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Seismic reliability assessment of structures using artificial neural network

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ABSTRACT

Localization and quantification of structural damage and estimating the failure probability are key outputs in the reliability assessment of structures. In this study, an Artificial Neural Network (ANN) is used to reduce the computational effort required for reliability analysis and damage detection. Toward this end, one demonstrative structure is modeled and then several damage scenarios are defined. These scenarios are considered as training data sets for establishing an ANN model. In this regard, the relationship between structural response (input) and structural stiffness (output) is established using ANN models. The established ANN is more economical and achieves reasonable accuracy in detection of structural damage under a set of ground motions. Furthermore, in order to assess the reliability of a structure, five random variables are considered. These are columns' area of the first, second, and third floor, elasticity modulus, and gravity loads. The ANN is trained by suing the Monte Carlo Simulation (MCS) technique. Finally, the trained neural network specifies the failure probability of the proposed structure. Although MCS can predict the failure probability for a given structure, the ANN model helps simulation techniques to receive an acceptable accuracy and reduce computational effort.

1. Introduction

The main reason for structural failure is a sudden damage. In the past decades, special attention was given to avoid the unexpected failure of structural components by damage detection in structures in the early states. To this end, in recent years, various developments of non-destructive techniques based on changes in the structural responses have been widely published. They can not only detect the presence of damage but also identify the location and quantification of it. Additionally, the dire need to detect the presence of damage in complex structures and infrastructures in the early stages has led to the increase of non-destructive techniques and new developments [1–3]. During the past decades, many types of research have been studying to propose different and efficient techniques. Friswell [4] presented a brief overview of the use of inverse methods in damage detection and location from response data. A review based on the detection of structural damage through changes in frequencies has been discussed by Salawu [5]. However, in the presence of complex structures, many of them are not applicable. Therefore, the methods that are much more economical to achieve reasonable accuracy are always required. In recent years, there has been a growing interest in using artificial neural networks (ANNs), a computing technique that was supposed to work in a way similar to that of biological nervous systems; however, nowadays, we know biological nervous systems are far more complicated than ANNs. By the way, a large number of studies corroborate this idea that in spite of simplicity, ANNs are a fruitful approach to solving the problems. Many researchers [6,7] used ANN to study a beam using multilayer perceptron (MLP) ANN. Furthermore, another application of ANN is to the evaluation of the failure probability and safety levels of structural systems. Bakhshi and Vazirizade [8] used a radial network in order to predict the stiffness of each member in a frame according to its response to a record. Although the ground motion records can be reduced [9], the full-length records have been used.

In fact, they showed ANN can provide a mapping from the maximum story drifts to column stiffness. Gomes et al. [10] and Bucher [11] used ANN for obtaining the failure probability for a cantilever beam and compared ANN with other conventional methods. They found that ANN methods that approximate the limit state function may decrease the total computational effort on the reliability assessment, but more studies, including large systems with non-linear behavior, must be conducted. Elhewy et al. [12] studied the ability of ANN model to predict the failure probability of a composite plate. They compared the performance of the ANN-based RSM (Response Surface Methods) (ANN-based FORM and ANN-based MCS) with that of the polynomial-

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based RSM. Their results showed that the ANN-based RSM was more efficient and accurate than the polynomial-based RSM. It was shown that the RSM may not be precise when the probability of failure is extremely small; and the RSM requires a relatively long computation time as the number of random variables increases [13,14]. Zhang and Foschi [15] employed ANN for seismic reliability assessment of a bridge bent with and without seismic isolation, but in that case they used explicit limit states. However, most of them utilized explicit and approximate limit states and more focused on the reliability assessment of components by ANN. In this regard, this study is focused on two separate parts; (1) localization and quantification of structural damages using ANN; (2) seismic reliability assessment of one steel structure using ANN-based MCS.

2. Artificial neural network (ANN)

Artificial neural networks are comparatively crude electronic models. The advances in biological research promise an initial understanding of the neural thinking mechanism [16]. The basic network includes nodes and connections, which link the nodes. Each link and node are related to a weight and bias properties, respectively, which are the principal mechanism by which a network stocks information. Before a neural network can approximate complex unities, it has to be trained for the specific problem by adjusting these weights and biases. One of the most widely used network types for approximation is the feed-forward multi-layer Perceptron (MLP) trained by the back-propagation algorithm. Fig. 1 shows this schematic network type which is used in this study. This network consists of an input layer, one hidden layer, and an output layer. The input and output layers contain three and two neurons, which means three and two sets of data for input and output, respectively.

A neuron from the hidden layer is shown in Fig. 2 with three inputs. Each input is weighted with an appropriate w. The sum of the weighted inputs and the bias forms the input to the transfer function. Transfer function prepares the data for the next layer. In this figure, the next layer is the output layer which contains two neurons.

The following equation simulates the mathematical relations between inputs and outputs in a network.

$$a^j{}_i = f(x) = f\left(\sum_{k=1}^{m} w^j{}_{k,i} a^{j-1}{}_k + b^j{}_i\right) \tag{1}$$

where a_i^j is the output value of ith neuron in the jth layer, which is sent to the $j+1$th layer. $a^{j-1}{}_k$ is the output value of kth neuron in the $j-1$th layer, which is sent to the jth layer. m is the number of data as inputs or the number of neurons in the j-1th layer, i is the number of the current neuron in the jth layer.$w^j{}_{k,i}$ is the synaptic weight factor for the connection of the neuron i in the jth layer with the neuron k in the j-1th layer. b^j_i is the bias value of ith neuron in the jth layer, and f is the transfer function. For the input layer j can be considered zero and m for

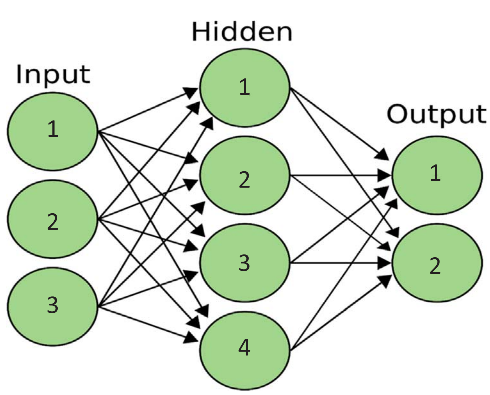

Fig. 1. Schematic structure of an artificial neural network.

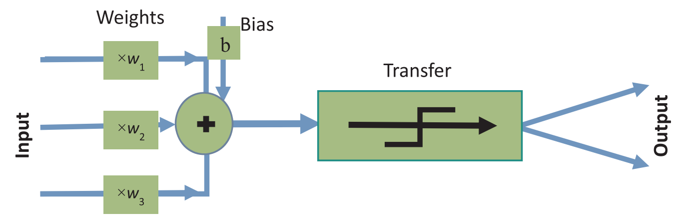

Fig. 2. Schematic neuron from the hidden layer.

this layer mean the number of network inputs. Subsequently, m for the last layer – output layer – is the number of output data of the network.

It is mentioned [17] that the number of training samples n should be larger than the number of adjustable parameters.

$$(m + 2)M + 1 < n \tag{2}$$

where m is the number of input values and M is the number of hidden neurons for a network with a single hidden layer. This leads to a much smaller number of required samples compared to RSM for high-dimensional problems if the number of hidden neurons taken is not too large. In Ref [18]. two other approaches are discussed to avoid over-training for a large number of hidden neurons and a small number of training samples: regularization and early stopping. For further details on ANN [19,20] can be referenced.

3. Methodology and ground motion record selection

In this study, a 3-story steel frame building is modeled by Open System for Earthquake Engineering Simulation Software (OpenSees) [21], Fig. 3. The steel constitutive behavior is modeled using the elastic-perfectly plastic steel model. The initial design of all stories for columns and beams is the same. In this study, a set of twenty earthquakes selected from FEMA440 [22] recorded on Site Class C, are used. These ground motion records are listed in Table 1. The analyses have been done for the set of ground motions and the mean and 95% confidence interval is computed.

3.1. ANN model for damage detection

In order to find the location and quantification of damages in the interested structure, two different data sets are considered; (a) 64 different damage scenarios—4 scenarios for each story—(b) 729 different damage scenarios—9 scenarios for each story. It is noteworthy that these damage scenarios are based on damages in the columns, which are presented as cross section reduction. The initial area of each

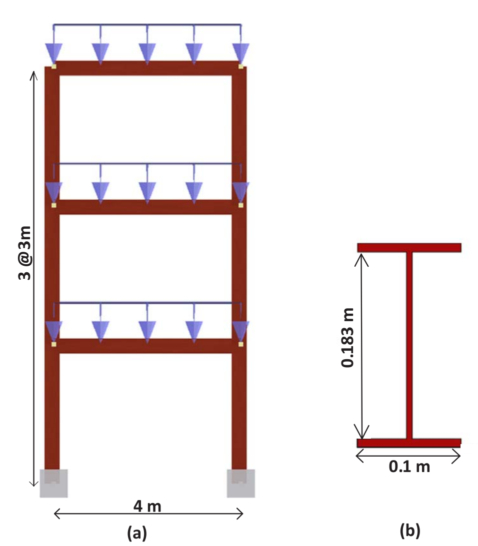

Fig. 3. a) Overview of the three-story frame b) Cross section of columns.