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PEAK GROUND ACCELERATION PREDICTION FOR CRITICAL AFTERSHOCKS

Elham RAJABI
Postdoctoral Fellow, Center of Excellence for Fundamental Studies in Structural Engineering, School of Civil Engineering, University of Science and Technology, Tehran, Iran
elhamrajabi674@gmail.com

Gholamreza GHODRATI AMIRI
Professor, Center of Excellence for Fundamental Studies in Structural Engineering, School of Civil Engineering, Iran University of Science and Technology, Tehran, Iran
ghodrati@iust.ac.ir

Vida GHASEMI
Research Assistant, School of Civil Engineering, Iran University of Science and Technology, Tehran, Iran
vida.ghasemi62@gmail.com

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Today, most structures are designed according to the modern seismic codes which only apply a single earthquake on the structure in the analysis and design process. In this case, the structures may damage in the event of the "Design earthquake", and this single seismic design philosophy does not take the effect of strong successive shocks on the accumulated damage of structures into account. Because aftershocks have the strong potential to cause additional cumulative damage to structures that have been already damaged by the preceding shock and threaten life safety even when only minor damage is present from the main shock. Since, the damage induced to structures from preceding main shocks, leads to degradation in structural parameters of the frame system, especially in stiffness and strength (Abdelnaby, 2018), the majority structures in the recent consecutive earthquakes that occurred in Kermanshah (2017), Nepal and Hindu-Kush (2015) tolerated accumulated damages under major successive shocks, and thousands of people died. Hence, it is essential to achieve the adequate identification of successive earthquake features in the structural analysis. Because the use of successive scenarios with unsuitable characteristics could lead to non-conservative predictions of structure response and behavior (Zhang et al., 2017).

This paper proposes a methodology using learning abilities of artificial neural networks in order to predict the peak ground acceleration of critical aftershocks based on the features of successive earthquakes. At first, a set of recorded consecutive earthquakes which has been contained critical main shocks and aftershocks is selected based on effective peak acceleration (EPA) from "PEER" and "USGS" centers. Consecutive earthquakes not only occurred in similar directions and same stations, but also their real time gaps between successive shocks are less than 10 days. In the following, the idealized multilayer artificial neural networks, with the least value of mean square error (MSE) and maximum value of regression (R) between outputs and targets were designed and trained to estimate the peak ground acceleration of critical aftershocks. In this regard, two-layer feed-forward (MLFF) neural networks (Figure 1) are used.

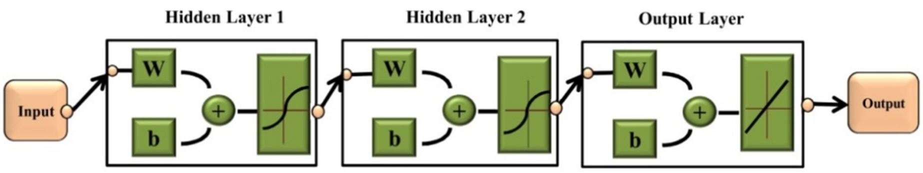

Figure 1. Schematic of studied artificial neural networks.

In these networks, the weight matrix is achieved through applying the back-propagation error training method which is employed for modifying the weights and biases. Since networks have biases, the sigmoid layers and a linear output layer are capable of approximating any function with a finite number of discontinuities, input vectors, and the corresponding target vectors are used to train a network until it can find the relationship between inputs and target, classify the inputs and approximate a function for them (Hagan, 2014). In the design of neural networks, the magnitudes of the main shock and aftershocks (M_m and M_a, respectively) and main shock PGA (PGA_m) are selected as inputs, and aftershock PGA (PGA_a) is introduced as target data to the neural network with the characteristics mentioned in Figure 1. Statistical properties of input and target data are shown in Table 1.

Table 1. Statistical properties of input and target data.

No.	Node	Minimum	Maximum	Average	Standard deviation
1	PGA_m	0.0242	1.6615	0.3042	0.3096
2	M_m	4.79	6.69	5.905	0.4086
3	M_a	4.37	6.05	5.53	0.3864
4	PGA_a	0.0229	0.6293	0.1591	0.1232

The optimal numbers of neurons in the first and second layers are 8 and 20, respectively. The average error for predicting the real PGAs is less than 10%. In other words, more than 80% of the simulated PGAs are within ±10% of the real values. Error distribution of the predicted values relative to the real values is shown in Table 2.

Table 2. Error distribution of predicted values relative to real values.

Range of error	± 5%	± 9%	± 15%	± 30%
Percentage to total data	42%	80%	86%	91%

According to Figure 2, the correlation coefficient between actual and estimated PGAs is more than 90.5%. This is also an indication that the network has learned to generalize the unseen information very well and reflects good precision in the simulation. In fact, the simulated aftershocks with larger PGAs are much less than those of the real aftershocks. A simulated aftershock with a PGA larger than that of a real aftershock can probably cause more cumulative damages to structures that have been already damaged by the preceding shock.

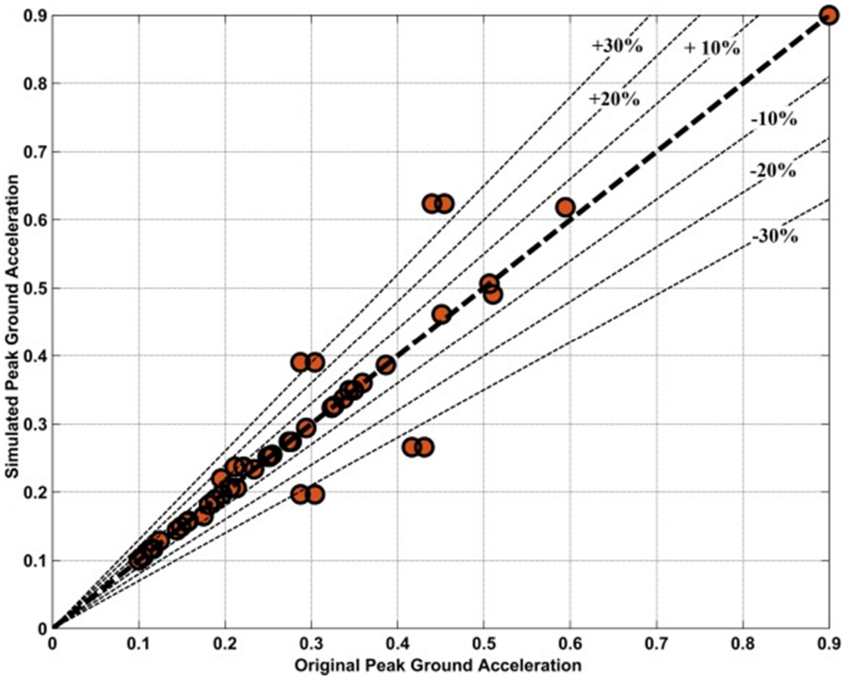

Figure 2. Comparison of predicted peak ground acceleration versus Original's.

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