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The impact force identification of composite stiffened panels under material uncertainty

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ABSTRACT

This paper presents a synthesis approach to address the problem of uncertainty in the impact force identification. The effects of material uncertainty on dynamic responses of the structure are studied by using Monte Carlo simulation. Six parameters, including mechanical properties and thermal coefficients, are considered as independent random variables. A parametric study is conducted to select four parameters as the optimization variables in the following step of model updating. The technique of model updating is used to correct the modeling errors caused by material uncertainty. Then, an improved inverse analysis technique based on the finite element method and mode superposition method is taken for impact force identification. In this study, the present method is performed on a composite stiffened panel, and the effect of noise on the performance of identification is also discussed. The results of the study show that the developed approach is capable of identifying the impact location and reconstructing the force history accurately by reducing material uncertainty through the modal updating procedure.

1. Introduction

External impact events on aircraft and spacecraft structures are common phenomena in aerospace industry, such as bird-strike, runway debris collision and other similar loading events. These impacts may cause some hidden damages in the interior of composite materials, which will grow progressively and result in catastrophic failure of the structures. In recent years, structural health monitoring (SHM), as a promising technique for ensuring the structural integrity, is receiving more and more attention to meet the high demands for operation safety of structures and low cost maintenance.

Generally, a SHM system is comprised of a sensing network, a signal processing module with advanced algorithms and other essential hardwares. According to the operating principle of sensors, it can be classified into two types of monitoring systems: active and passive damage detection [1]. For impact force identification, it can be regarded as a passive sensing system, which does not involve any actuation. Transducers built in structures are used to extract relevant signal information generated by impacts.

Impact force identification mainly includes the impact location estimation and the force history reconstruction. In the area of impact location estimation, the most popular method is based on time-of-flight (TOF) [2,3], which is realized by minimizing the deviations between measured TOFs and calculated TOFs. However, the limitation reveals in two aspects: firstly, it is difficult to determine the exact TOF of the impact wave; secondly, it requires an accurate wave velocity, which varies with the impact frequency and is also directionally dependent for anisotropic composites. Liang et al. [4] proposed a distributed coordination algorithm which fused the strengths of the triangulation method and the inverse analysis method. These two methods coordinated in parallel to improve the preciseness and real-time of impact location. In addition, Chang et al. [5,6] proposed a method to estimate the impact location by calculating the centroid of power distribution over the entire structure from sensor signals. Though this method is easy without any complex algorithms, the accuracy of the results depends on the number of sensors to a large extent. The artificial neural networks (ANNs) [7–11] have been adopted to detect the impact location due to the development of artificial intelligence techniques in recent years. Worden et al. [7] used ANNs to find the impact location successfully, but it failed to detect the magnitude of the impact force. Haywood et al. [8] and Park et al. [9] carried out experiments to detect impact locations with an ANN algorithm. A tutorial overview of the basic theory, like data and sensor fusion, feature extraction and selection, ANNs etc., was given in [10]. However, the above applications of ANNs require a huge amount of impact data for learning through training tests, which is not practical for application. Sharif-Khodaei et al. [11] have overcome the above limitation by developing a metamodel, but it also brings another limitation of the requirement of an accurate finite element (FE) model.

In the other field of the force history reconstruction, some researchers also developed various effective methods. Among these

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methods, one class is based on transfer function. Generally, the function can be obtained through three ways: analytical solutions [12,13], the FE method [14,15], and experimental tests [5,6,16,17]. Atobe [16] used experimental transfer matrices to estimate the structural response. It avoided using any analytical or numerical models of the structure. An optimization algorithm was then adopted to identify the force history by minimizing the deviation between the measured sensor responses and the estimated response. Park and Chang [5,6] developed an advantageous methodology which was based on a linear auto-regressive model with exogenous (ARX). Sets of limited training data in terms of impulse response were generated to derive ARX parameters. Recently, the time-reversal (T-R) technique in the application of impact identification has attracted much interest [15,17–20]. Based on the principle of the T-R concept, if sensor signals are reversed in time and re-emitted, the temporal and spatial convergence can be achieved simultaneously and the back-propagated elastic wave will converge at the impact location. Transfer function is usually used to realize the T-R procedure. Another class of impact identification methods relies on the numerical model of structures. Davendralingam [21] presented a method based on a sensitivity response approach in conjunction with a general finite element program to identify unknown parameter and force histories for nonlinear structures. Yan et al. [22] proposed a genetic algorithm-based approach for impact force identification. In this method, the impact location and force history are represented by a set of parameters, thus transforming it to a parameter identification problem. Hu et al. [23] employed Chebyshev polynomial to approximate the impact force history. By comparing the numerically estimated strains and the experimental ones, an optimization model was set up to solve this inverse problem by employing the quadratic programming method. The main drawback of Yan [22] and Hu [23] is its requirement of an accurate structural model, which is difficult for some complex structures. In addition, the technique of ANNs can also be used to reconstruct the force history [7].

Although a lot of techniques have been conducted on this issue during the past few years, there still exist many problems in the transition from theory to practical applications. One major obstacle for the slow progress of its application is the existence of various uncertainties. In general, uncertainty in structural dynamic can be categorized into two types: epistemic uncertainty and aleatory uncertainty [24]. Epistemic uncertainty, also referred to as reducible uncertainty, is a potential deficiency that is due to lack-of-knowledge of quantities or processes of the system. Aleatory or random uncertainty occurs due to the physical variability in the system, and the randomness of material properties or environmental and operational conditions typically leads to aleatory uncertainty. This type of uncertainty is not mainly due to a lack of knowledge and is also referred to as irreducible uncertainty. Sohn [25] reviewed the effects of environmental and operational variations on real structures and presented research progresses in the area of data normalization. For composite structures, aleatory uncertainty of material properties is particularly important but has always been ignored. Due to the increased structural complexity and some inherent uncertainties involved in the manufacturing process [26], material uncertainties of composites are relatively higher than isotropic materials, thus causing the variation of structural response, like eigenvalues and eigenvectors. A number of studies have been conducted on the damage detection of composite structures with consideration of material uncertainty [26–31]. Murugan [26] and Georgiou [28] investigated the effect of uncertainty in composite material properties on the aeroelastic behavior of composite structures based on the techniques of Monte Carlo simulations (MCS) and Polynomial Chaos Expansion (PCE) respectively. Gayathri [27,29] studied the material uncertainty effects on frequency of composite plates with damage of matrix crack. Singh [31] investigated the effects of dispersion in material properties on free vibration response of composite plates with geometric nonlinearity. For a detailed review, the reader can refer to [32] which presented a comprehensive review of uncertainties involved in flight vehicle structural damage monitoring, diagnosis, prognosis and control and its challenges.

In this work, material uncertainty is firstly considered before the impact force identification. Probabilistic analysis using MCS is performed to study the effect of uncertainty in mechanical and thermal properties on dynamic responses. Following that, a parametric study is conducted to find out the key parameters on the above responses. Secondly, modal updating is utilized to establish an accurate FE model. Then, Section 4 develops an inverse analysis technique for composite stiffened structures. It is based on the finite element method and mode superposition method to realize the impact force identification. Effect of noise in strain responses on the impact identification is finally examined in detail followed by conclusions.

2. Uncertainty analysis

2.1. Model description

An FE model of a stiffened composite panel is formulated in this section. A dynamic analysis is carried out to study the dynamic characteristics of the structure, which is achieved by the widely used finite element software MSC.Nastran. Fig. 1 shows the details of the structure, and the clamped boundary is imposed on the upper and lower edges of the plate. The mechanical properties of laminate [33] are presented in Table 1.

It is intuitive that temperature variation may change the dynamic response of structures. The effects of temperature variability mainly reveal in two aspects: the material stiffness and the boundary conditions of a system. In this section, the effect of thermal stress caused by temperature is considered, and it is applied on the structure as an initial condition, which may change the system stiffness and thus affect the dynamic behavior of structures. An initial temperature field is given as a prior condition and is shown in Fig. 2. The thermal properties, thermal expansion coefficients [34], are also listed in Table 1.

2.2. Probabilistic and parametric analysis

Probabilistic analysis is performed to study the effect of material uncertainty on the natural frequency of the structure. The technique of MCS, as a non-intrusive method, is performed in this study by considering mechanical properties ($E_1, E_2, \nu_{12}, G_{12}$) and thermal coefficients (α_1, α_2) as independent random variables, which are normally distributed. The coefficients of variation (COVs) for $E_1, E_2, \nu_{12}, G_{12}$ are given in Table 1 [33] and the COVs of α_1, α_2 are assumed as -0.05 and 0.05 respectively.

According to the sample points of MCS, a multivariate quadratic regression model is established as:

$$y_k = \beta_0 + \sum_{i=1}^{m} \beta_i x_i + \sum_{i=1}^{m} \beta_i x_i^2 + \sum_{i=1}^{m} \sum_{j=1, j \neq i}^{m} \beta_{ij} x_i x_j, (k = 1, \ldots, n) \tag{1}$$

where x and y refer to the independent random variables and natural frequencies respectively and m and n are the number of them. β represent the coefficients of the polynomial.

On the basis of the above multivariate quadratic regression model, the contribution of each independent random variable on the natural frequency can be further calculated. First, the range of each independent random variable is normalized to $[-1, 1]$, then the coefficients of the polynomial β can be updated to a new