Improved Rapid Assessment of Earthquake Hazard Safety of Structures via Artificial Neural Networks

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Abstract.
The vulnerability of structures mainly depends on the structural resistance system of buildings to earthquake. It is unlikely that all existing buildings can be inspected in detail. Therefore, rapid methods for evaluating buildings have been developed over the last decades. This paper investigates the earthquake susceptibility through the combination of buildings’ geometrical attributes that affect the vulnerability of building and can be used to obtain an optimal prediction of the damage state of reinforced concrete (RC) buildings using artificial neural networks (ANNs). In this regard, a multi-layer perceptron (MLP) network has been trained and optimized using a database of 145 damaged buildings from the Haiti earthquake. The results demonstrate the practicability and effectiveness of the selected ANNs approach to classify actual structural damage that can be used as a preliminary assessment procedure to recognize vulnerable buildings.

1 Introduction

In developing countries, there is a large amount of vulnerable buildings that are to be required for detail earthquake hazard safety evaluation. For instance, in Istanbul-Turkey as a high seismic area, around 90% of buildings are substandard, which can be generalized into other earthquake-prone regions in Turkey [1]. Therefore, it is essential to assess the seismic risk and vulnerability of buildings in urban areas as a primary parameter of the earthquake disaster management policy. Identifying most vulnerable buildings by visual inspection would reduce the time and cost of detailed evaluation. The term "seismic vulnerability" is defined as "the susceptibility of a population of buildings to undergo damage due to seismic ground motion" [2]. Rapid Visual Screening (RVS) is the simplest method among other vulnerability assessment methods, performing necessary structural estimates for quick evaluation of a large building stock [3]. Nevertheless, more detailed analysis might provide a better assessment, but such an approach would entail complicated challenges when an urban scale mitigation campaign is considered. This study introduces a method for improving rapid vulnerability assessment by considering only the RC buildings. For the applicability of the proposed methodology, Haiti, a Caribbean country, which is in a highly active seismic region and has experienced a severe earthquake recently, has been selected.

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2 Rapid Visual Screening methods

RVS has been widely used in seismic countries as a practical and simple tool for evaluating the vulnerability of buildings; therefore, this challenge is in the interest of many researchers and still is under developing and improving. In this manner, some efforts have been made to develop national RVS for U.S.A (FEMA 154)[4], India (IITK-GSDMA)[5], Turkey (EMPI)[6], Italy [7], Japan (JPDPA) [8], Philippine [9]. Some practical comparisons between different national RVS methods have been carried out, and their efficiency and robustness have been discussed [10–12]. Other than national and local RVS methods, different proposed methods are popular to use. For instance, an assessment method proposed by Hassan and Sozen [13] for RC buildings, priority for remedial action is manifested in terms of a Priority Index (PI) acquired by adding wall and column indices. Wall index is obtained by normalizing the total area of shear walls and infill walls with the total floor area of the building. Likewise, the column index is achieved by normalizing the total column area with the total floor area. Thus, the method is primarily based on two parameters, the total wall area and the total column area besides the total floor area. Additionally, there are many other RVS methods developed by using linear regression [14–16], Multi-criteria decision making [17], Fuzzy logic [18–20], change detection via images [21], or some other methods concerning their consideration and experiences on a region or country [22]. Still, each of them is based on the expert’s opinion, uncertainties, or assumed the linear relationship between parameters. By implementing neural networks, it might get rid of most of the vagueness and uncertainties because the neural networks can compute any function and relationship between variables.

3 Data Collection

In January 2010, a catastrophic earthquake with the magnitude $M_w=7.0$ occurred in Haiti. Many of the buildings were damaged, and many more rendered unstable [23]. In this study, a database of 145 damaged RC buildings suffered from the Haiti earthquake has been used from the open-access data on the Datacenterhub platform [24]. The observed structural damage has been classified into four damage grades, as shown in Table 1. Figure 1 illustrates the distribution of damage of the buildings investigated where most of the buildings have severe damage after the earthquake and no building collapsed. Some of the parameters used in this study which are presented in Table 2, are also the basis of the Priority Index proposed by Hassan [13], and this preference was due to the following grounds:

- Their effect has been examined and calibrated for use with structures that do not meet the code requirements for high earthquake risk areas
- They have been tested in areas with different construction practices, and it makes it applicable for different regions
- The required parameters are easy and visible to collect, which leads to less vagueness for investigators

4 Application of Artificial Neural Networks to the data

Artificial Neural Networks (ANNs) use their ability to predict future events using historical data of similar events that happened in the past. Traditional RVS methods use a form completed during an observational study of the building. These methods do not use additional data to predict the building vulnerability in case of earthquake events. Therefore, these methods are subjective to the expert that visit the building and subject to human errors. However,
Table 1: Damage distribution of the investigated buildings

| Damage grade | Extent of damage to buildings | Description of damages                        |
|--------------|------------------------------|-----------------------------------------------|
| 1            | Light                        | Hairline inclined and flexural cracks were observed in structural elements |
| 2            | Moderate                     | Wider cracks or spalling of concrete was observed |
| 3            | Severe                       | At least one element had a structural failure  |
| 4            | Collapse                     | At least one floor slab or part of it lost its elevation |

Table 2: Independent vulnerability predictors

| Predictor                | Unit  | Type     | Variable |
|--------------------------|-------|----------|----------|
| No. of Storey            | N     | Quantitative | $X_1$   |
| Total Floor Area         | $m^2$ | Quantitative | $X_2$   |
| Column Area              | $m^2$ | Quantitative | $X_3$   |
| Concrete Wall Area (Y)   | $m^2$ | Quantitative | $X_4$   |
| Concrete Wall Area (X)   | $m^2$ | Quantitative | $X_5$   |
| Masonry Wall Area (Y)    | $m^2$ | Quantitative | $X_6$   |
| Masonry Wall Area (X)    | $m^2$ | Quantitative | $X_7$   |
| Captive Columns          | $N$   | Dummy    | $X_8$   |

using ANNs help to improve these methods by considering data of the previous earthquake in the prediction of building states after any earthquake events. The advantage of these methods is that they are swift and reliable if existing data be sufficient for training an ANNs. A multi-layer feedforward neural network, which is called a multi-layer perceptron (MLP), is used to predict the building state after an earthquake. The network was trained by 115 buildings using a k-fold cross-validation method, and the rest 30 of buildings remained for the test. Three-layered (input layer, hidden layer, and output layer) feedforward multi-layer perceptron (MLP) was used and trained with the error backpropagation algorithm. The MLP architecture presented in Figure 2. The implementation of the model is carried out using Scikit-learn as it is the well-maintained, comprehensive, and open-sourced machine learning package in Python programming language.
5 Results and discussion

K-fold cross-validation (K=10) was performed to confirm the accuracy of the classification procedure during training procedures. A test dataset of 20% (30 buildings) was held to estimate the generalization capability of the proposed network. The hyper-parameter values of MLP model have been shown in Table 3. A 3-layer MLP (1 Hidden layer) trained with Adam solver and adaptive learning rate with 2000 iteration and 0.01 alpha. Two multi-class metrics have considered to evaluate model performance as a dataset is a multi-class dataset. These are balanced-accuracy (with class-balanced sample weights) and receiver operating characteristics (ROC). ROC curves typically feature a true positive rate on the Y-axis and false positive rate on the X-axis. It means that the top left corner of the plot is the “ideal” point, which means that a larger area under the curve (AUC) is usually better. Table 4 demonstrates the accuracy of the model for training and test dataset. Table 4 illustrates that the model reached an accuracy of 0.56 (or 56%) on the test dataset. Figures 3 to 5 show more details for each class based on the confusion matrix and also the ROC curves of training and test samples. From Figure 4, it is clear that the model can fit the trained data. However, as can be seen in Figure 5 for test data, the model has poor performance in class 1, which means that it cannot handle this class properly in compare to other classes. As it has been observed from the confusion matrix, most of class 0 categorized as class 2, which means that the feature of the building of light class is near to the feature of building in severe class. However, the model is fine for class 1 and class 2, where most of the buildings correctly classified. Figure 5 shows ROC of test dataset. According to this figure, class 1 has AUC of 0.72, which is the lowest AUC within all classes. Figure 5 also illustrates that the micro-average AUC is 0.77, which is a good AUC for such a small dataset. According to Table 4 and Figures 3, 4 and 5 it can be concluded that the model have high ability of classifying light and collapse buildings. Nevertheless, it suffers from classifying moderate building, which is not in high priority in case of rapid assessment where the most important buildings are buildings subject to severe damage or collapse during an earthquake.

Table 3: Hyper-parameter Values

| Hidden Layer sizes | Activation Function | Solvers | Alpha | Maximum Iteration | Learning Rate |
|--------------------|---------------------|---------|-------|-------------------|---------------|
| 10                 | Relu                | Adam    | 0.01  | 2000              | Adaptive      |
Table 4: Accuracy of the model on train and test dataset

| Class | Accuracy of train dataset | Accuracy of test dataset |
|-------|---------------------------|--------------------------|
| Class 0 | 0.76                      | 0.55                     |
| Class 1 | 1.00                      | 0.75                     |
| Class 2 | 0.98                      | 0.85                     |

- **Figure 3.** Confusion matrix of the test data (class 0: Light, 1: Moderate, and 2: Severe)

- **Figure 4.** ROC of training dataset for all classes (class 0: Light, 1: Moderate, and 2: Severe)

- **Figure 5.** ROC of test dataset for all classes (class 0: Light, 1: Moderate, and 2: Severe)

6 Conclusion

In this paper, a practical framework for the Improvement of Rapid Assessment of Earthquake Hazard Safety of structures via Artificial Neural Networks termed shortly IRAEHSAN within the application of eight performance modifiers, has been demonstrated. It must be mentioned that the accuracy of the study depends on the sample buildings chosen, the calculation methods, and the parameters that are present during the ANNs instruction and testing processes; however, in future studies, more data can be used. The method shows its robust ability to classify buildings into light and severe. However, it is weak to classify buildings accurately into moderate damage, which is not in high priority in the case of rapid assessment, where the most important buildings are buildings subject to severe damage or collapse during an earthquake. The proposed method helps to manage and implement strategies for the safety of the communities before an earthquake strike by investigating the vulnerability classes for each building and identifying highly vulnerable buildings that deserve further inquiry.
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