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An approximate stochastic dynamics approach for nonlinear structural system performance-based multi-objective optimum design

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ABSTRACT

A novel approach for structural system optimal design considering life cycle cost is developed. Specifically, a performance-based multi-objective design optimization framework for nonlinear/hysteretic multi-degree-of-freedom (MDOF) structural systems subject to evolutionary stochastic excitation is formulated. In the core of the stochastic structural analysis component of the proposed framework lies an efficient approximate dimension reduction technique based on the concepts of statistical linearization and of stochastic averaging for determining the non-stationary system response amplitude probability density functions (PDFs); thus, computationally intensive Monte Carlo simulations are circumvented. Note that the approach can readily handle stochastic excitations of arbitrary non-separable evolutionary power spectral density (EPSD) forms that exhibit strong variability in both the intensity and the frequency content. Further, approximate closed-form expressions are derived for the non-stationary inter-story drift ratio amplitude PDFs corresponding to each and every DOF. In this regard, considering appropriately defined damage measures structural system related fragility curves are determined at a low computational cost as well. Finally, the structural system design optimization problem is formulated as a multi-objective one to be solved by a genetic algorithm based approach. A building structure comprising the versatile Bouc-Wen (hysteretic) model serves as a numerical example for demonstrating the efficiency of the proposed methodology.

1. Introduction

Most structures and civil infrastructure systems are subject to excitations that exhibit strong variability in both the intensity and the frequency content. Clearly, a realistic system analysis and design necessitates the representation of this class of loads by non-stationary stochastic processes [1–3]. Further, structural systems under severe excitations, such as earthquakes, can behave in a nonlinear manner exhibiting a hysteretic restoring force-displacement characteristic. Thus, a sustained challenge in the area of structural dynamics has been the efficient analysis and design of nonlinear/hysteretic systems/structures under evolutionary stochastic excitation.

Performance-based earthquake engineering (PBEE) aims at providing information for facilitating risk-based decision-making via performance assessment and design methods that properly account for the presence of uncertainties [4,5]. In general, the PBEE framework includes four basic stochastic analysis components (see Section 3) which address the issue of stochastic structural design in a comprehensive and consistent manner. Considering the last component of a PBEE analysis, that of stochastic loss analysis, the seismic life-cycle cost is usually employed as a decision variable [6]. Indicatively, in [7], Kong and Frangopol addressed the bridge maintenance schedule optimal design problem and estimated the life-cycle cost performance. Further, adopting a median global Park-Ang damage index, Ang and Lee [8] considered repair costs for various ground motion intensity levels for the case of reinforced concrete buildings. In [9,10], a probabilistic multi-objective optimization framework was applied for the life-cycle cost optimal seismic design of steel structures. Further, Taflanidis and Beck [11] focused on assessing the performance of passive dissipative devices by utilizing an efficient simulation approach within a performance-based seismic design framework that optimized the

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expected life cycle cost of structural systems. Next, Takahashi et al. [12] relied on a Monte Carlo simulation approach for assessing the life-cycle cost of a structural system equipped with damping devices.

Focusing on the stochastic structural/damage analysis components of a PBEE framework, several approaches have been developed for relating the seismic hazard to the system fragility and for producing corresponding fragility curves, i.e. probabilities of exceeding specified damage states given an intensity measure (IM) value. These range from the ones that employ a limited number of nonlinear time-history analyses with prescribed IM level compatible scaled real earthquake records [13], to the ones that employ standard or efficient Monte Carlo simulation (MCS) based methodologies such as importance/line sampling, and subset simulation [14–16]. Nevertheless, note that there are cases where the computational cost of the MCS based techniques can be significantly high; thus, rendering their use computationally cumbersome, or even prohibitive. Clearly, there is a need for developing approximate analytical and/or numerical techniques for determining efficiently the response and reliability statistics of nonlinear systems subject to stochastic excitation [1,2,17–19]. Nevertheless, although there is a considerable body in the literature referring to the development of such techniques there are limited results related to adopting and implementing such techniques for efficient fragility analysis applications. An interesting contribution in this regard is the work by Der Kiureghian and Fujimura [20] where an efficient tail-equivalent linearization based approach was applied for fragility analysis of a nonlinear building structure.

In this paper, a performance-based multi-objective design optimization framework for nonlinear/hysteretic MDOF structural systems subject to evolutionary stochastic earthquake excitations is formulated. In the core of the stochastic structural analysis component lies an efficient approximate analytical dimension reduction approach for determining the system response evolutionary power spectral density (EPSD) matrix based on the concepts of statistical linearization and stochastic averaging [18]; thus, computationally intensive Monte Carlo simulations are circumvented. Note that the approach can readily handle stochastic excitations of arbitrary EPSD forms, even of the non-separable kind. Further, approximate closed-form expressions are derived for the non-stationary response amplitude PDFs of the inter-story drift ratios (IDRs) corresponding to each and every DOF. In this regard, considering appropriately defined damage measures structural system related fragility curves are determined at a low computational cost as well. Further, note that the multi-objective optimization [21] allows for objectives that exhibit potentially conflicting requirements to be treated simultaneously. In the present formulation, solving the multi-objective optimization problem typically suggests the determination of a set of Pareto optimal solutions.

Overall, the novelty of the proposed framework lies in that fact that it appears to be highly efficient for performing stochastic design optimization, reducing significantly the computational burden for this task. Specifically, the recently developed approximate nonlinear stochastic dynamics technique is appropriately tailored and incorporated in a robust performance-based framework for addressing the so called life-cycle cost stochastic design optimization problem; thus, circumventing computationally intensive Monte Carlo simulations that are ordinarily utilized in the literature so far. Further, an additional important feature relates to the utilization of the expected value of the life-cycle cost. In this manner, the contributions of all structural components are considered in the formulation herein, in contrast to the commonly adopted in the literature consideration of the most critical component contribution only.

2. Nonlinear system stochastic response determination

2.1. Statistical linearization treatment

In this section the most important elements of an approximate stochastic response determination technique developed by Kougioumtzoglou and Spanos [18] are included for completeness. Consider an n-degree-of-freedom nonlinear structural system governed by the equation

$$\mathbf{M}\ddot{\mathbf{q}} + \mathbf{C}\dot{\mathbf{q}} + \mathbf{K}\mathbf{q} + \mathbf{g}(\mathbf{q}, \dot{\mathbf{q}}) = \mathbf{f}(t), \tag{1}$$

where $\ddot{\mathbf{q}}$, $\dot{\mathbf{q}}$ and $\mathbf{q}$ denote the response acceleration, velocity and displacement vectors, respectively, defined in relative coordinates; $\mathbf{M}$, $\mathbf{C}$ and $\mathbf{K}$ denote the $(n \times n)$ mass, damping and stiffness matrices, respectively; $\mathbf{g}(\mathbf{q}, \dot{\mathbf{q}})$ is assumed to be an arbitrary nonlinear $(n \times 1)$ vector function of the variables $\mathbf{q}$ and $\dot{\mathbf{q}}$; and $\mathbf{f}(t)^T = (f_1(t), f_2(t), \ldots, f_n(t))$ is a $(n \times 1)$ zero mean, non-stationary stochastic vector process defined as $\mathbf{f}(t) = -\bar{\mathbf{M}}\boldsymbol{\gamma}\ddot{\alpha}_g(t)$, where $\boldsymbol{\gamma}$ is the unit column vector, $\ddot{\alpha}_g(t)$ is a stochastic non-stationary excitation process (e.g. earthquake excitation) and $\bar{\mathbf{M}}$ stands for the $(n \times n)$ mass matrix defined in absolute coordinates. Further, $\mathbf{f}(t)$ possesses an EPSD matrix $\mathbf{S_f}(\boldsymbol{\omega}, \mathbf{t})$ of the form

$$\mathbf{S_f}(\boldsymbol{\omega}, \mathbf{t}) = \begin{bmatrix} m_1^2 S_{\ddot{\alpha}_g}(\omega, t) & 0 & \cdots & 0 \\ 0 & m_2^2 S_{\ddot{\alpha}_g}(\omega, t) & \cdots & 0 \\ \vdots & \ddots & \cdots & \vdots \\ 0 & 0 & \cdots & m_n^2 S_{\ddot{\alpha}_g}(\omega, t) \end{bmatrix}, \tag{2}$$

while the non-stationary stochastic process $\mathbf{f}(t)$ is regarded to be a filtered stationary stochastic process [22]. Note that excitations exhibiting variability in both the intensity and the frequency content, and thus, possessing a non-separable EPSD can be considered as well.

In the following, a statistical linearization approach [1–3] is employed for determining the response EPSD matrix $\mathbf{S_q}(\omega, t)$. In this regard, a linearized version of Eq. (1) is given in the form

$$\mathbf{M}\ddot{\mathbf{q}} + (\mathbf{C} + \mathbf{C_{eq}})\dot{\mathbf{q}} + (\mathbf{K} + \mathbf{K_{eq}})\mathbf{q} = \mathbf{f}(t). \tag{3}$$

Relying next on the standard assumption that the response processes are Gaussian, the time-dependent elements of the equivalent linear matrices $\mathbf{C_{eq}}$ and $\mathbf{K_{eq}}$ are given by the expressions

$$c_{i,j}^{eq} = E\left\{\frac{\partial g_i}{\partial \dot{q}_j}\right\}, \tag{4}$$

and

$$k_{i,j}^{eq} = E\left\{\frac{\partial g_i}{\partial q_j}\right\}. \tag{5}$$

Next, omitting the convolution of the impulse response function matrix with the modulating matrix can lead to substantial reduction of computational effort, especially for the case of MDOF systems [23,24]. In this manner, the response EPSD matrix $\mathbf{S_q}(\omega, t)$ for the linearized system of Eq. (3) is given by

$$\mathbf{S_q}(\omega, t) = \mathbf{H}(\omega)\mathbf{S_f}(\omega, t)\mathbf{H}^{\mathbf{T}*}(\omega). \tag{6}$$

where $\mathbf{H}(\omega)$ is the frequency response function (FRF) matrix defined as

$$\mathbf{H}(\omega) = \left(-\omega^2\mathbf{M} + i\omega(\mathbf{C} + \mathbf{C_{eq}}) + (\mathbf{K} + \mathbf{K_{eq}})\right)^{-1}. \tag{7}$$

Note that Eq. (6) can be regarded as a quasi-stationary approximate relationship which, in general, yields satisfactory accuracy in cases of relatively stiff systems [23,24]. Considering next Eqs. (2)