

OBSERVATION BASED SEMI ACTIVE CONTROL OF STRUCTURES USING MR DAMPERS

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Abstract

MR damper is a semi-active control device used effectively to control the response of building frames for earthquakes. In most practical situations, it is not possible to take response measurements from all degrees of freedom and use them for developing feedback control algorithm to be used for actuating the MR dampers. Therefore, observer based control strategies are to be developed. Herein, an observer-based control algorithm is developed for semi-active control of building frames using MR dampers for stochastic control. The algorithm is developed using Kalman filter, LOG algorithm and clipped optimal control. The control of a ten storey building frame is achieved by employing a maximum number of 3 MR dampers and three displacement measurement locations employed strategically in the building frame. Locations of the MR dampers and measurement locations are determined using the genetic algorithm. The measurements are provided as feedback information to the control algorithm. The controlled responses of interest are the top storey displacement, maximum drift and the base shear of the frame. These three response quantities are determined for a number of real and artificial earthquakes. The artificial earthquakes considered are oftwo types, one broadband and the other narrowband. The results of the study suggest that; (i) the degree of control of the response quantities of interest varies with the earthquakes (ii) for the numerical problem solved here, the optimal locations of the dampers remain same for all the three response quantities of interest and for all earthquakes (iii) optimal locations of observations vary with the response quantities of interest and earthquakes. Therefore, no unique solution exists for the overall good performance of a partially observed controlled structure.

Keywords: MR Damper, LQG, Kalman Filter, Semi-active control



1. Introduction

In the last three decades, a significant contribution has been made by the researchers in the field of the structural control. As a result, many control devices and algorithms have been proposed [1-6] for the four categories of structural control namely, passive, active, semi-active and hybrid control systems. Amongst them, the semi-active control has recently become a preferred topic of interest because of its less power requirement. Previous studies indicate that for effective response reduction and satisfactory performance of the structures proper selection of semi-active control system is necessary. Various types of semi-active control systems have been investigated namely variable stiffness devices, smart tuned mass dampers, smart tuned liquid dampers, controllable friction dampers, controllable impact dampers, controllable fluid dampers and ER or MR dampers. Amongst them, MR dampers have attracted considerable attention due to its low power requirement, large force capacity and robustness. It is also stable and fail – safe, because the damper becomes passive when the control mechanism breaks down.

A large number of studies have been made on MR dampers using different control strategies. Dyke et al. [7] proposed a clipped optimal law based on acceleration feedback. The desired control force was predicted using H₂/LOG strategy. Jansen et al. [8]compared different control algorithms like Bang- bang control, clipped optimal control, Lyapunov control and modulated homogenous friction control algorithm by using multiple MR dampers. Xu et al. [9]proposed two optimal displacement control strategies for semi-active control of seismic response of framed structures using MR or ER dampers. Zapateiro et al. [10]used quantitative feedback theory for response reduction taking into account the nonlinear dynamics of MR damper. Bahar et al. [11]proposed a hybrid control system combining a nonlinear base isolator and MR damper. In the MR damper, the voltage was updated by a feedback control loop. Chang et al. [12]used recurrent neural network models for structural control. They emulated the inverse dynamics of MR damper to produce required command voltage. Two examples of structural control were taken: optimal prediction control of a single degree of freedom system and LQR control of a multi-degree of freedom system to illustrate the proposed scheme. Heon et al. [13]applied the neuro controller to a base-isolated benchmark problem. The training algorithm based on minimizing the cost function was used. A clipped optimal algorithm was then employed to produce the desired control force. Das et al. [14]used an ANN- cum- fuzzy control scheme for structural response mitigation. Bharti et al. [15]investigated the behavior of an asymmetric building plan with MR dampers.

Genetic algorithm introduced by Holland [16] has been used quite extensively in the structural control. Rao et al.[17]usedthe genetic algorithm to find the optimum location of active controllers for a two bay truss by minimizing the dissipation energy of active controller as the objective function. Furuya and Haftka [18] applied GA using an integer and binary coding to find the optimal location of actuators for large space structures. Dhingra and Lee[19], Abdullah et al. [20]used a hybrid optimization scheme based on GA and gradient based technique to solve a multi-objective optimization problem for the determination of the optimum number and location of actuators for active control under wind load. Ahlawat and Ramaswamy [22] proposed a multi objective genetic algorithm to determine the optimal configurations of a hybrid control system. Li et al. [23]proposed a two level genetic algorithm to determine the optimal number and position of actuators in active control structures. Cha et al. [24]proposed a multilevel genetic algorithm to determine the optimal number and location of active control structures. Cha et al. [24]proposed a multilevel genetic algorithm to determine the optimal number and location of active devices and sensors for a 20 story structure.

In this study, optimally placed MR dampers are employed for controlling the seismic response of partially observed building frames. The LQG control algorithm along with clipped optimal control is used for activating the MR dampers. Genetic algorithm (GA) is used for optimal placement of MR dampers and optimal location of sensors for response measurements. For this purpose, a single objective GA is used with response quantities of interest as base shear, top floor displacement and inter-story drift.

2. Theory:

The equation of motion for the building frame fitted with MR dampers in Figure 1 takes the form:



 $[\mathbf{M}]\{\ddot{\mathbf{x}}\} + [\mathbf{C}]\{\dot{\mathbf{x}}\} + [\mathbf{K}]\{\mathbf{x}\} = [\mathbf{G}]\{\mathbf{f}_{\mathbf{m}}\} - [\mathbf{M}][\mathbf{r}]\{\ddot{\mathbf{u}}_{\mathbf{g}}\}$ (1)

where, M, C, and K are the mass, damping and stiffness matrices of the system, respectively; f_m *is* the MR damper force vector, respectively; G is the damper location matrix; x is the displacement vector with respect to the ground; r is an influence coefficient vector; and \ddot{u}_g is the earthquake ground acceleration. The governing Eq. (1) is expressed in the state-space form as below:

$$\{\dot{z}\} = [A]\{z\} + [B]\{f_m\} + [E]\{\ddot{u_g}\}; y = [C]\{z\} + [D]\{f_m\} + v$$
(2, 3)

where A is a 2n x 2n system matrix, B is a 2n x $2n_c$ control matrix, E is a 2n x 1 disturbance (excitation) matrix, C is a p x 2n measurement matrix, D is a p x n_c matrix, z is a 2n x 1 state vector, y is a p x 1 vector of measured outputs and v is a p x 1 measurement noise vector; n is the number of states, n_c is the number of controllers and p is the number of measurements.

2.1 Linear Quadratic Gaussian Algorithm

The LQG controller is a combination of Kalman filter and linear quadratic regulator. The Kalman filter estimates the state by minimizing the covariance matrix of error at each time step and the LQR estimates the control force by minimizing the quadratic cost function. The following cost function is used:

$$\mathbf{J} = \mathbf{E}[\mathbf{x}^{\mathrm{T}}(\mathrm{T})\mathbf{F}\mathbf{x}(\mathrm{T})] + \int_{0}^{1} \mathbf{x}^{\mathrm{T}}(\mathrm{t})\mathbf{Q}\mathbf{x}(\mathrm{t}) + \mathbf{u}^{\mathrm{T}}(\mathrm{t})\mathbf{R}\mathbf{u}(\mathrm{t}) \,\mathrm{d}\mathrm{t}$$
(4)

where E denotes the expected value; T denotes the final time which may be finite or infinite and when T tends to infinity the first term of the cost function $\mathbf{x}^{T}(T)\mathbf{F}\mathbf{x}(T)$ becomes negligible; Q and R are the positive definite matrices.

For partially observed system, the full state $\hat{\mathbf{x}}(\mathbf{t})$ is estimated from the measurement $\mathbf{y}(\mathbf{t})$ by the following equation:

$$\hat{\mathbf{x}}(\mathbf{t}) = \mathbf{A}\hat{\mathbf{x}}(\mathbf{t}) + \mathbf{B}\mathbf{u}(\mathbf{t}) + \mathbf{K}(\mathbf{t})\big(\mathbf{y}(\mathbf{t}) - \mathbf{C}\hat{\mathbf{x}}(\mathbf{t})\big)$$
(5)

where **K**(**t**) is the Kalman gain associated with the Kalman filter. At each time step t, the Kalman gain estimates the state from past measurements and inputs. The Kalman gain is obtained from **A**, **B**, **V**, **W** matrices and $E(x(0)x^T(0))$ by solving the following Riccati equations. **V** and **W** are the covariance matrices of white gaussian noise **v**(**t**) and excitation **w**(**t**). Thus, excitations in Eqn. 1,2 and 3 should be ideally be white noise.

$$P(t) = P(t)A(t) + P(t)A^{T}(t) + P(t)C^{T}(t)V^{-1}(t)C(t)P(t) + W(t)$$
(6)

$$\mathbf{K}(\mathbf{t}) = \mathbf{P}(\mathbf{t})\mathbf{C}^{\mathrm{T}}(\mathbf{t})\mathbf{V}^{-1}(\mathbf{t}) \text{and} \mathbf{P}(\mathbf{0}) = \mathbf{E}\left(\mathbf{x}(\mathbf{0})\mathbf{x}^{\mathrm{T}}(\mathbf{0})\right)$$
(7)

The control force is given by the following equation:

$$\mathbf{u}(\mathbf{t}) = -\mathbf{L}(\mathbf{t})\hat{\mathbf{x}}(\mathbf{t}) \tag{8}$$

where **L**(**t**) is the feedback gain matrix and it is defined using **A**,**B**, **Q**, **R** matrices and **F** by solving the following Riccati equation:

$$-\dot{\mathbf{S}}(\mathbf{t}) = \mathbf{A}^{\mathrm{T}}\mathbf{S}(\mathbf{t}) + \mathbf{S}(\mathbf{t})\mathbf{A} - \mathbf{S}(\mathbf{t})\mathbf{B}^{\mathrm{T}}\mathbf{R}^{-1}\mathbf{B}^{\mathrm{T}}\mathbf{S}(\mathbf{t}) + \mathbf{Q}$$
(9)

$$\mathbf{L}(\mathbf{t}) = \mathbf{R}^{-1} \mathbf{B}^{\mathrm{T}} \mathbf{S}(\mathbf{t}) \text{and } \mathbf{S}(\mathbf{T}) = \mathbf{F}$$
(10)

In discrete form, LQG control is given in the following form:

$$\mathbf{x}_{i+1} = \mathbf{A}_i \mathbf{x}_i + \mathbf{B}_i \mathbf{u}_i + \mathbf{w}_i; \ \mathbf{y}_i = \mathbf{C}_i \mathbf{x}_i + \mathbf{v}_i$$
 (11,12)



where i is the discrete time index ; v_i , w_i represent the discrete measurement noise and excitation. The objective of the control algorithm is to find out the control force by minimizing the following cost function:

$$\mathbf{J} = \mathbf{E}(\mathbf{x}_{N}^{\mathrm{T}}\mathbf{F}\mathbf{x}_{N} + \sum_{i=0}^{N-1} \mathbf{x}_{i}^{\mathrm{T}}\mathbf{Q}_{i}\mathbf{x}_{i} + \mathbf{u}_{i}^{\mathrm{T}}\mathbf{R}_{i}\mathbf{u}_{i})$$
(13)

In partially observed system, the state estimation is achieved by using Kalman filter as follows:

The state $(\hat{\mathbf{x}}_{(i|i-1)})$ and the covariance estimation $(\mathbf{P}_{(i|i-1)})$ of the *i*th time step after the (i-1)th time step is given as:

$$\hat{\mathbf{x}}_{(i|i-1)} = A_i \hat{\mathbf{x}}_{(i-1|i-1)} + B_i \hat{\mathbf{u}}_i + W_i$$
(14)

$$P_{(i|i-1)} = A_i P_{(i-1|i-1)} A_i^{\mathrm{T}} + W_i$$
(15)

where W_i is the covariance matrix of disturbance noise.

Then the measurement residual (\tilde{y}_i) at ith time step is calculated as follow:

$$\widetilde{\mathbf{y}}_i = \mathbf{z}_i - \mathbf{C}_i \widehat{\mathbf{x}}_{(i|i-1)} \tag{16}$$

where z_i are the measurements at ith time step.

The optimal gain at ith time step is calculated as follow:

$$K_{i} = P_{(i|i-1)} C_{i}^{T} (C_{i} P_{(i|i-1)} C_{i}^{T} + V_{i})^{-1}$$
(17)

The updated state $\hat{\mathbf{x}}_{(i|i)}$ and covariance estimation $P_{(i|i)}$ at ith time step is given as:

$$\hat{\mathbf{x}}_{(i|i)} = \hat{\mathbf{x}}_{(i-1|i)} + \mathbf{K}_{i} \{ \mathbf{z}_{i} - \mathbf{C}_{i} \hat{\mathbf{x}}_{i-1} \}$$
(18)

$$P_{(i|i)} = A_i P_{(i-1|i-1)} A_i^{\mathrm{T}} + W_i$$
(19)

The control force is given by

$$\boldsymbol{u}_i = -\boldsymbol{L}_i \hat{\boldsymbol{x}}_i \tag{20}$$

where the feedback gain L_i is determined by solving the Riccati equation that runs backward in time.

$$S_{i} = A_{i}^{T} (S_{i+1} - S_{i+1} B_{i} (B_{i}^{T} S_{i+1} B_{i} + R_{i})^{-1} B_{i} S_{i+1}) A_{i} + Q_{i}$$
(21)

with
$$\mathbf{L}_{i} = \left(\mathbf{B}_{i}^{\mathrm{T}}\mathbf{S}_{i+1}\mathbf{B}_{i} + \mathbf{R}_{i}\right)^{-1}\mathbf{B}_{i}^{\mathrm{T}}\mathbf{S}_{i+1}\mathbf{A}_{i} \text{ and } \mathbf{S}_{\mathrm{N}} = \mathbf{F}$$
 (22)

In the development of Matlab coding the discrete frm of equations are used.

2.2 Genetic Algorithm

The concepts of the genetic algorithm are based on the Darwin theory of natural selection. In the genetic algorithm, a set of possible solutions to an optimization problem evolves towards the best solutions. The genetic algorithm is an iterative process and initially, a group of individuals is selected to form the initial population. Then the fitness of each is evaluated in the problem environment according to the objective function. The more fit individuals are choosen from the current population, and the gene of each is modified according to crossover and mutation. The cycle of fitness evaluation, selection, crossover and mutation are repeated until the population converges or the other criteria are satisfied.



2.2.1 Initialization:

Initially, in GA, a group of individuals is selected from the set of possible solutions. The selection of individuals is random, but any particular selection procedure can be adopted for selection

2.2.2 Selection:

In each successive generation, a part of the current population is selected for breeding a new generation. The selection of individuals is based on their fitness value i.e. individuals having higher fitness values have more chance of getting selected. The fitness function is always problem dependent and is defined over the genetic representation of the possible solutions. For the study, tournament selection procedure is selected.

2.2.3 Crossover and Mutation:

After selection, next generation of the population is generated from the selected population through the process of crossover and mutation. Mutation functions make small random changes in the individuals in the population, which provide genetic diversity and enable the genetic algorithm to search a broader space. Crossover combines two individuals, or parents, to form a new individual, for the next generation. Adaptive feasible (mutation function) and scattered (crossover function) are used for the study.

2.2.4 Termination

The generation process is repeated until a terminating condition is reached. Common terminating conditions are like fixed number of generations reached, allocated budget computation time reached, the highest ranking solution's fitness is reaching or has reached a condition such that successive iterations no longer produce better results or combinations of the above

3.Generation of Control Forces using MR Damper

Force in the MR damper is generated based on the movement of the piston and the viscosity of the MR fluid which is manipulated by applying the voltage to the magnetic coil of the MR damper. While the actuation of the piston is governed by the vibration of the structure, the applied voltage is governed by the control algorithm. The control algorithm is shown in Figure 1. Modified Bouc Wen model is used for predicting the MR damper force. Inputs to the model are the inter-story drifts and velocities. By comparing the generated control force with the desired control force, voltage is held constant or set to zero using clipped optimal control.

3.1 Modified Bouc Wen model

Equations governing the MR damper force predicted by this model is given as [25]:

$$f_{\rm m} = c_1 \dot{x} + k_1 (u_{\rm d} - x_0) \tag{23}$$

where, the evolutionary variable z is given as:

$$\dot{z} = -\gamma |v_d - \dot{x}|(z)|z|^{(n-1)} - \beta (v_d - \dot{x})|z|^n + A_m (v_d - \dot{x})$$
(24)

and \dot{x} is given as

$$\dot{\mathbf{x}} = \left\{ \frac{1}{c_0 + c_1} \right\} \left\{ \alpha_0 \mathbf{z} + \mathbf{c}_0 \mathbf{v}_d + \mathbf{k}_0 (\mathbf{u}_d - \mathbf{x}) \right\}$$
(25)

where, u_d is the displacement of the damper; x is the internal pseudo-displacement of the damper; z is the evolutionary variable that describes the hysteretic behavior of the damper; k_1 is the accumulator stiffness; c_0 is the viscous damping at large velocities; c_1 is viscous damping for force roll-off at low velocities; k_0 is the stiffness at large velocities; and x_0 is the initial stiffness of spring k_1 ; α_0 is the evolutionary coefficient; and



 γ , β , n and A_m are shape parameters of the hysteresis loop. The model parameters dependent on command voltage, c_0, c_1, α_0 , are expressed as follows:

$$c_0 = c_{0a} + c_{0b}U; c_1 = c_{1a} + c_{1b}U; \alpha_0 = \alpha_{0a} + \alpha_{0b}U$$
 (26, 27, 28)

where, U is given as output of first order filter following the condition as below

$$\dot{\boldsymbol{U}} = -\mathbf{h}(\boldsymbol{U} - \boldsymbol{V}) \tag{29}$$

3.2 Clipped Optimal Control Law

The input voltage to the MR damper is obtained using clipped optimal law [26]. When the absolute value of MR damper force is greater than the absolute value of LQG force, then the voltage is set to maximum, and when the absolute value of MR damper force is less than the absolute value of LQG force then the voltage is set to zero. The mathematical form of clipped optimal law is:

$$\mathbf{V} = \mathbf{V}_{\max} \mathbf{H} \{ (\mathbf{F}_{\mathbf{d}} - \mathbf{F}_{\mathbf{m}r}) \mathbf{F}_{\mathbf{m}r} \}$$
(30)

where V is the input voltage to the MR damper, H is the Heaviside function, V_{max} is the maximum input voltage, F_d is the LQG force and F_{mr} is the MR damper force. The voltage is maximum when Heaviside function is one and zero when Heaviside function is zero.



Figure 1- (a) Building equipped with three MR dampers and three sensors and (b)the control strategy

4.Numerical Study

For the study, a ten story linear shear type building is used having a mass of each floor as 18 ton and stiffness of each floor as 24965 KN/m. The building is subjected to two real earthquakes (Elcentro and Mexico earthquake) and two artificially generated (narrowband and white noise) earthquakes. The building is installed with three



MR dampers and three sensors. GA is used to find the optimal location of MR dampers and sensors. The narrowband earthquake is generated from a double filtered PSDF given as:

$$\ddot{\mathbf{S}}_{ug}(\mathbf{w}) = \frac{(1+4\beta_g^2(\frac{w}{w_g}))}{\left(1-\left(\frac{w}{w_g}\right)^2\right)^2 + 4\beta_g^2(\frac{w}{w_g})^2} \quad \mathbf{x} \quad \frac{\left(\frac{w}{w_f}\right)^4 * \mathbf{S}_o}{\left(1-\left(\frac{w}{w_f}\right)^2\right)^2 + 4\beta_f^2(\frac{w}{w_f})^2}$$
(31)

where $w_g = 6.28$, $\beta_g = 0.4$, $w_f = 0.628$, $\beta_f = 0.4$, $S_0 = 0.0058$, w is the frequency and \ddot{S}_{ug} is the PSDF ordinate corresponding to the frequency w. The time histories of the narrowband earthquake and white noise are shown in Figure 2. The values of the parameters used for MR damper are shown in Table 1 [25].

Parameter	Value [Unit]	Parameter	Value [Unit]	
<i>c</i> _{0<i>a</i>}	50.30 [kN.sec/m]	$lpha_a$	8.70 [kN/m]	
<i>C</i> _{0<i>b</i>}	48.70 [kN.sec/m.V]	$lpha_b$	6.40 [kN/m.V]	
k_0	0.0054 [kN/m]	γ	496 [m ⁻²]	
<i>c</i> _{1<i>a</i>}	8106.2 [kN.sec/m]	β	496 [m ⁻²]	
c_{1b}	7807.9 [kN.sec/m.V]	A	810.50	
k ₁	0.0087 [kN/m]	n	2	
x_0	0.18 [m]	η	$190 [sec^{-1}]$	

Table 1- Parameters for MR damper

Q and R matrices for the LQG algorithm are taken as: $Q = \begin{bmatrix} Q_1 & 0 \\ 0 & M \end{bmatrix}$ and R is an identity matrix of size 3 x 3 multiplied by a constant 10⁻⁴; where Q_1 is an identity matrix of size 10 x 10 multiplied by a constant 10⁶ and O is a null matrix of size 10 x10. The noise covariance matrix V is selected such that the optimum results are obtained. For this problema, V is a matrix of 3x3 with diagonal elements as 10⁻⁹.

Use of LQG algorithm for the partially observed system is not strictly valid for excitations and noises other than gaussian white. Therefore, LQG is used for the two real earthquakes and the synthetical earthquake with an assumption that they are gaussian white having a certain ratio between their intensities and the measurement noise intensities. The mean square value of excitations is taken as the covariance of the earthquakes.



Figure 2-Time histories of a) white noise and b) PSDF generated narrowband earthquake



Figure 3-Comparison of uncontrolled and controlled time histories of top floor displacement and base shear for generated narrow band earthquake



Figure 4-Variations of damper force with piston displacement and velocity for generated narrow band earthquake

For the narrowband earthquake, the comparison between the controlled and uncontrolled time histories of top floor displacement and base shear (Figure 3) shows that the building is well controlled. The maximum percentage reduction in top floor displacement and base shear is 38% and 24% respectively when LQG algorithm is used. For LQR algorithm, nearly the same reductions are obtained. Optimum locations of the dampers are found as first, second and third floors. The force-displacement and force-velocity plots for MR damper located at first floor are shown in Figure 4.



Figure 5-Comparison of uncontrolled and controlled time histories of top floor displacement and base shear for white noise earthquake



Figure 6-Variations of damper force with piston displacement and velocity for white noise earthquake

For white noise, the comparison between the controlled and uncontrolled time histories of top floor displacement (Figure 5) shows that the building is better controlled as compared to the narrowband excitation. However, the base shear reduction becomes less. The maximum percentage reduction for top floor displacement and base shear is 46% and 10% respectively. In this case also, no significant difference is observed between the responses obtained by using LQR and LQG algorithms. The force-displacement and force-velocity plots for the MR damper located on the first floor are shown in Figure 6. Here again, the optimum locations of the damper remains the same as those for the narrow band excitation.



Figure 7-Comparison of uncontrolled and controlled time histories of top floor displacement and base shear for El Centro (1940) earthquake



Figure 8-Variations of damper force with piston displacement and velocity for El Centro (1940) earthquake



Figure 9-Comparison of uncontrolled and controlled time histories of top floor displacement and base shear for Mexico (1986) earthquake



Figure 10-Variations of damper force with piston displacement and velocity for Mexico (1986) earthquake

For the two real earthquakes considered here, the response reductions were better as compared to the artificially generated ones. The time histories of controlled and uncontrolled responses for the two real earthquakes (El Centro and Mexico) are shown in Figs. 7 and 9. The force- displacement and force-velocity plots are shown in Figs. 8 and 10. The reason for better control of response for the case of real earthquakes may be attributed to the difference in the nature of earthquakes in comparison to that of artificial ones.

Out of the two real earthquakes, Mexico earthquake did not provide a significant reduction in response since the predominant frequencies of the earthquake were away from the building frequencies. Therefore, the building's fundamental period was increased to 2.5 seconds so that the fundamental frequency of the building matches the predominant frequency of maximum energy of Mexico earthquake. Further, the earthquake was scaled to 50 % to keep the response within the elastic range.

 Table 2-Comparison of Percentage reduction obtained through LQR and LQG control algorithms for different earthquakes (with optimum location of dampers and sensors)

Algorithm	Response quantity	%age reduction for El Centro	%age reduction for Mexico	% age reduction for White noise	%age reduction for Narrowband earthquake
LQG (LQR)	d	54.46 (50.83)	59.93 (58.16)	45.86 (41.37)	37.98 (39.13)
	F _d	44.09 (41.21)	49.65 (45.20)	9.48 (9.48)	23.70 (31.46)
	d _r	56.14 (51.75)	67.24 (60.97)	52.85 (64.28)	42.85 (63.49)



Percentage reduction in response quantities of interest for optimum location of dampers and sensors (response pickups) is summarized in Table 2. Here d = top floor displacement; $F_d = Base$ Shear; $d_r = maximum$ inter story drift. It is seen that the control of responses varies with the earthquakes especially the base shear response.

Responses	El Centro Earthquake	Mexico Earthquake	White Noise	Narrowband earthquake
Base Shear	1, 2 and 5	1,4 and 5	7,8 and 10	1, 4 and 8
Top floor displacement	2,4 and6	3,7 and 8	5,6 and 7	1,4 and 5
Max. Inter story Drift	1,4 and 7	8,9 and 10	7,8 and 9	3,7 and 8

Table 3-Best pick up locations for top floor displacement; base shear and maximum inter story drift

Table 4- Comparison of results of best locations of dampers with that of arbitrary locations of dampers

Location of Damper	Responses	%age reduction for El Centro	%age reduction for Mexico	% age reduction for White noise	%age reduction for Narrowband earthquake
Best Location	d	54.46 (36.54)	59.93 (56.67)	45.86 (35.70)	37.98 (29.29)
(Arbitrary Location)	F _b	44.09 (27.67)	49.65 (42.46)	9.48 (9.48)	23.70 (20.21)
	d _r	56.14 (28.50)	67.24 (40.75)	52.85 (27.14)	42.85 (4.7)

Tables 3 and 4 show the results of the Pareto optimal solutions. Parameters which are varied in the genetic algorithm are locations of the MR dampers (3 nos.) and sensors (3 nos.) The objective function is chosen as either base shear or top floor displacement or maximum inter-story drift. For all the three objective functions, Pareto optimal solutions obtained through genetic algorithm provide same locations of dampers i.e. at story 1, 2 and 3 but different locations of the sensors. Optimal locations of the sensors for each response quantity of interest are shown in Table 3. It is seen from the table that the optimal sensor locations are different for different response quantities and different earthquakes. Thus, there exists no unique solution for the optimally controlled responses using GA. Table 4 compares the responses between the optimally located dampers and dampers with arbitrary locations (placed at second, third and fourth floor). It is seen from the table that the optimally located dampers provide much better control of the top floor displacement and maximum drift.

5.Conclusions

The response of a ten story building is semi-actively controlled by MR dampers using LQG and clipped optimal control for earthquakes described by their PSDFs and for real earthquake records.For the latter, ergodic control is asumed, and the earthquake record represents the ensemble of a stationary process idealized as white noise with specified covariance function. The responses are partially observed and the full state of the system is obtained from the observations using Kalman filter. The control of response is achieved by three MR dampers and three observations (with sensors). Optimal locations of the dampers and observations are obtained by employing genetic algorithm. Three response quantities of interest namely, top floor displacement, maximum drift, and base shear are controlled. The following conclusions are drawn from numerical study:

- 1. The degree of control of the response quantities of interest varies with the earthquakes.
- 2. For the numerical problem solved here, the optimal locations of the dampers remain the same for all the three response quantities of interest and for all earthquakes.



- 3. Optimal locations of observations vary with the response quantities of interest and earthquakes. Therefore, no unique solution exists for the overall good performance of a partially observed controlled structure.
- 4. Both LQG and LQR control algorithms along with clipped optimal control provide nearly the same control of responses.
- 5. The desirable performance of the MR dampers for the seismic control of structure in the case of narrowband earthquakes may be difficult to achieve.

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