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Nonlinear model updating applied to the IMAC XXXII Round Robin benchmark system

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ABSTRACT

We consider the application of a new nonlinear model updating strategy to a computational benchmark system. The approach relies on analyzing system response time series in the frequency-energy domain by constructing both Hamiltonian and forced and damped frequency-energy plots (FEPs). The system parameters are then characterized and updated by matching the backbone branches of the FEPs with the frequency-energy wavelet transforms of experimental and/or computational time series. The main advantage of this method is that no nonlinearity model is assumed a priori, and the system model is updated solely based on simulation and/or experimental measured time series. By matching the frequency-energy plots of the benchmark system and its reduced-order model, we show that we are able to retrieve the global strongly nonlinear dynamics in the frequency and energy ranges of interest, identify bifurcations, characterize local nonlinearities, and accurately reconstruct time series. We apply the proposed methodology to a benchmark problem, which was posed to the system identification community prior to the IMAC XXXII (2014) and XXXIII (2015) Conferences as a "Round Robin Exercise on Nonlinear System Identification". We show that we are able to identify the parameters of the non-linear element in the problem with a priori knowledge about its position.

1. Introduction

Predictions from analytical and computational models are often called into question when they conflict with test results. *Model updating* concerns the correction of these models by processing and integrating dynamic response data from test structures [15]. More specifically, finite element (FE) model updating emerged in the 1990s as a topic thought to be very crucial for the design, construction and maintenance of mechanical systems and other engineering structures [7]. Reviews of existing FE model updating techniques are given in Datta [4], Friswell and Mottershead [7], Hemez and Doebling [8], and Mottershead and Friswell [15]. These give a clear overview of sensitivity-based updating methods. Sensitivity-based FE model updating methods have been embraced for damage assessment and structural health monitoring applications, *e.g.*, in Brownjohn et al. [3], Link et al. [14], Teughels et al. [20], but have been rather limited in application to non-linear systems (*e.g.,* [2]).

Data-driven modeling and model updating are increasingly important in science and engineering. There have been recent

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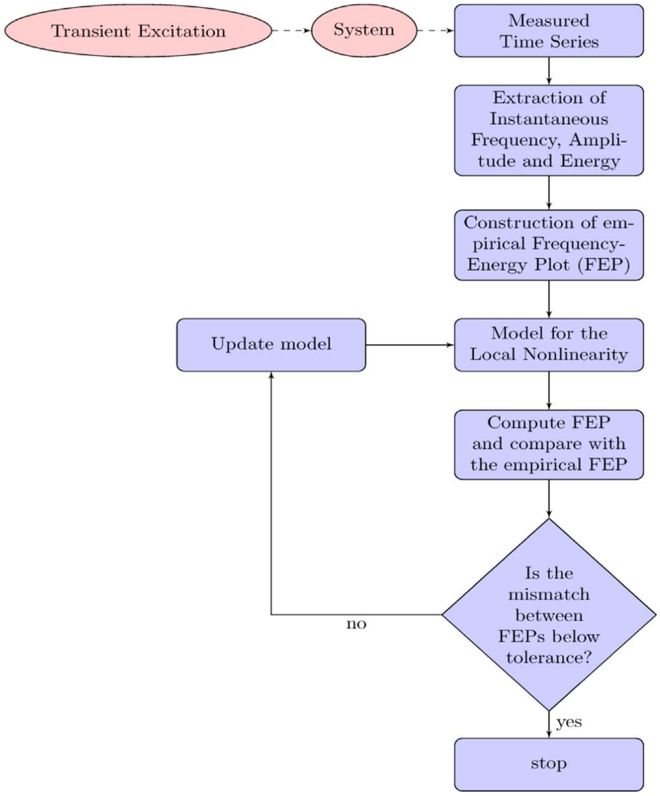

Fig. 1. Schematic diagram of the proposed nonlinear model updating approach.

attempts to utilize a data-driven approach in model updating, *e.g.*, [11,17,5,9]. Yang and Brown [21] proposed a model updating method using a perturbed boundary condition database. Friswell et al. [6] examined several methods for parameterizing finite element models for the purpose of model updating of the dynamics of joints in a T-joint structure and frame structure. Another model updating strategy, proposed by [12] for nonlinear vibrations of structures, is based on proper orthogonal decomposition and its nonlinear generalizations, as well as on auto-associative neural networks. Derkevorkian et al. [5] used data from relatively large-scale experimental soil-foundation-superstructure interaction (SFSI) systems to develop reduced-order computational models for response prediction, employing trained neural networks. Pokale and Gupta [17] applied a particle filtering algorithm on experimentally measured tip accelerations using Bayesian principles to estimate the changes in damping and flexural rigidity of a beam. Another Bayesian approach was proposed by [10], wherein a Bayesian FE model updating strategy using dynamic response data is employed for structural response prediction.

Applications of structural modification methods for data-driven modeling and updating were shown to be useful for large-scale structures when the modifications are confined to be local, and the nonlinearities in the dynamical system do not affect the global dynamics significantly. We note, however, that these methodologies don't account for strongly nonlinear effects on the global dynamics, *i.e.*, the system dynamics over broad frequency and energy ranges, so they are only applicable to specific classes of dynamical systems; in addition, some functional form must be assumed for modeling the system nonlinearities. On the contrary, the nonlinear model updating methodology proposed in this work relies solely on measured time series, with no *a priori* assumption regarding the nonlinearity of the system. Hence, the proposed methodology is data driven and applicable to a broad range of dynamical systems. Moreover, the approach accounts for strong nonlinearities, which, although locally confined in space, they can affect the global dynamics of the overall structure.

In Fig. 1, the general outline of the proposed nonlinear model updating approach is presented. The first step is the measurement of the time series of the system responses. In order to estimate the global frequency-energy relationship in the measured dynamics we record time series from a number of sensors throughout the system under transient excitation. Afterwards, we estimate the instantaneous frequency, amplitude, and energy of the measured time series by applying numerical wavelet transforms (WTs), and superposing the resulting WT spectra onto a "reference" frequency-energy plot (FEP) representing the different branches of nonlinear periodic solutions of the underlying Hamiltonian system (*i.e.*, the dynamical system with dissipative and forcing terms removed). A very useful feature of the reference FEP for system identification purposes is its relation to the transient dynamics of the corresponding weakly damped system. This is due to the assumption that *the effect on the dynamics of weak damping is expected to be parasitic*; that is, instead of introducing "new" dynamics, weak damping just causes transitions of the transient damped dynamics between branches of normal modes of the underlying Hamiltonian system, leading to multi-frequency nonlinear dynamical transitions. It has been shown that the superposition of a frequency-energy plot (FEP) depicting the periodic orbits of the underlying