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Model identification in computational stochastic dynamics using experimental modal data

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ABSTRACT

This paper deals with the identification of a stochastic computational model using experimental eigenfrequencies and mode shapes. In the presence of randomness, it is difficult to construct a one-to-one correspondence between the results provided by the stochastic computational model and the experimental data because of the random modes crossing and veering phenomena that may occur from one realization to another one. In this paper, this correspondence is constructed by introducing an adapted transformation for the computed modal quantities. Then the transformed computed modal quantities can be compared with the experimental data in order to identify the parameters of the stochastic computational model. The methodology is applied to a booster pump of thermal units for which experimental modal data have been measured on several sites.

1. Introduction

In industrial context, the quantification of the confidence in computational models must be established so that they can be used either in design purpose or in expertise purpose. A given dynamical system can operate at design conditions, at off-design conditions and at failure-mode conditions that apply in accident scenarios. An adapted way to take into account their generic characteristics and their capability to reproduce the behavior of the whole family of nominally identical structures is to consider no more deterministic but stochastic computational models (SCMs), using experimental data. The objective of this paper consists in identifying a SCM using some natural frequencies and the associated mass-normalized mode shapes, measured for a family of structures.

The identification or updating methods of deterministic computational dynamic models using modal data have been intensively studied during the last four decades. Efficient methods have been proposed (see for instance [29,49,19]) and are now commonly used in industry. There are two main types of methods: the global methods (see for instance [3,20,39,51]) which consist in directly modifying the stiffness and mass matrices and the local methods which consist in updating some physical parameters (see for instance [8,13]). The latter method can be described in three steps: (1) the first one consists in constructing a nominal computational model (NCM) for which the parameters are set to nominal values. These parameters can be related to material properties (Young's modulus, mass density, and so on), geometry (CAD, thickness, area moments of inertia, and so on) and boundary conditions. (2) The second step consists in performing a sensitivity analysis of the quantities of interest with respect to the parameters in order to select the most-sensitive parameters which have to be

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updated (see for instance [5,14]). (3) The third step consists in updating the most-sensitive parameters using experimental data. In general, this step is carried out by reducing a "distance" between the experimental modal data (eigenvalue, mode shape, modal mass, modal damping) and the corresponding computed quantities using the NCM.

We consider the random context for which the available experimental data are related to a family of several experimental configurations of a given dynamical structure. The observed variability between the experimental configurations of this family is induced (1) by the uncontrolled differences that can appear during the manufacturing process (manufacturing tolerances) and during the life cycle of the structure (natural damage, incidents, etc.) and (2) by some slight differences which are controlled and are related, for instance, to the boundary conditions, the embedded equipments, etc. These two types of variability induce differences for the data measured on two configurations of the given dynamical structure. It should be noted that the measurement errors can also yield fluctuations in the measured data. This last source of variability induced by the experimental process is not addressed in this paper because it is assumed to be of second-order with respect to the other sources of variability for the application which is presented.

In such a random context, we have to construct a stochastic computational model (SCM) for which two sources of uncertainties have to be taken into account (see for instance [46]): (1) the uncertainties relative to some model parameters of the NCM and (2) the modeling errors. The first one includes both the uncertainties induced by the above-mentioned observed variability (also called aleatory uncertainty in the literature) and the uncertainties induced by the lack of knowledge related to some uncertain parameters of the SCM (also called epistemic uncertainty in the literature). With respect to the computational model, this first source of uncertainty yields the *model-parameter uncertainties* while the uncertainties induced by the modeling errors yield the *model uncertainties*. The stochastic computational model which is constructed with these two sources of uncertainties (and with additional input and output noises if measurement errors are significant) must have the capability of representing the variability of all the measured configurations (as explained above).

In this paper, the uncertainties are taken into account using a probabilistic approach and then the SCM is constructed including both the model-parameter uncertainties and the model uncertainties in a separate way (using the *generalized probabilistic approach of uncertainties* proposed in [45,46]). Usually, a SCM is controlled by a set of hyperparameters such as mean values, coefficients of variation, and so on. These hyperparameters have to be identified using experimental data and realizations of the SCM. Several types of observation can be used in order to perform such an identification and the choice depends on the quantities of interest for the developed SCM (see for instance, [32,33,18,21,22] for model-parameter uncertainties, and [43,44,11,12,4,2,47] for both model-parameter uncertainties and model uncertainties). For example, if the computational model is devoted to the prediction of responses in the low-frequency band of analysis and if the resonances are relatively well-separated, then the modal quantities (eigenfrequencies, mode shapes) are suitable observations. In a random context and for the low-frequency dynamical analysis, the eigenfrequencies can be used if a one-to-one correspondence can be constructed between the computational modes and the experimental modes [43,4,2]. This means that the experimental variability and the randomness in the SCM should not induce mode crossing phenomena or mode veering phenomena (see [34,35,31]) for the experimental modes and for the computed stochastic modes. This is true if the variability is sufficiently small and if the resonances are well-separated. If this is not the case, information on the mode shapes has to be used in order to construct a one-to-one correspondence between the experimental data and the corresponding computational quantities.

The objective of this paper consists in identifying the hyperparameters of a SCM using natural frequencies and mass-normalized mode shapes measured for a family of structures. The methodology proposed introduces a random transformation of the computational observations (computational eigenfrequencies and computational mode shapes) in order to match them to the experimental observation of each measured structure. This methodology automatically takes into account the mode crossings and the mode veerings which can appear between two experimental configurations or between two computational realizations of the SCM. In Section 2, the construction of the SCM is summarized. Section 3 is devoted to the identification of the hyperparameters of the SCM using a new methodology. Finally, in Section 4, an application devoted to an industrial pump of a thermal unit is presented.

2. Construction of the stochastic computational model

The construction of an adapted SCM can be carried out using different approaches (a state-of-the-art concerning stochastic modeling of uncertainties can be found, for instance, in [37,38,46]). The objective of this section is to construct a parameterized SCM based on the use of the *generalized probabilistic approach of uncertainties* proposed in [45,46], for which both the model-parameter uncertainties and the model uncertainties are taken into account and are separately identified. First, the NCM is constructed using the Finite Element (FE) method. The probabilistic model of model-parameter uncertainties is constructed by replacing the uncertain model parameters by random variables and the probabilistic model of model uncertainties is constructed by replacing the mass and stiffness matrices by adapted random matrices. The prior probability distributions of the uncertain model parameters and of the random matrices depend on unknown parameters (called the hyperparameters) for which the identification is addressed in Section 3.

2.1. Construction of the nominal computational model

The NCM is constructed using the FE method and the boundary conditions of the structure are such that there are no rigid body modes. This computational model exhibits n_p uncertain model parameters denoted $h_1, \ldots, h_{n_p}$. Let $\mathbf{h} = (h_1, \ldots, h_{n_p})$