

## APPLICATION OF NEURAL NETWORK IN RELIABILITY PREDICTION OF SEISMICALLY ISOLATED STRUCTURES SUBJECTED TO RANDOM GROUND MOTIONS

Hesamaldin MOEINDARBARI

PhD Candidate, Amirkabir University of Technology, Tehran, Iran hessammoeen@aut.ac.ir

Touraj TAGHIKHANY Assistant Professor, Amirkabir University of Technology, Tehran, Iran ttaghikhany@aut.ac.ir

Keywords: Neural Network, Reliability, Base Isolation, Friction Pendulum

Base isolation, as an advanced effective technology in seismic resistant design of structures, has attracted lots of engineers in recent decades. Using low stiffness equipment at the base of the building to elongate the period of vibration is the principle role of base isolation that leads to reduction of seismic force response of the super structure. Among different types of base isolator systems, Single Friction Pendulum Bearing (SFPB), a first generation of friction concave isolators, is one of the common systems that was invented by Zayas in 1986 (Zayas et al., 1990). It consists of a spherical concave sliding surface and a slider as an innovative bearing that exerts friction as supplemental damping.

Stochastic nature of variables such as input ground motion, directs designers to probabilistic analysis in structural dynamics applying structural reliability methods, and reliability based analysis. The main goal of reliability methods is to determine the probability of failure  $(P_{f})$  for a specific structure. Simulation based methods of reliability analysis is an effective tool to calculate the probability of failure for an isolated structure subjected to random earthquake excitations.

In this study a 2D three-story concrete frame building (Figure 1) isolated with FPS, representing critical facilities, such as a data center, is considered for the purposes of the simulation. The frame is previously designed for gravitational and lateral loads based on ACI 318-05.



Figure 1. 2D 3-story concrete frame used in the simulation, and its simplified model

The isolated structure is subjected to random excitation using artificial earthquake ground motion, generated through the superposition of a random ground velocity record with a single, coherent, long-period velocity pulse. In this process six random parameters play key role in the generation of the artificial acceleration signal that are: *D* distance to the hypocenter,  $S_v$  the desired peak of random ground velocity,  $f_g$  frequency parameter,  $\zeta_g$  ground motion damping,  $V_p$  peak pulse

velocity and  $T_p$  which is the period of pulse (Seed and Idriss 1982).

For reliability analysis, due to the large uncertainty of input ground motion, the parameters of structure assumed to be deterministic.

The probability of failure or limit state probability for this system is calculated using a limit state function which is defined as the case where the facility floor accelerations reach a 100 milli-g acceleration level. Acceleration levels in the range of 100–200 milli-g are specified by computer producers for sensitive computers as the limit where they fail to operate (Alhan and Gavin, 2005). This can be formally stated with the limit state function as below:
(1)

$$g(X) = 100 - |a_i|$$

Where  $a_i$  is the peak acceleration of the  $i_{th}$  floor with facility installed, in milli-g. Then the probability of failure is:

$$P_f = P[g(X) \le 0]$$

For complex systems and for cases where it is difficult to obtain the joint probability distribution function, the probability of failure is evaluated via Monte Carlo simulation by determining the number of realizations with  $g(X) \le 0$  and dividing that number by the total number of simulations.

The probability of failure for a particular set of structure and isolation parameters was calculated using Monte Carlo Simulation at first. Then a set of neural networks were trained to predict the peak responses of the structure. Six random parameters of artificial earthquake ground motion were assumed to be the input variables of neural networks. The probability of failure was calculated again, using neural networks. The results show a good compatibility to the ones calculated using time history structural analysis. Figure 2 shows the comparison of probability of failure calculated by structural analysis and neural networks for the above mentioned structure. The radius of curvature of FPS is 1.5 meter and the friction coefficient assumed to be 0.05 for this case. The probability of failure  $(P_f)$  is calculated for both stories that the facilities are installed (Story 1 and 2).



Figure 2. Comparison of  $P_{e}$  calculated using neural networks and direct time history structural analysis

## REFERENCES

Alhan C and Gavin HP (2005) Reliability of base isolation for the protection of critical equipment from earthquake hazards, *Engineering Structures*, 27(9):1435-1449

Seed HB and Idriss IM (1982) Ground motions and soil liquefaction during earthquakes, Vol. 5: Earthquake Engineering Research Institute Berkeley

Zayas VA, Low SS and Mahin SA (1990) A simple pendulum technique for achieving seismic isolation, *Earthquake Spectra*, 6(2): 317-333



(2)