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Semi-active seismic control of a 9-story benchmark building using adaptive neural-fuzzy inference system and fuzzy cooperative coevolution

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Abstract. Control algorithms are the most important aspects in successful control of structures against earthquakes. In recent years, intelligent control methods rather than classical control methods have been more considered by researchers, due to some specific capabilities such as handling nonlinear and complex systems, adaptability, and robustness to errors and uncertainties. However, due to lack of learning ability of fuzzy controller, it is used in combination with a genetic algorithm, which in turn suffers from some problems like premature convergence around an incorrect target. Therefore in this research, the introduction and design of the Fuzzy Cooperative Coevolution (Fuzzy CoCo) controller and Adaptive Neural-Fuzzy Inference System (ANFIS) have been innovatively presented for semi-active seismic control. In this research, in order to improve the seismic behavior of structures, a semi-active control of building using Magneto Rheological (MR) damper is proposed to determine input voltage of Magneto Rheological (MR) dampers using ANFIS and Fuzzy CoCo. Genetic Algorithm (GA) is used to optimize the performance of controllers. In this paper, the design of controllers is based on the reduction of the Park-Ang damage index. In order to assess the effectiveness of the designed control system, its function is numerically studied on a 9-story benchmark building, and is compared to those of a Wavelet Neural Network (WNN), fuzzy logic controller optimized by genetic algorithm (GAFLC), Linear Quadratic Gaussian (LQG) and Clipped Optimal Control (COC) systems in terms of seismic performance. The results showed desirable performance of the ANFIS and Fuzzy CoCo controllers in considerably reducing the structure responses under different earthquakes; for instance ANFIS and Fuzzy CoCo controllers showed respectively 38 and 46% reductions in peak inter-story drift (J_1) compared to the LQG controller; 30 and 39% reductions in J_1 compared to the COC controller and 3 and 16% reductions in J_1 compared to the GAFLC controller. When compared to other controllers, one can conclude that Fuzzy CoCo controller performs better.

Keywords: semi-active seismic control; MR damper; Adaptive Neural-Fuzzy Inference System (ANFIS); Fuzzy Cooperative Coevolution (Fuzzy CoCo); Genetic Algorithm (GA)

1. Introduction

Today, protection of buildings against natural phenomena such as wind and earthquake is one of the fundamental concerns in structure engineering. This protection was traditionally only based on the ability of the structure itself, e.g., its ability to dissipate the energy generated by earthquake. However, structural vibrations generated by earthquake or wind can be controlled by various methods including passive, active, and semi-active control (Spencer and Nagarajaiah 2003, Housner *et al*. 1997). 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.

One of the effective factors in the successful implementation of structural control is an efficient control algorithm to compute the magnitude of control forces to be applied to the structure. Active and semi-active control methods used in structural control fall into two classes: 1-Classic control including Linear Quadratic Regulator (LQR), Linear Quadratic Gaussian (LQG), H_2, H_∞ and 2-Intelligent control including neural network and fuzzy control methods. In recent years, researches have shifted towards modifying the existing control algorithms or developing new algorithms like soft computing methods.

Neural network is known as one of the most effective tools in control applications. The first studies in applying Neural Networks in structural control were conducted simultaneously by Ghaboussi and Joghataie (1995), Chen *et al*. (1995). Kim *et al*. (2004) designed an optimal neural control method in their studies. They also eliminated the neural network controller in their further study and instead they used sensitivity analysis method. In order to train a neural network controller Karamodin and Kazemi (2008) proposed a semi-active control method for a seismically excited nonlinear benchmark building equipped with a Magneto Rheological (MR) damper. In this method, the

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neural network predictive control algorithm (NNPC) has been used. Ramezani and Zahrai (2016) used a new method in order to gain Tuned Mass Dampers (TMD) parameters. They examined structures with different numbers of stories under various earthquakes and used neural network in order to achieve optimal parameters. Hashemi *et al*. (2016) proposed a wavelet neural network-based semi-active control model in order to determine accurately computed input voltage applied to the MR dampers to generate the optimum control force in structures.

Application of the fuzzy control method has been studied by many researchers in recent years. Ahlawet and Ramaswamy (2004a, b) optimized designing and training of a fuzzy controller using genetic algorithm and studied the control of several buildings against wind and earthquake. Huang *et al*. (2009) used a model according to Bouc-Wen hysteresis model in order to control structure with a MR damper and predict both force-displacement behavior and complex nonlinear force-velocity response. Using fuzzy control for damper voltage determination, the results of investigation showed that the responses have reduced after optimization with genetic algorithm. Zahrai *et al*. (2013) used fuzzy control to reduce vibration response using TMD dampers by testing this control system on an 11-story building. Uz and Hadi (2014) used an integrated fuzzy control in order to render interactive relations between the forces and input voltage of MR damper according to modified Bouc-Wen model. They compared their findings with those of LQR and LQG methods. Their goal was to reduce responses as well as total cost of damper. Bathaei *et al*. (2017) investigated the performance of a semi-active TMD with adaptive MR damper using type-1 and -2 fuzzy controllers for seismic vibration mitigation of an 11-degree of freedom building model.

One of the most important and widely used types of neuro-fuzzy networks is Adaptive Neuro-Fuzzy Inference System (ANFIS) proposed by Jang (1993). This system is a combination of a 5-layer neural network with Fuzzy Inference System. Ali (2008), Ali and Ramaswamy (2006) designed their active control system using ANFIS controller and showed its efficiency in reducing structural vibration responses through a study on benchmark Highway Bridge using few sensors. Also, Reigles and Symans (2006) showed the efficacy of their proposed system using semi-active MR damper and ANFIS controller for controlling benchmark isolated building. Zhi and Oyadiji (2008), applied MR damper using ANFIS method in structure control. In order to obtain training data for ANFIS control using LQG control method. A Force-Feedback control design was used in order to overcome the problem of commanding MR damper which was considered in the output of a desired force. In this method, a force-feedback circle was used in order to induce MR damper to produce a desirable control force. Fayezioghani and Moharrami (2015) by integrating MR dampers dynamic equations and structural motion, and after solving them in a series, proposed a brief semi-active optimum control strategy. They also used ANFIS controller in their study. Ramezani *et al*. (2017) design fuzzy systems for optimal parameters of TMDs to reduce seismic response of tall buildings. The design of the fuzzy systems is performed by three methods: look-up table, the data space grid-partitioning, and clustering. After that, rule weights of Mamdani fuzzy system using the look-up table are optimized through genetic algorithm and rule weights of Sugeno fuzzy system designed based on grid-partitioning methods and clustering data are optimized through ANFIS.

One of the main disadvantages of fuzzy controllers is the lack of learning ability triggering use of knowledge and experience of the professionals specializing in controller database. A learning process should be employed to solve this problem and to automate the fuzzy controller design. Various methods have been proposed based on fuzzy controllers capable of learning. These controllers, in addition to the method of fuzzy decision-making ability, possess the ability to create or improve their control rules based on past information. One of the effective methods for designing fuzzy controllers is to exploit genetic algorithm inspired from evolutionary theory and seeking for appropriate fuzzy controller that can satisfy design criteria. Also, combination of Neural Networks with Fuzzy Inference System which uses neural network training and adaption capability is a suitable idea to resolve the fuzzy control deficiencies. ANFIS is one of the most well-known neuro-fuzzy networks. Both premise and consequent parameters of fuzzy membership and output functions of ANFIS have the ability for training and improvement but most researchers have focused on just consequent parameters. In order to optimize the controller performance, an approach is proposed in this paper where both premise and consequent parameters of fuzzy functions in an ANFIS network are adjusted simultaneously by GA.

In this study, two controllers are used for semi-active seismic control of structures. The first controller combines neural networks and fuzzy inference system. Genetic algorithm is used for training and optimizing ANFIS structure parameters. The second controller is based on a Fuzzy cooperative coevolution (Fuzzy CoCo). Fuzzy control is an intelligent control method in contrast to classical control with some specific capabilities such as handling nonlinear and complex systems, adaptability, and robustness to errors and uncertainties. However, due to lack of learning ability of fuzzy controller, it is used in combination with a genetic algorithm, which in turn suffers from some problems like premature convergence around an incorrect target. To resolve this problem, the Fuzzy CoCo controller is introduced in which the parameters of membership functions and rules will be searched in two separate species. In most studies that have been conducted in structural control, the design of the controllers has been based on the reduction of the peak inter-story drift, but in this study, the design of controllers is based on the reduction of the Park-Ang damage index. In order to assess the effectiveness of the designed control system, its function is numerically studied on a 9-story benchmark building, and is compared to those of Wavelet Neural Network (WNN), fuzzy logic controller optimized by genetic algorithm (GAFLC), Linear Quadratic Gaussian (LQG) and Clipped Optimal Control (COC) systems in terms of seismic performance.

2. Fuzzy genetic controller

Fuzzy controllers are nonlinear controllers with special structure which provide successful applications of fuzzy theory in practical issues. These controllers by applying fuzzy theory, indicate a behavior similar to that of expert humans when they are used as control system. Conversely, fuzzy controllers in comparison with classic controllers, without the need for mathematical model of the system, evaluate systems considering the experience of experts in the form of if - then fuzzy expression rules. Fuzzy control is a control method based on fuzzy logic. In fact, if fuzzy logic is simply called computation with words rather than number, fuzzy control is the one with statements rather than equations (Ross 2004).

A fuzzy system has various components and parameters. The purpose of designing a fuzzy system is to determine these components and parameters, so that the system has a high numerical accuracy and its interoperability property is preserved. The parameters of a fuzzy system are divided into four parts. The first part is the logical parameters of the fuzzy system. This part includes the form of membership functions and relationships that are used for fuzzy operators, and, or, arguments, aggregate rules and difuzzification. The second part of fundamental parameters of the system is mainly related to the size and magnitude of the fuzzy system. These include the number of membership functions and the number of fuzzy rules. The third part is the communication parameters related to the topology of the fuzzy system, which include the introduction, result, and weight of the fuzzy rules. Finally, the fourth part of the fuzzy system includes operation parameters that establish the relationship between the numerical values and the fuzzy values of the variables or in fact the same membership functions of the fuzzy system.

In the direct design of fuzzy systems, all these sections and parameters must be selected by the designer. Doing this requires sufficient knowledge of the system behavior, expertise and experience, and sometimes it requires trial and error. The use of direct method in complex and large systems, with their insufficient knowledge or the problem space and large number of parameters, is difficult and sometimes impossible. The use of automated modeling techniques has been considered for the design and modeling of fuzzy systems in complex and large issues. In these methods, the logical parameters of the fuzzy system that determines its overall characteristics are selected by the designer. Other parameters of the fuzzy system can be determined or searched by computational methods.

Evolutionary algorithms have the ability to search in large and complex spaces. These algorithms have shown their ability to search optimally in different fields. Fuzzy modeling can be considered as an optimization problem, whose objective function is the behavior of the system and the search space, the parameters of the fuzzy system.

The fuzzy system consists of three parts: fuzzifier, inference Engine and defuzzifier. The behavior of the fuzzy system is evaluated on the basis of a conduction criterion and placed on the genetic algorithm as a function of competence. Gene population algorithm populations in this system are parameters of a fuzzy system that are optimized in an evolutionary process.

Depending on the various criteria, including the available information and knowledge of the system, the number of parameters, the availability and completeness of the input and output data, genetic algorithm can be used in different ways to determine the parameters of the fuzzy system. The logical parameters of the fuzzy system are usually selected by the designer. But three other parts of fuzzy system parameters can be determined using genetic algorithm (Cord 2001).

The combination of fuzzy systems and evolutionary algorithms has problems such as duality and premature convergence. An evolutionary set of rules and membership functions can be an effective way to solve this problem (Pena-Reyes and Sipper 2001). For this reason, in this paper, the design and introduction of Fuzzy CoCo controller fellow is considered as one of the proposed controllers.

Fuzzy-Genetic controller comprises of a fuzzy controller and a genetic algorithm that is illustrated in Fig. 1.

3. Proposed Controllers

3.1 Fuzzy CoCo controller

Two types of coevolution are defined in fuzzy cooperative coevolution which are membership functions and rule base. This method is essentially based on the determined framework defined by (Potter 1997) and (Potter and Jong 2000). Fuzzy CoCo system allocates high degree of freedom to designing fuzzy systems until users can provide interaction between performance and justifiability.

The number of fuzzy modeling processes typically needs simultaneous operational and connected parameters. These parameters present a fully complete definition of language knowledge to describe fuzzy system and mapping values from symbolic definition to real values (a complete definition requires structural parameters as dependent variables and number of rules). Therefore, the fuzzy modeling consists of two separate but intertwined processes: (1) seeking for membership functions as fuzzy variables (functional parameters) and (2) seeking for rules (connected parameters) used to derive.

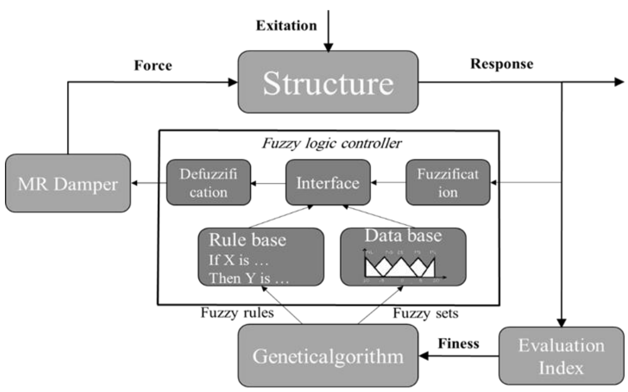


Fig. 1 The structure of fuzzy- genetic controller

Fuzzy modeling illustrates several properties that justify the use of cooperative coevolution:

- The required solutions can be very difficult because fuzzy systems use a large number of variables to define hundreds of parameters.
- The proposed solution (a fuzzy inference system) can be divided into two distinct components: rules and membership functions.
- Membership functions can be displayed continuously or in real numbers but the rules are displayed in discrete and symbolic values.
- These two components are interdependent because the membership functions are defined by the first part of values arranged by the second part (rules).

In this method, individuals in the first species encode the values that define all membership functions for all variables in the system, and individuals in the second species describe a set of rules.

In Fuzzy CoCo control, two evolutionary algorithms are used to control the evolution of two populations, which are examples of a simple genetic algorithm. Fig. 2 presents the Fuzzy CoCo algorithm in pseudo-code format.

A more detailed view of the fitness evaluation process is depicted in Fig. 3. An individual undergoing fitness evaluation establishes cooperation with one or more representatives of the other species, i.e., it is combined with individuals from the other species to construct fuzzy systems. The fitness value assigned to the individual depends on the performance of the fuzzy systems it participated in (specifically, either the average or the maximal value) (Pena-Reyes and Sipper 2001).

Fuzzy CoCo provides a lot of freedom in designing a variety of fuzzy systems and allows the designer to manage the balance between optimal behavior and interpretation of the system.

In Figs. 4 and 5, in the Fuzzy CoCo controller design, two input variables have seven membership functions and an output variable that has eleven output variables.

```
begin Fuzzy CoCo
  g:=0
  for each species S
    Initialize populations Ps(0)
    Evaluate population Ps(0)
  end for
  while not done do
    for each species S
      g:=g+1
      Es(g)= Elite-select [Ps(g - 1)]
      Ps'(g)= select [Ps(g - 1)]
      Ps''(g)= Crossover [Ps'(g)]
      Ps'''(g)= Mutate [Ps''(g)]
      Ps(g)= Ps'''(g)+ Es(g)
      Evaluate population Ps(g)
    end for
  end while
end GA
```

Fig. 2 Pseudo-code of Fuzzy CoCo (Pena-Reyes and Sipper 2001)

Input membership functions are presented in Fig. 4 after the design.

The linguistic variables used for fuzzy input and output values are presented in Tables 1 and 2, respectively. The fuzzy rules database used in control systems are also demonstrated in Table 3. For acceleration as an input variable, P and N stand for positive and negative values. In the Fuzzy CoCo controller, acceleration is used as input.

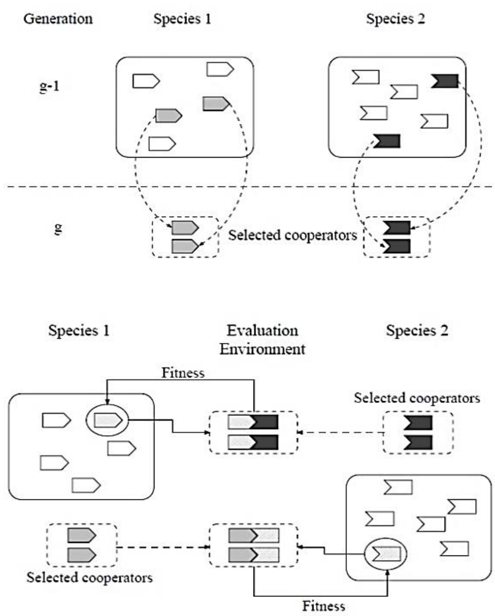


Fig. 3 Fitness evaluation in Fuzzy CoCo (Pena-Reyes and Sipper 2001)

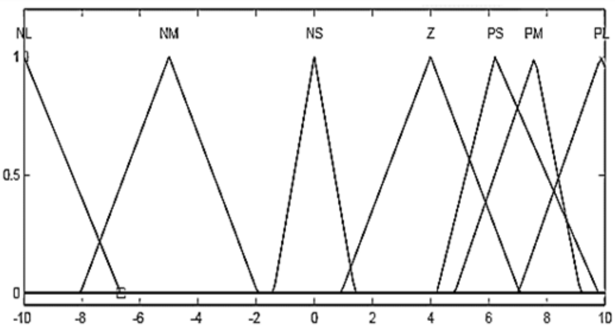


Fig. 4 Triangular membership functions for input variable

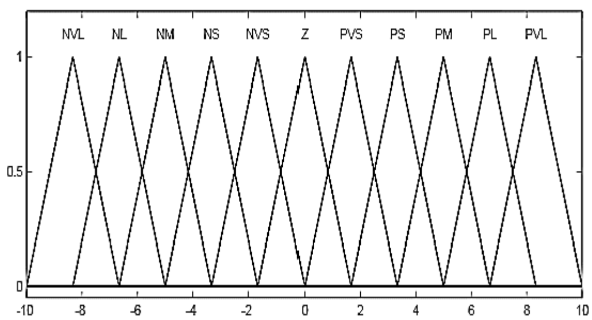


Fig. 5 Triangular membership functions for output variable

Table 1 The linguistic variables for input values of Fuzzy CoCo

Linguistic variable	Acceleration
L	Negative large
NM	Negative medium
NS	Negative small
ZR	Zero
PS	Positive small
PM	Positive medium
PL	Positive large

Table 2 The linguistic variables for output values of Fuzzy CoCo

Linguistic variable	Voltage
SS	Small small
SM	Small medium
SL	Small Large
MS	Medium small
MM	Medium medium
ML	Medium large
LS	Large small
LM	Large medium
LL	Large large
VL	Very large

Table 3 Fuzzy CoCo controller rules database

		Acceleration						
		PL	PM	PS	Z	NS	NM	NL
Acceleration	NL	VL	LM	ML	VL	SS	VL	LL
	NM	VL	MM	LL	ML	VL	MM	ML
	NS	LS	LL	LS	VL	LL	LM	ML
	Z	VL	LL	LS	ZR	LL	MM	ML
	PS	SL	MM	LM	VL	VL	VL	LL
	PM	VL	ML	LM	LS	SL	VL	MM
	PL	LL	LL	LS	LM	LS	LM	LM

3.1 ANFIS Controller

In this method, the acceleration and drift are considered as ANFIS input. For each input, 5 fuzzy membership functions are considered that are presented in Tables 4. Another important step is to choose the type and form of membership fuzzy functions. For inputs of the ANFIS network, Gaussian membership functions are considered because of norm changes and optimal function in neuro-fuzzy controllers. Gaussian membership fuzzy functions are defined by σ and C parameters that are related to the width and center of the functions. The parameters of used Gaussian membership functions are chosen in a way that they have uniform distribution over the entire range. Therefore according to the range of inputs (+1, -1), σ and C parameters are calculated as the amounts illustrated in Table 5. Fig. 6 shows these functions.

Table 4 The linguistic variables for input values of ANFIS controller

Linguistic variable	Acceleration & Drift
NB	Negative big
NS	Negative small
ZE	Zero
PS	Positive small
PB	Positive big

Table 5 The input parameters of membership functions in ANFIS controller

	NB	NS	ZE	PS	PB
σ	0.2	0.2	0.2	0.2	0.2
C	-1.00	-0.50	0	0.50	1.00

Table 6 ANFIS controller rules database

		Drift				
		NB	NS	ZE	PS	PB
Acceleration	NB	mf1	mf2	mf3	mf4	mf5
	NS	mf6	mf7	mf8	mf9	mf10
	ZE	mf11	mf12	mf13	mf14	mf15
	PS	mf16	mf17	mf18	mf19	mf20
	PB	mf21	mf22	mf23	mf24	mf25

mf: member function

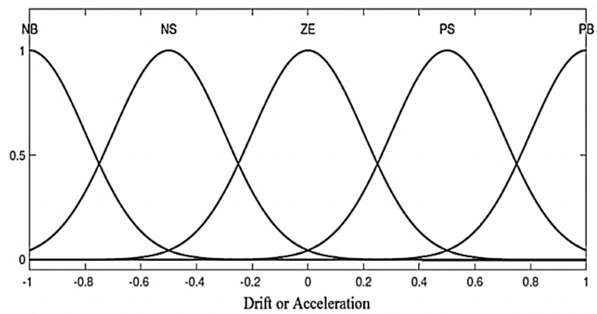


Fig. 6 Membership functions in the proposed ANFIS approach

The rules that comprise ANFIS network structure include if-then rules. In order to make the assumption part of these rules, the membership degree of each input is calculated in five fuzzy membership functions. In this way, 5 membership degrees are calculated for the acceleration and 5 membership degrees for drift resulting in totally 25 states from the combinatory forms. Therefore, the proposed ANFIS structure consists of 25 rules. It should be noted that making combination in the assumption part is from AND type and is conducted by T-norm operator (multiplication). Table 6 shows ANFIS rules database.

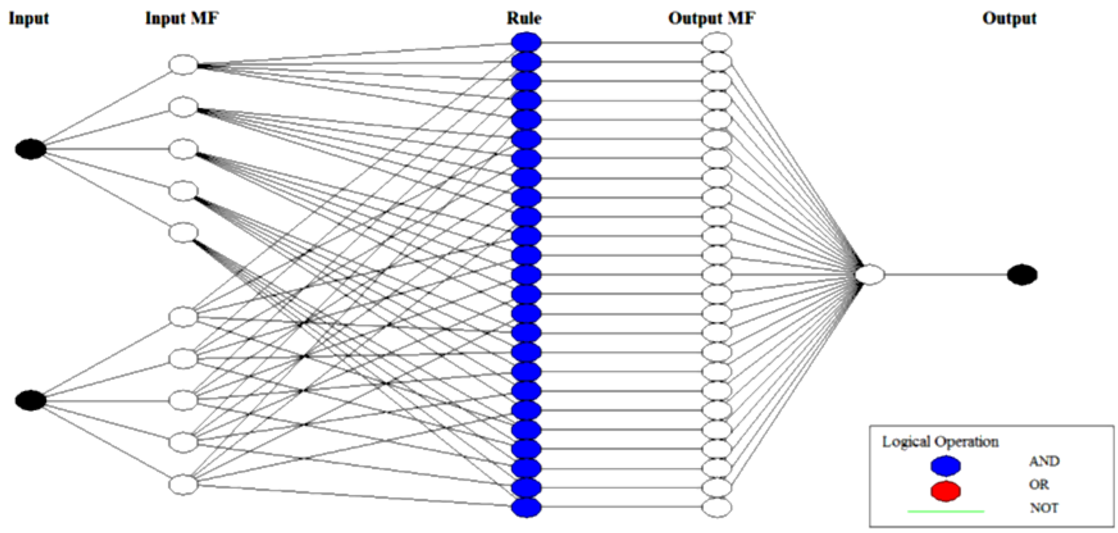


Fig. 7 Used ANFIS network in the proposed controller

Controller output is normalized voltage in the range of (0, +1) that by multiplying it in the maximum imposed voltage to the used MR damper, the necessary voltage for each damper is calculated. The result functions in ANFIS are from either zero degree (constant) or one degree (linear). Although using linear result functions causes more difficult and time lasting training, their use improves accuracy and the controller function. Therefore in this research, the following linear result functions are used for ANFIS networks used in the controller:

$$f_i = p_i x + q_i y + r_i \qquad , \qquad i=1,2,3,\ldots \tag{1}$$

In this equation x and y are network first input (acceleration) and second input (drift) and r_i, q_i, p_i are i-th parameters of result function. Thus parameters will comprise of genes in genetic algorithm. The designed ANFIS network structure as a controller is illustrated in Fig. 7 according to described inputs, membership and result fuzzy functions.

4. Benchmark building for numerical study

In this study, to evaluate controllers, a 9-story benchmark building is selected for numerical investigation, which is defined by Ohtori *et al*. (2004). The benchmark structure is 45.73 m by 45.73 m in plan, and 37.19 m in elevation. The bays are 9.15 m wide center to center, in both directions, with five bays each in the north-south (N-S) and east-west (E-W) directions. The building lateral load-resisting system comprises of steel perimeter moment-resisting frames (MRFs) with simple framing on the farthest south E-W frame. The interior bays of the structure contain simple framing with composite floors. Fig. 8 shows the details of the benchmark building.

In the evaluation model, the effects of nonlinear behavior of the plastic hinges are considered on the ends of the elements centrally. The behavior of these hinges is modeled as bilinear hysteresis model. A detailed description and mathematical modeling of the benchmark building can be found elsewhere (Ohtori *et al*. 2004).

4.1 Simulation of structural control system

The structure control system is simulated in the MATLAB (The MathWorks Inc., Natick, MA) software.
The environment of this software is very suitable for simulation of control systems due to strong mathematical facilities and a variety of tool box such as a control, a fuzzy system, a neural network toolbox, and genetic algorithm. In addition, SIMULINK software provides a good opportunity for this graphical simulation using computational blocks that exist in the MATLAB environment. Fig. 9 shows the simulation diagram of the structure control system in the SIMULINK software environment.

Two far-field and two near-field historical ground motion records are selected for evaluating the performance of proposed algorithms including the 1940 El Centro, 1968 Hachinohe, 1994 Northridge, and 1995 Kobe 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 the El Centro and Hachinohe and 0.5 and 1.0 times the magnitude of the Northridge and Kobe earthquakes (Ohtori *et al*. 2004, Hashemi *et al*. 2016).
In this research for modeling controllers, target function is to minimize the damage in structures. Also, damage control has been conducted based on the Park-Ang damage index while the controller has been designed to reduce this index. The relation of the Park-Ang damage index can be written as

$$D = \frac{\varphi_M - \varphi_y}{\varphi_u - \varphi_y} + \frac{\beta}{M_y \varphi_u} \int dE \tag{2}$$

In the relation, D= damage index, φ_M= maximum curvature (The result of nonlinear dynamic analysis), φ_u= ultimate curvature due to static load, φ_y= yield curvature of elastic state, M_y= yield moment member, $\int dE$= denotes the hysteretic energy absorbed by the element during the

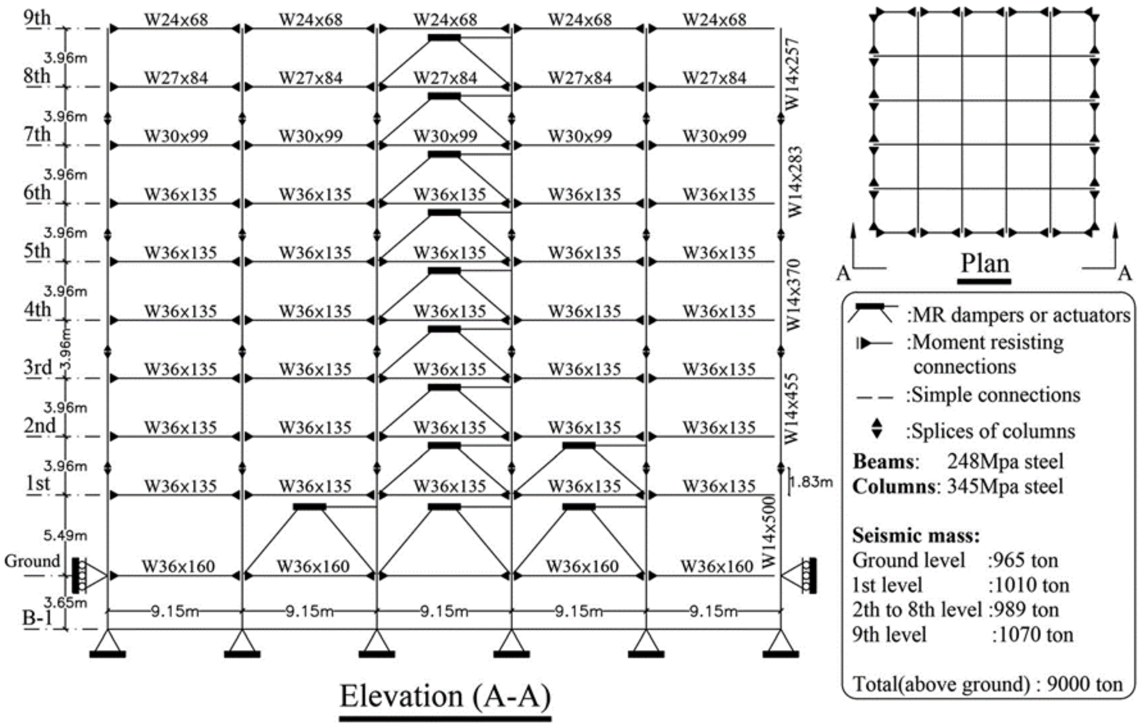


Fig. 8 Description of 9-story benchmark building for assessment in this study (Ohtori *et al*. 2004, Hashemi *et al*. 2016)

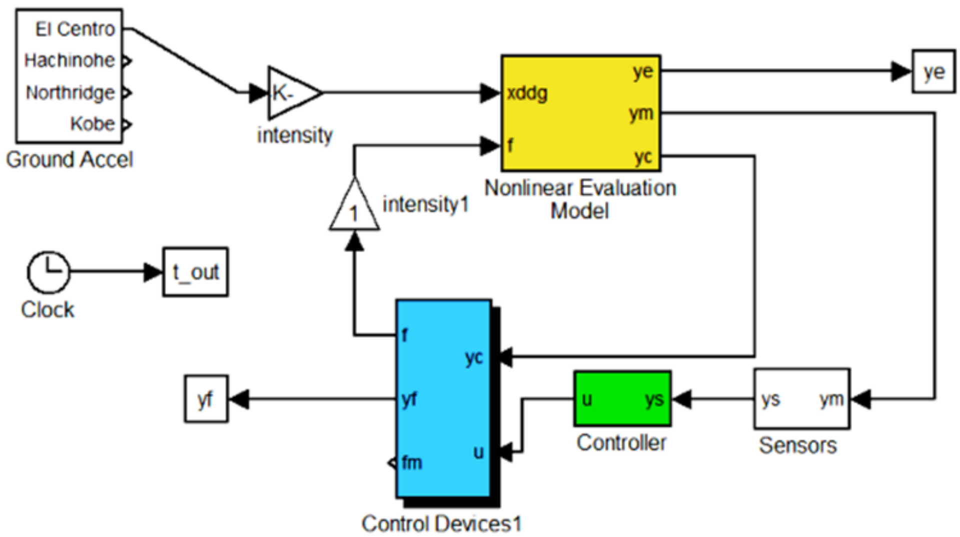


Fig. 9 SIMULINK Block Diagram for vibration control simulator (Ohtori *et al*. 2004)

earthquake, β= non-negative parameter representing the effect of cyclic loading on structural damage (Williams and Sexsmith 1995).

4.2 MR damper

A very interesting type of semi-active devices is MR damper that is capable of reversible changes in viscosity. This type of damper consists of magnetic polarized particles suspended in the oil. Their ability to convert from liquid to semi-solid state with controllable deliverable resistance in milliseconds by changing the magnetic field makes them ideal for controllable dampers. In addition to the low energy content, the other advantages are their simple mechanics, which makes it very easy to be maintained, because their only moving parts are pistons. Generally, they are inherently stable, reliable, and relatively cost-effective.

Appropriate modeling of MR damper is necessary for precise prediction of its behavior. A simple model of MR damper is shown in Fig. 10 indicating good compliance

with experimental results (Spencer *et al*.1997).
The governing equations for the model can be written as follows

$$f = C_0\dot{x} + \alpha z \tag{3}$$

$$\dot{z} = -\gamma\dot{x}|z||z|^{n-1} - \beta\dot{x}|z|^{n} + A\dot{x} \tag{4}$$

$$\alpha = \alpha(u) = \alpha_a + \alpha_b u \tag{5}$$

$$C_0 = C_0(u) = C_{0a} + C_{0b} u \tag{6}$$

In this equation, x is the relative displacement of two poles of damper and z is an evolutionary variable that shows its response dependence on its history. By adjusting γ, β, n and A parameters one can determine the slope of the linear behavior and the curvature of the transition part from linear behavior to surrender. α and C0 parameters are also variable and is adjustable with a controller. In these equations, u is the output of the damper electrical circuit that is defined according to below dynamic equation according to input voltage in circuit (Spencer *et al*. 1997)

$$\dot{u} = -\eta(u-v) \tag{7}$$

In this study, damper parameters are chosen in a way to have a capacity of 1000 kN for maximum voltage of V_{max}=10v. The mechanical properties of MR damper are presented in Table 7.

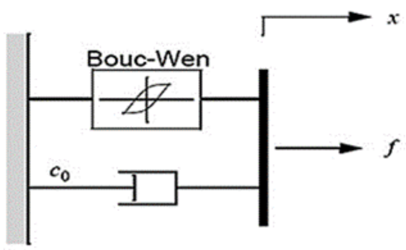


Fig. 10 Mechanical model of MR damper (Spencer e*t al*.1997)

Table 7 The mechanical properties of MR damper

Parameter	Value
α_a	1.0872×10^5 (N/cm)
α_b	4.9616×10^5 (N/cm/V)
C_{0a}	4.40(Ns/cm)
C_{0b}	44.0×10^5 (Ns/cm/V)
A	1.2
n	1
β	3.0 (cm^{-1})
γ	3.0 (cm^{-1})
η	50 (s^{-1})

4.3 Evaluation criteria

The benchmark problem (Ohtori *et al*. 2004) 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_6. These criteria, which are briefly presented in Table 8, are calculated as a ratio of the controlled and uncontrolled responses. The norm ‖.‖ is computed using the following equation

$$\|.\| = \sqrt{\frac{1}{t_f}\int_0^{t_f}[.]^2dt} \tag{8}$$

and t_f is a sufficiently large time to allow the response of the structure to attenuate (Hashemi *et al*. 2016).

5. The proposed controllers performance and numerical results

In this section, the performance of the proposed controllers and the optimization method in semi-active control of the 9-story benchmark structure are evaluated. The simulation of 9-story nonlinear benchmark building has been performed using MATLAB. In addition, the code is prepared in MATLAB software that can construct the ANFIS & Fuzzy CoCo and optimize the parameters of them using the GA.

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.

Comparison of the top floor drifts and acceleration of the structure for uncontrolled and ANFIS & Fuzzy CoCo controllers are shown in Figs. 11 and 12. Fig. 13 also shows the relative performance criteria for different controllers. Profiles of the peak inter-story drift and peak absolute acceleration are presented in Fig. 14. It can be seen that these two controllers have effectively reduced story drift and acceleration under different earthquakes. Also, it is shown the proposed controllers can significantly decrease the amount of permanent displacement of the structure. As shown in Figs. 11 and 12, it is obvious that the ANFIS and Fuzzy CoCo controllers perform very well for the 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 the Northridge and Kobe earthquakes, as two near-field records.

In order to quantitatively and accurately assess and compare this controller, J_1- J_6 criteria are used as already presented in Table 8. In order to do this, its function was compared to those of WNN, GAFLC, COC system (semi-active) and LQG controller (active) (Karamodin 2007, Hashemi *et al*. 2016). The amounts of these criteria for different controllers and under four different earthquakes with various intensities are presented in Table 9.

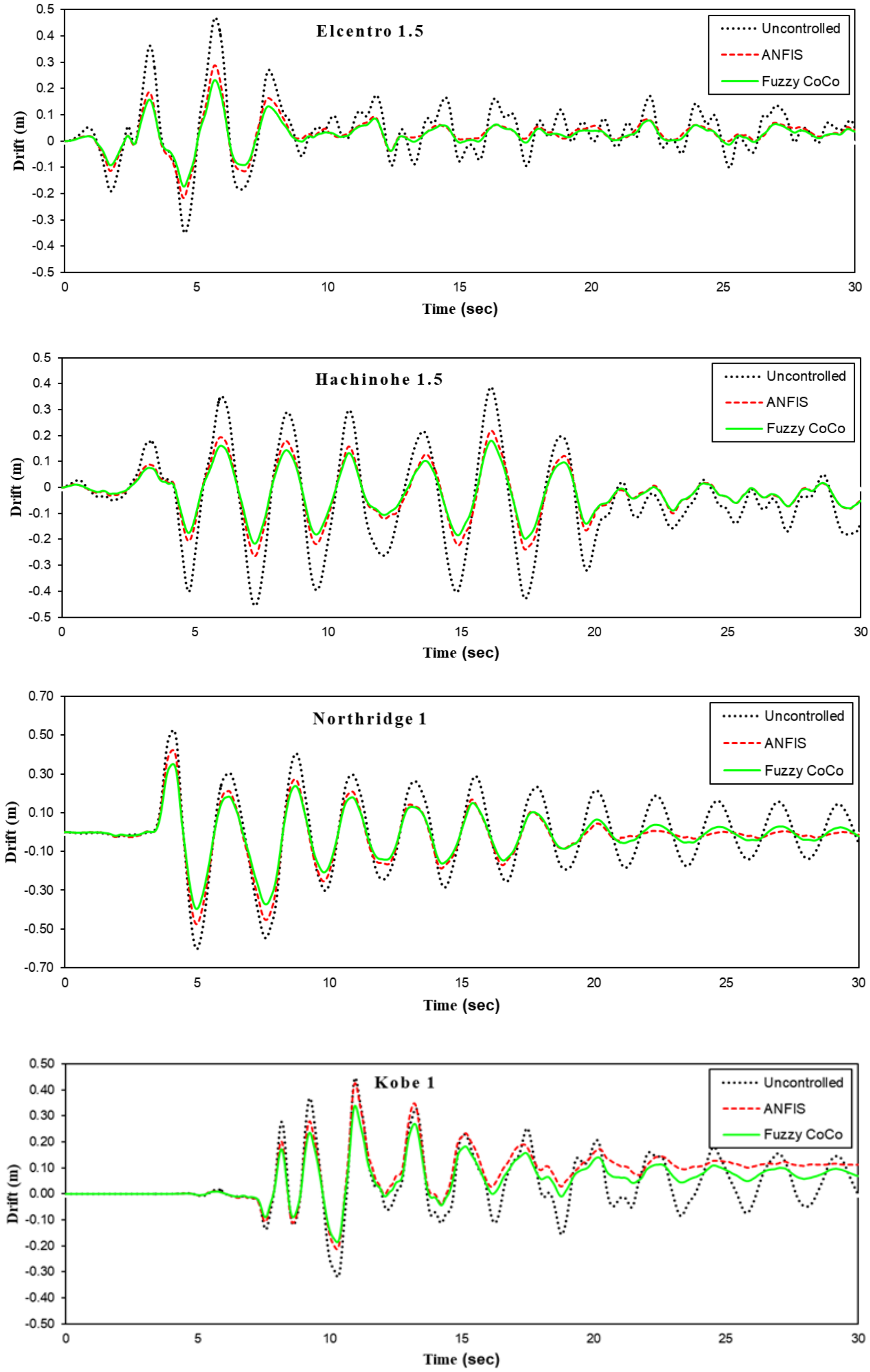


Fig. 11 Comparison of the top floor drifts for the 9-story benchmark building: uncontrolled and controlled with ANFIS & Fuzzy CoCo controllers

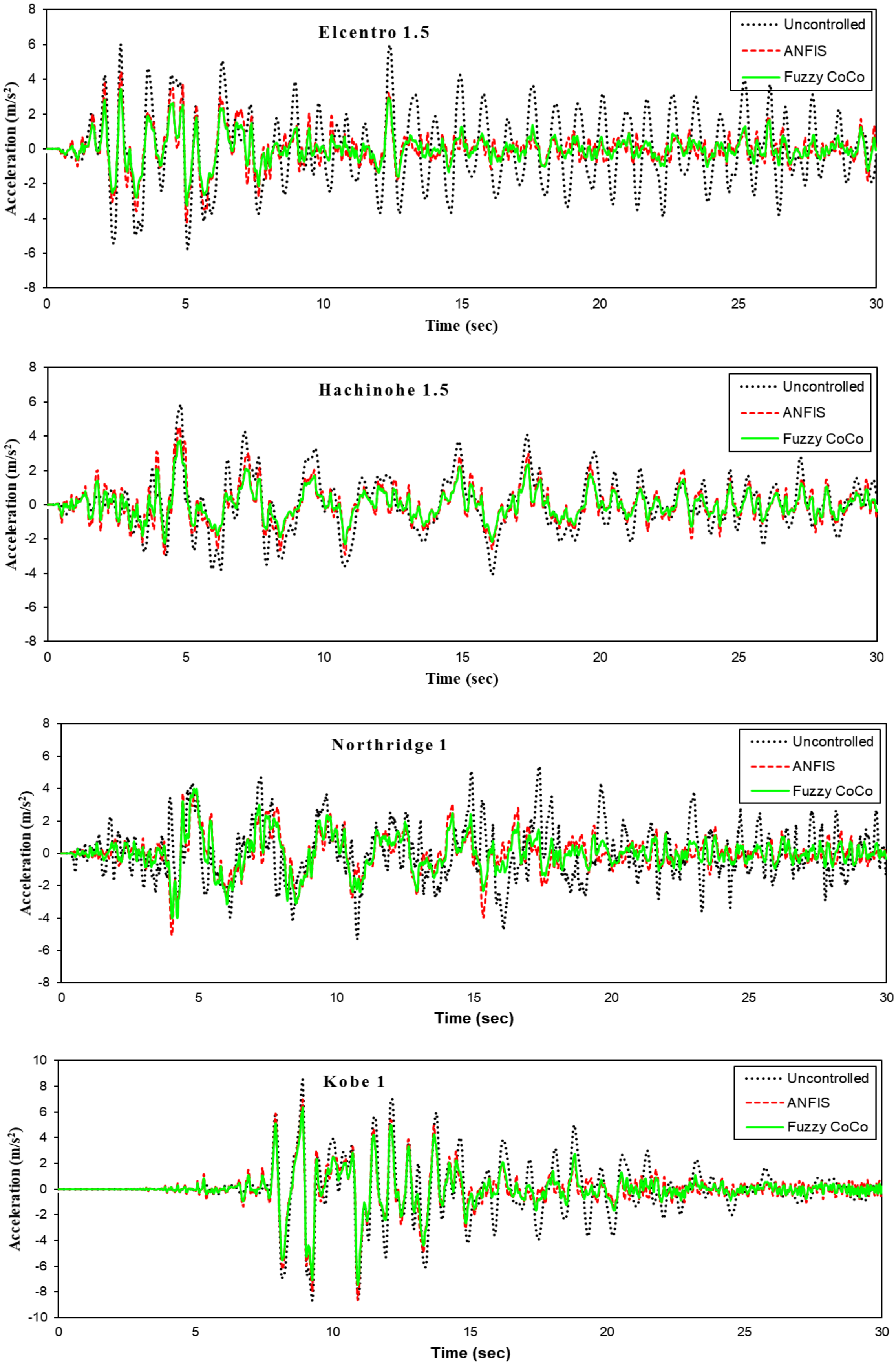


Fig. 12 Comparison of the top floor accelerations for the 9-story benchmark structure: uncontrolled and controlled with ANFIS & Fuzzy CoCo controllers

Table 8 Performance criteria

Interstory drift ratio	Level acceleration	Base shear
J_1 = max El Centro Hachinohe Northridge Kobe $\left\{ \dfrac{max_{t.i} \dfrac{\lvert d_i(t)\rvert}{h_i}}{\delta^{max}} \right\}$	**J_2 = max** El Centro Hachinohe Northridge Kobe $\left\{ \dfrac{max_{t.i} \lvert \ddot{x}_{ai}(t)\rvert}{\ddot{x}_{ai}^{max}} \right\}$	**J_3 = max** El Centro Hachinohe Northridge Kobe $\left\{ \dfrac{max_i \lvert \sum_i m_{\ddot{x}_{ai}(t)} \rvert}{F_b^{max}} \right\}$
Normed Interstory drift	**Normed level acceleration**	**Normed Base shear**
J_4 = max El Centro Hachinohe Northridge Kobe $\left\{ \dfrac{max_{t.i} \dfrac{\lVert d_i(t)\rVert}{h_i}}{\delta^{max}} \right\}$	**J_5 = max** El Centro Hachinohe Northridge Kobe $\left\{ \dfrac{max_{t.i} \lVert \ddot{x}_{ai}(t)\rVert}{\ddot{x}_{ai}^{max}} \right\}$	**J_6 = max** El Centro Hachinohe Northridge Kobe $\left\{ \dfrac{max_i \lVert \sum_i m_i \ddot{x}_{ai}(t) \rVert}{\lVert F_b^{max} \rVert} \right\}$

Table 9 Performance criteria for Fuzzy Cooperative Coevolution (Fuzzy CoCo), Adaptive Neuro-Fuzzy Inference System (ANFIS), Wavelet Neural Network (WNN), fuzzy logic controller optimized by genetic algorithm (GAFLC), Clipped Optimal Control (COC) and Linear Quadratic Gaussian (LQG) methods

Index	Controller	El Centro 0.5	El Centro 1.0	El Centro 1.5	Hachinohe 0.5	Hachinohe 1.0	Hachinohe 1.5	Northridge 0.5	Northridge 1.0	Kobe 0.5	Kobe 1.0	Average
J_1	LQG(Active)	0.809	0.869	0.958	0.845	0.941	0.868	1.093	1.049	0.863	1.089	0.938
	COC	0.583	0.807	0.853	0.621	0.709	0.786	0.891	0.963	0.805	1.307	0.832
	GAFLC	0.342	0.459	0.599	0.303	0.396	0.571	0.841	1.115	0.441	0.913	0.598
	WNN	0.327	0.437	0.559	0.300	0.373	0.529	0.835	1.118	0.433	0.845	0.576
	ANFIS	0.332	0.445	0.581	0.294	0.384	0.554	0.816	1.082	0.428	0.886	0.580
	Fuzzy CoCo	0.273	0.377	0.492	0.250	0.334	0.478	0.713	0.909	0.382	0.816	0.503
J_2	LQG(Active)	0.739	0.82	1.024	0.882	0.887	0.915	1.013	1.021	1.00	0.984	0.929
	COC	0.743	0.856	1.017	0.836	0.813	0.961	0.993	1.064	0.970	1.093	0.935
	GAFLC	0.676	0.580	0.820	0.570	0.570	0.816	1.002	0.888	0.779	0.906	0.761
	WNN	0.668	0.541	0.768	0.529	0.571	0.808	1.028	0.861	0.745	0.867	0.739
	ANFIS	0.656	0.563	0.795	0.553	0.553	0.792	0.972	0.861	0.756	0.879	0.738
	Fuzzy CoCo	0.563	0.505	0.714	0.516	0.538	0.736	0.904	0.820	0.697	0.782	0.678
J_3	LQG(Active)	0.801	0.948	0.953	0.865	0.945	0.954	0.987	0.996	0.979	0.986	0.941
	COC	0.716	0.965	1.022	0.635	0.871	0.990	1.056	0.993	0.880	1.029	0.916
	GAFLC	0.388	0.624	0.925	0.418	0.505	0.909	0.930	1.042	0.650	0.879	0.727
	WNN	0.375	0.584	0.902	0.417	0.499	0.854	0.924	1.035	0.647	0.851	0.709
	ANFIS	0.376	0.605	0.897	0.405	0.490	0.882	0.902	1.011	0.631	0.853	0.705
	Fuzzy CoCo	0.347	0.545	0.809	0.379	0.459	0.799	0.856	0.911	0.589	0.768	0.646
J_4	LQG(Active)	0.808	0.945	1.052	0.989	0.990	1.150	1.027	1.071	0.506	1.001	0.955
	COC	0.419	0.606	0.981	0.613	0.786	0.917	0.752	1.038	0.660	1.303	0.887
	GAFLC	0.228	0.318	0.554	0.291	0.454	0.488	0.590	1.167	0.183	1.277	0.555
	WNN	0.227	0.298	0.453	0.283	0.417	0.457	0.534	1.153	0.174	1.022	0.502
	ANFIS	0.221	0.308	0.537	0.282	0.440	0.473	0.572	1.132	0.178	1.239	0.538
	Fuzzy CoCo	0.191	0.260	0.441	0.240	0.378	0.408	0.472	0.944	0.159	1.203	0.470
J_5	LQG(Active)	0.728	0.779	0.766	0.910	0.960	0.966	0.979	0.964	0.802	0.952	0.881
	COC	0.586	0.571	0.597	0.820	0.787	0.855	0.741	0.777	0.648	0.809	0.719
	GAFLC	0.727	0.491	0.496	1.095	0.720	0.726	0.709	0.759	0.697	0.736	0.716
	WNN	0.434	0.389	0.444	0.547	0.512	0.654	0.546	0.707	0.435	0.674	0.534
	ANFIS	0.691	0.466	0.471	1.040	0.684	0.690	0.674	0.721	0.662	0.699	0.680
	Fuzzy CoCo	0.416	0.384	0.449	0.532	0.516	0.660	0.548	0.694	0.443	0.676	0.532
J_6	LQG(Active)	0.923	1.023	0.957	0.983	1.006	0.958	0.938	0.921	0.981	0.922	0.961
	COC	0.504	0.702	0.768	0.692	0.835	0.899	0.686	0.746	0.652	0.816	0.730
	GAFLC	0.474	0.516	0.685	0.529	0.585	0.750	0.517	0.718	0.581	0.783	0.614
	WNN	0.466	0.500	0.666	0.507	0.552	0.718	0.545	0.710	0.544	0.771	0.598
	ANFIS	0.460	0.501	0.664	0.513	0.567	0.728	0.501	0.696	0.564	0.760	0.595
	Fuzzy CoCo	0.407	0.453	0.609	0.451	0.516	0.665	0.506	0.641	0.498	0.698	0.544

Fig. 13 Comparison of performance criteria J_1–J_6 of Fuzzy Cooperative Coevolution (Fuzzy CoCo), Adaptive Neuro-Fuzzy Inference System (ANFIS), Wavelet Neural Network (WNN), fuzzy logic controller optimized by genetic algorithm (GAFLC), Clipped Optimal Control (COC) and Linear Quadratic Gaussian (LQG) methods

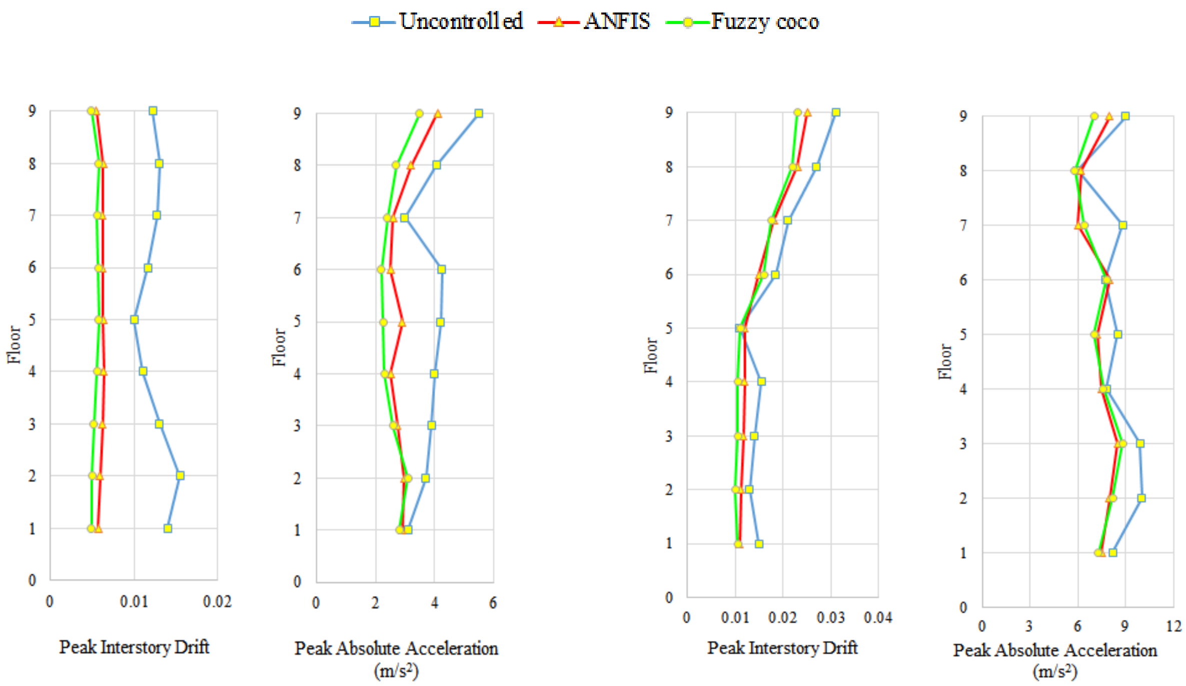
In Table 9, four controllers of Active, COC, GAFLC and WNN have been listed for comparison purposes. Active stands for the active LQG controller. In this model, three actuators are utilized on the first floor, two on the second floor, and one on each of the third to ninth floors, as shown in Fig. 8. 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 (Karamodin 2007). WNN is a semi-active control model combining the learning ability of neural networks and the capability of wavelet decomposition (Hashemi *et al.* 2016).

The J_1 criterion shows the inter-story drift ratio. The mean amount for this criterion in different earthquakes is calculated as 0.503 for the Fuzzy CoCo controller which is lower than the amounts calculated for other controllers. This shows that the performance of this controller in the field of reducing inter-story drift ratio is better than other controllers.

The performance of ANFIS and WNN are close together and have a better performance than GAFLC and other two controllers. ANFIS and WNN controller respectively showed 3, 38 and 30% reduction J_1 compared to the GAFLC, LQG and COC controller. Also, Fuzzy CoCo controller respectively showed 16, 46 and 39% reduction J_1 compared to the GAFLC, LQG and COC controllers.

The mean amount of J_2 (level acceleration) criterion is 0.678 for Fuzzy CoCo controller which is lower than those for the other controllers. This value is obtained for ANFIS controller 0.738. ANFIS and WNN controller respectively showed 3, 20 and 21% reduction for J_2 compared to the GAFLC, LQG and COC controller. Also, Fuzzy CoCo controller showed 20% reduction for J_2 compared to the LQG and COC controllers.

The mean amount for J_3 (base shear) criterion in different earthquakes is calculated as 0.705 and 0.646 for ANFIS and Fuzzy CoCo controllers respectively. ANFIS and WNN controller showed respectively 3, 25 and 23%



(a) El Centro (b) Kobe

Fig. 14 Profiles of various peak response values for uncontrolled and controlled benchmark structure subjected To full-scale earthquakes: (a) El Centro and (b) Kobe

reduction in J_3 compared to the GAFLC, LQG and COC controller. Also, Fuzzy CoCo controller showed respectively 11, 31 and 29% reduction in J_3 compared to the GAFLC, LQG and COC controllers.

The mean amount for J_4 (normed inter-story drift), J_5 (normed level acceleration) and J_6 (normed base shear) criterions in different earthquakes is calculated as 0.470, 0.532 and 0.544 using Fuzzy CoCo controllers respectively. Fuzzy CoCo controller showed respectively 41, 31 and 29% reductions in J_4, J_5 and J_6 compared to the GAFLC, LQG and COC controllers.

The mean amounts for J_4, J_5 and J_6 criteria using ANFIS controllers under different earthquakes are calculated as 0.538, 0.680 and 0.595 respectively. ANFIS controller respectively showed 33, 12 and 23% reductions in J_4, J_5 and J_6 compared to GAFLC, LQG and COC controllers.

One can conclude that despite the fact that ANFIS and Fuzzy CoCo controller is not trained for reducing acceleration and base shear, it can somewhat reduce the acceleration and base shear of the structure. When compared to other controllers, one can conclude that Fuzzy CoCo controller performs better.

6. Conclusions

Different control algorithms have been studied in structures. Among these algorithm, neural network based methods and fuzzy logic show higher efficacy in structural control with adaptability taking into consideration non-linear responses and uncertainties. While having simplicity, understandability, and no need to complex mathematical relationships, they are more suitable than other control algorithm. Using a combination of neural networks with fuzzy logic can provide benefits of these two methods and cover their deficiencies. Also, combination of fuzzy systems and evolutionary algorithms can be an effective way to efficient and optimized training fuzzy control.

In this paper, in order to improve the seismic behavior of structures, a semi-active control of a 9-story benchmark building was studied using Magneto Rheological (MR) damper. To determine input voltage of MR dampers, Adaptive Neural-Fuzzy Inference System (ANFIS) and Fuzzy Cooperative Coevolution (Fuzzy CoCo) control were utilized. Genetic Algorithm (GA) was used to train and optimize the performance of controllers. The floors accelerations being the inputs of the Fuzzy CoCo and the floors accelerations and drift being the inputs of the ANFIS and the output being the voltage to the MR dampers so that they are able to provide optimum force responses for the structure. The ability and efficiency of the proposed controllers were illustrated in terms of drift, acceleration, and base shear reduction under four types of the earthquakes applied to the structure. The proposed controllers were compared to Wavelet Neural Network (WNN), fuzzy logic controller optimized by genetic algorithm (GAFLC), Linear Quadratic Gaussian (LQG) and Clipped Optimal Control (COC) systems.

Based on the results of the study, the proposed controllers in particular Fuzzy CoCo were more effective in reducing all criteria than the other controllers. ANFIS controller respectively showed 31 and 29% reductions in J_1-J_6 compared to the LQG and COC controllers. Fuzzy CoCo controller respectively showed 38 and 36% reductions in J_1-J_6 compared to the LQG and COC controllers. The results show that the Fuzzy CoCo controller has more efficiency than the ANFIS controller on average about 10%. The proposed controllers perform very well under far-field earthquake records while they are effective in reducing the maximum responses of the structure subjected to near-field earthquake records.

The optimization has been performed for the El Centro earthquake (far-field) and other earthquake records have been used for testing the performance of the controller. For future research, it is suggested to use an earthquake supervisor to improve the performance of the proposed controller under the near-field earthquakes.

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