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Spectrum-based modal parameters identification with Particle Swarm Optimization

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ABSTRACT

The paper presents the new method of the natural frequencies and damping identification based on the Artificial Intelligence (AI) Particle Swarm Optimization (PSO) algorithm. The identification is performed in the frequency domain. The algorithm performs two PSO-based steps and introduces some modifications in order to achieve quick convergence and low estimation error of the identified parameters' values for multi-mode systems. The first stage of the algorithm concentrates on the natural frequencies estimation. Using the information about the natural frequencies, measurement data are filtered and corrected dampings as well as amplitudes are calculated for each preliminary identified mode. This allows regrouping particles to the area around proper parameters values. Particle regrouping is based on the physical properties of modally tested structures. This differs the algorithm from other PSO based algorithms with particles regrouping. In the second stage of the algorithm parameters of all modes are tuned together in order to adjust estimates. The procedure of identification, as well as the appropriate algorithm, is presented and some SISO examples are provided. Results are compared with the results obtained for the selected, already developed modal identification methods. The paper presents practical application of AI method for mechanical systems identification.

1. Introduction

Modal analysis is the study of the dynamic properties of structures. As the result, some characteristic parameters of the structure are identified. This is a well known problem and there are many computational methods developed over the years [1,2]. Most of the methods defined both in the frequency and the time domain are based on a polynomial formulation. On the other hand, the problem of modal identification can be transferred into a problem of searching for a set of optimal parameters of a mathematical model that describes the tested structure in the best way. This opens the possibility of introducing optimization techniques, including many Artificial Intelligence (AI) methods, to modal analysis. In the field of mechanical engineering some AI algorithms are applied including, for example, Artificial Bee Colony (ABC), Genetic Algorithm (GA), Particle Swarm Optimization (PSO) and Artificial Neural Neworks (ANN) in structural identification or damage detection tasks [3–8]. However, in the field of modal analysis AI algorithms usually play supportive, though an important role - for example in [9] and [10] Fuzzy Logic and GA combined with Fuzzy Logic are used for poles identification in stabilization diagrams obtained by other identification methods, in [11] ANN is used for model order identification.

The modal parameters identification method proposed in this paper is based on the Particle Swarm Optimization (PSO) algorithm which was proposed by Eberhart and Kennedy [12]. The PSO was inspired by observing birds flocking and searching for food which represents a form of social intelligence. It is classified as an Artificial Intelligence evolutionary computational technique, suited for many different classes of problems [13,14]. The basic form of the PSO algorithm is easy to implement and utilizes simple rules. Despite its simplicity it is an effective algorithm which outperforms some of the other AI algorithms, for example GA [15,16] in terms of convergence and computation speed. The PSO advantages emphasize especially in disturbed data conditions. It is also possible to stop PSO algorithm in any moment achieving sub-optimal, but usable result which may be an advantage in on-line, real time control or identification tasks. The PSO algorithm has been successfully applied for example in the optimization, control, image and sound recognition, planning, identification, ANNs and fuzzy systems tuning, and in many other fields [13,17]. The main PSO drawbacks are premature convergence to local optimum and stagnation as well as search pace reduction as the algorithm approaches optimum. It is also not suited for solving multi-objective optimization problems. There are many different techniques developed that help overcome these problems. Stagnation problems are commonly solved by particles repositioning (usually supported by stagnation detection) or introduction of the modified particle movement rules which are intended to prevent particle clustering. Although PSO has been used mainly to solve unconstrained,

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single-objective optimization problems, PSO algorithms have been developed to solve constrained problems, multi-objective optimization problems, problems with dynamically changing landscapes and to find multiple solutions. This is achieved for example by introducing multiple swarms, modification of the rules used for local vs. global goal search selection and by using more complex algorithms merely based on PSO. PSO is also hybridized with other AI algorithms, mainly GAs and ANNs. Review papers [13,17,18] gathers and discuses PSO algorithm itself and its most important modifications. These solutions reduce PSO limitations and drawbacks but they are not eliminated completely, especially for more complicated or uncommon problems. Many of the proposed methods complicate the algorithm or drift away from it. It must be also noticed, that many papers on PSO improvements concentrates on the algorithm itself, without relating it to the specific problem. On the other hand, there is a wide group of papers showing implementation examples but they usually concerns problems and systems other than mechanical (for example: control system tuning, ANN tuning, image processing, model optimization). The exception are works concerning PSO based structural parameters identification or structural damage detection.

The motivation for developing the algorithm proposed in this paper came from the practical problems encountered during performing identification tasks. The main problem which was encountered, mostly in the presence of significant measurement noise and in situations where registered response was short in time, was to obtain reliable damping assessment from classic time-domain identification algorithms. In some cases it was impossible to identify modal parameters using these methods. Additionally, they were prone to data selection – i.e. small change in the data time range selection sometimes resulted in a significant identification results differences [19]. Utilizing frequency domain methods only partially solved these problems.

The author studied the possibility of implementing the PSO algorithm for modal identification purposes [19]. The proposed algorithm was time-domain based and was limited to SISO (Single Input, Single Output) stationary systems with one dominant natural frequency (one mode). Further development revealed that its extension to multi-mode systems encountered a lot of difficulties. Due to this, a new, spectrum-based algorithm is proposed in this paper. The choice of the PSO algorithm as a base for developing the new one was motivated by its advantages and ease of its implementation.

The key elements proposed in the paper are: application of the PSO-based algorithm for the purpose of selected modal parameters identification; development of the original two-stage PSO-based algorithm; particle repositioning in the algorithm based on physical characteristics of the identified system; supplementary particle repositioning performed during the first stage of the algorithm also considering physical system dependencies.

2. Modal identification principles

One of the usual ways of performing an experimental modal test is to excite a structure with an impact made by a modal hammer and then observe free vibrations. Free vibrations consist of many exponentially damped sine signals having different amplitudes, frequencies and damping coefficients. The free vibration response can be described by the following equation:

$$y(t) = \sum_{m=1}^{nm} Y_{0m} e^{-2\pi f_m \xi_m t} \sin\left(2\pi f_m \sqrt{1-\xi_m^2} t\right) = \sum_{m=1}^{nm} Y_{0m} e^{-\beta_m t} \sin\left(\omega_m \sqrt{1-\left(\frac{\beta_m}{\omega_m}\right)^2} t\right) \quad (1)$$

where:

y – free vibration signal,
m – mode number,
nm – number of modes,
Y_{0m} – initial amplitude of vibration mode no. m,
ξ_m – dimensionless damping coefficient of mode no. m,
f_m – natural frequency of mode no. m,
t – time,

$$\omega_m = 2\pi f_m \text{ – angular frequency of mode no. } m, \quad (2)$$

$$\beta_m = \omega_m \xi_m \text{ – damping coefficient of mode no.} i\, m. \quad (3)$$

According to the above, the identification of modal parameters is a search for the values of the unknown parameters of the Eq. (1) which are Y_{0m} amplitudes, damping coefficients ξ_m and frequencies f_m. As it was mentioned, there are many different techniques for modal identification. Some of the commonly used are ERA (Eigensystem Realization Algorithm) [20–22], p-LSCF(d) (poly-reference Least Squares Complex Frequency-domain, also known as PolyMAX) [2,22,23], LSCE (Least Squares Complex Exponential) [1,22,24], ITD (Ibrahim Time Domain method) [22,25,26]. Identification quality and accuracy of these methods is usually high and ERA and PolyMax algorithms are regarded as being superior to other methods [27–29]. However the general comparisons are complicated by the fact, that the literature usually concentrates on some selected examples and that identification quality greatly depends not only on the algorithm but also on the quality of modal experiment itself. It should be properly planed and performed in order to obtain suitable measurement data. In general, the frequency of each mode is the most important parameter and usually it is identified with low error, at least for a few first modes (modes with the lowest frequencies). Damping coefficients are usually identified with higher error. Absolute amplitudes of structural modes depend on initial conditions (i.e. intensity of excitation) and thus – do not characterize the linear system's behavior, instead, relative values are analyzed. High measurement noise can make proper identification impossible or greatly reduce accuracy especially in terms of damping coefficients assessment. An example of such a situation for the ERA algorithm is presented in [30]. It is also recommended to validate the identified modal model. There are various indicators for modal analysis results quality assessment [21,31]. To calculate their values, modal shapes must usually be identified first. Moreover, some of the indicators are useful mainly in multiple excitations and multiple response measurements conditions. Additionally, in [31] it is suggested, that especially for complex structures, estimation quality assessment should be performed using multiple indicators because the results vary between indices.

3. Standard Particle Swarm Optimization algorithm

The PSO algorithm solves a problem by moving a number of possible solutions called particles within the search space. Each particle stores information about the current and the best solutions found so far and, additionally, it has the knowledge about the best solution found by all of the particles. The movement of each particle is described by the velocity and position update equations which consider information mentioned above. The PSO algorithm steps are as follows:

1. Arbitrary selection of ω, φ_p and φ_g parameters that appear later in the velocity update equation.
2. For each particle i:
   - initialize position $\mathbf{x}_i$ with a uniformly distributed random vector of size d within problem boundaries,
   - initialize particle velocities $\mathbf{v}_i$ for each $\mathbf{x}_i$ vector element,
   - remember current particle position as the best known particle position $\mathbf{p}_i = \mathbf{x}_i$.
3. Find the particle with the best value of fitness function $f(\boldsymbol{x}_i)$ and remember its position as the best known global position $\mathbf{g} = \mathbf{x}_i$.
4. For each particle i, repeat until the stop criterion is assured: