Localized genetically optimized wavelet neural network for semi-active control of buildings subjected to earthquake

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SUMMARY

Control algorithm is one of the most important aspects in successful control of buildings against earthquake. In recent years, because of their capabilities, soft computing methods, stemmed from human brain abilities, have become of particular interest to researchers. In this paper, a wavelet neural network-based semi-active control model is proposed in order to provide accurately computed input voltage to the magneto rheological dampers to generate the optimum control force of structures. This model is optimized by a localized genetic algorithm and then applied to a nine-story benchmark structure subjected to 1.5x El Centro earthquake. The results show an average of 43% reduction of maximum drift in the controlled structure versus the uncontrolled one. The capability of the controller is also validated by applying other far-field and near-field earthquakes. The capability and efficiency of the proposed model are demonstrated in terms of drift, acceleration and base shear reduction. The proposed wavelet neural network is also compared with a tangent hyperbolic-based feed forward neural network, linear quadratic Gaussian, clipped optimal controller, and genetic algorithm-based fuzzy inference systems to show the superiority of the proposed controller. Copyright © 2016 John Wiley & Sons, Ltd.

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KEY WORDS: semi-active control; 9-story benchmark building; MR damper; wavelet neural network; localized genetic algorithm

1. INTRODUCTION

Protection of buildings against earthquake is of particular interest to structural engineers. Until recently, this protection was only based on the ability of the structure itself, e.g. its ability to dissipate the energy generated by earthquake. Controlling structures against earthquake has received considerable attention from researchers over the past few decades. Structural vibrations generated by earthquake or wind can be controlled by various strategies including passive, active, and semi-active [1,2]. Because semi-active control combines the reliability associated with passive control and the adaptability associated with active control, it has generated great interest among researchers.

A key element in the successful implementation of structural control is an effective control algorithm to compute the magnitude of control forces to be applied to the structure. Early attempts in structural control were based on the use of existing control algorithms, such as the linear quadratic regulator and linear quadratic Gaussian (LQG) controllers developed in other fields, such as aerospace engineering [3–6]. However, in recent years, researches have shifted towards modifying the existing control algorithms or developing new algorithms like soft computing methods.

Soft computing methods stem from human brain abilities. In comparison with conventional methods, soft computing methods are capable of solving nonlinear problems that have no mathematical model. Also, they can deal better with uncertainty and imprecision. Some components of soft
computing methods are neural networks (NNs) and fuzzy logic and optimization methods as genetic algorithms (GAs) [7].

Neural networks are known as a powerful algorithm in structural control. Ghaboussi and Joghataie [8] used NN in structural seismic control for the first time. The most useful property of NNs is their learning ability, which enables them to approximate any function with any degree of accuracy. They have been proven to be useful for solving certain types of problems that are complex and poorly understood. The application of NN to the area of structural control has grown rapidly through system identification, system inverse identification, or controller replication [8–15].

In recent years, a number of studies have been conducted on the applications of wavelet neural networks (WNNs), which combine the learning ability of NNs and the capability of wavelet decomposition. Unlike the sigmoidal functions used in conventional NNs, wavelet functions are spatially localized. Therefore, the learning capability of WNN for system identification and control is more efficient than that of the conventional sigmoidal function NN. The training algorithms for WNN typically converge more rapidly than those of conventional NNs. Thus, WNN has been proved to be superior to the Gaussian-type NN in that the structure can provide more potential to enrich the mapping relationship between inputs and outputs. In structural control, WNNs are only used in few researches including Adeli and Kim [16,17] and Adeli and Jiang [18].

In this paper, a WNN algorithm is proposed for seismic semi-active control of a benchmark building that is equipped with the magneto rheological (MR) damper. The constructed WNN should be able to provide computed input voltage to the MR dampers so that they can generate the optimum control force of structures. In order to enhance the optimum value of building response, the parameters of WNN are optimized using a localized GA. The optimized network is then applied to the nine-story benchmark building subjected to several earthquakes, and the efficiency of the proposed combination of WNN and localized GA is evaluated. Furthermore, a feedforward neural network (FFNN) is designed and optimized by the proposed GA as the comparative controller. The efficiency of the WNN controller is evaluated in comparison with FFNN, a designed LQG controller, a clipped optimal controller (COC), and GA-based fuzzy inference systems.

2. PROPOSED CONTROLLER

2.1. Structure of the wavelet neural network

Taking advantage of the localization property of wavelets and the generalization ability of the WNN, a WNN was developed. The proposed structure of the WNN is assumed to be a three-layer network comprising an input layer with $D$ nodes, a hidden layer with $\hat{D}$ nodes (each of them having a wavelet activation function), and an output layer with $\lambda$ nodes with linear transfer function. A $\hat{D} \times D$ dimension weight matrix and a $\hat{D} \times 1$ dimension bias vector are applied to the outputs of the first layer. A weight matrix of dimension $\lambda \times \hat{D}$ will then be applied to outputs of the second layer, and the row summation will be outputted for each node of the third layer. The mathematical operation of the network is described as follows.

Assume the input vector of $X^D_{\eta}$ as the $\eta$th array set of dimension $D$ taken from the original set $\Gamma$. Then the input to the second layer is

$$I^2 = w^\sim_{\hat{D} \times D} X^D_{\eta} + b^\sim_{\hat{D} \times 1}$$

where

$$w^\sim_{\hat{D} \times D} = \begin{bmatrix} w^i_{\hat{D} \times D} \end{bmatrix}_{i=1:D, j=1:\hat{D}}$$

and

$$b^\sim_{\hat{D} \times 1} = \begin{bmatrix} b^i_{\hat{D} \times D} \end{bmatrix}_{i=1:\hat{D}}$$

in which $w^\sim_{\hat{D} \times D}$ and $b^\sim_{\hat{D} \times 1}$ are weights matrix and bias vector of first to second layer transition, respectively, and $\hat{D}$ is the number of neurons in the second layer. Outputs of the second layer are as
\[ O^2 = \varphi \left( \frac{t^2 - c_1}{c_2} \right) \] 

while

\[ c_1 = \{ c_i^{1j} \}_{i=1}^{\hat{D}} \]  

(4a)

and

\[ c_2 = \{ c_i^{1j} \}_{i=1}^{\hat{D}} \]  

(4b)

in which \( O^2 \) is the output vector of the second layer and \( \varphi(.) \) is the wavelet function. The Mexican hat function is used as the wavelet function in the network structure as follows:

\[ \varphi(t) = (2 - t^2) \exp \left( -\frac{t^2}{2} \right) \quad t = \frac{t^2 - c_1}{c_2} \] 

(5)

c_1 and c_2 are the shift and scale parameters of the wavelet function, respectively. The outputs of the third layer can be calculated as

\[ O^3 = \sum_{i=1}^{\hat{D}} w_{\lambda \times \hat{D}}^{i} O^2 \] 

(6)

where \( w_{\lambda \times \hat{D}}^{i} \) is the second to third layer weight matrix. Figure 1 shows the structure of the WNN used in this paper. Values of \( \hat{D} \) and \( \lambda \) will be found in Section 4 of this paper.

In addition, an FFNN is used in the numerical investigation, where its architecture is similar to Figure 1. The activation function of used FFNN is tangent hyperbolic in the hidden layer instead of Mexican hat function. In other words, in the used FFNN, Equation 3 of the WNN structure is substituted with Equation 7 as follows:

\[ O^2 = \frac{e^X - e^{-X}}{e^X + e^{-X}} \quad X = t^2 \] 

(7)

2.2. Localized genetic algorithm for optimization

The architecture of the model is presented in Figure 2. In this model, an earthquake is applied to the structure, and the response of the structure is monitored. The inputs of WNN are the structure’s responses, and its outputs specify the required voltage for MR dampers so that they will be able to provide optimum control force for the structure. A modified GA is used to optimize the structure parameters of the WNN including network weights, biases, and wavelet function (i.e., Mexican hat)
parameters. The main motivation to use a localized GA is to attain the global and local search capabilities of the optimization algorithm simultaneously. Conventional genetic algorithms yield the advantage of searching a solution space globally while lack the capability of fast convergence. However, several works can be found in the literature that use the GAs in connection with a local search tool, for example, particle swarm optimization [19]. In this paper, some modifications have been made to the conventional genetic algorithm to make it capable of both global search and fast convergence through introducing the localization operations and updating the operation probability values. The proposed localized GA is described in the succeeding texts.

Binary coding has been used here for chromosome representation. The binarization resolution is assumed to be \( r_b \) so that all parameters are converted to binary strings each one with \( r_b \) bits. It should be noted that the parameters are originally in the unit interval. A sequence of binarized parameters forms a chromosome (or an individual) of the proposed localized GA. The total number of parameters as weights, biases, and wavelet function parameters and then the length of chromosomes can be calculated as

\[
K = \hat{D} \times D + \hat{D} + 2\hat{D} + \lambda \times \hat{D} = (D + \lambda + 3)\hat{D}  \tag{8a}
\]

\[
L_{chr} = K \cdot r_b = (D + \lambda + 3)\hat{D} r_b  \tag{8b}
\]

The objective function is the \( J_1 \) criterion that is shown as \( J \) in the following equations. The aim is to minimize the objective function

\[
J_{opt} = \min \{ J \}_{P_{opt}}  \tag{9}
\]

where \( P_{opt} \) refers to the optimum parameter set in the network structure. To achieve the minimum objective value, optimum structure of the network should be found. Optimum structure is subject to the optimum parameter set, which is considered as the chromosomes after they are converted to binary format. A chromosome can be represented as

\[
C_{i}^j = [G_k]_{k=1:K, \ i=1:Population&j=1:Generation} = \text{binarized}(p^j)  \tag{10}
\]

Problems in which more precise structure identification is desired require more efficient structure optimization algorithms. Operations of the localized GA are defined as follows. Reproduction operation selects a chromosome with the probability of \( P_s \) where for chromosome \( C_{i}^j \), it is defined as...
\[ P_s^i(n_s) = \frac{J(l)}{\bar{J}(l)} \cdot \frac{\bar{J}(l)}{J(C_l^i)} \cdot 2^{-(n_s-1)} \]  

(11)

in which \( J \) and \( \bar{J} \) are the best network outputs (minimum objective values) gained in \( l \)th generation and the total generations, respectively. It can be shown that for the best chromosome in each population \( P_s^i = 1 \). \( P_s^i(n_s) \) refers to the \( n_s \)th-selected chromosome through this operation, and for the second selection, the last term in Equation 11 shows the coefficient of \( \frac{1}{2} \). This term constrains the number of chromosomes that are reproduced through this operation independent of their respective objectives.

Second operation is defined as crossing over two or more qualified parents to create an intelligent offspring with inheritable features. In this operation, two schemes of diversity preservation and good inheritance are embedded. Two or more parents, far from together, share their appropriate features to create a crossover offspring as

\[ C_l^{(n_c)} = \Omega \left( \{ C_l^{i_p} \} \right) \]

(12)

where

\[ \forall n_c, \quad P_c^i(n_c) = \frac{J(l)}{J(\Omega \{ C_l^{i_p} \})} \cdot \frac{\bar{J}(C_l^{i_p})}{J(\Omega \{ C_l^{i_p} \})} \cdot \alpha^{-(n_s-1)} \]  

(13)

in which \( 1 < \alpha < 2 \) and \( \Omega(\cdot) \) is the embedding function. Subscript \( cp \) determines the number of crossing parents, and this parameter is chosen according to the dimension of the solution space. Parameter \( cp \) is initially set as \( cp = \text{integer} \left( \sqrt{D + \lambda + 3} \right) \). \( P_c^i(n_c) \) refers to the probability of creation of the offspring \( C_l^{(n_c)} \) for the next generation. Smaller values of \( \alpha \) result in higher probability of the crossover operation and vice versa. Equation 13 applies higher probability of creation for the offspring, which is better than the average of its parents and also respective to the best chromosome in the \( l \)th generation.

The third operation is defined as the mutation operation, which mainly explores distinct offspring around superior chromosomes in the generation. A mutated offspring is created as

\[ C_l^{(n_m)} = \Psi \left( \{ C_l^{i} \} \right) \]

(14)

where

\[ \forall n_m, \quad P_m^i(n_m) = \frac{J(j)}{J(\Psi \{ C_l^{i} \})} \cdot \frac{\bar{J}(C_l^{i})}{J(\Psi \{ C_l^{i} \})} \cdot \beta^{-(n_s-1)} \]  

(15)

in which \( \Psi(\cdot) \) is the mutating function and \( 1 < \beta < 2 \) because the probability of mutation operator is preferred to be lower than the probability of crossover operation. Some newly created chromosomes are transferred to the next generation according to their probability of creation. Some other chromosomes are also created to enroll the local search around the local optimum values. To fulfill this aim, two operations are defined to trace the gradient of objective function in a discrete manner.

The progressive operation is proposed as the fourth operation, which is defined as follows:

\[ C_l^{(n_p)} = \Delta \left( \{ C_l^{i} \} \right) \]

(16)

where

\[ \Delta(C_l^{i}) = C_l^{(n_p)} + \delta (G) \]  

(17)

subject to

\[ J(\Delta(C_l^{i})) \leq J(C_l^{(n_p)}) \]  

(18)

while \( \delta (G) \) is the minimum possible parameter gradient regarding the conversion to binary. The probability of the progressive operation is the unit value, which means for a preset of \( \tau \) trial Equations. Equations 16–18 are retried iteratively to find a possible \( C_l^{(n_p)} \). If the search is not successful, subscript
k changes to its next value to do the search for another genome. Binary step size for the trials is a relatively short walk in the solution space randomly in all directions.

The shareholder operation as the fifth operation is another localized search operation that creates a number of offspring by contributing, randomly selecting a genome from K chromosomes and producing a chromosome from the selected genomes as

$$C^l(n_{sh}) = \Omega \left\{ G^i_k \right\}_{i=\text{randint}(1,\text{Population})&k=1,K}$$  \hspace{1cm} (19)

where $\Omega()$ is the embedding function for the K genomes randomly selected from K individuals in the lth generation. An assessment can be added to this operation to make it directional shareholder operations as

$$\text{for } k = 1 : K, \text{if } J\left(C^l(n_{sh})_G^i\right) < J\left(C^l(n_{i})_G^i\right) \rightarrow \text{select } G^i_k, \text{ otherwise change } i \hspace{1cm} (20)$$

The conditional term in Equation 20 implies the genome assessment of both created shareholder offspring and the best chromosome with this genome. Assessment is performed by comparing the created offspring with the best chromosome when the corresponding genome of the best chromosome is replaced with the genome under investment. Equation 19 determines whether the selected genome is selected appropriately or not with some level of confidence.

The flow diagram of the structure identification and optimization procedure is given in Figure 3 in which the proposed GA has been illustrated step by step. Yellow parts show the proposed modifications to the conventional GA.

3. BENCHMARK BUILDING

In this study, a nine-story benchmark building is selected for numerical investigation, which is defined by Ohtori et al. [20]. This benchmark structure is 45.73 m by 45.73 m in plan and 37.19 m in elevation.

![Figure 3. Flow diagram of localized genetic algorithm.](image-url)
The bays are 9.15 on center, in both directions, with five bays in the north–south direction and east–west direction. The lateral load-resisting system of the building consists of steel perimeter moment-resisting frames with simple framing on the furthest south east–west frame. The interior bays of the structure contain simple framing with composite floors. Figure 4 depicts the details of the benchmark model.

In the evaluation model, plane frame elements are employed to model the beams and columns of the structure, and a bilinear hysteresis model is used to represent plastic hinges. These are assumed to occur at the moment-resisting column–beam and column–column connections. The damping matrix is determined based on the Rayleigh damping formulation with 2% damping ratio for the first and fifth modes. A detailed description and mathematical modeling of the benchmark building can be found in [20].

Two far-field and two near-field historical ground motion records are selected for evaluating the performance of proposed algorithms including El Centro 1940, Hachinohe 1968, Northridge 1994, and Kobe 1995 earthquakes. In the benchmark study, various levels of each of the earthquake records are utilized including 0.5, 1.0, and 1.5 times the magnitude of El Centro and Hachinohe and 0.5 and 1.0 times the magnitude of Northridge and Kobe.

### 3.1. Magneto rheological damper

The MR damper is a smart semi-active control device that generates force in response to velocity and applied voltage. The MR damper is filled with a special fluid that includes very small polarizable particles that can change its viscosity rapidly from liquid to semi-solid and vice versa by adjusting the magnetic field produced by a coil wrapped around the piston head of the damper. The magnetic field can be tuned by varying the electrical current sent into the coil. When no current is supplied, the MR damper behaves similar to an ordinary viscous damper, whereas its fluid starts to change to semi-solid as the current is gradually sent through the coil. Thus, semi-active controls using MR dampers are powerful devices that enjoy the advantages of passive devices with the benefits of active control. MR dampers require little activation power. Additionally, they are inherently stable, reliable, and relatively cost-effective.
Appropriate modeling of MR damper is necessary for precise prediction of its behavior. It was demonstrated [21] that the simple mechanical model represented in Figure 5, which is based on a phenomenological Bouc-Wen model, predicts the behavior of MR damper accurately over a wide range of inputs. The model is characterized by the following equations [21]:

\[ f = c_0 \dot{x} + az \]  

\[ \dot{z} = -\gamma [\dot{x}]^n z^{n-1} - \beta [\dot{x}]^n + A \dot{x} \]  

where \( f \) is the damper force and \( z \) is the evolutionary variable that accounts for the history of the response. The model parameters depend on the commanded voltage, \( v \), sent to the current driver as follows:

\[ a = a_a + a_b u \]  

\[ c_0 = c_{0a} + c_{0b} u \]  

where \( u \) is given as output of the first-order filter:

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

Equation 24 is necessary to model the dynamics involved in reaching rheological equilibrium and in driving the electromagnet in the MR damper. The parameters of the MR damper model were selected so that the device has a capacity of 1000 kN, a value that is regarded as reasonable in recent experimental works. The resulting parameters are as follows: \( a_a = 1.0872 \times 10^5 \text{ N cm}^{-1} \), \( a_b = 4.9616 \times 10^5 \text{ N (cm V)}^{-1} \), \( c_{0a} = 4.40 \text{ Ns cm}^{-1} \), \( c_{0b} = 44.0 \text{ Ns (cm V)}^{-1} \), \( n = 1 \), \( A = 1.2 \), \( \gamma = 3 \text{ cm}^{-1} \), \( \beta = 3 \text{ cm}^{-1} \) and \( \eta = 50 \text{ s}^{-1} \).

The number of employed MR dampers has been shown in Figure 4. Three dampers are used on the first floor, two on the second floor, and one damper on each third to ninth floors.

### 3.2. Evaluation criteria

The benchmark problem [20] defines some evaluation criteria to evaluate the capabilities of each proposed control strategy. The performance criteria, which are used in this study, are specified by \( J_1 \) to \( J_7 \). These criteria, which are briefly presented in Table 1, are calculated as a ratio of the controlled and uncontrolled responses. The norm \( ||.|| \) is computed using the following equation:

\[ ||.|| = \sqrt{\frac{1}{t_f} \int_0^{t_f} [.]^2 \, dt} \]  

and \( t_f \) is a sufficiently large time to allow the response of the structure to attenuate.
4. NUMERICAL RESULTS

In this section, the proposed model and the optimization method in semi-active control of the benchmark structure are evaluated. The simulation of nine-story nonlinear benchmark building has been performed using MATLAB (MathWorks, Natick, MA, USA). In addition, a code is prepared in MATLAB software that can construct the WNN and optimize the parameters of WNN using the localized GA illustrated in the previous section. In order to evaluate the efficiency of the WNN and localized GA, as

Table I. Performance criteria.

<table>
<thead>
<tr>
<th>Performance Criteria</th>
<th>Interstory drift ratio</th>
<th>Level acceleration</th>
<th>Base shear</th>
</tr>
</thead>
<tbody>
<tr>
<td>$J_1$</td>
<td>$\max\left{ \frac{\max_j \delta_j(t)}{\delta_{\text{max}}} \right}$</td>
<td>$J_2$</td>
<td>$\max\left{ \frac{\sum_i \delta_i(t)}{\delta_{\text{max}}} \right}$</td>
</tr>
<tr>
<td>Normed interstory drift</td>
<td>$J_4 = \max\left{ \frac{\max_j \delta_j(t)}{\delta_{\text{max}}} \right}$</td>
<td>Normed level acceleration</td>
<td>$J_5$ = max\left{ \frac{\max_i \ddot{x}_i(t)}{</td>
</tr>
<tr>
<td>Ductility</td>
<td>$J_7 = \max\left{ \frac{\max_j \phi_j(t)}{\phi_{\text{max}}} \right}$</td>
<td>Normed base shear</td>
<td>$J_6$ = max\left{ \frac{\sum_i m_i \ddot{x}<em>i(t)}{F</em>{\text{max}}^{\text{base}}} \right}$</td>
</tr>
</tbody>
</table>

Table II. Objective function for different values of $\bar{D}$ as a comparison between FFNN and the proposed WNN.

<table>
<thead>
<tr>
<th>$\bar{D}$ for FFNN</th>
<th>5</th>
<th>9</th>
<th>11</th>
<th>13</th>
<th>15</th>
<th>17</th>
<th>19</th>
</tr>
</thead>
<tbody>
<tr>
<td>Objective function for FFNN</td>
<td>0.9059</td>
<td>0.8851</td>
<td>0.6222</td>
<td>0.599</td>
<td>0.579</td>
<td>0.8567</td>
<td>0.6456</td>
</tr>
<tr>
<td>$\bar{D}$ for WNN</td>
<td>2</td>
<td>3</td>
<td>5</td>
<td>7</td>
<td>9</td>
<td>11</td>
<td>15</td>
</tr>
<tr>
<td>Objective function for WNN</td>
<td>0.8186</td>
<td>0.6017</td>
<td>0.5588</td>
<td>0.5587</td>
<td>0.5558</td>
<td>0.5541</td>
<td>0.5587</td>
</tr>
</tbody>
</table>

FFNN, feedforward neural network; WNN, wavelet neural network.

Figure 6. Convergence of objective function during 100 generation of the genetic algorithm optimization process for (a) feedforward neural network and (b) wavelet neural network and for different values of $\bar{D}$.

4. NUMERICAL RESULTS

In this section, the proposed model and the optimization method in semi-active control of the benchmark structure are evaluated. The simulation of nine-story nonlinear benchmark building has been performed using MATLAB (MathWorks, Natick, MA, USA). In addition, a code is prepared in MATLAB software that can construct the WNN and optimize the parameters of WNN using the localized GA illustrated in the previous section. In order to evaluate the efficiency of the WNN and localized GA, as
fuzzy logic controller optimized by genetic algorithm; FFNN, feedforward neural network; WNN, wavelet neural network; NN, neural network; LQG, linear quadratic Gaussian; COC, clipped optimal controller; GAFLC, fuzzy logic controller optimized by genetic algorithm; FFNN, feedforward neural network.

mentioned before, an FFNN whose activation function is tangent hyperbolic in the mid-layer is also designed and optimized with localized GA.

The applied WNN has nine inputs that are floor accelerations (\(D=9\)). The nine outputs (\(\lambda=9\)) are the voltage level fed to the MR damper so that it will be able to provide optimum control force for the structure. The number of nodes in the middle layer (\(\tilde{D}\)) is an important factor in the network capability. To find the optimum number of the nodes in the hidden layer, different values of this parameter are considered. Table 2 shows the objective function for both WNN and FFNN versus different values of \(\tilde{D}\), while 1.5× El Centro earthquake is applied to the model. Convergence procedures of the objective function for both networks are also shown in Figure 6. The results given in Table 2 and the convergence process shown in Figure 6 imply that the optimum number of hidden nodes for FFNN and WNN are \(\tilde{D}=15\) and \(\tilde{D}=5\), respectively. This result indicates the modeling capability of the WNN compared with FFNN because fewer hidden nodes mean less complexity and more compact structure and then less effort is needed for the training procedure. According to the curves shown in Figure 6, one can conclude that a number of 100 generations are sufficient for the convergence of the objective function. Besides, trial-and-error procedure on optimizing the number of individuals in the population (population size) shows the appropriate population size is 100.

Table III. Performance criteria for WNN, NN, LQG, and COC algorithms (nine-story benchmark building).

<table>
<thead>
<tr>
<th>Earthquake</th>
<th>El Centro</th>
<th>Hachinohe</th>
<th>Northridge</th>
<th>Kobe</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intensity</td>
<td>0.5</td>
<td>1.0</td>
<td>1.5</td>
<td>0.5</td>
</tr>
<tr>
<td></td>
<td>1.0</td>
<td>1.5</td>
<td>0.5</td>
<td>1.0</td>
</tr>
<tr>
<td></td>
<td>1.5</td>
<td>0.5</td>
<td>1.0</td>
<td>1.5</td>
</tr>
</tbody>
</table>

Average

<table>
<thead>
<tr>
<th>Earthquake</th>
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<td>1.5</td>
<td>0.5</td>
</tr>
<tr>
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<td></td>
<td>1.5</td>
<td>0.5</td>
<td>1.0</td>
<td>1.5</td>
</tr>
</tbody>
</table>

Average

WNN, wavelet neural network; NN, neural network; LQG, linear quadratic Gaussian; COC, clipped optimal controller; GAFLC, fuzzy logic controller optimized by genetic algorithm; FFNN, feedforward neural network;

It must be noted that the optimization has been performed for the 1.5× El Centro earthquake and other earthquake records have been used for testing the performance of the controllers. Table 3 shows the results of the proposed model compared with three other controllers for four different types of earthquakes, while seven criteria of $J_1$ to $J_7$ are considered.

In Table 3, three controllers of Active, COC, and GAFLC have been listed for the comparison. Active stands for the active LQG controller. In this model, three actuators are utilized on the first floor, two on the second floor, and one on each third to ninth floors, as shown in Figure 4. COC is a semi-active controller in which the classical algorithm of clipped optimal is used. GAFLC is a semi-active control model in which conventional genetic algorithm is used for training the structure of fuzzy system [22]. It is noticeable that control devices in the COC and GAFLC are MR dampers and the number of them is similar to WNN as depicted in Figure 4.

It is obvious that WNN and FFNN controllers significantly reduce the peak interstory drift ratio ($J_1$) for all earthquake records, except for Northridge, by up to 70%. Also, the normed interstory drift criteria ($J_4$) is reduced noticeably on average by about 50% for WNN and 45% for FFNN controller. Reducing the peak story acceleration ($J_2$) is considerable for almost all earthquake records, although $J_2$ is slightly increased for 0.5× Northridge by approximately 3%. In addition, the performance of the proposed controllers is noticeable in decreasing the normed level acceleration criteria ($J_5$), where about 45% decrease is observed for the average. In terms of peak base shear ratio ($J_3$), the WNN
and FFNN controllers produce noticeable reduction, where more than 62% decrease is achieved for 0.5× El Centro earthquake record and about 30% for the average, while $J_3$ is increased for Northridge by 3.5%. A good performance of proposed controllers is observed in decreasing the normed base shear criteria ($J_6$) for all earthquake records. The ductility criteria ($J_7$) are reduced considerably on average by almost 48%. Thus, the damage imposing to the benchmark building is significantly minimized, and its serviceability improved using proposed controllers. Because the model parameters have been optimized for El Centro, as a far-field earthquake record, the WNN and FFNN perform better for this

Figure 8. Profiles of various peak response values for uncontrolled and controlled benchmark structure subjected to (a) El Centro, (b) Hachinohe, (c) Northridge, and (d) Kobe full-scale earthquakes. FFNN, feedforward neural network; WNN, wavelet neural network.
kind of earthquakes. Nevertheless, as can be seen from the results of Table 3, the proposed controllers work well also for near-field earthquakes. Finally, the WNN outperforms other controllers in almost all criteria. However, the tangent hyperbolic-based WNN also performs well compared with other methods. The better performance of WNN and FFNN in comparison with other controllers can prove the superiority of utilized GA.

Time histories of roof displacement and base shear of the uncontrolled and controlled structure subjected to different earthquake records are shown in Figure 7. It is observed from the plots that the proposed strategy can effectively damp out the responses. Profiles of the peak interstory drift and peak absolute acceleration are presented in Figure 8. It is evident that the peak interstory drift and the peak acceleration achieve smaller values for most of the floors and most earthquake records. Regarding Figures 7 and 8, it is obvious that the WNN and FFNN controllers perform very well for El Centro and Hachinohe earthquakes, as two far-field records. However, the proposed controllers are effective in reducing the maximum responses of the structure subjected to Northridge and Kobe earthquakes, as two near-field records.

Figure 9 represents the time history of control force produced by a selected MR damper at fifth floor of benchmark building, which is subjected to Northridge earthquake and controlled by WNN controller. Also, force–velocity curve of this MR damper has been shown for Northridge and El Centro ground motion records.

The results of Table 3 and Figures 7 and 8 demonstrate that the WNN controller comparatively outperforms FFNN. Furthermore, it should be taken cognizance of that the number of nodes in the mid-layer of FFNN is triple that of WNN. As a result, according to Equation 8a, the number of the model’s parameters to be optimized is 285 for FFNN as opposed to 105 for WNN, which complicates the model and learning process and in turn protracts the analysis for FFNN controller. Hence, it may be concluded that the proposed WNN algorithm is more efficient in terms of performance.

5. CONCLUSION

A WNN-based semi-active control model was proposed in this paper in order to provide accurate computation of the controller parameters applied to the MR dampers of a structure. The parameters...
of the proposed model were optimized by a proposed localized GA, the floors accelerations being the inputs of the WNN and the output being the voltage level fed to the MR dampers so that they are able to provide optimum force responses for the structure. The capability and proficiency of the proposed model were demonstrated in terms of drift, acceleration, and base shear reduction for four types of the earthquake applied to the structure. The proposed WNN was also compared with a tangent hyperbolic-based NN, LQG, COC, and a GA-based fuzzy inference system. The results showed that the proposed model is able to control the structures encountered far-field or near-field earthquakes superior than the conventional models.

REFERENCES