Experimental identification of turbulent fluid forces applied to fuel assemblies using an uncertain model and estimation of the fretting-wear

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COMPDYN 2009
ECCOMAS Thematic Conference on
Computational Methods in Structural Dynamics and Earthquake Engineering
M. Papadrakakis, N.D. Lagaros, M. Fragiadakis (eds.)
Rhodes, Greece, 22-24 June 2009

EXPERIMENTAL IDENTIFICATION OF TURBULENT FLUID FORCES APPLIED TO FUEL ASSEMBLIES USING AN UNCERTAIN MODEL AND ESTIMATION OF THE FRETTING-WEAR

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Keywords: Nonlinear dynamics, uncertainties, identification, fretting-wear.

Abstract. *This paper is devoted to the identification of stochastic loads applied to fuel assemblies using an uncertain computational model and experimental measurements of responses. The stochastic loads applied to the structure are induced by a turbulent flow. The structure is made up of a nonlinear complex dynamical system. The experimental responses of the structure are obtained from strain sensors located on the structure. There are several sources of uncertainties in this experimental identification problem of the stochastic loads: uncertainties on the nonlinear dynamical computational model of the structure (fuel assemblies), uncertainties on parameters of the mathematical model of the stochastic loads themselves and finally, measurements errors. All these sources of uncertainties are identified and taken into account in the identification process of the stochastic loads. Then, the stochastic nonlinear dynamical computational model of fuel assemblies on which the identified stochastic loads are applied yield interesting results concerning the robustness of the estimation of the fretting-wear of the fuel rods.*

1 Introduction

A fuel assembly is made up of thousands of fuel rods and tubes which are held in position by grids. This dynamical system bathes in a flow of a liquid (water) which induces turbulent forces that are likely to induce fretting-wear of the fuel rods. A fuel assembly is a very complex nonlinear dynamical system for which an accurate computational model (called the reference computational model) would be time consuming and generally, would induce many numerical problems due to the high modal density of such a structure. Therefore, the computational model must be simplified from an engineering design point of view. The model uncertainties are thus due to the simplification introduced by the mathematical-mechanical modeling process. The measurements are realized with an experimental setup which is constituted of a half fuel assembly which bathes in a turbulent fluid. The objectives of this paper are to identify the parameters of the mathematical model of the stochastic forces induced by the turbulent fluid which are applied to the experimental setup, using an uncertain stochastic simplified computational model and experimental responses. The general methodology used to solve this problem has been presented in [2]. The identified stochastic model is then used to analyze the robustness of the predictions and allows the fretting-wear of the rods to be estimated.

The uncertainties introduced in this methodology are summarized on Figure 1. In the prob-

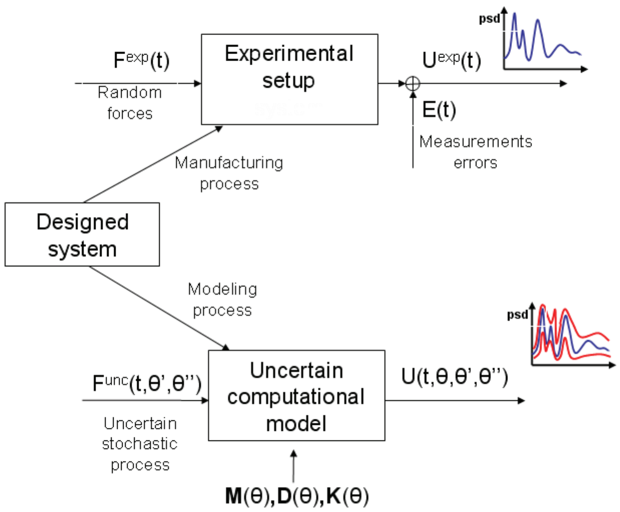

Figure 1: Designed system, experimental setup, uncertain computational model

lem under consideration, there are four sources of uncertainties:(1) The model uncertainties induced by the introduction of simplifications in the model. This type of model uncertainties are taken into account using the nonparametric probabilistic approach (see [4]) which consists in modeling the reduced mass and stiffness matrices by full random matrices defined on a probability space $(\Theta, \mathcal{T}, \mathcal{P})$ (2) The mean model of the stochastic loads (induced by the statistical fluctuations of the turbulent pressure applied to the structure) is a vector-valued Gaussian centered second-order stationary stochastic process defined on a probability space $(\Theta', \mathcal{T}', \mathcal{P}')$ (3) The uncertainties concerning the stochastic loads are taken into account by replacing the nominal value of the matrix-valued spectral density function (defined above) by a random matrix-valued spectral density function defined on a probability space $(\Theta'', \mathcal{T},'' \mathcal{P}'')$ (4) The uncertainties induced by measurement errors.

2 Experimental measurements

The experimental setup (see Figure 2) is composed of a half fuel assembly. All the structure bathes in a flow of a liquid (water) whose velocity is approximatively $1m/s$. One of the fuel rod is equipped with 7 strain sensors. The matrix-valued spectral density function of the vector-valued measured random signal is estimated by the periodogram method.

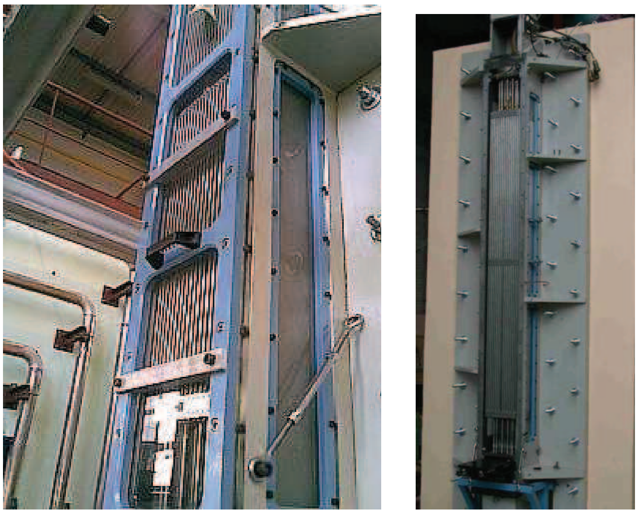

Figure 2: Experimental setup.

3 Reference computational model

The reference computational model is developed in order to construct an observation which will be useful for the identification of the dispersion parameters δ_M^A and δ_K^A controlling the level of uncertainties in the linear subsystem of the simplified computational model. In the reference model, all the 25 guide tubes, the 264 fuel rods and the grids are modeled by Timoshenko's beams. The bumps and springs are modeled by springs elements. For the fuel rod equipped with sensors for measurements, the bumps and springs are modeled accurately by elastic stops. The reference computational model is composed of two subsystems. The first one is linear and composed of all the guide tubes, the non-equipped fuel rods and the grids. The second one is the nonlinear fuel rod which is equipped with the sensors for measurements. The modal density is represented on Figure 3 in the frequency band of analysis. It can be seen that the modal density of the reference computational model is not homogeneous at all in the frequency band of analysis and have locally high values. Such a situation induces many numerical problem for the calculation of the stationary response of the stochastic nonlinear dynamical system with random parameters and random excitation. For this reason, the reference model must be simplified from the engineering design point of view.

4 Mean simplified computational model

The mean simplified computational model is derived from the reference computational model. Indeed, the linear subsystem of the reference computational model is replaced by an equivalent linear subsystem composed of two Timoshenko beams. The first one is equivalent to the 25 guide tubes and the other one is equivalent to the 263 non-equipped fuel rods. The nonlinear subsystem of the simplified computational model is the same that the nonlinear subsystem of

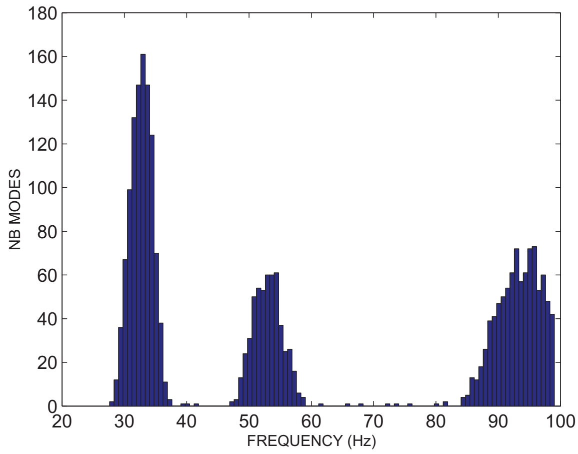

Figure 3: Modal density for the reference computational model.

the reference computational model. The linear subsystem and the linear part of the nonlinear subsytem are reduced using the Craig & Bampton method.

5 Stochastic simplified computational model

The simplifications introduced in the simplified computational model induce model uncertainties which have to be taken into account. In [2], the model uncertainties on the linear subsystem of the reference computational model are taken into account using the nonparametric probabilistic approach. For the linear subsystem, this method consists in replacing the reduced mass and the reduced stiffness matrices of the mean reduced simplified computational model by random matrices. The probability density functions of these full random matrices depend on the dispersion parameters δ_M^A and δ_K^A which are identified using the maximum likelihood method and the reference computational model as an observation. Then, the stationary stochastic process $\mathbf{Q}(t)$ which is a vector whose components are made up of the physical DOF at the coupling interface and of the generalized DOF for the two subsystems with fixed coupling interface satisfies the nonlinear stochastic differential equation

$$[\mathbf{M}]\ddot{\mathbf{Q}}(t) + [D]\dot{\mathbf{Q}}(t) + [\mathbf{K}]\mathbf{Q}(t) + \boldsymbol{\mathcal{F}}^{NL}(\mathbf{Q}(t), \dot{\mathbf{Q}}(t)) = \boldsymbol{\mathcal{F}}(t) \quad . \tag{1}$$

In this equation, the vector $\boldsymbol{\mathcal{F}}^{NL}(\mathbf{Q}(t), \dot{\mathbf{Q}}(t))$ is the generalized localized nonlinear forces due to the elastic stops, the vector $\boldsymbol{\mathcal{F}}(t)$ is the vector of the stochastic loads and $[\mathbf{M}]$ and $[\mathbf{K}]$ are two random matrices. The detailed construction of the different terms in Eq. (1) can be found in [2]. The stochastic equation (1) is solved using the Monte Carlo simulation method.

6 Identification of the uncertain stochastic loads

For the construction of the stochastic process $\tilde{\mathbf{F}}^{\text{unc}}$ modeling the random external applied loads and including a probabilistic model of uncertainties, we first introduce a stochastic process $\{\tilde{\mathbf{F}}(t), t \in \mathbb{R}\}$ of the stochastic loads without uncertainties. It is then assumed that the stochastic process $\tilde{\mathbf{F}}$ is a Gaussian stationary centered second-order stochastic process defined on a probability space $(\Theta', \mathcal{T}', \mathcal{P}')$ for which the matrix-valued spectral density function is $\{[S_{\tilde{\mathbf{F}}}(\omega)], \omega \in \mathbb{R}\}$. The uncertain stochastic process $\tilde{\mathbf{F}}^{\text{unc}}$ is then constructed as the stochastic process $\tilde{\mathbf{F}}$ for which the deterministic function $\{[S_{\tilde{\mathbf{F}}}(\omega)], \omega \in \mathbb{R}\}$ is replaced by a random function $\{[\mathbf{S}_{\tilde{\mathbf{F}}}(\omega)], \omega \in \mathbb{R}\}$ defined on a probability space $(\Theta'', \mathcal{T}'', \mathcal{P}'')$. The probability distribution of random function $\{[\mathbf{S}_{\tilde{\mathbf{F}}}(\omega)], \omega \in \mathbb{R}\}$ is constructed using the maximum entropy principle and depends on a dispersion parameter δ_F. Such a stochastic process and its generator of independent realizations are completely defined by (1) the spectral density function $[S_{\tilde{\mathbf{F}}^{\mathrm{unc}}}]$ and (2) its dispersion parameter δ_F. So the identification of the stochastic loads consists in identifying these two quantities.

6.1 Identification of the matrix-valued spectral density function of the uncertain stochastic loads

It is assumed that the algebraic representation of the spectral density function of the uncertain stochastic loads depends only on the two parameters A_X^G and A_Z^G which are the amplitudes of the PSD in each transversal direction. The identification of the spectral density function of the uncertain stochastic loads then consists in identifying the vector $\mathbf{r} = (A_X^G, A_Z^G)$. We introduce the vector-valued stochastic process $\{\Xi^{\mathrm{exp}}(t), t \in \mathbb{R}\}$ whose components are the 7 measured strains for which the matrix-valued spectral density function $\{[S_{\Xi^{exp}}(\omega)], \omega \in \mathbb{R}\}$ is estimated using the periodogram method. The corresponding stochastic process $\{\Xi(t; \mathbf{r}), t \in \mathbb{R}\}$ is calculated with the stochastic simplified computational model. The matrix-valued spectral density function $\{[S_{\Xi}(\omega; \mathbf{r})], \omega \in \mathbb{R}\}$ of the stochastic process $\Xi(t; \mathbf{r})$ is also estimated using the periodogram method. The identification is then performed by minimizing the distance between the experimental matrix-valued spectral density function $[S_{\Xi^{exp}}(\omega)]$ and the numerical matrix-valued spectral density function $[S_{\Xi}(\omega; \mathbf{r})]$. The optimal value $\mathbf{r}_{opt}$ of the parameter $\mathbf{r}$ is then given by

$$\mathbf{r}_{opt} = \arg \min_{\mathbf{r} \in \mathcal{C}_r} D(\mathbf{r}) \quad , \quad D(\mathbf{r}) = \int_{\mathcal{B}} \|[S_{\Xi}(\omega; \mathbf{r})] - [S_{\Xi^{exp}}(\omega)]\|_F^2 \, d\omega \quad , \tag{2}$$

in which $\mathcal{C}_r$ is the admissible set for the vector $\mathbf{r}$. The function $\mathbf{r} \mapsto D(\mathbf{r})$ is plotted in Figure **??**.

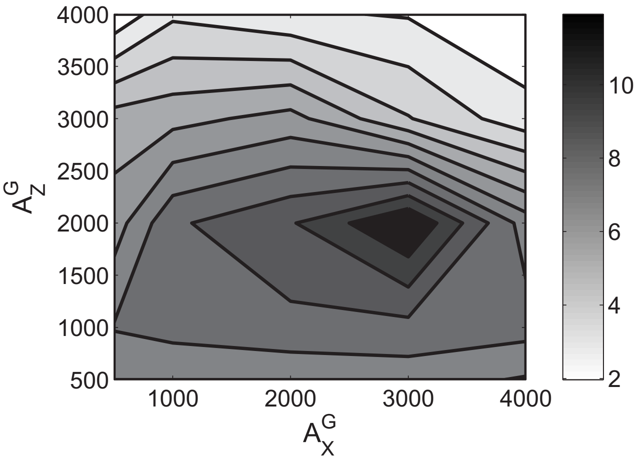

Figure 4: Graph of function $\mathbf{r} \mapsto D(\mathbf{r})$.

6.2 Identification of the dispersion parameter δ_F.

We introduce the random variable J_s which is such that for all $\theta \in \Theta$ and for all $\theta'' \in \Theta''$,

$$J_s(\theta, \theta'') = \int_{\mathcal{B}} \|[\mathbf{S}_{\mathbf{\Xi}}(\omega, \theta, \theta'')]\|_F^2 \, d\omega \quad . \tag{3}$$

The measurements errors on the experimental variable J_s^{exp} are modeled by a given additive noise $\mathcal{E}$, defined on a probability space $(\Theta''', \mathcal{T}''', \mathcal{P}''')$, for which the probability density function is $e \mapsto p_{\mathcal{E}}(e)$. We then have

$$J_s^{\mathrm{er}} = J_s + \mathcal{E} \quad . \tag{4}$$

The dispersion parameter δ_F is identified using the maximum likelihood method for the random variable J_s^{er} for which the probability density function is defined by

$$p_{J_s^{\mathrm{er}}}(y) = \int_{-\infty}^{+\infty} p_{J_s^{\mathrm{er}}|\mathcal{E}=e}(y|e) p_{\mathcal{E}}(e) de \quad , \tag{5}$$

where $x \mapsto p_{J_s^{\mathrm{er}}|\mathcal{E}=e}(y|e)$ is the conditional probability density function J_s^{er} given $\mathcal{E} = e$. It is assumed that the additive noise $\mathcal{E}$ is modeled by a centered Gaussian random variable for which the standard deviation is given. The graph of function $\delta_F \mapsto p_{J_s^{\mathrm{er}}}(J_s^{\mathrm{exp}}; \delta_F)$ is plotted in Figure 5.

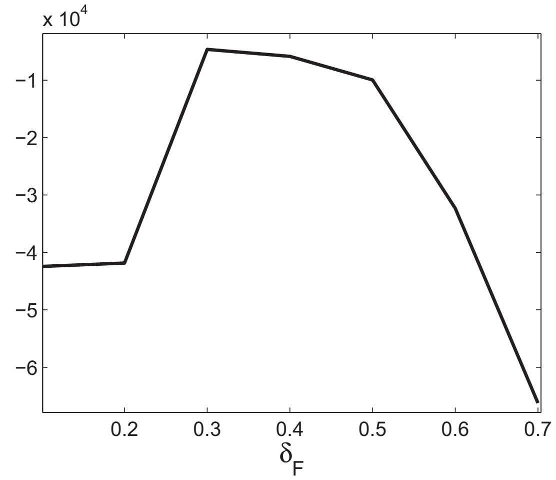

Figure 5: Graph of function $\delta_F \mapsto p_{J_s^{\mathrm{er}}}(J_s^{\mathrm{exp}}; \delta_F)$.

7 Random fretting-wear estimation

The random fretting-wear in the contacts rod/bump and rod/spring for the uncertain system submitted to the uncertain stochastic excitation is based on the use of the Archard power wear. The mean value, the dispersion (ratio of the standard deviation with the mean value), and quantiles 5% and 95% of the random fretting-wear for the first grid following x direction are reported in Table 1. The estimated dispersions are lower than $61\,\%$.

	mean	dispersion	quantile 5 %	quantile 95 %
low bump	0.024	60.1%	0.014	0.035
spring	0.029	51.7%	0.025	0.036
high bump	0.014	55.4%	0.01	0.019

Table 1: Statistics for the random fretting-wear on the first grid following x direction.

8 Conclusions

We have presented a complete methodology for the identification of turbulent fluid forces applied to fuel assemblies using an uncertain simplified computational model and experimental strain responses. All the sources of uncertainties have been taken into account in the identification process. The probabilistic model of model uncertainties in the simplified computational model depends on dispersion parameters which have been identified using the maximum likelihood method and a reference computational model. The uncertainties concerning the parametric representation of the uncertain stochastic loads have also been taken into account. The uncertain stochastic loads have been identified taking into account measurements errors. The identified stochastic loads has been applied to the stochastic simplified computational model in order to construct the statistics on the random fretting-wear of the fuel roads. The estimated dispersions of the random fretting-wear are about 61% that induces a relatively robustness with respect to uncertainties for this complex industrial problem.

Acknowledgment

We thank EDF R&D for their collaboration and in particular for the experimental results.

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