FORM or SORM or its improvements (see Hohenbichler et al. (1987), Hohenbichler and Rackwitz (1988)). The conditional expectation approach, however, is efficient only if the generated variables in *y*-space have small c.o.v.s because otherwise conditional failure probabilities may vary significantly and many samples may be necessary to reach the target c.o.v. Therefore, it may be worthwhile to consider the possibilities of including parts of the vector $\boldsymbol{Y}$ in $\boldsymbol{Z}$. Unfortunately, the separation usually is dictated by the mechanical context. Alternatively, one may apply one of the variance reduction techniques in simulation (see Rubinstein (1981)).

Kahn (1956) showed that the variance of the estimate reduces to zero if an adequate sampling density is used instead of $f_{\boldsymbol{Y}}(.)$. This ideal case, however, cannot be achieved without knowledge of P_f. In practice, the optimum sampling density is approximated during the sampling process, i.e. an initial sampling density is used and improved on the basis of partial results. The chosen sampling density being initially suboptimal the variance of the probability estimate is always biased and the bias decreases progressively during simulation. Of course, difficulties arise when choosing the initial sampling density and when improving it during simulation. These two problems were addressed in part successfully by several authors (see, e.g., Bucher (1988), Karamchandani (1990)) but it is not clear whether their conclusions remain valid for problems where little is known about the "important region". In any case, for an implementation in the standard space, the simplest and perhaps the most robust method consists in initially using a standard normal sampling density and in moving this density to the sample outcome y_i which yields the temporarily largest value integrand in (2). The convergence criterion remains unchanged.

3. Application to offshore structures

In what follows we consider the particular cases of fatigue and yielding failures of a tubular cross-section on an offshore steel jacket subjected to random waves. Failure criteria should be written in terms of the nominal stress on the circumference of the cross section but this stress field cannot be easily calculated. In practice, the stress spectrum is estimated in a finite number N_{hp} of points (hot spots) around the circumference only, using linear spectral theory. Then an individual failure criterion can be formulated in each hot spot. A state function for the cross-section is the union of all individual ones.

For the case of fatigue failure, the state function is given by

$$g(Y,Z)=\bigcup_{i=1}^{N_{hp}} g_i(Y,Z)=\bigcup_{i=1}^{N_{hp}}\left(\ln K-\ln\left(\nu_{0,i}\, t\lambda_{0,i}^{m/2}\left(2\sqrt{2}\right)^m\Gamma\left(1+\frac{m}{2}\right)\right)\right) \tag{5}$$

if, for simplicity of illustration, the damage indicator derived by Miles (1954) in case of a narrow band stress process is used. For the extreme load criterion, one obtains

$$g(Y,Z)=\bigcup_{i=1}^{N_{hp}} g_i(Y,Z)=\bigcup_{i=1}^{N_{hp}}(R-S_i)\ ,$$

where $F_{S_i}(s)=\exp\left(-\nu_{0,i}\, t\exp\left(-\frac{s^2}{2\lambda_{0,i}}\right)\right)$ (6)

using Rice's formula. In equations (5) and (6) t is the service time; $\ln K$ and m denote parameters in the S-N curve; R denotes the yield stress; $\nu_{0,i}$ and $\lambda_{0,i}$ are the zero upcrossing rate and the zero-th spectral moment of the hot spot stress S_i. Only a single sea state is considered.

In (5) and (6), the controlling set Z of random variables is respectively reduced to R and to $\ln K$ so that lower and upper bounds

$$\max_{1\le i\le N_{hp}}\left(P\left(g_i(Z,Y=y)\le 0\right)\right) \text{ and } \sum_{i=1}^{N_{hp}} P\left(g_i(Z,Y=y)\le 0\right) \tag{7}$$

for the conditional probability of failure given $Y=y$ are exactly calculated with FORM. All other properties, i.e. structural data, hydrodynamic coefficients and SCF's are regrouped in Y and generated. Then, lower and upper bounds can be estimated for the failure probability by using non-adaptive or adaptive conditional sampling.

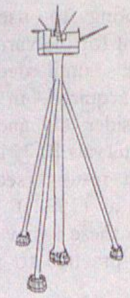

Figure 1. Example structure 1

Table 1. Stochastic model for controlling set Z

	Variable	Distribution	Mean value	C.o.V (%)
limit state (5)	ln K	Normal	120	20
	m	Constant	4	-
	service time t	Constant	5 years	-
limit state (6)	Yield stress R	Normal	360 MPa	10
	service time t	Constant	10 years	-

Table 2. Stochastic model for generated set Y

Variable	Distribution	Mean value	C.o.V. (%)
Young's modulus	Normal	2.1e+11 N/m^2	5
Mass density	Normal	7800 kg/m^3	5
Deck Load	Normal	3000 tons	5
C_d	Uniform	1.25	25
C_m	Uniform	1.50	19
SCF for N	Normal	2.00	10
SCF for *IPB*	Normal	2.00	10
SCF for *OPB*	Normal	2.00	10

4. Example 1

The aforementioned method is used to quantify the relative influence of system uncertainties on the reliability level of a simple tripode structure (see Karadeniz (1989)). The jacket is 70 m high and the deck is 20 m above the mean water level. Submerged members are empty and a mass of 3000 tons is fixed on the deck. A sketch of the structure is given in Figure 1. The computer model consists of 5 tubular beam elements and 6 nodes each having six degrees of freedom.

The stochastic models for the controlling set Z and the generated set Y are reported in Tables 1 and 2. A total number of 23 (1+22) random variables is used. Independent random properties are assumed for the beam elements. Same SCF's are used for all hot spots.

Table 3. Estimated upper bound for the failure probability (target c.o.v. 30 %)

Method	Run #	max E[P_f]	*Nsimul*
Conditional Sampling	1	2.98 10^{-4}	669
	2	2.62 10^{-4}	772
	3	2.74 10^{-4}	751
Ad. (SCF,Hyd) Con. Samp.	1	0.98 10^{-4}	421
	2	1.81 10^{-4}	1521
	3	2.43 10^{-4}	961
Adap. (Hyd) Cond. Samp.	1	1.44 10^{-4}	1590
	2	2.80 10^{-4}	3117
	3	1.46 10^{-4}	1339
Adap. (SCF) Cond. Samp.	1	1.35 10^{-4}	182
	2	1.39 10^{-4}	208
	3	2.73 10^{-4}	620

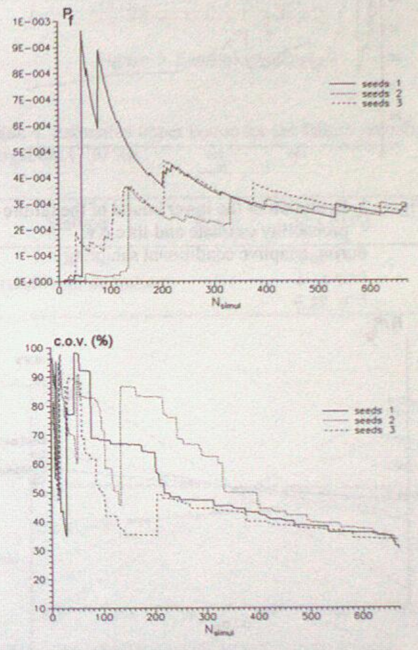

Figure 2. Evolution of the upper bound of the failure probability estimate and its c.o.v. during conditional sampling

For each sample y of the generated set Y, the structure is analyzed by the Finite Element code NASCOM (1994). A lumped mass matrix is used. Spectral analyses are further performed with an improved version of the code SAPOS written by Karadeniz (1989). The program uses a linearization technique of the drag term which was proposed by Bolotin (1981) and a mode acceleration technique. Spectral analyses are performed for single sea states only. For each sea state, sea waves are considered long crested and a Pierson-Moskowitz wave spectrum for the sea elevation process is assumed. Stress spectral moments are calculated at a number N_{hp} of hot spots on a cross section on the central column. It was found that the maximum hot spot stress was generally not missed with N_{hp} = 8. Numerical tests further proved that the two lowest modes (ω_1 and ω_2 ~ 2 rad/s) are sufficient to ensure convergence in the spectral moments. A structural damping equal to 1% of critical is assumed for each mode.

The results of spectral analyses are used to estimate bounds for the probability of failure under the condition $Y = y$. The state functions (5) and (6) are considered separately. All reliability calculations are performed within COMREL (1994). Samples of Y are generated until the coefficient of variation of the failure probability estimate reaches 30 %. Non-adaptive and adaptive schemes are used alternatively and sampling is performed for different starting seeds.

For fatigue failure it is found that system uncertainties generally can be neglected even if the structure is dynamically excited, for example, for the sea state T_z = 3 s, H_s = 6 m. The contrary is observed for extreme value failure. The upper bound obtained by conditional sampling for the probability of failure due to extreme load under the aforementioned sea condition without wave current is given in Table 3. Results obtained with adaptive conditional sampling are reported, too. The bounds for the failure probability are (1.55 10^{-7}, 2.85 10^{-7}) when uncertainty in structural properties is neglected. Typical evolutions of the probability estimate and its coefficient of variation during conditional and adaptive conditional sampling is shown on Figures 2 and 3.

Sensitivity analyses are further performed with conditional sampling. For example, Figure 4 illustrates the sensitivity of the upper bound of the failure probability to changes in the coefficient of variation of system properties. Computations are also performed for wave current velocities lying between -1.0 m/s and + 1.0 m/s, homogeneous and inhomogeneous wave-current conditions but no noticeable change is noticed in the general trends.

5. Example 2

The aforementionned methodology is now used to analyse a realistic structure. This second example jacket structure is 60 m high. The deck is 20 m above the mean water level. Submerged members are empty and a mass of 630 tons is fixed on the deck. A sketch of the structure is given in Figure 5. The computer model consists of 132 degrees of freedom. The two lowest modes are ω_1 and $\omega_2 \sim 3$ rad/s. The stochastic models used for the controlling set $\boldsymbol{Z}$ and the generated set $\boldsymbol{Y}$ are the same as for the first example structure, see Tables 1 and 2, with the expection of the deck load whose mean value now is 630 tons. A total number of 97 (1+96) random variables is used.

As for the first case study, it is found that the influence of system uncertainties on fatigue failure is negligible. Again, this is not the case for extreme load failure. For the extreme sea state $T_z = 2$ s, $H_s = 6$ m, the upper bound estimated by conditional sampling for the probability of failure on a cross section on the central column is reported in Table 4. The bounds for the failure probability are (7.52 10^{-8}, 1.38 10^{-7}) when uncertainty in structural properties is neglected. Adaptive conditional sampling yields same results because no updating of the sampling density occurs. Results of sensitivity analysis are given on Figure 6.

6. Discussion of methodological aspects

The foregoing detailed description of results for the example structure is necessary because otherwise misinterpretations of the methodological aspects are rather likely. The results so far must also be considered only valid for the studied structures. In any case, the results so far obtained indicate that uncertainties in structural data may have a non-negligible influence on extreme value failure. Although for the studied structures the influence of uncertain system properties on fatigue failure was negligible, significant effect must be expected for other structures.

From Tables 3 and 4 it can be concluded that results with non-adaptive conditional sampling procedures are fairly consistent. Indeed, only small differences are observed in the estimates of the failure probability but convergence depends on the starting conditions.

No such consistency is observed for the adaptive scheme even if the presence of multiple failure modes is considered, for example, according to Schueller and Stix (1987) or Fu and Moses (1987). Firstly, there is also a strong dependence of the probability estimate and its coefficient of variation on the

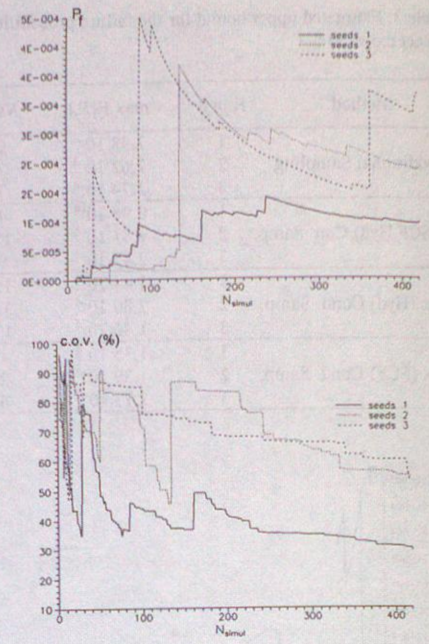

Figure 3. Evolution of the lower bound of the failure probability estimate and its c.o.v. during adaptive conditional sampling

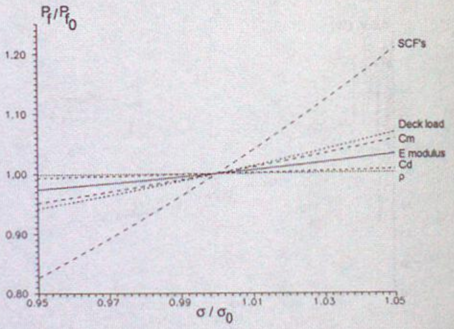

Figure 4. Effect of changes in the c.o.v. of system data on the upper bound of the failure probability

starting conditions and this is stronger for adaptive sampling than for non-adaptive sampling. Secondly, the convergence of the adaptive scheme is significantly affected by the number of $\boldsymbol{Y}$-variables involved. In fact, for a large number of $\boldsymbol{Y}$-variables there may be no or very little updating of the sampling density during simulation, at least for the simple updating scheme used. For example, for the second structure with 96 y-variables it is found that no updating of the sampling density occurred during simulation. This is in contradiction with results by

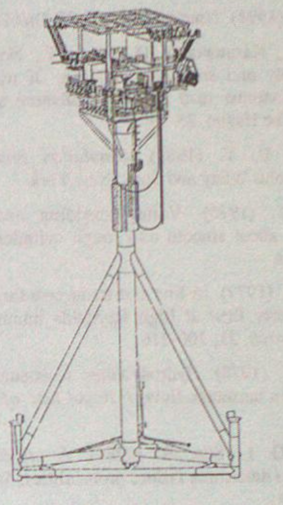

Figure 5. Example structure 2

Table 4. Estimated upper bound for the failure probability (target c.o.v. 30 %)

Method	Run #	max $E[P_f]$	*Nsimul*
Conditional Sampling	1	3.63 10^{-3}	285
	2	4.16 10^{-3}	267
	3	6.22 10^{-3}	557

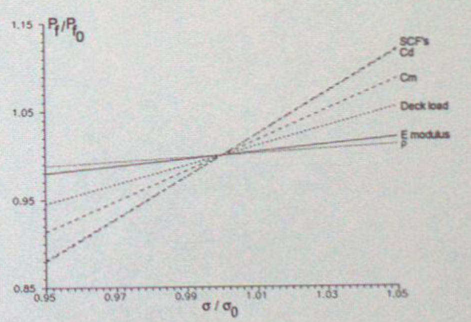

Figure 6. Effect of changes in the c.o.v. of system data on the upper bound of the failure probability

Karamchandani (1990) who found that sampling results are not directly affected by the number of random variables. In fact, he considered simple problems for which the initial location of the sampling density could be optimized and this was not possible in our study. As shown in Figures 2 and 3, during adaptive sampling jumps are observed in the probability estimate as well as in its coefficient of variation even for high number of samples, in contrast to simple conditional sampling where convergence is much more uniform. It follows that the coefficient of variation of the probability estimate is an inadequate measure of convergence for adaptive schemes. A similar conclusion was already drawn by Walsh (1956) and later by Ibrahim (1991) for simple importance sampling. Nevertheless, irrespective of the value of the coefficient of variation the probability estimate may already be good.

It is still maintained that a hybrid methodology, i.e. a combination of rigorous FORM/SORM and sampling methods, is the only possibility at present to analyze larger problems with non-negligible system uncertainties. The present study leads to the following conclusion and two open questions. Simple conditional expectation schemes are applicable only for small uncertainties in the $\boldsymbol{Y}$-vector. Otherwise, they can become time consuming. Adaptive schemes, even with multimodal sampling densities, are potentially superior to simple conditional expectation schemes. In order to judge convergence the coefficient of variation of the failure probability estimate from all generated samples certainly is inadequate. Therefore, it remains to define alternative convergence criteria. Further, in problems with large number of $\boldsymbol{Y}$-variables and with little prior knowledge of the failure function(s) the important regions on average are likely to be found only after a considerable number of samples. Cases will occur where the important regions are found very quickly and other cases where little knowledge about these regions will be acquired after a large number of samples. In any case, one does not know whether the sampling density is already well located or not. Hence, the second open question is how to use more information from previous sample points in order to update the sampling density more effectively.

Finally, non-adaptive or adaptive conditional sampling may be a valid alternative to semi-analytical stochastic finite element method combined with FORM/SORM even for large structures, in particular if multiple failure modes must be considered.

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