Neural Aided Discrete PID active Controller for Non-Linear Hysteretic Base-Isolation building

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Abstract— **The combination of isolation system and active control devices has been increasingly considered in the structural control community to design an efficient smart hybrid base-isolation system for seismic protection. In this paper, a control scheme based on a combination of discrete PID controller and discrete direct adaptive neural controller is proposed for the active control of a nonlinear base isolated building to reduce superstructure responses and base drifts under near-fault earthquake excitations. Even though the PID controller is a traditional and widely used in many control applications, the performance of PID controller is not satisfactory in time varying and nonlinear systems. But the efficiency of its performance can be enhanced by combining the PID controller along with neural controller. The neural controller is constructed based on a single hidden layer feed forward network and the parameters of the network are modified using extreme learning machine (ELM) -like algorithm. To ensure the stability of the system, unlike original ELM algorithm, Lyapunov update law is used to update the output parameters of the network. This approach is validated by simulating a non-linear three dimensional benchmark base-isolated structure with time history records of three near-fault earthquakes. The performance of the proposed control scheme is measured in terms of a comprehensive set of performance indices. The results show that the proposed neural aided discrete PID active controller is more effective in reducing the superstructure acceleration, inter-storey drifts and base displacement by giving an active feedback control force to the base-isolated structure.**

Keywords— Base-Isolation, direct adaptive, active control, discrete, neural controller, PID, Lyapunov, Extreme Learning Machine.

I. INTRODUCTION

A base isolation system needs to provide (i) horizontal flexibility to lengthen the building period while maintaining the vertical stiffness by rubber bearings, (ii) damping to restrict the relative deformation at the plane of isolation and limit it within the capacity of the bearings [1-3]. To enhance the functionality of a base isolation system, smart base isolation, which consists of linear, nonlinear bearings and control devices, is recommended. The super structure is considered to be a linear elastic system with lateral-torsional behavior. The nonlinearities due to the isolators and control devices are limited to the isolation level only. To maintain the performance of the structure in response to seismic excitations within the safety limits, many structural control strategies were proposed in smart base isolation system. In active control system, the desired control force as a function of external excitations or structural responses is computed based on a designed control algorithm and the actuators will be directly commanded to produce the control force. Similar control method can also be achieved in semi active control scheme, but the control actuators do not add mechanical energy directly to the structure and it can be viewed as controllable passive devices [4,5]. Since, a lot of work has been done to develop active control and a number of demonstration buildings with active control exist in Japan and elsewhere in Southeast Asia [6], active control strategy is considered in this paper.

The control system attempts to produce forces in the actuators which act to reduce the motion induced by the earthquake. Even though many linear and nonlinear control methods have been proposed for the active control of structures [7-9], the need to handle uncertain dynamic characteristics of nonlinear structural systems with limited state measurements motivated the use of adaptive controllers. The adaptive controllers can adapt themselves to modify the control law based on estimation of unknown parameters by a recursive algorithm. As neural networks have good nonlinear function approximation capabilities, significant research works has been carried out on neural network based adaptive controllers [10-16].

The parameters of discrete direct adaptive neural controller presented in this paper are adapted using ELM-like algorithm. In ELM based neural network, the inputs of the network are projected to a hyper dimensional space through randomly selected input weights and hidden layer bias and the output weights are determined analytically [17]. To improve the performance of ELM in sparse high-dimensional applications, many extensions of ELM have been developed [18-21]. In this paper, unlike original ELM algorithm, the output weights are adjusted using Lyapunov update law to ensure the stability of the closed loop system. In [20,21], it has been shown that similar kind of ELM based adaptive neural controller is effective in establishing the closed loop stability for a sliding mode control system. In [22], the performance of discrete direct adaptive neural controller using ELM-like algorithm is discussed. Even though the performance is comparatively good, the base drifts for all earthquakes are relatively high. Inorder to reduce the structural response further during seismic excitation, a combination of discrete direct adaptive

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neural controller along with proportional, integral and derivative (PID) controller is proposed in this paper. Traditionally, PID control has been used for many control applications, especially where it is not possible to derive an explicit formulation of the equation of motion. Despite decades of research in developing new control methods, the PID controller is still widely used, due to its simplicity and effectiveness. Since, PID controllers are not suitable for systems that are highly oscillatory, the implementation of PID controller alone is not satisfactory in time varying and non-linear system. In this paper, both the discrete PID controller and ELM-like discrete direct adaptive neural controller connected in parallel, is used as a feedback controller for effectively suppressing the structural responses for a nonlinear benchmark smart base-isolated building.

Numerical simulations are performed on a nonlinear three dimensional benchmark base-isolated building [23] with an isolation system comprising of hysteretic lead-rubber bearings (LRBs). The structure is excited simultaneously in two directions using a set of three near-fault earthquakes. The earthquakes considered in this study are the fault-normal (FN) and fault-parallel (FP) components of *El Centro, Kobe* and *Erzikan*. The performance of the proposed controller is measured using a comprehensive set of eight performance indices. The results clearly show that the proposed neural aided discrete PID controller is effective in minimizing the structural response under a wide range of seismic excitations.

The paper is organized as follows. Section 2 introduces simulation model of bench mark base-isolated structure and its mathematical model. The discrete direct adaptive Neural controller and the Lyapunov based parameter update law is given in section 3. In section 4, implementation of neural aided discrete PID controller in MATLAB-Simulink is explained. The results of the simulation studies on the benchmark structure are discussed in section 5 and followed by the conclusions.

II. Simulation Model of a Bench Mark Base-Isolated Building

The structural model represents a nonlinear three-dimensional base-isolated structure located in Los Angeles, USA. The building has a steel-framed superstructure and consists of eight-storey. The plan is L-shaped with asymmetry in both directions and has dimensions of 82.4m long and 54.3m wide..More details on structure and base-isolation can be found in [23]. The superstructure is assumed to remain in the linear-elastic regime, while the nonlinearities in the isolation system provide for the energy dissipation. The asymmetry in the plan causes the structure responses to contain significant torsional components in addition to the lateral components.

The full-order model was reduced to 24 degrees of freedom (24 DOF) at the centers of mass of the eight-floor levels using the rigid floor slab assumption. The nonlinear base-isolation model was integrated into the 24 DOF superstructure model. The isolation system of an eight-storey building consists of a combination of 31 linear elastomeric bearings and 61 nonlinear lead rubber bearings (LRBs). In this paper, the linear elastomeric bearings are modelled using linear spring elements, while a biaxial interaction hysteretic model is used to model the behavior of the lead-rubber composite bearings.

The combined discrete time model for the nonlinear base-isolated building can be expressed as

$$z(k+1) = f_1\left(z(k), \eta(k)\right) + G_1\, F_c\,(k) + G_1\, A_g\,(k) \tag{1}$$

$$\eta(k+1) = f_2\left(z(k), \eta(k)\right) + G_2\, A_g\,(k) \tag{2}$$

Where $A_g\,(k)$ represents the earthquake accelerations. $[z(k), \eta(k)] \in \Omega_{\mathrm{x}} \subset \Re^{\mathrm{n}}$ are the states of the discrete-time system corresponding to the base and the superstructure respectively on the compact set Ω_{x}, where $\left(\Omega_{\mathrm{x}} := \{\mathrm{z}, \eta, \|z\| \le M_z\,; \|\eta\| \le M_\eta\}\right)$, M_z, M_η are arbitrary positive constants, and $F_c \in \Omega_{\mathrm{u}} \subset \Re^{\mathrm{m}}$are the actuator inputs on the compact set Ω_{u}, $(\Omega_{\mathrm{x}} := \{\mathrm{u}, \|u\| \le M_u\,\})$, where M_u is a arbitrary positive constant.G_1 and G_2 are the discrete-time control matrices.

III. Direct Adaptive Neural Controller Design

The objective of adaptive neural control law is to minimize the vibrations caused by severe earthquake disturbances, i.e., To determine the control input $F_c^*(K)$, which will make the structural response of the base $z\ (k)$ to follow the desired response $zd\ (k)$, such that

$$\|z(k) - z_d(k)\| \le \epsilon \tag{3}$$

where ϵ is a small positive constant.

In the discrete time model of nonlinear-base building given in Equation (1) and Equation (2), the functions f_1 and f_2 are assumed to be smooth, nonlinear and continuous in the operating region. By assuming the system in Equation (1) and Equation (2 is observable, there exists a desired control force $F_c^*(k)$, as per the implicit function theorem in nonlinear adaptive control theory,

$$\begin{aligned} F_c^*(k) = \overline{g_1}(&F_c^*(k-1), \ldots .F_c^*(k-n), z(k-1), \\ &\ldots, z(k-n), A_g(k), \ldots A_g(k-n), z_d(k)) \end{aligned} \tag{4}$$

where $\overline{g_1}$ is smooth nonlinear mapping function and n represents number of delays. If it is assumed that the structural response follows the desired response and also if desired responses are assumed to be zero, then Equation (4) can be modified as,

$$F_c^*(k) = \bar{g}(z(k-1), .., z(k-n_1), A_g(k), \ldots A_g(k-n_1)) \tag{5}$$

where $n_1 \ge$ n. The Equation (5) can be simply represented as

$$F_c^*(k) = \bar{g}(v) \tag{6}$$

where, $\boldsymbol{v}$ consists of past states of the base and present and past values of the ground accelerations. As the functional mapping $\bar{g}$ is unknown, the control force $F_c^*(k)$ cannot be determined from the parameters of z and A_g (n_1 past values of $\mathbf{z}$,and n_1+1 current and past values of A_g, leads to totally $N = 2n_1+1$ parameters),but the functional relationship can be modeled using a linearly parameterized neural network.

A single hidden layer feed-forward network with additive nodes and RBF nodes, is used to approximate the unknown nonlinear control law in Equation (9) as follows:

$$\hat{F}_c(k) = \sum_{i=1}^{l} \beta_i G(v) = \sum_{i=1}^{l} \beta_{ik} G_i\left(\sum_{j=1}^{N} w_{ij}.v_j + b_i\right),$$

k = 1,…….M, (7)

where $\boldsymbol{v} \in \Re^{N\times N}$ is the input to the controller, w_{ij} ($\boldsymbol{w} \in \Re^{N\times l}$), b_i are the weight vector connecting the i[th] hidden node and the input nodes and i[th] hidden layer bias respectively. $\boldsymbol{\beta_{ik}}$ ($\beta \in \Re^{M\times l}$) is the output weight connecting the i[th] hidden node to the k[th] output node. The activation function G is sigmoidal which is infinitely differentiable. The above approximate control law Equation (10) can be written compactly as

$$\hat{F}_c(k) = H\beta, \tag{8}$$

where

$$H(w,b,v) = \frac{1-\exp(-w.v+b)}{1+\exp(-w.v+b)} \tag{9}$$

The approximate functional mapping obtained through neural network is represented as $g'(v)$ and hence the approximate control law is written as

$$g'(v) = H\beta, \tag{10}$$

According to universal approximation theorem of a SLFN, the optimal weight parameters β^* for approximating the nonlinear function is given as

$$\beta^* \triangleq \operatorname{argmin}[sup_{v\,\epsilon\,M_v}\|g'(v) - \bar{g}(v)\|], \tag{11}$$

such that

$$\bar{g}(v) = H(v)\beta^* + \epsilon_g(v) \tag{12}$$

Where $\|.\|$ represents the two-norm of a vector, M_v is the predefined compact set of input vector v. Also it is assumed that $\epsilon_g(v)$ caused by approximating $\bar{g}(\boldsymbol{v})$ are bounded with the constant ϵ and is given by

$$|\epsilon_g(v)| \leq \epsilon. \tag{13}$$

Hence Equation (12) can be written as

$$\bar{g}(v) = H(v)\beta^* + \epsilon \tag{14}$$

A. Disctrete- Time update law for output parameter

The control law derived above Equation (14) ,is substituted in the state equation of the base structure Equation (1) .

$$z(k+1) = f_1(\mu,k) + G_1[H(v)\beta^* + \epsilon] + G_1 A_g(k) \tag{15}$$

where $\mu=(z(k),\eta(k))$.

By substituting the approximate control law in Equation (8) in Equation (15).

$$\hat{z}(k+1) = f_1(\hat{\mu},k) + G_1[H\beta] + G_1 A_g(k) \tag{16}$$

The design of the neural controller is such that the tracking error

$$e_b(k) = \hat{z}(k) - z(k) \tag{17}$$

for the base structure is close to zero. The equivalent error dynamics of the base structure is given as

$$e_b(k+1) = f_1(\hat{\mu},k) - f_1(\mu,k) + G_1[H(v)\beta^* - H(v)\beta - \epsilon] \tag{18}$$

By including the nonlinear part $f_0(.)$ due to lead-rubber bearing and by representing the higher order terms by $\chi(\hat{\mu}-\mu) = f_0(\hat{\mu}) - f_0(\mu)$,the error dynamics in Equation (18) can be written as

$$e_b(k+1) = A_1\,\hat{\mu}(k) - A_1\,\mu(k) + f_0(\hat{\mu},k) - f_0(\mu,k) + G_1[H(v)\beta^* - H(v)\beta - \epsilon] \tag{19}$$

where $A_1 = f_1'\,|\,\hat{\mu} = \mu$

By defining $\boldsymbol{e_1}=\hat{\mu}-\mu$, the simplified error dynamics for the base is as follows

$$\boldsymbol{e_b}(k+1) = A_1\boldsymbol{e_1}(k) - \chi(\boldsymbol{e_1}) + G_1[H(v)\beta - (v)\beta^* - \epsilon] \tag{20}$$

Similarly, error dynamics for super structure

$$\boldsymbol{e_s}(k+1) = A_2\boldsymbol{e_1}(k) \tag{21}$$

Where $A_2 = f_2'|_0$.Combining Equation (20) and Equation (21),

$$\boldsymbol{e_1}(k+1) = \bar{A}\boldsymbol{e_1}(k) - \bar{D}\chi(\boldsymbol{e_1},k) + \bar{B}[H(v)\tilde{\beta} - \epsilon] \tag{22}$$

Where $\bar{A} = [f_1'|_0 \;\; f_2'|_0]^T$, $\bar{D} = [1\ 0]^T$,$\bar{B} = [G_1 \;\; 0]^T$ and the parameter error as $\tilde{\beta} = \beta - \beta^*$.

For deriving the stable tuning law, a positive definite Lyapunov function is defined as

$$V(k) = \frac{1}{2}\left[\boldsymbol{e_1}(k)^T P \boldsymbol{e_1}(k) + \frac{1}{\eta}\tilde{\beta}^T\tilde{\beta}\right] \tag{23}$$

where P and F are symmetric positive definite matrices, η is positive constant.

Using Equation (23) the first difference equation of the Lyapunov equation is given as,

$$\Delta V = -\frac{1}{2}e_1(k)^T J\, e_1(k) + e_1(k)^T P\bar{D}\chi + \left[e_1(k)^T P\bar{B}H + \frac{1}{\eta}\Delta\tilde{\beta}^T\right] - e_1(k)^T P\bar{B}\epsilon \tag{24}$$

where J=-($A^T P+PA$).J is symmetric positive definite matrix and is selected by the user. Equatin (24) facilitates the derivation of the parameter update law which ensures the negative semidefiniteness of the first difference equation of the Lyapunov function.The detail can be found in [23].

The parameter update law can be written as

$$\beta(k+1)^T = \beta(k) - \eta e_1 (k)^T P\bar{B}H \tag{25}$$

The error bound condition for the negative semi-definite of the Lyapunov difference in Equation (25) can be written as:

$$\|e_1\| \geq \frac{\lambda_{max}(P\bar{B})\epsilon}{\lambda_{min}(J)} = E_b \tag{26}$$

The bounds of the error can be reduced by an appropriate selection of the matrix $\boldsymbol{J}$. If the error is greater than the error bound (E_b) then the overall system is asymptotically stable in the sense of Lyapunov. If the bounds are not satisfied, the parameters may drift. To prevent such drifts in the controller parameter, we initialize them using off-line training. Subsequently, the offline trained controller parameters are used as the initial values for online adaptation. The offline training ensures that the estimation error bound (ϵ) for all the bounded inputs remain small, as well as the error bounds in the nonlinear terms remains relatively small.

The parameter update law given in Equation (25) requires measurement of all the states in the system. In civil structures, full state measurements are not practical and state estimation is cumbersome and undesirable. Hence, the update rules are approximated and specialized for the case of output feedback. By substituting, $e_1 (k)^T P\bar{B} = \boldsymbol{A_b}$ where $\boldsymbol{A_b}$ is the base acceleration, and κ is a small scalar quantity (of the order of 10^{-2} to 10^{-4}), the control is reduced to

$$\beta(k+1)^T = \beta(k) - \eta H\boldsymbol{A_b} \tag{27}$$

where η is a small scalar quantity (of the order of 10^{-2} to 10^{-4}).

Since the base accelerations are relatively easy to measure, the above approximated control law allows relatively straightforward implementation. The key advantage of the proposed controller is that the system information, namely the mass, stiffness and damping matrices, is not explicitly required for its implementation. This makes the controller inherently robust to parameter uncertainties.

IV. Controller Implementation

The MATLAB Simulink block diagram of the neural aided discrete PID active controller implementation is shown in Fig. 1. The inputs to the nonlinear structure are seismic excitations in both x and y directions and the control force.

Ym represents measurable sensor outputs which include i) the absolute acceleration at the center of the mass of all floor levels and the base ii) absolute accelerations and displacements at all the device locations in two translational directions iii) ground accelerations. *Ye* denotes the evaluation outputs, used for calculation of performance indices. Two centralized combination of neural and PID controllers are used to control the responses in x and y direction independently.

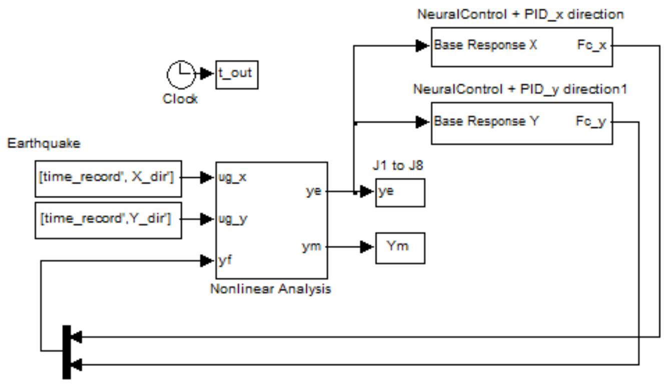

Fig. 1. MATLAB Simulink block diagram of the neural aided discrete PID active controller

A. Discrete Direct Adaptive Neuarl Controller

The input to the neural controller consists of base displacement, velocity and ground acceleration at the center of mass of the base. The base velocity is obtained by passing the base acceleration through a second order filter [23]. The ELM-like adaptive neural controller responses are based on present and 9 past values of ground acceleration, base displacement and base velocity. The number of hidden neurons are selected using constructive and destructive strategy, to project the input space to nonlinear feature space [18]. The parameters of hidden neurons are fixed and the output parameters are adapted using Lyapunov update law.

B. Discrete PID Controller

The base acceleration produced during an excitation of earthquake is compared with the reference acceleration limit (which is specified as 0.001m/s^2) and the error is calculated. Based on the error value, the discrete PID controller will produce the control force. The PID gain values calculated by trial and error are K_p=1, K_i=3. 5 and K_d=1e-5.

A total of 16 actuators, 8 in each direction are distributed with the base of the structure [23]. The sum of control forces produced from the neural adaptive controller and discrete PID controller are given to the actuators. The actuator dynamics are modeled using a first order filter of the form K/s+τ_c, where τ_c is the time constant assumed as 5 and K is the forward gain of the actuator, also kept as 5 [13]. The combined outputs of 8 actuators will produce the centralized control force in each direction. The controller parameters are initialized using an offline training with time history record of *Erzikan* earthquake, and the offline tuned controller is then adapted online using other two earthquakes namely, *El Centro and Kobe* along with *Erzikan*. The performance of the proposed controller is evaluated using the three earthquake records and the results are expressed in terms of a comprehensive set of performance indices [23].

Based on Ye, the performance indices (J_1-J_8) are calculated. The performance indices are Peak base shear (J_1), Peak structural shear (J_2), Peak isolator deformation (J_3), Maximum drifts (J_4), Peak acceleration (J_5), Peak control force (J_6), RMS deformation (J_7), RMS acceleration (J_8) .

V. Results And Discussion

The main objective of the proposed discrete direct adaptive neural controller using ELM-like algorithm along with discrete PID controller is to reduce base displacements and superstructure responses. The performance indices (J_1-J_8) used to assess the performance of the proposed controller are normalized by their respective uncontrolled values, which refers to the case when there is no force feedback to the base-isolated structure i.e., the control device is disconnected from the structure.

The objective of control design is to reduce the all performance indices except J_6. 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 i.e., peak control demand. Hence, the larger values of J_6 may represent low peak base shears. The indices J_7 and J_8 measure the RMS values of displacement and the base acceleration normalized by their uncontrolled values.

The structural responses are simulated by exciting the base-isolated structure simultaneously two components of earthquakes: Fault Normal (FN) and Fault Parallel (FP). By interchanging the directions of earthquake pairs, two sets of results are obtained and shown in the Table I. A set of three near-fault earthquake excitations are considered namely *El-Centro, Kobe* and *Erzikan.* It can be observed from the results presented in Table I that all the performance indices for the proposed controller are less than one, which indicates that the controlled responses are less than the corresponding uncontrolled responses. By computing the arithmetic average of the performance indices for all earthquakes in Table I, the percentage of reduction in comparison with the uncontrolled responses for all performance indices (J_1-J_8), except J_6 is shown in Table II. From the table-II, it is evident that the performance of the controller is not uniform for all the three earthquakes.

The time history plots of the base acceleration, base displacement and control forces for *El Centro, Kobe* and *Erzikan* earthquakes are shown in Fig 2, Fig 3 and Fig 4 along with the force-displacement loops for the isolation level force, which is transformed to the center of mass of the base. The performance of controller in reducing the base drift and base acceleration is considerably good for all the three earthquakes. Further, the reduction in inter-story drift and floor acceleration at each floor in both directions is given in Fig 5 and Fig 6 respectively, for the three earthquakes. Only in *El Centro*, the controlled and uncontrolled responses are nearer but for other two earthquakes the controller performance is good. As the structure is a nonlinear system and the earthquakes considered have different frequency characteristics and intensities, the variations in the performance indices are inevitable.

TABLE I. Performance Indices Of Hybrid Controller With Hysteretic Isolation

PI	DIR	Earthquake Records		
		El Centro	*Kobe*	*Erzikan*
J1	1	0.618	0.464	0.492
	2	0.621	0.474	0.474
J2	1	0.663	0.559	0.501
	2	0.667	0.505	0.476
J3	1	0.714	0.636	0.601
	2	0.709	0.652	0.568
J4	1	0.786	0.608	0.541
	2	0.784	0.548	0.458
J5	1	0.787	0.677	0.574
	2	0.711	0.685	0.514
J6	1	0.562	0.674	0.897
	2	0.579	0.703	0.862
J7	1	0.913	0.571	0.331
	2	0.986	0.637	0.298
J8	1	0.766	0.685	0.385
	2	0.816	0.721	0.326

TABLE II. Average Percentage Reduction In Performance Indices In Two Different Directions

PI	J1	J2	J3	J4	J5	J7	J8
Dir-1	48%	43%	35%	36%	32%	40%	39%
Dir-2	48%	45%	36%	41%	37%	36%	38%

Also table III shows the performance comparison of the proposed neural aided discrete PID controller with existing direct adaptive neural controller DANC [13], direct adaptive controller using EMRAN [14] and ELM controller [22] .

It is observed that except for peak base displacement (J_3) and RMS base displacement (J_7), all other performance indices get reduced. As EMRAN is designed for reducing the base drifts, other parameters are higher when compared to J_3, but for *Kobe* earthquake J_3 also reduced using the combined controller. The parameter J_7 is almost comparable with EMRAN with minor variation for *Kobe* and 27% variation for *El Centro*, but for *Erzikan* J_7 is reduced using the proposed controller. From the overall results, it is evident that the proposed neural aided discrete PID active controller suppress the structural vibrations efficiently.

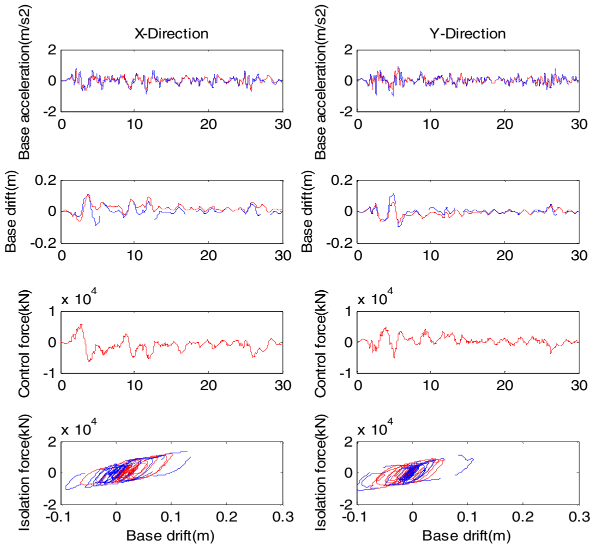

Fig. 2. Results of *El Centro* earthquake using neural aided discrete PID active controller --Time histories of base accelerations, base drifts, control force and total isolation force at the center of mass of base.
Red color-controlled response and blue color –uncontrolled response

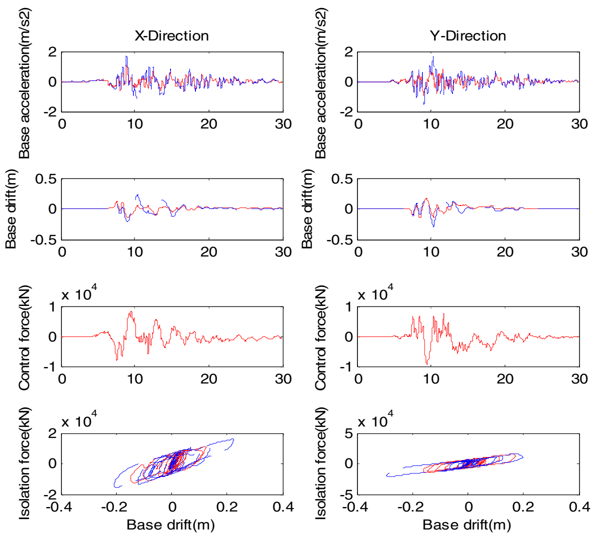

Fig. 3. Results of *Kobe* earthquake using neural aided discrete PID active controller --Time histories of base accelerations, base drifts, control force and total isolation force at the center of mass of base.

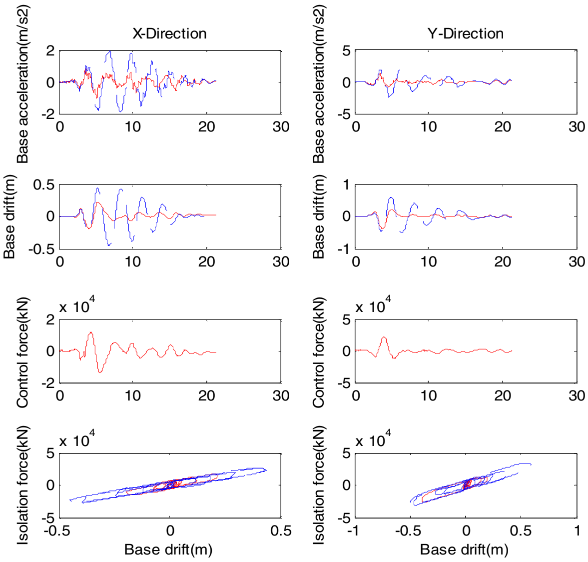

Fig. 4. Results of *Erzikan* earthquake using neural aided discrete PID active controller --Time histories of base accelerations, base drifts, control force and total isolation force at the center of mass of base.

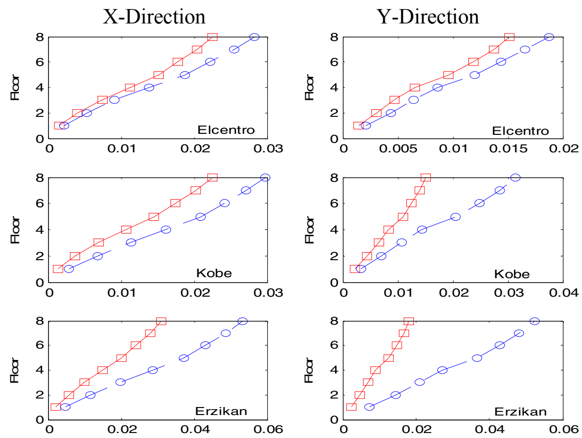

Fig.5. Results for maximum inter-storey drifts at various floors for three earthquakes using neural aided discrete PID active controller

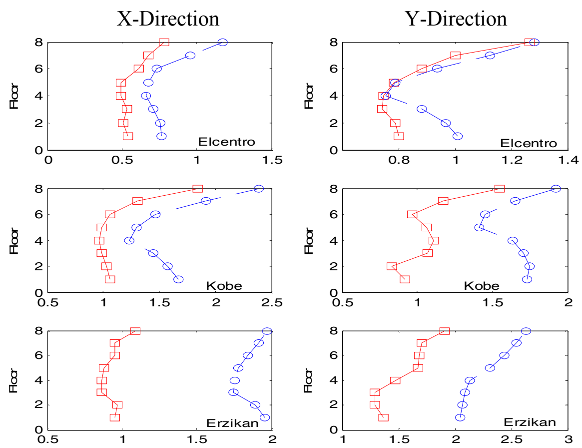

Fig.6. Results for maximum floor acceleration at various floors for three earthquakes using neural aided discrete PID active controller

TABLE III. COMPARISON OF PERFORMANCE INDICES WITH OTHER CONTROLLERS

PI	Controller Cases	Earthquake records for Dir-1		
		El Centro	*Kobe*	*Erzikan*
J1	DANC	0.717	0.515	0.565
	EMRAN	0.730	0.643	0.558
	ELM	0.687	0.502	0.551
	ELM+PID	**0.618**	**0.464**	**0.492**
J2	DANC	0.720	0.614	0.574
	EMRAN	0.790	0.732	0.549
	ELM	0.712	0.574	0.567
	ELM+PID	**0.663**	**0.559**	**0.501**
J3	DANC	0.853	0.694	0.645
	EMRAN	**0.524**	0.649	**0.537**
	ELM	0.867	0.694	0.651
	ELM+PID	0.714	**0.636**	0.601
J4	DANC	0.911	0.808	0.625
	EMRAN	0.937	0.770	0.594
	ELM	0.854	0.659	0.613
	ELM+PID	**0.786**	**0.608**	**0.541**
J5	DANC	0.924	0.888	0.640
	EMRAN	0.953	0.891	0.662
	ELM	0.828	0.747	0.645
	ELM+PID	**0.787**	**0.677**	**0.574**
J6	DANC	0.454	0.509	0.679
	EMRAN	0.657	0.398	0.739
	ELM	0.512	0.587	0.761
	ELM+PID	0.562	0.674	0.897
J7	DANC	0.835	0.651	0.377
	EMRAN	**0.643**	**0.512**	0.366
	ELM	0.889	0.638	0.365
	ELM+PID	0.913	0.571	**0.331**
J8	DANC	0.875	0.807	0.437
	EMRAN	0.968	0.912	0.467
	ELM	0.828	0.721	0.414
	ELM+PID	**0.766**	**0.685**	**0.385**

VI. CONCLUSION

A neural aided discrete PID active controller is presented for the active control of a 3-D non-linear base isolated benchmark structure with the hysteretic isolation system. To improve the efficiency of the performance of PID controller in nonlinear system, a neural controller is implemented along with PID controller. The advantage of ELM-like neural controller is its random projection of input data to high dimensional feature space and only the output weights are updated using Lyapunov synthesis inorder to achieve closed loop stability of the over all system. The performance of the proposed controller is evaluated on a benchmark nonlinear base isolated structure simulated by three earthquake samples. The results presented, in terms of a comprehensive set of performance indices and the comparison table with other existing neural controllers, using DANC, EMRAN and ELM controller [13,14,22] is effective in reducing the superstructure responses and isolation drifts during seismic excitations. Moreover, the time history analysis shows that the proposed hybrid controller is effective in decreasing the superstructure accelerations, inter-storey drifts and base displacements by increasing the active control force.

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