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Localization and identification of structural nonlinearities using cascaded optimization and neural networks

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ABSTRACT

In this study, a new approach is proposed for identification of structural nonlinearities by employing cascaded optimization and neural networks. Linear finite element model of the system and frequency response functions measured at arbitrary locations of the system are used in this approach. Using the finite element model, a training data set is created, which appropriately spans the possible nonlinear configurations space of the system. A classification neural network trained on these data sets then localizes and determines the types of all nonlinearities associated with the nonlinear degrees of freedom in the system. A new training data set spanning the parametric space associated with the determined nonlinearities is created to facilitate parametric identification. Utilizing this data set, initially, a feed forward regression neural network is trained, which parametrically identifies the classified nonlinearities. Then, the results obtained are further improved by carrying out an optimization which uses network identified values as starting points. Unlike identification methods available in literature, the proposed approach does not require data collection from the degrees of freedoms where nonlinear elements are attached, and furthermore, it is sufficiently accurate even in the presence of measurement noise. The application of the proposed approach is demonstrated on an example system with nonlinear elements and on a real life experimental setup with a local nonlinearity.

1. Introduction

Identification of structural nonlinearities in dynamic structures has become the interest of researchers in the past four decades [1]. Studies on this subject focused on two parts: localizing and characterizing the nonlinearity, and estimating the parameters of the nonlinearity based on experimentally measured data [2–6].

One of the main problems of nonlinearity identification is the determination of the location and the type of nonlinearity; in other words, classification of the nonlinear system by using system responses. For this problem, frequency domain methods are mostly preferred. He and Ewins [7] used frequency response functions (FRFs) obtained at different forcing levels in order to detect nonlinearities in a system. Similarly, the method developed by Özer et al. [4] determines possible locations of nonlinearities and identifies their types and parameters by using describing functions, which is a frequency domain method as well. Major restrictions of this method are the requirements of complete FRFs of the system for localization purposes.

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However, in a later study, Aykan and Özgüven [5] improved the method by using incomplete FRFs for localization purposes. A common feature of most of the methods in literature is the identification of types of nonlinearities by observing system responses or nonlinear restoring forces, which is a time consuming process and is not suitable to be applied to a series of products in order to identify nonlinearity due to manufacturing errors and assembly differences.

Parameter estimation of nonlinearities in a classified system is a relatively easier problem. There exist several time domain and frequency domain methods in literature targeting parameter identification [1,8,9]. Although these methods have their own drawbacks, they are promising in specific application areas. Masri and Caughey [10] developed a method called Restoring Force Surface (RFS) method to estimate parameters of nonlinearities using least squares approach in time domain. Conditioned Reverse Path (CRP) proposed by Richards and Singh [11] uses spectral analysis in frequency domain to compute the coefficients of nonlinearity matrix. Gondhalekar et al. [12] proposed a parameter identification method for nonlinear dynamic systems utilizing genetic optimization. Authors consider an example with a single nonlinear element the location of which is known. The type of the nonlinear element is estimated by the inspection of the frequency response functions. Possibilities are included into the problem as weighting coefficients of the terms of the fitness function associated with the possible nonlinear elements. The method requires measurement from the nonlinear degree of freedom (DOF) which is an important limitation of the method as indicated by the authors as well.

The method proposed in this study, classifies and identifies nonlinearities in the system utilizing cascaded optimization and neural networks (CONN). Neural network classifiers have been used for parameter identification of structural nonlinearities in the past [13–16]; however, nonlinearity classification using artificial neural networks (ANN) is a new approach in structural dynamics. A recently published study utilizes Hilbert transform and ANN to detect and characterize structural nonlinearities [17]. Yet, this method is limited to structures with a single type of nonlinearity at a single location. Moreover, the method is applicable to multi degree of freedom systems where the modes are well separated so that no linear or nonlinear mode coupling occurs. These are significant limitations which need to be overcome. The method proposed in this study is capable of classifying nonlinearities located at multiple locations in a structure. Moreover, in the proposed method the identified parameters are not taken as the final values; instead they are used as the starting point of an optimization step which improves the identified parameters further. In this way, ANN and the optimization tool performs two-stage identification process in cascaded form, where the output of the identification with neural networks is used as the input of the optimization problem. This increases the accuracy of the identification process without increasing the number of training data used. Constructed networks are to be trained with sample data sets which are FRFs of selected points on the system. Nonlinear frequency response functions of the system are obtained by analyzing possible nonlinear system configurations which can be obtained from the physics of the problem or experience. It should be noted that in order to perform these analyses, a mathematical model of the system is required. After training the networks, location and type of each nonlinearity is determined by running trained networks with measured system responses as the input. Parameters of the classified nonlinearities are identified by means of a regression network utilizing the same input data used for classification. One of the important advantages of the proposed method is that it does not require measurements from nonlinear DOFs; hence, system responses measured from arbitrary locations can be used for identification purposes. Moreover, with the proposed method, it is possible to reduce the undesirable effects of measurement noise by injecting noise into data during the training process. Once networks are trained, identification is very fast; hence, the method proposed is very suitable for identification of nonlinearities in a series of products due to manufacturing errors and/or assembly differences.

2. Theory

The proposed method can be divided into three parts. In the first part, a classification network is used to identify the locations and the types of the nonlinear elements, whereas in the second part, a regression network is utilized to determine the parameters associated with the identified nonlinearities. In the final part, an optimization problem is solved, which further improves the identified parameters. For training of the networks, FRF of an arbitrary location (i.e. degree of freedom) is used; therefore, a mathematical model of the system is required. There is no restriction on the mathematical model utilized; hence finite element models (FEMs) can be used with the proposed method. Using the mathematical model together with the nonlinear elements and their possible configurations, simulations are performed to generate training data employing harmonic balance method (HBM). Details of the neural network models and nonlinear mathematical modeling are explained in the following sections.

2.1. Neural network models

A typical neural network model is characterized by four items: number of neurons, number of layers, transfer functions and training algorithm. The fundamental element of a neural network is *a single neuron* which can be mathematically represented as:

$$o_j = f_j\left(\sum_{i=1}^{R} w_{ji} y_i + b_j\right) = f_j(\{w_j\}^T\{y\} + b_j) = f_j(n_j), \tag{1}$$