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Research Paper

Fault-Tolerant Damage Control of Nonlinear Structures Using Artificial Intelligence

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ABSTRACT: In this paper, the artificial intelligence is employed to design a Fault-Tolerant Controller (FTC) for structural vibrations. The FTC is designed to reduce the probability of damage considering sensor fault. For this purpose, Neural Networks (NNs) are used as fault detection and accommodation and fuzzy logic is used as a controller. This control strategy requires two groups of neural networks. The first group of neural networks finds the faulty sensor by estimating the structural responses and comparing them with the responses obtained from the sensors. The second group has the task of estimating the response of the faulty sensor using data obtained from healthy sensors. To evaluate this method, the time history analysis of a 3-story benchmark building equipped with accelerometers and active actuators has been used. This evaluation is based on determining the probability of structural damage and the generation of fragility curves under forty ground motions. To develop fragility curves, the criteria specified in the FIMA 356 (IO, LS and CP) for the moment frame based on the inter-story drift are used. This study show that in the absence of the neural networks, sensor fault reduces the performance of the fuzzy controller and it is even possible to increase the structural responses compared to the structure without the controller. In addition, results demonstrate that the proposed control strategy can rectify the deterioration of sensor faults and decrease the probability of failure.

Keywords: Fault Diagnosis, Fault-Tolerant Control, Fuzzy Logic Controller (FLC), Neural Networks, Probability of Damage.

INTRODUCTION

Researchers have used a variety of methods to reduce damage to structures as well as casualties. One of these methods is structural control, which is it in 4 forms: passive, semi-active, active and hybrid. In the active control system, the controller determines the magnitudes of control forces using the responses measured by the sensors. These forces are applied to the structure by the actuators. In this method, if each part of the

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control system does not work properly, the determined control forces may increase structural responses and the probability of failure instead of reducing the damage. Therefore, it is very important to have a robust controller that can work properly in different situations. One of the robust control systems is fault-tolerant control (FTC) system.

FTC systems are useful controllers that are robust to possible problems in the control system, including faults in the actuators, sensors, etc. FTC systems are divided into two categories: 1) passive; and 2) active. In the passive method, the control rules are set in some way to be less sensitive to changes in situations and faults (Schulte and Gauterin, 2015; Lebreton et al., 2016). In the active method, a Fault Detection and Isolation (FDI) mechanism is employed to determine when and how to improve the controller (Schuh et al., 2015; Lan and Patton, 2016). The active methods usually give better results because they can cover a wider range of different faults.

Typically, two types of FDI are used in the FTC systems: 1) hardware redundancy; and 2) analytical redundancy. In the first method, which is mostly used, the performance of different parts is controlled by using additional equipment to find the fault and its location in case of occurrence. In the second method, the logical relationship between the variables of different parts of the system is used to detect faults. Hardware redundancy methods require additional equipment, space and cost, and analytical redundancy methods require a precise model of the system. Because the second method requires a precise system model, it is mostly used for simple and linear systems (Raji et al., 2018; Fonod et al., 2015). Sometimes methods such as artificial neural networks, fuzzy sets, etc. are used to find the relationship between different parts of the system (Shen et al., 2014; Choi et al., 2015). One of the advantages of these methods is that they are capable of modeling complex and non-linear systems.

The purpose of the risk study is to estimate the level of damage to the structures under different seismic intensities (Abdollahzadeh et al., 2015). One way to do this is to use fragility curves. These curves express the probability that limit states will exceed certain values as a function of seismic intensities such as spectral acceleration. Several ways are used to derive fragility curves. According to the sources of data, these ways can be divided into 4 categories as: Empirical, Judgmental, Analytical and Hybrid (Kwon and Elnashai, 2006). Analytical methods are usually among the most widely used methods that do not require empirical data. In these methods, the probability of failure in structures is calculated through methods such as nonlinear static, elastic spectral and nonlinear time history analyses (Padgett and DesRoches, 2008).

This paper proposes a fault-tolerant sensor control system for nonlinear structures. Fuzzy logic controller and artificial neural networks (NNs) are used for this purpose because they do not need the system mathematical model. The fuzzy controller acts as the main controller, and neural networks are used as FDI. Here, two groups of NNs are used; one to detect fault and the other to estimate the response of the faulty sensor. The effect of this control system on reducing the probability of failure is investigated by examining the fragility curves of a 3-story nonlinear building.

STRUCTURAL DESCRIPTION AND CONTROL DEVICES

To investigate the performance of the control system the SAC 3 story nonlinear benchmark building is employed. Although it is designed for the Los Angeles area, it has not actually been constructed. The specifications of this building have been fully expressed by Ohtori et al. (2004). This building, which is shown in Figure 1, has a plan measuring 36.58 m by 54.87 m and a height of 11.89 m. There are 4 and 6 bays with a length of 9.15 meters for each bay in the north-south and east-west directions, respectively. The building uses the steel perimeter moment-resisting frames (MRFs) as a lateral load-resisting system. The interior frames of the building include simple joints. The floors are designed as composites and are assumed to be rigid on the horizon plane. Because the structure is regular in plan and height, only half of the structure is considered for analysis. In other words, an MRF in the north-south direction is analyzed with half of the seismic mass of the entire building. The periods of the first three modes of this frame are 1.01, 0.33 and 0.17 s, respectively.

Due to severe earthquakes, the response of structures may become nonlinear due to the yielding of members. Sometimes this nonlinearity is ignored for simplicity. This simplification can make a significant difference in the response. In this paper, nonlinear behavior is considered by modeling plastic hinges with a bilinear hysteresis model. It is assumed that these hinges occur at the ends of the beams and columns of the moment frame.

In this paper active actuators have been used to provide control forces. They are employed using Chevron braces arranged horizontally between two successive floors. The maximum force that any actuator can produce is limited to 1000 kN. Typically, this amount of force can be easily generated by actuators (Karamodin et al., 2012). Here, two actuators are assumed for each story to provide larger control forces.

GROUND MOTION RECORDS

To derive the fragility curves for a structure, it is very important to choose the appropriate ground motions that represent the seismic hazard in the target area. Usually the number of earthquakes recorded in each region is not enough to achieve the right accuracy. Somerville et al. (1997) provided 60 ground motions, including three sets of 20, for the Los Angeles area. The return period of these sets is 72, 474 and 2475 years and the probability of their exceeding in 50 years is 50, 10 and 2 percent, respectively. These sets of ground motions are hereafter referred to as the 50 in 50 set, 10 in 50 set, and 2 in 50 set. According to Bazzuro and Cornell (1994), the use of 5 to 7 input motion could be appropriate to represent the seismic hazard of the target area. Therefore, in this paper, two sets (2 in 50 set and 10 in 50 set) are used to develop fragility curves.

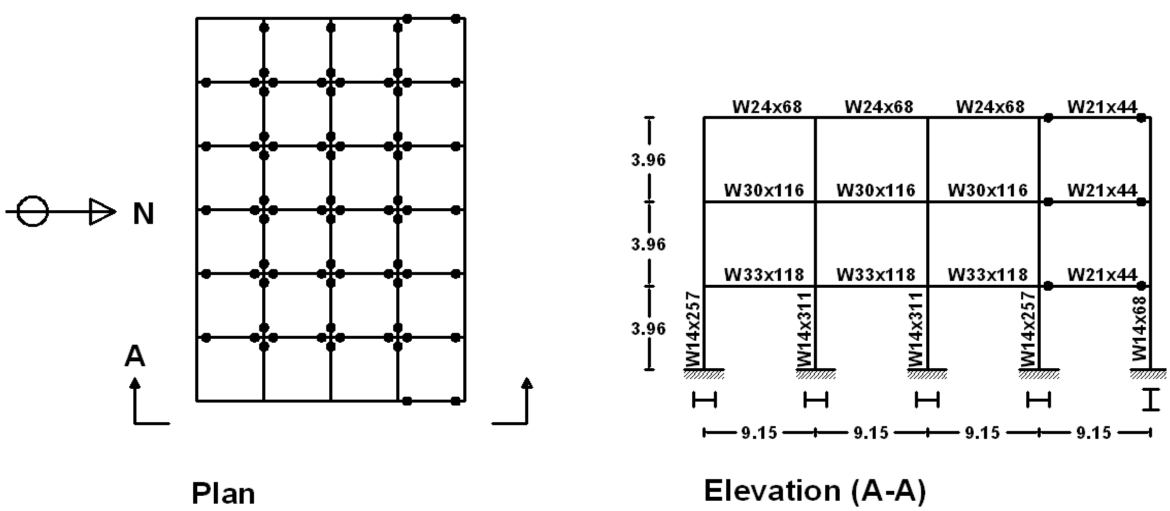


Fig. 1. Plan and elevation of 3 story nonlinear benchmark building

FRAGILITY ANALYSIS PARAMETERS

The probability of seismic demand (D) exceeding the structural capacity limits (C) for different seismic intensities is defined as fragility as shown Eq. (1) (Baghban et al., 2015, Mohammadizadeh et al., 2018).

$$Fragility = P[D \geq C|S] \tag{1}$$

Therefore, seismic demand and structural capacity need to be calculated to analyze fragility.

Demand Model

To develop fragility curves, it is necessary to determine the relationship between seismic intensity and seismic demand. This relationship (Eq. (2)) is usually considered as a power function (Padgett and DesRoches, 2008):

$$D = aS^b \tag{2}$$

where *a* and *b*: are unknown regression coefficients. To calculate these coefficients, the logarithmic transformation of Eq. (2) is used, which leads to Eq. (3).

$$ln(D) = ln(a) + bln(S) \tag{3}$$

In order to obtain *a* and *b*, nonlinear analysis of the structure and a linear regression are required.

Performance Limit States

Since the limit states are directly effective in fragility curves, the reasonable definition of these limits is very important (Erberik and Elnashai, 2004). In FEMA 356 (2000), three limit states are defined based on inter-story drift. These limits are the Immediate Occupancy (IO), the Life Safety (LS) and the Collapse Prevention (CP). For steel moment frames, the values specified by FEMA356 for the maximum inter-story drift ratio of the IO, LS and CP limit states are 0.7, 2.5 and 5%, respectively. These limits have been accepted and used by various researchers for generating fragility curves (e.g., Kazantzi, Righiniotis et al., 2008). Therefore, they have been selected as limit states in this study.

FRAGILITY CURVES

The fragility function can be determined using Eq. (4) when the performance limit states (*d*) are accepted as deterministic values.

$$P(D \geq d|S = s) = 1 - \Phi\left(\frac{\ln(C) - \lambda_{D|S}}{\beta_{D|S}}\right) \tag{4}$$

where Φ( ): is the standard normal cumulative distribution function and λ and β: are parameters of the lognormal distribution calculated from Eq. (2). The fragility curves for representative structure are shown in Figure 2, considering the limit states of the FIMA.

PROPOSED CONTROL STRATEGY

Fuzzy Logic Controller (FLC)

Recently, fuzzy controllers have been widely used in engineering sciences, including structural control (Karamodin et al., 2012; Ghaffarzadeh, 2013). There are many reasons to use these controllers. One of these reasons is their ability to control nonlinear systems. Another reason to use them is that they are not sensitive to uncertainty. They can also be used for systems whose mathematical models are not available. Therefore, here, these controllers are selected to control the nonlinear representative structure.

To design an FLC, two main parts must be determined: structure (input and output variables, the number and type of membership functions (MFs), the type of inference mechanism, operators, and defuzzification method) and parameters (parameters relating to MFs and fuzzy rules).

Generally, the structure and parameters are determined by experts according to their knowledge of the system. However, this method may not lead to the best results.

Here, a controller is designed for each story. These controllers include two inputs and one output. The input of each controller is the displacement and velocity of the floor and its output is the control force of that floor. 5 triangular membership functions are chosen for each input and output. Inputs and output are normalized in the range of -1 to 1. The MAX–MIN fuzzy inference method and the mean of centroid defuzzification method is chosen for the controllers. A description of fuzzy variables is given in Table 1. To find optimal values for the membership function parameters as well as fuzzy rule base a genetic algorithm was used. The goal of this optimization algorithm was to reduce story drifts. More details on this method have been given in Karamodin et al. (2012). The optimal membership functions and the optimal fuzzy rule base determined by the genetic algorithm are shown in Figure 3 and Table 2, respectively.

Table 1. Fuzzy variables

Variable	**Definition**
PL	Positive and Large
PM	Positive and Medium
PS	Positive and Small
ZO	Zero
NS	Negative and Small
NL	Negative and Large

The fragility curves of the representative structure are shown in Figure 4 with and without the use of the fuzzy controller. Clearly, the controller has significantly reduced the probability of failure.

Fault Detection and Isolation (FDI)

Researchers usually design control systems on the assumption that system states are available and measurable. It is difficult to meet this assumption in full scale structures in civil engineering. Because the control of these structures requires the relative displacements and velocities of structure and the measurement of these relative values must be performed relative to a reference. But in these structures, it is possible to easily measure absolute acceleration with available sensors.

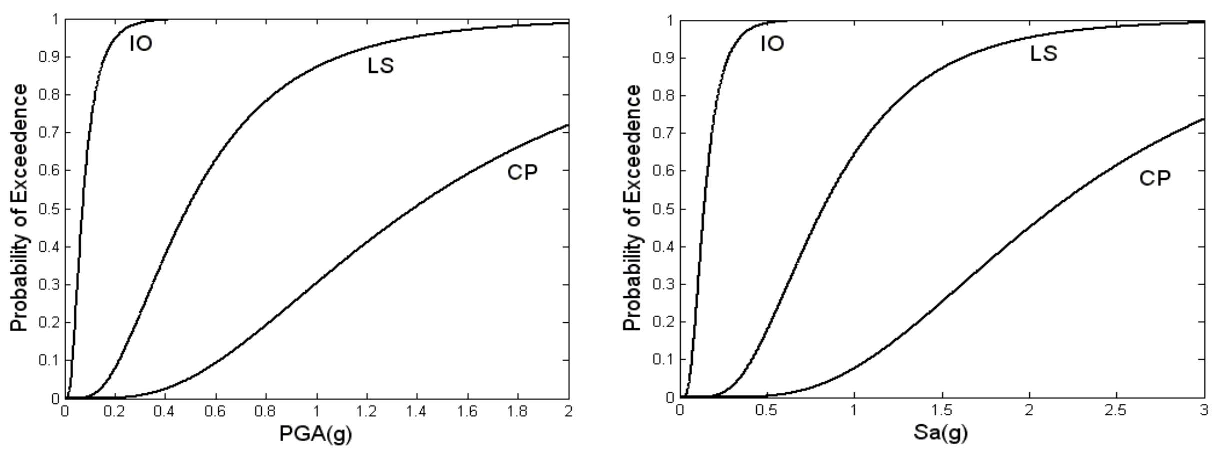


Fig. 2. Fragility curves for uncontrolled structure

Table 2. Fuzzy associative memory (FAM)

			Displacement		
Velocity	**NL**	**NS**	**ZO**	**PS**	**PL**
NL	None	PS	None	None	None
NS	ZO	NS	None	None	ZO
ZO	None	None	None	NL	None
PS	NL	ZO	ZO	None	NS
PL	None	NS	None	NL	NL

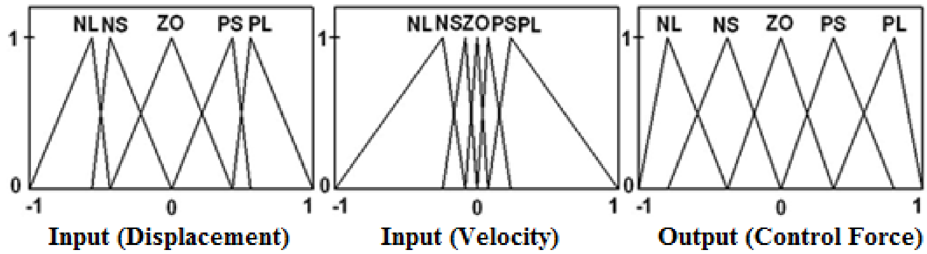


Fig. 3. Membership functions for inputs and output

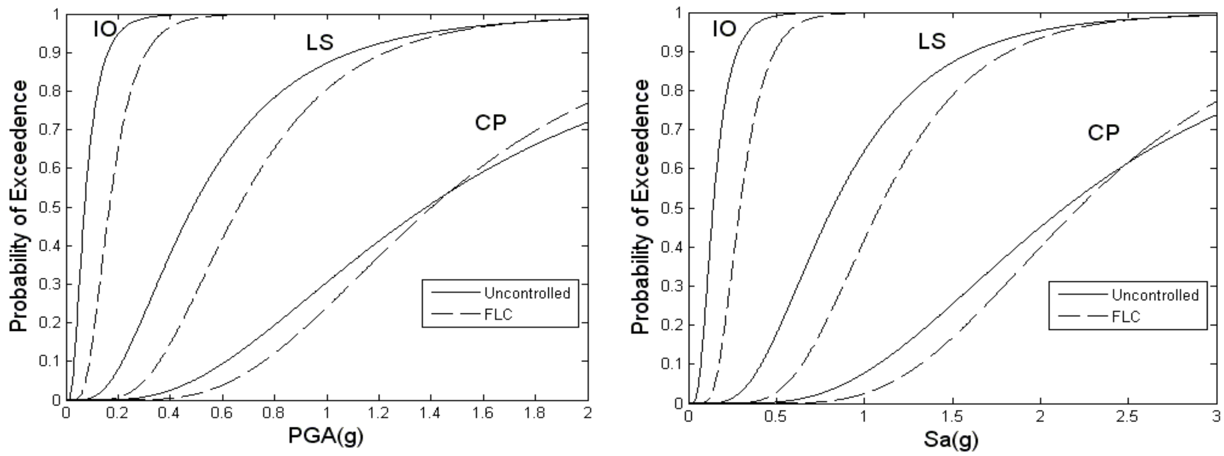


Fig. 4. Comparing fragility curves for uncontrolled and fuzzy logic controller

In this paper, 4 sensors are used to measure the acceleration of floors and ground. These sensors, which measure the total acceleration of floors 1 to 3 and the ground, are hereafter referred to as sensors 1, 2, 3, and g, respectively. However, due to the fact that in this paper, the controller needs the relative displacement and relative velocity of the floors to determine the control forces, first by deducting the ground acceleration from the acceleration of the floors, the relative acceleration of the floors is calculated. Then, by integrating the relative acceleration values, the relative velocity and relative displacement of the floors are obtained.

Here, two neural networks are employed to detect the faults. Both are used to estimate the velocity of the second floor. The first neural network tries to estimate the velocity of the second floor using the data obtained from the sensors 1 and g. The second neural network uses data from the sensors 3 and g to estimate this value. In addition, the velocity of this floor can be calculated using the data obtained from the sensors 2 and g. By comparing the three values obtained for the velocity of the second floor, the fault sensor can be detected. The schematic of this strategy is shown in Figure 5.

Here, it is assumed that only one of the sensors will be defective and will no longer be able to measure the structural response and will only send noise to the controller. This noise is assumed to be identically distributed, statistically independent Gaussian white noise processes. When the three values obtained for the velocity of the second floor are close together, it indicates that all the sensors are healthy. But if, for example, sensor 1 fails, the estimated velocity for the second floor by the first neural network will be different from the other two values. In this way, it can be recognized that sensor 1 is defective. If instead of sensor 1, sensor 2 or 3 is defective, they can be detected in a similar way. Sensor g malfunction is also detected when all three values obtained for the second floor velocity are different from each other.

As mentioned earlier, two NN models of the structure are required for the proposed

FDI strategy. The first NN (second NN) estimates the velocity of the second floor based on the current and few previous histories of velocity and displacement of the first floor (third floor). These NNs have been trained through training data generated using the analysis of the representative structure under four ground motions. The sampling rate of the training data was 200 Hz for 80 s period, which leads to 16000 patterns for training, testing, and validation. To design neural networks, it is necessary to determine the number of inputs, outputs, hidden layers, and nodes in the hidden layers. They are usually determined by trial and error. Here, the most appropriate choice for inputs was to use the current and the two previous histories for the velocity and displacement. Moreover, for these networks, a hidden layer with ten nodes and the tanning activation function was accepted. The output activation function was also considered linear.

Figure 6a shows velocity time history of second floor under one of the forty ground motions (the El Centro earthquake) as an example. To show the performance of FDI, it is assumed that the sensor 1 is fault at t=4 s. Figure 6b shows the difference between the values of velocity for second floor estimated by first NN and values measured by sensor 2 and g. As it is obvious, because the first NN uses the data receiving from sensor 1 and g, until the sensor 1 is healthy, estimated error is small, but when the sensor 1 faults at t=4 s, the estimated error increases. Figure 6c shows the difference between the values of velocity for second floor estimated by second NN and values of sensor 2 and g. Because the second NN uses the data receiving from sensor 3 and g, fault in sensor 1 does no effect on the estimated error and the error remains small.

Fault Accommodation

Once the faulty sensor has been detected by the FDI, care must be taken to ensure that the controller's performance is not affected by the sensor malfunction as much as possible. In this paper, artificial neural networks have been used for fault accommodation. These NNs use the data of healthy sensors to estimate what the faulty sensor should measure.

Here, three neural networks are needed to estimate the responses of floors 1 to 3. Each network estimates the displacement and velocity of one floor based on the current and two previous histories of velocity and displacement of adjacent floors. These NNs have been trained through training data created using the analysis of the representative structure. 16000 patterns were used for training, testing, and validation. One hidden layer with 20 nodes and the tanning activation function was adopted. The output activation function was also considered linear.

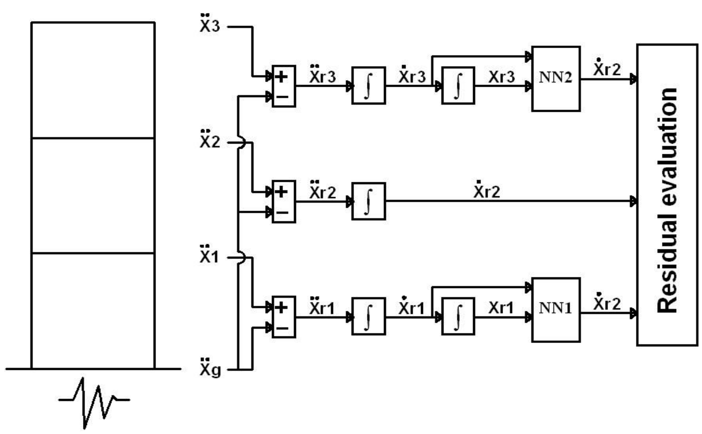
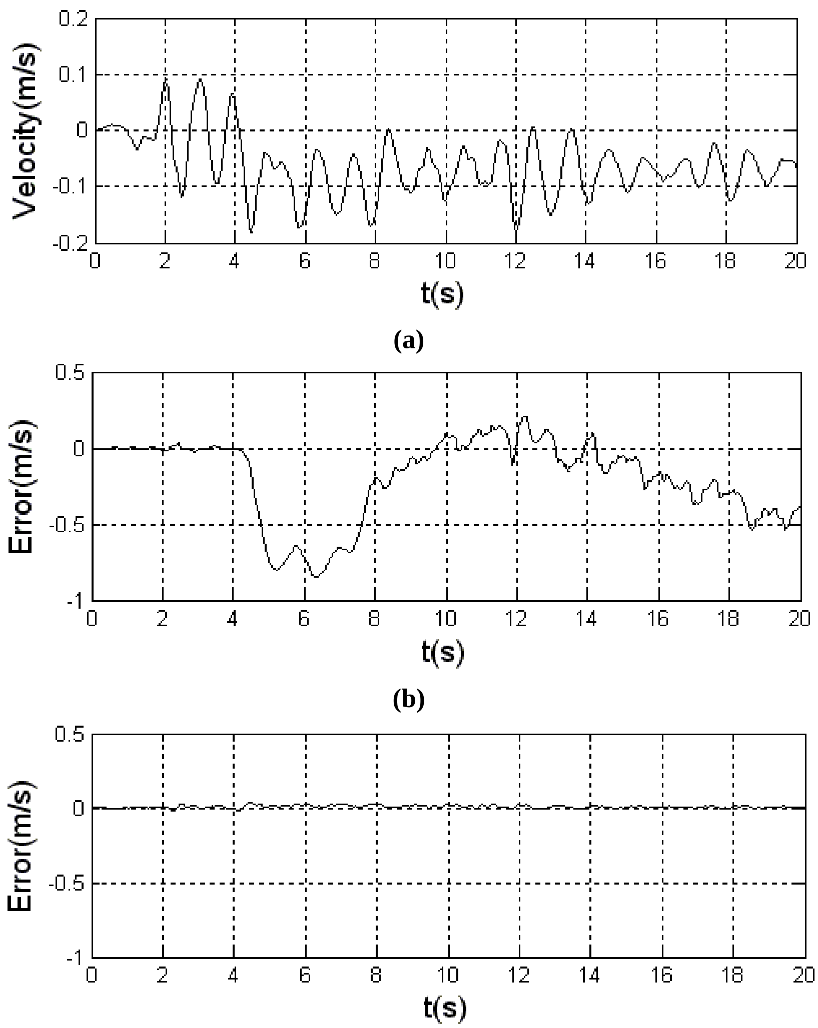


Fig. 5. Schematic of FDI strategy



(c)

Fig. 6. Velocity of story 2 and estimated error under El Centro earthquake: a) velocity of story 2; b) estimated error of the first NN; c) estimated error of the second NN

As mentioned earlier, when one of the floor sensors (sensors 1-3) fails, the neural networks try to estimate the value of input required by the controller using the values of the adjacent floors. But when the ground sensor (sensor g) is defective, it is very difficult to estimate what the sensor should measure. In this situation, instead of relative accelerations between the floors and the ground, relative accelerations between the adjacent floors are used by the fuzzy controller.

Figures 7 to 10 show the fragility curves for the structure, taking into account faults in various sensors. Clearly, when all the sensors are intact, the FLC (dashed lines) can greatly reduce the probability of damage compared to the uncontrolled structure (solid lines). This reduction is more noticeable in low intensities of ground motions. The fault of one of the sensors affects the performance of the FLC (dash-dot lines). In this case, in low seismic intensities, the controller cannot reduce responses as before, and in high seismic intensities, sometimes it increases them compared to the uncontrolled structure. Using the proposed controller (FTC) will greatly limit the effects of sensor fault (dotted lines). In fact, the FTC's performance is very close to the controller with healthy sensors.

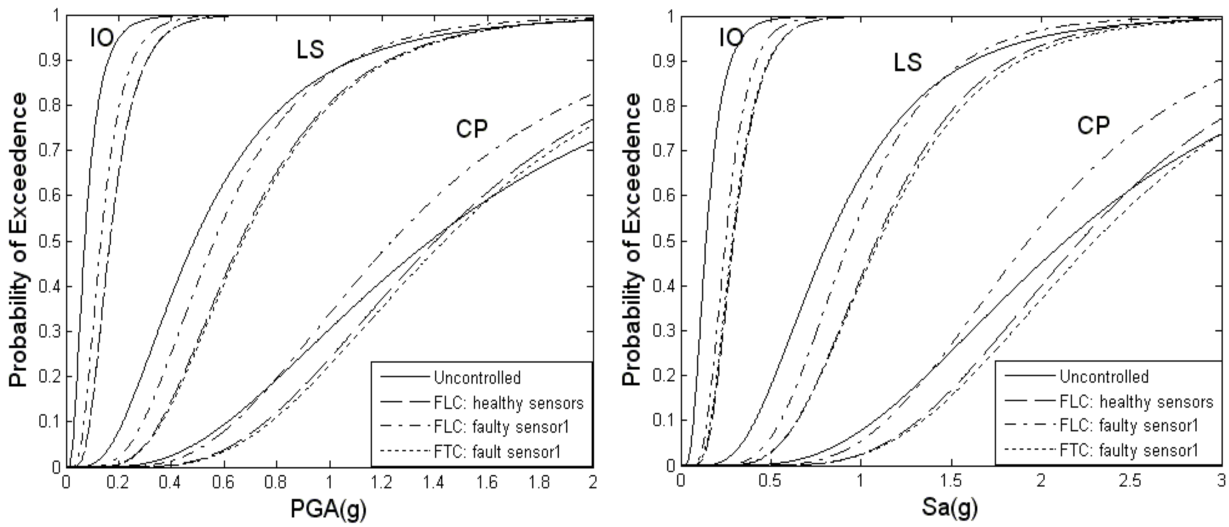


Fig. 7. Fragility curves for different controllers (fault can occur in sensor of story 1)

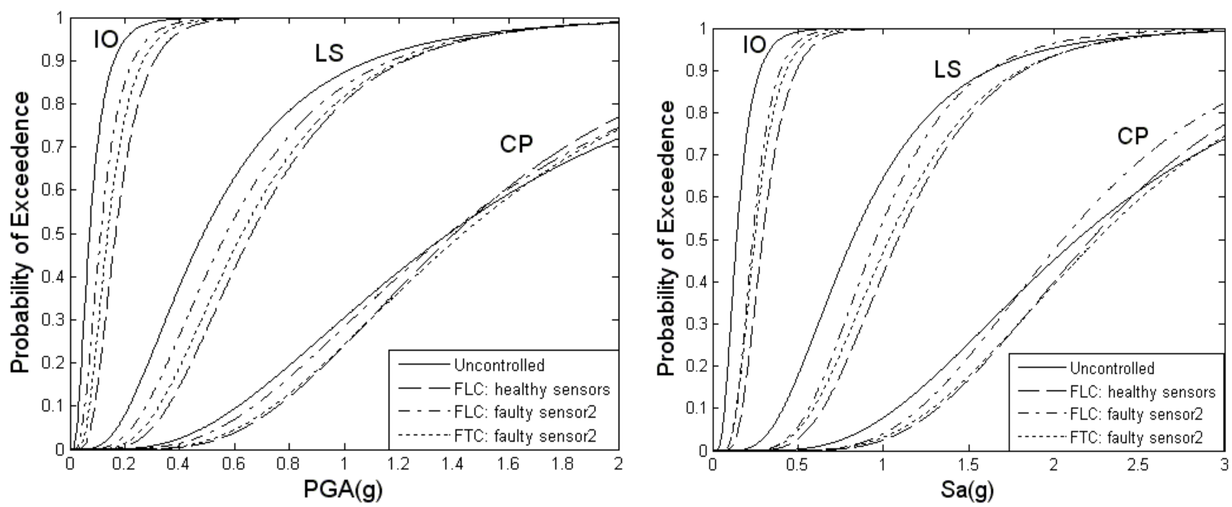


Fig. 8. Fragility curves for different controllers (fault can occur in sensor of story 2)

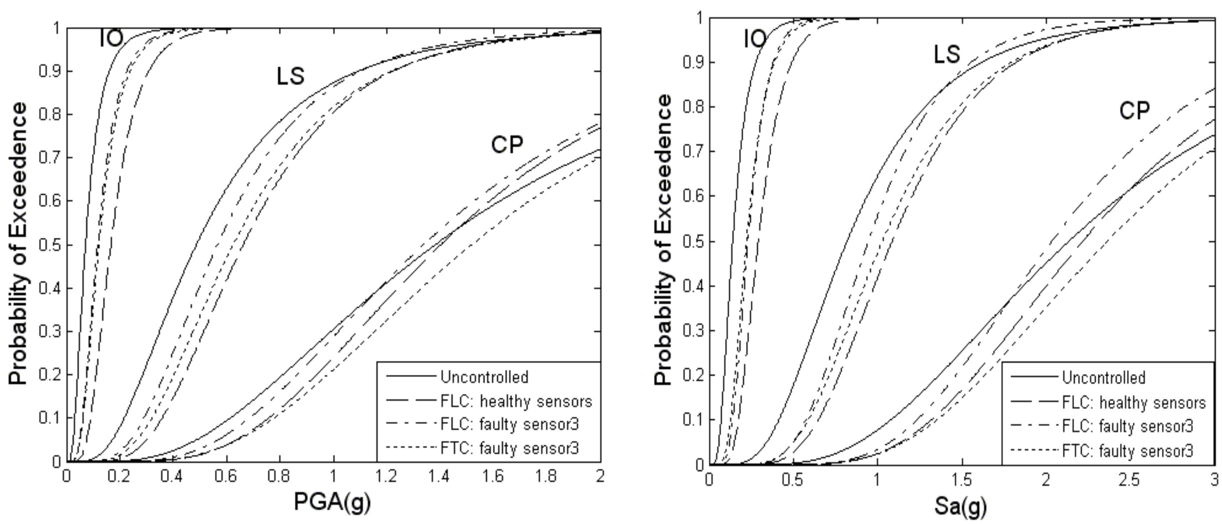


Fig. 9. Fragility curves for different controllers (fault can occur in sensor of story 3)

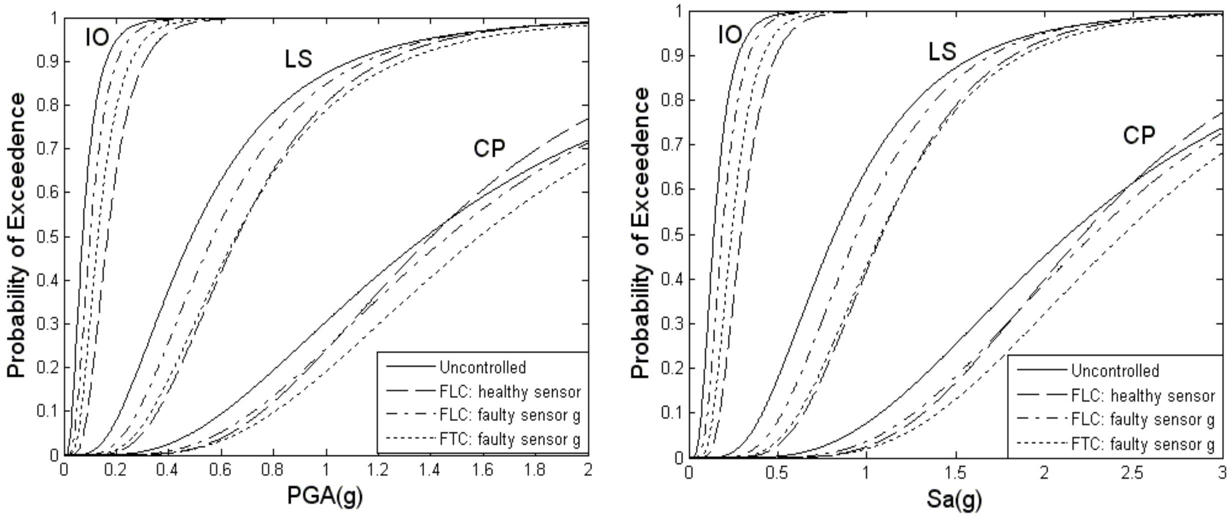
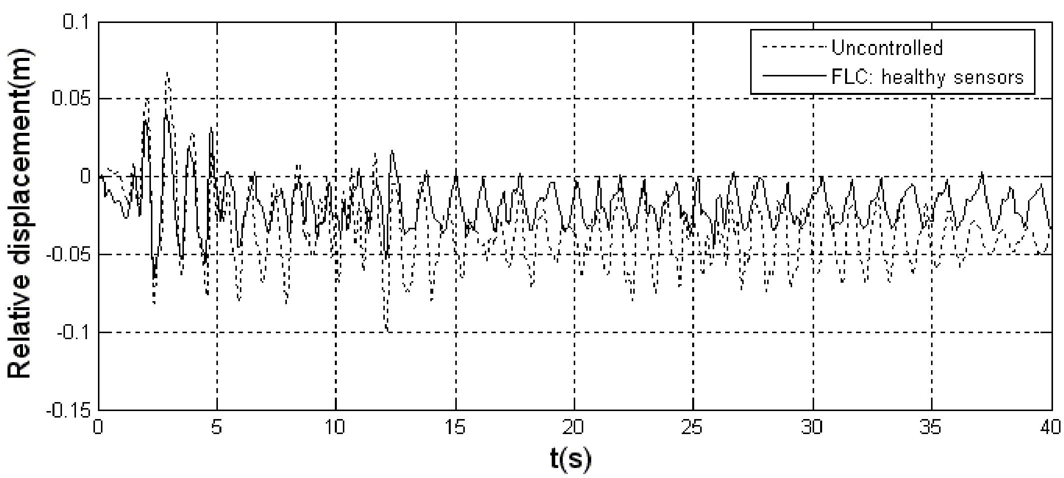


Fig. 10. Fragility curves for different controllers (fault can occur in sensor of ground)

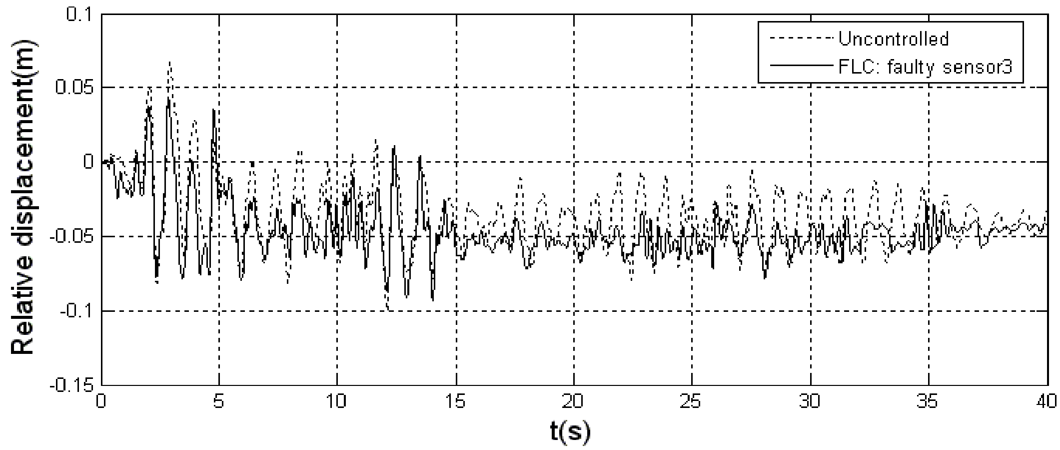
Although study on damage is the aim of this paper and developing the fragility curves can be enough for this purpose, usually time histories of response are depicted because they are more familiar for researchers. Relative displacement time histories of the story 3 under El Centro earthquake are shown in Figure 11 as an example for different controllers.

Figures 11a and 11b show the relative displacement of the story 3 in the case of using fuzzy controller without FDI unit. Figure 11a shows the uncontrolled and controlled relative displacement responses when all the sensors are healthy. It is clear that the controller has been able to greatly reduce the relative displacement. Figure 11b shows the uncontrolled and controlled responses when the sensor 3 is faulty. Comparing these figures illustrates that the fault undermines the beneficial effects of active control.

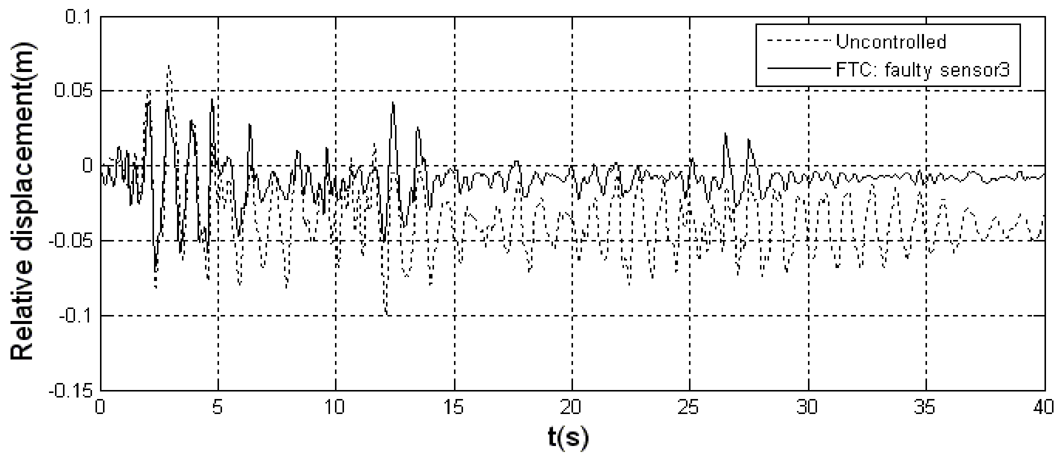
In Figure 11c, the response of the uncontrolled structure is compared with the response of the controlled structure considering the proposed FTC. This figure shows that the proposed control system has been quite effective in reducing the relative displacement of the story.



(a)



(b)



(c)

Fig. 11. Relative displacement response of story 3 under El Centro earthquake: a) comparing uncontrolled and FLC when are sensors are healthy; b) comparing uncontrolled and FLC when sensor 3 is faulty; c) comparing uncontrolled and FTC when sensor 3 is faulty

CONCLUSIONS

In this paper, artificial neural networks were used to detect fault sensors and improve the performance of controller when one of the sensors fails. The control strategy included a fuzzy logic controller (FLC) which determined the control force of actuators and neural networks for fault detection, isolation (FDI) and accommodation. When a fault occurred, in the first step, the faulty sensor was detected by comparing the responses measured by the sensors with what were estimated by the neural networks. In the second step, after diagnosing the faulty sensor, using the information obtained from the healthy sensors, the neural networks estimated the inputs required by the controller, which could not be measured by the faulty sensor. To investigate the performance of the proposed control system, a three-story building was nonlinearly analyzed by 40 ground motions and its fragility curves were generated.

The results illustrated that when all the sensors were healthy, the fuzzy controller was very effective in reducing the relative displacement and the probability of damage in the structure. This effect was more noticeable at low seismic intensities. If the FDI was not used, when one of the sensors failed, the fuzzy controller could not reduce the probability of damage as before, and even increase it in high seismic intensities. Using the proposed controller (FTC) greatly eliminated the negative effects of sensor malfunction and it kept the controller as effective as before in reducing response.

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