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An interval model updating strategy using interval response surface models

Sheng-En Fang [a,*], Qiu-Hu Zhang [b], Wei-Xin Ren [b]

[a] School of Civil Engineering, Fuzhou University, Fuzhou, Fujian Province 350108, PR China
[b] School of Civil Engineering, Hefei University of Technology, Hefei, Anhui Province 230009, PR China

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ABSTRACT

Stochastic model updating provides an effective way of handling uncertainties existing in real-world structures. In general, probabilistic theories, fuzzy mathematics or interval analyses are involved in the solution of inverse problems. However in practice, probability distributions or membership functions of structural parameters are often unavailable due to insufficient information of a structure. At this moment an interval model updating procedure shows its superiority in the aspect of problem simplification since only the upper and lower bounds of parameters and responses are sought. To this end, this study develops a new concept of interval response surface models for the purpose of efficiently implementing the interval model updating procedure. The frequent interval overestimation due to the use of interval arithmetic can be maximally avoided leading to accurate estimation of parameter intervals. Meanwhile, the establishment of an interval inverse problem is highly simplified, accompanied by a saving of computational costs. By this means a relatively simple and cost-efficient interval updating process can be achieved. Lastly, the feasibility and reliability of the developed method have been verified against a numerical mass–spring system and also against a set of experimentally tested steel plates.

1. Introduction

Deterministic model updating methods have been widely investigated in the solutions of parameter identification problems [1]. However once structural uncertainties cannot be overlooked, a model updating procedure must work together with probabilistic [2] or non-probabilistic algorithms [3] for the purpose of pursuing reliable results. To this end, different methods have been developed for quantifying reducible and irreducible uncertainties. At the early stage, reducible uncertainties were followed with interest [4–11] and the minimum variance methods were first used to handle the randomness caused by measurement noises [4,5]. The best estimation of parameter means were achieved when the variance estimates were minimized. Subsequently, Bayesian statistical frameworks were adopted to estimate the posterior probabilities of parameters [2,6,7]. The Markov Chain Monte Carlo methods were involved in Bayesian model updating in order to avoid the solution of the normalized constant in Bayes' formula [8,9]. However, high computational costs due to a

* Corresponding author at: School of Civil Engineering, Fuzhou University, Fuzhou, Fujian Province 350108, PR China. Tel.: +86 18959162363; fax: +86 591 22865355.
E-mail address: shengen.fang@fzu.edu.cn (S.-E. Fang).

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large amount of samples required for a satisfactory estimation greatly restrain the applications of Bayesian updating methods. Due to it, surrogate models such as polynomial chaos expansions were regarded as an effective way of alleviating the computational burden [10,11]. Besides the aforementioned methods, random matrix approaches could offer an alternative option when the eigenvalues and eigenvectors of a structure were uncertain [12].

On the other hand, stochastic model updating (SMU) focuses on identifying irreducible uncertainties [13–20], which are also called as “variability” due to manufacturing tolerances of geometric dimensions, discreteness of material properties, etc. In this aspect, an updating algorithm has been proposed based on the maximum likelihood function formulated by using the Monte Carlo or mean-centered first-order perturbation methods [13]. The Monte Carlo based inverse procedure is relatively easy to implement but it also requires considerable computational expense [14,15]. Alternatively, perturbation methods provide an efficient way for uncertainty propagation through expanding updating equation terms with a truncated Taylor series expansion around predefined parameter points [16–19]. Such methods own the superiority of computational efficiency over Monte Carlo based methods. Nevertheless, the prerequisite of small uncertainties, together with the Gaussian distribution assumption, also limit the applications to complex problems. Moreover, perturbation based predictions are sensitive to the initial estimates of parameters. Alternatively, new methods have also appeared in the literature, such as the extension of classic model updating techniques [20] and the decomposition of a stochastic updating process into a series of deterministic ones [21].

A successful SMU process highly relies on the efficient and accurate propagation of uncertainties. Presently three categories of probabilistic theories, fuzzy mathematics and interval analyses are usually employed for uncertainty propagation [3,22,23]. Probabilistic methods are popularly chosen that often assume that parameter variability follows normal distributions represented by means and variances [16]. However, an adequate probabilistic estimation always requires sufficient measurement data, which is often impractical in reality [24]. On the other hand, with respect to membership functions for fuzzy mathematics based methods, expert knowledge could produce additional uncertainties. And overestimation of the interval widths of response quantities could induce computational difficulty. Fortunately, sometimes only the upper and lower bounds of parameters and responses are concerned in practical cases. The parameter distributions within the bounds are out of interest. Under such circumstance, interval analyses [25,26] become useful especially when structural information is insufficient.

Concretely, the uncertain parameters of a system were expressed by interval numbers and then estimated by means of solving linear interval equations [27,28]. Meanwhile, reliable criteria should be established for the sake of distinguishing the presence of system changes from the randomness caused by uncertainties [29,30]. In the field of interval model updating (IMU), the inclusion theorem was employed to establish an interval inverse problem. And the convergence was achieved when measured responses fall into numerically predicted intervals [31–36]. Due to the consideration of easy implementation, IMU problems are usually solved within a deterministic framework where the upper and lower bounds of parameters are sought separately. For example, an IMU problem was decomposed into two deterministic constrained optimization processes, by which means the midpoints and interval radii of parameters were separately estimated [32]. Here the first-order Taylor expansion was adopted to express the characteristic matrices of a structure and the interval modal data were chosen as the responses. Meanwhile, an interval satisfaction degree representing the possibility that one interval is smaller than another could also be used to deal with uncertain constraints finally transformed to deterministic ones [33]. Thus traditional optimization algorithms can be applied to solving the transformed inverse problem. Alternatively, the vertex solution theorem [34] is effective and cost-efficient for IMU due to its easy implementation, particularly in the solution of eigenvalue problems [35]. The theorem avoids the overestimation of intervals due to the so-called dependency problem [25] after interval arithmetic operations. But the vertex solution was valid only for particular parameterization of an FE model without the involvement of eigenvectors [36,37], which highly limits its further applications. Due to this drawback, global optimization algorithms were taken into account for more general solutions. Surrogate models such as the Kriging predictor were used to improve the efficiency of gradient computation and thus to facilitate the convergence [36,37]. On the other hand, an interval inverse problem could be formulated as a nested double loop procedure where the Taylor inclusion function was introduced to compress the interval overestimation [38]. For practical applications, an interval inverse procedure has been developed to evaluate the load under which a reinforced concrete beam changed from its elastic behavior to a nonlinear one [30]. And the extension of IMU to the area of damage detection has also been investigated [39,40].

So far most of IMU problems are solved within a deterministic framework since direct interval arithmetic operations are difficult to implement during inverse solutions. Therefore the upper and lower bounds of parameters should be sought separately through a deterministic inverse procedure. Additionally, global optimization of interval variables is difficult to realize due to the fact that the interval arithmetic is quite different with the traditional mathematical arithmetic. Consequently, some modifications need to be performed on objective functions and optimization algorithms. To overcome such inconvenience, this study proposes a new concept of interval response surface model (IRSM) in the interest of easy implementation of an IMU process. Firstly the mathematical expressions of traditional response surface models (RSM) are transformed into a complete square form. Then the real parameters in the expressions are replaced by interval parameters, which finally generates IRSMs. By this means the interval arithmetic can be directly performed on IRSMs during the solution of an inverse problem. Simultaneously, the phenomenon of interval overestimation can be avoided when IRSMs are adopted for uncertainty propagation. Furthermore, the IRSM based IMU method does not require monotonic relationships between parameters and responses, which presents a superiority over the vertex method. Finally, the feasibility and reliability of this method have been validated using both numerical and experimental examples.