Springer

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Journal of Mechanical Science and Technology 26 (8) (2012) 2523~2534
www.springerlink.com/content/1738-494x
DOI 10.1007/s12206-012-0625-y

Parameter identification of Bouc-Wen model for MR fluid dampers using adaptive charged system search optimization †

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(Manuscript Received January 4, 2012; Revised February 26, 2012; Accepted March 8, 2012)

Abstract

In this article, the charged system search (CSS) optimization method is improved to identify the parameters of a non-linear hysteretic Bouc-Wen differential model. The CSS is suitable for those optimization problems involving non-smooth or non-convex domains. Bouc-Wen is a well-established non-linear model which has been used to portray the hysteretic and high non-linear real behavior of numerous physical and mechanical systems. To improve the effectiveness and adaptability of the CSS algorithm, it is combined with sub-optimization mechanism. The obtained results show that the adaptive CSS embodies great robustness and accuracy to be successfully employed in such highly non-linear identification problems.

Keywords: Bouc-Wen model; Charged system search; Hysteresis; MR damper; Optimization; Parameter identification; Sub-optimization mechanism

1. Introduction

Hysteresis is a memory-dependant non-linear behavior in which the system output is not only dependant on the instantaneous input but also on the past history of the input. This type of inelastic behavior is encountered in many scientific and engineering fields. Structural materials and elements, such as reinforced concrete, steel, wood, base isolators, dampers and soil profiles commonly involve non-linear hysteretic mechanism to supply restoring force against movement and to dissipate input energy. For efficient description of such inelastic systems, over the past years, many mathematical models have been proposed to be used in time history and random vibration analyses.

For design purposes, it is absolutely indispensable to distinguish the explicit parameters governing the mechanical properties of the non-linear systems which are mathematically expressed by a set of constitutive relations. Therefore, the need of a comprehensive optimization methodology to get to the bottom of parameter identification problems becomes far more touchable. Parameter identification procedure involves estimating the optimal values of the parameters of the mathematical model for non-linear systems due to the diversity of the operating conditions using the time history of systems' response obtained from experimental data.

The intent of this paper is to introduce a new promising identification method for highly non-linear hysteretic systems described by using any mechanical model through adapting the recently meta-heuristic optimization approach proposed by Kaveh and Talatahari [1] called as charged system search (CSS). The CSS algorithm is based on principles from physics and mechanics, which has been inspired by the governing Coulomb and Gauss laws from electrostatics and the governing equations of motion from Newtonian mechanics and outperforms many of other optimization algorithms [1]. Herein, to clearly demonstrate vast potential efficiency and robustness of the adaptive CSS method in dealing with non-linear problems, we want to find optimum values for the parameters of well-known hysteretic Bouc-Wen model to predict the extremely high non-linear behavior of the MR dampers.

2. A review for previous works

Bouc [2] suggested a versatile and smooth hysteresis model for an inelastic SDOF system subjected to forced vibration, and subsequently Wen [3] generalized Bouc's hysteretic constitutive law and developed an approximate solution procedure for random vibrations [4, 5]. Since then the Bouc-Wen model has been widely used as a mathematical description of systems with hysteresis and non-linear behavior, especially in

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civil and mechanical engineering. In this model, non-linear restoring force is related to the system deformation through a first order non-linear differential equation which has a range of undefined parameters. By setting these parameters to proper values, the response of the model will coincide with the actual behavior of non-linear system. Identification process of this set of parameters is mostly conducted through solving an optimization problem to match the Bouc-Wen model response to that of the experimentally obtained data. In other words, a mathematical description or a physical model of system must be constructed when the input signal and its corresponding output are known.

In the past two decades, many research works have addressed the utilization of Bouc-Wen model to describe the real hysteretic behavior of systems and identification process of its parameters. Charalampakis et al. [6, 7] used Bouc-Wen model to portray the test results of a full-scale steel cantilever beam which indicated a clear non-degrading behavior. They employed a hybrid evolutionary algorithm [6] as well as simple and enhanced particle swarm optimization [7] methods to identify the Bouc-Wen model parameters. Baber and Wen [8] extended the Bouc-Wen model to take the degradation in strength or stiffness of structural systems into account and then this version expanded by Baber and Noori [9] for the pinching phenomenon. Foliente [4] showed that Bouc-Wen-Baber-Noori (BWBN) model could produce previously observed inelastic behavior of wood joints and structural systems that involve pinching and degradation of strength and stiffness. General non-linear models based on BWBN model were also proposed for SDOF and MDOF structural systems and numerically used to non-linear dynamic analysis of a wooden SDOF system subjected to seismic excitation. Zhang et al. [10] used a set of realistic BWBN model parameters to numerically generate the experimental data for a Kawai's benchmark timber shear wall with both pinching and degradation characteristics in hysteretic trace and conducted a comparative study in identification process of 13 parameters of BWBN model for three different algorithms based upon the simplex, extended Kalman filter and generalized reduced gradient methods. Ma et al. [11] applied BWBN model and devised differential evolution identification approach to fit the model to experimental hysteresis trace of a simple wooden T-connection. Song and Kiureghian [12] generalized Bouc-Wen model for highly asymmetric hysteresis systems and employed it to model the hysteretic behavior of flexible strap connectors, which are inserted for thermal expansion between electrical substation. This model includes time-independent parameters to be usable in time history analyses. Ni et al. [13] utilized the Bouc-Wen model for mapping the hysteretic trace of non-linear isolators and developed a frequency domain parametric identification method from periodic vibration experimental data.

Employing the Bouc-Wen model to portray the highly non-linear force-displacement and force-velocity behavior of MR dampers is proposed by Spencer et al. [14] in which they used

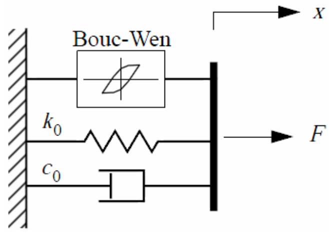

Fig. 1. The Simple Bouc-Wen model of MR damper schematic [14].

a new efficient phenomenological model based on Bouc-Wen hysteretic law. Yang et al. [15] employed the Bouc-Wen model and developed a new mechanical model for a large-scaled MR damper that accounts for MR fluid Stiction phenomenon, as well as inertial and shear thinning effects. In the well-known papers that deal with identification of MR dampers using Bouc-Wen model, usually a constrained non-linear least-squares optimization scheme is used to determine the model parameters according to experimental data [14-16]. Kwok et al. [17] also applied the Bouc-Wen model to model non-symmetrical behavior of MR dampers and identified its parameters by means of genetic algorithm. Ikhouane et al. [5, 18, 19] used mathematical rules and discovered that Bouc-Wen model hysteresis response under periodical inputs approaches to a limit cycle. Regarding to this, they suggested a powerful numerical identification technique to find the model parameters from experimental data. More survey on utilization and identification of hysteretic Bouc-Wen model could be found by Ismail et al. [20].

3. Bouc-Wen models for MR dampers

3.1 Simple Bouc-Wen model

High non-linearity and hysteretic demeanor of Magneto-rheological (MR) fluid dampers requires an accurate tractable model to make them available for control purposes. Hence, several parametric mechanical models have been proposed to describe the non-linear behavior of MR dampers [14, 21-23]. The most reputable model that suitably predicts their behavior [14] and has been used to simulate MR dampers semi-active control system is smooth Bouc-Wen model [16, 24-31]. Fig. 1 illustrates the simple Bouc-Wen model for MR dampers. In this case, non-linear force of damper is calculated from Eq. (1) as fallows [14]:

$$F = \alpha z + c_0\dot{x} + k_0(x - x_0) \tag{1}$$

where α is the Bouc-Wen model parameter related to the MR material yield stress; k_0 and c_0 are spring stiffness and dashpot damping coefficient respectively; and z is hysteretic deformation of the model which is defined by following equation:

$$\dot{z} = -\gamma\,|\,\dot{x}\,|\,z\,|\,z\,|^{n-1} - \beta\dot{x}\,|\,z\,|^{n} + A\dot{x} \tag{2}$$

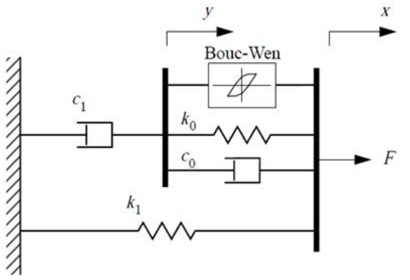

Fig. 2. The modified phenomenological Bouc-Wen model of MR damper schematic [14].

in which A, β and γ are the Bouc-Wen model parameters.

For achieving optimal performance of a control systems equipped with MR dampers, applied voltage to the current driver must be varied according to the measured feedback at any moment, to change the damping force. Thus, for accounting this accordance, the coefficient α, damping coefficient c_0 and stiffness k_0 in Eq. (1) are defined as a linear function of the efficient voltage as given by the following equations [16, 24, 29]:

$$\alpha(u) = \alpha_a + \alpha_b u \,, c_0(u) = c_{0a} + c_{0b} u \text{ and } k_0(u) = k_{0a} + k_{0b} u \,. \tag{3}$$

To accommodate the dynamics involved in the MR fluid reaching rheological equilibrium, the following first order filter is employed to calculate efficient voltage, u [16, 24, 29]:

$$\dot{u} = -\eta(u - v) \tag{4}$$

where v is the applied voltage for current generation.

3.2 Modified Bouc-Wen model

The modified version of phenomenological Bouc-Wen model is illustrated in Fig. 2, for which non-linear force generated by MR damper is calculated by Eq. (5).

$$\begin{aligned} F &= \alpha z + c_0(\dot{x} - \dot{y}) + k_0(x - y) + k_1(x - x_0) \\ &= c_1 \dot{y} + k_1(x - x_0) \end{aligned} \tag{5}$$

In this case, hysteretic displacement z is given by

$$\dot{z} = -\gamma|\dot{x} - \dot{y}|z|z|^{n-1} - \beta(\dot{x} - \dot{y})|z|^n + A(\dot{x} - \dot{y}) \,. \tag{6}$$

According to Fig. 2, $\dot{y}$ is defined by the following equation:

$$\dot{y} = \frac{1}{(c_0 + c_1)}\{\alpha z + c_0\dot{x} + k_0(x - y)\} \,. \tag{7}$$

To determine a comprehensive model that is valid for fluctuating magnetic fields, the parameters α, c_0 and c_1 in Eqs. (5) and (7) are defined as a linear function of the efficient voltage, u, as given by Eq. (8) [14, 28]:

$$\alpha(u) = \alpha_a + \alpha_b u \,, c_0(u) = c_{0a} + c_{0b} u \text{ and } c_1(u) = c_{1a} + c_{1b} u \tag{8}$$

in which, u is related to applied voltage through Eq. (4).

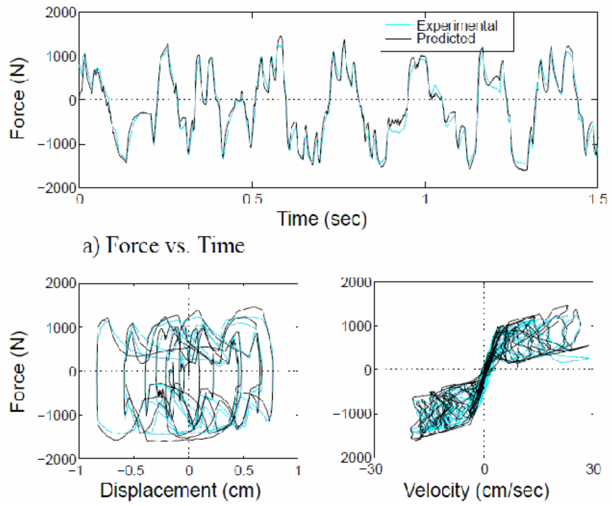

Fig. 3. Predicted response by the modified Bouc-Wen model in comparison with the experimental data for a 3 kN MR damper in a control simulation test [14, 31].

3.3 Parameter identification

By adjusting twelve parameters of simple Bouc-Wen model (α_a, α_b, c_{0a}, c_{0b}, k_{0a}, k_{0b}, x_0, γ, β, A, n, η) or fourteen parameters of modified model (α_a, α_b, c_{0a}, c_{0b}, c_{1a}, c_{1b}, k_0, k_1, x_0, γ, β, A, n, η) through solving an optimization problem with an objective of fitting model response to the experimental data for a prototype MR damper, it is possible to predict the response of damper to any random inputs (displacement and applied voltage) before and after the yield areas. Fig. 3 illustrates the comparison between the response of this system and the experimental results for a 3kN MR damper excited by random inputs. It is obvious that Bouc-Wen model is capable of predicting MR damper non-linear behavior very well.

High non-linearity in the identification of Bouc-Wen hysteretic systems, make this process a challenging problem even for the simplest single-degree-of-freedom case [6]. Consequently, it has been tackled by a variety of methods [5-7, 10, 11, 20].

4. Statement of the optimization problem

In order to obtain the optimal values for the parameters of Bouc-Wen model, an appropriate objective function must be minimized through optimization procedure. In the present study, the normalized mean square error (MSE) of the predicted force time history $\hat{f}(t \mid \mathbf{p})$ (for any obtained parameters' vector p) in comparison with the experimentally obtained force time history $f(t_i)$ at each time step t_i is considered as the objective function [6, 7]. Thus, discrete time objective function is expressed as

$$OF(\mathbf{p}) = \frac{\sum_{i=1}^{N} (f(t_i) - \hat{f}(t_i \mid \mathbf{p}))^2}{N\sigma_f^2} \tag{9}$$

in which **p** is the vector of Bouc-Wen model parameters that includes twelve and fourteen elements for simple and modified Bouc-Wen model respectively. Here, σ_f^2 is the variance of experimental force time history, **Σ** represents the summation of the subsequent term (*N* discrete values) and N is the number of used points in optimization process that depends upon the number of experimental measured data. For optimization operations, in parallel with produced force, the time history of excitations (displacement and velocity) and the time history of applied voltage to the current driver for the case of MR damper are also required to calculate the model response at the used points. Generally speaking, the optimization problem involves the minimization of the objective function when the parameters vector is varied between the following side constraints [6, 7]:

$$\mathbf{p}_{\mathbf{min}} \le \mathbf{p} \le \mathbf{p}_{\mathbf{max}} \tag{10}$$

where $\mathbf{p}_{\mathbf{min}}$ and $\mathbf{p}_{\mathbf{max}}$ are the vectors which include the lower and upper bounds of the model parameters, respectively.

5. Standard charged system search

In physics, the space surrounding an electric charge has a property known as the electric field which exerts a force on other electrically charged objects according to the Coulomb's law. Coulomb confirmed that the electric force between any two small charged spheres is inversely proportional to the square of the separation distance between the particles directed along the line joining them and proportional to the product of the charges of the two particles. Also, the magnitude of the electric field at a point inside a charged sphere can be obtained using Gauss's law that it is proportional to the separation distance between the particles. Utilizing these principles, the charged system search (CSS) defines a number of solution candidates which are called charged particle (CP). Each CP is treated as a charged sphere and can exert an electrical force to other agents [1, 32].

On the other hand, the Newton's second law explains that the acceleration of an object is directly proportional to the net force acting on that object. Thus the resultant electrical force affecting on a CP results in its acceleration. The CSS uses the governing laws of motion from the Newtonian mechanics to determine the position of CPs. Application of these laws provides a good balance between the exploration and the exploitation of the algorithm. The pseudo-code for the standard CSS algorithm is summarized as follows [1]:

Step 1) Initialization: The magnitude of charge for each CP is defined as

$$q_i = \frac{fit(i) - fit_w}{fit_b - fit_w} \quad i = 1, 2, ..., N \tag{11}$$

where fit_b and fit_w are the best and the worst fitness of all the CPs; $fit(i)$ represents the fitness of the agent i; and N is the total number of CPs. The separation distance r_{ij} between two charged particles is defined as follows:

$$r_{ij} = \frac{\| \mathbf{X}_i - \mathbf{X}_j \|}{\| (\mathbf{X}_i + \mathbf{X}_j)/2 - \mathbf{X}_{best} \| + \varepsilon} \tag{12}$$

where $\mathbf{X}_i$ and $\mathbf{X}_j$ are the positions of the ith and jth CPs respectively, $\mathbf{X}_{best}$ is the position of the best current CP, and ε is a small positive number. The initial positions of CPs are determined randomly.

Step 2) CM creation: A number of the best CPs and the values of their corresponding fitness functions are saved in the charged memory (CM).

Step 3) The probability of moving determination: The probability of moving each CP toward the others is determined using the following function:

$$p_{ij} = \begin{cases} 1 & \dfrac{fit(i) - fit_b}{fit(j) - fit(i)} > rand \vee fit(j) > fit(i) \\ 0 & \text{otherwise}\,. \end{cases} \tag{13}$$

Step 4) Forces determination: The resultant force vector for each CP is calculated as

$$\mathbf{F}_j = q_j \sum_{i, i \ne j} \left(\frac{q_i}{a^3} r_{ij} \cdot i_1 + \frac{q_i}{r_{ij}^2} \cdot i_2 \right) p_{ij} (\mathbf{X}_i - \mathbf{X}_j)$$
$$\begin{cases} j = 1, 2, ..., N \\ i_1 = 1, i_2 = 0 \Leftrightarrow r_{ij} < a \\ i_1 = 0, i_2 = 1 \Leftrightarrow r_{ij} \ge a\,. \end{cases} \tag{14}$$

Step 5) Solution construction: Each CP moves to the new position as

$$\mathbf{X}_{j,new} = rand_{j1} \cdot k_a \cdot \frac{\mathbf{F}_j}{m_j} \cdot \Delta t^2 + rand_{j2} \cdot k_v \cdot \mathbf{V}_{j,old} \cdot \Delta t + \mathbf{X}_{j,old} \tag{15}$$

$$\mathbf{V}_{j,new} = \frac{\mathbf{X}_{j,new} - \mathbf{X}_{j,old}}{\Delta t} \quad (16)$$

where k_a and k_v are the acceleration and the velocity coefficients respectively; and $rand_{j1}$ and $rand_{j2}$ are two random numbers uniformly distributed in the range (0,1).

The k_v and k_a can affect on the influence of the pervious velocity and the resultant force acting on a CP, respectively. Excessive search in the early iterations may improve the exploration ability; however, exploitation ability must be increased gradually. For k_a, as a control parameter of the exploitation, choosing an incremental function can improve the performance of the algorithm [1], in which selecting a large value for this parameter may cause a fast convergence and vice versa a small value can increase the computational time. Also, the direction of the pervious velocity of a CP is not necessarily the same as the resultant force. Thus, it can be concluded that the velocity coefficient k_v controls the exploration process and therefore a decreasing function can be selected. Thus, k_v and k_a are defined as

$$k_a = 0.5(1 + iter/iter_{\max}), \quad k_v = 0.5(1 - iter/iter_{\max}) \quad (17)$$

where $iter$ is the actual iteration number and $iter_{max}$ is the maximum number of iterations. With this equation, k_v decreases linearly to zero while k_a increases to unity when the number of iterations rises. In this way, the balance between the exploration and the fast rate of convergence is provided [1].

Step 6) CP position correction: If each CP swerves off the predefined bounds, its position is corrected using the harmony search-based handling approach as described in Ref. [33].

Step 7) CM updating: The better new vectors are included to the CM and the worst ones are excluded from the CM.

Step 8) Terminating criterion control: Steps 3-7 are repeated until a terminating criterion is satisfied.

6. Description of the numerical examples

In order to present an adaptive CSS algorithm, first two numerical examples are considered and optimized utilizing the standard CSS; then the results direct us to present an efficient adaptive CSS method. To fulfill this aim, a series of realistic Bouc-Wen model parameters for a prototype 1000 kN MR damper are used to numerically generate the experimental data. Two sets of identified parameters for simple and modified Bouc-Wen model related to this damper are listed in Table 1.

Table 1. Identified parameters of Bouc-Wen model for a 1000 kN MR damper [16].

Parameter	Unit	Simple B-W model values (9 parameters)	Modified B-W model values (13 parameters)
x_0	m	-	-
γ	m^{-2}	141	164
β	m^{-2}	141	164
A	-	2075	1107.2
n	-	2	2
α_a	kN/m	26	46.2
α_b	kN/m/V	29.1	41.2
c_{0a}	kN.s/m	105.4	110
c_{0b}	kN.s/m/V	131.6	114.3
c_{1a}	kN.s/m	-	8359.2
c_{1b}	kN.s/m/V	-	7482.9
k_0	kN/m	-	0.002
k_1	kN/m	-	0.0097
η	s^{-1}	100	100

Table 2. Alternative optimal values for the simple Bouc-Wen model.

Alternative parameter	Unit	Value
$\bar{\gamma} = \mathbf{A}^{\mathbf{n-1}}\gamma$	m^{-2}	292575
$\bar{\beta} = \mathbf{A}^{\mathbf{n-1}}\beta$	m^{-2}	292575
$\bar{\mathbf{A}} = \frac{\mathbf{A}}{\mathbf{A}}$	-	1
$\bar{\mathbf{n}} = \mathbf{n}$	-	2
$\overline{\alpha_a} = \mathbf{A}\alpha_a$	kN/m	53950
$\overline{\alpha_b} = \mathbf{A}\alpha_b$	kN/m/V	60382.5
$\overline{c_{0a}} = c_{0a}$	kN.s/m	105.4
$\overline{c_{0b}} = c_{0b}$	kN.s/m/V	131.6
$\bar{\eta} = \eta$	s^{-1}	100

It has been corroborated that simple Bouc-Wen model suffers from parameter redundancy [34] and multiple sets of parameters could be the solution of a specified problem resulting in similar fairly low MSE. For example to conduct the most common transformation in the parameter space, z is replaced with $A\bar{z}$ [34] and the corresponding alternative optimal values for the simple Bouc-Wen model parameters are gained as listed in Table 2. As it can be observed, the parameter A will be equal to unity and is eliminated from optimization process. However, it should be mentioned that to conduct a full survey on effectiveness of the CSS algorithm, the redundant version of simple Bouc-Wen model is considered in the current study which contains one more parameter to be specified.

The device is assumed to be in a real operating condition that a MR damper will experience while it is employed in a semi-active control system of a building. In other word, to accurately evaluate the performance of the identification algorithm, experimental data are obtained due to just one representative test of random inputs (displacement and voltage) to the damper. The input control signal, piston movement and response of the MR damper for the simple Bouc-Wen model is determined from numerical simulation of a 3-storey case-study building of Ref. [28] in which a direct modulating controller was designed in order to control the dampers' force and

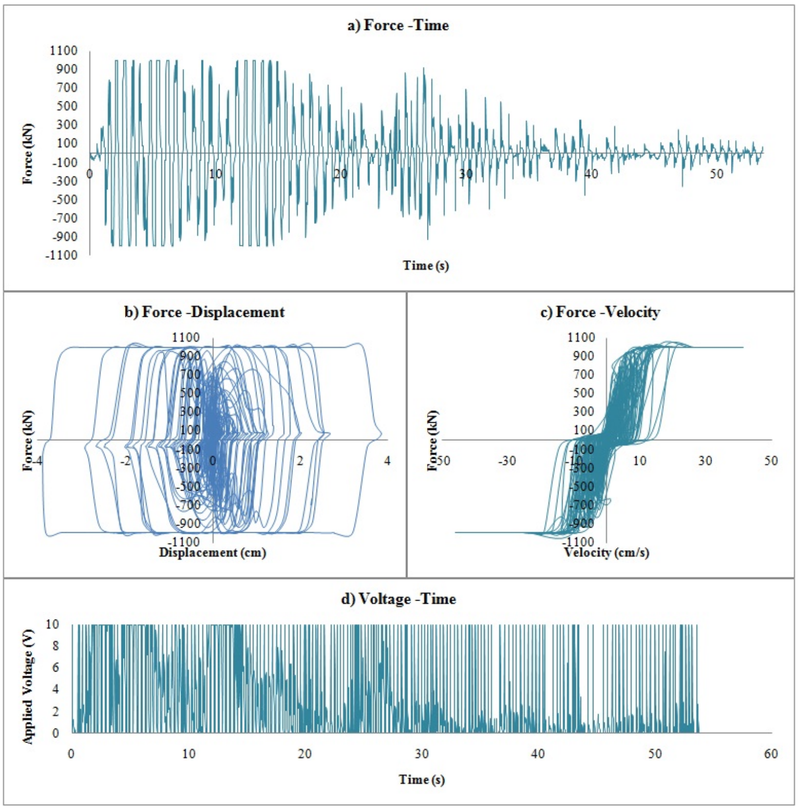

Fig. 4. Numerically obtained experimental data for simple Bouc-Wen model of a 1000 kN MR damper under the control system simulation.

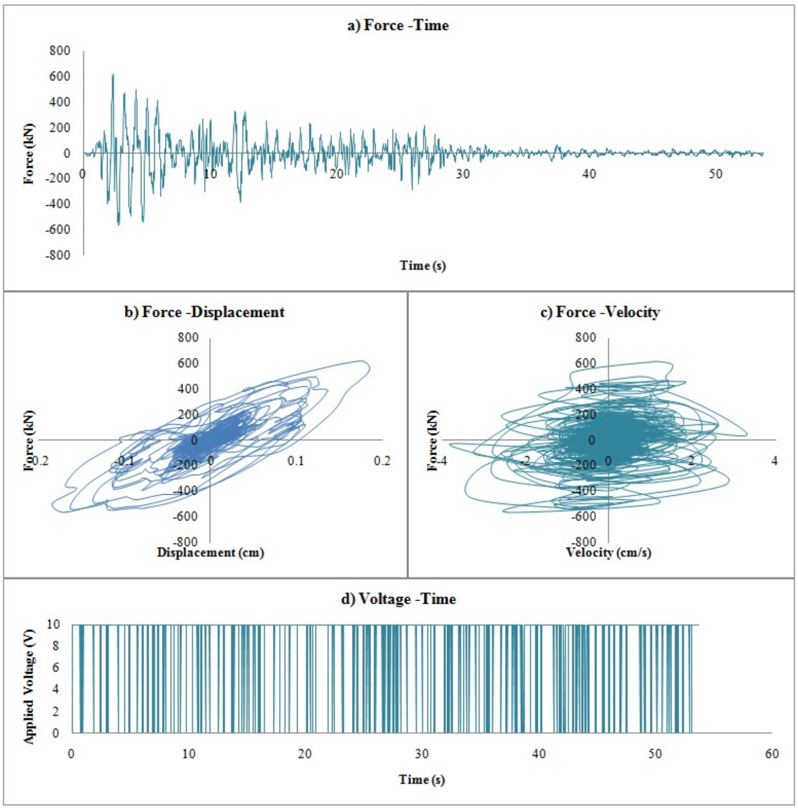

Fig. 5. Numerically obtained experimental data for modified Bouc-Wen model of a 1000 kN MR damper under the control system simulation.

mitigation of structural responses due to El Centro earthquake, and for the modified model it is determined from numerical simulation of a 11-storey example subjected to El Centro earthquake in Ref. [29] controlled using clipped-optimal control algorithm. The sample displacement and control voltage history are applied simultaneously to the MR damper and the assumed experimental results for simple and modified models are shown in Figs. 4 and 5 respectively.

7. Discussion on the results of the standard CSS

The used time duration of experimental response as well as the parameter bounds are two major factors on the performance of the optimization algorithm; here these factors are discussed as two following subsections.

7.1 Influence of the used time duration of experimental response for identification procedure

Duration of numerically recorded experimental response of the damper is equal to 53.74s which is the duration of El Centro earthquake. To conduct a detailed survey on sensitiveness of the CSS method to the duration of discrete-time data utilized for optimization process, a set of diverse durations of data were opted and fed into the standard CSS algorithm. The results are collected in Fig. 6 for the simple and modified Bouc-Wen models.

As it can be seen, by taking more discrete-time data into account, the required time for convergence of the results is increased and MSE dramatically decreases whilst the number of search iterations remains constant (200 iterations). For example, for the simple Bouc-Wen model, the outcome of the MSE for 5s duration of the experimental data is found to 3.93E-6 while it is equal to 2.21E-7 when the whole experimental response is employed. Despite, the difference between the MSE values is far small from viewpoint of optimization; however such small differences for MSE evaluations may cause large errors on estimating the required parameters. Therefore, finding more accurate results as well as smaller MSE is inevitable; and also the required time to obtain these two results is completely different. As indicated in Fig. 6(c), the time increases almost linearly by increase of the duration of experimental response. The required computational time is 1,850s when the 5s duration of the experimental data is utilized while it is 19,700s when the total experimental response is used.

To sum up, on one hand the outcomes of MSE must become as small as possible which is out of question without using a large duration of experimental data, and on the other hand utilizing a small duration of experimental data is indispensible to reduce the computational cost. Subsequently in section 8, an adaptive algorithm based on the CSS is presented that is a simple but quite useful approach to make a suitable trade-off between these two contributors and work out this problem.

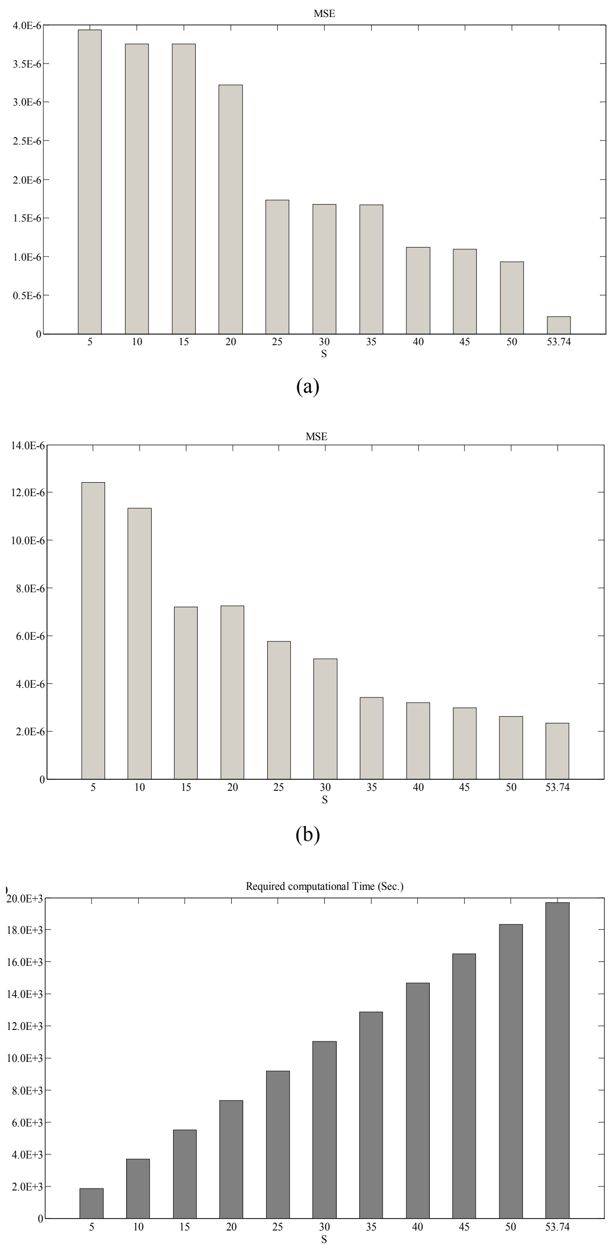

Fig. 6. MSE behavior and computational time for various duration of experimental data: (a) MSE behavior for simple Bouc-Wen model; (b) MSE behavior for modified Bouc-Wen model; (c) Computational time.

7.2 Influence of the parameter bounds on accuracy of the result

One of the major challenging tasks on parameter identification procedures is to estimate the initial side-bound of parameters. Herein, the effect of parameter limits on the accuracy of the obtained results is thoroughly investigated by conducting a comprehensive critical analysis. Five different search domains were radially designated around the actual values of the parameters. In other word, two values are necessary to define the

Table 3. MSE behaviour for various search domains using the standard CSS.

Domain limits	Simple Bouc-Wen model	Modified Bouc-Wen model
10%	1.183E-07	2.225E-07
20%	3.177E-07	8.338E-07
50%	2.279E-06	8.275E-6
100%	3.935E-06	1.240E-05
200%	2.564E-03	6.321E-03

search domain; first, the center point of the search domain which utilizes the true values for each parameter (shown by PAR_{expr} as presented in Table 1) and the second an adaptable value to determine the length of the domain; for instant, if the domain limit is set to 10%, the search space will be determined as [0.95 × PAR_{expr}, 1.05 × PAR_{expr}]. A comprehensive set of domain limits ranged from 10% to 200% is considered to investigate the effect of parameter bounds on the obtained results.

From Table 2 it can be observed that the alternative values discussed in section 6 are far out of the maximum determined search domain (i.e. domain limit = 200%). Similarly, other sets of alternative parameter values would result from functional multiplication or division by other parameter values of Table 1 which are quite different from each other. Hence, it seems extremely implausible to have more than one solution within the determined search domains and our optimization problem will inevitably converge to the parameters given in Table 1.

Using the 5s duration of the experimental data, the outcome of the MSE for search domain limits of 10%, 20%, 50%, 100%, and 200% are collected in Table 3. Different random seeds in starting each run are used to perform a strong statistical study. The number of independent runs is set to 20 for each scenario in this study. It is found that the best solutions are insensitive to the initial setting of the parameters. From Table 3, it is clearly depicted that the small domains result in far better MSE values as could be anticipated. While the search limit is set to 200%, which can be accepted as a non-constrained search domain, the MSE value becomes significantly worse than when it is set to 10%. As a result, it seems that a reasonable approximate calculation of a proper initial search domain for the parameters is quite vital which is really a complicated task especially for the modified Bouc-Wen model of MR dampers that contains a couple of dependent non-linear differential equations or even Bouc-Wen-Baber-Noori model that involves intricate equations accounting for pinching and degradation in hysteretic systems. Then to get to the bottom of such optimization problems without having helpful information related to the parameters' behavior, it will get extremely difficult. In other word, overlooking the individual parameters' behavioral anticipation may result in defining a digressed search domain for optimization process which leads to the loss of a desired result. However, obtaining such information on variation form of individual parameters within a high non-linear problem is either infeasible or requires more investigation as well as more computational costs.

8. Adaptive CSS

Considering the previous section, one recognizes that to reach an accurate result, utility of a large duration of experimental data as well as defining the proper initial search domains are necessary and both of these points result in increasing the computational cost. Here, a useful approach to reduce the computational cost with improving (or at least saving) the MSE qualities is presented. To fulfill this aim, sub-optimization mechanism (SOM) [35] is utilized which is based on the principles of finite element method. The finite element method requires division of the problem domain into many sub-domains and each domain is called a finite element. These element patches are considered instead of the main domain. As the number of finite elements increases, the obtained approximate solutions become nearer toward the exact solutions and vice versa. If a small number of finite elements are used, the amounts of calculations as well as the accuracy of solutions are decreased [35]. Similarly, SOM divides the search space into sub-domains and performs optimization process into these patches, and then based on the resulted solutions the undesirable parts are deleted, and the remaining space is divided into smaller parts for more investigation in the next stage. This process continues for determined numbers or until the remaining space gets less than the required accuracy or specified value.

For parameter identification of the Bouc-Wen model for MR dampers, the adaptive CSS method utilizes the idea of the SOM as the following steps:

Step 1) Determining a search domain for each variable. Due to lack of information related to search space, a large domain (200%) as a simplest choice can be utilized.

Step 2) Determining the required duration of the experimental data. Due to high computational cost for large durations, a small duration is selected (5s).

Step 3) Employing the standard CSS algorithm considering the defined search domain and the duration of the experimental data to find the optimum results. In this step, since we do not need exact results, the search process can be circumscribed to 150 iterations instead of 200 iterations. This reduces the computational time from 1,850s to 1,385s.

Step 4) Determining a new search domain for each variable using the optimum results obtained in the previous step. Using the information obtained in the previous search ($\mathbf{X}_{opt}$), it is possible that the search domain becomes defined again more accurately. In this way, the previous optimum result is considered as the center point of the domain and the domain will be as

$$[(1-\gamma)\mathbf{X}_{opt},\ (1+\gamma)\mathbf{X}_{j,old}] \tag{18}$$

Table 4. Defined parameters for general search limit of 200% and utilization of 5s duration of experimental data using the adaptive CSS method.

Parameter	Unit	Defined parameters for simple B-W model		Defined parameters for modified B-W model	
		Value	Error (%)	Value	Error (%)
x_0	m	-	-	-	-
γ	m^{-2}	134.14	4.87	151.66	7.53
β	m^{-2}	140.47	0.38	155.22	5.35
A	-	2069.98	0.24	1186.32	7.15
n	-	2.03	1.69	1.99	0.50
α_a	kN/m	26.10	0.37	45.03	2.53
α_b	kN/m/V	29.22	0.42	38.28	7.10
c_{0a}	kN.s/m	101.99	3.24	106.26	3.40
c_{0b}	kN.s/m/V	132.11	0.39	114.45	0.14
c_{1a}	kN.s/m	-	-	8256.38	1.23
c_{1b}	kN.s/m/V	-	-	7481.87	0.01
k_0	kN/m	-	-	0.00	2.09
k_1	kN/m	-	-	0.01	1.10
η	s^{-1}	99.52	0.48	100.98	0.98
MSE response:		4.37E-07		1.44E-06	

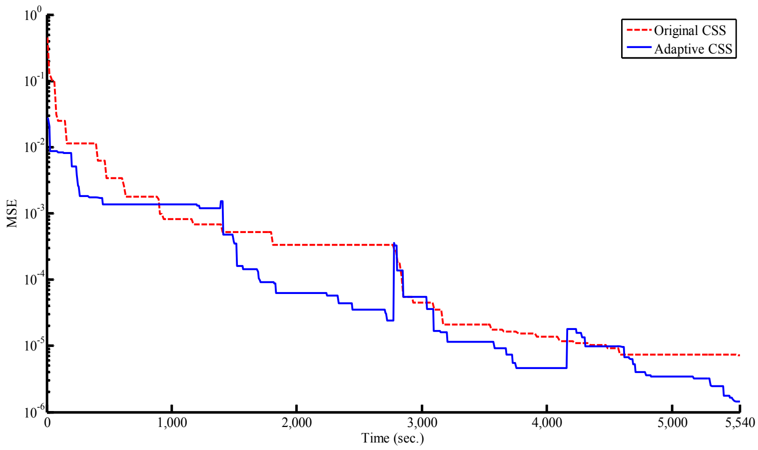

Fig. 7. Convergance history for the original and adaptive CSS algorithm.

where γ is the domain limit and is set to 150%, 100% and 50% for level 1, 2 and 3 of the repetition respectively.

Step 5) Utilizing the CSS algorithm to find new $\mathbf{X}_{opt}$ considering the defined search domain of Step 4 and for 150 iterations.

Step 6) Repeating steps 4 and 5 for definite times (three times in this paper).

The optimum values for the parameters using the described adaptive CSS algorithm are listed in Table 4. The MSE value for the simple Bouc-Wen model is found 4.373E-07 by the adaptive CSS which is much better than 2.564E-03 obtained by the standard CSS for the 200% domain limit. The total required time to identify the optimum values by the adaptive algorithm is equal to 5,540s which is slightly less than the required time for the original algorithm when 15s duration of experimental data are utilized while its corresponding MSE value is 3.74E-6 which is almost 10 times bigger than the one obtained by the revised adaptive algorithm. For the modified Bouc-Wen model, the related MSE for the adaptive CSS algorithm is 1.438E-06 whereas it is 6.321E-03 for the original algorithm. Also when the same computational time is considered for the adaptive and the original algorithm (using 15s duration of experimental data), the convergence history is compared in Fig. 7. Clearly the performance of the adaptive CSS algorithm is better than the original one.

Furthermore, the time history of the force for the first 15s predicted by the obtained parameters of the adaptive CSS in comparison to experimental data are shown in Figs. 8 and 9 for both simple and modified models. It is noticeable that predicted results by defined parameters perfectly portray the experimental results.

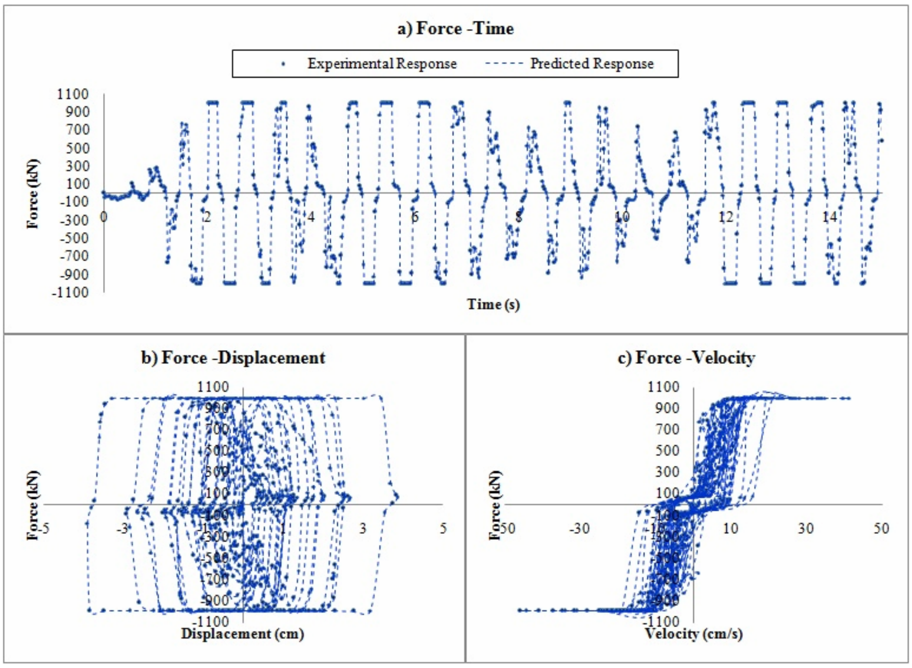

Fig. 8. Comparison between experimental and predicted response of damper with simple B-W model.

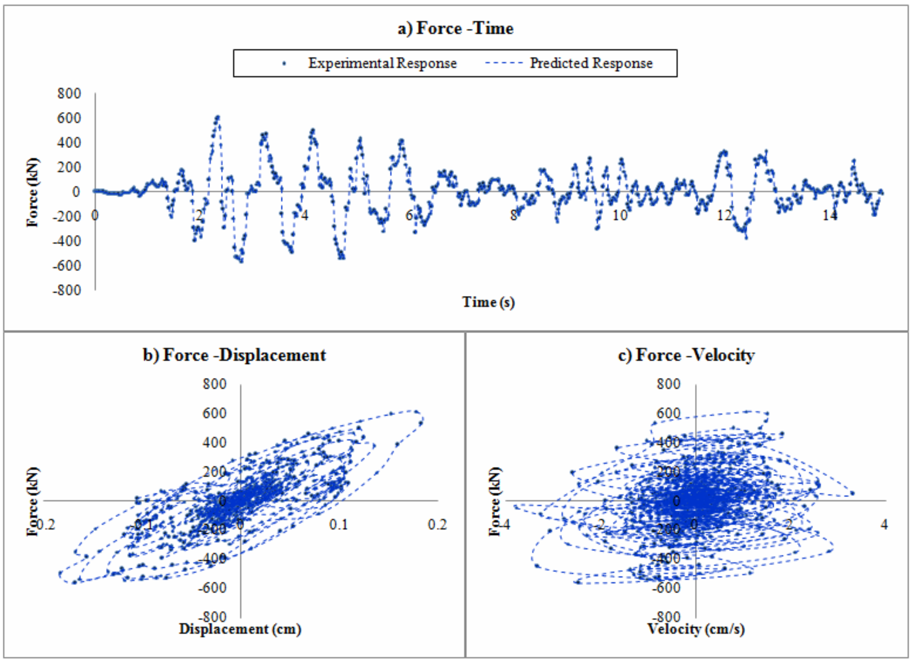

Fig. 9. Comparison between experimental and predicted response of damper with modified B-W model.

9. Summary and conclusion

In order to distinguish the explicit parameters governing the mechanical properties of non-linear systems, the need of a comprehensive optimization methodology to get to the bottom of parameter identification problems becomes far more touchable. This article aims to identify the parameters of the non-linear hysteretic Bouc-Wen differential model of MR fluid dampers. MR fluid dampers are excellent semi-active control devices which have some advantageous characteristics, such as low power source requirement and quick controllable response. However, high non-linearity and hysteretic demeanor of MR dampers requires an accurate tractable model to make them available for control purposes. This aim is fulfilled by using the Bouc-Wen models.

A new promising identification method for highly non-linear hysteretic Bouc-Wen differential model of MR fluid dampers is introduced by adapting the CSS algorithm as the main contribution of the paper. The CSS algorithm is inspired by the governing Coulomb and Gauss laws from electrostatics and the governing motion from Newtonian mechanics. This algorithm does not need the gradient information and it can efficiently be utilized in all optimization fields. It is also suitable for those optimization problems involving non-smooth or non-convex domains. To adapt the CSS for reaching a higher efficiency and susceptible parameter identification algorithm, two series of realistic Bouc-Wen model parameters containing simple and modified Bouc-Wen models are used. Then two major matters are studied carefully; influence of the used time duration of experimental response and influence of the parameter bounds on accuracy of the result and required computational time. The results of the standard CSS show that although utility of a large duration of experimental data guarantees to reach good results, it is a time consuming task. Meanwhile, a rational approximate calculation of a proper initial search domain for the parameters is really a complicated task especially for the modified Bouc-Wen model of MR dampers that contain a couple of dependent non-linear differential equations. The results indicate that a small search domain will improve the final results, however defining such a proper small search domain may result in losing a desire solution.

To solve these problems, a useful approach is presented here which combines the major idea of sub-optimization mechanism (SOM) with the CSS algorithm to reach an adaptive CSS. SOM like finite element methods divides the search space into sub-domains and performs optimization process into these patches, and then based on the resulted solutions the space domain is decreased into smaller parts to perform more investigation into these spaces. The obtained results show that the adaptive CSS algorithm embodies great inherent robustness and accuracy to be successfully employed in such highly non-linear identification problems.

We have used a small part of the data set in our examples; however as a future work, the quality and amount of information contained in the data set should be considered in a way that the selected data set mobilizes all linear and non-linear characteristics of the Bouc-Wen model; thus the meta-heuristic algorithms can easily be assisted in the identification process. Another future work will consider a search space reduction methodology, as described in Ref. [7], in which the algorithm gets a small number of runs using only 5s of data and a wide range of parameters at the beginning, and as the reduction progresses, it will use larger and larger data set. In the end, the algorithm can use the whole data set with narrow parameter ranges. Due to the use of several runs to guide the reduction process, it seems this methodology can be very robust.

Acknowledgement

The second author is grateful to the Iran National Science Foundation for the support.

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