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Parameter selection for model updating with global sensitivity analysis

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ABSTRACT

The problem of selecting parameters for stochastic model updating is one that has been studied for decades, yet no method exists that guarantees the 'correct' choice. In this paper, a method is formulated based on global sensitivity analysis using a new evaluation function and a composite sensitivity index that discriminates explicitly between sets of parameters with correctly-modelled and erroneous statistics. The method is applied successfully to simulated data for a pin-jointed truss structure model in two studies, for the cases of independent and correlated parameters respectively. Finally, experimental validation of the method is carried out on a frame structure with uncertainty in the position of two masses. The statistics of mass positions are confirmed by the proposed method to be correctly modelled using a Kriging surrogate.

1. Introduction

Finite element model updating has become a useful and widely-used tool to improve the correlation between test data and computational prediction [1,2]. Usually, there are many candidate parameters that could be used to produce the required change in the model output. One approach is to allow all the parameters to participate in the updating procedure, but to constrain them in the sense of the minimum norm. An alternative approach is to select a certain subset of the updating parameters based on physical meaning or engineering experience [3] – this introduces the problem of parameter selection for model updating.

In the early days, parameter selection was done by using engineering experience, but is considered to be too subjective. Ahmadian et al. [4] used a matrix decomposition to update the eigenvalues and eigenvectors of individual finite elements or substructures. This approach often leads to non-physical updated models that reproduce test data with good accuracy. Of course, the need (or otherwise) for physical meaning depends upon the purpose of the model. Most parameter selection methods are based upon the matrix of local sensitivities, normally evaluated through gradients or partial derivatives of the response of model at the updating parameters.

There are numerous studies based on local sensitivity methods [5,6]. Subset parameter selection methods choose parameters or groups of parameters that minimize a residual function for updating [7–9]. Friswell et al. [3] developed an improved parameter subset selection method by taking account of side constraints on the parameter values. Kim and Park [10,11]

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presented an improved parameter selection method by creating substructures from elements with similar sensitivity. The problem with local sensitivity methods is that they are based entirely upon the local gradient of the response of an analytical model (at a certain parameter point), which means that such methods are only applicable in the space close to the initial parameter estimate. Also, they are only able to identify 'sensitive' parameters and cannot locate the uncertainty in the model because local sensitivity methods take no account of test data. Global sensitivity methods, as the name implies, offer advantages not possessed by local methods.

There are several statistics-based parameter selection approaches, such as the Bayesian evidence statistic [12] and the F-test [13,14]. Among these methods, global sensitivity analysis (GSA) [15] is the most widely used. In contrast to local sensitivity analysis, such methods consider the whole variation range of the inputs [16] and are therefore referred to as 'global'. The calculation of GSA indices may be carried out in different ways. For example, Boscato et al. [17] used a derivative-based approach, also known as the elementary effects (EE) method. They concluded that GSA is better suited than local sensitivity-based methods to complex structures, such as historical buildings with high uncertainty. Wan and Ren [18] used the more widely accepted variance-based GSA method using Sobol indices to give a more sophisticated measurement of the input effect on the output. This was done by calculating the indices by integration over the whole input domain rather than a limited selection of observations.

Wan and Ren [18], used the sum of squares of modal frequency residuals normalized by the standard deviation as the objective function and a Gaussian process emulator (GPE) to replace the expensive finite element code. They concluded that the total sensitivity indices should be used along with the first-order sensitivity indices to avoid discarding the parameters with the negligible first-order effects but significant total sensitivity. Sudret [19] described an improved method whereby the Sobol indices were determined analytically from the generalized polynomial chaos expansion (PCE). Thus, the computational cost of the sensitivity indices was practically reduced to that of estimating the PCE coefficients. Practical application of GSA research in damage identification includes the full-scale seven-storey shear wall building structure tested on the UCSD-NEES shake table [20].

Silva et al. [21] developed a decomposition of the scaled output covariance matrix using the columns of the local sensitivity matrix. They selected the parameters that contributed most to the test output covariances by projecting the sensitivity-matrix columns onto the matrix of left singular vectors (with non-zero singular values). This has the advantage of computational efficiency; not requiring the expensive sampling required for the computation of Sobol indices, but is not able to discriminate between parameter uncertainty that is accurately modelled and that which is not. It is only the latter that accounts for the difference in output variability between the test and the model. This latter point (on the discrimination between true and erroneous parameter distributions) also applies to methods based on objective functions that take the form of the square of the response residuals normalised by the mean or standard deviation – they aim only to find the parameters that reproduce the output variability and not necessarily the erroneous parameters.

The purpose of this research is to propose a global sensitivity-based parameter selection method, based on an evaluation function, with built-in test data, and based on the multivariate normal distribution. Then by using the global sensitivity method, a composite sensitivity index is formed, which separates sets of parameters with correctly-modelled and erroneous statistics. This represents a more powerful parameter selection approach than is presently available by existing methods, which only select parameters that contribute to observed variability (whether or not the statistics of the parameters are modelled correctly). The effectiveness and robustness are validated with several computational cases on a truss model. Both the cases of independent parameters and correlated parameters are studied and discussed. After the simulation cases, an experimental frame with uncertain mass locations is studied. The positions of masses on the structure are arranged on the basis of a correlated number pair array. The goal, in this case, is to correctly identify that the uncertain mass positions are responsible for observed natural frequency variation.

2. Parameter selection by GSA

The parameter selection method is described by the flowchart shown in Fig. 1 and details are provided in the following sections.

2.1. Building the evaluation function

Consider an analytical finite element model with input parameter vector $\mathbf{p} = (p_1, p_2, \ldots, p_n)^T$ and the output of modal frequencies $\boldsymbol{\omega}_A = (\omega^1, \omega^2, \ldots, \omega^k)_A^T$, where n is the number of parameters to be selected and k is the number of output modal frequencies. The model can be described as a function,

$$\boldsymbol{\omega}_A = f_A(\mathbf{p}) \tag{1}$$

The model output is described here as the modal natural frequencies, but could include mode shapes, frequency response functions or any other model output.

The corresponding test data measurement can be described as a random vector for each of k natural frequencies $(\boldsymbol{\omega}_M^i)^T = (\omega_1^i, \omega_2^i, \ldots, \omega_m^i)_M; \quad i = 1, 2, \ldots, k$ obtained typically from tests carried out on m nominally identical structures.