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Reliability assessment of semi-active control of structures with MR damper

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Abstract. Structural control systems have uncertainties in their structural parameters and control devices which by using reliability analysis, uncertainty can be modeled. In this paper, reliability of controlled structures equipped with semi-active Magneto-Rheological (MR) dampers is investigated. For this purpose, at first, the effect of the structural parameters and damper parameters on the reliability of the seismic responses are evaluated. Then, the reliability of MR damper force is considered for expected levels of performance. For sensitivity analysis of the parameters exist in Bouc- Wen model for predicting the damper force, the importance vector is utilized. The improved first-order reliability method (FORM), is used to reliability analysis. As a case study, an 11-story shear building equipped with 3 MR dampers is selected and numerically obtained experimental data of a 1000 kN MR damper is assumed to study the reliability of the MR damper performance for expected levels. The results show that the standard deviation of random variables affects structural reliability as an uncertainty factor. Thus, the effect of uncertainty existed in the structural model parameters on the reliability of the structure is more than the uncertainty in the damper parameters. Also, the reliability analysis of the MR damper performance show that to achieve the highest levels of nominal capacity of the damper, the probability of failure is greatly increased. Furthermore, by using sensitivity analysis, the Bouc-Wen model parameters which have great importance in predicting damper force can be identified.

Keywords: semi-active control; reliability analysis; uncertainty; MR damper

1. Introduction

Structural control is a method used to reduce the response of structures under excitations such as earthquakes and winds which is generally classified into three categories of passive control, active control and semi-active control (Soong and Spencer 2002). Among them, semi-active control systems have attract considerable attention because of their compatibly with the environmental conditions and also, their reliably due to applying a small amount of energy on the structure.

Magneto-Rheological (MR) dampers are semi-active control devices that can become controllable dampers by using MR fluids. MR fluids are the magnetic analogs of electro-rheological fluids and typically consist of micron-sized, magnetically polarizable particles dispersed in a carrier medium such as mineral or silicone oil. When a magnetic field is applied to the fluids, particle chains form, and the fluid becomes a semi-solid and exhibits visco-plastic behavior. Transition to rheological equilibrium can be achieved in a few milliseconds, allowing construction of devices with high bandwidth (Yang *et al*. 2002).

There are different models exist to portray real 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 real MR damper responses. Some studies have investigated the use of MR dampers in reducing the seismic response of structures (Dyke *et al*. 1996, Mohajer Rahbari *et al*. 2013, Zafarani and Halabian 2018). The capability of generating force by MR damper is intensively depends on the applied voltage. Several control algorithms such as clipped optimal control (Dyke and Spencer 1996), fuzzy logic control (Choi *et al*. 2004), simple adaptive control (Bitaraf *et al*. 2010) and sliding mode (Baradaran-nia *et al*. 2012) are proposed to calculate the command voltage.

In real engineering systems, there are various uncertainties in all stages of design, construction, and maintenance of structures. Analytical modeling, poor knowledge of structural model and human factors are some causes of uncertainty. These uncertainties can be examined based on probabilistic models, and reliability analysis can assess safety levels using the probability of failure for engineering problems (Ditlevsen 1982). In general, for estimating the probability of failure based on probabilistic model and reliability analysis in the structure, various analytical methods such as first-order reliability method (FORM) (Liu and Der Kiureghian 1991), second-order reliability method (SORM) (Kiureghian and Stefano 1991), simulation methods (Azar *et al*. 2015, Rashki *et al*. 2012), response surfaces (Goswami *et al*. 2016, Hadidi *et al*. 2017) and neural networks (Vazirizade *et al*. 2017) are used. In the meantime, the first-order reliability method is widely used in reliability analysis of engineering systems due to its

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simplicity and efficiency. The main idea of this method is to solve the computational problems, and to simplify the integral. In this method, the limit state function is linearized using Taylor's first-order expansion (Hao *et al*. 2013).

Due to the uncertainty in structural control systems, it is possible to investigate the probability of their instability (Spencer *et al*. 1992). Considering the uncertainties of the structural parameters, optimal probabilistic-based optimal control methods are used to increase the safety and reliability of the structure (Spencer *et al*. 1994). By using reliability analysis, the stability of structural control systems can be studied (Battaini *et al*. 1998, Breitung *et al*. 1998) and reliability can become a criterion for the effectiveness of structural control methods in uncertain systems (Venini and Mariani 1999). 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.

In this paper, by accepting the existence of uncertainty in structural parameters, the reliability of the uncontrolled and controlled structures with the semi-active MR dampers is evaluated using first-order reliability method (FORM). For this purpose, the effect of uncertainty on structural parameters and the Bouc-Wen model of MR damper parameters, are investigated. Given the fact that, the performance of the semi-active control system with the MR damper is influenced by the produced force of the damper, here, the reliability of the damper performance is evaluated with attention to uncertainty in the parameters of the Bouc-Wen model. Also, the sensitivity analysis is used to illustrate the importance of each parameter of Bouc-Wen model in damper behavior.

The structure of the paper is as follows: firstly, the FORM is explained in detail to calculate reliability index. Then, the formulation of mathematical model of MR dampers is briefly described. In section 4, numerically example of reliability analysis of semi-active control of structure equipped with MR damper using FORM is presented. In section 5, the obtained results will be discussed and finally, the concluding remarks are detailed in section 6.

2. Statement of reliability in structures

Reliability is defined as the probability of a limit state function $g(X)$ greater than zero, $P\{g(X)>0\}$ (Du 2005). In other words, reliability equals to the probability of random variables X, falling into the safe region, defined by $g(X)>0$. The probability of failure is defined as the probability $P\{g(X)<0\}$, and equals to the probability of random variables X, existed in the fracture region defined by $g(X)<0$. If the probability distribution function of the random variables X is $f_x(x)$, then the probability of failure can be calculated using the following integral (Du 2005)

$$p_f = P\{g(X) < 0\} = \int_{g(X)<0} f_x(X)dx \tag{1}$$

and reliability can be calculated as follows

$$Reliability = 1 - p_f = P\{g(X) > 0\} = \int_{g(X)>0} f_x(X)dx \tag{2}$$

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

$$P_f = \int_{g(X)\leq 0} \dots \int f_X(x)dX \approx \Phi(-\beta) \tag{3}$$

where P_f is failure probability, $g(X)$ is the limit state function which separates design regions into safe and failure as $g(X) > 0$ and $g(X) < 0$ denotes safe and failure regions, respectively, by using the basic random variables X. In many engineering problems, the limit state function g(X) is a complex and implicit function.

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

$$p_f = P\{g(U) < 0\} = \int_{g(U)<0} \phi_u(u)du \tag{4}$$

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

Also, the FORM analysis uses a linear approximation method (Taylor's first expansion) as follows (Der Kiureghian 2005)

$$g(U) \approx g(u^*) + \nabla g(u^*)(U - u^*)^T \tag{5}$$

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

If all the random variables are transformed into statistically independent standard normal ones and simultaneously the limit state function $g(\mathbf{u})$ is linear, then the reliability index (β), will have the shortest distance in U space from the origin to the failure surface given by $g(\mathbf{u}) = 0$. The failure probability P_f is then calculated by

$$P_f = \Phi(-\beta) = 1 - \Phi(\beta) \tag{6}$$

where $\Phi(\beta) = \int_{-\infty}^{\beta} \frac{1}{\sqrt{2\pi}} exp\left(-\frac{1}{2}u^2\right) du.$

Thus, a failure point on the limit state surface with minimum distance to origin should be ascertained to calculate the reliability index. Therefore, this problem may be described by (Lee *et al*. 2002)

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

subjected to $g(\mathbf{u}) = 0$.

The main effort in the FORM is to search the maximum probable point (MPP, i.e., U^*), which is a point located closest to the origin transformed into normal standard space**.** This distance is defined as the reliability index. Consequently**,** $\beta = \|U^*\|$ (Lee *et al*. 2002). According to the FORM, Fig. 1 shows the reliability index schematically.

Hasofer and Lind proposed an iterative method for finding the most probable failure point (MPP) which is a point on the failure surface with minimum distance from origin in the standard normal space (Hasofer and Lind 1974). Hasofer and Lind used this method for variables with normal distribution, that later Rackwitz and Flessler

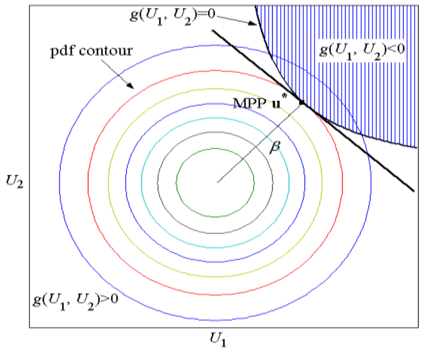


Fig. 1 Reliability index in FORM

(Rackwitz and Flessler 1978) extended this algorithm for random variables with any desired distribution; That's why, 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. Santosh *et al*. (2006) improved the HL-RF method based on Armijo rule. Recently for searching the MPP, there are various FORM algorithms such as finite-step length (Gong and Yi 2011), non-gradient-based algorithm (Gong *et al*. 2014), conjugate gradient (Mohammadi Farsani and Keshtegar 2015), chaotic conjugate search direction (Keshtegar 2016) and stability transformation method (Meng *et al*. 2017). The modified HL-RF methods which are formulated by using the steepest descent search direction are applied to find MPP.

2.1 Modified HL-RF method

The iterative equation of FORM can be described by the following relation

$$U_{k+1} = U_k + s_k d_k \tag{7}$$

where s_k is step size. In HL-RF method, the step size is considered as 1. d_k is search direction vector, which can be computed as follows (Makhduomi *et al*. 2017)

$$d_k = \frac{\nabla^T g(U_k) U_k - g(U_k)}{\nabla^T g(U_k) \nabla g(U_k)} \nabla g(U_k) - U_k \tag{8}$$

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

$$\nabla g(U_k) = \left\{\frac{\partial g}{\partial u_1}, \frac{\partial g}{\partial u_2}, \dots, \frac{\partial g}{\partial u_n}\right\} = \left\{\sigma_1 \frac{\partial g}{\partial x_1}, \sigma_2 \frac{\partial g}{\partial x_2}, \dots, \sigma_n \frac{\partial g}{\partial x_n}\right\} \tag{9}$$

According to Eq. (7), 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. (7), where α_k is the adjusted step size. In this study, the step size of MHL-RF method in Eq. (8) 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

$$m(U_k) = \left\| U_k - \frac{\nabla^T g(U_k) U_k}{\nabla^T g(U_k) \nabla g(U_k)} \nabla g(U_k) \right\|^2 + \frac{g(U_k)^2}{g(U_0)^2} \tag{10}$$

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 second term of this merit function is a positive dimensionless value that should be decreased for sequence iterations of MHL-RF to satisfy the constraint of the probabilistic optimization model as $g(U_k)^2 > g(U_{k-1})^2$. If $m(U_k)$ equals to zero, then a fixed point will be obtained or the MHL-RF will be converged. Thus, $g(U_k) = 0$ and $U_k - (\nabla^T g(U_k) U_k / \nabla^T g(U_k) \nabla g(U_k)) \nabla g(U_k)$, when $m(U_k) = 0$; it is assumed that for $k \to \infty$ then, $m(U_k) = 0$. This means that $s_k d_k \approx 0$; consequently, $U_{k+1} \approx U_k$. Therefore, U_{k+1} is a fixed point and the proposed method is converged. It is assumed that $m(U_k) < m(U_{k-1})$ thus $m(U_k) = 0$ for $k \to \infty$. As a result, the step size can be calculated as follows (Makhduomi *et al*. 2017)

$$s_{k+1} = \begin{cases} \frac{m(U_{k-1})}{m(U_k)} s_k & m(U_k) \geq m(U_{k-1}) \\ s_k & m(U_k) < m(U_{k-1}) \end{cases} \tag{11}$$

in which the initial step size is considered as 1.5 (i.e., $s_0 = 1.5$). According to the adaptive step size in Eq. (11), it can be concluded that $s_{k+1} \leq s_k$.

In this method, similar to other optimization algorithms, the convergence criterion is used. First, the design point should be placed close to the limit state surface (Du 2005)

$$\left|\frac{g(U^*)}{g_0}\right| \leq e_1 \tag{12}$$

that, g_0 is a scale factor, usually the initial step value of the limit state function, and e_1 is a threshold, that is assumed to be about 0.001. Secondly, the design point should be the closest point to the origin on the limit state surface. For this case, this should be the gradient projection point. For example, the gradient vector of the limit state function must has to pass the origin. This convergence criterion is defined as

$$\|U^* - (\alpha^T U^*)\alpha\| \leq e_2 \tag{13}$$

that, e_2 is a threshold of about 0.001. Since in the second criterion, the deviation between the two vectors is measured as a distance, the more the distance from the origin, the more stringent the convergence criterion is. This is a problem solved by a scaling as follows

$$\left\| \frac{U^*}{\|U^*\|} - \left(\alpha^T \frac{U^*}{\|U^*\|}\right) \alpha \right\| \leq e_2 \tag{14}$$

since α is a unit vector, this criterion is expressed as

$$1 - \frac{\alpha^T U^*}{\|U^*\|} \leq e_2 \tag{15}$$

In FORM analysis, it is common to replace the gradient vector by its negative and normalized version, called the importance vector

$$\alpha = -\frac{\nabla g}{\|\nabla g\|} \tag{16}$$

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

$$\alpha = \frac{\partial \beta}{\partial U^*} \tag{17}$$

Importance vectors are intended to reveal the relative importance of different parameters. This is the primary

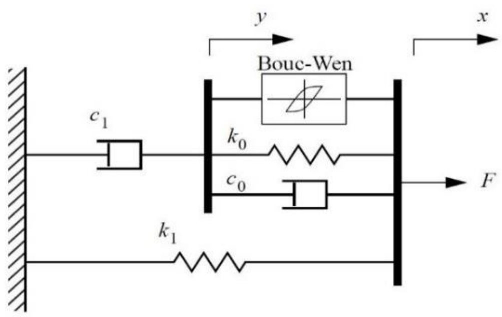


Fig. 2 Modified Bouc-Wen model of MR damper

importance vector for the random variables in the standard normal space. The higher absolute value of α is the more important random variable. Furthermore, the sign of the components of the alpha-vector tells whether the random variable is a "load variable" or a "resistance variable".

3. Semi-active MR damper

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. The most reputable model that suitably predicts their behavior and has been used to simulate MR dampers semi-active control system is smooth Bouc-Wen model (Spencer Jr. *et al*. 1997, Dyke *et al*. 1996).

3.1 Modified Bouc-Wen model

The modified version of phenomenological Bouc-Wen model is illustrated in Fig. 2 for which non-linear force generated by the MR damper is calculated by Eq. (18) (Spencer *et al*. 1997).

$$\begin{aligned} F &= \alpha z + k_0(x-y) + c_0(\dot{x}-\dot{y}) + k_1(x-x_0) \\ &= c_1\dot{y} + k_1(x-x_0) \end{aligned} \tag{18}$$

in this case, hysteretic displacement *z* is given by

$$\dot{z} = -\gamma|\dot{x}-\dot{y}|z|z|^{n'-1} - \beta(\dot{x}-\dot{y})|z|^{n'} + A(\dot{x}-\dot{y}) \tag{19}$$

in which, $\dot{y}$ is defined by the following Eq. (20) according to Fig. 2

$$\dot{y} = \frac{1}{(c_0+c_1)}\{\alpha z + c_0\dot{x} + k_0(x-y)\} \tag{20}$$

To validate the model for fluctuating magnetic fields, α, c_0 and c_1 parameters in Eqs. (18)-(20) are defined as a linear function of the efficient voltage u as given by Eqs. (21)-(23)

$$\alpha(u) = \alpha_{\mathrm{a}} + \alpha_{\mathrm{b}}u \tag{21}$$

$$c_0(u) = \mathrm{c}_{0\mathrm{a}} + \mathrm{c}_{0\mathrm{b}}u \tag{22}$$

$$k_0(u) = \mathrm{k}_{0\mathrm{a}} + \mathrm{k}_{0\mathrm{b}}u \tag{23}$$

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

$$\dot{u} = -\eta(u-v) \tag{24}$$

in Eq. (24), v is the voltage applied to the current driver.

4. Numerical study

4.1 Example 1

Uncertainty in structures equipped with semi-active control using MR damper can be seen either in structural parameters such as mass, stiffness and damping or in the parameters of the Bouc-Wen model of MR damper. Hence, the reliability analysis of the controlled structure by the MR damper is performed in two cases:

Case 1: Structural model parameters such as mass, stiffness and damping of stories are assumed as random variables. Also, the MR damper behavior is selected as deterministic in which the parameters of the Bouc-Wen model are assumed to be constant.

Case 2: In this case, uncertainty is considered in all parameters such as structural and MR damper parameters so that they can be chosen as random variables.

To evaluate the reliability of controlled structures with MR damper, an 11 story shear frame structural model is used (Azar *et al*. 2011). Specifications of the mass and stiffness of this structural model are shown in Table 1. For the deterministic parameters, the mean value is used and for random variables, the mean value and standard deviation with lognormal distribution are assumed. The damping of this model is determined by the Rayleigh method as follow

$$C = a_0M + a_1K \tag{25}$$

and

$$a_0 = \xi\frac{2\omega_1\omega_2}{\omega_1+\omega_2}, \quad a_1 = \xi\frac{2}{\omega_1+\omega_2} \tag{26}$$

in which ω_1 and ω_2 are frequency of first and second modes, respectively, and ξ is damping ratio that is taken 5% for first two modes. According to Rayleigh method, the damping of the structure is proportional to the mass and the stiffness, and as a result, the uncertainty in the damping of the structure is indirectly considered.

For semi-active control of the structure, three 1000 kN MR dampers are used, that are installed in first three story of structure and simulated with modified Bouc-Wen model. The parameters of the modified Bouc-Wen model are listed in Table 2. The input voltage is generated using both fuzzy logic controller (FLC) with maximum voltage of 10V. The parameters of the FLC such as membership functions and rule bases are selected from paper (Yan and Zhou 2006). The seismic structural responses are determined subjected to El-Centro, 1940-NS earthquake with PGA 0.349 g using dynamic time history analysis. In this paper, the seismic analysis of the controlled structures was simulated in Simulink toolbox of MATLAB software.

The reliability index (β) is determined for both cases. Given the importance of the inter-story drift in structural responses, the limit state function is defined based on the maximum drift (Guo *et al*. 2002)

$$g(X) = \mathrm{Drift}_{all} - \mathrm{Drift}_{\max} \tag{27}$$

Table 1 An 11 story model structural parameters

Story	Mass (ton)		Stiffness (kN/m) × 10^3	
	Mean	Standard deviation (10% of mean)	Mean	Standard deviation (10% of mean)
1	215	21.5	468	46.8
2	201	20.1	476	47.6
3	201	20.1	468	46.8
4	200	20.0	450	45.0
5	201	20.1	450	45.0
6	201	20.1	450	45.0
7	201	20.1	450	45.0
8	203	20.3	437	43.7
9	203	20.3	437	43.7
10	203	20.3	437	43.7
11	176	17.6	312	31.2

in which Drift_{all} and $\mathrm{Drift}_{\max}$ are allowable interstory drift and maximum drift response of structure respectively. Also, the FORM algorithm is coded in MATLAB using the convergence criterion as 0.0001.

4.2 Example 2

The performance of a 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. For this purpose, a limit state function is used based on the force of the damper in different expected capacities. So, the damping force is calculated based on the input signal with experimental data of MR damper, and the reliability of the Bouc-Wen model is determined for different levels of the damper's expected capacity, based on the identified parameters.

As mentioned, the parameters of the modified Bouc-Wen model are assumed as random variables. The reliability of the force produced by the MR damper is investigated in terms of expected capacity. To this end, the limit state function is defined as

$$g(X) = F_{exp} - F_{max} = cr.F_{nom} - F_{max} \tag{28}$$

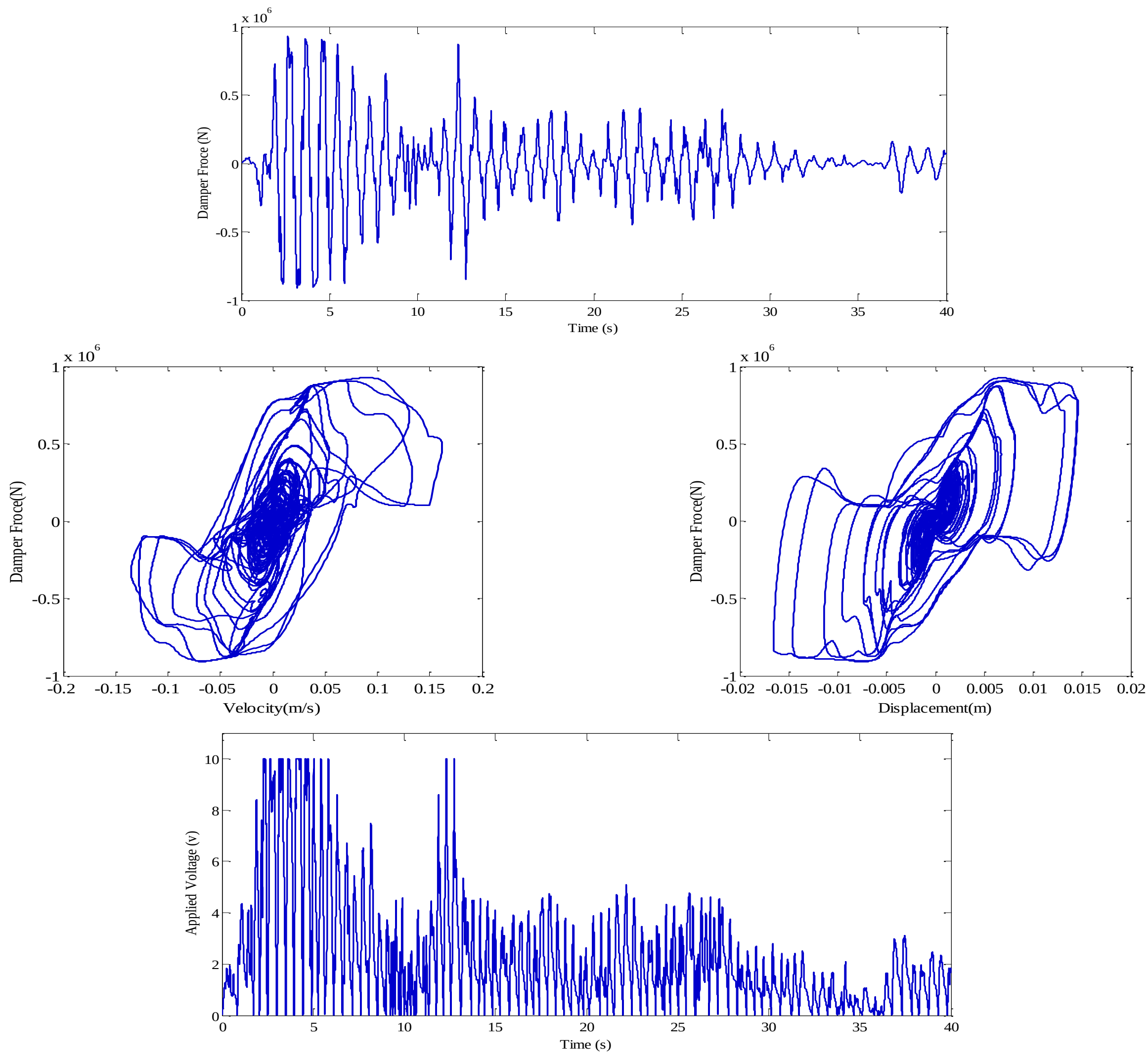


Fig. 3 Numerically obtained experimental data for the modified Bouc-Wen model, of a 1000 kN MR damper under the fuzzy control system simulation

Table 2 Parameters of modified Bouc-Wen models for a 1000 kN MR damper

Parameter	Unit	Value	
		Mean	Standard deviation (10% of mean)
k_1	kN/m	0.0097	0.00097
k_0	kN/m	0.002	0.0002
c_{0a}	$kN.s/m$	110	11
c_{0b}	$kN.s/m/V$	114.3	11.43
α_a	kN/m	46.2	4.62
α_b	$kN/m/V$	41.2	4.12
c_{1a}	$kN.s/m$	8359.2	835.92
c_{1b}	$kN.s/m/V$	7482.9	748.29
β	m^{-2}	164	16.4
γ	m^{-2}	164	16.4
A	-	1107.2	110.72
η	s^{-1}	100	10
n'	-	2	0.2

Table 3 Reliability index (β) for case study 1 for standard deviation of 10% of the mean

Standard deviation		10% of mean value					
		Reliability index (β)			Probability of failure (P_f)		
Drift$_{All}$		0.02	0.25	0.03	0.02	0.25	0.03
Uncontrolled		0.962	0.976	2.524	0.168	0.1645	0.0058
controlled	Case 1	2.212	3.822	Inf	0.0135	0.000066	0
	Case 2	2.099	3.661	4.945	0.0179	0.0001255	0.00000038

that, $F_{\max}$ is the maximum force created by the damper, F_{exp} is the expected force of MR damper, F_{nom} is 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 expected capacity ratio of 70, 80, 90 and 95%. Also, the importance vector (α) is used to identify the most important parameters in Bouc-Wen model.

The experimental data required for damper force prediction is collected through modeling the 11-story building equipped with three 1000 kN MR dampers installed in first three stories with the mean value of realistic parameters listed in Table 2. 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. 3.

5. Results and discussion

5.1 Example 1

In this section, the results of the reliability analysis in the semi-active controlled structure by the MR damper are presented. According to the results of example 1, the reliability index and probability of failure in different cases

Table 4 Reliability index (β) for case study 1 for standard deviation of 20% of the mean

Standard deviation		20% of mean Value					
		Reliability index (β)			Probability of failure (P_f)		
Drift$_{All}$		0.02	0.25	0.03	0.02	0.25	0.03
Uncontrolled		0.483	0.488	1.262	0.3145	0.3127	0.1034
controlled	Case 1	1.106	1.911	2.587	0.1344	0.028	0.00484
	Case 2	1.050	1.830	2.473	0.1467	0.0336	0.0067

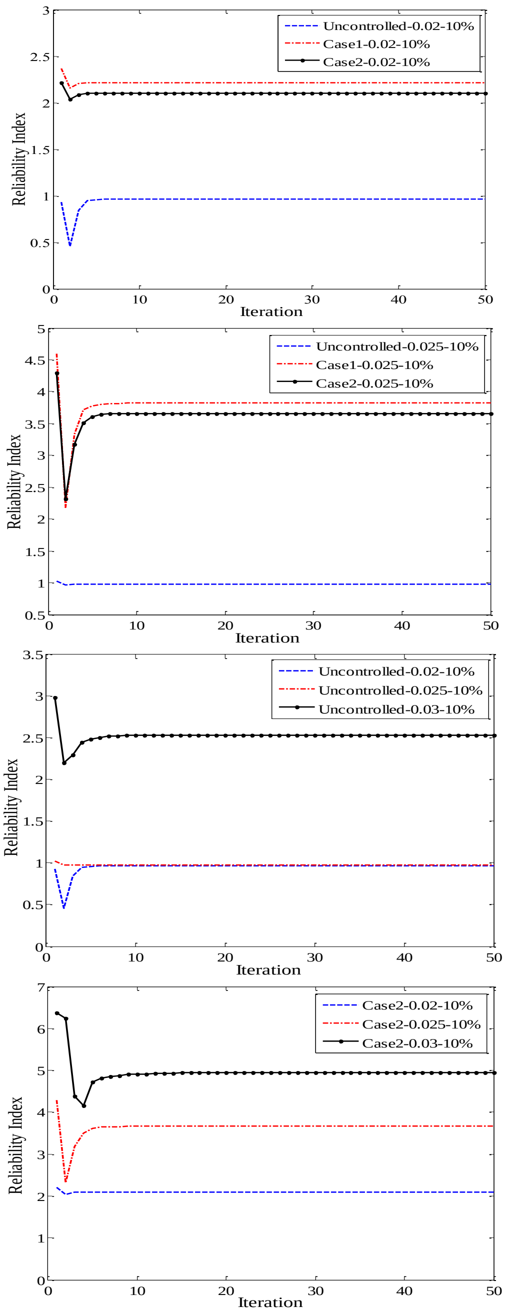
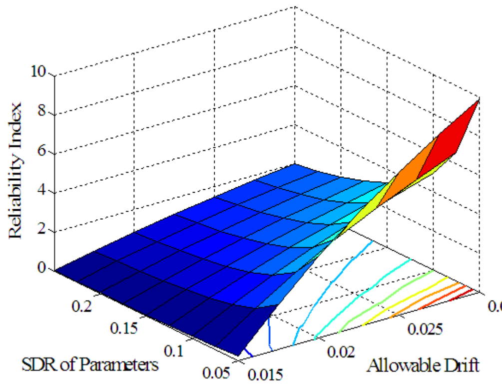
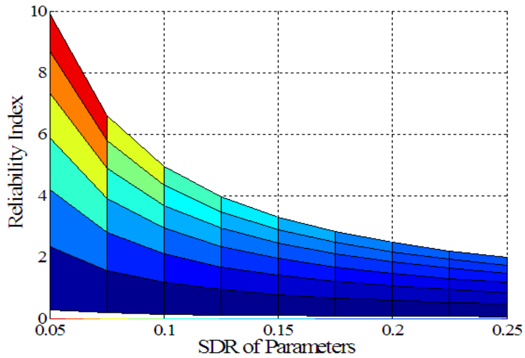


Fig. 4 Convergence history of Reliability index (β) for case study 1

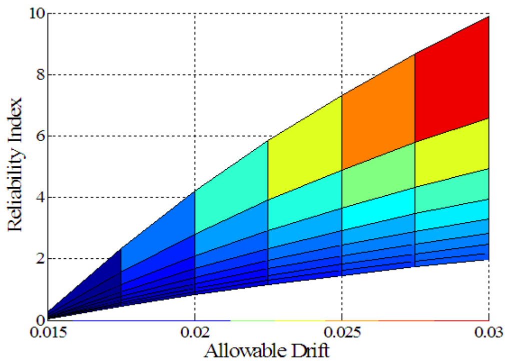
and for the different limit values of drift is collected in Table 3. These results show that, the MR damper significantly increases the structural reliability. Also, by adding the uncertainty to damper parameters in *case* 2, the



(a) Reliability index surface.

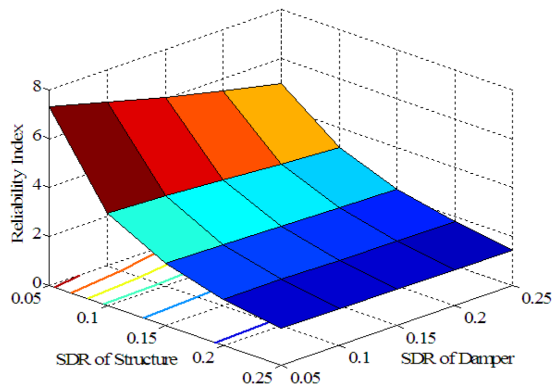


(b) Effect of standard deviation ratio.

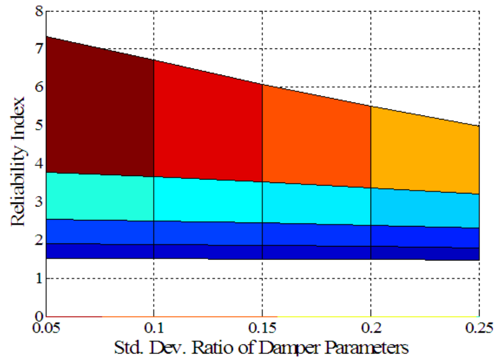


(c) Effect of allowable drift

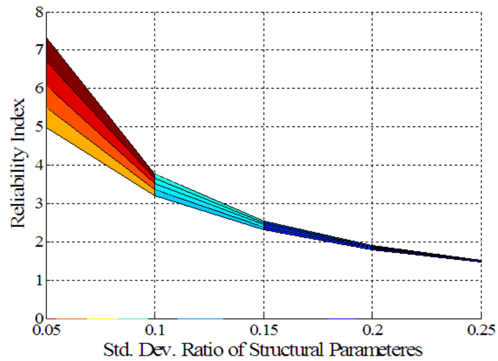
Fig. 5 Reliability Index (β) variation against the variation of allowable drift and standard deviation ratio of parameters for case study 1



(a) Reliability index surface.



(b) Effect of damper parameters SDR



(c) Effect of structural parameters DSR

Fig. 6 Reliability Index (β) variation against the variation of standard deviation ratio of structural parameters and MR damper parameters for case study 1

reliability index (β) decreases in comparison to case 1.

To investigate the effect of the uncertainty of random variables on the reliability of the structure, standard deviation in the probability distribution of random variables are altered. Table 4 shows the reliability index (β) and probability of failure (P_f) for random variables with a standard deviation of 20% of the mean value. By increasing the standard deviation in the probability distribution of parameters, the reliability of the structure decreases.

The convergence history of the reliability index using the HL-RF method and the reliability index value for each of the scenarios are shown comparatively in Fig. 4. According to these results, the method used for reliability analysis has a high convergence rate.

For comprehensive study on the values of structural reliability index, due to changes in the limit state function and parameters uncertainty, the reliability analysis for example 1 was performed for different values of allowable drift and standard deviation ratio (SDR) of all structural and damper parameters. Fig. 5 shows the surface of reliability index versus the allowable interstory drift and the standard deviation ratio of random variables.

To investigate the importance and influence of uncertainty in structural parameters (mass and stiffness of different stories) and MR damper parameters (Bouc-Wen model parameters), the reliability index in the structural model according to case 2 is evaluated for different values of standard deviation.

The surface of reliability index versus the change in the standard deviation ratio of all structural parameters and the Bouc-Wen model parameters of MR damper, is depicted in Fig. 6. As it can be seen, the reliability of a controlled

Table 5 Reliability index (β) for MR damper force in case study 2

Standard deviation Ratio		10% of mean value		20% of mean value	
Capacity Ratio	Expected force (kN)	Reliability index (β)	Probability of failure (P_f)	Reliability index (β)	Probability of failure (P_f)
70%	700	2.517	0.00591	1.258	0.1042
80%	800	1.326	0.0924	0.663	0.2536
90%	900	0.255	0.3993	0.128	0.4491
95%	950	0.234	0.4075	0.117	0.4534

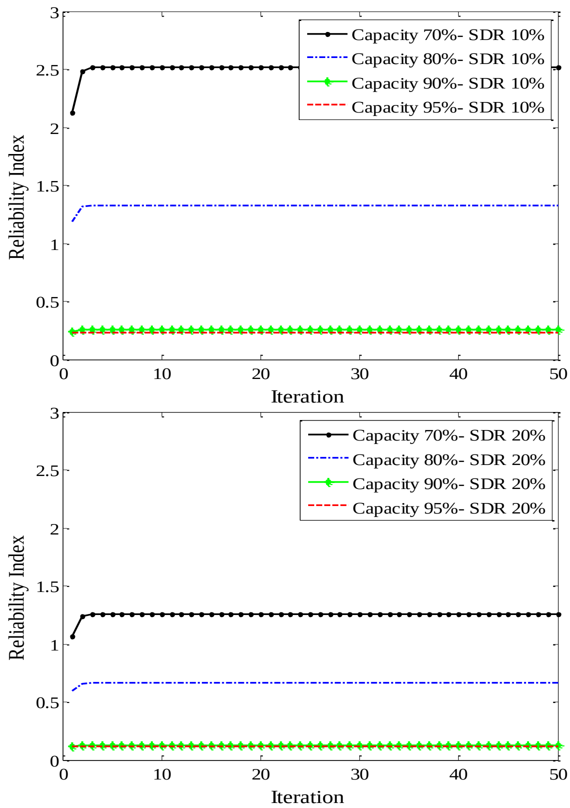
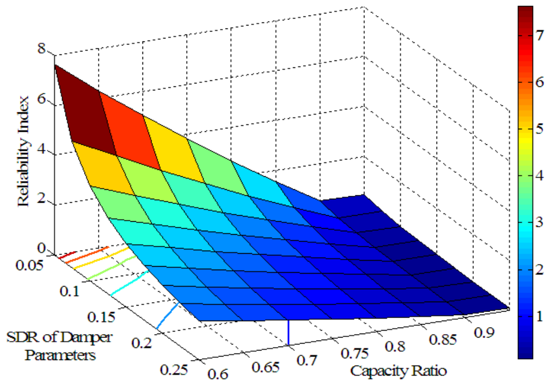
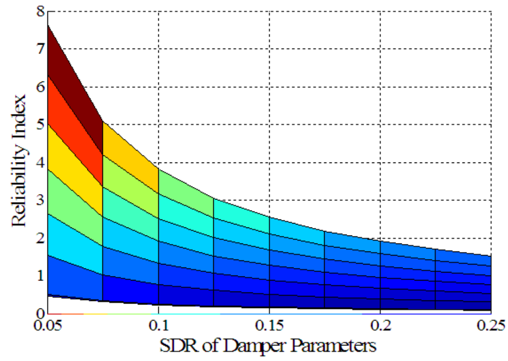


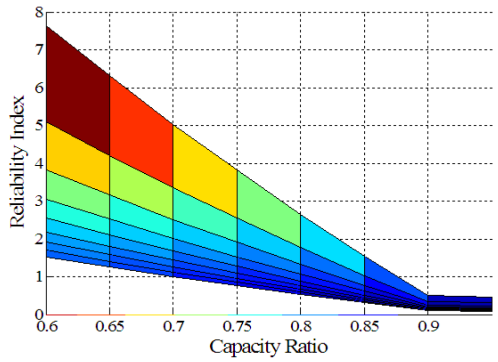
Fig. 7 Convergence history of Reliability index (β) for case study 2



(a) Reliability index surface



(b) Effect of damper parameters SDR



(c) Effect of damper capacity ratio

Fig. 8 Reliability Index (β) variation against the variation of damper capacity ratio and standard deviation ratio for case study 2.

structure using MR dampers, is dependent on the standard deviation of random variables. In accordance with Fig. 6(c), the value of reliability index is strongly influenced by uncertainty in structural parameters. By increasing the standard deviation of structural parameters such as mass and stiffness of stories, the reliability in the structure is noticeably decreased. However, uncertainty in the Bouc-Wen model parameters of MR damper have less effect on the reliability index in structures equipped with MR damper, than uncertainty in structural parameters.

5.2 Example 2

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

Table 5 shows the reliability index and failure probability for different levels of expected force in MR damper with a nominal capacity of 1000 kN. By increasing the expected capacity of the MR damper, the damper reliability decreases, so the probability of achieving to the expected level of MR damper performance is greatly decreased.

The convergence history of the reliability index for the different levels of expected force and different standard deviation of the Bouc-Wen model parameters, based on FORM analysis is depicted in Fig. 7 and it can be concluded from Fig. 7 that, the used method has a high convergence rate. By increasing the uncertainty in the parameters of the Bouc-Wen model, the reliability of the damper performance is strongly affected. Fig. 8(a) shows the reliability index

Table 6 Importance of modified Bouc-Wen model in reliability of damper force

Standard deviation	Importance vector (α)			
capacity	10% of mean value			
parameter	70%	80%	90%	95%
k_1	-0.0000018	-0.0000016	-0.0000015	-0.0000014
k_0	-0.000000020	-0.000000015	0.000000014	-0.000000013
c_{0a}	-0.0111649	-0.0099793	-0.0087732	-0.0081740
c_{0b}	-0.1137632	-0.1017049	-0.0894324	-0.0833322
α_a	-0.0935291	-0.0887255	-0.0834506	-0.0806365
α_b	-0.8179883	-0.7761503	-0.7301616	-0.7056072
c_{1a}	-0.0012986	-0.0013622	-0.0013785	-0.0013698
c_{1b}	-0.0113122	-0.0118687	-0.0120133	-0.0119385
β	0.1634833	0.1811394	0.1959117	0.2020467
γ	0.1634833	0.1811394	0.1959117	0.2020467
A	-0.3762328	-0.3916288	-0.3982871	-0.3989979
η	-0.0385928	-0.0399162	-0.0398650	-0.0393876
n'	0.335346	0.3981743	0.4633509	0.4960485

surface, in variations of expected level of damper force and the uncertainty in the parameters of the Bouc-Wen model. It is clearly observed in Figs. 8(b)-(c) that, changes in the uncertainty rate relative to the expected capacity will have further effect on the damper's reliability.

Table 6 shows the importance vector for the 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 sign 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 the failure. As it can be seen, the importance of the Bouc-Wen model parameters for the different levels of MR damper performance is relatively similar.

It can be concluded from the obtained results that, by omitting the parameters with low importance coefficient, there will be a considerable decrease in the computational costs on optimization and parameters' identification problems. In another word, the parameters, which highly affect the performance of the MR damper, are α_b, A and *n*. Also, the parameters which almost have not an effect on the performance of the MR dampener are k_0 and k_1.

6. Conclusions

The existence of uncertainty in the parameters of a structural system can effect its performance. These uncertainties can be observed in structural parameters and control devices. By using reliability analysis, uncertainty can be modeled in a semi-active controlled structure. In this paper, reliability is investigated in a structure equipped with a semi-active MR damper and the effect of the structural parameters and damper parameters' uncertainty on the reliability of the seismic response are evaluated. Uncertainty in structural parameters includes mass, stiffness and damping, and in the MR damper, the parameters of the modified Bouc-Wen model may have uncertainties. Thus, they are modeled using random variables with probabilistic distribution functions. In another case, the reliability of the MR damper is evaluated for expected levels of performance. Using the importance vector, the significance of the Bouc-Wen model parameters are determined in predicted force of the MR damper. For reliability analysis, the improved FORM method is used. An 11-story structure equipped with 3 MR dampers is selected as a numerical example.

The results show that, by increasing uncertainty in structural and damper parameters, the reliability of the structure decreases significantly. Also, the effect of uncertainty of the structural model parameters on the reliability of the structure is more than the uncertainty in the damper parameters. The obtained results from the reliability analysis of the MR damper performance show that, the probability of achieving the highest levels of nominal capacity of the damper is greatly reduced. Also, using reliability analysis and importance vectors, the parameters with high importance in the MR damper performance can be identified in modified Bouc-Wen model.

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