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Author(s)	Misraji, A. Mauricio; Valdebenito, A. Marcos; Faes, G.R. Matthias
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Importance Line Sampling for Dynamic Reliability of Linear Stochastic Systems

Mauricio A. Misraji[1, *], Marcos A. Valdebenito[1], and Matthias G.R. Faes[1,2]

[1]*Chair for Reliability Engineering, TU Dortmund University, Leonhard-Euler-Straße 5, 44227, Dortmund, Germany.*
E-mail: {mauricio.misraji,marcos.valdebenito,matthias.faes}@tu-dortmund.de
[2]*International Joint Research Center for Engineering Reliability and Stochastic Mechanics, Tongji University, 200092, Shanghai, China.*
**Corresponding Author*

This work introduces the Importance Line Sampling (ILS) technique for estimating the first excursion probability in linear dynamic systems subjected to Gaussian loading. The proposed method addresses the problem of estimating low failure probabilities, for which the failure domain is defined in a high-dimensional stochastic space. The linearity of the loading-response relationship results in a specific geometry of the failure domain, consisting of thousands of partially overlapping hyperplanes. This geometric information is exploited to combine multiple coordinate systems with an importance sampling density within the Line Sampling framework, thereby guiding the exploration of the stochastic space toward the most relevant failure regions. In this way, the failure domain is explored along lines perpendicular to the hyperplanes, resulting in a highly efficient estimator. The effectiveness of the method is demonstrated through a large-scale example, in which the proposed estimator is compared with different methods from the literature and is shown to be the most efficient among the methods considered.

Keywords: First excursion probability, linear structure, Gaussian load, Line Sampling, Importance Sampling.

1 Introduction

Accurate estimation of the first excursion probability remains a central challenge in stochastic dynamics (Schüeller and Pradlwarter 2007). This probability quantifies whether a response of interest, such as displacement, exceeds a prescribed threshold within a given time interval under stochastic excitation. In engineering applications, the problem is often formulated in a high-dimensional stochastic space, and closed-form solutions are generally not available. However, specialized simulation methods have been developed to address this issue and reduce the computational cost associated with multiple dynamic analyses (Koutsourelakis et al. 2004).

A relevant class of problems arises when the loading is modeled as a Gaussian process and the system response depends linearly on it. This setting is encountered in practical applications where serviceability requirements (Honfi 2012) must be satisfied or vibration levels must remain within prescribed limits. Such characteristics have been exploited by several methods in the literature (Der Kiureghian 2000, Au and Beck 2001, Misraji et al. 2020, Valdebenito et al. 2021) to construct estimators of the first excursion probability. For this class of problems, the special structure of the failure domain allows the sampling procedure to focus directly on the regions that are most relevant for probability estimation, resulting in efficient estimators. Even so, the problem remains computationally demanding, especially when large-scale models are considered.

To address this issue, this work proposes a novel technique called Importance Line Sampling for estimating the first excursion probability of dynamic linear systems subjected to Gaussian loading. The method combines multiple coordinate systems with an importance sampling density (Au and Beck 2001) within the Line Sampling (Koutsourelakis et al. 2004) framework, enabling a targeted exploration of the failure domain. This leads to a highly efficient estimator for low failure probabilities, of the order of 10^{-3}. The method is illustrated through a large-scale finite element example and its performance is compared with similar techniques from the literature.

2 Problem Statement

2.1 *Gaussian Loading*

The stochastic loading acting on a system is modeled as a discrete Gaussian process of duration T, sampled at n_T time instants with time step Δt, where the k-th time instant is given by $t_k = (k-1)\Delta t$, $k = 1, \dots, n_T$. The loading is represented by a Karhunen-Loève expansion (see, e.g., Stefanou 2009) as:

$$p(t_k, \boldsymbol{z}) = \mu_k + \boldsymbol{\psi}_k^T \boldsymbol{z}, \tag{1}$$

where $p(t_k, \boldsymbol{z})$ denotes the load at time t_k, $\boldsymbol{z}$ is a realization of the standard Gaussian vector $\boldsymbol{Z} \in \mathbb{R}^{n_{KL} \times 1}$ with joint probability function $f_{\boldsymbol{Z}}(\boldsymbol{z})$, n_{KL} is the truncation order of the expansion ($n_{KL} \leq n_T$), μ_k is the mean value of the stochastic process at time t_k (assumed to be zero), and $\boldsymbol{\psi}_k^T \in \mathbb{R}^{n_{KL} \times 1}$ contains the covariance information of the Gaussian process. Note that this formulation readily allows the definition of stochastic excitations such as white noise and filtered white noise, the latter for instance through a Clough–Penzien filter (see Zerva 2009).

2.2 *Structural System*

The equation of motion of a linear elastic, classically damped dynamic system (Chopra 1995) is given by:

$$\boldsymbol{M}\ddot{\boldsymbol{x}}(t,\boldsymbol{z}) + \boldsymbol{C}\dot{\boldsymbol{x}}(t,\boldsymbol{z}) + \boldsymbol{K}\boldsymbol{x}(t,\boldsymbol{z}) = \boldsymbol{g}p(t,\boldsymbol{z}), t \in [0,T], \tag{2}$$

where $\boldsymbol{x}$, $\dot{\boldsymbol{x}}$ and $\ddot{\boldsymbol{x}}$ denote the displacement, velocity and acceleration vectors, respectively, all of dimension $n_D \times 1$, with n_D being the number of degrees of freedom of the system. The mass, damping, and stiffness matrices, $\boldsymbol{M}$, $\boldsymbol{C}$, and $\boldsymbol{K}$, are of dimension $n_D \times n_D$, whereas the loading-coupling vector $\boldsymbol{g}$ has dimension $n_D \times 1$.

The solution of Eq. (2) allows defining a set of n_η responses of interest denoted by $\eta_i(t,\boldsymbol{z})$, $i = 1, \dots, n_\eta$, which may represent, for instance, displacements, accelerations, or internal stresses. Due to the linearity of the system, each response of interest can be calculated using the convolution integral, as:

$$\eta_i(t,\boldsymbol{z}) = \int_0^t h_i(t-\tau)p(\tau,\boldsymbol{z})d\tau, \qquad i = 1, \dots, n_\eta, \tag{3}$$

where h_i denotes the unit impulse function of the i-th response of interest, which can be obtained through modal analysis (Chopra 1995).

The discretized definition of the Gaussian loading in Eq. (1) allows the numerical integration of Eq. (3). The response of interest can then be written as follows:

$$\eta_i(t_k,\boldsymbol{z}) = \boldsymbol{a}_{i,k}{}^T\boldsymbol{z}, \tag{4}$$

where $\boldsymbol{a}_{i,k} \in \mathbb{R}^{n_{KL}}$ is the discretized convolution of the unit impulse response function and the deterministic part of the Gaussian loading, expressed as:

$$\boldsymbol{a}_{i,k} = \sum_{m=1}^{k} \Delta t \epsilon_m h_i(t_k - t_m)\boldsymbol{\psi}_m, \tag{5}$$

with ϵ_m chosen according to the adopted integration rule; for the trapezoidal rule, $\epsilon_m = 1/2$ for $m = 1$ or $m = k$, and $\epsilon_m = 1$ otherwise.

2.3 *First Excursion Probability*

The design requirements are defined for each response of interest through the vector $\boldsymbol{b} \in \mathbb{R}^{n_\eta}$, whose i-th element, b_i, $i = 1, \dots, n_\eta$, represents the exceedance limit associated with the response of interest η_i. Thus, the performance function indicates whether the response of interest exceeds the corresponding exceedance limit at any time instant, and is given by:

$$g(\boldsymbol{z}) = 1 - \max_{i=1,\dots,n_\eta}\left(\max_{k=1,\dots,n_T}\left(\frac{|\eta_i(t_k,\boldsymbol{z})|}{b_i}\right)\right), \tag{6}$$

where $|\cdot|$ corresponds to absolute value, $g(\boldsymbol{z}) \leq 0$ indicates that the exceedance condition is met, whereas $g(\boldsymbol{z}) > 0$ indicates that it is not. The corresponding failure domain in the probabilistic space is defined as $F = \{\boldsymbol{z}: g(\boldsymbol{z}) \leq 0\}$, and its indicator function $I_F(\mathbf{z})$ is equal to 1 if $\mathbf{z} \in F$, and 0 otherwise. In particular, the failure domain is composed of elementary failure domains $F_{i,k}$, each associated with the exceedance of the i-th response at the k-th time instant. Moreover, each elementary failure domain can be decomposed into its positive and negative parts, denoted by $F_{i,k}^+$ and $F_{i,k}^-$, such that $F_{i,k}^+ \cup F_{i,k}^- = F_{i,k}$. Then, the probability of occurrence of F is the so-called first excursion probability (Soong 1993):

$$p_F = \int_{\mathbb{R}^{n_{KL}}} I_F(\mathbf{z}) f_{\boldsymbol{Z}}(\boldsymbol{z}) d\boldsymbol{z}. \tag{7}$$

Note that, according to Eq. (6), the failure domain is composed of a total of $n_\eta \times n_T$ elementary failure domains, each of which corresponds to the event that the i-th response of interest exceeds its threshold at the k-th time instant.

3 Importance Line Sampling

The first excursion probability estimator proposed in this contribution is based on the concepts of classical Line Sampling and Importance Sampling. As discussed in Section 2.3, the failure domain is defined by the union of elementary failure domains in a high-dimensional space, each bounded by a hyperplane. Owing to the linearity of the problem, each elementary failure domain can be fully characterized by its design point and associated reliability index, which provide valuable information about its relevance to the failure probability. This information is used in two ways. First, it defines a mixture representation of the failure probability in terms of different coordinate systems, whose parallel axes are aligned with the directions of the corresponding design points. In this way, the same failure probability is reformulated in several rotated coordinate systems, each defined by a corresponding design point; this aspect is

discussed in Section 3.1. Second, it enables the construction of an importance sampling density associated with those coordinate systems, as discussed in Section 3.2. Based on these two definitions, the resulting estimator is presented in Section 3.3.

3.1 *Coordinate-system Mixture Formulation*

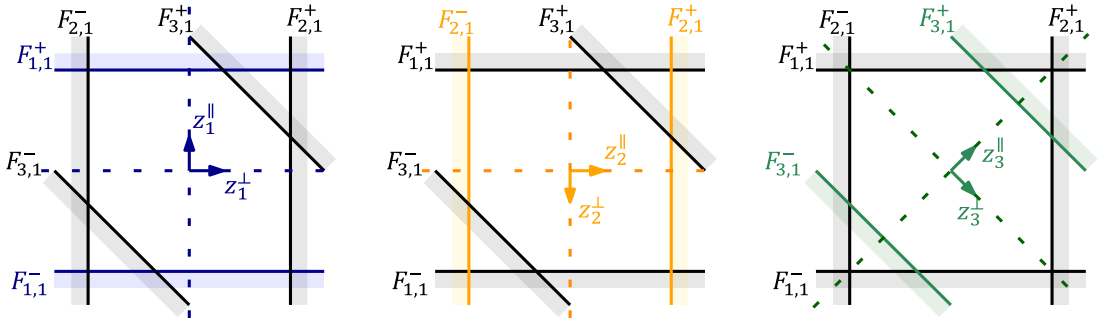
The first excursion probability in Eq. (7) can be evaluated using different coordinate-system definitions. This yields several equivalent representations of the same failure probability. Accordingly, p_F can be written as the following weighted mixture:

$$p_F = \sum_{j=1}^{n_c} \rho_j p_F^j, \tag{8}$$

where p_F^j denotes the failure probability represented in the j-coordinate system, ρ_j is the corresponding weight, and n_c is the number of coordinate systems considered, with $\sum_{j=1}^{n_c} \rho_j = 1$. Thus, the first excursion probability associated with the j-coordinate system can be written as:

$$p_F^j = \int_{\mathbb{R}^{n_{KL}-1}} \int_{\mathbb{R}} \mathbb{I}_F(z_j^{\parallel}, \boldsymbol{z}_j^{\perp}) f_{\boldsymbol{Z}}(z_j^{\parallel}, \boldsymbol{z}_j^{\perp}) dz_j^{\parallel}\, d\boldsymbol{z}_j^{\perp}, \tag{9}$$

where $z_j^{\parallel} \in \mathbb{R}$ and $\boldsymbol{z}_j^{\perp} \in \mathbb{R}^{n_{KL}-1}$ are the coordinates of $\boldsymbol{z}$ in the j-th coordinate system, with $z_j^{\parallel}$ corresponding to the direction normal to the j-th elementary failure domain and $\boldsymbol{z}_j^{\perp}$ collecting the remaining orthogonal coordinates. In this work, each coordinate system is associated with one elementary failure domain $F_{i,k}$. For convenience, these coordinate systems are re-indexed by a single index j, establishing a one-to-one correspondence between the pair (i,k) and j. Accordingly, $n_c = n_\eta n_T$. To illustrate the different coordinate-system definitions, Fig. 1 shows three representative systems, for a case where $n_\eta = 1$ and $n_{KL} = n_T = 3$. In Fig. 1a, the coordinate system is oriented with respect to $F_{1,1}$; Fig. 1b with respect to $F_{2,1}$; and in Fig. 1c with respect to $F_{3,1}$.



a) $j = 1$ system b) $j = 2$ system a) $j = 3$ system

Figure 1. Three representative coordinate-system definitions for a case where $n_\eta = 1$ and $n_{KL} = n_T = 3$.

3.2 *Importance Sampling Density*

Based on the geometry of the failure domain and the concepts proposed by Au and Beck (2001), an importance sampling density is defined within the Line Sampling framework. Since this density is formulated in the standard Gaussian space, it can be equivalently expressed in any rotated coordinate system. In the j-th coordinate system, it is given by (Au and Beck 2001):

$$f_{\boldsymbol{Z}}^{\mathrm{IS}}(\boldsymbol{z}) = f_{\boldsymbol{Z}}^{\mathrm{IS},j}(z_j^{\parallel}, \boldsymbol{z}_j^{\perp}) = \sum_{i=1}^{n_\eta} \sum_{k=1}^{n_T} \omega_{i,k} f(\boldsymbol{z}_j^{\perp} | F_{i,k}) f(z_j^{\parallel}), \tag{10}$$

where $\omega_{i,k}$ is the weight assigned to the elementary failure domain $F_{i,k}$. The weights are chosen proportional to the corresponding probabilities, that is:

$$\omega_{i,k} = \frac{P[F_{i,k}]}{\sum_{l=1}^{n_\eta} \sum_{m=1}^{n_T} P[F_{l,m}]}, \tag{11}$$

where $P[\cdot]$ denotes probability of occurrence.

Therefore, within the Line Sampling framework, the importance sampling density in Eq. (10) defines a mixture over the elementary failure domains through the weights $\omega_{i,k}$. Although Eq. (10) is expressed in the j-th coordinate system, the density itself does not depend on j; the index only identifies the rotated representation adopted for the parallel-perpendicular decomposition. Since the density is built from conditional distributions associated with failure events, it naturally assigns greater weight to the domains that are closer to the origin in the standard Gaussian space and therefore more relevant to the failure probability.

3.3 *First Excursion Probability Estimator*

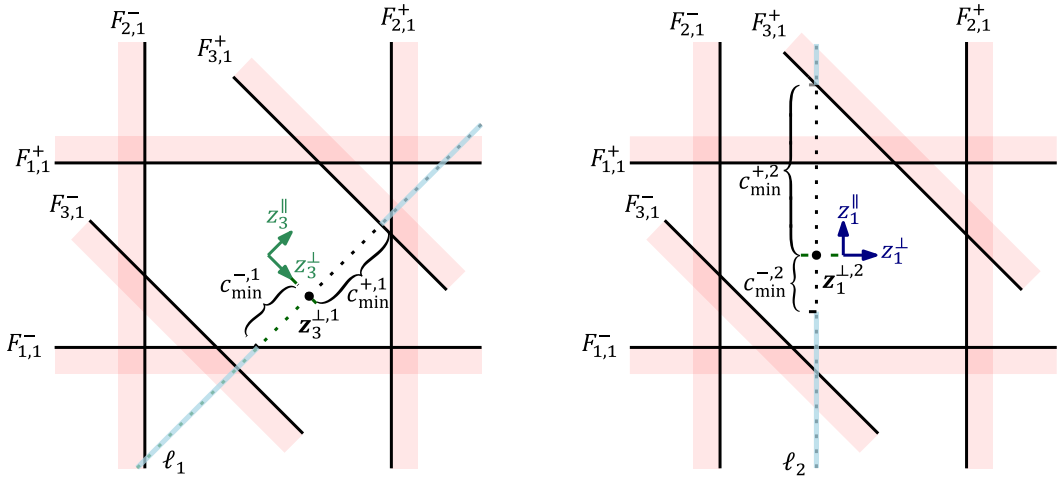
By combining Eqs. (8) and (9), the first excursion probability defined in Eq. (7) is represented as a weighted mixture over different coordinate systems. This representation can be further enriched by incorporating geometric information of the failure domain through the importance sampling density introduced in Eq. (10) of Section 3.2, resulting in:

$$p_F = \sum_{j=1}^{n_c} \rho_j \int_{\mathbb{R}^{n_{KL}-1}} \int_{\mathbb{R}} \mathbb{I}_F\left(z_j^{\parallel}, \mathbf{z}_j^{\perp}\right) \frac{f_{\mathbf{Z}}\left(z_j^{\parallel}, \mathbf{z}_j^{\perp}\right)}{f_{\mathbf{Z}}^{\mathrm{IS},j}\left(z_j^{\parallel}, \mathbf{z}_j^{\perp}\right)} f_{\mathbf{Z}}^{\mathrm{IS},j}\left(z_j^{\parallel}, \mathbf{z}_j^{\perp}\right) dz_j^{\parallel}\, d\mathbf{z}_j^{\perp}. \tag{12}$$

Note that Eq. (12) involves the evaluation of an integral in a one-dimensional Gaussian space with respect to $z_j^{\parallel}$ and includes both a discrete and a continuous random variable. The discrete random variable corresponds to the selection of the coordinate system j, with probability mass function ρ_j, whereas the continuous random variable is the orthogonal component of the Gaussian vector in that coordinate system, that is, $\mathbf{z}_j^{\perp}$. Since the importance sampling density can be expressed in any coordinate system, it is conveniently written here in terms of the j-th one; this does not imply any conditioning on j. Therefore, by simulating the discrete random variable associated with the probabilities ρ_j and the continuous random variable $\mathbf{z}_j^{\perp}$, the estimator of the first excursion probability using Importance Line Sampling is given by:

$$\tilde{p}_F = \frac{1}{N} \sum_{i=1}^{N} \int_{\mathbb{R}} \mathbb{I}_F\left(z_{j_i}^{\parallel}, \mathbf{z}_{j_i}^{\perp,i}\right) \frac{f_{\mathbf{Z}}\left(z_{j_i}^{\parallel}, \mathbf{z}_{j_i}^{\perp,i}\right)}{f_{\mathbf{Z}}^{\mathrm{IS},j_i}\left(z_{j_i}^{\parallel}, \mathbf{z}_{j_i}^{\perp,i}\right)} dz_{j_i}^{\parallel}, \tag{13}$$

where j_i denotes the index of the coordinate system selected at the i-th simulation, with probability mass function ρ_j, $j = 1, \ldots, n_c$, and $\mathbf{z}_{j_i}^{\perp,i}$ denotes the realization of the orthogonal component of the Gaussian vector in that coordinate system.



a) Simulation for $i = 1$ b) Simulation for $i = 2$

Figure 2. Two sample realizations of the explored line for a case where $n_\eta = 1$ and $n_{KL} = n_T = 3$.

The line explored through each simulation can be defined as $\ell_i := \left\{\left(z_{j_i}^{\parallel,i}, \mathbf{z}_{j_i}^{\perp,i}\right) : z_{j_i}^{\parallel,i} \in \mathbb{R}\right\}$. Therefore, the inner integral in Eq. (13) can be written as:

$$\mathrm{A}(\ell_i) = \int_{\ell_i} \mathbb{I}_F\left(z_{j_i}^{\parallel}, \mathbf{z}_{j_i}^{\perp,i}\right) \phi\left(z_{j_i}^{\parallel}\right) dz_{j_i}^{\parallel,i} = \Phi\left(c_{\min}^{-,i}\right) + \Phi\left(-c_{\min}^{+,i}\right), \tag{14}$$

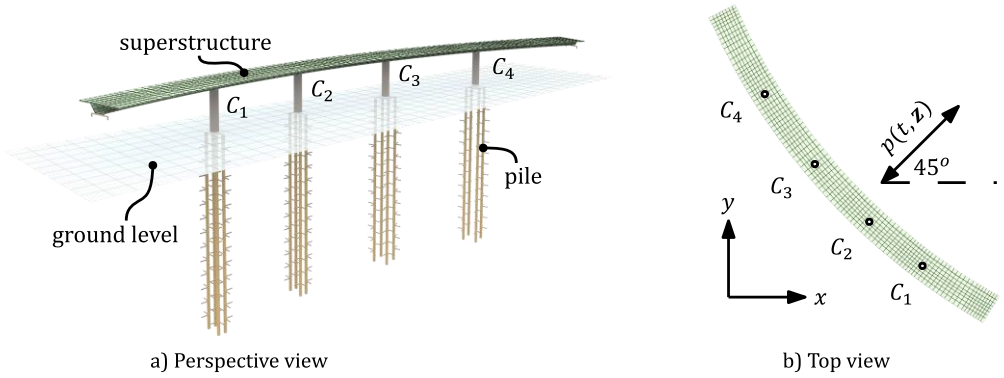
where $c_{\min}^{-,i}$ and $-c_{\min}^{+,i}$ denote the intersection distances from the sampled point to the failure domain along ℓ_i, in the directions opposite and parallel to $z_{j_i}^{\parallel}$, respectively. Note that, if ℓ_i lies entirely in the failure domain, then $\mathrm{A}(\ell_i) = 1$. The simulation process is schematically illustrated in Fig. 2. For each realization i, the importance sampling density generates a sample of the orthogonal component $\mathbf{z}_{j_i}^{\perp,i}$, which defines the explored line ℓ_i in the selected rotated coordinate system. The parallel component is then treated through the one-dimensional integral along this line. In panel a), the sample is generated with respect to $F_{1,1}$, and the coordinate system is selected with respect to $F_{3,1}$; in panel b), the sample is generated with respect to $F_{3,1}$ and the coordinate system is selected with respect to $F_{1,1}$. The one-dimensional contribution $\mathrm{A}(\ell_i)$, shown in pale blue, is then obtained from the segment of ℓ_i lying in the failure domain, determined by the distances $c_{\min}^{-,i}$ and $-c_{\min}^{+,i}$.

Writing the failure probability estimator in Eq. (13) as $\tilde{p}_F = 1/N(\sum_{i=1}^{N} q_i)$, the corresponding coefficient of variation is given by:

$$\delta_{\tilde{p}_F} = \frac{1}{\tilde{p}_F}\sqrt{\frac{1}{N(N-1)}\sum_{i=1}^{N}(q_i - \tilde{p}_F)^2}. \tag{15}$$

4 Numerical Example

The numerical example corresponds to a three-dimensional finite element model of a curved bridge with 10068 degrees of freedom, based on an example presented in Jensen et al. (2015). The bridge substructure comprises four columns with a diameter of 1.6 m and a height of 8 m. Each column is supported by four piles, 35 m in length and 0.6 m in diameter, with the pile–soil interaction modeled through translational stiffnesses in the x and y directions, varying linearly from $k_s = 112$ MN/m at the deepest point of the pile to 0 MN/m at the ground level. The superstructure is modeled as a monolithic box girder curved in the x–y plane, with a total length of 119 m. It consists of five spans with lengths of 24 m, 20 m, 23 m, 25 m, and 27 m, respectively. The model is illustrated in Fig. 3, where a) shows a perspective view and b) a plan view. The bridge columns are denoted by C_k, $k = 1, \dots, 4$. All elements in the model are assumed to be made of reinforced concrete, with a Young's modulus of $E = 2.09 \times 10^{10}$ N/m², Poisson ratio $\nu = 0.2$ and density $\rho = 2500$ kg/m³. Classical damping of 3% is assumed for all mode shapes.



a) Perspective view b) Top view

Figure 3. Curved bridge finite element model.

The ground motion acting on the bridge is modeled as a discrete white noise with spectral intensity $S = 5 \times 10^{-4}$ m²/s³, and duration $T = 10$ s, discretized into 1001 time instants with time step $\Delta t = 0.01$ s. The excitation is applied at an angle of 45°, as shown in Fig. 3b. In addition, the white-noise process is passed through a Clough–Penzien filter (Zerva 2009) and modulated by the function $m(t)$, defined as:

$$m(t) = \begin{cases} (t/5)^2 & 0 \le t \le 5\ s \\ 1 & 5\ s \le t \le 6\ s \\ e^{-(t-6)^2} & t > 6\ s \end{cases}. \tag{16}$$

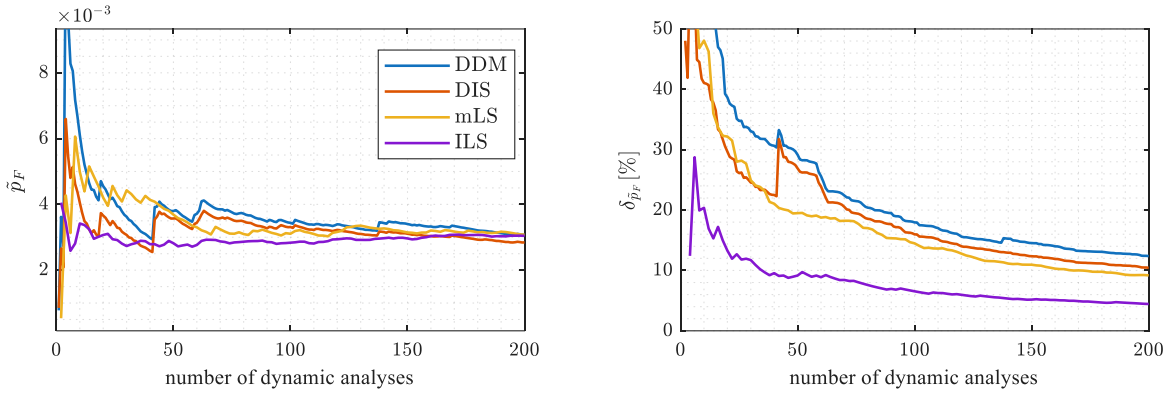
The structure is assumed to be initially at rest. Failure is defined as the exceedance of a column-drift threshold $b_i = 0.02$ m for all $i = 1, \dots, n_\eta$, in either the x- or y-direction during the stochastic excitation. This is a challenging problem involving 8008 elementary failure domains, resulting from the time discretization into 1001 instants and the consideration of 8 responses of interest. In addition, the dynamic analysis is carried out using a truncation to 100 mode shapes to ensure an accurate representation of the response. The objective is the estimation of the first excursion probability using Importance Line Sampling (ILS), and to assess its efficiency relative to existing methods in the literature, namely the Domain Decomposition Method (DDM; Katafygiotis, 2006), Directional Importance Sampling (DIS; Misraji, 2020), and multidomain Line Sampling (mLS; Valdebenito, 2021).

Table 1. Number of dynamic analyses required by each method to attain a coefficient of variation of 10%.

	DDM	DIS	mLS	**ILS**
Dynamic Analyses for $\delta_{\tilde{p}_F} = 10\%$	330	215	172	**52**

The comparison in Fig. 4 is performed in terms of the number of dynamic analyses. This is relevant because DDM and DIS are directional-based methods, requiring only one dynamic response evaluation per sample, whereas mLS and ILS require two evaluations per sample, corresponding to the parallel and perpendicular responses. Under this measure of computational effort, Fig. 4a shows that all methods tend to stabilize around similar values of the first excursion probability, which is approximately 3.0×10^{-3}, as the number of dynamic analyses increases. For validation purposes, crude Monte Carlo simulation (Fishman, 1996) with $N = 10^5$ samples was also performed, yielding an estimate of approximately 3.0×10^{-3} with a coefficient of variation of about 6%, which is consistent with the values approached

by all considered methods in Fig. 4a. On the other hand, Fig. 4b reveals important differences in the coefficient of variation. In particular, for 50 dynamic analyses, ILS presents a coefficient of variation approximately 10% while the coefficient of variation of the other approaches ranges between 20% and 30%. Consistently, as summarized in Table 1, ILS reaches a coefficient of variation of 10% with substantially lower computational effort than the other considered methods. In particular, the number of dynamic analyses required by ILS is reduced by factors of about 3.3, 4.1, and 6.3 relative to mLS, DIS, and DDM, respectively. These results clearly show that ILS is significantly more efficient than the other considered methods.



a) First excursion probability

b) Coefficient of variation

Figure 4. Comparison of the considered methods as a function of the number of dynamic analyses.

5 Conclusions

This contribution has presented an Importance Line Sampling (ILS) approach for estimating the first excursion probability of a linear system subjected to Gaussian loading. The proposed method combines an importance sampling density that preserves the Line Sampling spirit with multiple coordinate systems within a unified framework. By exploiting the linearity of the system, the resulting estimator incorporates geometrical information from the Gaussian space. Comparisons with related methods show that ILS significantly improves efficiency and is effective for estimating low failure probabilities in high-dimensional Gaussian spaces.

Future work includes sensitivity estimation, alternative weighting strategies for coordinate-system selection, and further refinement of the importance sampling density. These aspects are currently under investigation.

Acknowledgments

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