International Congress on Civil Engineering

10th

International

CERTIFICATE

This is to certify that the f

as a poster in the 10th Internatio

held at the University of

Ar

Improving fragility curves for c

Dr. Nasser Taghizadieh

Secretary of the 10th ICCE

Improving fragility curves for controlled structures including sensor fault

A. Baghban, A. Karamodin, H. Haji-Kazemi
Department of Civil Engineering, Ferdowsi University of Mashhad, Iran

Baghban.K@gmail.com

Abstract

In this study the effect of sensor fault on damage of active controlled nonlinear structures is investigated. A fault detection neural network and a fault accommodation neural network are proposed to reduce the effect of sensor fault. The fault detection network monitors structural responses and automatically detects faulty sensor that can reduce control performance and effectiveness, while the fault accommodation network accounts for the faulty sensors. Fault is accommodated by using data from the remaining healthy sensors to estimate what the faulty sensors should have been reading. To demonstrate the performance of proposed method, a 3-story full-scale nonlinear benchmark building and several ground motions are selected. The fragility curves are developed for structures using nonlinear dynamic time history analysis through the computer simulation. Fuzzy logic controller (FLC) is employed as a sample of intelligent controller to control the structure using actuators. Here, the fragility curves are represented by lognormal distribution function with two parameters and developed considering three performance levels specified in FEMA 356 includes the Immediate Occupancy (IO), the Life Safety (LS) and the Collapse Prevention (CP). Results show that the sensor fault can reduce the effect of controllers and even can increase the probability of damage compare to the uncontrolled structure. Moreover, results of the proposed method confirm its effectiveness for decreasing the probability of damage of faulty control system.

Keywords: fault-tolerant controller (FTC), fault detection, fault accommodation, fuzzy logic controller (FLC), fragility curves.

1. INTRODUCTION

In structural engineering field, mitigation of structural damage and human loss is a major problem. Structural control has shown its effectiveness for attaining this purpose by different control strategies such as passive, active and semi-active. The active control system involves sensor to measure the building's response and actuators to apply control forces to the structure in a prescribed manner. Since in this system external source supply the control forces, not properly working of controller can increase structural energy and damage. One challenge of employing a control system is designing robust controller to treat properly in different probable situation. One way to guarantee reliable operation of a system is fault-tolerant control (FTC) strategies.

FTC strategies provide a valuable tool for designing robust systems against actuator, sensor and/or other components faults. FTC can be achieved either passively by the use of a control law designed to be insensitive to some known faults [1, 2], or actively by a fault detection and isolation (FDI) mechanism, and the redesign of a new control law [3, 4]. The active methods are more realistic because all the faults that may affect the system cannot be known a priori. The design of an FTC requires quick FDI to retain the system stability and performance. Generally two FDI methods can be used: (1) hardware redundancy; and (2) analytical redundancy. In hardware redundancy the outputs of identical components are compared to check if one of them is faulty. Most applications of FTC schemes are based on the hardware redundancy which needs more equipment, space and cost. To overcome these problems, analytical redundancy methods have been developed. In these methods, the relations among the system variables are compared to check inconsistencies. Because these methods need to have an accurate model of the systems, they are applicable to linear and simple systems [5, 6]. These methods are known as model-based FDI methods. An evolution of these model-based FDI methods is data-based FDI methods, such as neural networks, fuzzy sets or their combination [7, 8]. These methods are borrowed from the qualitative reasoning in artificial intelligence, with the aim of understanding the human common sense to catch the interactions between physical phenomena, without knowing the quantitative aspects.

One method in estimation of seismic damage in buildings and bridges and evaluation of the effects and robustness of control methods is so called fragility curves. The fragility curves show the probability of structural damages as a function of ground motion indices such as peak ground acceleration (PGA), spectral acceleration (Sa), spectral displacement (Sd) and so forth. Different methods have been used to develop fragility curves. These methods may be sub-divided into four categories based on the sources of data as: Empirical, Judgmental, Analytical and Hybrid vulnerability methods [9]. In the absence of adequate empirical data, analytical methods usually have been used to develop fragility curves. In these methods, the structural demands and/or capacities used to evaluate failure probability are estimated through such methods as elastic spectral, nonlinear static and nonlinear time history analyses [10].

In this paper the design and application of a fault-tolerant controller for a nonlinear structure is presented considering sensor fault. Here, the fault-tolerant controller includes the FLC as a controller and NNs as an FDI. The FLC and NNs are used because they are free of mathematical models and because of the ability to handle and estimate the non-linear behavior of the structures. Effectiveness of the proposed method is examined for a 3-story full-scale nonlinear benchmark building by developing fragility curves. The fragility curves are developed based on interstory drift as a function of peak ground acceleration (PGA) and spectral acceleration (Sa) using nonlinear dynamic time history analysis.

2. STRUCTURAL DISCRIPTION

The representative structure employed in this study is the SAC 3 story nonlinear benchmark building. The structure is designed for the Los Angeles, California area and defined by Ohtori et al. [11]. It's 36.58 m by 54.87 m in plan, and 11.89 m in elevation, Fig.1. The bays are 9.15 m on center, in both directions, with four bays in the north-south (N-S) direction and six bays in the east-west (E-W) direction. The building's lateral load-resisting system is comprised of steel perimeter moment-resisting frames (MRFs) with simple framing between the two furthest south E-W frames. The interior bays of the structure contain simple framing with composite floors. The floor system is assumed to be rigid in the horizontal plane. Since the building is quite regular in plan and elevation, only half of the building is considered for further analysis. The MRF to be analyzed is one of the two in the North-South direction and was assigned half the seismic mass of the whole structure. The first, second and third periods of frame are 1.01, 0.33 and 0.17 s, respectively.

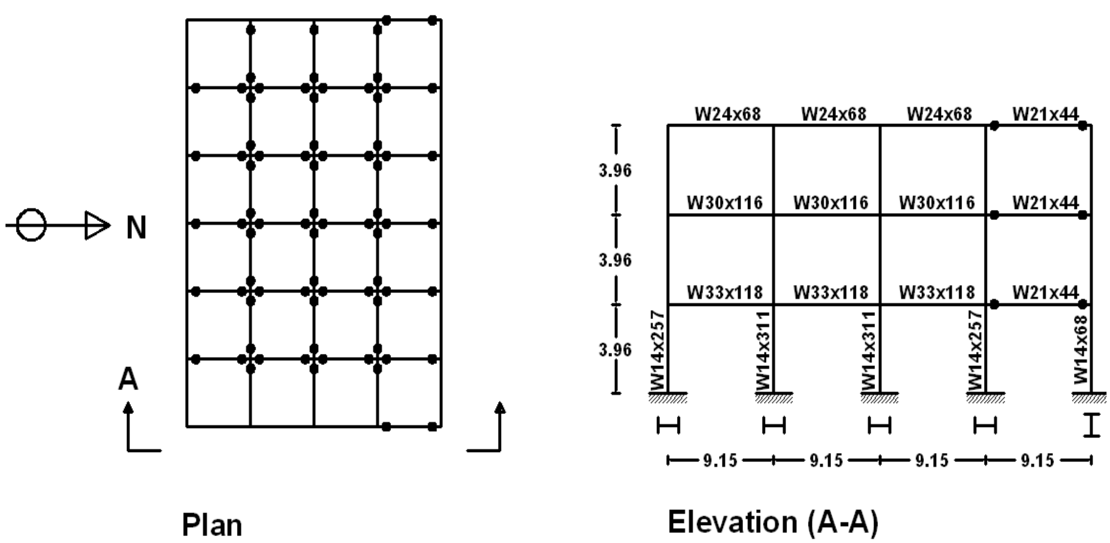


Fig. 1. Plan and elevation of 3 story nonlinear benchmark building.

During large seismic events, structural members can yield, resulting in nonlinear response behavior that may be significantly different than a linear approximation. To represent the nonlinear behavior, a bilinear hysteresis model is used to model the plastic hinges. These plastic hinges, which are assumed to occur at the moment resisting column-beam and column-column connections, introduce a material nonlinear behavior of structures.

3. GROUND MOTION RECORDS

When developing fragility curves, selection of representative set of earthquakes that represents the variability in seismic input is an important step. Usually the number of available and usable actual ground motion records is not sufficient to obtain the accurate results. Somerville et al. [12] generated three set of 20 ground motions for the SAC project to represent ground motions having probabilities of exceedance of 50% in 50 years (corresponding to a return period of 72 years), 10% in 50 years (corresponding to a return period of 474 years), and 2% in 50 years (corresponding to a return period of 2475 years) in the Los Angeles region. These sets of ground motions are referred to as the 50 in 50 Set, 10 in 50 Set, and 2 in 50 Set, respectively. The acceleration histories have been scaled so as to conform roughly to the 1997 NEHRP design spectrum for firm soil for the specified return periods. The time histories for both the 50 in 50 Set and the 10 in 50 Set are all derived from actual recordings of crustal-earthquakes on stiff soils. For the 2 in 50 Set, five of the time histories are from recorded near-fault events and the other five were synthetically generated. The synthetic time histories were generated using different methods for the short-period and the long-period portions of the spectral acceleration curve. The results from these two methods were then merged near a period of 1 s (the first mode of the structure) [13]. Since Bazzuro and Cornell [14] suggested that five to seven input motion are sufficient for representing the hazard, in this study only two sets of ground motions (2 in 50 set and 10 in 50 set) including 40 earthquakes are used as a seismic input.

4. PARAMETERS FOR FRAGILITY ESTIMATION

The fragility defines the conditional probability of the seismic demand (D) placed upon the structure exceeding its capacity (C) limits for a given level of earthquake intensity (S), as shown in the following equation

$$Fragility = P[D \geq C|S] \quad (1)$$

Therefore, estimates of the seismic demand and capacity limits are required for fragility analysis.

4.1. DEMAND MODEL

For a realistic model of a system, the nonlinear behavior must be considered in fragility analysis. To find the relationship between seismic demand and earthquake intensity, usually a power-law function is assumed as shown in Eq. (2), (e.g., [10], [15])

$$D = aS^b \quad (2)$$

where a and b are unknown regression coefficients determined by a logarithmic transformation of Eq. (2) to a linear form as Eq. (3)

$$\ln(D) = \ln(a) + b\ln(S) \quad (3)$$

Using nonlinear time history analysis and a linear regression through the Eq. (3), a and b can be determined.

4.2 LIMIT STATE CAPACITIES

Definition of limit states plays a significant role in the construction of the fragility curves. Well defined and realistic limit states are of paramount importance since these values have direct effect on the fragility curve parameters [16]. They usually are defined based on experimental data, expert judgment, analytical methods, or combinations thereof. In FEMA 356 [17], three limit states are defined based on inter-story drift. These limit states are the Immediate Occupancy (IO), the Life Safety (LS) and the Collapse Prevention (CP). FEMA specifies 0.7, 2.5 and 5% for the maximum inter-story drift ratio of steel moment frames associates with the IO, LS and CP limit stats, respectively. Several researchers have adopted these limits (e.g., [15]

,[18]) for generating fragility curves. Kazantzi et al. [18] stated a pushover analysis indicates the FEMA 356 limits are reasonable. Therefore, in this study, FEMA limits are adopted as limit state capacities.

5. FRAGILITY ANALYSIS

When the limit state capacity is assumed as a deterministic response, the fragility can be calculated as

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

where $\Phi(\ )$ is the standard normal cumulative distribution function, d is the limit state capacity, and λ and β are parameters of the lognormal distribution determined from Eq. (2). Fig. 2 shows the fragility curves for representative structure under two sets of ground motions considering FEMA limits.

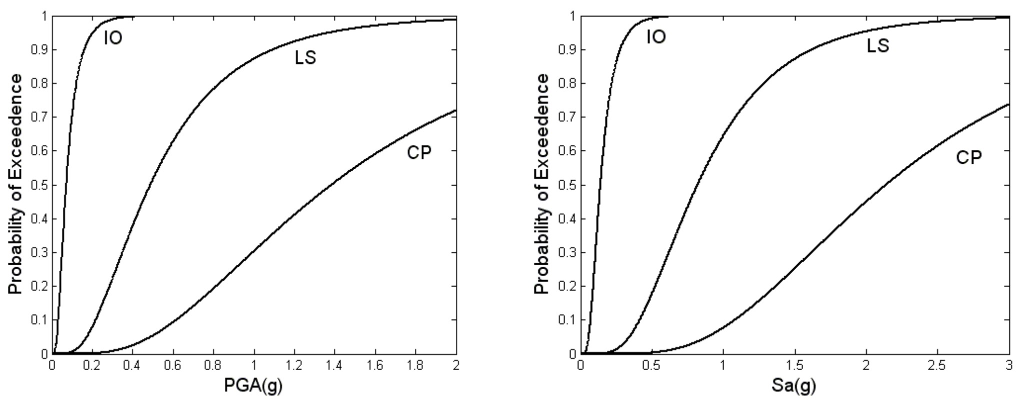


Fig. 2. Fragility curves for uncontrolled structure.

6. PROPOSED CONTROL STRATEGY

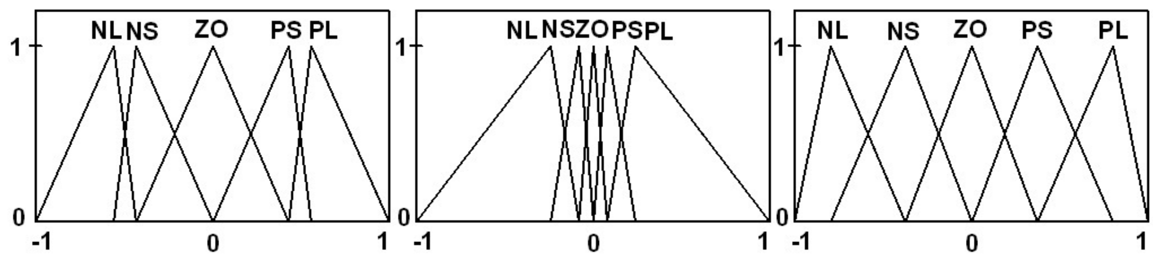
6.1 FUZZY LOGIC CONTROLLER (FLC)

In recent years, there has been a growing trend toward utilization of FLC [19-20]. Here, FLC is selected for control of the nonlinear structure because: (1) the ability to handle the non-linear behavior of the structures (2) the ability to tolerate the uncertainties (3) It is one of the few mathematical model free approaches for structural control. 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). In most cases, structure and parameters are determined by experts with a, knowledge of the system being analyzed. However, human experts cannot be expected to provide an optimal system. Often, a system is modified iteratively while trying to obtain optimality.

Here, the controller is designed using two input variables including velocity and displacement and one output variable including control force of each story of building. Each one of these three variables includes five membership functions. The membership functions chosen for the input and output variables are triangular shaped for its simplicity. Numerical inputs are normalized in the range [-1,1] for fuzzification. The point-valued MAX–MIN fuzzy inference method is chosen to combine the fuzzy IF–THEN rules in the fuzzy rule base into a mapping, from a fuzzy input set to a fuzzy output set. Fuzzy linguistic output inferred by fuzzy rules is converted to its corresponding crisp value in the range [-1,1] by the mean of centroid method. The fuzzy variables used to define the fuzzy space are described in Table 1. A genetic algorithm is employed to find optimum fuzzy control rules as well as to adjust the membership functions to minimize the maximum drift of stories. Fig. 3 shows the optimum inputs and output and Table 2 shows the optimum fuzzy rules found by the genetic algorithm.

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



Input (Displacement) **Input (Velocity)** **Output (Control Force)**

Fig. 3. Membership functions for inputs and output (active system).

Table ٢: Fuzzy associative memory (FAM) (active system).

D / V	*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. 4 shows fragility curves for uncontrolled and active fuzzy logic controlled structure. As it is obvious, FLC can reduce probability of damage significantly.

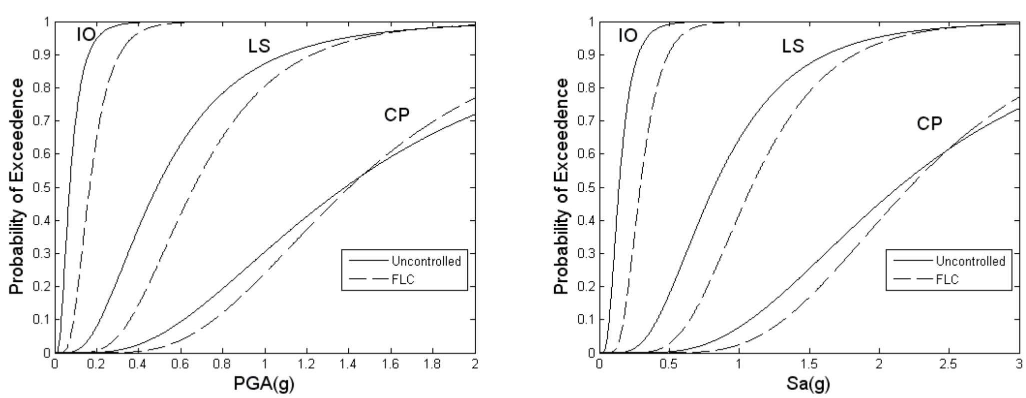


Fig. 4. Comparing fragility curves for uncontrolled and fuzzy logic controller.

6.2 FAULT DETECTION AND ISOLATION (FDI)

Many control studies have been performed based on the assumption that all states of the system can be measured. However, for the control of full scale civil engineering structures, displacements and velocities are difficult to obtain; because they are relative quantities and must be measured relative to a frame of reference. However, accurate and reliable absolute acceleration measurements can be readily obtained for a full scale structure.

Because in this study the displacements and velocities of stories are required, it is assumed which three accelerometers measure absolute accelerations of stories and one accelerometer measures absolute acceleration of the ground. By subtraction ground acceleration from absolute accelerations of stories, relative accelerations of stories are obtained. Then, displacement and velocity of each story are calculated through the integration of relative acceleration. Sensors of stories 1, 2, 3 and ground are known in this paper as sensors 1, 2, 3 and g, respectively.

For fault detection, two neural networks are used. The first NN uses the measurements of sensors 1 and g, and the second NN uses the measurements of sensors 3 and g. Each NN estimates the velocity of story 2. The actual velocity of story 2 is also obtained through the sensors 2 and g.

Here, it's assumed that among four sensors, only one sensor is faulty. The faulty sensor can't measure the acceleration and only noise is sent. The measurement noise is assumed to be identically distributed, statistically independent Gaussian white noise processes. During normal operation, all three measured and estimated velocity of story 2 are close to each other. If, for example, sensor 1 fails, the output of second NN and actual response of story 2 are still close, but the output of first NN is expected to differ. So, in this case, sensor 1 is detected as a faulty sensor. Sensors 2 and 3 faults are detected in an analogous manner. Sensor g is detected as a faulty sensor when all tree responses for velocity of story 2 are different.

As discussed above, the FDI strategy proposed in this paper requires two NN model of the structure. The first NN (second NN) calculates the velocity of story 2 based on the current and few previous histories of velocity and displacement of story 1 (story 3). These NNs are trained using input–output data generated analytically using the simulated structure under four ground motions. The sampling rate of the training data was 200 Hz for 80 s period, which resulted in 16000 patterns for training, testing, and validation.

6.3 FAUT ACCOMODATION

As discussed earlier, here, the NNs are used for fault accommodation. The purpose of these NNs is to receive notification regarding faulty sensor from the FDI and to accommodate fault in order to retain performance and effectiveness of the control system. The fault is accommodated by using data from the remaining healthy sensors to estimate what the faulty sensor should have been reading.

Here three NNs are used for fault accommodation. The first, second and third NNs calculate the velocities and displacements of stories 1, 2 and 3, respectively, based on the current and two previous histories of velocities and displacements of their adjacent stories. These NNs are trained using input–output data generated analytically using the simulated structure under four ground motions. 16000 patterns were used for training, testing, and validation. One hidden layer with twenty nodes was adopted for the NNs. The tansig activation function is used for the hidden layer and the linear function for the output layer, which represents the velocity and displacement.

As discussed above, when a sensor of stories 1, 2 or 3 is detected as a faulty sensor, the NNs are used to estimate the response of that story, but when the sensor g is detected as faulty sensor, estimating acceleration of the ground is difficult, if not possible. In this case, instead of relative accelerations between the stories and the ground, relative accelerations between the adjacent stories are used to control the structure.

Figs. 5-7 show fragility curves for the structure considering fault in sensors 1, 2 and g as an example. In these figs, solid lines show the fragility curves for the uncontrolled structure, dashed lines show the fragility curves for the structure including FLC and healthy sensors, dash-dot lines show the fragility curves for the structure including FLC and one faulty sensor and dotted lines show the fragility curves for the structure including FTC and one faulty sensor. As it's obvious, when the sensors are healthy, FLC can reduce the probability of damage compared with the uncontrolled structure, significantly. This reduction is more considerable in low intensities of ground motions. When a sensor faults, the controller can't work as well as before. In this case, the controller decreases the probability of damage in low intensities of the ground motions, but increases it in high intensities. Using the FTC can improve this deterioration associated with the sensor fault and decrease the probability of damage. In fact, the fragility curves of FTC are reasonably close to those obtained without the sensor fault.

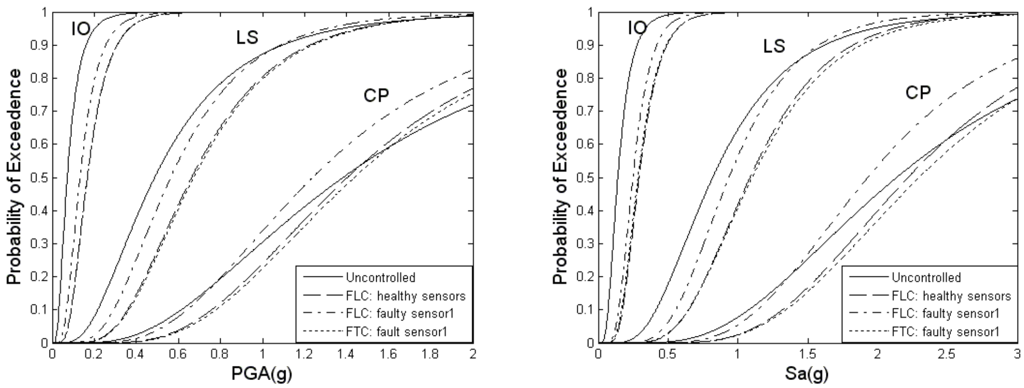


Fig. 5. Fragility curves for different controllers (fault can occur in sensor of story 1).

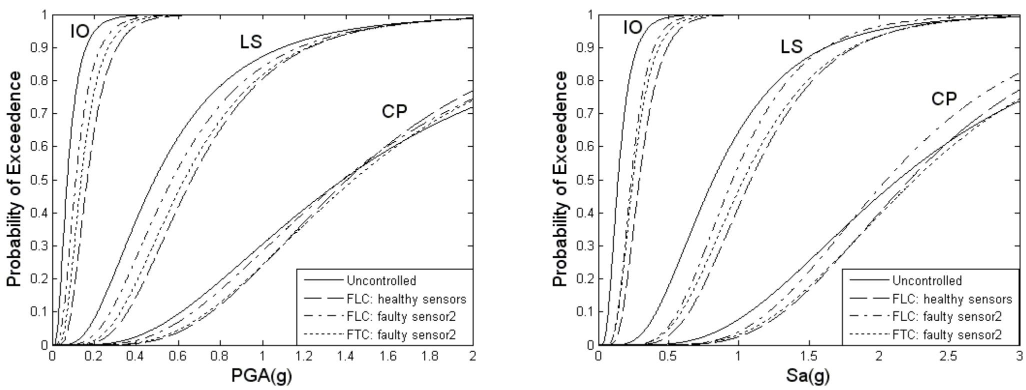


Fig. 6. Fragility curves for different controllers (fault can occur in sensor of story 2).

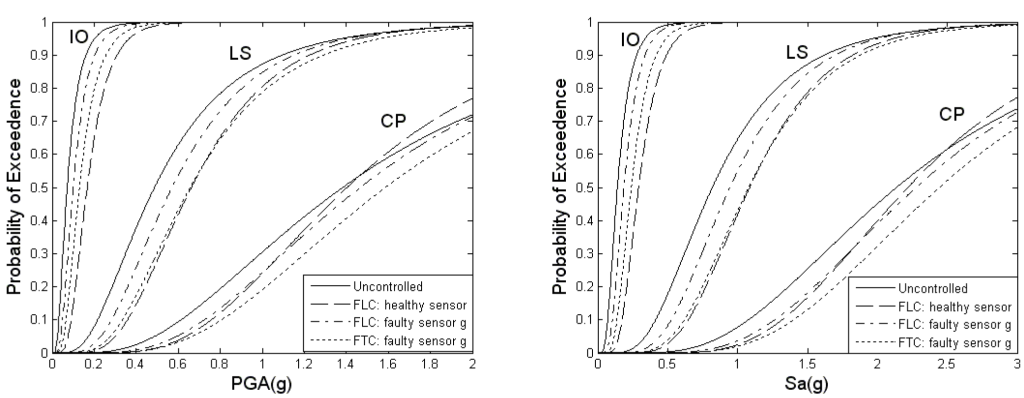


Fig. 7. Fragility curves for different controllers (fault can occur in sensor of ground).

7. CONCLUSION

This paper develops a fault-tolerant damage controller based on Artificial intelligence for accommodating sensor faults in nonlinear structures. The controller includes a fuzzy logic controller (FLC) which determined the control forces of actuators and neural networks for fault detection, isolation (FDI) and accommodation. Fault is detected through the comparing the relations among the system variables to find inconsistencies and is accommodated by using data from the remaining healthy sensors to estimate what the faulty sensors should have been reading. Performance of the proposed method is examined for a 3-story full-scale nonlinear benchmark building. To calculate the probability of damage, fragility curves are developed for the structure using 40 nonlinear dynamic time history analyses.

Results show that, when the sensors are healthy, the FLC can reduce the probability of damage, meaningfully. This reduction is more considerable in low intensities of ground motions. When the control system doesn't have the FDI architecture and a sensor faults, the controller can't work as well as before. In this case, the controller decreases the probability of damage in low intensities of the ground motions, but increases it, in high intensities. Adding The FDI architecture can rectify this deterioration and reduce the probability of damage for a wide range of intensities.

8. REFERENCES

[1] C. Seo, and B. Kim, "Robust and reliable h∞ control for linear systems with parameter uncertainty and actuator failure", Automatica, 32(3), pp. 465-467, 1996.
[2] C. Cheng, and Q. Zhao, "Reliable control of uncertain delayed systems with integral quadratic constraints", IEE Proceedings Control Theory Applications, 151(6), pp. 790-796, 2004.
[3] Y. M. Zhang, and J. Jiang, "An active fault-tolerant control system against partial actuator failures", IEE Proceedings C Control Theory and Applications 149(1), pp. 95–104, 2002.
[4] J. Jiang, and Y. M. Zhang, "Accepting performance degradation in fault-tolerant control system design", IEEE Trans. on Control Systems Technology 14, pp. 284–292, 2006.
[5] Z. Li, B. H. Koh, and S. Nagarajaiah, "Detecting sensor failure via decoupled error function and inverse input–output model", Journal of Engineering Mechanics, 133, pp. 1222-1228, 2007.
[6] L. Huo, G. Song, S. Nagarajaiah, and H. Li, "Semi-active vibration suppression of a space truss structure using a fault tolerant controller", Journal of Vibration and Control, 18(10), pp. 1436–1453, 2011.
[7] X. Zhang, Y. Liu, R. Rysdyk, et al., "An intelligent hierarchical approach to actuator fault diagnosis and accommodation", Aerospace Conference, New York, IEEE, 2006.
[8] H. Xue, J. G. Jiang, "Fault detection and accommodation for nonlinear systems using fuzzy neural networks", 5th International Power Electronics and Motion Control Conference, New York, IEEE, 2006.
[9] O-S. Kwon, and A. Elnashai, "The effect of material and ground motion uncertainty on the seismic vulnerability curves of RC structure," Engineering Structures, 28, pp. 289-303, 2006.
[10] J. E. Padgett, and R. DesRoches, "Methodology for the development of analytical fragility curves for retrofitted bridges," Earthquake Engng Struct. Dyn., 37, pp. 1157-1174, 2008.
[11] Y. Ohtori, R. E. Christenson, B. F. Spencer, and S. J. Dyke, "Benchmark control problems for seismically excited nonlinear buildings," Journal of Engineering Mechanics, 130 (4), pp. 366–387, 2004.
[12] P. Sommerville, N. Smith, S. Punyamurthula, and J. Sun, "Development of ground motion time histories for phase II of the FEMA/SAC steel project," SAC Background Document Report No. SAC/BD-97/04, 1997.
[13] L. R. Barroso, and S. Winterstein, "Probabilistic seismic demand analysis of controlled steel moment-resisting frame structure," Earthquake Engng Struct. Dyn., 31, pp. 2049-2066, 2002.
[14] P. Bazzuro, and C. A. Cornell, "Seismic hazard analysis of nonlinear structures I: methodology," Journal of Structural Engineering (ASCE), 120(11), pp. 3320-3344, 1994.
[15] E. Taylor, "The Development of fragility relationship for controlled structures," Masters Thesis, Washington University, St. Louis, Missouri, 2007.
[16] M. A. Erberik, and A. S. Elnashai, "Fragility analysis of flat-slab structure," Engineering Structures, 26, pp. 937-948, 2004.
[17] FEMA 356, Prestandard and commentary for the seismic rehabilation of buildings, Federal Emergency Management Agency, 2000.
[18] A. K. Kazantzi, T. D. Righiniotis, and M.K. Chryssanthopoulos, "Fragility and hazard analysis of a welded steel moment resisting frame," Journal of Earthquake Engineering, 12, pp. 596-615, 2008.
[19] L-Y. Lu, C-C. Lin, G-L. Lin, and C-Y. Lin, "Experiment and analysis of a fuzzy-controlled piezoelectric seismic isolation system," Journal of Sound and Vibration, 329, pp. 1992-2014, 2010.
[20] A. Karamodin, F. Irani, and A. Baghban, "Effectiveness of a fuzzy controller on the damage index of nonlinear benchmark buildings," Scientia Iranica A, 19(1), pp. 1-10, 2012.