Neuro-PD Controller of Structural System to Mitigate Earthquake Vibrations

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Abstract:
In this paper, stabilization of the structural system against earthquake is presented. Because the conventional PD controller is popular and simple in design, our controller is based on PD controller. The main problem of such a controller is its inability to produce desired response and instability against variations in the properties of the structural system. To obviate this issue, the neural network is implemented to tune the gains of the PD controller. Not only the stability of the closed loop system in the presence of structural uncertainty is warranted but also the closed loop system has a more suitable response when it is compared with fixed gains PD controller. The simulation results show the outperformance of the closed loop system.

Keywords: Structural Control; Neural Network; NeuroPD controller; NeuroPD.

1.Introduction

In last decade different methods have been proposed to improve the performance of the vibration control. In the presence of the earthquake with high magnitude and acceleration, the control system should be able to face with uncertainty and Earth's intense variations. To achieve a suitable controller, optimum design of tuned mass damper was proposed by [1].

In some researches, the controller was designed to stabilize the structural system against wind [2]. As far as most of the structural systems are modeled in linear mode, different linear methods were implemented in literature. [2, 3] applied LQR method, some robust methods such as H_2 and H_∞ and compared the results. Shear building models of the multi-story structures were considered by [4]. To increase the reliability of the controller, the genetic algorithm was proposed.

PID controller is popular, but its performance against intense variations is not good enough. To enhance the performance of the PID controller, genetic algorithm was used to tune the gains [5]. Applications of fuzzy control are well known. Fuzzy system has the ability to be applied in linear and nonlinear control problems. [6]

considered the nonlinear model of the structural dynamic and to omit the influences of the earthquake on the structure, fuzzy logic control was developed. Combination of fuzzy system and neural network to active structural control was considered by [7].

In this paper, we use the PD controller and enhance its performance by tuning the gains. Different methods were employed to tune the gains of the PD controller [8, 9]. Neural network is a powerful tool that can be used in control and identification problems. We apply neural network to tune the gains of the PD controller. Diverse models for tuning the weights of the neural network were proposed during years. The algorithm that is used in our work is based on [10]. To design the controller, firstly; PD controller with fixed gains is considered. Then two variables is added to the gains that are tuned by neural network. To analyze the performance of fixed and adjustable gains PD controller, some simulations are carried out. The results show that the proposed method has suitable response in the presence of uncertainty.

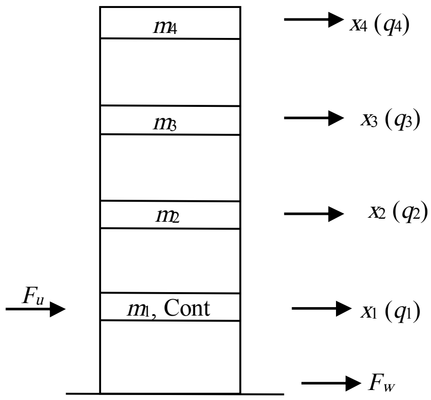

Fig. 1. Structural System

2.System Models

A 4-story active structural system is considered, it is shown in Fig 1. The control system is used only in first story. Simple linear model of the structural system that can be obtained from linearization and simplification of the nonlinear model is used to introduce the dynamic of the involved system. The equation of linear structural system can be described as follow [2, 3]:

$$M\ddot{q} + C\dot{q} + Kq = F_u + F_w \quad (1)$$

Where q is displacement vector, M is a mass matrix, C is a damping coefficient matrix, K is a stiffness coefficient matrix, F_u is input vector and F_w is disturbance signal that is produced by earthquake. We define $x = [q, \dot{q}]^T$. System (1) in state space model is as follow:

$$\dot{x} = Ax + B(F_u + F_w) \quad (2)$$

Where

$$A = \begin{bmatrix} 0 & I \\ -M^{-1}K & -M^{-1}C \end{bmatrix}, \; B = \begin{bmatrix} 0 \\ M^{-1} \end{bmatrix}, \quad (3)$$

$$F_u = [u, 0, 0, 0]^T, \; F_w = [w, 0, 0, 0]^T$$

where A is an 8×8 matrix, B is an 8×4 matrix and F_u, F_w are 4×1 matrices.

3.PD Controller

The PD controller has been employed in different systems. Regarding to the system, the model of the controller can be PID, PD or PI controllers. In this paper, we design PD controller for the first floor and in the simulation part will show that this controller makes the closed loop stable; but this is not enough suitable to reject the earthquake disturbance. The PD controller is as follow:

$$u = K_{pd}(e + T_d \frac{de}{dt}) \quad (4)$$

where $e = x_{1r} - x_1$. The desired response is $x_{r1} = 0$. So, the error can be computed as $e = -x_1, \quad \dot{e} = -\dot{x}_1 = -x_5$. Different methods were proposed to design the gains of the PID controllers. In this paper, after doing some trial and error, the best gains that result the best response for the PD controller is obtained as follow:

$$K_{pd} = 3\times 10^{6},\ T_d = 200 \qquad (5)$$

In the simulation part, we will show that fixed gains PD controller can improve the response of closed loop system, but there still exits large variations in the output of the system. To obviate this undesired response, we add some new parameters to the gains of PD controller and, by using neural network, will try to tune the gains to get better responses.

4.Neuro-PD Controler

Different methods were designed to tune the weights of the neural network. In this paper we use the method that was proposed by [10]. By adding the new adjustable gains to the PD controller, the new controller is:

$$u = K_{pd}(k_{pn}e + (k_{dn} + T_d)\frac{de}{dt}) \qquad (6.a)$$

where k_{pn} and k_{dn} are the gains that are tuned by the neural network. Also, we will show that the control signal can be solely designed based on k_{pn} and k_{dn} as follows:

$$u = k_{pn}e + k_{dn}\frac{de}{dt} \qquad (6.b)$$

The general formulation of tuning the weights of the neural network is as follows:

$$\dot{w}_{ij} = \mu'(f_i)\frac{v_j}{v_i}\sum_{n\in N} w_{ni}\dot{w}_{ni} - \lambda\mu'(f_i)v_j e_i \qquad (7)$$

For instance, If we consider the s-th layer of the neural network, f_i is the input and v_i is the output of the i-th neuron in the s-th layer, v_j is the output of the j-th neuron in the (s-1)th layer, γ is adaption coefficient, w_{ni} is the weight between i-th neuron in the s-th layer and n-th neuron in the (s+1)th layer, e_i is the error that is chosen to tune the weights and μ is activation function. General description of Eq (7) can be found in [10]. The model of the neural network is depicted in Fig 2. The linear and sigmoid functions are used in the output and hidden layer, respectively.

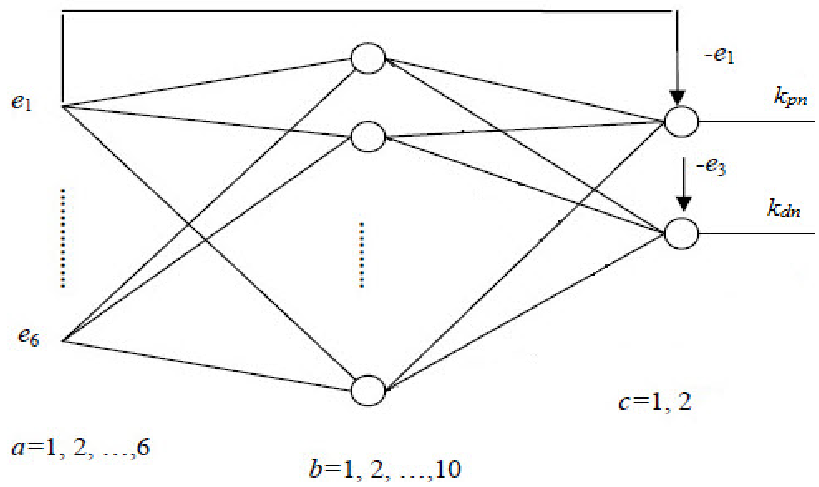

Fig.2. neural network model

Let's define P as follow:

$$P = [x_{1i}(t_k), x_1(t_k), x_5(t_k), \ldots \\ x_{1i}(t_{k-1}), x_1(t_{k-1}), x_5(t_{k-1})]^{\mathrm{T}} \quad (8)$$

where x_{1i} is defined as:

$$x_{1i} = \int_0^t x_1(\tau)d\tau \quad (9)$$

The inputs of the neural network are chosen as follows:

$$[e_1, e_2, e_3, e_4, e_5, e_6]^T = \left|P - P_r\right| \quad (10)$$

where |.| is absolute value and $p_r = 0$ is reference of measured variables. To gain the rule for w_{bc}, because the layer c is output layer and the linear function is used as activation function, from Eq (7) we have:

$$\dot{w}_{bc} = -\gamma\mu'(f_c)v_b e_i = -\gamma v_b e_c, \; e_c = \begin{cases} -e_2, & c = 1 \\ -e_3, & c = 2 \end{cases} \quad (11)$$

For w_{ab} we have:

$$\dot{w}_{ab} = \mu'(f_b)\frac{v_a}{v_b}\sum_c w_{bc}\dot{w}_{bc} - \lambda\mu'(f_b)v_a e_i \quad (12)$$

But, the main problem is the value of the e_i. In this paper, we replace e_i with $-e_a$. So, for hidden layer e_a is both error and input. So, Eq (12) can be written as follows:

$$\dot{w}_{ab} = \mu'(f_b)\frac{v_a}{v_b}\sum_c w_{bc}\dot{w}_{bc} + \lambda\mu'(f_b)v_a e_a \\ e_a = e_1, e_2, \ldots, e_6, \; for \;\; a = 1, 2, \ldots, 6 \quad (13)$$

The activation function of hidden layer is sigmoid function, so we have:

$$\mu'(f_b) = \mu(f_b)\mu(-f_b), \; v_b = \mu(f_b), \; v_a = e_a \quad (14)$$

By substituting Eq (14) in Eq (13) we have:

$$\dot{w}_{ab} = \mu(-f_b)e_a\sum_c w_{bc}\dot{w}_{bc} + \lambda\mu'(f_b)e_a^2 \quad (15)$$

5.Simulation

The equations (1), (4), (5), (6) were used in this part to show the performance of the closed loop system. The parameters of the system were taken from [3]. In first simulation, the PD controller and combined model for PD and neural network gains are used. Fig 3 shows the responses of the opened and closed loop systems. Although the PD controller stabilizes the system, the variations of the output of the system are still large. The maximum domain of the input for PD controller is 4.8×10^6. In other side, the performance of the combined model is suitable and after 20 second, the maximum domain of the output is less than 0.5 mm while the maximum domain for input is 6.7×10^6.

In comparison with the PD controller and the robust method that proposed by [3], the proposed neural network based controller has a outperformance. In [3] the maximum input domain is 19.5×10^6. They used the control system in each floor while in our proposed method the control system was implemented only at the first floor.

To consider the responses of the system in the presence of uncertainties, the mass of the system was changed to $M_{new} = M_{old} + 0.5M_{old}$. The responses were shown in Fig 4. The domain of the response of the PD controller increases.

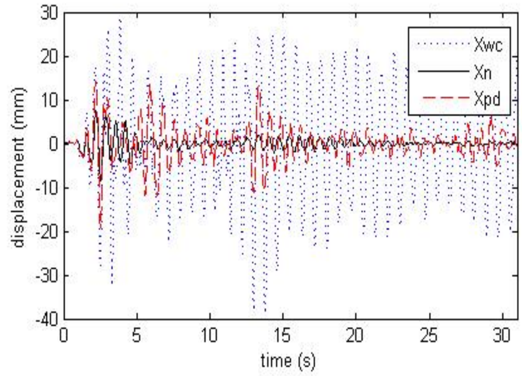

Fig. 3. The response of the closed loop system

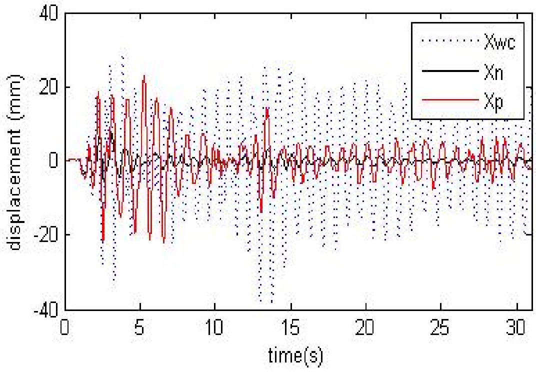

Fig. 4. The responses of the system with uncertainty

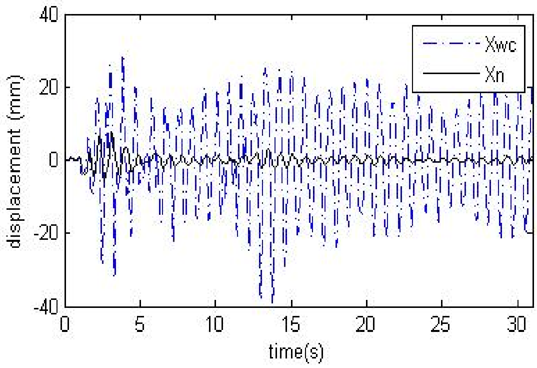

Fig. 5. The response of the system by using only neural network

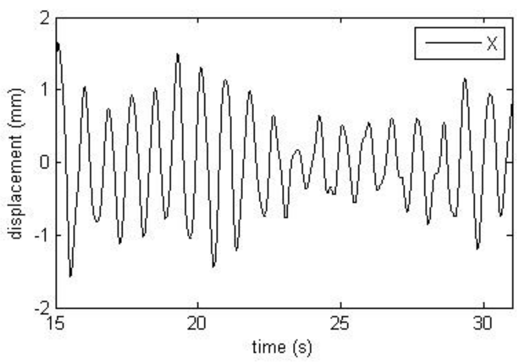

Fig.6. The response of neural network in time span [15,30]

The NN-PD based controller still has desired performance. Fig 5 shows the response of the closed loop system that Eq (6.b) was used as controller. As this figure shows, the neural network can desirably tune the gains. The response of the system in time span [15, 30] was demonstrated in Fig 6. The figure shows that the response after 15 second is less than 2 mm.

6. Conclusion

Conventional PID controller has been used in different systems. The PD controller was employed in this paper to stabilize the system against earthquake. Although it could stabilize the system, the response of system still have large domain in output. To overcome to this problem, neural network was applied. The adjustable gains were added to the gains of the PD controller and also independently were used as gains of the PD controller. In both cases, the simulations showed the outperformance of the proposed method to overcome earthquake and omit the variations in the output of the system.

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