Earthquakes and Structures, *Vol. 11, No. 2 (2016) 347-369*
DOI: http://dx.doi.org/10.12989/eas.2016.11.2.347

Robust multi-objective optimization of STMD device to mitigate buildings vibrations

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(Received August 8, 2014, Revised August 2, 2016, Accepted August 9, 2016)

Abstract. The main objective of this paper is the robust multi-objective optimization design of semi-active tuned mass damper (STMD) system using genetic algorithms and fuzzy logic. For optimal design of this system, it is required that the uncertainties which may exist in the system be taken into account. This consideration is performed through the robust design optimization (RDO) procedure. To evaluate the optimal values of the design parameters, three non-commensurable objective functions namely: normalized values of the maximum displacement, velocity, and acceleration of each story level are considered to minimize simultaneously. For this purpose, a fast and elitist non-dominated sorting genetic algorithm (NSGA-II) approach is used to find a set of Pareto-optimal solutions. The torsional effects due to irregularities of the building and/or unsymmetrical placements of the dampers are taken into account through the 3-D modeling of the building. Finally, the comparison of the results shows that the probabilistic robust STMD system is capable of providing a reduction of about 52%, 42.5%, and 37.24% on the maximum displacement, velocity, and acceleration of the building top story, respectively.

Keywords: semi-active control system; multi-objective optimization; robust design; genetic algorithm; fuzzy logic controller; earthquake excitation

1. Introduction

One of the most important tasks of structural engineers is to reasonably minimize undesired vibrations of structures due to environmental dynamic loads such as earthquake excitations. Various strategies and theories are investigated and developed to approach this goal over the years (Adhikari and Yamaguchi 1997, Alhan and Gavin 2004, Amezquita-Sanchez *et al*. 2014, Chooi and Oyadiji 2008, Rama Mohan Rao and Sivasubramanian 2008). Use of control systems is one of these methods to enhance the structural performance against vibration excitations. The Control systems are divided into four groups of passive, semi-active, active, and hybrid systems based on

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http://www.techno-press.com/journals/eas&subpage=7 ISSN: 2092-7614 (Print), 2092-7622 (Online)

the performance and rate of energy consumption and the type of their installation to the main structure (Datta 1996).

Passive systems dissipate vibration excitations without using any external power source for operation and utilize the motion of the structure for this purpose. Since the properties of these types of control systems cannot be modified after installation, they are regarded as passive. These systems are simple, inexpensive, and reliable to suppress undesired vibrations of structures. Another advantage of these systems is their low costs of repair and maintenance. Passive tuned mass damper (TMD) system is one of these systems (Boudaoud *et al.* 2008, Fangfang *et al*. 2013, Cao and Li 2004, Pinkaew and Fujino 2001, Soong and Dargush 1997).

An active control system may be defined as a system which typically requires a large power source for operation of electrohydraulic or electromechanical actuators which supply control forces to the structure. Control forces develop based on feedback from sensors that measure the excitation and/or the response of the structure (Symans and Constantinou 1999, Blachowski, 2007). Active systems are more costly, complex, need careful maintenance; and furthermore, they need huge source of energy difficult to provide in severe earthquakes.

The above limitations of passive and active control systems resulted in developing semi-active control systems. Semi-active control systems maintain the reliability of passive control systems while taking advantage of the adjustable parameter characteristics of an active control system (Mehrparvar and Khoshnoudian 2012, Symans and Constantinou 1999, Pneumatikos and Hatzigeorgious 2014). In these systems, the stiffness or damping ratio of the control device changes proportional to the relative displacement or velocity of the structure by receiving information from sensors in every second (Mulligan 2007). Therefore, they do not require large power supply, and they do not add additional energy to the main structure and guarantee stability of the system. In order to regulate the stiffness or damping ratio of these devices, fuzzy logic can be utilized. Semi-active tuned mass damper (STMD) system with variable damping is a kind of these systems investigated in the present study.

Various studies confirm the efficiency of STMDs and show that the application of TMDs is much better when they behave as STMDs, especially in wind and earthquake excitations. Therefore, modeling procedure of the STMD system automatically includes modeling of the TMD system which uses the passive fluid viscous damper. The theory of TMD system has been used for the first time by Frahm in 1909 to reduce the movement of a structure subjected to monotonic harmonic forces. Hrovat *et al.* (1983) used STMDs for the control of tall buildings against wind pressure. Abe and Igusa (1996) developed analytical theory for optimum control algorithms for semi-active absorbers. Agrawal and Yang (2000) proposed particular tools namely semi-active algorithms to protect unstable structures subjected to near field earthquakes. Pinkaew and Fujino (2001) studied controlling effects of STMDs with different dampers for single-degree-of-freedom systems subjected to harmonic excitations. Lin *et al*. (2005) suggested a new semi-active control system that used variable damping and MR damping. Pourzeynali and Datta (2005) studied application of STMD system to control the suspension bridge flutter using fuzzy logic.

In the present study, the robust STMD system is studied with variable damping produced by a semi-active fluid viscous damper. A passive fluid viscous damper is similar to the shock absorber in automobiles. The configuration of this damper includes a hydraulic cylinder filled with a damping fluid like silicone or oil and a piston head with a small orifice. As the damper strokes the damping fluid flows through the orifice at high speed from one side to the other and produces a damping pressure creating the damping force. An external bypass loop containing a controllable valve to a passive fluid damper provides a semi-active fluid damper. The behavior of the semi-active fluid damper is essentially similar to passive fluid damper except that the former has an external valve connecting two sides of the cylinder and modulates the output force. In this kind of damper, adjustable damping property makes it capable to generate wide range of damping force. Since a small power or source just used for closing or opening external valve, it can produce very large damping force without need of large input energy and can therefore operate on batteries (Pourzeynali and Mousanejad 2010).

The main objective of this paper is to find the optimal values of the parameters of the STMD system as a kind of semi-active control device using genetic algorithms (GAs) and fuzzy logic to simultaneously minimize the building selected responses. Three non-commensurable objective functions namely: the maximum normalized displacement, maximum velocity, and maximum acceleration of each story level of the building are considered to be minimized simultaneously. For the numerical analysis, a reality 12-story building has been chosen. The torsional effects due to irregularities exist in the building and/or unsymmetrical placements of the dampers are taken into account through 3-D modeling of the building.

Moreover, the optimal design of a system requires that the uncertainties, which may exist in the system, be taken into account in the dynamic analyses. This can be done by the robust design optimization (RDO) approach. This method is based on the non-deterministic optimization approach through which the probabilistic uncertainties can be considered for uncertain parameters and the stochastic optimal design processes can be performed for the system (Khalkhali *et al*. 2016). The Hammersley Sequence Sampling (HSS) method which is a direct and simple numerical method is used in the present study to perform the RDO procedure. Finally, the robust optimal values of the STMD parameters are evaluated for the example building structure.

2. Methods

2.1 Mathematical modeling of the building

For an n-story building structure with an STMD control system installed on its top floor and subjected to earthquake horizontal acceleration components, as shown in Fig. 1, the equations of motion can be given as (Cao and Li 2004)

$$[M]\{\ddot{u}(t)\}+[C]\{\dot{u}(t)\}+[K]\{u(t)\}=-[M][R]\{\ddot{u}_g(t)\}+\{l\}(c_d(t)\dot{u}_{rd}+k_d u_{rd}) \quad (1)$$

$$m_d\ddot{u}_{rd}(t)+c_d(t)\dot{u}_{rd}(t)+k_d u_{rd}(t)=-m_d\{l\}^T\{\ddot{u}(t)\}-m_d\,\ddot{u}_{gx}(t) \quad (2)$$

where [M], [C], and [K] are the $3n\times3n$ mass, damping, and stiffness matrices of the main structure, respectively; n is the number of stories; $\{u(t)\}$ is the $3n\times1$ displacement vector of the building with respect to the ground; $u_{rd}(t)$ is the relative displacement of the STMD with respect to the building top floor; m_d, k_d and $c_d(t)$ are the mass, stiffness, and time dependent damping of the STMD; [R] is the $3n\times3$ influence matrix (Salimi 2011); and $\{\ddot{u}_g(t)\}$ shows the acceleration of earthquake acting on the base of the main structure.

The simplest procedure to define mass properties of the building is to assume that the entire mass is concentrated at the center of mass of each floor (rigid floor assumption), and therefore, the mass matrix of the building is considered to be lumped matrix (Clough and Penzien 1993). The damping matrix of the building is also considered to be a linear combination of the mass and

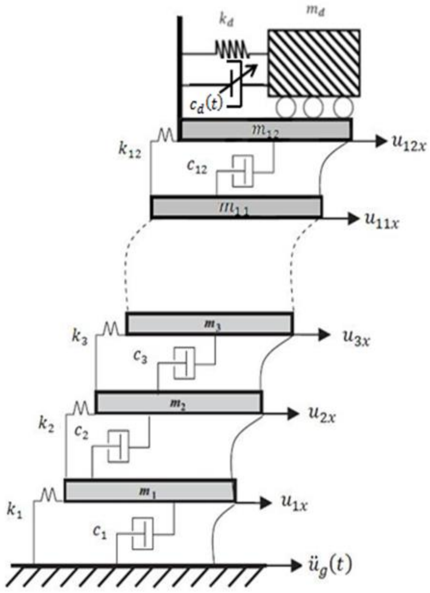

Fig. 1 Example building model and the STMD mounted on its top floor

stiffness matrices called as Rayleigh damping (Chopra 1995), for which the proportionality coefficients are calculated by assuming the modal damping ratio of the building fundamental mode and that of the middle mode are the same (Pourzeynali and Esteki 2009).

The response of the building depends on its mode shapes and natural frequencies and can be estimated by considering the dominant modes of the building. Therefore, in this study to obtain the uncontrolled responses of the building, a classical modal analysis is performed. According to the Zuo and Nayfeh (2003) the first vibrational mode is dominant in earthquake excitation if modal frequencies are well-separated. In this study, the first three frequencies of the example building are very close, thus, the first three modes of the main structure in each direction are considered in the modal analysis of the building. Consequently, the displacement vector of the building can be expressed as

$$\{u(t)\}=[\Phi]\{q(t)\} \tag{3}$$

$$[\Phi]=[\{\phi\}_1 \quad \{\phi\}_2 \quad \{\phi\}_3\ ] \quad , \quad \{q(t)\}=\begin{Bmatrix} q_1(t) \\ q_2(t) \\ q_3(t) \end{Bmatrix} \tag{4}$$

where $\{\phi\}_i$ is the i^{th} mode shape of the building; and $q_i(t)$ is the i^{th} generalized modal coordinate of the structure.

Now, by selecting the generalized modal coordinates $\{q(t)\}$, stroke of the STMD mass block $u_{rd}(t)$, and their time derivatives as the state variables, the state equations of the system can be expressed in the standard state-space form as the following

$$\{\dot{Z}(t)\}=[A]\{Z(t)\}+[D]\{\ddot{u}_g(t)\} \tag{5}$$

in which $[A]$ is the system matrix; $[D]$ is the disturbance matrix ; and $\{Z(t)\}$ is the state vector (Salimi *et al*. 2011).

In order to optimally design the parameters of the STMD system, its mass is assumed as a part of the total mass of the building ($m^t_{Building}$) and expressed as

$$m_d = m_0 \times m^t_{Building} \tag{6}$$

where m_0 is the mass ratio of the STMD system. In this research study the STMD control device is considered to be installed on the building top story and moves only in x direction and therefore, the application of STMD can absorb the entrance energy in this direction. Consequently, to design the STMD system, its frequency should be tuned close to the fundamental frequency of the building in x direction in which the control device is installed. Therefore, the frequency of the STMD, ω_d, is expressed as

$$\omega_d = (\beta \times \omega_{1x}) \tag{7}$$

in which β is the frequency ratio of the STMD; and ω_{1x} is the fundamental frequency of the building in x direction. Therefore, the damping coefficient of the STMD, $c_d(t)$, can be expressed as

$$c_d(t) = 2 \times \xi_d(t) \times \sqrt{(m_d \times k_d)} \tag{8}$$

The parameters m_0, and β are the design variables in the multi-objective optimization procedure. In this study, the time dependent damping ratio of the STMD system $\xi_d(t)$, is evaluated using the fuzzy logic explained in the following section.

2.2 Fuzzy Logic Controller (FLC)

In this paper, a fuzzy logic controller regulates the damping ratio of the STMD system. For the first time, Fuzzy set theory was proposed by Zadeh in 1965 (Zadeh 1965). Nowadays, fuzzy systems are used in a wide range of science and technology such as control, signal processing and etc. The main part of a fuzzy system is a knowledge database which is composed of IF-THEN rules based on classical control theories. A fuzzy system consists of four parts, namely: fuzzifier, fuzzy rule base, inference engine, and the defuzzifier. The fuzzy rule base in this paper is based on a Mamdani linguistic fuzzy model written as

$$R^i : IF\ x_1\ is\ A_{1i}\ AND\ x_2\ is\ A_{2i}\ THEN\ y\ is\ B \tag{9}$$

where, x_1 and x_2 are input linguistic variables; y is the output linguistic variable. A_{1i}, A_{2i}, and B are the values for input and output linguistic variables, respectively. Herein, x_1 and x_2 are the displacement and velocity of the building top floor, respectively; and y is the damping ratio of the STMD system. The design of a fuzzy system involves decisions about a number of important design parameters that should be determined before the actual system starts. These parameters are fuzzy sets in the rules, the rules themselves, scaling factor in input and output, inference methods, and the defuzzification procedures (Deb *et al.* 2002). Because of a crisp number for real application, defuzzifier maps the system output from the fuzzy domain into the crisp domain. The center of area (COA) and the mean of maximum (MOM) are the two most commonly used methods in generating the crisp system output (Holland 1975). In this study, the center of area method is selected to produce the crisp system output in discrete universe of discourse (Shin and

Xu 2009)

$$x^* = \frac{\sum_{i=1}^{n} x_i . \mu_A(x)}{\sum_{i=1}^{n} \mu_A(x_i)} \tag{10}$$

where n is the number of the discreet elements in the universe of discourse; x_i is the value of discrete element; and $\mu_A(x_i)$ offers the corresponding membership function value at the point x_i. To achieve a fuzzy system with minimum design variables, the ideas proposed by Park *et al*. (1995) are used. In this method, the membership functions are considered as triangular functions; and since often the behavior of the dynamic systems such as vibratory buildings is symmetric, the number of membership functions should be odd and symmetric with respect to the vertical axis. Therefore, five triangular membership functions are considered for each input and output variables (Fig. 2). In order to design these membership functions, it is assumed that all universes of discourses are normalized to lie between -1 and 1, and the first and last membership functions have their apexes at -1 and 1, respectively. Also, the apex of each triangle is in one point with the tip base of two lateral triangles, and as respected, the universe of discourse is laid between -1 and 1, so the position of the apexes of each triangular membership function (C_i) can be found with the parameter P_s and the number of membership functions as below

$$C_i = \left(\frac{i}{n}\right)^{Ps}, \quad n = \frac{N-1}{2} \quad , \qquad i = -n, \ldots, 0, 1, \ldots, n \tag{11}$$

where N is the number of membership functions. It can be concluded that if P_s is less than one the apexes are spaced out and if P_s is more than one, then the apexes are closed together in the center. Fig. 2 depicts five membership functions with three different P_s values.

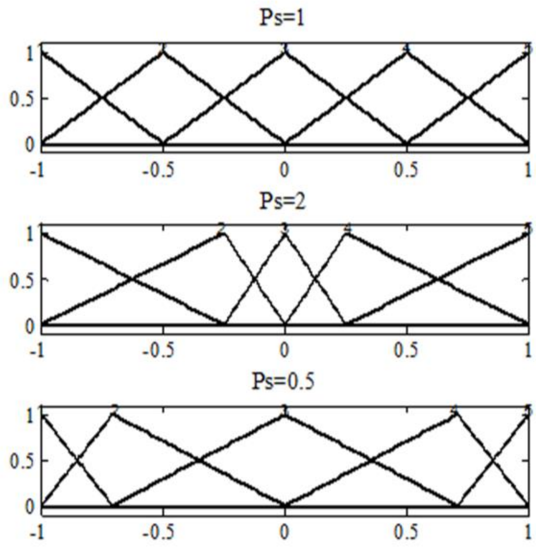

Fig. 2 Membership functions with different P_s

Another design challenge of fuzzy systems is to find the rule bases of the system. There are different strategies to get the rule bases, which mostly are based on the experience and knowledge of human beings, but, intelligent design methods such as design with genetic algorithms consider some characteristic parameters to design the rule bases. In the present study, according to Park *et al*. (1995), two characteristic parameters are used from which one is the spacing parameter P_i for the inputs and the output, and the other is the angle θ for the output. The spacing parameter P_i determines the layout of different values of the inputs towards the origin (zero point). Therefore, the space parameter P_i grids the rule base space, so that these lines divide this space into different regions with the number of output linguistic variables. If the values of the inputs are considered as *BN*[1], *SN*[2], *Z*[3], *SP*[4] and *BP*[5], and the distance between *SP* and *Z* is *a*, and that of the *SP* and *BP* is *b*, then the parameter P_i is defined as (Fig. 3)

$$\mathrm{P_i} = \frac{b}{a} \tag{12}$$

Since the input variables are symmetric, therefore, the distance between the *SN* and *Z*, and that of the SN and *BN* are also *a* and *b*, respectively. According to Eq. (12), if P_i is more than one, then the *SP* value is close to zero, while if P_i is less than one, then the value of *SP* is far from the zero, and if P_i is equal to one, then the inputs are placed with the same intervals with respect to each other and zero. These concepts are shown in Fig. 4.

The angle θ is measured with respect to the horizon for the grid lines which divide the rule base space into different regions for the value of output linguistic variables. For example, in Fig. 4, the angle θ is 45 degrees for all cases. In this method, it will be assumed that if the inputs are zero, then the output is also zero, and if the inputs have their maximum value, then the output is also maximum. By considering above assumptions, the output linguistic variable places in various regions according to Fig. 4. As a result, for each combination of input linguistic variables, proper output is equal to the amount which is located in the desired area. As an example, according to Fig. 4(b), if the first input is *SP* and the second input is *BN*, then the output is *SN*. Consequently, in this research, the design variables are $\{P_s\}$, $\{P_i\}$, θ, m_0, β and $\xi_d(t)$ which should be designed by multi-objective optimization method.

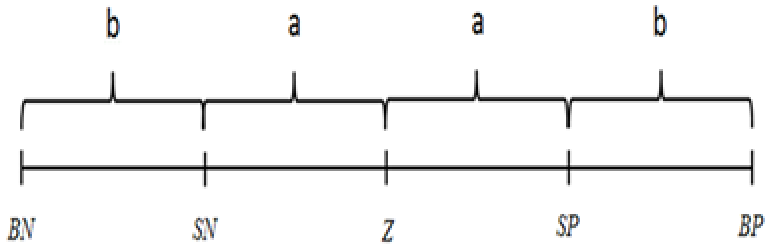

Fig. 3 Definition of the P_i parameter

[1]Big Negative
[2]Small Negative
[3]Zero
[4]Small Positive
[5]Big Positive

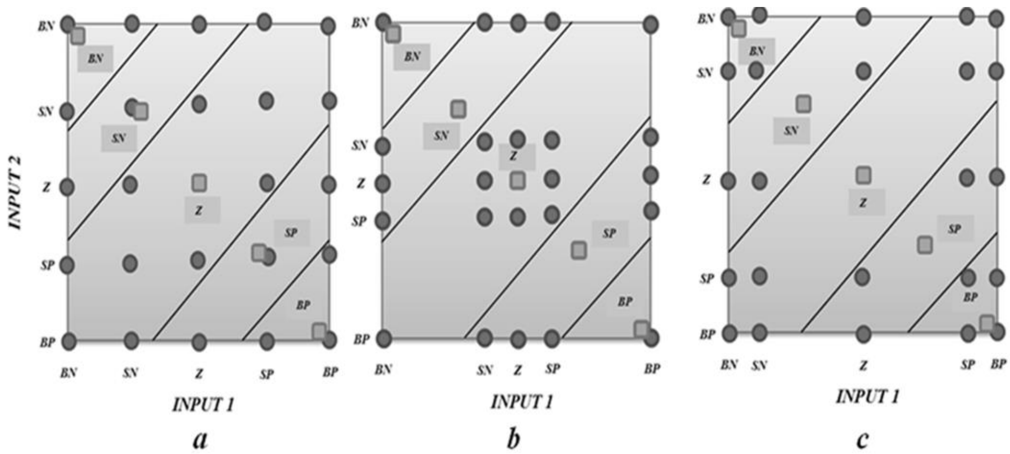

Fig. 4 Rule base construction with a) P_i=1, b) P_i>1, c) P_i<1

2.3 Robust design of the Semi-Active Tuned Mass Damper (STMD) system

In many engineering problems, due to uncertainties may exist in the system, the mathematical model considered in the analyses and the actual ones are different. Performance of these systems can be sensitive to these uncertainties, even though the design has been accomplished optimally. Therefore, the optimal design of a system requires that the uncertainties, which may exist in the system, be taken into account. This can be done by the robust design optimization (RDO) procedure. This method is based on the non-deterministic optimization approach through which the probabilistic changes can be considered for uncertain parameters, and the designer performs the stochastic optimal design process for the system. Therefore, the robust design involves some probabilistic metrics often called random variables (Ray and Stengel 1993). In RDO approach, the optimally evaluated random variables related to the stochastic performance of the system are expected to be less sensitive to the random variation of the uncertain parameters.

A great amount of research activity exist for simulation of the stochastic behaviour of uncertain systems, and the Monte Carlo simulation (Wang and Stengel 2002, Crespo and Kenny 2005, Smith *et al*. 2005; Pnevmatikos and Thomos 2014, Pnevmatikos and Hatzigeorgiou 2014) is the most prominent method used in many robust design methods. Monte Carlo simulation (MCS) is a direct and simple numerical method but can be computationally expensive. In this method, random samples are generated assuming some pre-defined probabilistic distributions for uncertain parameters. The system is then simulated with each of these randomly generated samples, and the percentage of cases produced in failure region, defined by a limit state function, approximately reflects the probability of failure (Crespo and Kenny 2005).

In order to improve the precision of this method, the number of simulation should approach to the infinity, but it leads to computationally expensive problems. Therefore, there have been many research activities on sampling methods to reduce the number of samples keeping a high level of accuracy. Alternatively, many researches use the quasi-MCS known as Hammersley Sequence Sampling (HSS) (Crespo and Kenny 2005, Smith *et al*. 2005). In the present study, HSS method has been used to generate samples for the probability estimation of failures.

The goal of RDO is to minimize the mean value E(X) of the random variable X and its variance σ^2(X). Therefore, the mean and its variability should be minimized simultaneously (Hajiloo *et al.*

2007). In this paper, in order to minimize the mean and variance simultaneously, the objective function for each random variable X is considered as

$$J = \frac{E(X)}{E_0} + \frac{\sigma^2(X)}{\sigma_0^2} \tag{13}$$

in which the mean and the variance of the random variable are normalized by desired mean (E_0) and desired variance (σ_0^2) which can be chosen by the designer. If some data for random variable X is available, then the values of E_0 and σ_0 can easily be calculated using the standard statistical analysis, otherwise those can be chosen from the literature.

3. Results and discussion

3.1 Numerical study

In order to investigate the performance of the proposed control device in reducing the responses of the building structures under earthquake excitations, a 12-story steel building having plan dimensions of 15 m×15.5 m is selected. This building is modeled as a 3-D frame to show more the realistic behavior of the building and the control system in earthquake events. The typical plan and 3-D frame of the building are shown in Fig. 5.

This building is analyzed under the application of worldwide earthquake accelerogrames. For this purpose, necessary correction processes are performed on the uncorrected accelerogrames, including a band-pass filtering of low- and high-frequency noises, as well as the instrumental and base-line corrections. All the corrected accelerogrames are scaled such that they are the representative of accelerogrames compatible with a design response spectrum (IBC 2006). In the present study, 16 worldwide strong ground motion accelerogrames with the effective duration more than 10 seconds are selected according to IBC 2006 and used in the time history analyses. In Table 1, for brevity, only seven important accelerogrames out of these 16 reference accelerogrames are presented.

Now, using the state-space equation of the building without any control system Eq. (5) when

Table 1 The earthquake accelerogrames considered in this study

No.	Earthquake	Date	Effective Duration (sec)		Magnitude (Ms)	Corrected PGA (g)	Total Duration (sec)	Nearest fault Distance (km)
			T	L				
1	Kobe	1995	13.16	12.87	6.9	0.694	40.96	26.4
2	Cape Mendocino	1992	20.79	19.85	7.1	1.497	44	44.6
3	Whittier Narrows	1987	12.72	12.56	5.7	0.333	32.06	69.7
4	Morgan Hill	1984	21.28	19.02	6.1	0.405	36	54.1
5	San Fernando	1971	17.77	16.04	6.6	0.136	29.74	81.6
6	Northridge	1994	18.43	19.71	6.7	0.877	34.99	71.1
7	Coalinga	1983	21.38	20.19	6.5	0.733	40	55.2

Table 2 Top Story maximum uncontrolled responses

Earthquakes	Dis	Vel	Acc
Kobe	10.6	0.48	2.54
Cape Mendocino	15.44	0.60	2.56
Whittier Narrows	2.85	0.12	1.99
Morgan Hill	6.23	0.3	2.78
San Fernando	3.72	0.15	1.35
Northridge	9.91	0.4	2.47
Coalinga	16.8	0.69	3.69
Average responses	**10.6**	**0.46**	**2.82**

Note: Dis=displacement (cm), Vel= velocity (m/s) and Acc=acceleration (m/s^2)

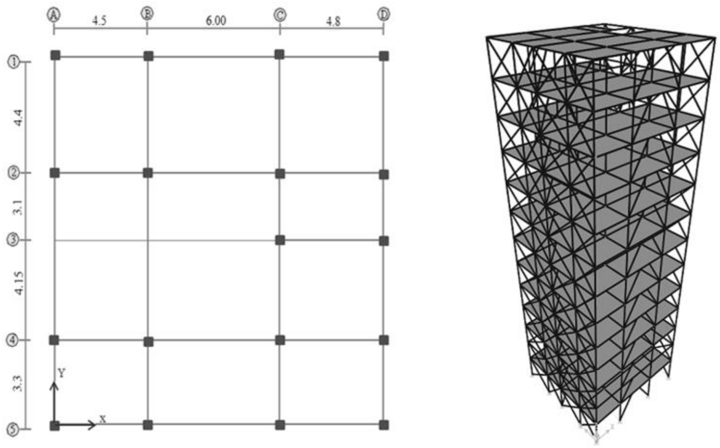

Fig. 5 Typical plan and 3-D frame of the example building

the parameters of the STMD system are eliminated from the related equations) the uncontrolled responses of the building are calculated under the application of the all 16 reference earthquake accelerogrames. The maximum responses of the building for 16 accelerogrames are evaluated from which, for brevity, only the results of 7 reference accelerogrames of the Table 1 are presented in Table 2. Moreover, the average values of the maximum responses corresponding to all 16 accelerogrames are provided in the last row of the table.

3.2 Design of STMD system

In the present study, the STMD system with variable damping produced by a semi-active fluid viscous damper is investigated. A fuzzy logic controller (FLC) is utilized to regulate the variable damping ratio of the STMD system. In this system, the variable damping ratio is represented in the following form

$$\xi_{STMD}(t) = \xi_{0STMD} + \frac{\xi_{0STMD}}{2} \lambda\left(u_{x12}, \dot{u}_{x12}\right) \tag{14}$$

where ξ_{0STMD} is the nominal damping ratio of the STMD system; λ is a fuzzy function with values between -1 and 1; and u_{x12} and $\dot{u}_{x12}$ are the displacement and velocity of the building top story, respectively. The performance of the control system is optimized using the multi-objective genetic algorithms. For this purpose, the parameters m_0, β, ξ_{0STMD}, $\{P_s\}$, $\{P_i\}$ and θ are chosen as the design parameters which to be optimally calculated using genetic algorithms. For doing this, three non-commensurable objective functions namely: maximum normalized displacement, maximum normalized velocity, and maximum normalized acceleration of each story level of the building are selected to minimize, simultaneously, by multi-objective optimization. These objective functions can be expressed as the following

$$J_1 = \max_i \left[\max_t \left| D_i^c(t) \right| \Big/ \max_t \left| D_i^{uc}(t) \right| \right], \quad J_2 = \max_i \left[\max_t \left| V_i^c(t) \right| \Big/ \max_t \left| V_i^{uc}(t) \right| \right],$$
$$J_3 = \max_i \left[\max_t \left| A_i^c(t) \right| \Big/ \max_t \left| A_i^{uc}(t) \right| \right] \tag{15}$$

where i=1,…,12 indicates the number of floors of the building; and $D_i^c(t)$, $D_i^{uc}(t)$, $V_i^c(t)$, $V_i^{uc}(t)$, $A_i^c(t)$ and $A_i^{uc}(t)$ are the displacement, velocity and acceleration of each floor of the building in controlled and uncontrolled cases, respectively.

It is impossible to illustrate the trade-off point when more than two objective functions are considered. To overcome this difficulty, several multidimensional visualization methods are proposed in the literature. One of these methods which leads to comprehensive analysis of the Pareto front is called *Level Diagrams* method (Blasco *et al*. 2008) and is used here to visualize the Pareto fronts of the multi-objective optimization. In this method, each point of Pareto fronts must be normalized to bring it between 0 and 1 based on its minimum and maximum values (Blasco *et al*. 2008) as presented in the following

$$J_i^M = \max J_i \ , \qquad J_i^m = \min J_i \ , \quad i = 1,2,3 \qquad \bar{J}_i = \frac{J_i - J_i^m}{J_i^M - J_i^m} \tag{16}$$

The distance of each Pareto front point from the origin can be used for comparison. Here, the Euclidean norm of all objective functions $\left(\left\| \bar{J} \right\|_2 = \sqrt{\sum_{i=1}^{3} \bar{J}_i^2} \right)$ is used for this purpose. To represent the Pareto front, Y axis represents the Euclidean norm of all objective functions and X axis specifies each objective function; therefore, each objective function has its own graphical representation whilst Y axis of all graphs would be the same.

The Pareto fronts for Coalinga earthquake resulted from this analysis are shown in Fig. 6. It is obvious from the figure that these three objective functions are in conflict with each other. The maximum responses of the building (maximum displacement, velocity, and acceleration) at each story level obtained using the optimal values of the STMD design parameters are shown in Table 3 for 7 earthquake accelerogrames (for brevity). In the last row of the table, the average values of the maximum responses obtained from the results of 16 reference accelerogrames are also shown for comparison with the uncontrolled ones.

It can be seen from the table that the average values of maximum displacement, velocity, and acceleration of the top story of the building controlled by STMD system in comparison with the uncontrolled ones are approximately reduced to about 34.53%, 34.78%, and 28.72%, respectively.

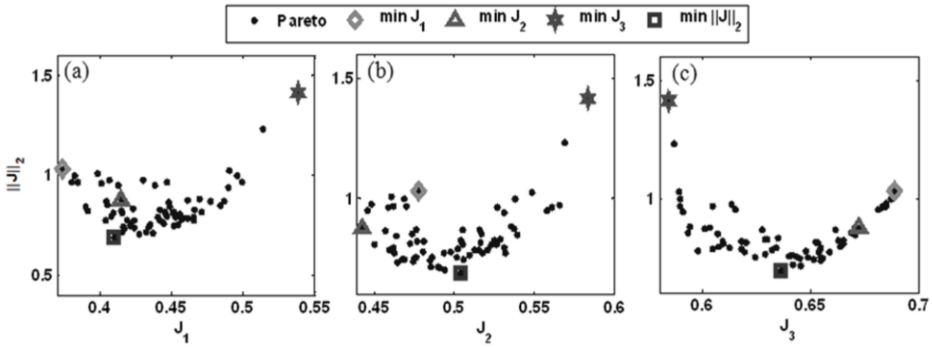

Fig. 6 2-Norm Level Diagrams of Pareto front of the STMD for Coalinga earthquake (a) J_1, (b) J_2 and (c) J_3

Table 3 Top Story maximum controlled responses with STMD system

Earthquakes	Dis	Vel	Acc
Kobe	4.17	0.19	1.29
Cape Mendocino	8.64	0.31	1.25
Whittier Narrows	1.45	0.08	1.54
Morgan Hill	3.80	0.18	2.08
San Fernando	1.67	0.08	0.77
Northridge	5.53	0.28	1.71
Coalinga	7.23	0.35	2.47
Average responses	**5.91**	**0.26**	**1.91**

Note: Dis=displacement (cm), Vel= velocity (m/s) and Acc=acceleration (m/s^2)

Table 4 The optimal values of the STMD design parameters and the corresponding values of the objective functions for 7 reference accelerogrames

Earthquakes	Design parameters and objective functions						
	m_0	β	ξ_{0STMD}	J_1	J_2	J_3	$\| J \|_2$
Kobe	2.81	0.832	6.9	0.39	0.39	0.51	0.09
Cape Mendocino	2.85	1.187	5.45	0.56	0.52	0.49	0.67
Whittler Narrows	2.14	0.956	26.5	0.51	0.64	0.77	0.59
Morgan Hill	2.9	1.003	11.3	0.61	0.62	0.75	0.62
San Fernando	2.48	0.912	34.33	0.45	0.53	0.57	0.44
Northridge	2.87	0.875	13.83	0.56	0.70	0.69	0.48
Coalinga	2.99	1.033	6.6	0.43	0.50	0.67	0.69
Average	**2.71**	**0.97**	**13.88**	-	-	-	-

The optimal values of the STMD design parameters and the corresponding objective function values for the optimum point with the lowest value of $||J||_2$ for 7 earthquake excitations are given in Table 4. Furthermore, the optimal values of the fuzzy controller design parameters and the maximum value of the optimal damping ratio of the STMD system, ξ_{max}, are presented in Table 5.

Moreover, Fig. 7 compares the time histories of the controlled and uncontrolled responses of the building top story for Coalinga earthquake and for the optimum point with the lowest value of $||J||_2$. This figure shows that the STMD system properly reduces the building seismic responses.

The fuzzy tuned damping ratio of the optimum STMD device for the trade-off point (min $||J||_2$) is shown in Fig. 8 for Coalinga earthquake. It is clear from the figure that the maximum value of the STMD damping ratio is about 8.5%, which is in a reasonable range. In optimal design procedure of the STMD system, the optimal values of its parameters for each reference accelerograme are calculated separately. Therefore, the final decision about the optimal values of the design parameters must be made based on the different values obtained for separate

Table 5 The values of the optimum parameters of the fuzzy controller for 7 different earthquake excitations and the maximum value of the STMD damping ratio (ξ_{max})

Earthquakes	Design parameters of the fuzzy controller							
	P_{S1}	P_{S2}	P_{S3}	P_{i1}	P_{i2}	P_{i3}	θ	ξ_{max}
Kobe	0.80	0.77	1.06	1.10	0.74	0.65	35	8.03
Cape Mendocino	0.86	0.66	0.81	0.60	0.70	1.25	126	7.17
Whittler Narrows	0.87	0.85	0.60	0.97	0.87	0.57	43	32.79
Morgan Hill	0.76	0.77	1.35	1.00	1.13	1.22	50	14.24
San Fernando	0.77	0.85	1.71	0.85	0.89	1.49	17	41.21
Northridge	0.87	0.81	0.78	1.03	1.21	1.25	17.5	17.55
Coalinga	0.84	0.98	0.75	1.05	0.70	0.95	86.4	8.36

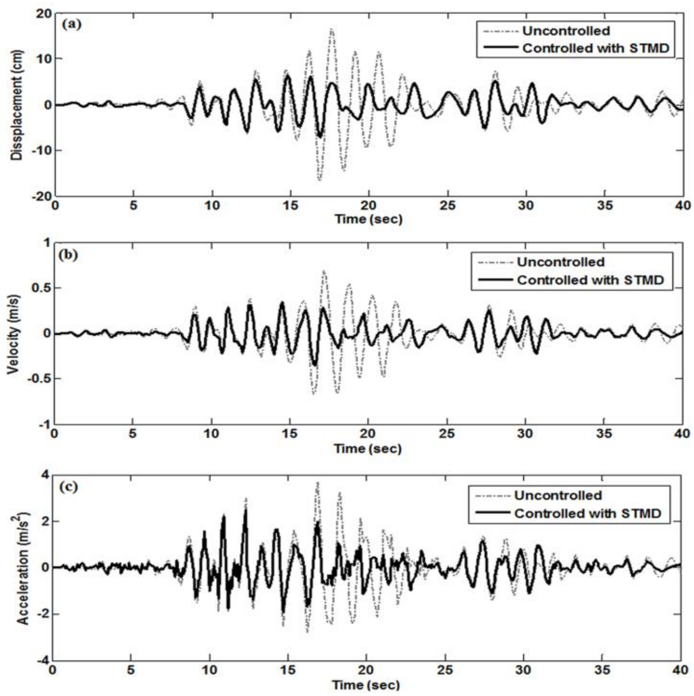

Fig. 7 Comparison of the controlled and uncontrolled responses of the building top story for Coalinga earthquake: (a) displacement, (b) velocity, and (c) acceleration

accelerogrames. For this selection, three methods explained in the following, are examined to obtain the optimal value of any design parameter:

I. The expected mean value calculated for the reference accelerogrames: $E = \frac{\sum x_i}{n}$, where E is the expected mean value; x_i is the optimal value of the parameter obtained for each accelerograme; and n is the number of total accelerogrames.

II. The expected mean value + one standard deviation σ: $E+1\sigma$

III. The weighted mean value, for which the reduction ratio of controlled displacement to uncontrolled one is selected as the weighting coefficient.

The results of optimal values of the STMD design parameters calculated by applying these three methods are shown in Table 6.

In order to determine the final values of the STMD parameters among these three groups, the average values of the maximum displacement, velocity, and acceleration of each story level calculated by applying the 16 reference earthquake accelerogrames and the optimal values of the parameters are presented in Table 7. By comparing the response values given in the table, it can be concluded that the first method is more effective to determine the design parameters of the STMD system and provides significant reduction in the structural responses. Consequently, the final optimal values proposed for the STMD design parameters are

$$m_0 = 2.71\% \ , \ \beta = 0.97 \ , \ \xi_{0STMD} = 13.88\%$$

$$P_s = \{0.84, 0.79, 0.92\} \ , \ P_i = \{0.89, 0.86, 0.98\} \ , \ \theta = 47.35^\circ$$

According to Table 7, the results obtained from the first method give reduction ratios (as mentioned earlier) about 34.53%, 34.8% and 28.72% for the maximum values of displacement, velocity, and acceleration of the building top story with STMD system, respectively.

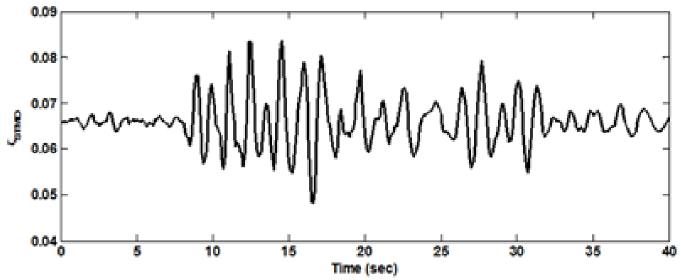

Fig. 8 Time history diagram of the fuzzy tuned damping ratio of the STMD system corresponding to trade-off point for Coalinga earthquake

Table 6 The final optimal values of the STMD design parameters obtained using the proposed three methods

	STMD Parameters									
	m_0	β	ξ_{0STMD}	P_{S1}	P_{S2}	P_{S3}	P_{i1}	P_{i2}	P_{i3}	θ
First Method	2.71	0.97	13.88	0.84	0.79	0.92	0.89	0.86	0.98	47.35
Second Method	2.95	1.10	23.37	0.96	0.88	1.24	1.04	1.03	1.27	82.55
Third Method	2.72	0.96	14.11	0.84	0.80	0.95	0.91	0.85	0.97	47.54

Table 7 The average values of the maximum responses of the building for three methods

$m_0 = 2.71\%$, $\beta = 0.97$, $\xi_{0STMD} = 13.88\%$

The First Method		Stories of the building											
		1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th	11th	12th
Average values	$D_{\max}$	0.22	1.00	1.49	2.00	2.54	3.11	3.71	4.34	4.99	5.63	6.27	6.94
	$V_{\max}$	0.01	0.04	0.06	0.09	0.11	0.13	0.16	0.19	0.22	0.24	0.27	0.30
	$a_{\max}$	0.07	0.29	0.43	0.58	0.74	0.91	1.08	1.27	1.45	1.64	1.82	2.01

$m_0 = 2.95\%$, $\beta = 1.1$, $\xi_{0STMD} = 23.37\%$

The Second Method		Stories of the building											
		1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th	11th	12th
Average values	$D_{\max}$	0.24	1.05	1.57	2.11	2.68	3.27	3.90	4.57	5.25	5.93	6.61	7.31
	$V_{\max}$	0.01	0.04	0.07	0.09	0.11	0.14	0.16	0.19	0.22	0.25	0.27	0.30
	$a_{\max}$	0.07	0.29	0.43	0.58	0.74	0.90	1.08	1.26	1.45	1.63	1.82	2.01

$m_0 = 2.72\%$, $\beta = 0.96$, $\xi_{0STMD} = 14.11\%$

The Third Method		Stories of the building											
		1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th	11th	12th
Average values	$D_{\max}$	0.23	1.01	1.50	2.02	2.56	3.13	3.72	4.36	5.02	5.67	6.31	6.99
	$V_{\max}$	0.01	0.04	0.06	0.09	0.11	0.13	0.16	0.18	0.21	0.24	0.27	0.30
	$a_{\max}$	0.07	0.29	0.44	0.59	0.74	0.91	1.08	1.27	1.46	1.64	1.83	2.02

Note: D_{max}=maximum displacement (cm), V_{max}=maximum velocity (m/s) and a_{max}=maximum acceleration (m/s^2).

3.3 Robust design of the STMD system with uncertain parameters

The dynamic behavior of a building depends on its natural frequencies and mode shapes. Moreover, the damping of the structure has an important role in reducing the seismic responses of the building. These two are the most important parameters of the structures which could be affected by different sources. Therefore, in this study, it is assumed that the stiffness matrix and the structural damping ratio of the building may be different from those considered in the deterministic analyses, and consequently, should be treated as the uncertain parameters by assuming pre-defined probabilistic distributions. Therefore, in order to minimize the performance degradation of the control system from its ideal deterministic position, the uncertainties which exist in these parameters must be taken into account through a stochastic robust design optimization (RDO) approach. The control system which is designed by stochastic robust optimization approach is then less sensitive to random variation of the uncertain parameters.

There are many probability distribution functions representing a variety of conditions. In this study, the well-known standard Beta distribution with shape coefficients a=b=2 has been used for which the PDF is expressed as (Montgomery 2003)

$$y = \frac{1}{B(a,b)} x^{a-1}(1-x)^{b-1} I_{(0,1)}(x) \tag{17}$$

where $B(.)$ is the Beta function; and the indicator function $I_{(0,1)}(x)$ ensures that only the values of x in the range of (0,1) have non-zero probability.

In this research study, to perform stochastic RDO procedure, the stiffness and damping ratio of the building are considered as the uncertain random variables with maximum ±20% variation around their numerical values. For the accomplishment of this procedure, the building uncertain stiffness matrix, $[K_u]$, and that of the damping ratio, ξ_u, are defined as the following

$$[K_u] = \alpha_1 [K] \tag{18a}$$

$$y = \frac{1}{B(a,b)} x^{a-1}(1-x)^{b-1} I_{(0,1)}(x) \tag{18b}$$

where $[K]$ and ξ are the deterministic values of the stiffness matrix and damping ratio of the building; and the uncertainty coefficients α_1 and α_2 , with mean values of 1 and coefficient of variations (COV) of ±20%, are considered to incorporate the uncertainties which exist in $[K]$ and ξ. The coefficients α_1 and α_2 follow the probabilistic beta distribution given in Eq. (17). It is noted that in Eq. (17) the value of x varies between 0 and 1, while the uncertainty coefficients α_1 and α_2 vary between 0.8 and 1.2. This incompatibility is accomplished through the computer programming procedure. In this study, the Hammersley Sequence Sampling (HSS) method is used to simulate the probabilistic behavior of the building. The advantage of this method in comparison with the Monte Carlo method is that this method uses the specified pattern with a uniform distribution to generate the random numbers between 0 and 1; therefore, better results can be achieved with fewer samples (Hajiloo *et al.* 2007). This simulation and mapping procedure is depicted in Fig. 9, when uncertain variable x varies between 0 and 1 following the standard beta distribution. In this figure, y_1 and y_2 are the random numbers uniformly distributed between 0 and 1.

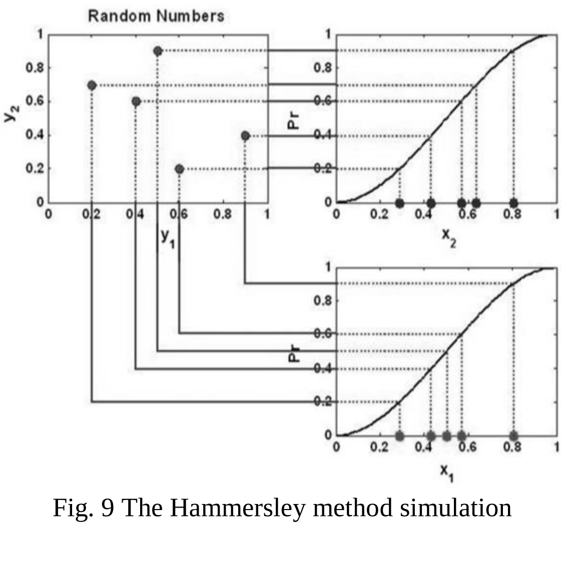

Fig. 9 The Hammersley method simulation

In the present study, to perform the stochastic RDO procedure using HSS approach, 50 pairs of uniformly distributed random variables are simulated between 0 and 1 using which 50 pairs of random uncertainty coefficients α_1 and α_2 are simulated through a similar mapping procedure shown in Fig. 9 by considering a beta distribution for these two variables. Then, using these 50 pairs of coefficients α_1 and α_2, 50 pairs of uncertain stiffness matrix, $[K_u]$, and damping ratio, ξ_u, are being simulated resulting in 50 buildings with different stiffness matrix and damping ratio. Now, these 50 buildings are analyzed under the application of 16 reference earthquake accelerogrames. The average values of maximum responses of these buildings top story level for the 16 reference accelerogrames are provided in Table 8. These results will be used for comparison with the controlled responses of the robust STMD system in the next sections.

For the stochastic robust design optimization of the STMD system, three objective functions are defined as follows

$$J_1=\frac{E\left(\max_i\left[\max_t\left|D_i^c(t)\right| \Big/ \max_t\left|D_i^{uc}(t)\right|\right]\right)}{E_{01}}+\frac{\sigma^2\left(\max_i\left[\max_t\left|D_i^c(t)\right| \Big/ \max_t\left|D_i^{uc}(t)\right|\right]\right)}{\sigma_{01}^2} \tag{19a}$$

$$J_2=\frac{E\left(\max_i\left[\max_t\left|V_i^c(t)\right| \Big/ \max_t\left|V_i^{uc}(t)\right|\right]\right)}{E_{02}}+\frac{\sigma^2\left(\max_i\left[\max_t\left|V_i^c(t)\right| \Big/ \max_t\left|V_i^{uc}(t)\right|\right]\right)}{\sigma_{02}^2} \tag{19b}$$

$$J_3=\frac{E\left(\max_i\left[\max_t\left|A_i^c(t)\right| \Big/ \max_t\left|A_i^{uc}(t)\right|\right]\right)}{E_{03}}+\frac{\sigma^2\left(\max_i\left[\max_t\left|A_i^c(t)\right| \Big/ \max_t\left|A_i^{uc}(t)\right|\right]\right)}{\sigma_{03}^2} \tag{19c}$$

where, E_{0i} and σ_{0i}^2 are the desired mean and variance of each random variable, respectively, which can be chosen by the designer. For example, the deterministic values of the objective functions for trade-off point (the point with lowest $||J||_2$) are used as the E_{0i} in which for Coalinga earthquake are given as: E_{01}=0.43, E_{02}=0.5, E_{03}=0.67. Furthermore, in order to have the minimum variation, the values of σ_{0i}^2 are considered as 0.001. In multi-objective optimization process using NSGA-II approach (Deb *et al*. 2002), the above three objective functions should be simultaneously minimized to get the perfect performance of the control system. Similar to the previous sections, 2-Norm *Level Diagrams* of Pareto fronts for Coalinga earthquake are shown in Fig. 10 for the robust STMD system. It can be seen from the figure that there is a conflict between J_1 and J_3. It means that the STMD system with lower displacement has higher acceleration. The same confliction can be found from Fig. 10 between J_2 and J_3. The squared point in Pareto front which has the lowest value of the 2-norm of the *Level Diagram* has the low value of each objective function; therefore, it is considered as an outstanding optimum point. The parameters of this optimum point and the mean and variance of each random variable, as well as the values of the STMD design parameters obtained for Coalinga earthquake are given in Table 9.

The average values of the optimized stochastic responses of top story level of the 50 buildings simulated for the robust design of the STMD system (corresponding to the point having the lowest

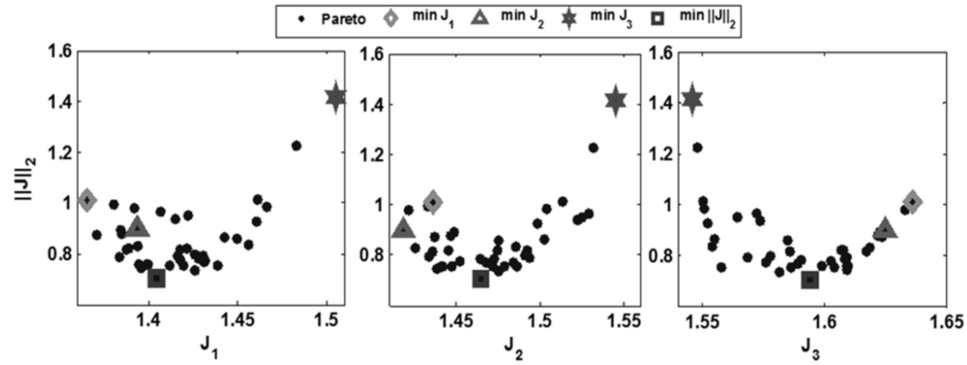

Fig. 10 2-Norm Level Diagrams of Pareto front of the robust STMD for Coalinga earthquake

value of the $||J||_2$) are presented in Table 10 for 7 accelerogrames. Moreover, in the last row of the table the ensemble average values of these responses for all 16 accelerogrames are given which can be used for the comparison with those of the uncontrolled ones. This table shows that the average values of the stochastic displacement, velocity, and acceleration of the top story of the building obtained for robust design of the STMD system in comparison with those of the uncontrolled ones are approximately reduced to about 52%, 42.5%, and 37.24%, respectively; while these reduction ratios obtained from deterministic analysis are about 34.53%, 34.8%, and 28.72%, respectively.

Furthermore, the values of the design parameters of the STMD device evaluated during the RDO procedure of this system, and the corresponding objective function values for optimum point with the lowest value of $||J||_2$ for 7 earthquake excitations are presented in Table 11. It is seen from the table that the stochastic average optimal values of the design parameters m_0, β and ξ_{TMD} are obtained as 2.37%, 0.92, and 16.9% respectively; while from deterministic analysis these values are obtained about 2.71%, 0.97, and 13.38%, respectively.

Moreover, Fig. 11 compares the time histories of the robust controlled and uncontrolled responses of the building top story for Coalinga earthquake and for optimum point with the lowest value of $||J||_2$. This figure also shows that the robust STMD system is an appropriate device to control the building seismic responses.

The stochastic time history responses of the building top floor for the above mentioned optimum robustly designed STMD system is shown in Fig. 12. In this figure, the dashed lines show the stochastic responses of the building top floor calculated for 50 simulated sample buildings, and the solid line shows the mean values of these responses. It is evident from the figure that all the individual stochastic responses corresponding to 50 sample buildings and their mean value are very close to each other. It means that the robust design of control system significantly reduces the effect of uncertainties which exist in the structure leading to a control system with less sensitivity to the uncertainties of the system.

In order to compare the results of the deterministic and robust optimization design methods, the 50 sample buildings simulated in previous sections are analyzed by considering the optimal values of the STMD design parameters (m_0, β, and ξ_{0TMD}) obtained from these two methods. For this purpose, the above 50 sample buildings are analyzed by considering the optimal STMD system for the trade-off point (the point with the minimum value of $||J||_2$) in each earthquake excitation. The PDFs of the normalized maximum responses of the 50 sample buildings are shown in Fig. 13

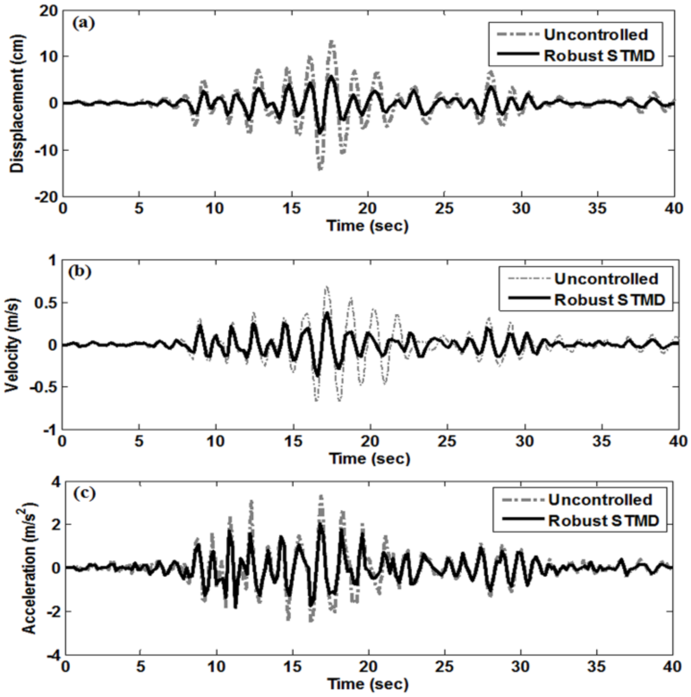

Fig. 11 Comparison of the robust controlled and uncontrolled responses of the top story of the building for Coalinga earthquake: (a) displacement, (b) velocity, and (c) acceleration

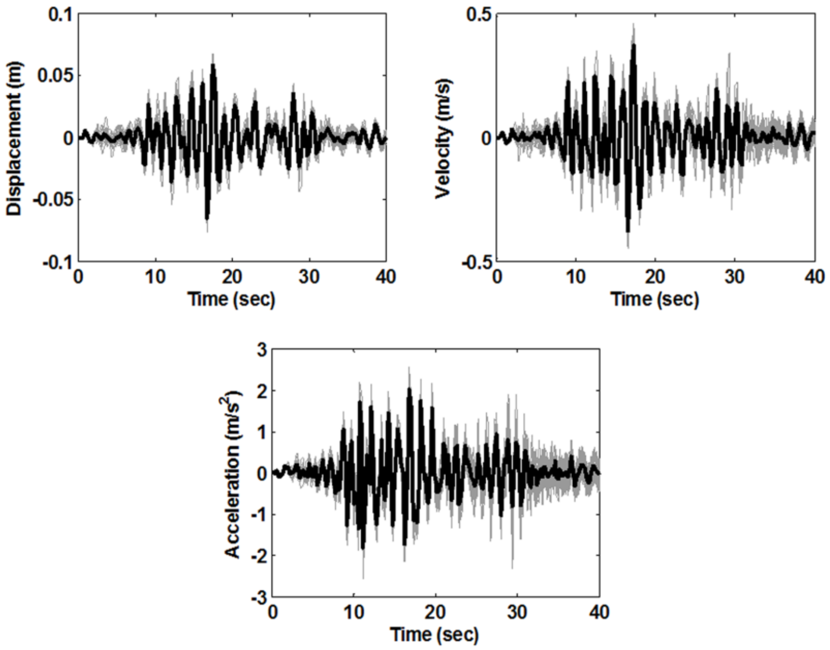

Fig. 12 Stochastic response of the top floor for the trade-off point (dashed lines are each sample response and solid line is mean of the responses)

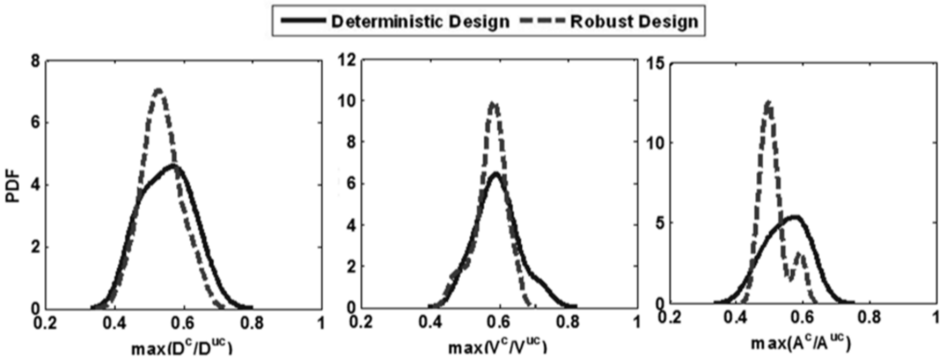

Fig. 13 The PDFs of each objective function for Coalinga earthquake

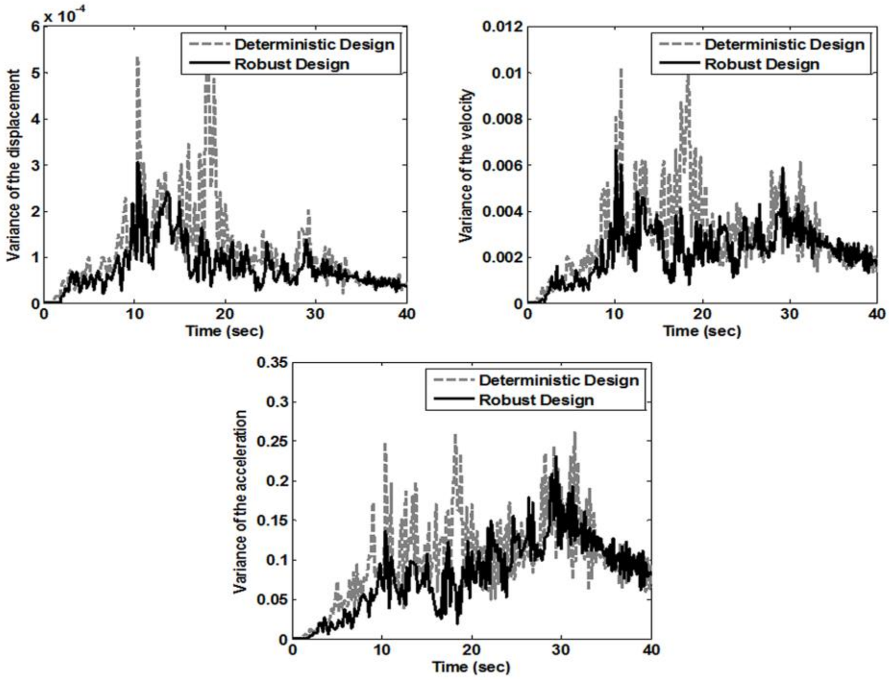

Fig. 14 Variance of the stochastic response

for the final optimal STMD design parameters for the two cases of the robust and deterministic designs of the STMD system for Coalinga earthquake. It is clear from the figure that with the robust design of the STMD system the variation of each objective function from its mean value is very low in comparison with that of the deterministic design, indicating that the robust design is more reliable than the deterministic one.

Moreover, to show the supremacy of the robust design, the variances of the top story responses of the simulated buildings are shown for the trade-off points of the robust and deterministic designs in Fig. 14. It is seen from the figure that the stochastic behavior of the uncertain system can have less variation if and only if the system is designed robustly. Finally, from the above discussion it is obvious that the robust design is necessary to achieve a safe design compatible with the variation in parameters and conditions of the system.

4. Conclusions

The main objective of this paper is to find the optimal values of the parameters of the STMD system as a kind of semi-active control device using genetic algorithms (GAs) and fuzzy logic. For this purpose, three non-commensurable objective functions namely: the maximum displacement, velocity, and acceleration of each story level of the building are chosen to minimize simultaneously. For the numerical analysis, a reality 12-story building has been chosen. The torsional effects due to irregularities which exist in the building and/or unsymmetrical placements of the dampers are taken into account through the 3-D modeling of the building. Moreover, in the optimal design procedure of a system, it is required that the uncertainties which may exist in the system be taken into account in the dynamic analyses. In the present study, this consideration is performed through the robust design optimization (RDO) procedure. Hammersley Sequence Sampling (HSS) method, which is a direct and simple numerical method, is used to perform the RDO procedure. Finally, the robust optimal values of the STMD design parameters are evaluated for the example building structure. Based on the multi-objective GAs of this work, the point which has the lowest value of the Euclidean norm of all objective functions is used to compare the application of this device. The numerical studies of this research work lead to the following conclusions:

1. In this study, by performing both deterministic multi-objective optimization procedure and probabilistic robust design optimization (RDO) procedure, the optimum values of the design parameters for STMD control system are obtained for the two cases.

2. It is observed that the robust optimization of the STMD system provides more reduction on building responses in comparison with that of its deterministic design.

3. It is found that with the robust design of the STMD system, the variation of each objective function from its mean value is very low in comparison with that of the deterministic design, indicating that the robust design is more reliable than the deterministic one.

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