SEISMIC DAMAGE ASSESSMENT TO CIVIL STRUCTURES USING ANN

LALIT KUMAR 1*, Dr. MOHAMMED ARIF 2*

1. Research Scholar, Dept of CIVIL, AMU, Aligarh, UP.
2. Prof, Dept of CIVIL, AMU, Aligarh, UP.

Abstract:

Damage to structure may be caused as a result of accidents, deterioration or severe natural event such as earthquake and storms. Sometimes the extent and location of damage can be determined through visual inspection. But visual inspection technique has a limited capability to detect damage, especially when damage lies inside the structure and is not visible. So an effective and reliable damage assessment methodology will be a valuable tool in timely determination of damage and deterioration state of structural member. Damage identification plays an important role in structural health monitoring systems. Despite variety in damage identification methods, little attention has been paid to the seismic damage identification of foundations. When shear walls serve as the lateral load resistance system of structures, foundations may subject to the high level of concentrated moment and shear forces. Consequently, they can experience severe damage. Since such damage is often internal and not visible, visual inspections cannot identify the location and the severity of damage. Therefore, a robust method is required for damage localization and quantification of foundations.

Introduction

In recent years a significant amount of effort has been devoted to damage assessment schemes based on analysis of measured responses of the structure before and after damage. Sanayei and Onipede1 used static displacement to find damage under applied loads. In a truss model damage is introduced by reduction of cross-sectional area. Pandey et al.2 utilized curvature damage factor to find damage of cantilever and simply supported beam structure. Wu et al.3 used the pattern matching capability of a neural network to recognize the location and the extent of individual member damage from the measured frequency spectrum of the damaged structure.

In recent decades, Structural Health Monitoring (SHM) has opened its way toward new generation of non-destructive tests. Damage detection algorithms, as an important part of SHM systems, have caught researchers’ attention. Despite variety in damage identification methods, most of them have concentrated on the damage detection of specific structural elements like columns and beams and little attention has been paid to the seismic damage identification of foundations.

Generally, foundations serve as an element that transmits loads from the vertical components to the supporting soil. When shear walls serve as the lateral load resistance system of structures, foundations may subject to the high level of concentrated moment and shear forces in such cases, foundations can experience severe damage. Since damage of foundations often is not visible, visual inspections cannot identify the locations and the severity of damage. Therefore, a promising method for seismic damage detection of foundation is required.
According to the concept of performance-based seismic design of structures, the seismic behavior of foundations is considered as Force-Controlled. Therefore, for seismic damage identification of foundations seismic-induced internal forces should be estimated and compared with the capacity of elements.

Application of ANN (artificial neural networks) for damage detection of civil engineering structures covers vast variety of subjects. Neural network for damage detection of a cracked column. The natural frequencies of the cracked column were selected as input data sets for a neural network while the patterns of crack sizes and locations were selected as output data sets.

The obtained results from the trained neural network showed that the back-propagation neural network (BPNN) was a useful tool for prediction of crack size and location. Jeyasehar and Sumangala used neural networks for damage assessment of prestressed concrete beams. They used the natural frequencies of damaged beams to identify damage.

They showed that the trained neural network was able to estimate the damage size with less than 10% error. In another research, Yun et al. employed a BPNN for damage assessment of steel beam-column connections.

They found that by using the proposed approach joints damage could be detected reliably. Mehrjoo et al. employed neural network for joint damage detection of a truss bridge. They used natural frequencies and mode shapes as input parameters for a neural network. Joint damage was introduced to the bridge by reducing the area of cross sections of elements that were linked into the joints. The obtained results from numerical examples demonstrated the applicability of the proposed methods for damage identification of large structural systems.

**Research Methodology**

Artificial neural network (ANN) can effectively deal with qualitative, uncertain, and incomplete information, thereby making it highly promising for detecting structural damage, as most of the in situ measured data of large civil engineering structures such as buildings and bridges are not precise and often incomplete. A robust damage assessment methodology must be capable of recognizing patterns in the observed response of the structure resulting from individual member damage, including the capability of determining the location and extent of damage. This capability is within the scope of the pattern matching capabilities of ANNs.

The utilization of these capabilities in damage assessment is the basis of study described here. In the present study, ANNs are used to extract and store the knowledge of the patterns, which is the response of the undamaged and damaged structure. Thus the need for construction of mathematical models and comprehensive inverse search is avoided.

Artificial Neural Networks are known as a promising tool for pattern recognition. In this study, this capability of neural networks was employed for seismic damage detection of foundations. At first, the FE (finite element) model of the selected structure was created. Then, several NTH (nonlinear time history) analyses were carried out and the critical locations of the foundation of the selected structure were identified. Then, a BPNN was trained in order to monitor the variation of moments and shear forces demands at the critical locations. The displacements of stories were considered as the input parameters for the neural network.

Moreover, moment and shear force demands at critical locations were taken into account as output parameters. By using the results of NTH analysis, well-distributed data sets were created and used for training the neural network. In order to test the generalization ability of the trained neural network, additional NTH analyses were carried out and the predictions of the neural network for the unseen data sets were compared with targets.
ANNs form a class of systems that are derived from biological neural networks. ANN is a framework consisting of many number of neuron like processing units. Each neuron is simulated by the sum of the incoming weighted signals and transmits the activated response to the other connected neuron units. Such a network represents an efficient and parallel computational entity and will reflect the level of simulations by different input signals. The dynamic weights, which connect neurons of different layers, are continuously modified during the process of learning.

The back-propagation algorithm uses this information to adjust the weights such that a “mean square” error is minimized. Rumelhart et al.8 provided an excellent algorithm that allows the multi layer neural network to internally organize itself to be able to reconstruct the presented patterns. This method leads to the recent most popular neural network learning scheme called the Error Back Propagation.

CASE STUDY

A building is Selected of five-story concrete shear wall building that settles on a mat foundation with the thickness of 65 cm. Fig. 1 shows the typical plan of stories and the foundation plan of the selected building. The thickness of shear walls for the first three stories is 40 cm and for the rest is 35 cm. Longitudinal reinforcement ratios of shear walls along the height of the building are tabulated and presented in Tables 1. Table 2 displays the reinforcement ratios and the size of columns. The size of beams for all stories in the X direction is 32×20 cm, while in the Y direction is 42×20 cm. Furthermore, the diaphragms of stories consist of a two-way concrete slab with the thickness of 12 cm.

Table 1  Longitudinal rebar ratio of concrete shear walls (%).

<table>
<thead>
<tr>
<th></th>
<th>Wall 1</th>
<th>Wall 2</th>
<th>Wall 3</th>
<th>Wall 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>1st Story</td>
<td>1.7</td>
<td>1.2</td>
<td>2</td>
<td>1.8</td>
</tr>
<tr>
<td>2nd Story</td>
<td>1.3</td>
<td>0.5</td>
<td>1.3</td>
<td>1.4</td>
</tr>
<tr>
<td>3rd Story</td>
<td>0.5</td>
<td>0.5</td>
<td>0.5</td>
<td>0.6</td>
</tr>
<tr>
<td>4th &amp; 5th Stories</td>
<td>0.5</td>
<td>0.5</td>
<td>0.5</td>
<td>0.5</td>
</tr>
</tbody>
</table>

Fig. 1 Stories typical plan and foundation plan.
In this study, two multi-layer neural networks were trained to map the input data sets to the output data sets. The first neural network was trained to monitor moment demand at the critical locations while the second neural network was used to monitor shear force demand at the critical locations. However, the output layers of the first and second neural networks had two nodes that represented the moment and shear forces at two different locations respectively. In addition, by using trial and error method, it was found that, when twenty neurons were considered in the hidden layer of the neural networks the best performance was obtained.

The neural networks were trained by Levenberg-Marquardt back propagation algorithm. In addition, a hyperbolic tangent was used as the transfer function. From the NTH analyses, totally 4,408 data sets were obtained. All data sets were scaled before feeding to the neural networks. The scaling transformed data sets into a range of [-1+1]. The neural networks were trained using 70 percents of the data sets. The rest of data sets were equally assigned to validation and testing samples.
After training the networks, the correlation between targets and the predictions of the neural networks were calculated. The obtained results showed that the correlation factors ($R^2$) for the first and second neural networks were 0.97 and 0.98 respectively. The strong correlations between predictions and targets imply that the trained neural networks successfully estimate moment and shear force demands.

**Testing the Trained Neural Networks for Unseen Data Sets**

In order to make sure that the trained networks can generalize their outputs to the unseen data sets, additional NTH analyses were carried out. Fig. 2 shows the earthquake records used for generating new data sets for testing the trained neural networks by unseen samples. It should be mentioned that, the PGAs of all earthquake records were scaled to 0.1 g and 0.3 g.

In addition, in order to study how well the neural networks predict moment and shear forces for the PGAs greater than those the neural networks were trained by, the PGAs of three of the earthquake records were scaled to 0.4 g and new testing samples were obtained. Fig. 3 compares the time histories of moment demands obtained by NTH analysis against those predicted by the trained neural network for Record (J) when the PGA = 0.1 g. As can be seen, the trained neural network predicts the moment demands accurately and only a small difference between the results of NTH and predictions of the trained neural network exist.
Fig. 4 compares the time history of shear force demands obtained by NTH analysis against those predicted by the trained neural network for Record (J) when PGA = 0.1 g. As can be seen, the trained network predicts the shear force demand accurately and only a small difference between the results of NTH and predictions exists.

Fig. 5 compares the maximum negative and positive moment demands obtained by NTH analyses versus predictions of the trained neural network. From this figure, the maximum prediction errors for the positive and negative moment demands are obtained 17% and 19% respectively. Fig. 6 compares the maximum shear force demands obtained from nonlinear time history analysis with those predicted by the trained neural network. The maximum prediction error for shear force demand is 17%. The obtained results indicate that the trained neural networks estimate the moments and shear force demands with a good precision.
Fig. 6 Comparison of the maximum shear forces predicted by the intersection of axis B and axis 4; (b) At the intersection of axis B and trained network versus results of NTH analysis: (a) At the axis 3.

Conclusions

In concrete shear wall buildings during strong ground motions considerable amount of shear forces and moments are transferred to foundations through concrete shear walls. In such cases, foundations can experience severe damage. Since such damage often cannot be observed by visual inspections, a method is required to identify them.

In this study, a real-time seismic damage detection method was proposed for seismic health monitoring of foundations. The proposed method was based on neural networks and it employed nonlinear time history analysis to create training samples. The proposed method was tested on a five-story concrete shear wall building. The obtained results showed that the trained neural networks estimated the maximum moment and shear force demands with a good precision.

References


