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RESEARCH ARTICLE

Neural Network Based Vibration Control of Seismically Excited Civil Structures

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Abstract

This study proposes a neural network based vibration control system designed to attenuate structural vibrations induced by an earthquake. Classical feedback control algorithms are susceptible to parameter changes. For structures with uncertain parameters they can even cause instability problems. The proposed neural network based control system can identify the structural properties of the system and avoids the above mentioned problems. In the present study it is assumed that a full state of the structure is known, which means the at each floor horizontal displacements and rotations about the vertical axis are measured. Additionally, it is assumed the acceleration signal coming from the earthquake is also available. The proposed neural control strategy is compared with the classical linear quadratic regulator (LQR) not only in terms of displacement responses, but also required control forces. Moreover, the influence of different weighting matrices on performance of the proposed control strategy has been presented.

The effectiveness of the neuro-controller has been demonstrated on two numerical examples: a simple single degree of freedom (DOF) structure and a multi-DOF structure representing a twelve story building. Both structures under consideration have been excited with El Centro acceleration signal. The results of numerical simulations on the SDOF system indicate that using neuro-controller it would be possible to obtain smaller amplitudes as compared with the LQ regulator, but it would require higher control effort.

Keywords

vibration control, artificial neural networks, seismic excitation

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1 Introduction

Many civil structures located in seismic zones are subjected to extreme loading induced by earthquakes. Such an extreme loading can cause significant damage to the structure if it is not properly predicted by the designer. This is especially important for high-rise buildings and long-span bridges. Fundamental guidelines from earthquake engineering require that structures should be designed in such a way that damage occurs in a controlled manner. This means that the whole structure can be easily repaired. Moreover, to reduce unwanted vibrations caused by earthquakes many structures are equipped with vibration-attenuation systems. There are three types of such systems, namely: passive, active and semi-active.

Passive vibration-attenuation systems have been described by Soong and Dargush (1997) [1]. Examples of passive systems can be the tuned mass damper or the viscous fluid damper. Another interesting passive control system is a density-variable tuned liquid damper, which has been investigated by Xin et al (2009) [2]. Passive systems are effective if the properties of a system are precisely known. In the case when the structure parameters are not known precisely or the system behaves nonlinearly, passive systems can become ineffective. To preserve the efficiency of applied vibration-reduction systems on structures with unknown or changing parameters such structures are equipped with active vibration control systems.

During the past two decades many different active control strategies have been proposed. Among them are the pole placement method (Pnevmatikos and Gantes, 2010) [3], model predictive control (Blachowski, 2007) [4] or direct velocity feedback (Preumont and Seto, 2008) [5].

The third group of vibration-attenuation strategies are semi-active methods. Examples of semi-active methods are presented in the paper by Lee at al. (2006) [6], where the authors utilized a magnetorheological damper to reduce vibration of an 8-story steel braced building, or in the paper by Michajlow et al (2017) [7], where an electric motor was used to attenuate vibration of a rotating mechanical structure.

Besides of two mentioned case studies, the research papers in semi-active vibration control usually belong to one of the two groups: the first one deals with development of physical devices implementing existing control strategies, and the second one with development of control algorithms for exiting smart devices.

Examples of the first group are papers by Mirtaheri et al (2017) [8] in which a novel semi-active frictional damper was designed, or by Chu et al (2017) [9] where a new stiffness-controllable tuned mass damper was proposed.

Interesting papers within the second group are: Yu et al (2016) [10] who applied second-order sliding mode control for magnetorheological elastomer base isolator or Pourzeynali et al (2016) [11] who proposed a genetic algorithm and fuzzy logic to control a semi-active tuned mass damper. Additionally, development of a control algorithm based on a robust market method was proposed by Song et al (2016) [12] and design of a decoupled proportional-integral-derivative (PID) controller using multi-objective cuckoo search was investigated by Etedali et al (2016) [13].

From the above three types of methods active control has the biggest potential to deal with large scale civil structures. Apart from the above-mentioned classical active control strategies neural networks emerged as an attractive tool to design vibration controllers.

The development of the neural-network theory has been inspired by research on the human brain (Grossberg 1982) [14]. Before neural networks attracted attention of researchers working in active control based protection of structures located in earthquake zones, they have been applied in many fields of science and engineering. Examples of these are robotics, telecommunication and transportation (Demuth et al, 2007) [15]. Pioneering research on application of neural control to reduce vibration of seismically excited structures has been conducted in the middle of the 1990s by Chen [16], Ghaboussi and Joghataie [17].

Chen et al. (1995) proposed a back propagation-through-time neural controller, which consisted of two components: a) a neural emulator to represent a structure to be controlled and b) a neural network to determine the control action on the structure. Ghaboussi and Joghataie (1995) developed neural-network-based control for a three-story frame structure subjected to ground excitations. Their neural emulator forecast the future response not only of the structure, but also of the actuator. Then, Bani-Hani and Ghaboussi (1998a,b) [18], [19] applied the previously developed neuro-controller in the benchmark problem of the active tendon system.

The research group of Liut (1999, 2000) [20], [21] proposed a training scheme for a neural-network-based controller, which did not require the emulator of the structure to be controlled. Optimal structural control using neural networks has been proposed by Kim et al (2000) [22]. Their controller minimized a quadratic cost function representing the total energy of the controlled structure.

Another neural network based control strategy has been proposed by Hung et al (2000) [23]. The approach, called Active Pulse Control algorithm, was used to calculate the control force during an earlier period and applied to the structure during a later period at each time step. Thus, the problem of the time delay effect due to the computation time was circumvented.

Cerebellar Model Articulation Controller (CMAC) used originally by Albus (1975) [24] in robotics has been applied to reduce vibration of seismically excited structures by Kim et al (2002) [25]. The advantage of CMAC over a multi-layer neural network (MLNN) was the fact that the training of CMAC is done locally. Additionally it has faster convergence than MLNN.

The influence of the number of neurons in a hidden layer of a neural network on its overall performance has been studied by Cho et al. (2005) [26]. Recently, nonlinear vibration control of 3D irregular structures has been investigated by Kim et al. (2016) [27].

This paper presents neural networks based control algorithm, which was originally presented by Kim et al (2000). The algorithm aims to minimize an instantaneous performance index, consisting of the mechanical energy of the structure and the control effort. The effectiveness of the algorithm has been demonstrated on two examples: a single DOF structure and a multistory building. Additionally, the present paper compares the efficiency of neural control with the linear quadratic regulator, similarly as it was done in the case of Lyapunov based control by Achour-Olivier and Afra (2016) [28]. However, contrary to the above mentioned paper, in this work we analyze not only displacement responses obtained using neural network based and LQR control strategies, but also the required control forces.

2 Theoretical background

2.1 Classical theory for optimal control of structural vibrations

Equations of motion

Motion of a structural system under seismic excitation is governed by the following set of second order differential equations

$$\begin{aligned} &\boldsymbol{M}\ddot{\boldsymbol{q}}(t)+\boldsymbol{C}\dot{\boldsymbol{q}}(t)+\boldsymbol{K}\boldsymbol{q}(t)= \\ &-\boldsymbol{M}\boldsymbol{I}_x\ddot{q}_{xg}(t)-\boldsymbol{M}\boldsymbol{I}_y\ddot{q}_{yg}(t)-\boldsymbol{M}\boldsymbol{I}_z\ddot{q}_{zg}(t)+\boldsymbol{B}\boldsymbol{u}(t). \end{aligned} \tag{1}$$

where $\boldsymbol{M}$, $\boldsymbol{C}$, $\boldsymbol{K}$ are mass, damping and stiffness matrices, respectively; $\boldsymbol{q}(t)$ is a vector of relative displacements, $\dot{\boldsymbol{q}}(t)$ is a vector of velocities and $\ddot{\boldsymbol{q}}(t)$ is a vector of accelerations; $\ddot{q}_{xg}(t), \ddot{q}_{yg}(t), \ddot{q}_{zg}(t)$ denote components of ground accelerations in x, y and z direction, respectively; $\boldsymbol{B}$ indicates location of control forces, and finally $\boldsymbol{u}(t)$ represents the time history of control forces.

State equations

The equations of motion can be easily transformed into state space representation, which is frequently used in the control engineers community.

$$\dot{\boldsymbol{x}}(t) = \boldsymbol{A}_c \boldsymbol{x}(t) + \boldsymbol{B}_{c1}\boldsymbol{u}(t) + \boldsymbol{B}_{c2}\boldsymbol{w}(t)$$

$$\text{where } \boldsymbol{A}_c = \begin{bmatrix} 0 & \boldsymbol{I} \\ -\boldsymbol{M}^{-1}\boldsymbol{K} & -\boldsymbol{M}^{-1}\boldsymbol{C} \end{bmatrix}, \ \boldsymbol{B}_{c1} = \begin{bmatrix} 0 \\ \boldsymbol{M}^{-1}\boldsymbol{B} \end{bmatrix}, \quad (2)$$

$$\boldsymbol{B}_{c2} = \begin{bmatrix} 0; & -\boldsymbol{I}_{xyz} \end{bmatrix}^T \text{ and } \boldsymbol{w}(t) = \begin{bmatrix} \ddot{q}_{xg}(t), \ddot{q}_{yg}(t), \ddot{q}_{zg} \end{bmatrix}^T.$$

The above state space representation is continuous in time. However, for practical purposes we usually have to discretize the state equations. Applying zero-order-hold (ZOH), which assumes that control forces are constant during a single time step T_S we can rewrite the above equations (2) in the following form

$$\boldsymbol{x}(n+1) = \boldsymbol{A}\boldsymbol{x}(n) + \boldsymbol{B}_1\boldsymbol{u}(n) + \boldsymbol{B}_2\boldsymbol{w}(n)$$

$$\text{where } \boldsymbol{A} = \exp(\boldsymbol{A}_c T_s), \ \boldsymbol{B}_1 = \boldsymbol{A}_c^{-1}(\boldsymbol{A}-\boldsymbol{I})\boldsymbol{B}_{c1}, \quad (3)$$

$$\boldsymbol{B}_2 = \boldsymbol{A}_c^{-1}(\boldsymbol{A}-\boldsymbol{I})\boldsymbol{B}_{c2}$$

The performance index is defined as follows

$$J = \sum_{n=1}^{N_s} J_n = \frac{1}{2} T_s \sum_{n=1}^{N_s} \left\{ \boldsymbol{x}(n)^T \boldsymbol{Q}\boldsymbol{x}(n) + \boldsymbol{u}(n)^T \boldsymbol{R}\boldsymbol{u}(n) \right\} \quad (4)$$

where $\boldsymbol{Q}$ and $\boldsymbol{R}$ are weighting matrices responsible for amplitude reduction and control effort, respectively. Finally, the feedback control scheme considered in this paper is presented in Fig. 1.

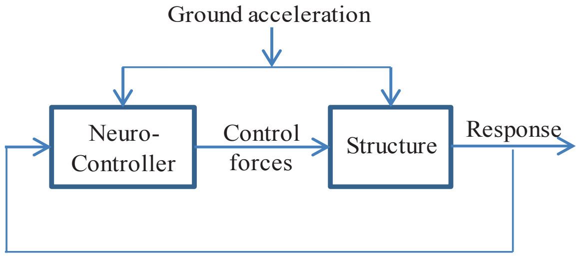

Fig. 1 General idea of neural networks based feedback control

2.2 Mathematical model of a single neuron

The mathematical model of a single neuron is inspired by the biological neural system, in which a single neuron receives a number of input signals from neighbouring neurons. Then, based on the strength of the cumulative signal coming to the neuron, it is activated or not.

In Fig. 2 the individual symbols have the following meaning: in_i denotes the i-th input to the neuron, net denotes the cumulative signal coming to the neuron, $f(net)$ is the activation function, and finally out is the output from the neuron.

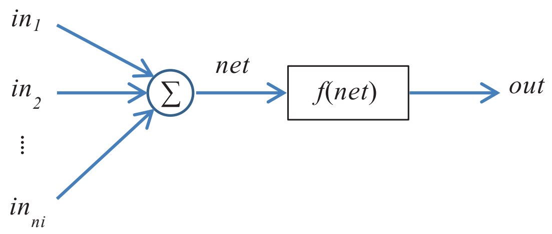

Fig. 2 Mathematical representation of single neuron

Based on the above figure, the following equations for cumulative signal resulting in the output of the neuron can be derived: $net = \sum_{i=0}^{ni} in_i$ and $out = f(net)$.

For a biological system the activation function is usually assumed to be the Heaviside step function. However, for engineering systems two other functions are applied. They are:

linear function $f(net) = net$

or sigmoid function $f(net) = \dfrac{1}{1+e^{-net}}$.

2.3 Multi-layer neural network for vibration control

As it was shown in Fig. 3, the neural networks applied in vibration engineering generally consist of three types of layers. They are: input, hidden and output layer. The number of layers and neurons in individual layers depends on the problem under consideration. In the current study the network consisting of three layers has been used. The input to the neural controller are the ground acceleration and state vector of the structure, and its output are control forces. The parameter to be assigned are weights between input and hidden layers, and hidden and output layers.

In order to find optimal control forces the weights have to be determined is such a way that the performance index (4) is minimized at every time instant. When searching for these optimal values of weights we will mimic the steepest decent rule, which means that weights will be improved at every iteration based on current inputs, i.e.

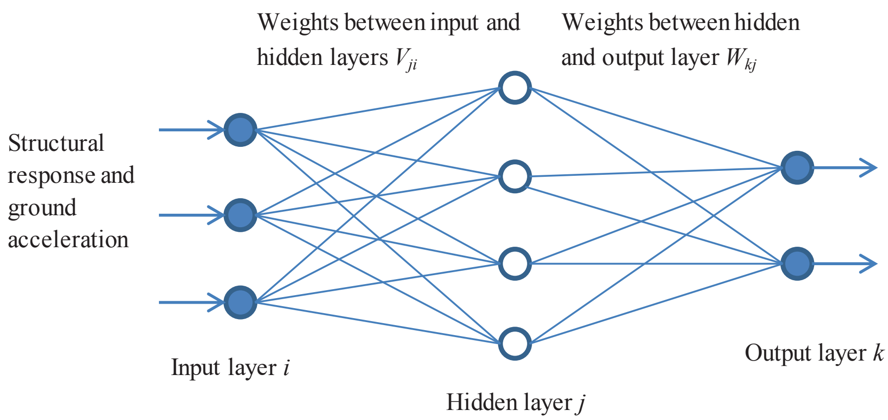

Fig. 3 Three layer based neural network

$$W_{kj}(n+1) = W_{kj}(n) + \Delta W_{kj} \tag{5}$$

where $W_{kj}(n)$ denotes weights between hidden and output layers at the n-th iteration. ΔW_{kj} is the weight update, which is determined using the following formula

$$\Delta W_{kj} = -\eta \frac{\partial J_n}{\partial W_{kj}} \tag{6}$$

where η is the learning rate.

Using Eq. 4 and performing all necessary differentiations we will get the following formula for the weight update

$$\Delta W_{kj} = \eta \delta_k f(net_j) \tag{7}$$

where

$$\delta_k = -T_s \left(\boldsymbol{x}^T \boldsymbol{Q} \frac{\partial \boldsymbol{x}}{\partial u_k} + r_k u_k \right) g'(net_k) \tag{8}$$

In the above formula r_k is the weighting factor for the k-th control force and $g'(net_k)$ is the derivative of the activation function for the output layer. Similarly, we can determine the weight update for the weights between hidden and input layers

$$\Delta V_{ji} = -\eta \frac{\partial J_n}{\partial V_{ji}} \tag{9}$$

and finally

$$\Delta V_{ji} = \eta \delta_j \, in_i \tag{10}$$

where

$$\delta_j = -T_s \left(\boldsymbol{x}^T \boldsymbol{Q} \frac{\partial \boldsymbol{x}}{\partial u_k} + r_k u_k \right) \frac{\partial \boldsymbol{u}}{\partial V_{ji}} \tag{11}$$

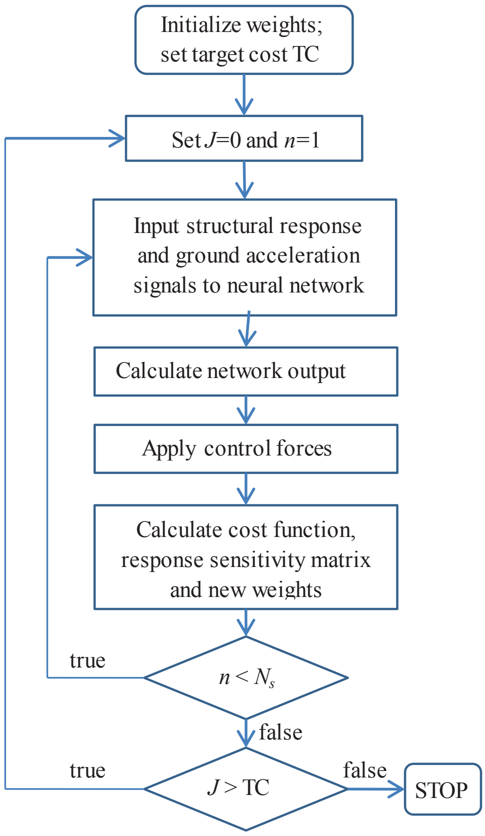

Fig. 4 Flow chart of the considered optimal neuro-controller

The training procedure of the neuro-controller presented above (cf. Fig. 4) can be summarized as follows:

Step 1. Initialize weights; set target cost (TC).

Step 2. Set cost function J to zero and let $n = 1$.

Step 3. Feed input signals to neural network, delayed signals of state and ground acceleration.

Step 4. Calculate network output, $f(net_j)$, $j = 1,2,...,M$ and $g(net_k)$, $k = 1,2,...,N$.

Step 5. Apply control force u_k, $k = 1,2,...,N$ to the structure and obtain responses.

Step 6. Calculate cost function J_n and $J = J + J_n$.

Step 7. Calculate response sensitivity $[\partial x/\partial u]$.

Step 8. Calculate δ_k, $k = 1,2,...,N$; ΔW_{kj}, $k = 1,2,...,N$; and $j = 1,2,...,M$.

Step 9. Calculate δ_j, $j = 1,2,...,M$; ΔV_{ji}, $j = 1,2,...,M$; and $i = 1,2,...,L$.

Step 10. Update weights $W_{kj} = W_{kj} + \Delta W_{kj}$, $V_{ji} = V_{ji} + \Delta V_{ji}$, and $n \leftarrow n + 1$.

Step 11. If $n < N_s$ then go to step 3, else go to next step.

Step 12. If $J >$ TC then go to step 2, else STOP.

In the above algorithm N_s corresponds to the time horizon used in the performance index.

3 Illustrative examples

3.1 Single degree of freedom (SDOF) system

The first example is a simple single degree of freedom system. It consists of a mass, a viscous damper and elastic columns. For the SDOF system presented in Figure 5 the equation of motion has the following form

$$m\ddot{q} + d\dot{q} + kq = -m\ddot{q}_{xg} + u \tag{12}$$

The structural parameters of the system are $m = 1$ kg, $d = 1.25$ N/m/s, $k = 39$ N/m. The structure is subjected to ground acceleration, which occurred during the El Centro earthquake (Figure 6). The sampling time is $T_S = 0.02$ s.

The neural controller consists of three layers (input, hidden and output layer) having 3,4 and 1 neuron, respectively. The structural response of the system with and without control is presented in Figure 7.

The responses of the SDOF system subjected to the neural network based control and classical linear quadratic regulator (LQR) are compared in Fig. 8. One can notice that the control forces obtained by LQR are higher than those obtained by the neuro-controller. However, the application of smaller the neuro-controller based forces results in higher structural responses (Figure 7). This is especially evident for the first 5 seconds while the neuro-controller works in a training mode.

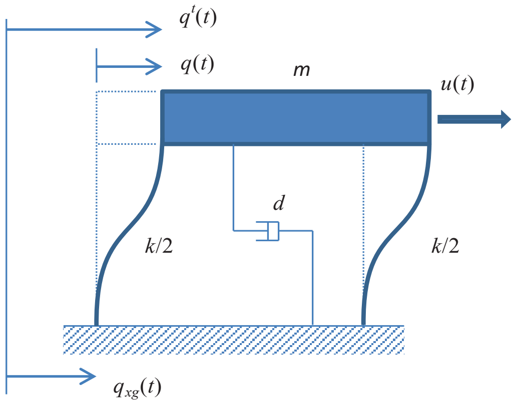

Fig. 5 Single degree of freedom system subjected to ground acceleration

3.2 Multi - degree of freedom (MDOF) system

The second example is a 12 story building (Figure 9) investigated earlier by Jiang and Adeli (2008) [29]. For this structure a 3D finite element model has been created. In the next step, to reduce the number of DOFs in the dynamic model of the system the floor diaphragm assumption has been applied followed by the Guyan condensation. Eventually, the initial FE model having 462 DOFs, has been reduced to 36 DOFs.

The next step was modal analysis. The first mode shapes of the structure and corresponding natural frequencies have been presented in figure 10. El Centro earthquake was applied as a seismic excitation.

In Figs 11, 12 and 13 the responses of the MDOF system have been presented. These plots correspond to three different values of the weighting factor R, namely 10^{-4}, 10^{-5} and 10^{-6}, respectively. Looking at these responses we can conclude that the higher the weight the slower the influence of the controller on the vibration level. In Fig. 11 the approximate time of training is 25 seconds, which corresponds to the weighting factor $R = 10^{-4}$. While in figure 12 and 13 for smaller R values, we observe faster training of the neuro-controller and after 7 seconds significant attenuation of the structural vibration can be observed. The control forces for the above values of the weighting factor are shown in figs 14–16.

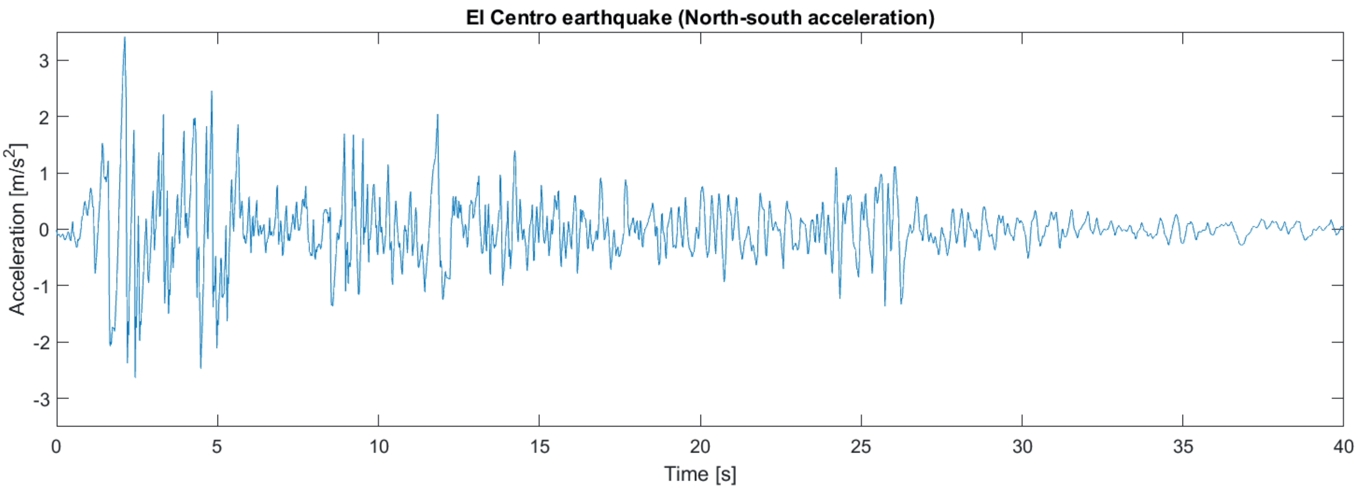

Fig. 6 Time history of the applied acceleration signal

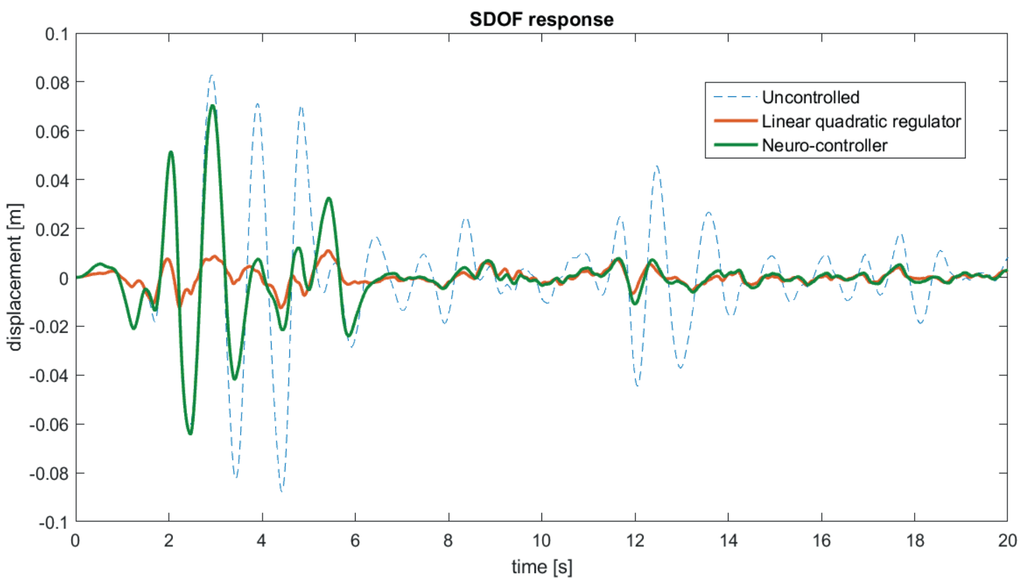

Fig. 7 Response of the SDOF system subjected to the El Centro earthquake

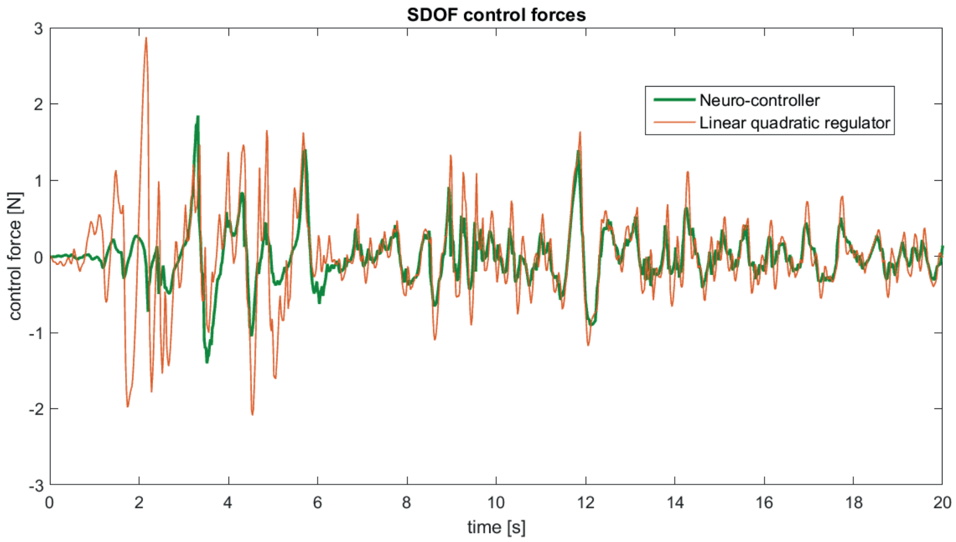

Fig. 8 Comparison of control forces for the linear quadratic regulator and neuro-controller

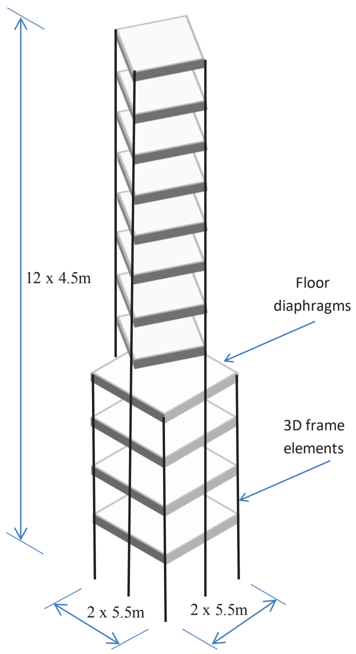

Fig. 9 The twelve story building under consideration

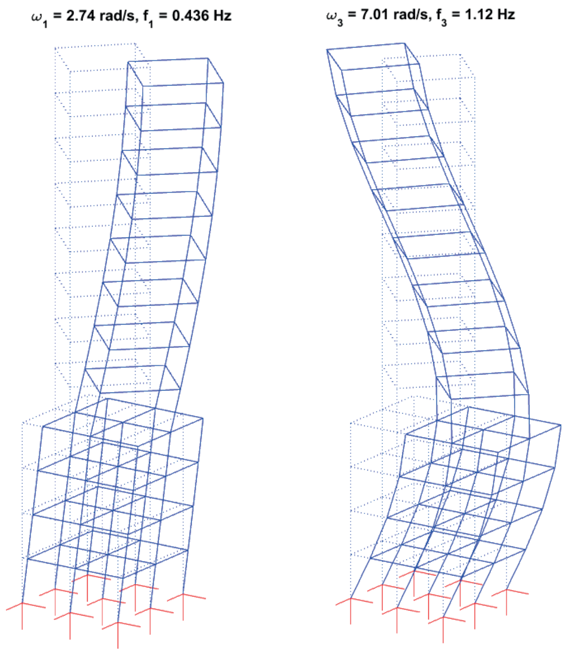

Fig. 10 Mode shapes of the twelve story building

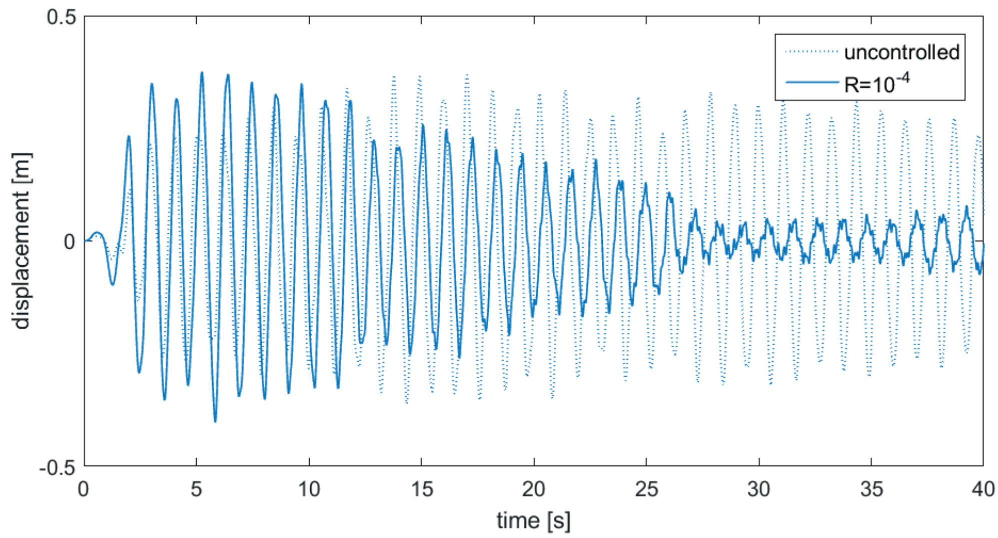

Fig. 11 Top floor response of the 12 story building with the weighting factor for control forces $R = 10^{-4}$

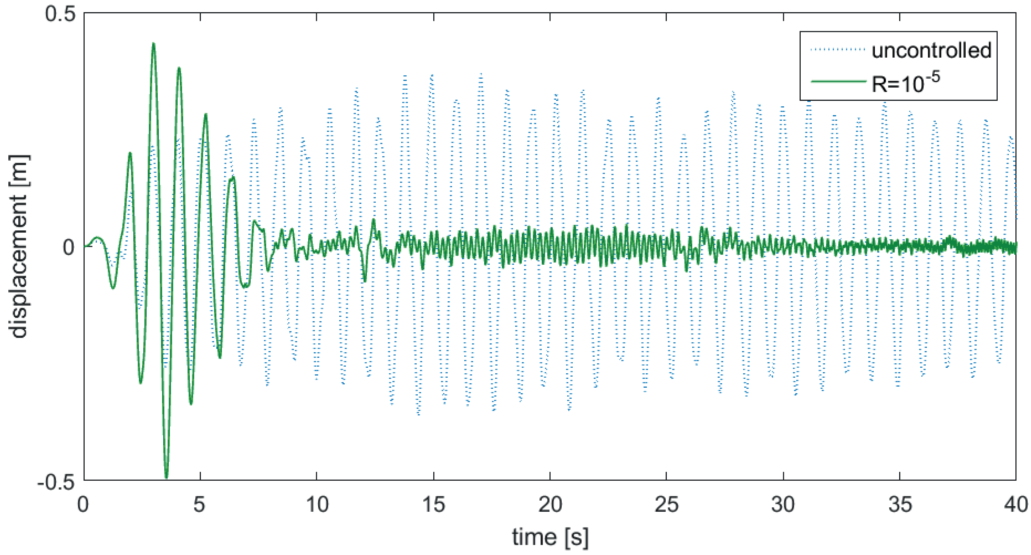

Fig. 12 Top floor response of the 12 story building with the weighting factor for control forces R = 10^{-5}

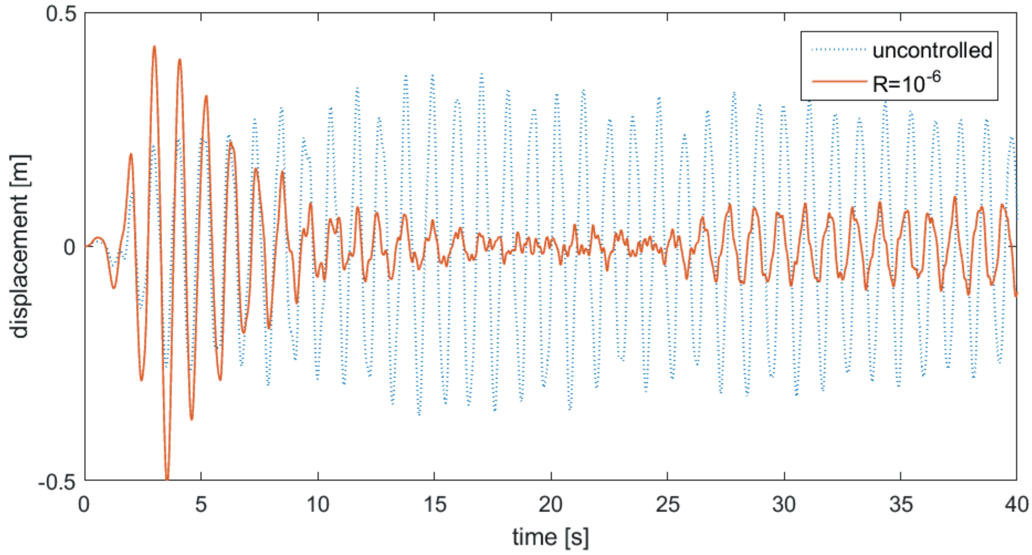

Fig. 13 Top floor response of the 12 story building with the weighting factor for control forces R = 10^{-6}

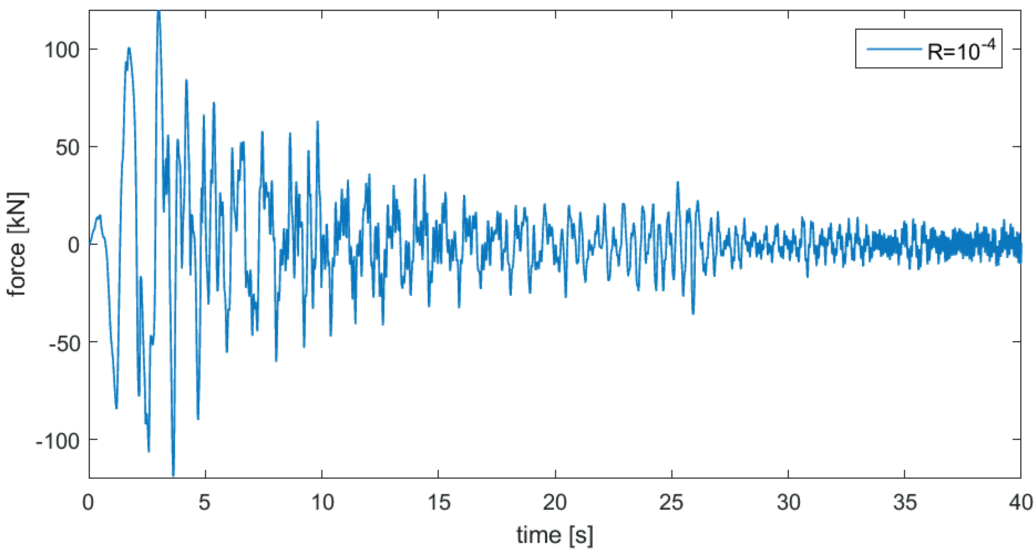

Fig. 14 Time history of control force with the weighting factor R = 10^{-4}

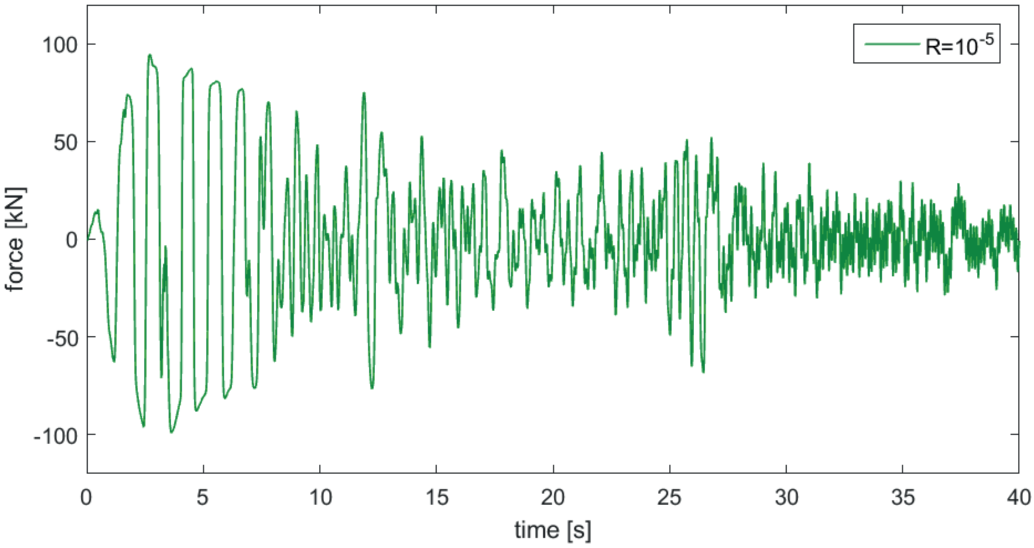

Fig. 15 Time history of control force with the weighting factor R = 10^{-5}

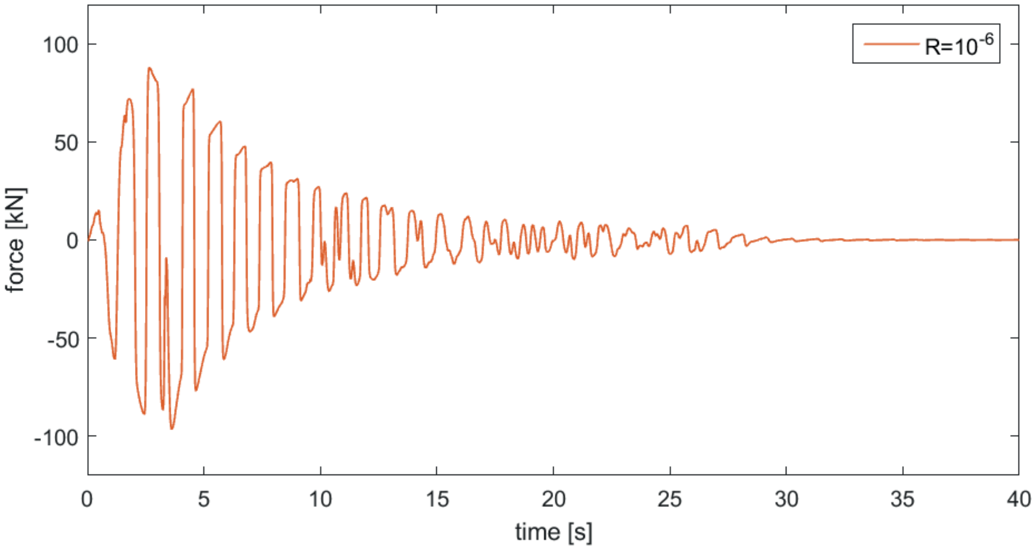

Fig. 16 Time history of control force with the weighting factor R = 10^{-6}

4 Conclusions

In the present study neural network based control has been proposed to attenuate vibration of structures subjected to earthquake excitation. The influence of parameters such as the learning rate η of a neuron and the weighting factor R of a performance index have been investigated. It was found that a wrong selection of these parameters can reduce the effectiveness of the neuro-controller and even cause stability problems. Additionally, it was observed that the weighting factor has strong influence on the time history of control forces. It was demonstrated on the example of a real engineering structure that in some cases the control forces tend to high frequency oscillation, which would be undesirable for hardware implementation of such control forces.

Eventually, one has to mention also the advantage of the neural network based control, which is related to the flexibility of the training process. It allows one to find proper weighting matrices of the neuro-controller for any structure even in the case when its dynamic properties are not known properly in advance.

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