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Steady-state response of a random dynamical system described with Padé approximants and random eigenmodes

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Abstract

Designing a random dynamical system requires the prediction of the statistics of the response, knowing the random model of the uncertain parameters. Direct Monte Carlo simulation (MCS) is the reference method for propagating uncertainties but its main drawback is the high numerical cost. A surrogate model based on a polynomial chaos expansion (PCE) can be built as an alternative to MCS. However, some previous studies have shown poor convergence properties around the deterministic eigenfrequencies. In this study, an extended Padé approximant approach is proposed not only to accelerate the convergence of the PCE but also to have a better representation of the exact frequency response, which is a rational function of the uncertain parameters. A second approach is based on the random mode expansion of the response, which is widely used for deterministic dynamical systems. A PCE approach is used to calculate the random modes. Both approaches are tested on an example to check their efficiency.

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1. Introduction

Uncertainty propagation aims to find the statistics of the model outputs. The classical method is the Monte Carlo simulation (MCS) approach. As this method requires a large computation cost, alternative methods have been developed. One of the most popular method is based on a surrogate model built with a polynomial chaos expansion (PCE) [1]. The PCE has been recently used by the authors to study the steady-state response of a linear dynamical system [2]. This method has been very successful far from the “deterministic eigenfrequencies”, but it turns out that the polynomial expansion converges very slowly around these frequencies. The Padé approximant (PA) approach [3,4] is a well-known method to improve the convergence acceleration of a Taylor expansion by calculating a sequence

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of rational functions. In this study the probability density function of the steady-state response is estimated with a generalization of the Padé approximants [5], the “extended” Padé approximants (XPA). The modal approach is widely used to solve deterministic structural dynamics problems, but has been very rarely used to study uncertain dynamical system. The main issue is to calculate the random modes. In this study the PCE random mode approach proposed by Dessombz [6,7] is used to derive the pdf of the steady-state response of a linear dynamical system.

The paper is organized as follows: first the linear uncertain dynamical systems is presented as well as the PCE; second the XPA is developed; third the random modes are described according to a PCE approach; finally the methods are applied to an example.

2. Random dynamical system

2.1. Motion equation

A linear random N -dof dynamical system, which is excited with harmonic force vector \mathbf{F} with frequency ω , is investigated. The uncertain dynamical system is defined by the mass, stiffness, and damping matrices (\mathbf{M} , \mathbf{K} , and \mathbf{D}). These matrices are random and depend on an r -element uncertain parameter vector, Ξ : element i of this vector, ξ_i , is the i -th zero mean random parameter. The dynamical response, $\mathbf{X}(\omega, \Xi) \in \mathbb{R}^N$, is the solution of the motion equation

$$(-\omega^2 \mathbf{M} + i\omega \mathbf{D} + \mathbf{K}) \mathbf{X}(\omega, \Xi) = \mathbf{F}(\omega) \quad (1)$$

where $i^2 = -1$, and each of the uncertain matrices can be expanded as $\mathbf{A}(\Xi) = \mathbf{A}_0 + \sum_{i=1}^r \xi_i \mathbf{A}_i$. The related so-called deterministic dynamical system is characterized by the mean matrices (\mathbf{M}_0 , \mathbf{K}_0 , and \mathbf{D}_0).

2.2. Polynomial chaos expansion

A polynomial chaos $\Psi_j(\Xi)$ is an element of a multivariate orthogonal polynomial family [1]. The response of a random dynamical system may be expanded in terms of polynomial chaos Ψ_j as

$$\mathbf{X}^P(\omega, \Xi) = \sum_{i=0}^P \mathbf{Y}_i^P(\omega) \Psi_i(\Xi) \quad (2)$$

where P depends on the number of random variables and the PC degree [1]. In this study, the polynomial chaos set is based on a product of normalized Hermite or Legendre polynomials. Coefficients \mathbf{Y}_i^P are determined by replacing \mathbf{X}^P by its expansion in Eq. (1) and by using the orthogonality properties of the polynomial chaos [2]. Once the coefficients of the PCE are calculated, the probability density function (pdf) can then be estimated with an MCS directly applied to Eq. (2).

3. Extended Padé approximant

A Padé approximant (PA) of response vector $\mathbf{X}(\Xi)$ is a rational function derived from the Taylor series of $\mathbf{X}(\Xi)$. The Padé approximant converges much faster than the Taylor expansion [3,4] when the function has poles. The PA has been extended to the case of multivariate functions [8–12]. In the random dynamical system context, PC expansion is much more interesting than a Taylor series. Such a generalization had been defined and studied in many papers [3,5,13–16]. The extended Padé approximants can be defined as

$$[M_k/N_k]_{\mathbf{X}_k^{PC}}(\Xi) = \frac{\sum_{j=0}^{n_k} N_{k,j}^{XPA}(\omega) \Psi_j(\Xi)}{\sum_{j=0}^{d_k} D_{k,j}^{XPA}(\omega) \Psi_j(\Xi)} \quad (3)$$

where $n_k = \#M_k - 1$ and $d_k = \#N_k - 1$ (where $\#m$ denotes the maximum number of coefficients of a multivariate polynomial of degree m); k refers to the k -th dof; usually $D_{k,0}^{XPA}$ is equal to unity.

$N_{k,i}^{XPA}$ and $D_{k,i}^{XPA}$ are derived by comparing Eq. (2) to Eq. (3), and then by projecting the resulting equation on $\Psi_l(\Xi)$. More details can be found in [17].

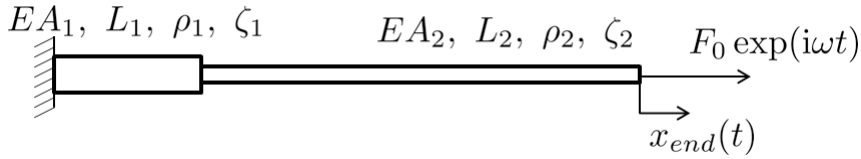


Fig. 1. Uncertain bar

4. Random modes

A classical way to obtain the response of an N -dof deterministic dynamical system is to expand the solution on the deterministic eigenvectors. This can be done with a random system, and the steady-state response described with the random modes reads

$$\mathbf{X}(\omega) = \sum_{n=1}^N \tilde{q}_n(\omega) \tilde{\boldsymbol{\phi}}_n \tag{4}$$

where $\{\tilde{\omega}_k, \tilde{\boldsymbol{\phi}}_k\}$ are the k -th random natural frequency and mode. Modal coordinate \tilde{q}_n is derived by substituting Eq. (4) in Eq. (1) and by projecting this latter equation on each $\tilde{\boldsymbol{\phi}}_n$. Then the modal coordinate reads

$$\tilde{q}_n(t) = \frac{\tilde{\boldsymbol{\phi}}_n^T \mathbf{F}}{\tilde{m}_n (\tilde{\omega}_n^2 - \omega^2 + 2\tilde{\eta}_n \tilde{\omega}_n \omega)} \tag{5}$$

where $\tilde{\eta}_n$ (resp. \tilde{m}_n) is the damping ratio (resp. the generalized modal mass) of mode n .

The random mode statistics can be determined with an MCS. However, an alternative is to expand the random modes on the polynomial chaos [6,7]

$$\tilde{\omega}_k^2 = \omega_k^2 \left(\sum_{p=0}^P \alpha_p^k \Psi_p(\boldsymbol{\Xi}) \right) \tag{6}$$

$$\tilde{\boldsymbol{\phi}}_k = \boldsymbol{\phi}_k + \sum_{n=1, n \neq k}^N \sum_{p=0}^P \lambda_{np}^k \Psi_p(\boldsymbol{\Xi}) \boldsymbol{\phi}_n \tag{7}$$

where $(\omega_k, \boldsymbol{\phi}_k)$ denotes the k -eigenmode of the deterministic system. The $N \times (P+1)$ unknowns that define the random modes (see Eqs. (6) and (7)) are calculated by projecting the random eigenproblem on each deterministic eigenmode $\{\boldsymbol{\phi}_n\}_{n=1 \dots N}$ and each PC $\{\Psi_p(\boldsymbol{\Xi})\}_{p=0 \dots P}$ [6,7].

5. Example

5.1. Bar with uncertain stiffness

The uncertain system is shown in Fig. 1. The quantity $EA = E \times A$ (E : Young’s modulus; A : cross-section area) is assumed to be uncertain. In fact, the bar is divided in two parts and EA_1 (resp. EA_2) is constant along part 1 (resp. part 2) but uncertain. The bar is modelled with a finite element model. L_1 and n_1 (resp. L_2 and n_2) are the length and the number of elements of part 1 (resp. part 2). The damping matrix is supposed to be deterministic and defined as $\mathbf{D} = 2 \zeta \mathbf{M}(\mathbf{M}^{-1} \mathbf{K}_0)^{1/2}$ ($\zeta = 0.25\%$). The bar is excited by a harmonic force, $F_0 \exp(i\omega t)$, located at the end of the bar. The requested frequency response is the displacement at the end of the bar, x_{end} . EA_i is modelled by a random variable: normal laws were addressed in this example, but similar results have been obtained with a uniform law [17]. The characteristics of the uncertain system are listed in Tables 1 and 2.

The mean of the frequency response, as well as the probability density function, were derived with several methods, which included the MCS, the PCE, the XPA, and the random modes methods. The reference results were obtained with Monte Carlo simulation: a Latin Hypercube Sampling (LHS) method was used with 10,000 samples.

Table 1. Bar: uncertain parameters

part 1		part 2	
mean	st. dev.	mean	st. dev.
EA_1^m	$\delta_{k1} \times EA_1^m$	EA_2^m	$\delta_{k2} \times EA_2^m$

Table 2. Bar characteristics

EA_1^m (MN)	δ_{k1} (%)	EA_2^m (MN)	δ_{k2} (%)	F_0 (kN)	L_1 (m)	L_2 (m)	n_1	n_2
88	10	22	10	10	1	3	2	6

Table 3. Kullback-Leibler divergence - $|x_{end}|$ pdf

	PCE ($P=495$)	PCE 4 ($P=14$)	Padé [1/2] ($P=14$)	Mode + PCE ($P=5$)
D_{KL}	0.93	4.63	0.02	0.01

5.2. Frequency response

The mean of the frequency response was derived with PCEs of degrees 4 and 30, a XPA [1/2], and the random mode approach. The results are plotted in Fig. 2. The results with a PCE of order 30 are still not very good around the second and the third deterministic eigenfrequencies, even if the results were better than the ones obtained with a PCE of order 4. However the XPA results are in very good agreement, even though they are based on a PCE of order 4. The random mode method provided very accurate results. It is also interesting that the calculations are much faster in the latter case compared to the other ones. Indeed, in that case, the random modes are independent of the frequency, whereas the PCE and the XPA are frequency dependent, and then the PCE coefficients must be calculated for each frequency. However, the random mode approach assumes that the random modes are orthogonal with respect to the damping matrix, which is not the case. In particular, the damping is proportional only when $\xi_1 = \xi_2 = 0$ (mean stiffness matrix). Even so, it is striking that the results are excellent.

5.3. Probability density function

The pdf of x_{end} has been estimated at the second deterministic eigenfrequency with the MCS, PCE, XPA, and random modes methods: the results are illustrated in Fig. 3. They were compared to the reference pdf with the Kullback-Leibler divergence [18–20], D_{KL} , defined as

$$D_{KL}(p_{ref}(x)||p(x)) = \int_{D_x} p_{ref}(x) \ln \left(\frac{p_{ref}(x)}{p(x)} \right) dx \quad (8)$$

where D_x is the domain of a random variable x . D_{KL} is always nonnegative and is equal to zero when $p_{ref}(x) = p(x)$ almost everywhere. This indicator is listed in Table 3 for the PCE, XPA and random modes approach. The Kullback-Leibler divergence shows that the XPA and the random modes methods are much more efficient than the PCE approach.

The excellent agreement of the results obtained with the XPA and the random modes approaches explains why the mean frequency responses obtained with these methods were excellent.

6. Conclusion

Two approaches were presented to estimate the probability density function of a random system response. The first one is based on a PCE and can be viewed as a numerical approach; the second one is based on the random modes and hence is a more physical approach. Both methods are shown to be very efficient, not only to estimate the mean frequency response function, but also to evaluate the probability density function at critical frequencies (deterministic eigenfrequencies).

The main advantage of the random modes method is that the random modes are independent of the frequency, which is not the case for the PCE coefficients and hence for the XPA. As a consequence, the statistics of the frequency

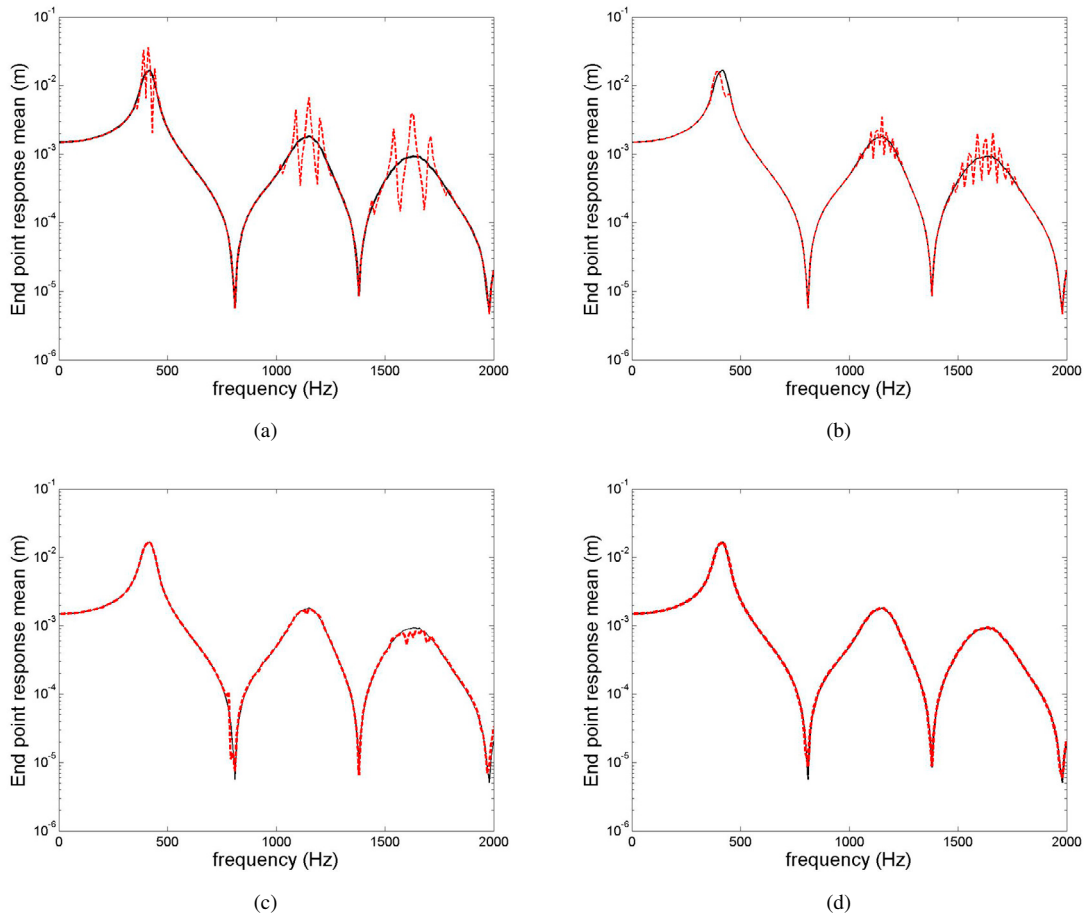


Fig. 2. Mean of the end displacement (m) for several approaches - MCS: black solid lines - red dashed line: (a): PC ($P = 14$); (b): PC ($P = 495$); (c): Padé ($P = 14$); (d): Modal-PC ($P = 5$)

response function can be estimated very quickly. However, the efficiency of this method relies on the assumption that the modes are uncoupled through the damping contributions, which is true when the damping is proportional. This assumption may be violated for some uncertain systems: in particular, this is the case in the example presented in this paper. Accordingly, it is important to verify that the coupling through the damping matrix is statistically negligible.

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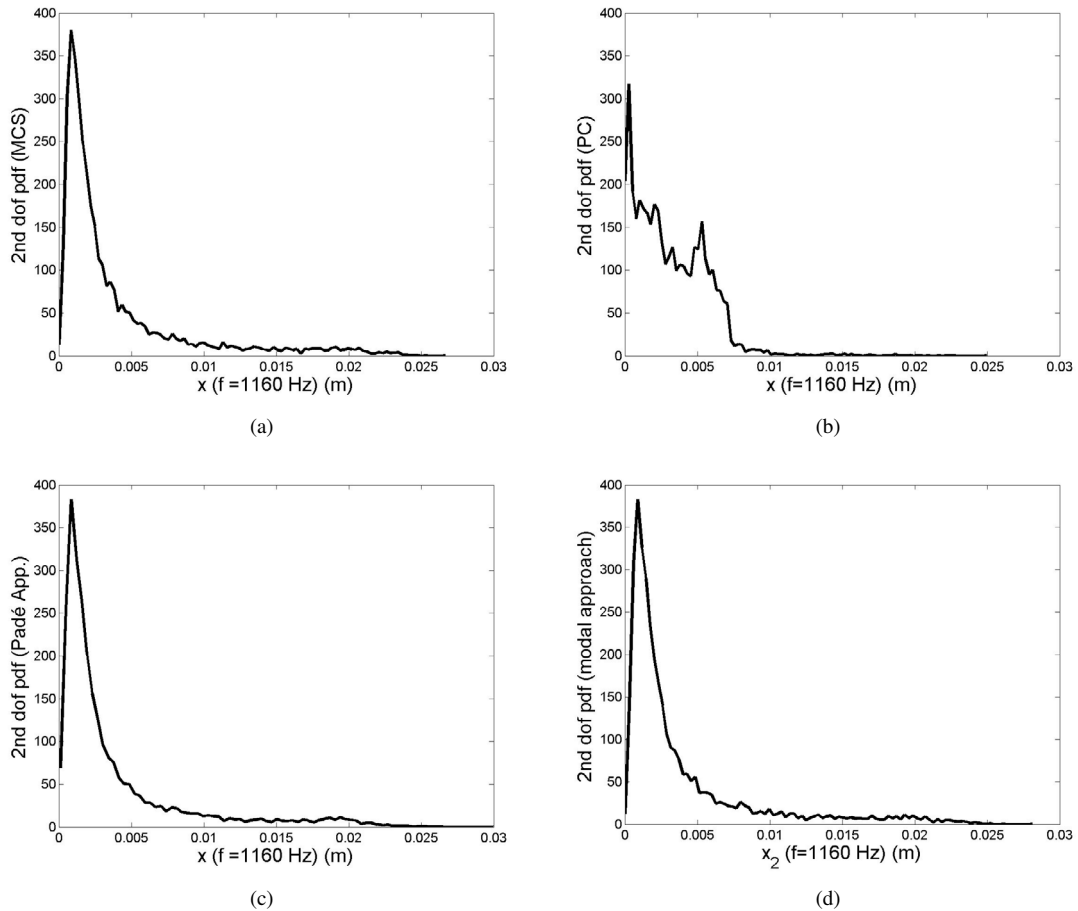


Fig. 3. Probability density function of the response, x_{end} , at the second deterministic eigenfrequency; (a): MCS (10,000 samples); (c): PCE ($P = 495$); (b): XPA ($[0/1]$, $P = 14$); (d): Modal approach ($P=5$)

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