Applied Soft Computing 22 (2014) 458–464

Contents lists available at ScienceDirect

Applied Soft Computing

journal homepage: www.elsevier.com/locate/asoc

Parametric identification of seismic isolators using differential evolution and particle swarm optimization

Giuseppe Quaranta [a,*], Giuseppe Carlo Marano [b], Rita Greco [b], Giorgio Monti [c]

[a] Department of Structural and Geotechnical Engineering, Sapienza University of Rome, via Eudossiana 18, 00184 Rome, Italy
[b] Department of Civil Engineering and Architecture, Technical University of Bari, via Orabona 4, 70125 Bari, Italy
[c] Department of Structural and Geotechnical Engineering, Sapienza University of Rome, via Gramsci 53, 00197 Rome, Italy

ARTICLE INFO

Article history:
Received in revised form 13 March 2014
Available online 9 May 2014

Keywords:
Bouc–Wen model
Differential evolution
Hysteresis
Parametric identification
Particle swarm optimization
Seismic isolator

ABSTRACT

The objective of a base isolation system is to decouple the building from the damaging components of the earthquake by placing isolators between the superstructure and the foundation. The correct identification of these devices is, therefore, a critical step towards reliable simulations of base-isolated systems subjected to dynamic ground motion. In this perspective, the parametric identification of seismic isolators from experimental dynamic tests is here addressed. In doing so, the focus is on identifying Bouc–Wen model parameters by means of particle swarm optimization and differential evolution. This paper is especially concerned with the assessment of these non-classical parametric identification techniques using a standardized experimental protocol to set out the dynamic loading conditions. A critical review of the obtained outputs demonstrates that particle swarm optimization and differential evolution can be effectively exploited for the parametric identification of seismic isolators.

1. Introduction

The use of base-isolators for protecting buildings, bridges, liquid storage tanks, oil pipelines, and nuclear reactor plants against the damaging effects of seismic loadings has become very frequent in recent decades [1,2]. The advantage of base isolation systems lies in avoiding that the damaging effects of the earthquakes reach the structures by placing particular devices (isolators) between the protected system and the foundation. In most of the seismic isolators, thin reinforcing steel plates are alternated with thick rubber pads. Conventional isolators are basically produced in two phases: first, the compounded rubber sheets with the interleaved steel plates are put into a mold, and heating under pressure for several hours (the so-called vulcanization) is then performed to complete the manufacturing process. The performance of a seismic isolator depends on many factors, such as the rubber typology, the compound, the thickness and the process of vulcanization of the pads. So far, the Bouc–Wen hysteretic model is considered the most appropriate to simulate the nonlinear behavior of seismic isolators. However, because of the lack of settled relationships between mechanical model and properties of the isolator (i.e., the degree of vulcanization or the precise compound used to build the device), the correctness of the structural simulations requires a reliable identification of the model parameters from experimental tests.

Among the available numerical techniques, non-classical approaches based on soft computing methods are attracting growing interests in system identification and damage detection, see for instance Refs. [3,4]. Within this framework, the parametric identification problem for multi-degree-of-freedom structural linear systems was resolved using genetic algorithm (GA) [5], Big Bang–Big Crunch optimization [6], particle swarm optimization (PSO) and differential evolution (DE) [7]. Soft computing-inspired techniques are also exploited for the parametric identification of nonlinear dynamic systems. An overview about the most recent applications in this field [8] revealed that GAs are frequently employed in the parametric identification of hysteresis models, such as the Bouc–Wen model, the Jiles–Atherton model, and the Preisach model. On the other hand, PSO and DE were considered in the parametric identification of hysteresis models [9,10], viscous damping [11,12], and Van der Pol-Duffing oscillators [13].

The use of non-classical methods for the parametric identification of Bouc–Wen-type models has been continuously gaining increased attention in literature. For instance, a multi-species GA was proposed in Ref. [14] to identify Bouc–Wen models from noisy data. A Bouc–Wen model was identified by means of DE in Ref. [15], where the authors presented some results for experimental data

* Corresponding author. Tel.: +39 06 44585294.
E-mail addresses: giuseppe.quaranta@uniroma1.it (G. Quaranta), g.marano@poliba.it (G.C. Marano), r.greco@poliba.it (R. Greco), giorgio.monti@uniroma1.it (G. Monti).

http://dx.doi.org/10.1016/j.asoc.2014.04.039
1568-4946/

obtained from a nuclear power plant. Kwok and co-authors [16] used a GA to identify a non-symmetrical Bouc–Wen model proposed to represent the hysteretic behavior of magnetorheological fluid dampers. A memetic GA and a PSO algorithm were adopted in Refs. [17,18], respectively, to reproduce the cyclic response of a bolted–welded steel connection through a Bouc–Wen model. A generalized Bouc–Wen model was considered in Ref. [19] for predicting the cyclic response of a T-connection consisting of two wood members joined by plywood gusset plates, and the parametric identification problem was solved by using a DE algorithm. Recently, Worden and Manson [20] investigated the effectiveness of a self-adaptive DE algorithm for the parametric identification of the Bouc–Wen model using simulated noisy data.

In this paper, the focus is on identifying Bouc–Wen parameters for seismic isolation devices by means of non-classical methods, a problem which has received very few attention. A recent article by Sireteanu and co-authors [21] on this topic addressed the GA-based parametric identification of an extended Bouc–Wen model for elastomeric bearings. Differently from that paper, the parametric identification of seismic isolators is here performed for the first time by means of PSO and DE. Such techniques have a simple structure and require few control parameters, whose optimal values lie within a rather small interval. These characteristics, together with the numerical robustness, are especially important for industrial applications. The feasibility of these soft computing techniques is critically reviewed with reference to experimental data. In this sense, other significant contributions are concerned with the experimental protocol and the completeness of the final results. The examined device was subjected to loading conditions imposed by standardized qualification tests for seismic isolators (the current Italian building code [22] is taken into account in this study). This is to ensure the objectivity of the results with respect to the current state-of-the-practice about the experimental qualification of seismic isolators. In doing so, this study also benefits of a larger experimental database than the considered one in previous researches [21]. Moreover, although identification methods for nonlinear systems are usually examined by considering the displacement-force curves only (as in Ref. [21]), this paper also evaluates the quality of the whole procedure with reference to the velocity-force curves. This complete analysis turns out to be very important for assessing the real effectiveness of such techniques for industrial applications. Final results demonstrate that PSO and DE can be viable tools for the parametric identification of seismic isolators, and that the DE algorithm is significantly better than PSO.

2. Parametric identification of seismic isolators

2.1. Hysteresis model for seismic isolators

The seismic isolator is modeled as nonlinear single-degree-of-freedom system:

$$m\ddot{y}(t) + \phi(t) = g(t), \tag{1}$$

where m is the mass, $y(t)$ is the displacement (overdots denote the time-derivative), $\phi(t)$ is the restoring force and $g(t)$ is the excitation dynamic load. As usual in nonlinear modeling of isolators [23], damping is represented by taking into account the inelastic (hysteretic) response of the isolators whereas viscous damping is not included. So doing, by assuming a Bouc–Wen hysteresis model, the restoring force $\phi(t)$ is:

$$\phi(t) = \alpha k_i y(t) + (1-\alpha) k_i z(t), \tag{2}$$

where $\alpha = (k_f/k_i)$ is the ratio of the post-yield k_f to pre-yield k_i (elastic) stiffness whereas $z(t)$ is the hysteretic parameter given by the following nonlinear differential equation:

$$\dot{z}(t) = A\dot{y}(t) - \beta|\dot{y}(t)||z(t)|^{(\eta-1)}z(t) - \gamma\dot{y}(t)|z(t)|^{\eta}. \tag{3}$$

Parameters β and γ control the shape of hysteretic loops, and do not have precise physical meaning. For what concerns the parameter η, it controls the sharpness of the transition from initial slope to the slope of the asymptote. For increasing values of η, the loading path of a softening hysteresis approaches the ideal bilinear model.

The identification problem can be simplified accounting for some parameter constraints, i.e. $A = 1$ in order to remove the intrinsic redundancy of the Bouc–Wen model [18]. On considering the aforementioned constraint, the Bouc–Wen hysteresis model is fully described if the parameters k_f, α, β, γ and η are identified (the mass m is assumed as given parameter).

2.2. Parametric identification problem

The parametric identification of the considered Bouc–Wen model is formulated as minimization problem:

$$\begin{aligned} \min \quad & \{f(\mathbf{x})\} \\ & s.t. \\ & \mathbf{x}^l \le \mathbf{x} \le \mathbf{x}^u \end{aligned}, \tag{4}$$

where $f : \mathbb{R}^n \to \mathbb{R}$ is the objective (or cost) function and $\mathbf{x} \in \mathbb{R}^{1\times n}$ is the vector which collects the n unknown model parameters (lower-bounded by $\mathbf{x}^l$ and upper-bounded by $\mathbf{x}^u$).

In this study, the objective function $f(\mathbf{x})$ is defined as a normalized mean-square error between the experimental response and that predicted using a given parameter estimate $\mathbf{x}$ [20], that is:

$$f(\mathbf{x}) = \frac{100}{S\sigma_y^2}\sum_{a=1}^{S}(y(t_a) - \hat{y}(t_a|\mathbf{x}))^2, \tag{5}$$

where t_a indicate the sampling instant time (being S the total number of samples), σ_y^2 is the variance of the measured sequence of displacements $y(t_a)$ and $\hat{y}(t_a|\mathbf{x})$ is the predicted sequence of displacements when the parameter estimate is $\mathbf{x} = \{k_f \quad \alpha \quad \beta \quad \gamma \quad \eta\}$. The best parameter estimation $\mathbf{x}^*$ is the global minimum of the objective function in Eq. (5).

3. Non-classical methods for parametric identification

3.1. Particle swarm optimization algorithm

The ith particle (with $i = 1, \ldots, m$) at the kth iteration has two attributes, a velocity ${}^k\mathbf{v}_i = \{{}^k v_{i1} \ \cdots \ {}^k v_{ij} \ \cdots \ {}^k v_{in}\} \in \mathbb{R}^{1\times n}$ and a position ${}^k\mathbf{x}_i = \{{}^k x_{i1} \ \cdots \ {}^k x_{ij} \ \cdots \ {}^k x_{in}\} \in \mathbb{R}^{1\times n}$. In order to protect the cohesion of the swarm, the absolute value of the velocity ${}^k v_{ij}$ is assumed to be less than a maximum velocity $v_j^{\max}$, with $\mathbf{v}^{\max} = \{v_1^{\max} \ \cdots \ v_j^{\max} \ \cdots \ v_n^{\max}\}$. It is assumed $\mathbf{v}^{max} = \gamma(\mathbf{x}^u - \mathbf{x}^l)/\Delta\tau$, with $\gamma = 0.50$ [13]. The internal time variable $\Delta\tau = 1$ is introduced to provide a physically consistent formalism. The initial set of candidate solutions ${}^0\mathbf{x}_i$ is obtained by generating m pseudo-random samples within the assigned search space. Similarly, the particle's velocities ${}^0\mathbf{v}_i$ are obtained by generating m pseudo-random samples between $-\mathbf{v}^{max}$ and $\mathbf{v}^{max}$. When $k \ge 1$, the ith particle velocity ${}^k\mathbf{v}_i$ and the ith particle position ${}^k\mathbf{x}_i$ are computed as follows:

$${}^k\mathbf{v}_i = {}^k\omega^{(k-1)}\mathbf{v}_i + {}^k c_1 {}^k\mathbf{r}_{1i} \times ({}^k\mathbf{x}_i^{Pb} - {}^{(k-1)}\mathbf{x}_i) + {}^k c_2 {}^k\mathbf{r}_{2i} \times ({}^k\mathbf{x}_i^{Gb} - {}^{(k-1)}\mathbf{x}_i), \tag{6a}$$

$${}^k\mathbf{x}_i = {}^{(k-1)}\mathbf{x}_i + \Delta\tau\,{}^k\mathbf{v}_i. \tag{6b}$$