

Uncertainty Quantification in Computational Mechanics

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Uncertainties need to be taken into account for credible predictions of the response of complex mechanical systems. Such uncertainties should include uncertainties in the system parameters and those arising due to the modelling of a complex system. In spite of extensive research over the past four decades a general purpose probabilistic predictive code for real-life mechanical systems is still not available. The reasons behind this include: (a) the computational time can be prohibitively high compared to a deterministic analysis, and (b) the detailed and complete information regarding parametric and model uncertainties are in general not available. In this work various methods are investigated to address these two problems in the context of computational mechanics. The proposed methods can be broadly categorised as (a) parametric methods and (b) non-parametric methods. Under the parametric approaches, we have developed (1) doubly spectral stochastic finite elements method, and (2) Gaussian Process (GP) emulator approach. Under the nonparametric approaches we have developed a random matrix based approach. Several numerical and analytical techniques have been proposed and the results were validated against experimental results. This poster is aimed at summarise these works and present some representative results.

Uncertainty Quantification



Doubly Spectral Finite Element Method for Stochastic Field Problems in Structural Dynamics

For distributed parameter systems, parametric uncertainties can be represented by random fields leading to stochastic partial differential equations. A linear damped distributed parameter dynamical system in which the displacement variable $U(\mathbf{r}, t)$, where \mathbf{r} is the spatial position vector and t is time, specified in some domain \mathcal{D} , is governed by a linear partial differential equation

Experimental Validation

The uncertain dynamics is realized by 10 sprung-mass oscillators with randomly distributed stiffness properties attached at random locations. One hundred nominally identical dynamical systems are created and individually tested. The probabilistic characteristics of the frequency response functions are obtained in the low, medium and high frequency ranges. Special measures were taken so that the uncertainty in the response of the main structure primarily emerges from the random attachment configurations of the subsystems having random natural frequencies.

Complex mechanical systems can have millions of degrees of freedom and significant uncertainty in their computational models. The Sources of uncertainty include:

(a) parametric uncertainty - e.g., uncertainty in geometric parameters, friction coefficient, strength of the materials involved;
(b) model inadequacy - arising from the lack of scientific knowledge about the model which is a-priori unknown;

(c) experimental error - uncertain and unknown error percolate into the model when they are calibrated against experimental results;

(d) computational uncertainty - e.g, machine precession, error tolerance and the so called 'h' and 'p' refinements in finite element analysis, and

(e) model uncertainty - genuine randomness in the model such as uncertainty in the position and velocity in quantum mechanics, deterministic chaos.



$$p(\mathbf{r},\theta)\frac{\partial^2 U(\mathbf{r},t)}{\partial t^2} + L_1 \frac{\partial U(\mathbf{r},t)}{\partial t} + L_2 U(\mathbf{r},t) = p(\mathbf{r},t); \quad \mathbf{r} \in \mathcal{D}.$$
(1)

Here $\rho(\mathbf{r}, \theta)$ is the random mass distribution of the system, $p(\mathbf{r}, t)$ is the distributed time-varying forcing function, L_1 is the random spatial self-adjoint damping operator and L_2 is the random spatial self-adjoint stiffness operator. When parametric uncertainties are considered, the mass density $\rho(\mathbf{r}, \theta)$ as well as the damping and stiffness operators involve random processes. A random process $H(\mathbf{r}, \theta)$ can be expressed in a spectral decomposition as

$$H(\mathbf{r},\theta) = H_0(\mathbf{r}) + \sum_{i=1}^{\infty} \sqrt{\lambda_i} \xi_i(\theta) \varphi_i(\mathbf{r})$$
(2)

where $\xi_i(\theta)$ are uncorrelated random variables, λ_i and $\varphi_i(\mathbf{r})$ are eigenvalues and eigenfunctions satisfying an integral equation over the auto-correlation function. Over the past two decades spectral stochastic finite element method has been developed to discretise the random fields based on this decomposition. On the other hand, for deterministic distributed parameter linear dynamical systems, spectral finite element method has been developed to efficiently solve the problem in the frequency domain. In spite of the fact that both approaches use spectral decomposition (one for the random fields and while the other for the dynamic displacement fields),





The role of uncertainty in computational mechanics.

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Input	System	Output	Problem	Main tech-	Input	System	Output	rioblem	niques
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Known (determin- istic)	Incorrect (determin- istic)	Known (determin- istic)	Updating /calibration	Modal up- dating	Known (random)	Incorrect (random)	Known (random)	Probabilistic updating /calibration	Bayesian cal- ibration
(determin- istic)	UIIKIIOWII	(determin- istic)	tification	Kaman mter	Assumed (ran-	Unknown (random)	Prescribed (random)	Probabilistic design	RBOD
Assumed (determin- istic)	Unknown (determin- istic)	Prescribed	Design	Design opti- misation	Known (random /dotormin	Partially known (random)	Partially known (random)	Joint state and pa-	Particle Kalman Fil- ter/Encomble
Unknown	Partially Known	Known	Structural Health Mon- itoring	SHM meth- ods	istic)		(random)	estimation	Kalman Fil- ter
17	17		(SHM)		Known (random	Known (random)	Known (experi-	Model valida- tion	Validation methods
Known (determin- istic)	Known (determin- istic)	Prescribed	Control	Modal con- trol	/determin- istic)		ment and model)		
Known	Known	Unknown	Random	Random	Known (random	Known (random)	Known	Model verifi-	verification

there has been very little overlap between them in literature. In this work these two spectral techniques have been unified with the aim that the unified approach would outperform any of the spectral methods considered on its own.

Random Matrix Theory

The equation of motion of a damped n-degree-of-freedom linear dynamic system can be expressed as

$$\mathbf{M}\ddot{\mathbf{q}}(t) + \mathbf{C}\dot{\mathbf{q}}(t) + \mathbf{K}\mathbf{q}(t) = \mathbf{f}(t)$$

where **M**, **C** and **K** are the mass, damping and stiffness matrices respectively. In order to completely quantify the uncertainties associated with system (3), we need the probability density functions of the random matrices **M**, **C** and **K**. We have shown^{8–11} that these matrices can be expresses as central or non-central Wishart matrices:

Wishart matrix: An $n \times n$ random symmetric positive definite matrix **S** is said to have a Wishart distribution with parameters $p \ge n$ and $\Sigma \in \mathbb{R}_n^+$, if its pdf is given by

 $p_{\mathbf{S}}(\mathbf{S}) = \left\{ 2^{\frac{1}{2}np} \Gamma_n\left(\frac{1}{2}p\right) |\mathbf{\Sigma}|^{\frac{1}{2}p} \right\}^{-1} |\mathbf{S}|^{\frac{1}{2}(p-n-1)} \operatorname{etr} \left\{ -\frac{1}{2} \mathbf{\Sigma}^{-1} \mathbf{S} \right\}$ (4)

Noncentral Wishart matrix: A $n \times n$ symmetric positive definite random matrix **S** is said to have a noncentral Wishart distribution with parameters $p \ge n$, $\Sigma \in \mathbb{R}_n^+$ and $\Theta \in \mathbb{R}_n^+$, if its pdf is given by (c) Medium-frequency response (d) High-frequency response Comparison of the mean and standard deviation of the amplitude of the near-field cross-FRF of the plate at point 2 (nodal coordinate: (6,11)) with 10 randomly placed oscillators; — ensemble mean from Wishart model; - - - ensemble mean from experiment; -. -. standard deviation from Wishart model; standard deviation from experiment.

Selected Publications

(3)

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There are two approaches to quantify uncertainties in a model:
 Parametric approach: This is suitable to quantify aleatoric uncertainties. Here the uncertainties associated with the system parameters are quantified and propagated, for example, using the stochastic finite element method¹⁻⁷.

• Nonparametric approach: This is aimed at quantifying epistemic uncertainty which do not explicitly depend on the system parameters. For example, there can be unquantified errors associated with the equation of motion. Random matrix theory based on central and non-central Wishart distribution⁸⁻¹⁰ has been proposed for this purpose.

 $p_{\mathbf{S}}(\mathbf{S}) = \left\{ 2^{\frac{1}{2}np} \Gamma_n\left(\frac{1}{2}p\right) |\mathbf{\Sigma}|^{\frac{1}{2}p} \right\}^{-1} \operatorname{etr} \left\{ -\frac{1}{2}\mathbf{\Theta} \right\} \operatorname{etr} \left\{ -\frac{1}{2}\mathbf{\Sigma}^{-1}\mathbf{S} \right\} \\ |\mathbf{S}|^{\frac{1}{2}(p-n-1)} {}_0F_1(p/2,\mathbf{\Theta}\mathbf{\Sigma}^{-1}\mathbf{S}/4).$ (5)

where $_{0}F_{1}$ the hypergeometric function (Bessel function) of matrix argument.

Here etr $\{\bullet\} \equiv \exp\{\operatorname{Tr}(\bullet)\}$ and $|\bullet| \equiv$ determinant of a matrix. The function $\Gamma_n(a)$ is the multivariate gamma function, which can be expressed as $\Gamma_n(a) = \pi^{\frac{1}{4}n(n-1)} \prod_{k=1}^n \Gamma\left[a - \frac{1}{2}(k-1)\right]$; for $\Re(a) > \frac{1}{2}(n-1)$. putational Mechanics, Vol. 40, No. 4, September 2007, pp. 739–752.

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