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Opposition based charged system search for parameter identification problem in a simplified Bouc-Wen model

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Abstract. In this paper, a new opposition based charged system search (CSS) is proposed to be used as a parameter identification of highly nonlinear semi-active magneto-rheological damper. By replacing the opposition particles with current solutions, the mentioned strategy is used to enhance the search space and to increase the exploration of CSS. To investigate the effectiveness of the proposed method, a nonlinear modified Bouc-Wen model of MR damper is considered to find its parameters, and compare it with those achieved from experimental model of MR damper. Also, by exploiting the sensitivity analysis and using the importance vector, the less importance parameters in the Bouc-Wen model are eliminated which makes the MR damper model simpler. Results demonstrate the new proposed algorithm (OBLCSS) has a high ability to tackle highly nonlinear problems. Based on the results of the α importance vector, a simplified model is proposed and its parameters are identified by using the presented OBLCSS algorithm. The simplified proposed model also has a high capability of estimating damper responses.

Keywords: parameter identification; Bouc-Wen model; charged system search; opposition based learning; MR damper; importance vector; reliability analysis

1. Introduction

One of the complex behavioral models is completely nonlinear hysteresis behavior. So far, there has not been a fundamental theory for the modeling the hysteresis behavior in the mathematical framework. Also, for specific problems, descriptive models of hysteresis systems are presented using the governing physical rules of the problem. Some models such as the Bouc-Wen model attempt to provide general features of hysteresis. The Bouc–Wen model is often used to describe non-linear hysteretic systems. It was introduced by Bouc (Bouc 1967) and extended by Wen (Wen 1976, 1980, 1989), who demonstrated its versatility by producing a variety of hysteretic patterns. The Bouc–Wen model has quickly gained popularity and has been extended and applied to a wide variety of engineering problems (Spencer *et al*. 1997, Song and Der Kiureghian 2006, Ikhouane *et al*. 2007, Ismail *et al*. 2009, Rakotondrabe 2011, Azar *et al*. 2020).

There are different models in hand to portray the real hysteretic behavior of MR damper (Spencer *et al*. 1997, Choi *et al*. 2001, Kwok *et al*. 2006, Hong *et al*. 2008, Graczykowski and Pawłowski 2017, Bai *et al*. 2019). Among them, modified Bouc-Wen model, which is the most accepted one, has attracted considerable attention due to its compatible feature with the responses of real MR dampers. In the Bouc-Wen model, the system deformation through a first-order non-linear differential equation which has a range of undefined parameters relates to non-linear restoring force. By selecting proper values for the parameters used in the Bouc-Wen model, the response of the model will coincide with the actual behavior of the non-linear system.

The process of finding the optimal values of the mentioned parameters is the so-called "Parameter Identification" or "System Identification" which needs to be obtained through solving an optimization problem. Different optimization algorithms can be used to tackle this problem (Back and Schwefel 1993, Sun *et al*. 2013). Charalampakis (Charalampakis and Dimou 2010) successfully used a hybrid particle swarm optimization (PSO) approach to find the optimal set of Bouc Wen model parameters for producing the experimentally obtained hysteretic behavior of a steel cantilever beam. Kwok *et al*. (2007) applied the genetic algorithm (GA) to identify the Bouc–Wen relations modeling hysteretic non-linear behavior of MR dampers. Liu *et al*. (2006) and Talatahari *et al*. (2012) also utilized the simulated annealing algorithm (SA) and the adaptive charged system search (CSS) respectively to optimally find the Bouc–Wen model parameters of MR dampers. Also, Talatahari and Mohajer (2015) proposed the enriched imperialist competitive algorithm (EICA) to solve this problem.

There are various uncertainties in all structural parameters and control methods. These uncertainties can be examined based on probabilistic models, and reliability analysis can assess safety levels using the probability of

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failure for engineering problems (Ditlevsen 1982). In general, for estimating the probability of failure and reliability analysis in the structures based on probabilistic model, various analytical methods such as first-order reliability method (FORM) (Liu and Der Kiureghian 1991 and Hao *et al*. 2013), second-order reliability method (SORM) (Kiureghian and Stefano 1991), simulation methods (Azar *et al*. 2015), response surfaces (Hadidi *et al*. 2017) and neural networks (Vazirizade *et al*. 2017) are used. Due to the uncertainty in structural control systems, it is possible to investigate the probability of their instability (Spencer *et al*. 1992). Some researchers have examined the uncertainty in the control devices and their effects on the reliability of the structure (Guo *et al*. 2002, Gavin and Zaicenco 2007). Also, some others studied reliability-based optimization (Mrabet *et al*. 2015) and reliability-based design (Hadidi *et al*. 2016) in structures equipped with control devices. Moreover, the effect of uncertainty in different parameters on the reliability of MR damper performance was investigated (Hadid *et al*. 2019).

In this paper, an optimization algorithm is presented with opposition based learning of the CSS algorithm, so-called OBLCSS, and is used to identify the parameters in the Bouc-Wen model of MR dampers. Given the fact that the performance of the semi-active MR damper is influenced by uncertainty in the parameters of the Bouc-Wen model, the sensitivity analysis is used to illustrate the importance of each parameter of Bouc-Wen model in the damper behavior. Thus, by using the sensitivity analysis based on importance vectors in reliability analysis, unimportant parameters are identified in the Bouc-Wen model. The α importance vector is calculated using the first-order reliability method (FORM) for the reliability of the expected force of MR damper. Subsequently, by eliminating the parameters that, have the least importance in the MR damper performance, a simplified model is proposed for the Bouc-Wen model. Finally, the parameters of this model are identified using the OBLCSS algorithm and its effectiveness is evaluated in the simulation of MR damper behavior.

2. Development of improved algorithm

To solve the optimization problems, meta-heuristic algorithms can be combined together or modified for high-performance search (Kave and Talatahari 2012, Kave and Shokohi 2016, Ye *et al*. 2017, Zhang *et al*. 2017 and Shahrouzi *et al*. 2019). In this paper, to find solutions, the opposition based learning strategy is used to improve the exploration property of charged system search (CSS) algorithm which is developed by Tizhoosh (2005), and Kaveh and Talatahari (2010) respectively. In this section, a new improved CSS method is presented. To improve the CSS, the opposition based learning is used, and the positive features of the OBL are added to CSS. The opposition based CSS utilizes the opposition location of particles to improve the searching process. A summary of these methods is described in the following subsections.

2.1 Standard CSS

One of the efficient meta-heuristic optimization algorithms is Charged System Search (CSS) that, proposed by Kaveh and Talatahari, which is based on electrostatics and Newtonian mechanics laws. The Coulomb and Gauss laws provide the magnitude of the electric field at a point inside and outside of a charged insulating solid sphere, respectively, as follows (Kaveh and Talatahari 2010)

$$\begin{cases} \vec{E}_{ij} = k_e \dfrac{q_i}{\vec{r}_{ij}^{\,2}} & : \ \vec{r}_{ij} \geq a \\ \vec{E}_{ij} = k_e \dfrac{q_i}{a^3} \vec{r}_{ij} & : \ \vec{r}_{ij} < a \end{cases} \tag{1}$$

where $\vec{E}_{ij}$ is the magnitude of the electric field; k_e is a constant known as the Coulomb constant; $\vec{r}_{ij}$ is the separation of the center of a sphere and the selected point; q_i is the magnitude of the charge, and a is the radius of the charged sphere. Using the principle of superposition, the resulted electric force ($\vec{F}_{ij}$) due to N charged spheres equals to

$$\begin{aligned} &\vec{F}_{ij} \\ &= k_e q_j \sum_{i,i\neq j} \left(\frac{q_i}{a^3} \vec{r}_{ij}.i_1 \right. \\ &\left. + \frac{q_i}{\vec{r}_{ij}^{\,2}}.i_2 \right) \frac{\vec{r}_i - \vec{r}_j}{\|\vec{r}_i - \vec{r}_j\|} \end{aligned} \qquad \begin{cases} i_1 = 1 \ , & i_2 = 0 \ \leftrightarrow \ \vec{r}_{ij} < a \\ i_1 = 0 \ , & i_2 = 1 \ \leftrightarrow \ \vec{r}_{ij} \geq a \end{cases} \tag{2}$$

Also, according to Newtonian mechanics

$$\begin{gathered} \Delta\vec{r} = \vec{r}_{new} - \vec{r}_{old} \\ \vec{V} = \frac{\vec{r}_{new} - \vec{r}_{old}}{t_{new} - t_{old}} = \frac{\vec{r}_{new} - \vec{r}_{old}}{\Delta t} \\ \overrightarrow{acc} = \frac{\vec{V}_{new} - \vec{V}_{old}}{\Delta t} \end{gathered} \tag{3}$$

where $\vec{r}_{old}$ and $\vec{r}_{new}$ are the initial and final positions of the particle, respectively; $\Delta\vec{r}$ is the relative displacement of particles; $\vec{V}$ is the velocity of the particle; $\overrightarrow{acc}$ is the acceleration of the particle, and $\vec{V}_{old}$ and $\vec{V}_{new}$ are the initial and final velocity of the particle, respectively. Combining the equations above, and using Newton's second law, the displacement of any object as a function of time can be obtained by

$$\vec{r}_{new} = \frac{1}{2}\frac{\vec{F}}{m}.\Delta t^2 + \vec{V}_{old}.\Delta t + \vec{r}_{old} \tag{4}$$

where m is the mass of particles, and Δt is the time step. CSS algorithm can be presented by combining electrostatic and Newtonian mechanics laws. The steps for implementing the algorithm state as:

Step 1. An array of charged particles (CPs) can be generated by random positions and initial velocities of the CPs assumed as zero. A charge magnitude (q_i) defined for each CP, according to its cost function, as follows

$$q_i = \frac{cost(i) - cost_{worst}}{cost_{best} - cost_{worst}} \quad , \quad i = 1,2,\dots,N \tag{5}$$

where $cost_{best}$ and $cost_{worst}$ are the best and the worst cost of all particles respectively; *cost(i)* represents the cost of agent *i*. $\vec{r}_{ij}$ is the separation distance between two charged particles that defined as

$$\vec{r}_{ij} = \frac{\left\|\vec{R}_i - \vec{R}_j\right\|}{\left\|(\vec{R}_i - \vec{R}_j)/2 - \vec{R}_{best}\right\| + \varepsilon} \tag{6}$$

where $\vec{R}_i$ and $\vec{R}_j$ are the positions of the *i*th and *j*th CPs, respectively; $\vec{R}_{best}$ is the position of the best current CP, and ε is a small positive value to avoid singularities.

Step 2. The cost function is evaluated for all CPs and it is sorted in increasing order. Then, the charged memory (CM) is created and the first CPs that equal to the size of the CM are stored.

Step 3. The probability of moving each CP toward the other particles is determined based on cost functions as follows

$$P_{ij} = \begin{cases} 1 & \frac{cost(i)-cost_{best}}{cost(j)-cost(i)} > rand \quad \vee \quad cost(j) > cost(i) \\ 0 & otherwise \end{cases} \tag{7}$$

and calculating the attracting force for each CP toward the other ones is as follows

$$\vec{F}_j = q_i \sum_{i,i\neq j} \left(\frac{q_i}{a^3} \vec{r}_{ij}.i_1 + \frac{q_i}{\vec{r}_{ij}^2}.i_2 \right) P_{ij}\left(\vec{R}_i - \vec{R}_j\right) \quad \begin{cases} j = 1,2,\dots,N \\ i_1 = 1\ , \quad i_2 = 0 \ \leftrightarrow \ \vec{r}_{ij} < a \\ i_1 = 0\ , \quad i_2 = 1 \ \leftrightarrow \ \vec{r}_{ij} > a \end{cases} \tag{8}$$

where $\vec{F}_j$ is the resultant force affecting the *j*th CP.

Step 4. Update the position and velocity of each CP using Newtonian mechanics laws and move CPs to the new position using the following equations

$$\vec{R}_{j,new} = rand_{j1}.k_a.\frac{\vec{F}_{j1}}{m_j}.\Delta t^2 + rand_{j2}.k_v.\vec{V}_{j,old}.\Delta t + \vec{R}_{j,old} \tag{9}$$

$$\vec{V}_{j,new} = \frac{\vec{R}_{j,new} - \vec{R}_{j,old}}{\Delta t} \tag{10}$$

where $rand_{j1}$ and $rand_{j2}$ are two random numbers in the range (1,0) with uniform distribution; m_j is the mass of the CPs, which is equal to q_i in this paper. Δt is the time step, and it is set to 1. k_a and k_v are the acceleration and velocity coefficients, respectively. They are taken as

$$k_v = c_v(1 - iter/iter_{max}) \tag{11}$$

$$k_a = c_a(1 + iter/iter_{max}) \tag{12}$$

where c_v and c_a are two constants to control the exploitation and exploration of the algorithm; *iter* is the iteration number, and $iter_{max}$ is the maximum number of iterations.

Step 5. The cost function for the new CPs is evaluated, and they are sorted in increasing order. This mechanism repeats until a terminating criterion is satisfied.

2.2 Opposition based learning

The OBL strategy is defined based on the opposite solution of the available solution, and the cost function (*f*) value is calculated for both current and opposite solutions to find the best solutions. The concept of OBL was first proposed by (Tizhoosh, 2005) which assumed an opposite value $\bar{w}$ for a real value $w \in [lb, ub]$, where *lb* and *ub* are lower bond and upper bond of variable. An opposite value is calculated as follows

$$\bar{w} = ub + lb - w \tag{13}$$

The definition of OBL can be applied to n-dimensional problems as the following equation

$$i = 1,2,\dots,N \qquad \bar{w}_i = ub_i + lb_i - w_i \tag{14}$$

where $\bar{w} \in R^n$ is the opposite vector with respect to the real vector $w \in R^n$. Also, by using the optimization procedure, the opposite and current solutions (*w* and $\bar{w}$) are compared, and by comparing the cost function, the best of these solutions is saved, while the other is removed. For example, if $f(w) \leq f(\bar{w})$ (for minimization), then *w* is saved; otherwise, $\bar{w}$ is stored.

2.3 Opposition based charged system search

In this section, the structure of the proposed algorithm is described to enhance the performance of the CSS algorithm. In this base, the CSS is modified by combining its original formulation with the OBL strategy to provide the extensive exploration ability in the search domain and find the optimal value as fast as possible. The proposed algorithm is called the OBLCSS algorithm, and its flowchart is shown in Fig. 1.

At the end of the CSS exploration phase, the OBL strategy is implemented to save 50% of the domain space. This step allows the original domain space to quickly find optimal value and repair the out-of-range values. In general, the proposed OBLCSS has two steps: 1) initial step 2) update step.

In the initial step, the OBLCSS algorithm starts by specifying the initial parameter values of the CSS algorithm; Then, CSS randomly generates particles with the size and dimensions of the problem. The OBL is used to calculate the opposite solution for each solution in the particles, and the cost function is calculated for each solution in *w* and its $\bar{w}$. Finally, at the end of the initial step, the best N solutions from the pair of the two particle groups (*w* and $\bar{w}$) are selected.

In the updating step, the location of each particle is updated according to Eq. (9) and the cost function is calculated for them. Then, the best solution and cost value are saved. At the same time, the OBL strategy takes the updated particles from the CSS and selects some of them

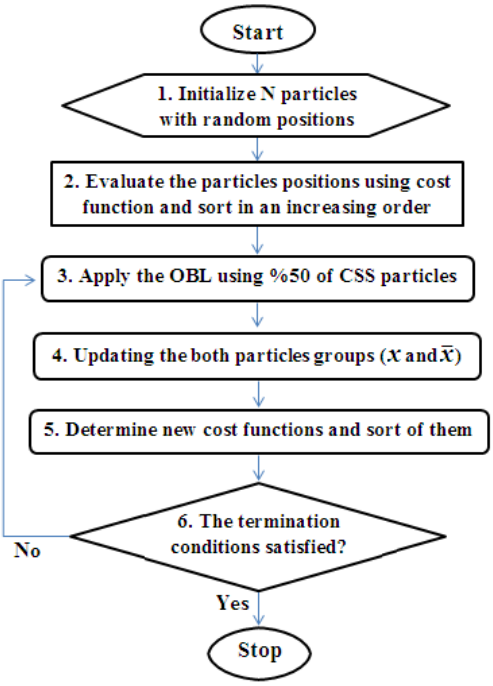

Fig. 1 The flowchart of OBLCSS algorithm

Table 1 Benchmark functions for numerical problem

ID	Equation	Lower	Upper	Dim	Type	f_{min}
F1	$f(w)=\sum_{i=1}^{n} w_i^2$	-100	100	10	Unimodal	0
F2	$f(w)=\sum_{i=1}^{n} \lvert w_i\rvert + \prod_{i=1}^{n} \lvert w_i\rvert$	-10	10	10	Unimodal	0
F3	$f(w)=\sum_{i=1}^{n} \left(\sum_{j=1}^{i} w_i\right)^2$	-100	100	10	Unimodal	0
F4	$f(w)=\sum_{i=1}^{n} ([w_i+0.5])^2$	-100	100	10	Unimodal	0
F5	$f(w)=\sum_{i=1}^{n-1} \left[100\left(w_{i+1}-w_i^2\right)^2+(w_i-1)^2\right]$	-30	30	10	Unimodal	0
F6	$f(w)=\sum_{i=1}^{n} -w_i \sin\left(\sqrt{\lvert w_i\rvert}\right)$	-500	500	10	Multimodal	418.9829
F7	$f(w)=\sum_{i=1}^{n} \left[w_i^2-10\cos(2\pi w_i)+10\right]$	-5.12	5.12	10	Multimodal	0
F8	$f(w)=\frac{1}{4000}\sum_{i=1}^{n} w_i^2-\prod_{i=1}^{n} \cos\left(\frac{w_i}{\sqrt{i}}\right)+1$	-600	600	10	Multimodal	0
F9	$f(w)=(4w_1^2-2.1w_1^4+\frac{1}{3}w_1^6+w_1w_2-4w_2^2+4w_2^4)$	-5	5	2	Multimodal	-1.0316
F10	$f(w)=\left(w_2-\frac{5.1}{4\pi^2}w_1^2+\frac{5}{\pi}w_1-6\right)^2+10\left(1-\frac{1}{8\pi}\right)cosw_1+10$	-5	5	2	Multimodal	0.398

(i.e., 50%) to calculate the opposite solutions. In this study, the selected solutions are the best 50% of solutions based on the cost functions. Afterward, the result will be reevaluated by the cost function. If the cost value is better than the current value, the OBLCSS will select the opposite solutions and updates the particles with this value in the next iteration. This process is repeated as a loop until stopping criteria are satisfied.

2.4 Validation of algorithm

To evaluate the performance of the proposed algorithm, two experiments were used. The first experiment compares the traditional CSS with the OBLCSS using ten various benchmark functions. The second experiment evaluates the performance of the OBLCSS in solving parameter identification problems. To calculate the statistical results of algorithms, 30 independent runs are applied. Similar to all meta-heuristic methods, in the OBLCSS algorithm, as the number of agents increase, the ability of algorithms in the exploration phase and consequently the computational cost increases. In numerical examples, the number of particles

Table 2 The comparison of optimization results obtained over all test functions

ID	CSS			OBLCSS		
	Best	Ave	STD	Best	Ave	STD
F1	1.9688e-011	1.7626e-005	4.1185e-005	1.7882e-015	3.4134e-010	1.6403e-009
F2	3.013e-005	0.019959	0.047602	9.3802e-007	0.011098	0.023504
F3	0.0003242	0.1963	0.33547	3.0701e-006	0.012135	0.02513
F4	0	0.76667	1.2507	0	0.3	0.53498
F5	0	6.9667	2.9418	0	0.0333	0.18257
F6	-4189.8281	-4181.955	15.8585	-4189.8288	-4189.7958	0.1291
F7	0	1	1. 4142	0	0.1	0.40258
F8	0.00015516	0.091902	0.093176	2.4331e-006	0.064527	0.044855
F9	-1.0316	-1.0044	0.14901	-1.0316	-1.0316	6.1849e-016
F10	0.39789	0.39789	0	0.39789	0.39789	0

and maximum iteration is selected 20 and 200, respectively.

The benchmark functions are described in Table 1, and these functions are divided into two types: The unimodal functions with only one extreme point and the multimodal functions with more than one extreme point in their domain (Saremi *et al*. 2017). To assess the convergence speed of the algorithms, the unimodal functions are used, whereas the multimodal functions are used to assess the performance of the algorithm to skip the local point and find the global minimum.

To evaluate the performances of the presented method, the OBLCSS and CSS algorithms are experimented by determining the optimal solution for the test functions that are defined in Table 1. The comparison of performances of these algorithms is done by using the results of best, average and standard deviation (STD) of solutions. The results are given in Table 2 in which the size of the particles is selected 20 and the Maximum iteration is set to 200. The results presented in this table show that in terms of the best cost values, the OBLCSS provides better results than the CSS for most functions, and the two algorithms provide equivalent results for functions F4, F5, F7, F9, and F10. Also in terms of the average cost values, the OBLCSS provides better results than the CSS for most functions, and the two algorithms provide nearly equivalent results for function F10. Moreover, in the values of the STD measure, the OBLCSS shows better results than the CSS for most test functions, so the stability of the proposed OBLCSS algorithm is higher than the stability of the original CSS.

3. Sensitivity analysis based on importance vector

The probability of failure equals to the probability that the random variables X fall into the fracture region, in other words, it is defined as the probability $P\{g(X) < 0\}$. If the probability distribution function of the random variables X is $f_x(X)$, then the probability of failure (P_f) can be calculated by the mass of probability in the failure region (Du 2005):

$$P_f = P\{g(X) < 0\} = \int_{g(X)<0} f_x(X)dX \tag{15}$$

Reliability is defined as the complementary of failure probability, $P\{g(X) > 0\}$. In other words, reliability can be calculated by the mass of probability in the safe region. So, reliability can be calculated as follows

$$Reliability = 1 - P_f = P\{g(X) > 0\} = \int_{g(X)>0} f_x(X)dX \tag{16}$$

The failure probability can approximately be calculated according to the reliability index (β) as follows (Kiureghian 2005)

$$P_f = \int_{g(X)\leq 0} \dots \int f_x(X)dX \approx \Phi(-\beta) \tag{17}$$

where P_f is failure probability, $g(X)$ is the limit state function which separates design regions into safe and failure regions by using the basic random variables X.

The limit state function g(X) is expressed as complex and implicit in many real engineering problems. To simplify the calculation, all random variables $X = (X_1, X_2, \dots, X_n)$ are transferred from their original random space to standard normal space with $U = (U_1, U_2, \dots, U_n)$ variables. So after transformation, the probability integral equals to

$$P_f = P\{g(U) < 0\} = \int_{g(U)<0} \phi_u(U)dU \tag{18}$$

where $\phi_u(U)$ is the probability distribution function (pdf) in U space.

The first-order reliability method (FORM) uses a linear approximation method (Taylor's first expansion) as follows (Kiureghian 2005)

$$g(U) \approx g(U^*) + \nabla g(U^*)(U - U^*)^T \tag{19}$$

where u^* is the expansion point, and $\nabla g(U^*)$ is the gradient of the g function at U^*.

If all the random variables with Arbitrary distribution are transformed into standard normal space, and the limit state function g(U) is linearized, the reliability index (β) will have the shortest distance in U space from the origin to the failure surface given by g(U)=0. Therefore, there will be a point with minimum distance to the origin on the limit state surface to calculate the reliability index. Therefore,

this problem may be described as an optimization problem: (Lee *et al*. 2002)

find u; which minimizes $\beta = |U| = \sqrt{U^T U}$

subjected to $\mathrm{g}(\mathbf{U}) = 0$

The main goal in FORM is to find the most probable point (MPP, i.e., U^*), which is the shortest point of origin in standard normal space. This distance is defined as the reliability index. Consequently, $\beta = \|U^*\|$ (Lee *et al*. 2002).

Hasofer and Lind proposed an iterative method for finding the most probable point (MPP) (Hasofer and Lind 1974) and used this method for variables with normal distributions. Rackwitz and Flessler (Rackwitz and Flessler 1978) extended this algorithm for random variables with any desired distribution; So it is called HL-RF. Liu and der Kiureghian (Liu and Der Kiureghian 1991) improved the HL-RF method by using a merit function to enhance the convergence properties. Recently, various FORM algorithms have been used for searching the MPP (Gong and Yi 2011, Keshtegar 2016, Meng *et al*. 2017). The modified HL-RF method formulated by using the steepest descent search direction, and are applied to find MPP. The iterative equation of FORM can be described by the following relation

$$U_{k+1} = U_k + s_k d_k \tag{20}$$

where U_{k+1} and U_k are the new and old position in standard normal space respectively; s_k is step size and d_k is search direction vector, which can be computed as follows (Makhduomi *et al*. 2017)

$$d_k = \frac{\nabla^T g(U_k) U_k - g(U_k)}{\nabla^T g(U_k) \nabla g(U_k)} \nabla g(U_k) - U_k \tag{21}$$

in which $\nabla g(U_k)$ is gradient vector of the limit state function $g()$ at point U_k, and for random variables with normal distribution

$$\begin{aligned} \nabla g(U_k) &= \left\{ \frac{\partial g}{\partial U_1}, \frac{\partial g}{\partial U_2}, \dots, \frac{\partial g}{\partial U_n} \right\} \\ &= \left\{ \sigma_1 \frac{\partial g}{\partial X_1}, \sigma_2 \frac{\partial g}{\partial X_2}, \dots, \sigma_n \frac{\partial g}{\partial X_n} \right\} \end{aligned} \tag{22}$$

where σ_i is the standard deviation for i-th variable.

According to Eq. (20), the step size and search direction are two effective parameters in the iterative FORM formula. The iterative FORM formula can be controlled according to the step size to search MPP. Therefore, the iterative formula of modified HL-RF (MHL-RF) can be obtained from Eq. (20), where s_k is the adjusted step size. In this study, the step size of the MHL-RF method in Eq. (20) can be dynamically adjusted in a range of 1.5 to 0. It is assumed that the step size is adjusted by the following merit function

$$m(U_k) = \left\| U_k - \frac{\nabla^T g(U_k) U_k}{\nabla^T g(U_k) \nabla g(U_k)} \nabla g(U_k) \right\|^2 + \frac{g(U_k)^2}{g(U_0)^2} \tag{23}$$

It is clear that the merit function is a positive value $m(U_k) \geq 0$, and it is computed based on the previous results as well as the HL-RF method. The step size can be calculated as follows (Makhduomi *et al*. 2017)

$$s_{k+1} = \begin{cases} \dfrac{m(U_{k-1})}{m(U_k)} s_k & m(U_k) \geq m(U_{k-1}) \\ s_k & m(U_k) < m(U_{k-1}) \end{cases} \tag{24}$$

In which the initial step size is considered to be 1.5 (i.e., $s_0 = 1.5$). According to the above adaptive step size in Eq. (24), it can be concluded that, $s_{k+1} \leq s_k$.

In FORM analysis, the Importance vector is used to evaluate the importance of each random variable in the reliability index, which is defined as a negative and normalized of the gradient vector.

$$\alpha = -\frac{\nabla g}{\|\nabla g\|} \tag{25}$$

Also, the reliability index can be written as $\beta = \alpha^T U^*$. Thus,

$$\alpha = \frac{\partial \beta}{\partial U^*} \tag{26}$$

Importance vectors are applied to show the relative importance of different parameters in reliability analysis. The α importance vector is the primary importance vector for the random variables in the standard normal space in which higher absolute value of components is the most important random variable.

4. Modified bouc-wen model for MR dampers

Due to controling purposes and following the nonlinear and hysteretic behavior of MR dampers, a tractable model with high accuracy is required. Until now, different parametric mechanical models have been proposed to describe the nonlinear behavior of MR dampers (Dyke *et al*. 1996, Spencer *et al*. 1997, Choi *et al*. 2001, Yang *et al*. 2002, Hong *et al*. 2008). The most commonly used model that provides an appropriate prediction of semi-active MR dampers behavior is the modified Bouc-Wen model. Fig. 2 illustrates the modified Bouc-Wen model for MR dampers. The damper force (F), in this case, is calculated from Eq. (27) as follows

$$\begin{aligned} F &= \delta z + k_0(x - y) + c_0(\dot{x} - \dot{y}) + k_1(x - x_0) \\ &= c_1 \dot{y} + k_1(x - x_0) \end{aligned} \tag{27}$$

in this case, hysteretic displacement (z) is given by

$$\dot{z} = -\gamma |\dot{x} - \dot{y}| z |z|^{n'-1} - \rho(\dot{x} - \dot{y}) |z|^{n'} + A(\dot{x} - \dot{y}) \tag{28}$$

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

$$\dot{y} = \frac{1}{(c_0 + c_1)} \{\delta z + c_0 \dot{x} + k_0(x - y)\} \tag{29}$$

where A, ρ, γ and n' are the parameters of the Bouc-Wen hysteresis equation. Also k_0, k_1, c_0, c_1 and δ are the parameters of the Bouc-Wen model elements.

To validate the model for fluctuating magnetic fields, δ, c_0 and c_1 parameters in Eqs. (27) and (29) are defined as a

linear function of the efficient voltage u as given by Eqs. (30) - (32)

$$\delta(u) = \delta_{\mathrm{a}} + \delta_{\mathrm{b}} u \tag{30}$$

$$c_0(u) = \mathrm{c}_{0\mathrm{a}} + \mathrm{c}_{0\mathrm{b}} u \tag{31}$$

$$c_1(u) = \mathrm{c}_{1\mathrm{a}} + \mathrm{c}_{1\mathrm{b}} u \tag{32}$$

Accounting the dynamics involved in the MR fluid reaching rheological equilibrium, the following first-order filter is employed to calculate the efficient voltage u:

$$\dot{u} = -\eta(u - v) \tag{33}$$

where u is related to the applied voltage (v) through Eq. (33).

5. Statement of the identification problem

Determining optimal values for the parameters of a mathematical model is defined as an optimization problem that requires an appropriate objective function. In this study, the normalized mean square error (MSE) is assumed as the objective function to be optimized, in case that the time history of predicted response $\tilde{f}(t_i|\mathbf{p})$ (for any generated parameters vector $\mathbf{p}$) is compared to the time history of experimentally obtained response $f(t_i)$ at each time step t_i. The discrete-time MSE based objective function can be stated as Eq. (34) (Charalampakis and Koumousis 2008):

$$OF(\mathbf{p}) = \frac{\sum_{i=1}^{N} \left(f(t_i) - \tilde{f}(t_i|\mathbf{p})\right)^2}{N.\sigma_f^2} \tag{34}$$

in which, $\mathbf{p}$ is the vector of model's parameters; σ_f^2 is the variance of experimental response time history; $\sum$ illustrates the summation of its subsequent term (N discrete values), and N is the number of experimental data employed in the optimization process. It should be noted that the optimization problem can be performed to minimize the objective function according to the parameters vector that has constraints as follows:

$$\mathbf{p}_{min} \leq \mathbf{p} \leq \mathbf{p}_{max} \tag{35}$$

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

6. Numerical Study

6.1 Case 1: parameter identification of modified bouc-wen model

By determining the parameters of the modified Bouc-Wen model, the MR damper force can be calculated for any desired inputs. Determination of the parameters of this model is defined as an optimization problem to achieve the optimum values to well-matched the response of the experimental model with a numerical one. In this paper, to investigate the superiority of the proposed OBLCSS algorithm over its constitutive (CSS), a numerical example is selected to parameter identification of the modified Bouc-Wen model. The parameters which are defined as design variables are k_1, k_0, c_{0a}, c_{0b}, δ_{a}, δ_{b}, c_{1a}, c_{1b}, ρ, γ, A, η and n'. These parameters will be identified using proposed OBLCSS and minimizing the Eq. (34) as a cost function. The domain limits of the design variables defined as Eq. (35) are considered as 50% of realistic parameters.

The experimental data required for parameter identification are collected through modeling the 11-story building (Azar *et al*. 2011, Rahbari *et al*. 2013) equipped with 1000 kN MR damper with the realistic parameters listed in Table 3. The input applied voltage, displacement and force of the MR damper for the modified Bouc–Wen model are determined from the mentioned case study subjected to El-Centro 1940 NS earthquake. The input voltage is generated using the fuzzy logic controller (FLC) with a maximum voltage of 10V. The parameters of the FLC such as membership functions and rule bases are selected from paper (Yan and Zhou 2006). As a brief, experimental data obtained by modeling the 11-story building used for parameter identification of the modified Bouc-Wen model are demonstrated in Fig. 3 in the cases of

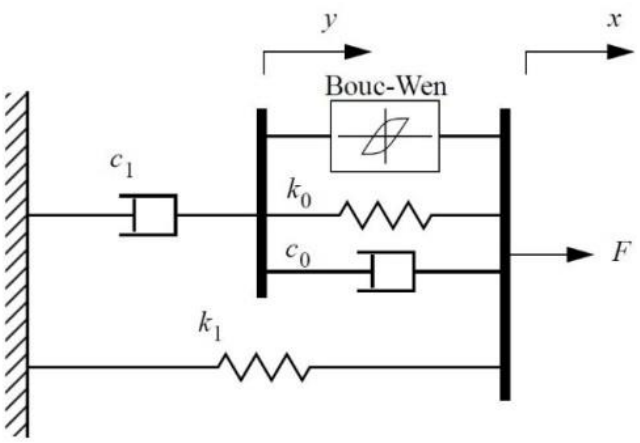

Fig. 2 Modified Bouc-Wen model of MR damper

Table 3 Parameters of Bouc–Wen models for a 1000kN MR damper

Parameter	Unit	Modified Bouc-Wen Model (13 Parameters)
x_0	M	-
k_1	kN/m	0.0097
k_0	kN/m	0.002
c_{0a}	kN.s/m	110
c_{0b}	kN.s/m/V	114.3
δ_a	kN/m	46.2
δ_b	kN/m/V	41.2
c_{1a}	kN.s/m	8359.2
c_{1b}	kN.s/m/V	7482.9
ρ	m^{-2}	164
γ	m^{-2}	164
A	-	1107.2
η	s^{-1}	100
n'	-	2

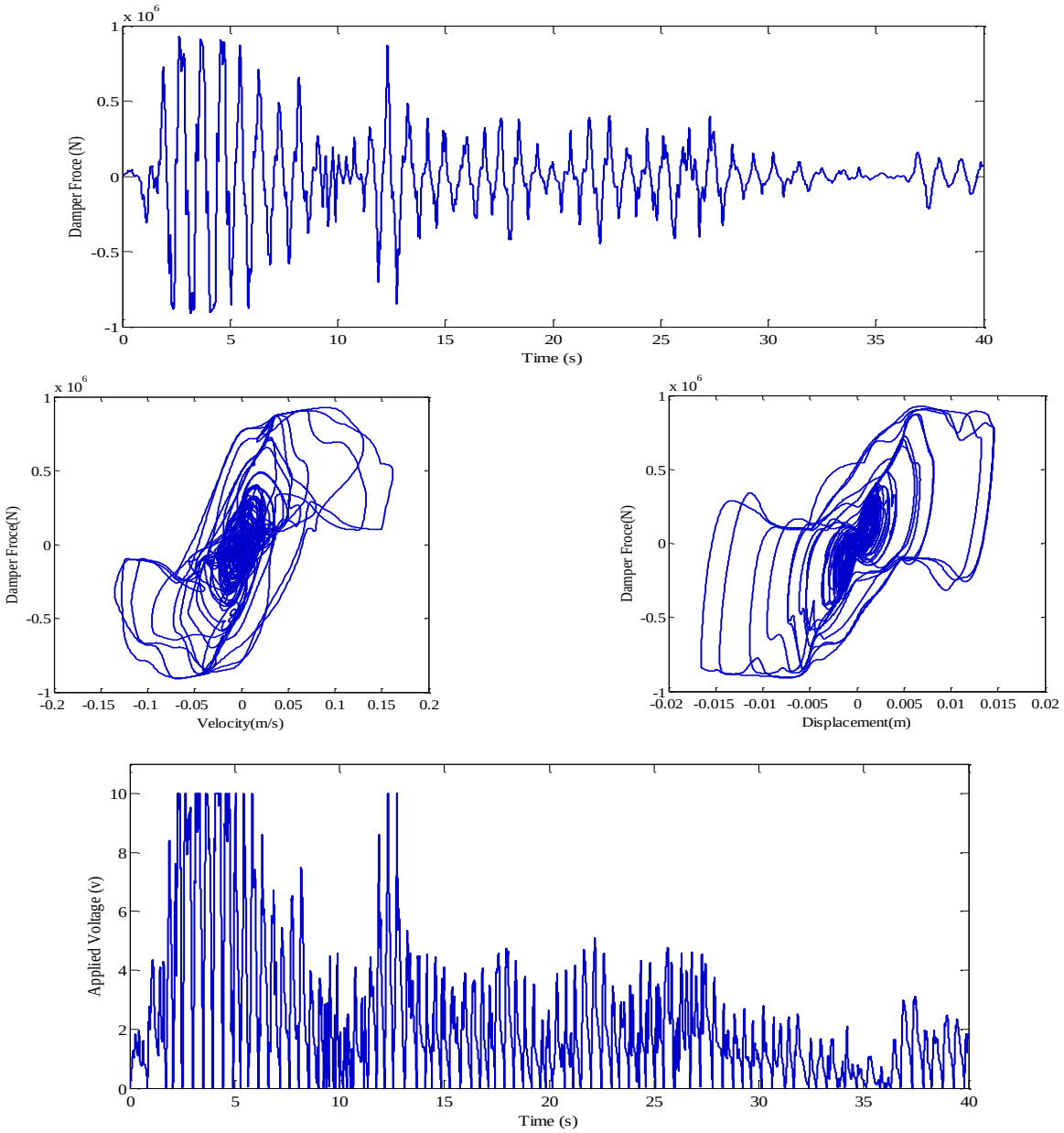

Fig. 3 Numerically generated experimental data for the modified Bouc-Wen model of 1000 kN MR damper under the fuzzy logic controller simulation

using FLC.

6.2 Case 2: sensitivity analysis of MR damper force

The performance of the semi-active controlled structure is influenced by the force produced by the MR damper. Due to the existence of various uncertainties in the MR damper and the Bouc-Wen model parameters, the reliability analysis of the predicted force is necessary. Failure to exceed the expected capacity in the damping force is defined as the failure limit state. For this purpose, a limit state function is defined based on the force of the MR damper in different expected capacities. As mentioned, the parameters of the modified Bouc-Wen model are assumed as random variables. The random variables have normal probability distributions, and the standard deviation is %10 of the mean value. The reliability of the produced force by the MR damper is investigated in terms of expected capacity. To this end, the limit state function is defined a

$$g(X) = F_{max} - F_{exp} = F_{max} - cr.F_{nom} \quad (36)$$

that F_{max} is the maximum force created by the damper, F_{exp} is the expected force of MR damper, F_{nom} is the nominal capacity of the damper, which in this study is 1000 kN, and cr is the nominal expected capacity ratio of the damper in percentage terms. The reliability of MR damper will be studied for the expected capacity ratio of 80% and 90%. The i-HL-RF algorithm is used for reliability analysis that is Implemented in MATLAB. Also, the importance vector (α) is used to identify the most important parameters in the Bouc-Wen model. The experimental data required for damper force prediction is collected through modelling the

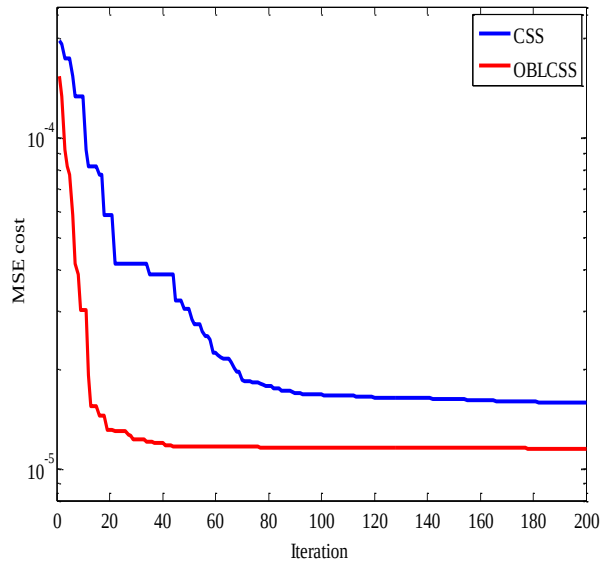

Fig. 4 Convergence of MSE versus of iteration for both methods in case of FLC signals

Table 4 Identified parameters set for modified Bouc-Wen with FLC signal

Parameter	Unit	Identified parameters for modified Bouc-Wen model			
		CSS		OBLCSS	
		Value	Error%	Value	Error%
x_0	M	-	-	-	-
k_1	kN/m	0.0094634	2.44	0.0095126	1.93
k_0	kN/m	0.0020898	4.49	0.0020138	0.69
c_{0a}	kN.s/m	123.16	11.96	113.16	2.87
c_{0b}	kN.s/m/V	117.71	2.98	117.60	2.88
δ_a	kN/m	49.381	6.88	46.157	0.09
δ_b	kN/m/V	45.019	9.27	41.502	0.73
c_{1a}	kN.s/m	8170.70	2.26	8214.80	1.73
c_{1b}	kN.s/m/V	7426.60	0.75	7563.30	1.07
ρ	m^{-2}	170.87	4.19	165.19	0.72
γ	m^{-2}	164.79	0.48	165.1	0.67
A	-	1013.83	8.43	1101.7	0.49
η	s^{-1}	100.282	0.282	100.82	0.82
n'	-	2.1197	5.985	2.0024	0.12
MSE	-	1.5805e-005		1.1493e-005	

11-story building equipped with three 1000 kN MR dampers installed in the first three stories with the mean value of realistic parameters listed in Table 3. The input applied voltage (which is generated using FLC), displacement, and force of the MR damper are determined using the numerically obtained values subjected to El-Centro 1940 NS earthquake as depicted in Fig. 4.

6.3 Case 3: parameter identification of simplified bouc-wen model

In order to simplify the MR damper model, it is possible to eliminate the unimportant parameters considering the results of the importance vector on the MR damper force reliability. The elimination of trivial parameters accelerates

Table 5 Importance of modified Bouc-Wen model in reliability of damper force

	Importance vector (α)	
Standard deviation	10% of mean value	
Capacity	80%	90%
Parameter		
k_1	-0.0000016	-0.0000015
k_0	-0.000000015	0.000000014
c_{0a}	-0.0099793	-0.0087732
c_{0b}	-0.1017049	-0.0894324
δ_a	-0.0887255	-0.0834506
δ_b	-0.7761503	-0.7301616
c_{1a}	-0.0013622	-0.0013785
c_{1b}	-0.0118687	-0.0120133
ρ	0.1811394	0.1959117
γ	0.1811394	0.1959117
A	-0.3916288	-0.3982871
η	-0.0399162	-0.0398650
n'	0.3981743	0.4633509

the solution of the differential equations of the Bouc-Wen model. Thus, according to *Case 2* in section (6-2), after determining the importance vector for Bouc-Wen model parameters in the reliability of the expected force of damper, the low effect parameters of the Bouc-Wen model are omitted from the damper model, and a simplified model is proposed. In order to evaluate the accuracy of this presented model, the parameters of this model are identified using the OBLCSS algorithm. To this end, a parameter identification problem is solved to find the best fit in the experimental and numerical responses. The experimental data used for this problem are selected according to Fig. 3.

In this paper, the Bouc-Wen model of MR damper is simulated in Simulink toolbox of MATLAB software. Also, the FORM algorithm and OBLCSS optimization algorithm are coded in MATLAB to model sensitivity analysis and parameter identification, respectively.

7. Results and discussion

7.1 Case 1

The proposed OBLCSS algorithm, as well as CSS, is used to find the optimum values for the 13 parameters of the modified Bouc-Wen model of the MR damper in the case of using FLC. The convergence history of MSE for both methods is shown in Fig. 4 for the FLC signal case in the logarithmic scale. The obtained values for these parameters and also the outcome of the MSE criterion from the aforementioned optimization algorithms are tabulated in Table 4. As can be seen, although both optimization methods could find a good estimation of optimal solutions for the parameters of the modified Bouc–Wen model, the OBLCSS shows significantly superior performance. For concise description, in the case of using FLC, the OBLCSS algorithm has relatively 27.28% (((1.5805e-05)-(1.1493e-05))*100/(1.5805e-05)=27.28%) MSE less than the CSS algorithm.

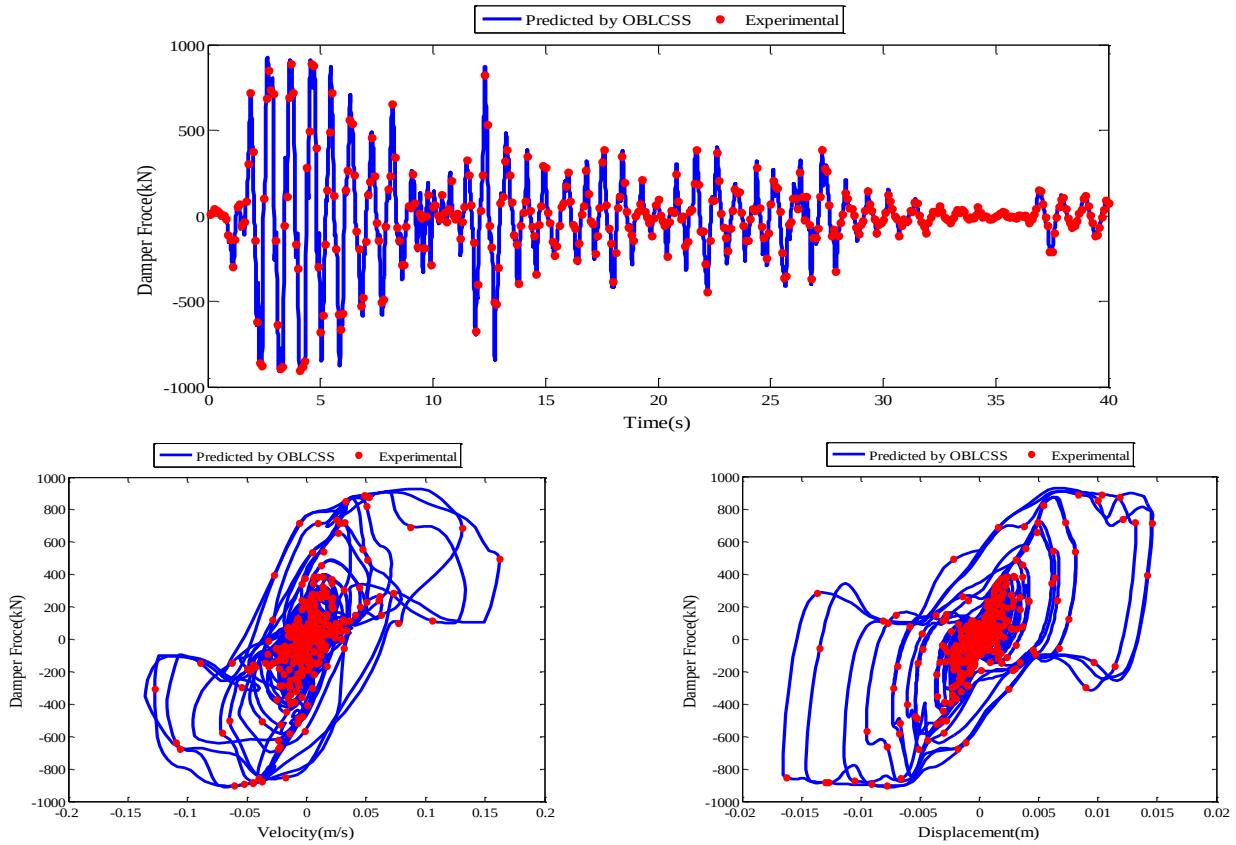

Fig. 5 Comparison of experimental and predicted damper responses with modified Bouc–Wen model with FLC signal

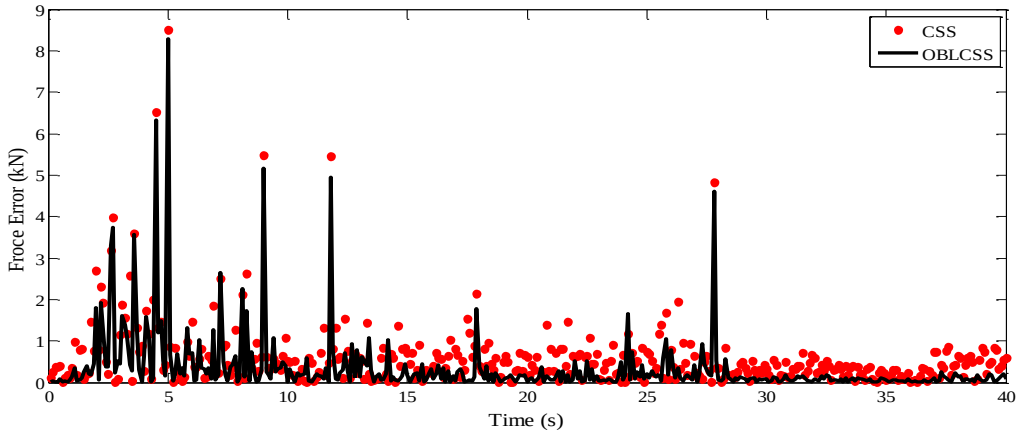

Fig. 6 Comparison between damper force error with FLC signal

To investigate the superiority of the proposed OBLCSS algorithm in finding the parameters of the modified Bouc-Wen model of the MR damper, one can compare the deviation of obtained results for the 13 parameters with its realistic ones. As seen from Table 4, the error is between 0.28% and 11.96% for the CSS algorithm and 0.09% and 2.88% For the proposed OBLCSS which shows great robustness and accuracy of the OBLCSS over its constitutive. The similarity of experimentally responses and numerical responses obtained from the identified parameters by the proposed OBLCSS method is shown in Fig. 5 for the case of FLC signals. Also, time history of the error occurred in the prediction of damper force by the identified parameters, by both methods, is shown in Fig. 6. As can be seen, in comparison with the CSS algorithm, the proposed OBLCSS method has lower error in the prediction of damper's response.

7.2 Case 2

The performance of the semi-active controlled structure is influenced by the generated force of MR damper. In the analytical case, this force is predicted by the Bouc-Wen model. Therefore, it is necessary to implement the reliability of the expected force produced by MR damper based on the uncertainty of Bouc-Wen model parameters.

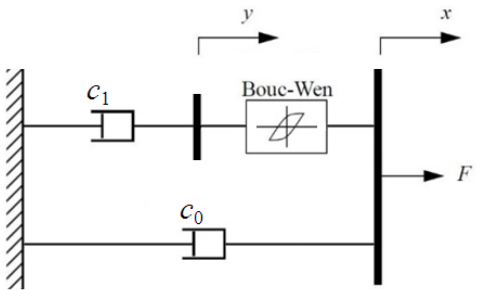

Fig. 7 Proposed simplified Bouc-Wen model

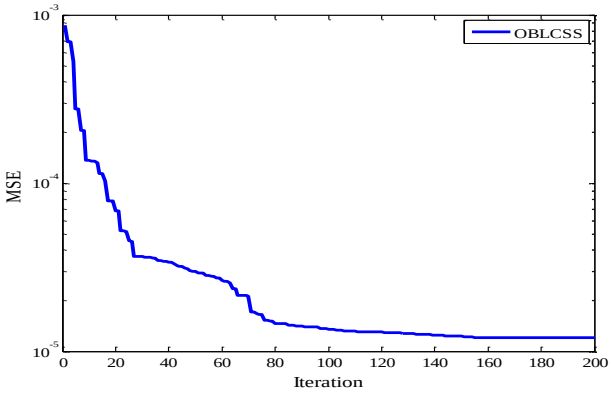

Fig. 8 Convergence history of MSE for proposed simplified Bouc-Wen using OBLCSS

Table 6 Identified parameters set for modified Bouc-Wen with FLC signal

Parameter	Unit	Identified parameters for modified Bouc-Wen model
		OBLCSS
		Value
c_{0a}	kN.s/m	96.627
c_{0b}	kN.s/m/V	119.25
δ_a	kN/m	59.158
δ_b	kN/m/V	52.293
c_{1a}	kN.s/m	8123.3
c_{1b}	kN.s/m/V	7426.7
ρ	m^{-2}	208.19
γ	m^{-2}	208.19
A	-	844.79
η	s^{-1}	100.42
n'	-	2.0083
MSE	-	1.2006e-005

Table 5 shows the importance vector for Bouc-Wen model parameters of the MR damper. Each array of this vector points out the importance of random variables in the reliability of the damper performance. The parameters with positive signs indicate load variables, and as they increase, the system comes close to the failure. On the other hand, negative parameters represent the resistance variables and the more they decrease, the more the system approaches to failure. As can be seen, the importance of the Bouc-Wen model parameters for different levels of MR damper performance is relatively similar.

It can be concluded from the obtained results that by omitting the parameters with a low importance coefficient, there will be considerable decrease in computational costs on optimization and parameter identification problems. In other words, the parameters with high effect on the performance of the MR damper are δ_b, A, and n'. Also, the parameters which almost do not have any effect on the performance of the MR damper are k_0 and k_1.

7.3 Case 3

Due to low importance of the parameters k_0 and k_1 in the Bouc-Wen model behavior, these elements can be eliminated from the physical model. Thus, in this paper a simplified model is proposed for the Bouc-Wen model of MR dampers. The proposed simplified Bouc-Wen model is shown in Fig. 7 schematically. In this case, the force of damper can be calculated as follows

$$F = \delta z + c_0\dot{x} = c_1\dot{y} + c_0\dot{x} \tag{37}$$

In this case, hysteretic displacement z is given by

$$\dot{z} = -\gamma|\dot{x}-\dot{y}|z|z|^{n'-1} - \rho(\dot{x}-\dot{y})|z|^{n'} + A(\dot{x}-\dot{y}) \tag{38}$$

in which, $\dot{y}$ is defined by the following equation according to Fig. 11

$$\dot{y} = \frac{1}{c_1}\delta z \tag{39}$$

where, δ, c_0, and c_1 are defined as a linear function of the efficient voltage u according to Eqs. (30) - (32). According to Eq. (39), the value of $\dot{y}$ can be calculated directly and without solving a differential equation, which makes it easy to solve the Bouc-Wen equations and calculate the MR damper force

For this case, the parameters defined as design variables are c_{0a}, c_{0b}, δ_a, δ_b, c_{1a}, c_{1b}, ρ, γ, A, η, n'. They will be identified using proposed OBLCSS and minimizing the Eq. (34) as a cost function.

The proposed OBLCSS algorithm is used for finding the optimum values for the 11 parameters of the simplified Bouc-Wen model of the MR damper in the case of using FLC input voltage. The convergence history of MSE for the OBLCSS method has been shown in Fig. 8 for the case FLC signal in the logarithmic scale. The obtained values for these parameters and also the results of the MSE criterion from the aforementioned optimization algorithms are tabulated in Table. 6 considering the FLC signal. For a concise description, by using the OBLCSS algorithm in the case of the FLC signal, the MSE of identified parameters for the proposed simplified Bouc-Wen model is 5.23e-5 Which shows that the proposed simplified Bouc-Wen model has a good ability to predict the behavior of the damper.

The matching of experimentally responses and numerical responses obtained from the identified parameters by the proposed OBLCSS method is shown in Fig. 9 for the case of the FLC signal. Also, the time history of the error that occurred in the prediction of the damper force by the identified parameters of the simplified model by the OBLCSS algorithm is shown in Fig. 10. As can be

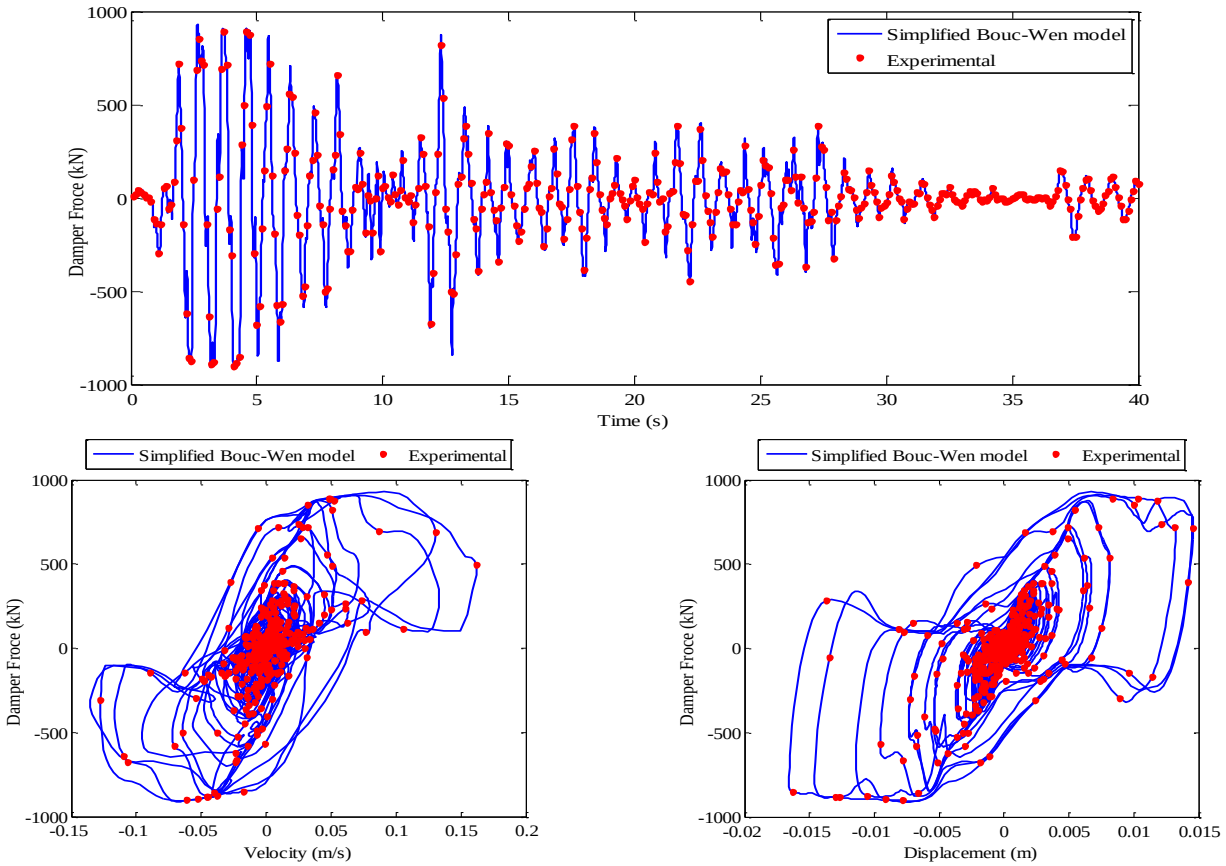

Fig. 9 Comparison between experimental and predicted damper responses with propose simplified Bouc-Wen model with FLC signal

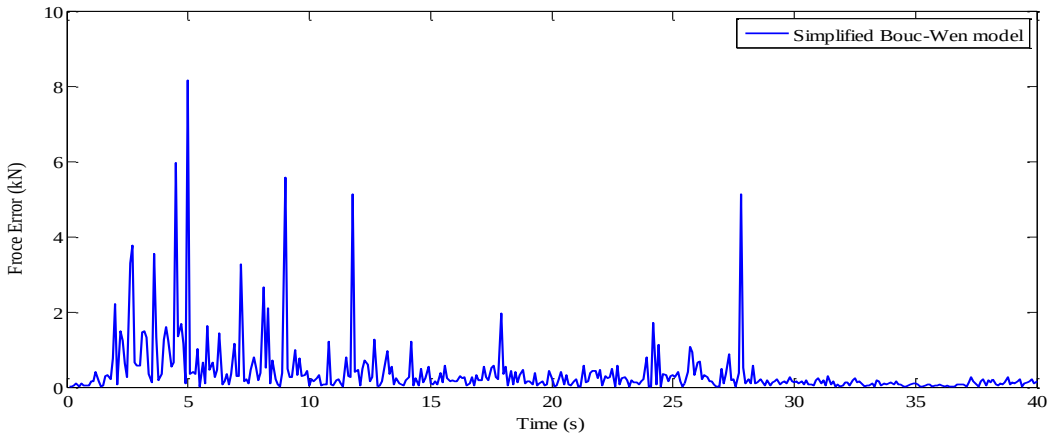

Fig.10 Time history of damper force error for proposed simplified model

seen in Figs. 9 and 10, in comparison with experimentally and numerically responses, the proposed model has a lower error in prediction of the response of the MR damper.

8. Conclusions

In this paper, a new improved method is introduced for solving the parameter identification problems in highly nonlinear systems. The OBLCSS algorithm is used opposition based learning of particles to enhance the exploration property of charged system search (CSS) to achieve better searching procedure. The initially selected particles evaluated and sorted based on the cost function. Then, some of the current solutions are replaced with opposition solutions to enhance the exploration all of the search domain. To evaluate the performance and efficiency of the proposed method, a parameter identification problem is used for the modified Bouc-Wen model of MR damper concerning the applied voltage signal. The results show the high ability of the OBLCSS method to solve nonlinear problems toward its components. The Bouc-Wen model of

MR damper consists of parameters, that each of them has a certain importance in the damper responses. By using the α importance vector in the first-order reliability analysis, the importance of the Bouc-Wen model parameters can be calculated. Therefore, based on the sensitivity analysis on the damper force, and with the elimination of low importance parameters, a simplified model is proposed for simulation of the MR damper. Then, the proposed simplified model parameters are identified using the proposed OBLCSS algorithm. The results show that the proposed model has the proper ability to predict damper responses, and the performance of it is reliable in predicting of MR damper force.

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