Control of MR Damper Connected Buildings by Output Feedback

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The control of seismic response of buildings connected by a magnetorheological (MR) damper is studied. The desired control force is obtained using Linear Quadratic Gaussian (LQG) control based on the feedback of states estimated via measured outputs or Optimal Static Output Feedback (OSOF) control using the direct feedback of measured outputs. The damper input voltage is predicted using a Recurrent Neural Network (RNN), which proves more effective than the Clipped Voltage Law (CVL). Various sensor configurations and state weightings are considered to obtain effective control. LQG-RNN/OSOF-RNN yield significant reduction in response and base shear and require much less control effort compared to passive-on control with saturation voltage. Compared to passive-off control, they are very effective in attenuating maximum-peak/RMS responses and storeywise responses of the flexible building, except for max-peak accelerations that increase slightly. However, passive-off control is unable to transfer base shear to the stiffer building. LQG-RNN/OSOF-RNN also yield control at least as effective as LQR-RNN by deploying much fewer sensors but using a somewhat higher damper force. They are mostly comparable to each other, but OSOF-RNN requires an order-of-magnitude less CPU time for the control loop. Effective control is possible using few sensors.

1. INTRODUCTION

An earthquake induced response of adjacent buildings can be mitigated by connecting them with dampers. Semiactive devices, such as MR dampers, provide controllable damping with a low power expenditure.

Modelling of MR dampers is notably due to: Song et al.\textsuperscript{1} who presented a model of an MR damper using polynomial functions and a first-order filter; Chang and Zhou\textsuperscript{2} who proposed a recurrent neural network (RNN) model of an MR damper, which is appropriate for closed loop control; Spencer et al.\textsuperscript{3} who proposed the modified Bouc-Wen model, containing additional stiffness and damping elements to model an accumulator and low-velocity behavior, respectively; Wang and Kamath\textsuperscript{4} who proposed a phase-transition model involving a nonlinear differential equation for damper force with velocity as input; and Jimenez and Alvarez-Icaza\textsuperscript{5} who presented a modified LuGre friction model by replacing material dependency with voltage dependency.

Predicting applied voltage to produce a desired damper force is difficult. This is due to the non-invertible force-voltage dynamics of hysteretic models for MR dampers. The controllers considered are notably due to: Xu and Shen\textsuperscript{6} who used intelligent bi-state control with a Bingham model and on-off current law and later Xu and Guo\textsuperscript{7} who proposed a neuro-fuzzy controller for damper current; Dyke et al.\textsuperscript{8} who used the modified Bouc-Wen model with acceleration feedback LQG control for desired damper force and proposed an on-off Clipped Voltage Law (CVL); Yuen et al.\textsuperscript{9} who used reliability based robust linear control for desired force and CVL for command voltage; Karamodin and Kazemi\textsuperscript{10} who used LQG control for desired force and a semiactive neural controller (using acceleration/velocity feedback) for damper voltage; and Bahar et al.\textsuperscript{11} who designed a hierarchical controller with velocity feedback for the desired force and proposed an inverse Bouc-Wen model for voltage.

Control of connected buildings with base excitation is notably due to: Aida and Aso\textsuperscript{12} who used an optimal controller and showed that damping improves when the connector is placed near the top and the natural frequencies are well separated; Ni et al.\textsuperscript{13} who experimentally showed, using an MR damper connector, that the optimum damper location is at the top of the shorter building; Zhu et al.\textsuperscript{14} who considered passive/active/semiactive connection elements, albeit without damper dynamics; Qu and Xu\textsuperscript{15} who used the Bingham MR model and instantaneous sub-optimal control with the damper relative displacement as the control input to study the whipping of a tall building connected to a podium; Xu et al.\textsuperscript{16} and Jing et al.\textsuperscript{17} who experimentally verified the results of Qu and Xu\textsuperscript{18} using single and multiple dampers, respectively; Christiansen et al.\textsuperscript{19} who considered a semiactive damper without its dynamics and a clipped optimal controller that yields applied force instead of command voltage; and Cimellaro and Lopez-Garcia\textsuperscript{19} who performed constrained optimization design, using multiple passive dampers, to achieve performance equal to an LQR controller for white noise excitation.

In this study, a five-storey and a three-storey building are coupled with a single MR damper placed at the top of the shorter building. The system undergoes earthquake excitation. The objectives of the present study are: (i) Applying LQG control (with full state feedback and an optimal observer for state estimation based on measured outputs), and OSOF control (based directly on measured outputs), to obtain the desired control force. The hysteretic force-velocity behavior is modelled using the more accurate modified Bouc-Wen model. The aim here is to study the effectiveness of LQG/OSOF controllers that use fewer measured outputs than LQR control. (ii) Predicting, via RNN, the damper voltage required to produce the desired damper force obtained from LQG/OSOF control.
The aim here is to compare the effectiveness of semiactive (i.e., LQG/OSOF/LQR) controllers based on RNN voltage law, with that of passive (constant voltage) controllers and semiactive controllers based on CVL (on-off) voltage law.

2. SYSTEM MODEL

The five- and three-storied buildings, B5 and B3, respectively, are assumed to have a symmetric plan, with the mass concentrated at rigid slabs. They are subject to the same horizontal uniaxial ground acceleration (Fig. 1). Let the location matrix of the passive (constant voltage) controllers and passive controllers based on CVL (on-off) voltage law.

\[ \mathbf{f} = c_1 \dot{y} + k_1 (z_8 - z_3); \]  

where, 
\[ \dot{y} = \frac{1}{(c_0 + c_1)} \left\{ \alpha z_d + c_0 (z_{16} - z_{11}) + k_0 (z_8 - z_3 - y) \right\}; \]

\[ z_d = -\gamma |z_{16} - z_{11} - \dot{y}|z_d|z_d|^{n-1} - \beta (z_{16} - z_{11} - \dot{y})|z_d|^n + A (z_{16} - z_{11} - \dot{y}); \]

\[ \dot{u} = -\eta (u - v); \]

\[ \alpha = \alpha_a + \alpha_b u; \quad c_1 = c_{1a} + c_{1b} u; \quad c_0 = c_{0a} + c_{0b} u. \]

Here \( z_3 (= x_3) \), \( z_8 (= x_8) \) are the displacements, and \( z_{11} (= x_{11}) \), \( z_{16} (= x_{16}) \) are the velocities of storey three of B5, B3, \( y \) is an internal pseudo-displacement; \( z_d \) is the evolutionary variable describing damper hysteresis; \( u \) is the output of a first order filter, which models delay dynamics of the current and of the fluid to reach rheological equilibrium; \( v \) is the command voltage supplied to the damper. Data for hysteresis loop parameters \( (\gamma, \beta, A, \eta) \), spring stiffnesses \( (k_0, k_1) \), and viscous damping coefficients \( (k_0, c_1) \), are considered from Spencer et al.3

3. CONTROLLER DESIGN

Implementation of LQR control requires that all states be measured for feedback. This is often not possible. Hence, controllers using measured output to estimate states and then obtain the control input, or controllers that directly feed back measured outputs to obtain the control input, are considered. The control input thus obtained is the desired damper force \( f_d \). Further, inverting damper dynamics to obtain command voltage \( v \), that is required to produce \( f_d \), is a nontrivial task (Eqs. (7)–(11)). Hence, voltage laws are considered to obtain \( v \) that produces a control input \( f \) as close as possible to the desired control input \( f_d \).

3.1. LQG Control

A Kalman filter (optimal observer) is designed to estimate the states for subsequent use in the LQR controller. The state equations describing plant dynamics, i.e., Eq. (5), contain ground acceleration \( \ddot{x}_g \) as the plant noise. Measured outputs are given by

\[ y = \mathbf{C} x + \mathbf{D}_1 f + \mathbf{v}; \]

The measurement noise, \( \mathbf{v} \), is assumed uncorrelated with the plant noise, and both are assumed as zero-mean white noise.
processes. Table 1 shows the combinations of measured outputs (comprising storey accelerations, interstorey drifts, and relative displacement of damper) considered. For example, for (8A,11D) sensor configuration the output and direct transmission matrices are

\[
C = \begin{bmatrix}
-M_s^{-1}K_s & -M_s^{-1}C_s \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 1
\end{bmatrix}; \quad D_1 = \begin{bmatrix}
M_s^{-1}D_s \\
0
\end{bmatrix}.
\] (13)

The estimated state vector, \( \tilde{z} \), is obtained via the observer dynamics, i.e.,

\[
\dot{\tilde{z}} = (A - L_1C)\tilde{z} + (B - L_1D_1)f + L_1y;
\] (14)

in which the optimal observer gain \( L_1 \) (obtained by minimizing the covariance of state estimation error \( z - \tilde{z} \)) is given as

\[
L_1 = P^*C^TR^{-1};
\] (15)

where \( P^* \) is the solution of the algebraic Riccati equation

\[
AP^* + P^*A^T - P^*C^TR^{-1}CP^* + GQG^T = 0.
\] (16)

Here \( Q^* \) and \( R^* \) are spectral density matrices corresponding to plant noise and measurement noise, respectively. For seismic excitation \( Q^* = [Q^*] \), a scalar. Measurement noise is assumed identical for all sensors, i.e., \( R^* = R_i^*I \), where \( I \) is the identity matrix. \( Q^*/R^* = 50 \) is considered.\(^5\) The optimal state feedback control is obtained by minimizing the quadratic performance index (PI) \( J^* = \frac{1}{2} \int_0^\infty [z^TQz + f^T Rf]dt \). Here, \( Q \) is the positive semi-definite state weighting matrix and \( R \) is the positive definite control force weighting matrix. The minimization, subject to state equations as constraint (i.e., Eq. (5) without external excitation term), yields the desired control force as

\[
f_d = -R^{-1}B^TP\tilde{z} = -K\tilde{z};
\] (17)

where estimated states, \( \tilde{z} \), are used in place of unmeasurable states, \( z \), and \( P \) is the solution of the algebraic Riccati equation

\[
A^TP + PA - PBR^{-1}B^TP + Q = 0.
\] (18)

### 3.2. OSOF Control

The desired control input is obtained based on measured output feedback instead of full state feedback as done in LQR/LQG control. Thus, OSOF control, like LQG, uses fewer sensors than LQR. However, OSOF, unlike LQG, dispenses with observer design. Thus OSOF requires less CPU time (due to fewer on-line computations) as compared to LQG.

The system dynamics represented by state equations (without plant noise, i.e., external excitation), the control input obtained by output feedback (i.e., desired damper force \( f_d \)), and the measured output \( y \) considered as a combination of states only (i.e., without feed-through \( D_1f \) and measurement noise \( v \)), are given as\(^20\)

\[
\dot{z} = Az + Bf_d; \quad f_d = -Ky; \quad y = Cz.
\] (19)

The matrix of constant feedback gains \( K \) (and hence control input \( f_d \)) is determined by minimizing the PI, \( J^* \), subject to closed loop dynamics, Eq. (19), as constraint. In general, if the controller is effective for random initial conditions, it is also effective for random input excitations.\(^21\) The closed loop system matrix is \( A_c = A - BK \). For asymptotically stable \( A_c \), it can be shown that \( J^* = \frac{1}{2} tr(PQ) \), where \( Q = z(0)z^T(0) \).

Minimizing \( J^* \) yields the design equations\(^20\)

\[
A_c^TP + PA_c + C^TK^TRKC + Q = 0;
\] (20)

\[
A_sS + SA_c^T + \dot{Q} = 0;
\] (21)

\[
R^{-1}B^TPSC^T(CS^T)\Sigma = K;
\] (22)

with unknowns \( P \) (symmetric, positive semi-definite), \( S \) (matrix of Lagrange multipliers), and \( K \) (optimal gain). The dependency on initial states is eliminated by minimizing the expected value of PI instead of PI itself.\(^22\) For uncorrelated initial states, \( E\{Q\} = I \), the identity matrix, and the optimal cost is \( E\{J^*\} = J = \frac{1}{2} tr[P] \). The Moerder-Calise algorithm,\(^23\) converging to a local minimum of \( J \), is used to solve Eqs. (20)–(22) as follows:

**Step 1**: For iteration counter \( k = 0 \), initial gain \( K_0 \) is chosen such that \( A_c \) is asymptotically stable. \( K_0 = 0 \) is chosen since \( A \) is stable.

**Step 2**: \( A_k \leftarrow (A - BK_kC), \quad A_c \leftarrow A_k, \quad K \leftarrow K_k \). Solve Eqs. (20) and (21) for \( P \) and \( S \). Then \( P_k \leftarrow P, \quad S_k \leftarrow S, \quad J_k = \frac{1}{2} tr[P_k] \). If \( k > 0 \) and \( |\Delta K| < \epsilon \), where \( \epsilon \) is a small tolerance, the algorithm has converged, go to Step 4.

**Step 3**: \( K_{k+1} \leftarrow K_k + \alpha \Delta K \), where \( \Delta K = R^{-1}B^TP_kS_kC^T(CS^T)\Sigma - K_k \) and \( \alpha \) is chosen such that \( A_{k+1} \) is asymptotically stable, where \( A_{k+1} \leftarrow (A - BK_{k+1}C) \). \( k \leftarrow k + 1 \). Go to Step 2.

**Step 4**: \( K = K_k \).

When using acceleration feedback, as done here, the measured output and the desired control input obtained from output feedback are

\[
y = Cz + D_1f_d; \quad f_d = -Ky;
\] (23)

which yields

\[
f_d = -(I + KD_1)^{-1}Ky = -\dot{K}y.
\] (24)

Thus, \( K \) is determined using the Moerder-Calise algorithm,\(^23\) and \( K \) is obtained as

\[
K = K(I - D_1K)^{-1}
\] (25)

for controller implementation. This modification is necessary when using acceleration output feedback, instead of only displacement and velocity feedback for determining the desired control input \( f_d \). A single damper is considered. Hence \( f_d = [f_d] \) and \( R = [R] \) are scalars in LQG/OSOF controller design.

### 3.3. Clipped Voltage Law (CVL)

Using \( f_a \) and \( f_e \), the command voltage, \( v \), to the damper is obtained as follows.\(^8\) If \( |f_a| < 0 \), then \( v = v_{\text{min}} = 0 \) V; else \( v = v_{\text{max}} = 2.25 \) V when \( |f_a| > |f_e| \) or \( v = v_{\text{min}} = 0 \) V when \( |f_a| < |f_e| \), or \( v \) is held at its present value when \( f_a = f_e \). Here \( f_a \) is the desired damper force obtained from the controller (Eq. (17) for LQG / Eq. (19b) for OSOF), and \( f \) is the applied damper force (Eq. (7)). Thus, saturation voltage (\( v_{\text{max}} \))
respectively; the matrices of weights for the hidden layer and output layer, respectively; damper force, respectively; voltage, relative displacement, and damper force, respectively; and voltages applied delays (desired force between the ends of the damper (9) used for previous instants); and voltages applied for previous instants. The delay transfer function is from Eq. (7) used for previous instants); and voltages applied

is applied when the magnitude of the desired damper force exceeds that of the available damper force and both are in the same direction; else zero voltage is applied, except when the desired and applied forces are equal for which case the voltage is held at the same value as at the previous time step. The schematic for implementation of LQG-CVL or OSOF-CVL is shown in Fig. 2.

3.4. Recurrent Neural Network (RNN) Voltage Law

A RNN model is considered in order to emulate the inverse dynamics of the MR damper. It contains 12 input-layer neurons, 18 hidden-layer neurons, and 1 output-layer neuron, and has output fed back to make it suitable for closed loop control applications (Fig. 3). Model inputs are: relative displacement, and damper force with delays (desired force in the same direction; else zero voltage is applied, except when the desired and applied forces are equal for which case the voltage is held at the same value as at the previous time step. The schematic for implementation of LQG-CVL or OSOF-CVL is shown in Fig. 2.

\[
\begin{align*}
L_v &= 1.25 V, \\
C_v &= 80 \text{ cm}, \\
\alpha &= 126, \\
\beta &= 73.
\end{align*}
\]

The trained network is validated for the following data sets: (I) \( x = \sin(6\pi t) \) cm, \( v = 1.5 \) V; (II) \( x = \sin(6\pi t) \) cm, \( v = \text{GWN with amplitude } \pm 0.75 \text{ V and bias } 1.5 \) V; (III) \( x = \text{GWN with amplitude } \pm 2 \text{ cm and } v = 1.5 + 0.75 \sin(6\pi t) \) V. Using RNN inputs as \( x \) and the target force (obtained from Eqs. (7)–(10) for the chosen data set), the command voltages are predicted via the trained RNN. Then, using \( x \) and the predicted voltages, the available damper force is obtained via Eqs. (7)–(10). Target and available forces match extremely well for data set I and II, and quite well for set III (Fig. 5). RMS difference between the target and available forces is 73.97, 73.44, and 126.46 N, for data I, II, and III, respectively. These differences are small compared to the force range (around 2300 N for data I and II, and 3700 N for data III).

The MR constraint filter is used for controller implementation. Neglecting stiffness terms in Eqs. (7) and (8), with steady state \( u = v \) from Eq. (10), yields the approximate bounds of damper force as,

\[
f \approx \frac{\left( c_{1a} + c_{1b} \right) \left( (c_a + c_b) v + (c_{0a} + c_{0b}) \dot{x}^* \right)}{\left( c_{0a} + c_{1a} \right) + \left( c_{0b} + c_{1b} \right) v};
\]
where \( z_u = \pm (A/\gamma + \beta) \pi \) are the limits of \( z_d \) obtained from Eq. (9). Here, \( x^* = z_u - z_3 \) and \( \dot{x}^* = z_{16} - z_{11} \), i.e., relative displacement and relative velocity of the damper, respectively. Equation (28) yields limiting straight lines in \( f - \dot{z}^* \) plane when \( v = 0 \) V and \( v = 2.25 \) V, for which the damper force is minimum \((f_{\text{min}})\) and maximum \((f_{\text{max}})\), respectively. The region between these straight lines is the realizability zone. This lies in the first and third quadrants for positive and negative values, respectively, of \( z_d \). The desired force, \( f_d \), obtained from LQG/OSOF control, and the measured relative velocity \( \dot{x}^* \), are provided to the MR constraint filter, which then generates the command voltage as follows:

i) If \( \dot{x}^* f_d > 0 \) and \( f_d \) lies outside the realizable zone, then the control voltage is set to the appropriate limiting value. Thus, if \(|f_d > f_{\text{max}}|\), then \( v = v_{\text{max}} = 2.25 \) V, else if \(|f_d < f_{\text{min}}|\), then \( v = 0 \) V.

ii) If \( \dot{x}^* f_d > 0 \) and \( f_d \) lies within the realizable region, i.e., \(|f| \leq |f_{\text{max}}|\), then the control voltage to be applied is obtained from the RNN model. The inputs to the RNN are \( f_d(t), \dot{x}^*(t), \) and the time histories of \( f \) (actual damper force), \( x^* \) (relative displacement), and \( v \) (applied voltage), i.e., as per Eq. (27).

iii) If \( \dot{x}^* f_d < 0 \) then \( v = v_{\text{min}} = 0 \) V.

### 3.5. Controller Implementation

The schematic for actual implementation and simulation of LQG/OSOF control using RNN/CVL is shown in Fig. 2. Structure and MR damper equations (comprising the plant) are integrated using applied voltage \( v \) and states \((x, y, z_d, v)\) at the beginning of each time step. The applied damper force \( f \), computed via Eq. (7), and the states are thus obtained at the end of each time step. Measured outputs \((y, \text{ damper relative displacement } x^*, \text{ and damper relative velocity } \dot{x}^*)\) are then obtained as shown and fed to the controller along with measured \( f \). For LQG control, the desired damper force \( f_d \) is computed based on estimated states (obtained by integrating the observer, using measured outputs and the damper force as inputs to the observer). For OSOF control, \( f_d \) is computed directly using measured outputs. Then \( f_d \) and all measured quantities are fed to the CVL/RNN control laws to obtain \( v \) at the start of the next time step. Measured quantities \( f \) for CVL, and \( f, x^*, \dot{x}^* \) for RNN. Although \( x^*, \dot{x}^* \) are measured outputs, they are not included in \( y \) since they are not used to obtain \( f_d \) herein. However, this does not preclude them from being part of \( y \) in future applications.

Thus, both OSOF-RNN and LQG-RNN require measurements of the same quantities, i.e., \( f, x^*, \dot{x}^* \), and \( y \), for their implementation. However, OSOF-RNN dispenses with the observer dynamics since it is based on direct output feedback, whereas LQG-RNN requires the time-intensive online-simulation of observer dynamics since it is based on the feedback of all estimated states. The on-line CPU times required for both controllers are compared in section 4.1.

### 4. RESULTS AND DISCUSSIONS

The mass, damping and stiffness coefficients (Fig. 1) considered are: \( m_1a = m_2a = m_1b = m_2b = m_3b = 100 \) kg, \( m_{3a} = 95 \) kg, \( m_{4a} = m_{3a} = 90 \) kg; \( c_1a = 125 \) Ns/m, \( c_2a = c_3a = c_4a = c_5a = c_6a = c_7a = 50 \) Ns/m; \( c_{1b} = 100 \) Ns/m; \( k_{1a} = 1.7 \times 10^{10} \) N/m, \( k_{2a} = k_{3a} = k_{4a} = k_{5a} = 2.9 \times 10^{10} \) N/m, \( k_{1b} = 3.3 \times 10^{10} \) N/m, \( k_{2b} = k_{3b} = 4.25 \times 10^{10} \) N/m; \( c_e = 10 \) Ns/m; \( k_e = 100 \) N/m. These are adapted from the experimental model of Dyke et al.5 so as to yield natural frequencies that are well separated, i.e., 7.13, 21.16, 45.79, 53.17 Hz for B5 and 13.56, 39.24, 58.46 Hz for B3.

Equation (5) and Eqs. (7)–(10) are integrated for zero initial conditions using MATLAB ode45. The N-S component of the El-Centro ground motion data measured at Imperial Valley is used after suitable time-scaling.3 The following responses are obtained: (i) Uncontrolled, i.e., without coupler; (ii) Passive-off control, i.e., with applied voltage \( v = 0 \) V; (iii) Passive-on control with \( v = v_{\text{max}} = 2.25 \) V (damper saturation voltage); (iv) Semi-active control using LQG-CVL, LQG-RNN, OSOF-CVL, and OSOF-RNN controllers.

Various sensor configurations (Table 1) using accelerometers (o) and LVDT sensors (x) have been considered in order to obtain a well-distributed measurement of response for feedback to the controller. Various state weightings \( Q \) (Table 2), and control weightings \( R \) in the interval \([10^{-16}, 10^{01}]\), have been considered in order to achieve better control.

#### 4.1. Controller Evaluation

Performance criteria defined by Ohtori et al. are evaluated.24 Quantities \( J_1 \sim J_8 \) are controlled responses normalized with the corresponding uncontrolled response. The responses considered are: Maximum peak displacement, \( J_1 \); Maximum peak interstorey drift, \( J_2 \); Maximum peak absolute acceleration, \( J_3 \); Peak base shear of the combined system, \( J_4 \); Maximum RMS

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**Table 1. Sensor configurations.**

<table>
<thead>
<tr>
<th>Storey</th>
<th>Sensor Configuration</th>
<th>o Accelerometer</th>
<th>x LVDT</th>
</tr>
</thead>
<tbody>
<tr>
<td>3b</td>
<td>8A,1bD</td>
<td>o</td>
<td>x</td>
</tr>
<tr>
<td>2b</td>
<td>8A</td>
<td>o</td>
<td>x</td>
</tr>
<tr>
<td>1b</td>
<td>8A</td>
<td>o</td>
<td>x</td>
</tr>
<tr>
<td>5a</td>
<td>8A</td>
<td>o</td>
<td>x</td>
</tr>
<tr>
<td>4a</td>
<td>8A</td>
<td>o</td>
<td>x</td>
</tr>
<tr>
<td>3a</td>
<td>8A</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td>2a</td>
<td>8A</td>
<td>o</td>
<td>x</td>
</tr>
<tr>
<td>1a</td>
<td>8A</td>
<td>o</td>
<td>x</td>
</tr>
</tbody>
</table>

**Figure 4.** Target and predicted voltages, training data.

**Figure 5.** Target and predicted forces, validation data III.

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Amongst LQG-CVL controllers, LQG-CVL-1 is the most effective. It affords the lowest $J_1$, $J_2$, $J_3$, $J_4$, and $J_5$ compared to OSOF-CVL-2/OSOF-CVL-3; and $J_5$ is 8% lower than OSOF-CVL-2/OSOF-CVL-3. Amongst OSOF-CVL controllers, OSOF-RNN-1 and OSOF-CVL-2 yield comparable results, and both are better than OSOF-RNN-3. OSOF-RNN-1 requires fewer sensors than OSOF-RNN-2 (i.e., 5ID compared to 8A,1ID), and it affords the lowest $J_1$, $J_2$, $J_3$, $J_4$, and $J_5$. Hence, it is chosen as the most effective OSOF-RNN controller. Thus very effective control is possible using few sensors, as in LQG-RNN-1 (3A), OSOF-CVL-1 (5A), and OSOF-RNN-1 (5ID).

Henceforth only the most effective controllers, i.e., LQG-CVL-1, LQG-RNN-1, OSOF-CVL-1, and OSOF-RNN-1, selected on the basis of performance criteria $J_1$ to $J_{10}$ and the effective usage of sensors, are considered. They are denoted LQG-CVL, LQG-RNN, OSOF-CVL, OSOF-RNN. Online CPU time required by LQG-CVL, LQG-RNN is 22.12 s, 30.15 s, and for OSOF-CVL, OSOF-RNN it is 1.76 s, 2.96 s, respectively. Thus, time taken by OSOF controllers is an order of magnitude less than LQG controllers. This is expected since OSOF, unlike LQG, dispenses with running observer dynamics for state estimation.

Peak base shear for various controllers (including the four most-effective semiactive LQG/OSOF controllers) is shown in Table 3. Reduction, vis-a-vis passive-on control, in peak base shear of building $B_5/B_3$ is 25%[28%] with LQG-CVL, 31%[19%] with LQG-RNN, 25%[23%] with OSOF-CVL, and 31%[23%] with OSOF-RNN. Thus all four semiactive controllers provide considerable reduction in peak base shear vis-a-vis passive-on control, with the RNN controllers being more effective in reducing the peak base shear of $B_5$. Semiactive and passive-on controllers result in a re-distribution of base shear from flexible $B_5$ to stiffer $B_3$, thus yielding a higher base shear.

### Table 2. Response quantities weighted in PI, corresponding state weighting $Q$.

<table>
<thead>
<tr>
<th>Notation</th>
<th>Response weighted</th>
<th>$Q$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$Q_1$</td>
<td>5a, 1b, accelerations</td>
<td>$\hat{Q}_C$</td>
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### Table 3. Peak base shear (N).

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### Fig. 6. Performance criteria for effective controllers: (a) LQG-CVL, (b) LQG-RNN.

**Displacement, $J_1$; Maximum RMS interstorey drift, $J_2$; Maximum RMS acceleration, $J_3$; RMS base shear of the combined system, $J_4$; $J_5$ is the maximum peak damper force normalized with the combined weight of the connected buildings. $J_{10}$ is the maximum peak damper stroke normalized with the maximum peak uncontrolled displacement. The maximum for $J_1$, $J_2$, $J_3$, $J_4$, $J_5$, $J_{10}$ is taken across all storeys of the interconnected system. For $J_1$ and $J_{10}$, the maximum is taken across all dampers. A single damper is considered in the present case. Lower values of the performance criteria correspond to better control.

Since earthquake induced vibrations occur for small durations, their control is essential mainly for maintaining structural integrity. Hence, interstorey drift and base shear are more critical than displacement and acceleration. Further, base shear is more critical than interstorey drift, since controlling the former is essential for maintaining the integrity of the overall structure. Hence, the indices based on peak values are ranked ($J_2$, $J_3$, $J_4$, $J_5$), and those based on RMS values are ranked ($J_1$, $J_6$, $J_7$, $J_8$) in decreasing order of importance. Low values of damper force and stroke imply less power expended for control. Hence, $J_2$ and $J_{10}$ are also important in determining control effectiveness.

$J_1$ to $J_{10}$ for effective controllers, obtained by varying sensor configurations, state weighting and control weighting, as shown in Tables 1 and 2, are compared in Fig. 6 and Fig. 7. The controllers are labeled LQG-CVL-1 (8A, $Q_2$, $R = 10^{-11}$), LQG-CVL-2 (3A, $Q_2$, $10^{-05}$), LQG-CVL-3 (1A, $Q_2$, $10^{-10}$); LQG-RNN-1 (3A, $Q_2$, $10^{-08}$), LQG-RNN-2 (8A,1ID, $Q_2$, $0.5 \times 10^{-08}$), LQG-RNN-3 (1A, $Q_2$, $10^{-05}$), LQG-RNN-4 (5ID, $Q_5$, $10^{-14}$); OSOF-CVL-1 (5A, $Q_3$, $10^{-06}$), OSOF-CVL-2 (8A,1ID, $Q_1$, $10^{-08}$), OSOF-CVL-3 (8A,8ID, $Q_3$, $0.5 \times 10^{-11}$); OSOF-RNN-1 (5ID, $Q_4$, $10^{-13}$), OSOF-RNN-2 (8A,1ID, $Q_1$, $0.75 \times 10^{-08}$), OSOF-RNN-3 (8A,8ID, $Q_4$, $0.5 \times 10^{-11}$). It is concluded, from the values obtained for $J_1$ to $J_{10}$ that LQG-CVL-1, LQG-RNN-2, OSOF-CVL-1, OSOF-RNN-1 yield most effective control.

Amongst LQG-CVL controllers, LQG-CVL-1 is the most effective since it affords the lowest $J_3$, $J_4$, $J_5$, $J_6$, with $J_3$ and $J_4$ being at least 15% and 7% lower, respectively, than the LQG-CVL-2/LQG-CVL-3 controllers. Amongst LQG-RNN controllers, LQG-RNN-2 appears the most effective since it affords the lowest $J_1$, $J_2$, $J_3$, $J_4$, and $J_5$. However, LQG-RNN-1 is comparable to LQG-RNN-2, except $J_4$ for which it is 5% higher. Thus LQG-RNN-1 is chosen as the most effective controller since it requires fewer sensors than LQG-RNN-2 (i.e., 3A instead of 8A,1ID). Note that LQG-RNN-3 is also comparable to LQG-RNN-1, except for $J_7$ and $J_8$, i.e., it is possible to realize quite effective control using a single accelerometer feedback. LQG-RNN-4 is the least effective of the four LQG-RNN controllers.
for B3 compared to B5. This is re-confirmed from storeywise acceleration responses in Fig. 12. Although passive-off control provides the lowest maximum peak base shear, it is unable to re-distribute it to the stiffer building.

Performance criteria for passive controllers are shown in Fig. 8. The constant applied voltage is varied in the range [0, 2.25] V. The performance criteria increase/decrease almost monotonically with voltage, i.e., there is no distinct minima indicating an optimal passive-on voltage. $J_1$ and $J_2$ are minimum for passive-on with saturation voltage (2.25 V), $J_3$, $J_4$, and $J_5$ are minimum for passive-off (0 V), $J_6$ and $J_7$ are minimum for 0.05 V and 0.25 V, respectively (i.e., almost passive-off voltage), their minimum values being respectively 2% and 1% lower than the corresponding passive-off values. $J_8$ and $J_9$ are minimum for 0.95 V and 1.15 V, respectively, their minimum values being respectively 7% and 5% lower than the corresponding passive-on values. If $v = 1.05$ V is chosen as the optimal passive-on voltage, the performance indices $J_3$–$J_6$ reduce by 15%, 19%, 7%, 5%, 12%, 13%, and 32%, respectively, compared to the passive-off values. However, in that case, the passive-on controller is quite ineffective in re-distributing base shear to B3, i.e., it acts almost like the passive-off controller. Thus, for future comparisons, passive-on control is considered with the saturation voltage (2.25 V) applied.

4.2. Peak/RMS Response

Maximum and storeywise values of peak/RMS responses are compared (the maximum across all storeys of the connected system is considered). The maximum drifts and displacements occur in B5, at storey one and five, respectively, for all controllers. Maximum accelerations occur at storey-five B5 for uncontrolled and passive control, and at different storeys of B3/B5 for semiactive control.

Performance criteria are shown in Fig. 9 for passive controllers and the most effective LQG/OSOF/LQR semiactive controllers. Figure 9 shows that passive controllers yield 37–62% reduction in max-peak responses and 72–85% reduction in max-RMS responses, when compared with the uncontrolled case. Compared to passive-off control, passive-on control provides comparable max-peak drift/displacement and at least 15% reduction in the corresponding max-RMS values, but an increase of 35%/25% in max-peak/max-RMS acceleration. Thus passive-on control is effective in drift/displacement control, but very ineffective in attenuating accelerations, vis-a-vis passive-off control. This is also evident from storeywise responses in Figs. 10–12.

For LQG/OSOF semiactive control, Fig. 9 shows that the RNN controllers outperform the corresponding CVL ones. Thus only LQG-RNN and OSOF-RNN are chosen for further comparisons.

Passive-off versus LQG/OSOF semiactive control

Figure 9 shows that the overall performance of LQG-RNN/OSOF-RNN semiactive controllers is superior to passive-off control. However, passive-off control provides the lowest max-peak acceleration, peak base shear, and peak damper force. Note that passive-off control does not reduce the base shear in the flexible building (B5) by re-distributing it to the stiffer building (B3). Compared to passive-off control, LQG-RNN/OSOF-RNN afford a reduction of 28–30% in max-peak displacement/drift, but an increase of up to 7% in max-peak accelerations; a reduction of 34–36% in max-RMS displacement/drift, and 13–18% in max-RMS acceleration. Thus, compared to passive-off control, LQG/OSOF control is very effective except for max-peak accelerations, which increase slightly. Figures 10–12 show that compared to passive off control, LQG/OSOF provide an attenuation of the storeywise responses of B5 but not B3.

Passive-on versus LQG/OSOF semiactive control

Figure 9 shows that, except for the damper stroke, passive-on control performs the worst. Compared to passive-on control, LQG-RNN/OSOF-RNN afford a reduction of: 24% in max-peak displacement, 31% in max-peak drift, and 20–25% in max-peak acceleration; 23–25%, 19–22%, and 30–34%, in the corresponding max-RMS values; and 7–8% in peak damper force. Simulations show that LQG-RNN/OSOF-RNN also yield a reduction of around 36% in RMS damper forces compared to passive-on control. Thus the LQG/OSOF controllers require less control effort and provide better response attenuation, i.e., they are very effective compared to passive-on control.

Figures 10, 11, and 12 show storeywise comparison of displacement, drift, and acceleration. The LQG-RNN and OSOF-RNN controllers yield comparable peak drifts, with the former somewhat better for RMS drifts. They yield substantial reduction in drift vis-a-vis passive-on control (reduction of up to 41% in peak drift and 38% in RMS drift). Attenuations for B5 are somewhat higher than for B3. They also outperform passive-on control in displacement control (reduction of 19–31% in peak displacement and 15–32% in RMS displacement). When compared to passive-on control, LQG/OSOF attenuate peak acceleration by 23–55% and RMS acceleration.
by up to 36% across B5. However, there is an increase in peak and RMS accelerations across B3, i.e., up to 37% and 35%, respectively. Thus, semiactive LQG-RNN/OSOF-RNN controllers yield considerable attenuation in storeywise peak/RMS responses of both buildings, except accelerations of B3, which increase considerably.

**Comparison of LQR/LQG/OSOF semiactive controllers**

LQG/OSOF controllers require fewer sensors compared to LQR. The latter requires that all states be measured. Performance criteria in Fig. 9 show that LQR-RNN is either more effective or comparable vis-a-vis LQR-CVL. Various combinations of \( Q \) and \( R \), as considered for LQG/OSOF, were also considered for LQR. The most effective LQR controllers, whose performance criteria are shown in Fig. 9, were obtained for (\( Q_2, R = 0.5 \times 10^{-8} \)) for LQR-CVL and (\( Q_3, R = 0.25 \times 10^{-4} \)) for LQR-RNN. Hence, LQG-RNN/OSOF-RNN/LQR-RNN controllers, being the most effective, are compared. They yield comparable max-peak responses, while LQG-RNN/OSOF-RNN yield up to 8% attenuation in max-RMS responses as compared to LQR-RNN. OSOF-RNN and LQG-RNN yield somewhat lower max-peak acceleration and peak base shear, as compared to LQG-RNN. LQR-RNN yields the lowest peak damper force amongst semiactive (and passive-on) controllers (Fig. 9).

LQG-RNN is now compared with LQR-RNN for storeywise responses. Figures 10–12 show that LQG-RNN is as effective or better in reducing RMS responses (especially accelerations) of B3/B5. It is also effective in reducing peak accelerations of B5 to some extent, but it is not effective in reducing peak drifts/accelerations of B3, vis-a-vis LQR-RNN. For B5 the peak-displacements and peak-drifts from LQG-RNN are comparable with LQR-RNN (except storey five where the peak-drift increases 14%). However, across B3 the peak-displacements increase 6–7% and the peak-drifts increase up to 25%, when using LQG-RNN. Peak accelerations reduce up to 33% across B5 (except storey five where it increases 14%), but they increase up to 9% across B3. RMS-displacements reduce 7–8% and RMS-drifts reduce up to 10% across B5, and are comparable across B3. RMS accelerations reduce up to 12% across B5, and 8–15% across B3.

Next, OSOF-RNN is compared with LQR-RNN for storeywise responses. Figures 10–12 show that OSOF-RNN is more effective in reducing RMS-accelerations of B3 and to some extent peak-accelerations of B5, but it is somewhat less effective in reducing peak-drifts of B3. It is comparable to LQR-RNN for other peak/RMS responses. For B5 the peak-drifts lie within −7% (attenuation) and 15% (accenntuation), and the RMS-drifts lie within −5% and 10% of LQR-RNN values. For B3, OSOF-RNN yields an increase of up to 17% in peak-drifts, while RMS-drifts are comparable to LQR-RNN. The peak/RMS displacements are comparable across B5 and B3. For B5 the peak-accelerations lie within −27% and 16%, and the RMS-accelerations lie within −13% and 11% of LQR-RNN values. For B3, OSOF-RNN yields an attenuation of up to 7% in peak-accelerations and 9–19% in RMS-accelerations.

Table 3 shows that all three semiactive controllers yield a comparable peak base shear (LQG-RNN is 7% higher than LQR-RNN for B3). The damper forces from LQG-RNN/OSOF-RNN are around 18% higher in peak value and 8% higher in RMS value when compared with LQR-RNN.

LQG-RNN and OSOF-RNN yield comparable max-peak/max-RMS responses (OSOF-RNN yields 6% lower[higher] max-peak[max-RMS] acceleration). They are now compared for storeywise responses. Figures 10–12 show that they yield comparable peak-displacements/peak-drifts. LQG-RNN yields somewhat lower RMS-displacements/RMS-drifts for B3/B5, and significantly lower peak/RMS accelerations for B5. OSOF-RNN yields a peak-drift between −6% to 8% higher and RMS-drift up to 10% higher, as compared to LQR-RNN. For B5, OSOF-RNN yields peak accelerations up to 11% higher and RMS accelerations up to 20% higher than LQG-RNN. For B3, OSOF-RNN attenuates peak accelerations up to 13%.

Summarizing, the three semiactive controllers are comparable in peak drift and peak displacement control. OSOF-RNN and LQG-RNN are somewhat more effective in the peak-acceleration control of B3 and B5, respectively. LQG-RNN is somewhat more effective in RMS response control. The three semiactive controllers yield comparable peak base shear, but the peak damper force is lower for LQR-RNN control. Thus, OSOF-RNN/LQG-RNN controllers are quite effective in...
attenuating storeywise/max-peak/max-RMS responses, when compared with LQR-RNN.

4.3. Time History

Figure 13 shows the time history of interstorey drift at storey-one B5 (where the max-peak/max-RMS drift occurs for all passive/semiactive controllers). The response at storey-one B3 is also shown. LQG-RNN and OSOF-RNN provide a significant control of drift, as seen by the early attenuation (i.e., for \( t < 1.1 \) s), when compared with passive-on control. Figure 14 shows the time history of accelerations at storey-two B3 and storey-five B5 where max-peak acceleration occurs for OSOF-RNN and passive-on controllers, respectively (note that OSOF-RNN yields lower max-peak acceleration than LQG-RNN). It is clear that both semiactive controllers attenuate the acceleration of B5 but not B3.

Figure 15 shows the time history of applied voltage resulting from OSOF-RNN and OSOF-CVL controllers. The voltage is ‘off’ (\( v = 0 \)) for around 81% of the duration and ‘on’ (\( v = 2.25 \) for CVL and \( 0 \leq v \leq 2.25 \) for RNN) for the remainder. Thus the CVL and RNN semiactive controllers afford power savings while also providing effective control vis-a-vis passive-on control (for which the voltage is always ‘on’, \( v = 2.25 \) V).

The time history of applied and desired damper forces, resulting from LQG-RNN and OSOF-RNN, are compared in Fig. 16. Both semiactive controllers produce applied forces that closely follow the desired forces. The RMS of difference between the applied and desired forces is 278.12 N for OSOF-RNN and 231.89 N for LQG-RNN. The difference between applied and desired forces is mainly due to three reasons. Firstly, inverting damper dynamics (i.e., predicting the command voltage for a given force) is difficult. Thus one has to resort to ‘approximate’ voltage laws like CVL/RNN. Secondly, damper saturation occurs at \( v = 2.25 \) V. This limits the maximum damper force generated, irrespective of the force desired. Thirdly, the damper constitutive law (Eqs. (7)–(11)) yields applied-force versus velocity lying predominantly in the 1\textsuperscript{st} and 3\textsuperscript{rd} quadrants (Fig. 17(a) and Fig. 17(d)). However, LQG-RNN and OSOF-RNN controllers yield desired-force versus velocity lying in all quadrants (Fig. 17(b) and Fig. 17(e)). Hence desired forces in the 2\textsuperscript{nd} and 4\textsuperscript{th} quadrants are unrealizable. Thus, differences in applied and desired forces would occur even if a more accurate force-voltage law is devised. LQG-RNN appears somewhat better than OSOF-RNN in producing damper forces close to the desired ones (Fig. 17(c) and Fig. 17(f)).

4.4. Controller Effectiveness—Performance for Other Base Excitations

The results presented so far pertain to the El-Centro excitation. Now, in order to assess the effectiveness of the semiactive controllers, their performance is evaluated and compared with that of passive controllers for the following excitations: (i) Gaussian White Noise (GWN), (ii) Hachinohe—N-S
Figure 17. Applied/Desired force versus velocity: (a,b,c) LQG-RNN, (d,e,f) OSOF-RNN.

Table 4. Peak base shear (N).

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Component, Japan, 1968, (iii) Managua, Nicaragua, 1972, (iv) Northridge—N-S component, Sylmar County Hospital, California, 1994, and (v) Kobe—N-S component, Kobe Japanese Meteorological Agency station, 1995. The excitations in (ii)–(v) are time-scaled by a factor of $\frac{19}{2}$, $\frac{2}{11}$, and $\frac{25}{5}$, respectively, in order to excite the fundamental mode of the experimental building. The sensor configurations, state weighting $Q$, and control weighting $R$ are considered the same as those obtained for the most effective controllers during the El-Centro study.

Table 4 shows the peak base shear obtained using passive controllers and semiactive controllers. The uncontrolled case generally yields the highest peak base shear. When compared to the passive controllers, the semiactive controllers mostly yield a lower peak base shear for the flexible building (B5). In fact, when compared with passive-on control, the semiactive controllers afford marginal to substantial reductions in peak base shear for both buildings, except for B5 in the case of the Kobe excitation. Semiactive and passive-on controllers mostly result in a re-distribution of base shear from B5 to B3. Passive-off control yields the lowest peak base shear for B3, except in the case of the Kobe excitation. However, it is unable to re-distribute the base shear.

The performance criteria obtained from the five controllers are shown in Fig. 18.

Max-peak displacement ($J_1$): Passive-off control is the least effective. Compared to passive-off control, the performance of semiactive controllers is 9–25% better for the El-Centro, Hachinohe, and Managua excitations, but 18–29% worse for the Kobe excitation. For the GWN and Northridge excitations, the performance of LQR-RNN/LQG-RNN is comparable with passive-on control, while that of OSOF-RNN is 11–15% worse than that of passive-on control.

Max-peak drift ($J_2$): Passive-off control is the least effective. Compared to passive-on control, the performance of semiactive controllers is up to 31% better, except for the Kobe excitation for which it is 16–34% worse.

Max-peak acceleration ($J_3$): Passive-on is the least effective, except in the case of the Kobe excitation for which it is comparable to semiactive control. Compared to passive-off control, the performance of semiactive controllers is 6–31% better for the Managua, Northridge, and Kobe excitations, comparable for the El-Centro and Hachinohe excitations, but up to 15% worse for the GWN excitation.

Peak combined base shear ($J_4$): Passive-on is the least effective, except in the case of the Kobe excitation for which it is comparable to semiactive control. Compared to passive-off control, the performance of semiactive controllers is up to 34% better for GWN, Hachinohe, Managua, and Kobe excitations, comparable for the Northridge excitation, but 16–27% worse for the El-Centro excitation.
Max-RMS displacement ($J_5$): Passive-off control is the least effective. Compared to passive-on control, the performance of semiactive controllers is up to 24% better, except in the case of the Kobe excitation for which it is comparable when using LQR-RNN and LQG-RNN, but 20% worse when using OSOF-RNN.

Max-RMS drift ($J_6$): Passive-off control is the least effective. Compared to passive-on control, the performance of semiactive controllers is up to 22% better, except in the case of the Kobe excitation for which it is comparable when using LQR-RNN and LQG-RNN, but 24% worse when using OSOF-RNN.

Max-RMS acceleration ($J_7$): Semiactive controllers perform up to 40% better than passive-off control and up to 34% better than passive-on control.

RMS combined base shear ($J_9$): Passive-on is the least effective, except in the case of the Kobe excitation for which it is comparable to semiactive control. Compared to passive-off control, the performance of semiactive controllers is up to 36% better for the Hachinohe, Managua, Northridge, and Kobe excitations, comparable for the El-Centro excitation, but up to 10% worse for the GWN.

Peak damper force ($J_{10}$): As expected, passive-off control yields the lowest peak damper forces. However, it is unable to reduce the base shear of the flexible building B5 by redistributing it to the stiffer building B3. Passive-on control and semiactive controllers yield comparable peak damper forces.

Peak damper stroke ($J_{10}$): Passive-on control is the most effective in reducing the peak damper stroke, while passive-off control is the least effective in this regard.

Thus, for the range of ground excitations considered, the performance of semiactive controllers is generally superior to that of passive controllers. The exceptions are in the case of the Kobe excitation for which passive-on yields the lowest max-peak/max-RMS displacement/drift, the GWN excitation for which passive-off yields the lowest max-peak acceleration and RMS combined base shear, and the El-Centro excitation for which passive-off yields the lowest peak combined base shear. However, passive-off control is unable to redistribute the base shear from the flexible B5 to the stiffer B3. In general LQG-RNN performs somewhat better than OSOF-RNN.

5. CONCLUSIONS

Seismic control is studied for a five-storey flexible building coupled by an MR damper to a three-storey stiff building. LQG/OSOF control determines the desired damper force, following which CVL/RNN determine the command voltage required to produce this force. Various sensor configurations and state/control weightings are considered so as to obtain the most effective controllers on the basis of performance criteria $J_1$–$J_{10}$. Semiactive and passive controllers are compared. This permits the following conclusions:

(i) When compared to passive-on control, LQG/OSOF provide a significant reduction in responses, base shear, damper force, and ‘on’ duration of applied voltage. Only the storeywise accelerations of the B3 increase significantly, thus resulting in the re-distribution of base shear from the flexible to stiff building. Thus semiactive controllers require considerably less control effort and power and yet provide better response attenuation.

(ii) Semiactive controllers using RNN outperform those using CVL. All three semiactive RNN controllers are comparable in max-peak response control (LQG-RNN yields somewhat higher max-peak accelerations). LQG-RNN/OSOF-RNN yield somewhat better attenuation (up to 8%) in max-RMS responses compared to LQR-RNN. Storeywise peak displacements/drifts are comparable across the three semiactive controllers. LQG-RNN, and to an extent OSOF-RNN, are more effective in attenuating storeywise peak-accelerations compared to LQR-RNN. LQG-RNN is the most effective in storeywise RMS response control. All three semiactive controllers yield a comparable peak base shear. LQG-RNN/OSOF-RNN require somewhat higher damper forces (peak value 18% higher than LQR-RNN) to achieve comparable control. Thus, using much fewer sensors, LQG-RNN/OSOF-RNN yield control that is as at least as effective as LQR-RNN, albeit by using a somewhat higher damper force.

(iii) LQG-RNN and OSOF-RNN yield comparable max-peak/max-RMS responses and storeywise peak displacements/drifts. LQG-RNN yields somewhat lower storeywise RMS displacements/drifts than OSOF-RNN. For the flexible building, B5, LQG-RNN yields significantly lower peak/RMS accelerations, while for the stiffer building, B3, OSOF-RNN yields substantially lower peak accelerations. Both controllers yield comparable peak base shears. However, OSOF requires an order-of-magnitude lesser online computation time. Thus, both LQG-RNN and OSOF-RNN provide effective control, but OSOF-RNN is quicker.

(iv) For the range of ground excitations considered, the performance of semiactive controllers is generally superior to that of passive controllers. However, in the case of Kobe excitation, passive-on yields the lowest max-peak/max-RMS displacement/drift. In general LQG-RNN performs somewhat better than OSOF-RNN.

(v) Choice of feedback and state weighting is crucial in obtaining effective control. For example LQG-RNN with only drift feedback and $Q_2$ state weighting, or OSOF-RNN with only acceleration feedback and $Q_2$ state weighting, yield ineffective control since desired and applied forces have opposite signs, i.e., the desired force cannot be realized.

(vi) Effective control is possible using few sensors. For example LQG-RNN with (8A,1ID), (3A), (1A), sensor configurations are comparable. Also, OSOF-RNN with (8A,1ID), (5ID), (5A) sensor configurations are comparable. Thus an effective controller can even be designed using a single accelerometer (at storey-five of B5).
REFERENCES


