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Direct Adaptive Neural-Control System for Seismically Excited Non-linear Base-isolated Buildings

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Abstract— **This paper presents a direct adaptive control design to suppress vibrations in nonlinear base-isolated buildings arising due to severe earthquakes. The control design is based on discrete direct adaptive neural control, where the neural controller parameters are adapted using Lyapunov-based tuning laws. There is no explicit identification phase in this control scheme, and the resulting controller operates directly on measurements without a state estimator. Performance of the proposed control scheme is evaluated on a full-scale nonlinear three-dimensional base-isolated benchmark structure incorporating lateral-torsion superstructure behavior, and biaxial interaction of nonlinear bearings. The results show that the proposed controller scheme is capable of achieving good response reductions for a wide range of near-fault earthquakes, without corresponding increases in the superstructure responses.**

I. INTRODUCTION

The problem of vibration minimization in seismically excited linear/nonlinear structures have received significant attention in the literature [1]–[4]. Recently, considerable attention is on the development of adaptive control algorithms such as adaptive back-stepping, feedback linearization and intelligent control, to effectively control the vibration of nonlinear structures with parameter uncertainties [5]–[7]. The results from these works indicate the potential importance of using adaptive control algorithms to control nonlinear structural systems.

In [5], adaptive back-stepping controller is designed for an uncertain base-isolated hysteretic structure with nonlinearities. However, the numerical sensitivity in its implementation influences the steady-state performance of the controller considerably. In [6], [8], function approximation capabilities of Gaussian kernels are exploited to approximate the nonlinear control law, and the proposed controller is capable of handling parameter uncertainties and unknown nonlinearities. Here, the initial controller parameters are obtained using off-line training process with a perturbed structure model. Recently, a direct adaptive controller using extended minimal resource allocation network (EMRAN) [7] with-out off-line learning process is proposed to handle uncertainty and failures in base-isolated structure. Here, the EMRAN controller uses computational intensive extended Kalman filter for controller parameter updates, and does not provide a mathematical proof for overall system stability.

The main idea of this paper is to present a discrete direct adaptive control design using linearly parameterized neural controller to handle uncertainties and system nonlinearities. Using Implicit function theorem, the existence of a nonlinear control law for vibration minimization of base-isolated system is shown, and it is approximated using linearly parameterized neural network. The proposed direct adaptive controller projects the structural response to a nonlinear hyper-dimensional space using random input weights [9], and active control input is determined as linear function of random projections. The neural controller weights are adapted online and the update laws are derived using Lyapunov approach. Unlike classical approaches using NNs where a formal identification phase precedes controller development, there is no need for identification, which is the main advantage of the proposed controller.

Numerical simulations are performed on the nonlinear benchmark base-isolated building [10] with an isolation system comprising of hysteretic lead-rubber bearings (LRBs). The structure is excited simultaneously in two directions using a suite of severe near-fault earthquakes. The earthquakes considered in this study are the fault-normal (FN) and fault-parallel (FP) components of Newhall, Sylmar, and El Centro. The performance of the controller is measured using a comprehensive set of eight performance indices. The results clearly show that the proposed linearly parameterized direct adaptive control design is effective in minimizing the structural response under a wide range of seismic excitations.

II. PROBLEM STATEMENT

A nonlinear three-dimensional base-isolated benchmark structure based on a full-scale structure located in Los Angeles, USA is considered in this study [10]. This structure is a eight story steel-braced base-isolated building, with isolators connected between the ground and a rigid concrete base slab. More details on structure and base-isolation can be found in [11]. A three degree-of-freedom (3-DOF) model at the center of mass is used to construct the mathematical model of the structural system (3-DOF for the base and 24-DOF for the superstructure).

A. Base-Isolation Model

The isolation system consists of a linear elastomeric bearing with a lead core (31 linear elastomeric bearings and 61 nonlinear lead rubber bearings). The lead core provides the energy dissipation due to plastic deformations, while the elastomeric part provides the re-centering stiffness. A biaxial interaction hysteric model given in [1] is used to model the behavior of the lead-rubber composite bearing, and is

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described as:

$$U^y \left\{ \begin{array}{c} \dot{z}_x \\ \dot{z}_y \end{array} \right\} = \alpha \left\{ \begin{array}{c} \dot{U}_{bx} \\ \dot{U}_{by} \end{array} \right\} - \mathbf{Z}_w \left\{ \begin{array}{c} \dot{U}_{bx} \\ \dot{U}_{by} \end{array} \right\}$$
$$\mathbf{Z}_w = \left[\begin{array}{cc} z_x^2(\gamma sgn(\dot{U}_{bx}z_x)+\beta) & z_x z_y(\gamma sgn(\dot{U}_{by}z_y)+\beta) \\ z_x z_y(\gamma sgn(\dot{U}_{bx}z_x)+\beta) & z_y^2(\gamma sgn(\dot{U}_{by}z_y)+\beta) \end{array} \right] \quad (1)$$

where, z_x and z_y are dimensionless hysteretic variables bounded by values ± 1. α, β and γ are dimensionless quantities, and U_{bx}, U_{by}, $\dot{U}_{bx}$ and $\dot{U}_{by}$ are the displacements and velocities in the x and y directions, respectively, at the isolation bearing, and U^y is the yield displacement.

The forces f mobilized in the elastomeric isolation bearings can be modeled by a elastic-viscoplastic model with strain hardening:

$$f_x = k_p U_{bx} + c_v \dot{U}_{bx} + (k_e - k_p) U^y z_x \quad (2)$$
$$f_y = k_p U_{by} + c_v \dot{U}_{by} + (k_e - k_p) U^y z_y \quad (3)$$

where, k_e is the pre-yield stiffness, k_p is the post-yield stiffness, c_v is the viscous damping coefficient of the elastomeric bearing, and U^y is the yield displacement. The details of the isolation system parameters have been specified in the benchmark definition papers [2], [10], [11].

B. Superstructure Model

The equations of motion for the linear superstructure are expressed as,

$$\mathbf{M}_{n\times n}\ddot{\mathbf{U}}_{n\times 1} + \mathbf{C}_{n\times n}\dot{\mathbf{U}}_{n\times 1} + \mathbf{K}_{n\times n}\mathbf{U}_{n\times 1} = -\mathbf{M}_{n\times n}\mathbf{R}_{n\times 3}(\ddot{\mathbf{U}}_g + \ddot{\mathbf{U}}_b) \quad (4)$$

in which, n is three times the number of floors (excluding base), $\mathbf{M}$ is the superstructure mass matrix, $\mathbf{C}$ is the superstructure damping matrix in the fixed base case, $\mathbf{K}$ is the superstructure stiffness matrix in the fixed base case and $\mathbf{R}$ is the matrix of earthquake influence coefficients, i.e. the matrix of displacements and rotation at the center of mass of the floors resulting from a unit translation in the X and Y directions and unit rotation at the center of mass of the base. Furthermore, $\ddot{\mathbf{U}}$, $\dot{\mathbf{U}}$ and $\mathbf{U}$ represent the floor acceleration, velocity and displacement vectors relative to the base, $\ddot{\mathbf{U}}_b$ is the vector of base accelerations relative to the ground and $\ddot{\mathbf{U}}_g$ is the vector of ground accelerations.

C. Base Model

The equations of motion for the base are given by,

$$\left. \begin{array}{r} \mathbf{R}^T_{3\times n}\mathbf{M}_{n\times n}\left[(\ddot{\mathbf{U}})_{n\times 1} + \mathbf{R}_{n\times 3}(\ddot{\mathbf{U}}_g + \ddot{\mathbf{U}}_b)_{3\times 1}\right]_{n\times 1} \\ +\mathbf{M}_{b_{3\times 3}}(\ddot{\mathbf{U}}_g + \ddot{\mathbf{U}}_b)_{3\times 1} + \mathbf{C}_{b_{3\times 3}}\dot{\mathbf{U}}_{b_{3\times 1}} \\ +\mathbf{K}_{b_{3\times 3}}\mathbf{U}_{b_{3\times 1}} + \mathbf{f}_{b_{3\times 1}}\left(\mathbf{U}_b, \dot{\mathbf{U}}_b\right) + \mathbf{f}_{c_{3\times 1}} \end{array} \right\} = 0 \quad (5)$$

where $\mathbf{f}_b$ consists of f_x, f_y and f_r, which are the forces in the nonlinear isolation system at the center of mass of the base in the x, y, and rotational directions respectively. f_r is calculated by transforming the spatially distributed f_x and f_y to the center of mass of the base. $\mathbf{M}_b$ is the diagonal mass matrix of the rigid base, $\mathbf{C}_b$ is the resultant damping matrix of viscous isolation elements, $\mathbf{K}_b$ is the resultant stiffness matrix of elastic isolation elements, $\mathbf{f}_b$ is the vector containing the nonlinear bearing forces and $\mathbf{f}_c$ is the vector containing the control forces.

D. Combined Model

Using Eq. 5 and Eq. 4, the discrete-time model for the nonlinear base-isolated building can be written as

$$\mathbf{z}(k+1) = f_1(\mathbf{z}(k), \eta(k)) + \mathbf{G}_1\mathbf{F}_c(k) + \mathbf{G}_1\mathbf{A}_g(k) \quad (6)$$
$$\eta(k+1) = f_2(\mathbf{z}(k), \eta(k)) + \mathbf{G}_2\mathbf{A}_g(k) \quad (7)$$

where, $\mathbf{A}_g(k)$ are the earthquake accelerations, $[\mathbf{z}(k) \quad \eta(k)]^T \in \Omega_x \subset \Re^n$ are the states of the discrete-time system corresponding to the base and the superstructure respectively on the compact set Ω_x, where $\left(\Omega_x := \left\{\mathbf{z}, \eta, \|\mathbf{z}\| \le M_z; \|\eta\| \le M_\eta\right\}\right)$, M_z, M_η are arbitrary positive constants, and $\mathbf{F}_c \in \Omega_u \subset \Re^m$ are the actuator inputs on the compact set Ω_u, $(\Omega_u := \{\mathbf{u}, \|\mathbf{u}\| \le M_u\})$, where M_u is a arbitrary positive constant. $\mathbf{G}_1$ and $\mathbf{G}_2$ are the discrete-time control matrices.

III. DIRECT ADAPTIVE NEURAL CONTROL DESIGN

The control objective in this paper is to construct a robust adaptive nonlinear control law which minimizes the vibrations caused by severe earthquake disturbances. Assume that the disturbance input to the structure is bounded and the nonlinear functions f_1 and f_2 are smooth and continuous in the operating region. Based on existing studies in nonlinear adaptive control [12], [13], the theoretical nonlinear adaptive control input ($\mathbf{F}_c^*$) which satisfies the objective can be expressed as:

$$F_c^*(k) = \bar{\mathscr{G}}_1 \left(\begin{array}{c} F_c^*(k-1), \cdots, F_c^*(k-n), \mathbf{z}(k-1), \cdots, \\ \mathbf{z}(k-n), \mathbf{A}_g(k), \cdots, \mathbf{A}_g(k-n), \mathbf{z}_d(k) \end{array} \right) \quad (8)$$

where, $\bar{\mathscr{G}}_1$ is a smooth nonlinear map and n represents the number of delays. The number of delays depends on the order of the system. The above form of control law is known to exist and is unique [14]–[16]. If the structural response follows the desired response, then the signal from $F_c^*(k-1)$, $\cdots$, $F_c^*(k-n)$ can be expressed in terms of the reference outputs and structural responses. Also, if the desired response is assumed to be near zero, then Eq. 8 can be simplified further as:

$$F_c^*(k) = \bar{\mathscr{G}}\left(\mathbf{z}(k-1), \cdots, \mathbf{z}(k-n_1), \mathbf{A}_g(k), \cdots, \mathbf{A}_g(k-n_1)\right) \quad (9)$$

where $n_1 \ge n$. The above equation can be written as,

$$F_c^*(k) = \bar{\mathscr{G}}(\mathbf{v}) \quad (10)$$

where, $\mathbf{v}$ consists of past states and present and past values of the ground accelerations. If the mapping $\bar{\mathscr{G}}$ is known in Eq. 9, then the desired control force $F_c^*(k)$ can be calculated using n_1 past values $\mathbf{z}$, and n_1+1 current and past values of the earthquake disturbance (define $l = 2n_1+1$). Since the function map $\bar{\mathscr{G}}$ is unknown, estimating control force $F_c^*(k)$ is not possible. However, since the relationship given by Eq. 9 exists, $\bar{\mathscr{G}}$ can be modeled using a linearly parameterized neural network.

A. Linearly Parameterized Neural Network

A linearly parameterized single hidden layer neural network is used to approximate the unknown nonlinear control law given in Eq. 9 as follows:

$$F_c^*(k) = \sum_{i=1}^{h^*} \alpha_i^* \sigma_i(\mathbf{v}) \tag{11}$$

where $\mathbf{v} \in \Re^{l\times 1}$ is the input to the controller, the nonlinear function $\sigma : \Re^{h^*} \to \Re^{h^*}$ is continuous with respect to its arguments for all finite $(\mathbf{W}, \mathbf{v})$, and the adjustable parameters of the controller are elements of $\alpha \in \Re^{m\times h^*}$. Note that $\sigma_i \in \Re^h$ is the basis function. According to Universal Approximation principle [17], a sufficiently large number of hidden neurons (h^*) in a linearly parameterized neural network can approximate any continuous function, to any desired accuracy .

Using this principle, a bipolar sigmoidal basis function is used to approximate the nonlinear control law. The above equation is written in the matrix form as:

$$\mathbf{F}_c^*(k) = \alpha^* \sigma(\mathbf{v}) \tag{12}$$

where

$$\sigma_i = \frac{1.0 - exp(-\mathbf{w}_i\mathbf{v})}{1.0 + exp(-\mathbf{w}_i\mathbf{v})} \tag{13}$$

where $\mathbf{w}_i \in \Re^l$ are the input weights. In this paper, the input weights are chosen randomly. The underlying premise in this formulation is that a single hidden layer feed-forward network with random input weights can approximate a given continuous function [9]. The number of random nodes to approximate the nonlinear control law is determined using the procedure given in [18].

For the unknown nonlinear control law given in 9, the following approximation holds over the compact input $\mathbf{v} \in \Omega_v$:

$$\bar{\mathscr{G}}(\mathbf{v}) = \alpha^* \sigma(\mathbf{v}) + \varepsilon \tag{14}$$

where ε is the approximation error, and α^* is the unknown constant/optimal controller parameter. Here, it is assumed that the approximation error (ε) over the compact input region $\mathbf{v} \in \Omega_v$ is bounded according to:

$$\|\varepsilon(\mathbf{v})\| \le \varepsilon_m \tag{15}$$

where $\varepsilon_m \ge 0$ is an unknown bound.

Remark: The optimal controller parameter α^* is for analytical purposes only. Typically, α^* is chosen as the value of α and $\mathbf{W}$ that minimizes ε for all $\mathbf{v} \in \Omega_v$, where $\Omega_v \subset \Re^m$ is a compact set, i.e.,

$$(\alpha^*) := arg \min_{\alpha \in \Omega_w} \left\{ \sup_{\mathbf{v}\in\Omega_v} \left\| \alpha^T \sigma(\mathbf{v}) - \bar{\mathscr{G}}(\mathbf{v}) \right\| \right\} \tag{16}$$

in which $\Omega_w := \{(\alpha) | \|\alpha\| \le M_\alpha\}$, M_α is a positive constant. The approximated adaptive control force is then given by,

$$\hat{\mathbf{F}}_c = \alpha\sigma(\mathbf{v}) \tag{17}$$

B. Robust Direct Adaptive Control Design

In this section, the control design procedure for the system given in Eqs. 6-7 is presented.

Substituting the control law given in Eq. 14 in Eq. 6,

$$\mathbf{z}(k+1) = f_1(\xi, k) + \mathbf{G}_1[\alpha^*\sigma(\mathbf{v}) + \varepsilon] + \mathbf{G}_1\mathbf{A}_g(k) \tag{18}$$

where, $\xi = (\mathbf{z}(k), \eta(k))$. Now, substituting the approximate control law given in Eq. 17 in Eq. 6,

$$\hat{\mathbf{z}}(k+1) = f_1\left(\hat{\xi}, k\right) + \mathbf{G}_1[\alpha\sigma(\mathbf{v})] + \mathbf{G}_1\mathbf{A}_g(k) \tag{19}$$

The control objective is to make $\mathbf{z}(k)$ follow a desired response $\mathbf{z}_d(k)$. The neural controller is selected to force the error between the actual and desired base structural responses. Define error: $\mathbf{e}_b(k) = \hat{\mathbf{z}}(k) - \mathbf{z}(k)$; then, the error dynamics of the system can be written as,

$$\mathbf{e}_b(k+1) = f_1(\hat{\xi}, k) - f_1(\xi, k) + \mathbf{G}_1[\alpha\sigma(\mathbf{v}) - \alpha^*\sigma(\mathbf{v}) - \varepsilon] \tag{20}$$

The error dynamics in Eq. 20 can be written as:

$$\mathbf{e}_b(k+1) = \begin{cases} \mathbf{A}_1\hat{\xi}(k) - \mathbf{A}_1\xi(k) + f_0(\hat{\xi}, k) - f_0(\xi, k) \\ +\mathbf{G}_1[\alpha\sigma(\mathbf{v}) - \alpha^*\sigma(\mathbf{v}) - \varepsilon] \end{cases} \tag{21}$$

where, $f_0(\cdot)$ is the nonlinear part due to lead-rubber bearing system. Let the nonlinear higher order term be represented by $\gamma(\hat{\xi} - \xi) = f_0(\hat{\xi}) - f_0(\xi)$.

Hence, the simplified error dynamics for the base can be written as,

$$\mathbf{e}_b(k+1) = \mathbf{A}_1\mathbf{e}_1(k) + \gamma(\mathbf{e}_1) + \mathbf{G}_1[\alpha\sigma(\mathbf{v}) - \alpha^*\sigma(\mathbf{v}) - \varepsilon] \tag{22}$$

Where, $\mathbf{e}_1 = \hat{\xi} - \xi$, and $\mathbf{A}_1 = f_1'|_{\hat{\xi}=\xi}$.

Similarly,

$$\mathbf{e}_s(k+1) = \mathbf{A}_2\mathbf{e}_1(k) \tag{23}$$

where, $\mathbf{A}_2 = f_2'|_0$. Combining Eq. 22 and Eq. 23,

$$\mathbf{e}_1(k+1) = \bar{\mathbf{A}}\mathbf{e}_1(k) + \bar{\mathbf{D}}\gamma(\mathbf{e}_1, k) + \bar{\mathbf{B}}[\alpha\sigma(\mathbf{v}) - \alpha^*\sigma(\mathbf{v}) - \varepsilon] \tag{24}$$

where $\bar{\mathbf{A}} = \left[f_1'|_0 \quad f_2'|_0\right]^T$, $\bar{\mathbf{D}} = [1 \quad 0]^T$, and $\bar{\mathbf{B}} = [\mathbf{G_1} \quad \mathbf{0}]^T$. Define the parameter errors as, $\tilde{\alpha} := \alpha - \alpha^*$. Then, the error dynamics can be written as,

$$\mathbf{e}_1(k+1) = \bar{\mathbf{A}}\mathbf{e}_1(k) + \bar{\mathbf{D}}\gamma(\mathbf{e}_1, k) + \bar{\mathbf{B}}[\tilde{\alpha}\sigma(\mathbf{v}) - \varepsilon] \tag{25}$$

Now, the parameter update law is presented such that overall system stability is ensured in a Lyapunov sense. It will also be shown that the neural network parameters are bounded for suitably small tracking error $\mathbf{e}_1$, and hence the control inputs are bounded.

First, assume that the neural network can approximate the control law $F_c^*(k)$ given in Eq. 8 with a given accuracy of ε_n, for all input $\mathbf{v}$ in a compact set.

With the above assumption, define a positive definite Lyapunov function,

$$V = \frac{1}{2}\left[\mathbf{e}_1(k)^T\mathbf{P}\mathbf{e}_1(k) + tr\left(\tilde{\alpha}(k)\mathbf{F}_1\tilde{\alpha}(k)^T\right)\right] \tag{26}$$

where $\mathbf{F}_1$ is a constant matrix that satisfies $\mathbf{F}_1 = \mathbf{F}_1^T > 0$. The matrix $\mathbf{P}$ is a positive-definite symmetric solution obtained from $\bar{\mathbf{A}}^T\mathbf{P} + \mathbf{P}\bar{\mathbf{A}} = -\mathbf{Q}$, where $\mathbf{Q}$ is a positive definite matrix.

The first difference of the Lyapunov function can then be written as,

$$\Delta V = \begin{cases} -\mathbf{e}_1^T\mathbf{Q}\mathbf{e}_1 - \mathbf{e}_1^T\mathbf{P}\bar{\mathbf{B}}\varepsilon + \mathbf{e}_1^T\mathbf{P}\bar{\mathbf{D}}\gamma(\mathbf{e}_1) \\ +tr\tilde{\alpha}[\sigma\mathbf{e}_1^T\mathbf{P}^T\bar{\mathbf{B}} + \mathbf{F}_1\Delta\tilde{\alpha}^T] \end{cases} \quad (27)$$

Assume that $\mathbf{F}_1\Delta\tilde{\alpha}^T = -\sigma\mathbf{e}_1^T\mathbf{P}^T\bar{\mathbf{B}}$. Then, the first difference of Lyapunov function reduces to,

$$\Delta V = -\mathbf{e}_1^T\mathbf{Q}\mathbf{e}_1 - \mathbf{e}_1^T\mathbf{P}\bar{\mathbf{B}}\varepsilon + \mathbf{e}_1^T\mathbf{P}\bar{\mathbf{D}}\gamma(\mathbf{e}_1) \quad (28)$$

Using the error dynamics and parameter update laws, Eq. (28) can be re-written as:

$$\Delta V \leq \begin{cases} \|\mathbf{e}_1\|\lambda_{min}(\mathbf{Q})\|\mathbf{e}_1\| + \|\mathbf{e}_1\|\lambda_{max}(\mathbf{P})\|\bar{\mathbf{B}}\|_F\varepsilon_M + \\ \|\mathbf{e}_1\|\lambda_{max}(\mathbf{P}\bar{\mathbf{D}})\gamma_h \end{cases} \quad (29)$$

where, γ_h is the upper bound of magnitude error for nonlinear terms in lead rubber bearing $(\gamma_h = max\left(|f_0(\hat{\xi}) - f_0(\xi)|\right)$.

Since the ideal parameters are constant (α^*, the adaptive update laws for the parameters can be written as,

$$\alpha(k+1)^T \quad = \quad \alpha(k)^T - \mathbf{F}_1^{-1}\sigma\mathbf{e}_1^T\mathbf{P}^T\bar{\mathbf{B}} \quad (30)$$

The error bound condition for the negative semi-definiteness of the Lyapunov difference in Eq. 27 can be written as,

$$\|\mathbf{e}_1\| > \frac{\lambda_{max}(\mathbf{P})\left[\|\bar{\mathbf{B}}\|_F\varepsilon_M + \bar{\mathbf{D}}\gamma_h\right]}{\lambda_{min}(\mathbf{Q})} \quad (31)$$

To prevent large parameter errors, the parameters of the network are initialized off-line, using finite time samples generated from an approximate model. For offline training, we have used perturbed structural system and Sylmar earthquake records. The offline training strategy is similar to the one described in [8]. The estimated parameters so obtained are used as a starting point for the on-line adaptation. For the error analysis, consider maximum value for structural system, i.e., $\|z_x\| = 1$ and $\|z_y\| = 1$. The bound γ_h depends on the $\mathbf{e}_b$. Since, the network is trained off-line, the actual base states approximately follows the estimated states. Hence, the term γ_h is small and it can be neglected.

Hence, the error bound condition is reduced to,

$$\|\mathbf{e}_1\| > \frac{\lambda_{max}(\mathbf{P}\|\bar{\mathbf{B}}\|_F)\varepsilon_M}{\lambda_{min}(\mathbf{Q})} = E_a \quad (32)$$

By using Universal Approximation theorem [17], it can be said that the approximation error ε_M is reduced to zero by a proper selection of network parameters. By the proper selection of a user defined matrix P, the error bound E_a is reduced to a small quantity. If $\|\mathbf{e}_1\|$ is less than the error bound, then it will result in a drift of parameters. Such parameter drifts can be prevented using a projection algorithm explained in [19]. The projection algorithm directs the parameters within the radius of ball Ω_w, and ensures that the parameters do not grow unbounded.

The parameter update laws in Eqs. 30 requires access to all the states in the system. In civil structures, full state measurements is not practical. For nonlinear systems, state estimation is cumbersome and undesirable. Hence, the update rules are approximated and specialized for the case of output feedback. Making the following substitution: $\mathbf{e}_1^T\mathbf{P}^T\bar{\mathbf{B}} = \eta\mathbf{A}_b$, where $\mathbf{A}_b$ is the base acceleration, and η is a small scalar quantity (of the order of $10^{-2} - 10^{-4}$), the following update law is obtained:

$$\alpha(k+1)^T \quad = \quad \alpha(k)^T - \eta\mathbf{F}_1^{-1}\sigma\mathbf{A}_b \quad (33)$$

Since the base accelerations are relatively easy to measure, the above simplified control law (33) allows for a relatively straight-forward implementation. From the update law in Eq. 33, it can be observed that superstructure properties such as the stiffness, damping and the nonlinear force terms in the isolation layer do not appear in the update laws. Hence, the controller is robust to the uncertainties in the system properties.

IV. SIMULATION RESULTS

The performance of the proposed adaptive controller is evaluated using Newhall, Sylmar and El Centro earthquake records, and the results are expressed using a set of performance indices defined in [10]. The indices J_1 through J_5 measure the peak values of base shear, structural shear, base displacement, inter-story drift and floor accelerations, respectively. These values are normalized by their respective uncontrolled values, which refers to the case when there is no force feed back to the structure and the control device is disconnected from the structure. The performance index J_6 measures the maximum control force (normalized with respect to the peak base shear in the controlled structure) developed in the device, or in other words, measures the peak control demand. The indices, J_7 and J_8 measure the RMS values of displacement and base acceleration normalized by their uncontrolled values. Readers are referred elsewhere for details [10]. The performance of proposed controller is compared with online learning EMRAN controller [7] and off-line/online adaptive Gaussian controller [6].

The results of the proposed neural adaptive control scheme along with existing EMRAN and Gaussian controllers are reported in Table I. It can be observed from the results presented in Table I that all the performance indices for the adaptive controllers are less than 1, which means that the controlled responses are less than the corresponding uncontrolled responses. From the table, we can see that the proposed discrete direct adaptive control design performs better than comparable controllers, namely EMRAN controller and Gaussian controllers for a majority of cases. From Table I, we can see that in some measures EMRAN performs better than the proposed controller. Such discrepancies are due to large variation in the magnitude and spectral content of the selected earthquakes. Hence, the such discrepancies are to be expected in the controller performances.

V. CONCLUSIONS

A discrete direct adaptive controller using linearly parameterized neural network was presented and shown to

TABLE I
PERFORMANCE INDICES FOR THE PROPOSED ADAPTIVE CONTROL SCHEME

Per. Mea.	Cases	New Hall	Sylmar	El Centro
J_1	Proposed	0.676	**0.458**	**0.698**
	EMRAN	**0.667**	0.684	0.730
	Gaussian	0.874	0.721	0.785
J_2	Proposed	0.651	**0.446**	**0.715**
	EMRAN	**0.625**	0.666	0.790
	Gaussian	0.866	0.743	0.822
J_3	Proposed	0.991	0.608	0.841
	EMRAN	**0.650**	**0.598**	**0.524**
	Gaussian	0.909	0.768	0.634
J_4	Proposed	0.611	**0.489**	**0.917**
	EMRAN	**0.604**	0.621	0.937
	Gaussian	0.800	0.689	0.933
J_5	Proposed	**0.662**	**0.519**	0.863
	EMRAN	0.733	0.738	0.953
	Gaussian	0.750	0.757	**0.834**
J_6	Proposed	0.654	0.629	0.458
	EMRAN	0.497	0.476	0.657
	Gaussian	0.402	0.512	0.331
J_7	Proposed	0.933	**0.507**	0.896
	EMRAN	**0.695**	0.651	**0.643**
	Gaussian	0.989	0.650	0.882
J_8	Proposed	**0.793**	**0.463**	**0.910**
	EMRAN	0.818	0.595	0.968
	Gaussian	0.913	0.695	0.930

be effective in reducing the response of nonlinear base isolated structures subjected to earthquake excitations. The paper uses random projection of output measurements to higher dimensional space with linear parameters for approximation of nonlinear control law. The linearly parameterized controller is shown to stable in Lyapunov sense. The performance comparison with other existing nonlinear adaptive control schemes clearly show that the proposed discrete direct adaptive control is effective and also decreases superstructure drifts and accelerations while reducing the base displacements.

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