Damage Assessment Using Neural Network and Genetic Algorithm

Kayvan Saberi-Haghighi[1], Mohsen Ghafory-Ashtiany[2], and Caro Lucas[3]

1. Ph.D. Department of Science and Research, Azad Islamic University, Tehran, I.R. Iran
2. Associate Professor and President, International Institute of Earthquake Engineering and Seismology (IIEES), Tehran, I.R. Iran
3. Professor, Intelligent Systems Research Faculty, Tehran, I.R. Iran

ABSTRACT: *In this paper a damage assessment procedure has been proposed based on backpropagating feedforward neural network simulators and a genetic algorithm identifier. Damage assessment is performed in two steps. First, neural networks are utilized to locate possible damage states associated with the changes in vibration signature. Second, genetic based identification procedure has been applied to evaluate the dynamic parameters of the structure at damaged locations. The stiffness of the damaged parts of the structure has been identified by the genetic algorithm such that the difference between analytically predicted and experimentally observed response is minimized throughout the response time history. The amount of stiffness reduction is assumed as the degree of damage. To verify the performance of the proposed scheme, the location and degree of damage in computer-simulated linear and nonlinear structures has been detected. Also to investigate the performance of the proposed method in conjunction with real data, experiments on a $\frac{1}{2}$ scale model of a four-story steel structure has been performed.*

Keywords: Damage assessment; System identification; Neural network; Genetic algorithm

1. INTRODUCTION

Following a strong motion earthquake, quick and critical decisions have to be made on the safety condition of the damaged structures. Structural damage assessment is also essential in the economical repair and retrofit of aging structures.

In today's engineering practice the extent and the location of damage can be evaluated through visual inspection and simple nondestructive tests. However, in some cases visual inspection may not be feasible and it is not always reliable because a building with light or no apparent structural damage could be structurally damaged to an extent that it becomes unsafe to occupy.

In recent years, there has been a considerable demand for more reliable techniques to detect the location of damage. Researchers have proposed damage assessment schemes based on analysis of measured dynamic response of the structure before and after damage through using non-destructive evaluation (NDE) techniques.

NDE techniques provide a more feasible method to monitor the presence of defects or damage in the structure through the measured structural response and have been the focus of research studies for many years. Beck and Jennings [1] have defined the structural damage by reduction in stiffness parameters. Next, the measured response is compared with the response of the reduced stiffness model subject to the same excitation. The reduced stiffnesses are chosen such that the difference between the responses is minimized. Casas and Aparicio [2], Beck et al [3], Liu [4] have used modal output errors and modal parameters, extracted from measured response. The difference between these measured modal parameters and computed modal parameters of the model are compared and the stiffnesses of the model are determined based on minimization of this modal space difference.

Ghanem et al [5], Saito and Hoshiya [6] have used the extended Kalman filtering model to identify structural parameters based on linear system models, either in time or frequency domain. Ge and Soong [7] have presented the regularization method to provide an estimate of the underlying damage process of a system from noisy output measurements by proposing a cost function. Chen and Garba [8] have focused on analytical techniques that use online measurements of responses, such as frequencies, mode shapes, static displacements and damping ratio to assess the presence of damage in structures.

Sorace [9] has proposed a procedure based on local and global permanent deformation measurements and on site dynamic test to assess damage in steel structures not supplied with monitoring systems. Agbabian et al [10] have proposed a method of system identification in time-domain based on excitation and acceleration response records. Dipasqual and Cakmak [11] have proposed a procedure to detect the serviceability of damaged structures after earthquake based on the changes in fundamental period by analyzing recorded response of the structure during earthquake. Hjelmstad and Shin [12] have introduced a damage detection and assessment procedure based on parameter estimation with an adaptive parameter-grouping scheme. Damage is characterized by a reduction in a constitutive property of a parameterized finite element model between two time-separated inferences, assuming that the baseline parameters are known.

Among the promising NDE methods are those based on the analysis of structural dynamic response measurements to identify a suitable mathematical model corresponding to the changing state of the physical structure.

In order to decide whether a structure that has experienced a strong motion event can still be considered safe or whether some repair is required, it is necessary to define a damage index function. The calculated index provides the basis for judgment about the post-earthquake serviceability and safety condition of the structure, and reference for retrofit decision making. When recorded response data are available, such as in the case of instrumented buildings, the seismic demand can be easily quantified, so that all uncertainties in damage calculation are restricted to estimating the mechanical capacity. In the absence of a monitoring system, only a posteriori global field testing, properly accompanied by supplementary localized diagnostic checks, can be performed. In this hypothesis, damage is defined as a function of the changes of a selected structural property compared to its initial value. Vibration tests are typically conducted, and parameters are computed from the obtained responses, the reduction of stiffness is generally derived from these measurements as the degree of damage [9].

Reduction of stiffness in a structural element, which has experienced a strong motion earthquake, is illustrated in Figure 1.

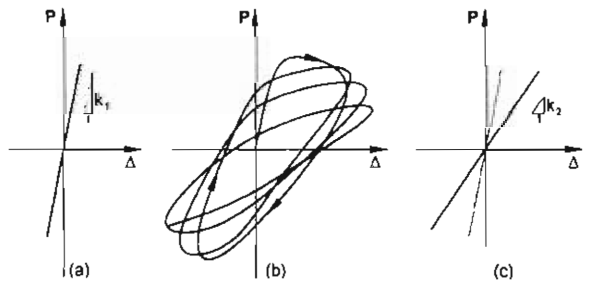


Figure 1. Behavior of a structural element, (a) before earthquake, (b) during earthquake, (c) after earthquake.

Before earthquake and under working loads the response is linear with stiffness equal to k_1 (Figure 1a). During strong motion earthquake the element undergoes nonlinear behavior (Figure 1b), simultaneously some damage occurs resulting a reduction in the stiffness of the element. After earthquake event, again the response is linear but with reduced stiffness equal to k_2 (Figure 1c).

Recorded history of element contains useful information for detecting damage state, especially, strong motion records, which contain useful information about the history of stress and strain that an element has experienced during earthquake. Thus due to the limited number of instrumented buildings, practically, damage may be detected only by comparing the stiffness of the element before and after earthquake. This is why in practical methods that are based on vibration tests, it is assumed that damage is path-independent and is modeled through reduction in the stiffness of structural elements.

In this paper a damage assessment procedure has been proposed based on backpropagating feedforward neural network (NN) simulators and a genetic algorithm (GA) identifier. The objective of this kind of combination is to make the best use of the power of NNs in pattern recognition beside the robustness of GA in nonlinear optimization.

Damage assessment is performed in two steps. In the first step, NNs are trained to simulate the response of the structure at its pre-selected degrees of freedom. The network is trained to simulate the nonlinear transfer function between the acceleration or velocity of the two adjacent degrees of freedom. When the trained NN is tried to be tested for another adjacent location, some simulation error will occur. The amount of error, which is due to the difference between the behavior of trained and tested location, may indicate the state of damage.

In the second step, genetic based identification procedure has been applied to evaluate the dynamic parameters of the structure at damaged locations. The stiffness parameters of the damaged parts of the structure are selected by the GA such that the difference between the response of the analytically predicted and experimentally observed response is minimized throughout the response time history. The amount of stiffness reduction is assumed as the degree of damage [13, 14].

To verify the performance of the proposed scheme, the location and degree of damage in computer-simulated linear and nonlinear structures has been detected. Also to investigate the performance of the proposed method in conjunction with real data, experimental study were performed on a $\frac{1}{2}$ scale model of a typical Iranian four-story steel structure.

2. DAMAGE LOCATION DETECTION

In recent years, neural networks application have attracted increasing attention due to their capabilities such as pattern recognition, classification, function approximation, etc. However, few researchers have applied NNs in the field of damage assessment. Pandey and Barai [15] has adopted backpropagation NNs to model a typical bridge truss with simulated damaged states from its deformation under static loads. Elkordy et al [16] have adopted backpropagation NNs to model damage states of a five story steel frame. The analytically trained networks generated states of damage were used to diagnose damage states obtained experimentally from a series of shaking tests. Wu et al [17] have used the pattern-matching capability of a NN to recognize the location and the extent of individual member damage from the measured frequency spectrum of the damaged structure. Tsou and Herman Shen [18] have proposed a new architecture for a NN by combining three multi-layer subnets that perform the tasks of input pattern generation, damage location identification and damage severity determination, respectively. Teboub and Hajela [19] have employed the classification ability of a NN to identify the damage in composite material beams. Szewczyk and Hajela [20] have used a modified counterpropagation NN to develop the inverse mapping between a vector of the stiffness of individual structural elements and the vector of the global static displacements under a testing load. Masri et al [21] have proposed an approach that relies on the use of vibration measurements obtained from a "healthy" system to train a NN for identification purposes. Subsequently, the trained network is fed comparable vibration measurements from the same structure under different episodes of response in order to monitor the health of the structure.

Saberi, Nikzad and Ghafory-Ashtiany [22, 23] have applied backpropagating NN to identify stiffness parameters of a Duffing system. They also have proposed a method to identify the stiffness parameters of a nonlinear system through backpropagating system restoring force error [24].

In general, NN-based damage detection procedures listed above inherently involves the following drawbacks:

- So far the applied approaches are based on the use of vibration measurements to train NN for identification purposes. To diagnose damage correctly, NN must be trained with successfully diagnosed damage states. Although training samples can be developed over time as actual damage states are experienced by the structure or they can also be obtained from a destructive test program in which the variations in vibration signatures are recorded. Both of these methods of obtaining learning samples are difficult to implement and make the approach impractical.
- Models are required to provide the training cases for the networks and the algorithms should be robust against systematic errors between the model used for training and the actual structure.
- Essential features of damaged structure should be known and must be represented in the training data of the NN.
- When the input testing pattern is beyond the representative domain, the NN may fail to extrapolate such pattern. So in most cases, NN may only be applied to detect damage in the trained system.

To overcome these problems, in this study NNs have been trained only to locate possible damage states associated with the change in vibration signature through simulating the response of the system. To simulate the response of the system, a backpropagating feedforward NN is created as shown in Figure 2. At the input layer previous values of the acceleration or velocity of two adjacent degrees of freedom from the last few time steps are fed to the network. At the output layer the network predicts the acceleration of one of these DOFs at the current time step. Number of input neurons (i.e. n and m) and number of hidden neurons are problem dependent.

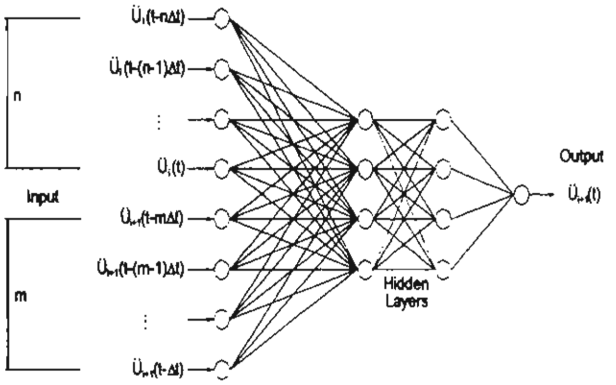


Figure 2. Input and output of the NN-simulator.

Figure 3, schematically shows how NN detects the location of the damage. First NN is trained to simulate the nonlinear transfer function between base and first floor acceleration or velocity (Figure 3a). Second the trained NN is examined for the next floor, in which some simulation error occur (Figure 3b). If the amount of error is negligible, the NN is retrained to minimize this error (Figure 3c). When the error is considerable, it indicates that, there may be a type of damage in the system (Figure 3d). This procedure may be utilized as many times as required to detect damage in all parts of the structure.

The average network estimation error is shown in Figure 4. For an undamaged structure, error for each floor has approximately regular linear decrements (Figure 4a). However for a damaged structure, for example damaged at third floor, NN error shows irregularity at the location of damage (Figure 4b).

Although detectable changes cannot (with present knowledge) be directly attributed to a specific physical parameter, this approach can provide a sensitive indicator of the presence of potentially serious damage in the monitored system.

It should be noted that the procedure is independent of the structural model (linear or nonlinear) and it does not

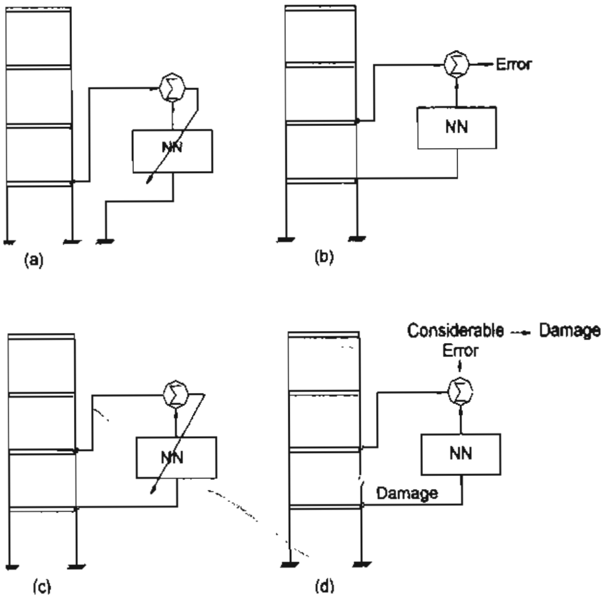


Figure 3. Detecting damage location using single NN Simulator (SNN).

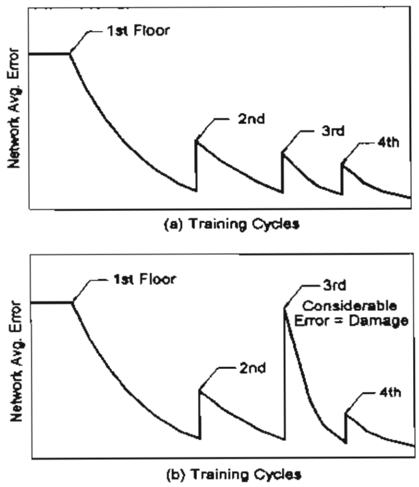


Figure 4. Training cycles vs. NN average error. (a) For undamaged structure, (b) for damaged structure.

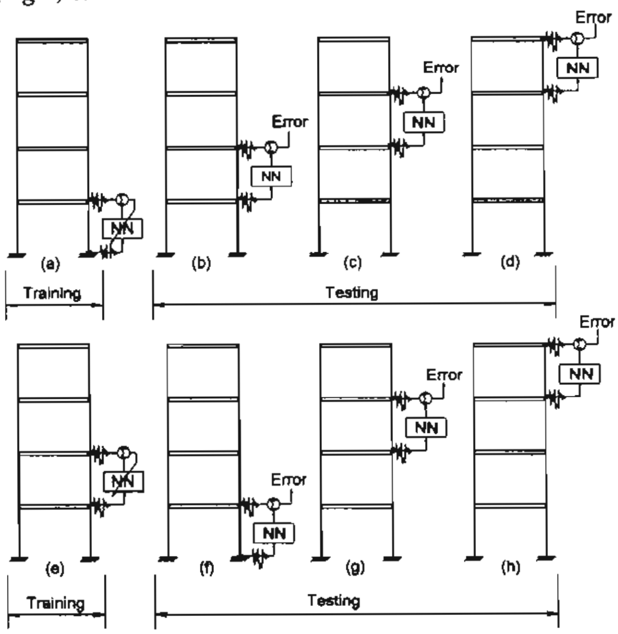


Figure 5. Detecting location of damage with multiple NNs (MNN).

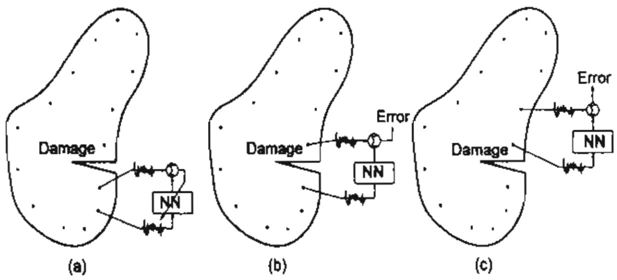


Figure 6. Detecting damage location for an irregular shaped object.

require any prior knowledge of the system property.

The method explained above may be applied in two ways:

1. Using only a single NN (SNN method) to train and test all parts of the system for damage identification, as shown in Figure 3; or
2. Using multiple NNs (MNN method) for damage identification; In this case, for each part of the system, one NN is created and trained once and is tested for all other parts of the system. In this method, damaged locations are verified several times. The use of this method for two lower stories is shown schematically in Figure 5.

The performed studies have shown that MMN is more reliable especially in the case of high noise level [13].

The proposed method is general and it can be applied to different type of structures. For example the location of damage in an irregular shaped object may be detected as shown in Figure 6.

3. DAMAGE EVALUATION

Genetic algorithm has been the subject of considerable interest in recent years, since it provides a robust search procedure for solving difficult problems an has been applied to a wide range of optimization problems in engineering, such as the design of structures and parametric system identification. Dunn [25] has used GA to identify the dynamic parameters of 2 and 12 DOF linear systems. Furukawa and Yagama [26] have applied GA to identify dynamic characteristics of nonlinear systems. Friswell et al [27] have used the GA to identify the damage location and the eigensensitivity is used to identify the damage extent. Chou and Ghaboussi [28] have used static measurements made from regular scheduled monitoring to identify the changes of characteristic properties of the structural members such as Young's modulus and cross sectional area, which are indicated by the difference of measured and computed responses.

The detection and identification of the structural damage being categorized in the field of inverse problems, in most cases is very difficult to directly formulate the problem, since the system parameters can not be expressed in terms of the output error. However, the problem can be formulated as an optimization problem by evaluating the parameters that minimize that output error. It is possible to use the GA to solve this optimization problem [28]. GA may be utilized to minimize the difference between analytically predicted and experimentally observed response.

Genetic algorithm is a powerful search technique based on the process of natural evolution [29]. This algorithm detects the global minimum of the objective function without the use of, or evaluating the gradient of the objective function. This feature is very significant, since in most optimization problems, evaluating the gradient of the objective function is not straightforward and is very complex. In this algorithm the parameters are encoded as strings that are called chromosomes. Each chromosome is composed of a certain set of binary numbers that represent the state of parameters in the design space. At the beginning, the parameters are set random and initial chromosomes are generated.

Genetic algorithm consists of the following three main operational steps: Selection, Crossover and Mutation.

3.1. Step 1: Selection

In the GA, definite number of chromosomes are gathered in a mating pool. For each chromosome the design parameters are decoded and the objective function is calculated. According to the associated value of the objective function for each chromosome, selection operator selects the best chromosomes among the chromosomes in the mating pool and the other chromosomes are extinguished. Selection may be performed in several ways. Choosing tournament selection in this study, the mating pool is divided to smaller parts and for each part the best chromosome or chromosomes are selected.

3.2. Step 2: Crossover

To generate even better chromosomes from mating pool, the chromosomes are randomly paired off and a crossover operator is applied to each pair. In this way new offspring are created. Crossover simply divides each chromosome of a pair into two or more parts and alternately replaces each part of one chromosome with associative part of the other one.

3.3. Step 3: Mutation

To extend the exploration range in the design space and also to escape from local minima, sometimes the new offspring are mutated just like nature. Mutation, which is performed with a small probability, changes one or more bits of a chromosome from 0 to 1 or vice versa.

In this study, three operators described above were incorporated in a general purpose and flexible GA software in C++ language with the flow chart shown in Figure 7. As the identification part of the procedure, in this study GA is utilized to evaluate the dynamic parameters of the system under consideration.

After damage location detection through using NNs procedure in Section 2, a computer-simulated model of the structure should be developed in which the stiffness of the damaged parts has to be evaluated. The stiffness parameters will be selected by the GA in way that minimizes the difference between the response of the model and the measurements throughout the response time history. The amount of stiffness reduction is considered as the degree of damage.

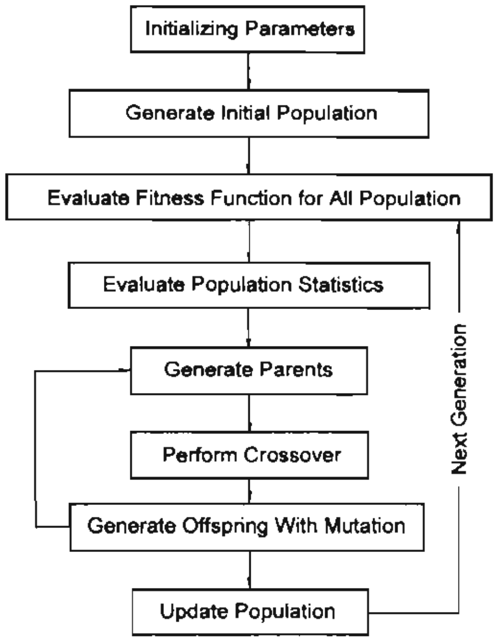


Figure 7. Flow chart of the GA software.

The main modules of the proposed GA identifier are shown in Figure 8. GA tunes the stiffness parameters of the model in such a way that the model response fits to the measured response of the real structure. As it can be seen, for each chromosome at each generation, the response of the system's model has to be computed. However at the present state of the art in damage detection, time efficiency should not be the main issue in developing a reliable damage detection and assessment algorithm.

Moreover in the proposed procedure, damage location is identified separately from damage extent. This advantage enables the analyst to use substructure concept to condense the model at undamaged parts of the structure in order to speed up the computation. The flow chart of the proposed procedure is shown in Figure 9.

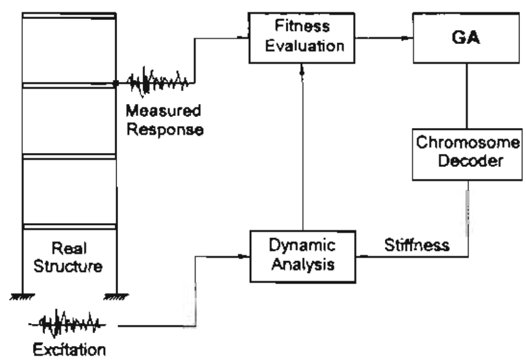


Figure 8. GA identifier.

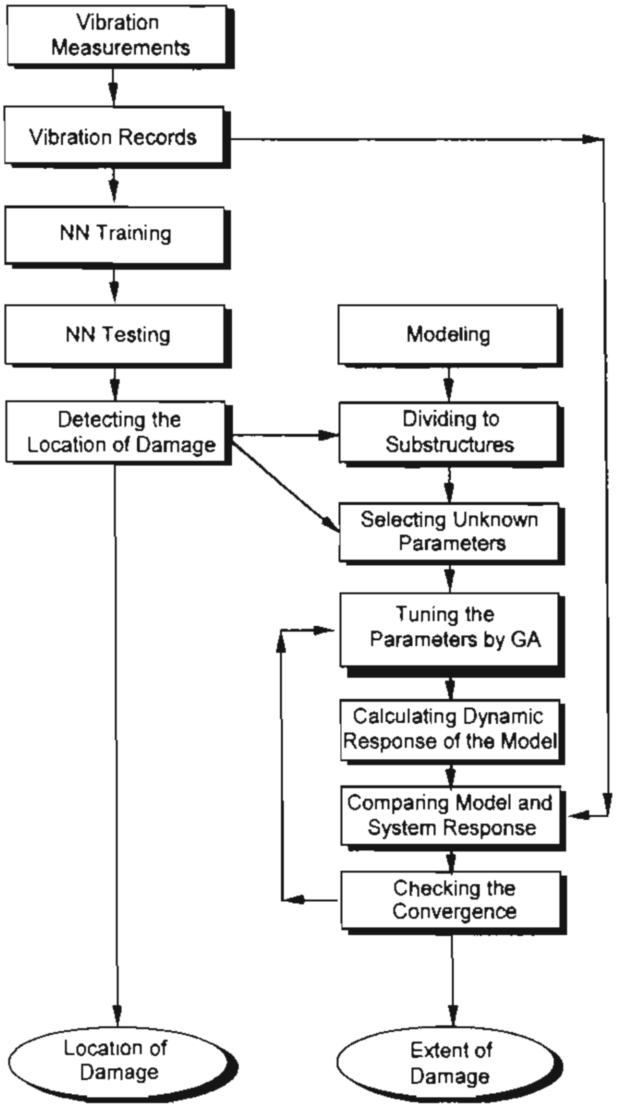


Figure 9. Flow chart of the proposed procedure.

4. VERIFICATION OF THE PROPOSED PROCEDURE

To verify the performance of the proposed scheme, several tests were performed on computer-simulated linear and nonlinear, plane and space frames. Also the effect of change in some vital parameters on the performance of the procedure is investigated. In order to verify the performance of the proposed method in conjunction with real data, experiments on a $\frac{1}{2}$ scale model of a four-story steel structure has been performed. In this paper only the results obtained from some of these tests are presented.

4.1. Computer-simulated Tests

4.1.1. Test (I): Linear Braced Plane Frame

In the first test, detecting the location and degree of damage in a concentrically X-braced plane frame is shown. Properties and geometry of the model used for this test are shown in Figure 10.

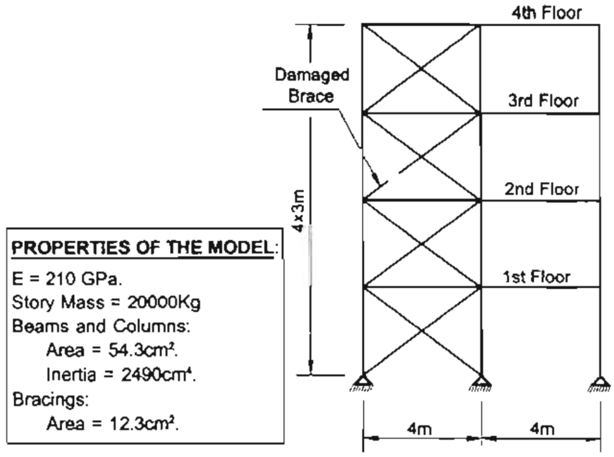


Figure 10. Model of test (I).

In this test, damage has been simulated by equating the cross section area of one diagonal element of the third floor to zero. The response of the system due to ambient excitation is computed and NN with the architecture shown in Figure 11 has been used to detect the location of damage. For most of the performed tests, the performance of the architecture with two hidden layers was better than that of a single layer.

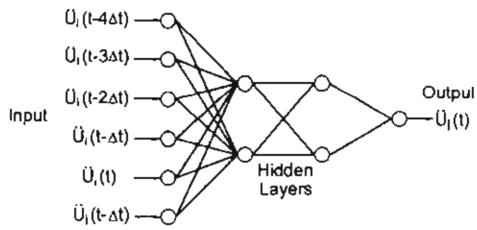


Figure 11. Architecture of NN.

As it can be seen in Figure 12, except in Figure 12c, network average error for the third floor is greater than the other floors. Based on this result, it is concluded that there may be a damage in third floor.

To estimate the stiffness of the brace in third floor, GA is applied with a population of 100 chromosomes, each having 16 bits length (8 bits for the stiffness of each diagonal). Tournament selection is applied by choosing one point crossover operation and the mutation probability of 0.02. Using the square root of sum of squares (SRSS) of the roof acceleration error as the objective function, after 2000 generations the following results have been obtained:

- ❑ Damaged brace area = 5.53cm^2.
- ❑ Undamaged brace area = 6.93cm^2.

It should be noted that since only the horizontal response of the model is considered for damage detection, only the shear stiffness of each story or the sum of the area of both braces might be evaluated. This is why in this test both for damaged and undamaged braces the area is evaluated approximately equal to half of really undamaged brace (i.e. 12.3cm^2).

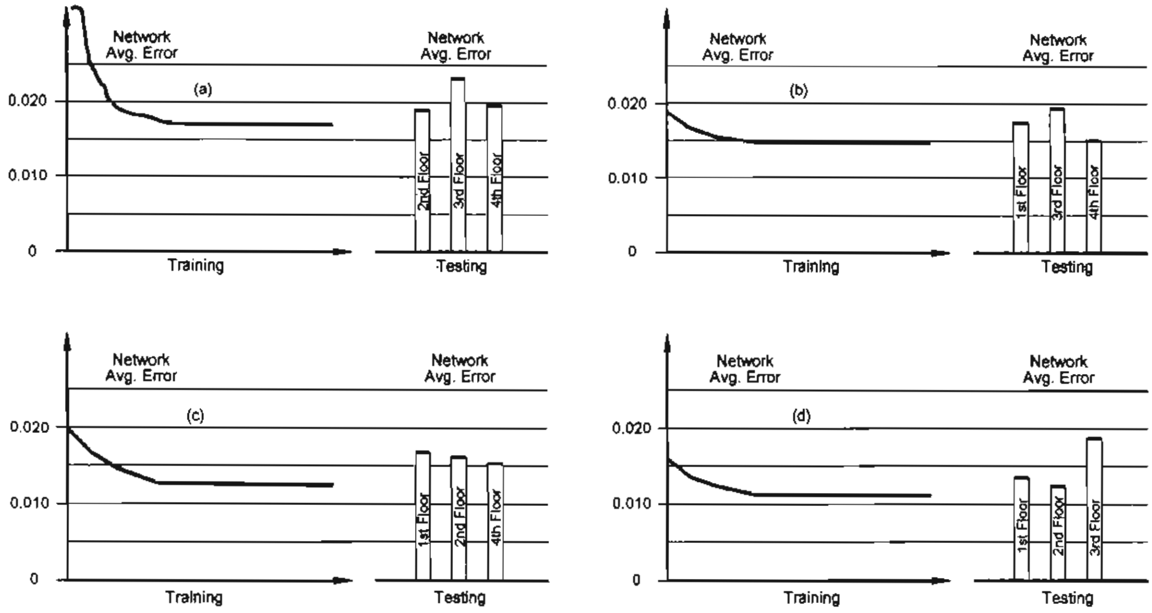


Figure 12. Network average simulation error.

4.1.2. Test (II): Nonlinear Braced Plane Frame

In this test, the structural model is the same as before except that nonlinear behavior is assumed for the braces as shown in Figure 13.

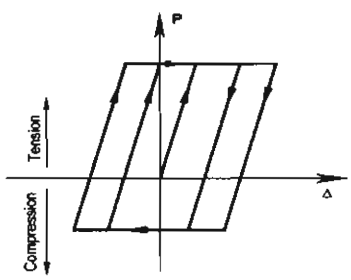


Figure 13. Hysteresis loop of each diagonal bracing before damage.

To simulate the damage state, the stiffness of one of the diagonal brace at the third floor is reduced to zero. The system response due to the recorded ambient excitation at its base level has been evaluated. The excitation records are scaled such that all the braces become plastic, even if it is for a short interval of time. The dynamic response of the aforementioned system is computed for a duration of 2 seconds utilizing Hilber's method with time steps of 0.01 seconds. Again NN has been used to detect the location of damage. The architecture of the NN used for this test is shown in Figure 14.

As it can be seen in Figure 15, except for Figure 15c, network average error for the third floor is greater than the other floors. Thus it is concluded that there may be a damage in the third floor.

To estimate the stiffness of the braces in the third floor, GA is applied with a population of 100 chromosomes, each having 32 bits length (8 bits for the stiffness of each diagonal and 2 × 8 bits for the value of yield forces). Tournament selection is applied by choosing one point crossover operation and the mutation probability of 0.02. Using the SRSS value of the roof acceleration error as the objective function, after 2500 generations the following results are obtained:

- ❑ Damaged brace area= 0.3cm^2.
- ❑ Undamaged brace area = 11.7cm^2.

In this test due to the difference between tension and compression yield forces of bracing elements, unlike the previous test, area of each diagonal brace is evaluated with a good accuracy.

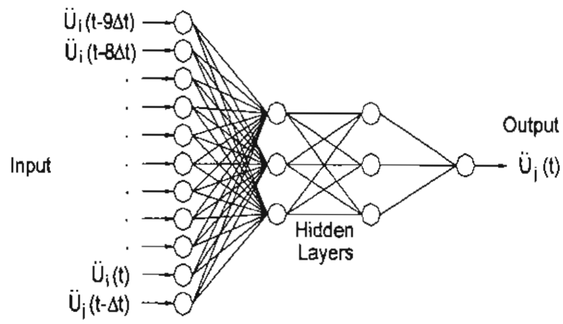


Figure 14. Architecture of NN.

4.1.3. Test (III): Two-Way Concrete Slab

To further show the application of the proposed method, damage in two-way concrete slab with linear behavior is simulated by reducing the modulus of elasticity in one of the elements of its model in one direction (Figure 16).

NNs, scanning through line A-A, have detected the correct location of damage as it can be seen in Figure 17. Using GA identifier, the damaged value of stiffness for element No. 19 is estimated to be 970 KN/cm^2, which has only 3 percent error from its actual value.

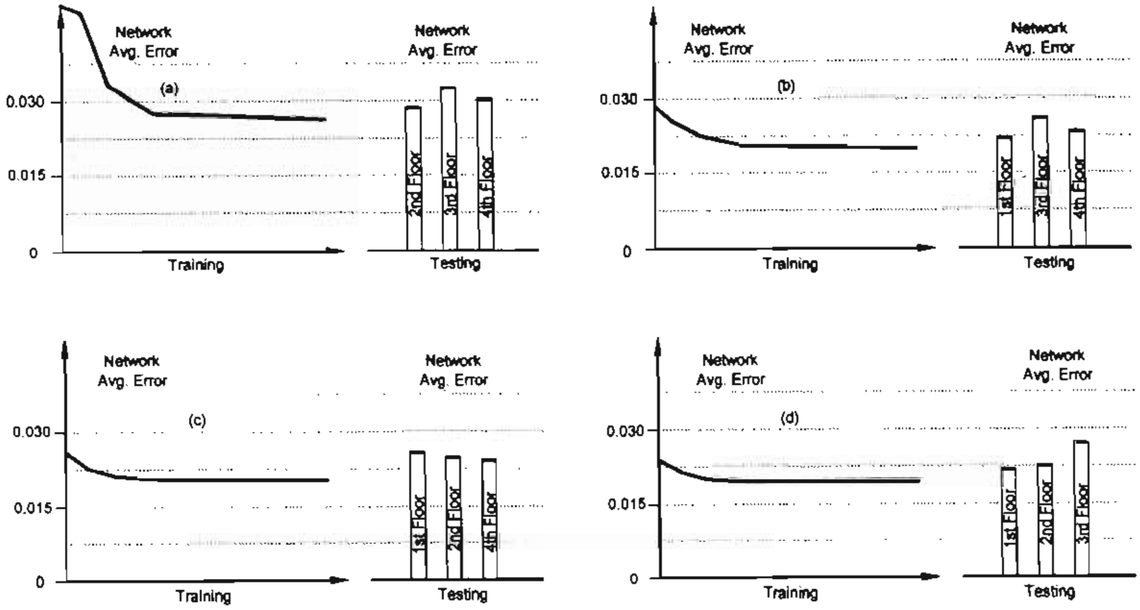
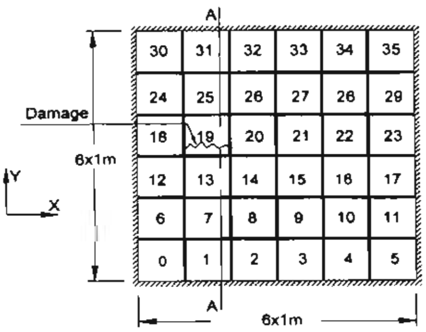


Figure 15. Network average simulation error.



PROPERTIES OF THE MODEL:

- 36 x 8 Nodes Isoparametric Serendipity Elements.
- Elements Dimension = 1 x 1m, Thickness = 0.15m.
- Modulus of Elasticity = 2000KN/cm^2.
- Modulus of Elasticity of Element No 19. (Damaged Element) = 1000KN/cm^2.
- Poisson's Ratio = 0.2.
- Mass = 375 Kg/m^2.

Figure 16. Model of test (III).

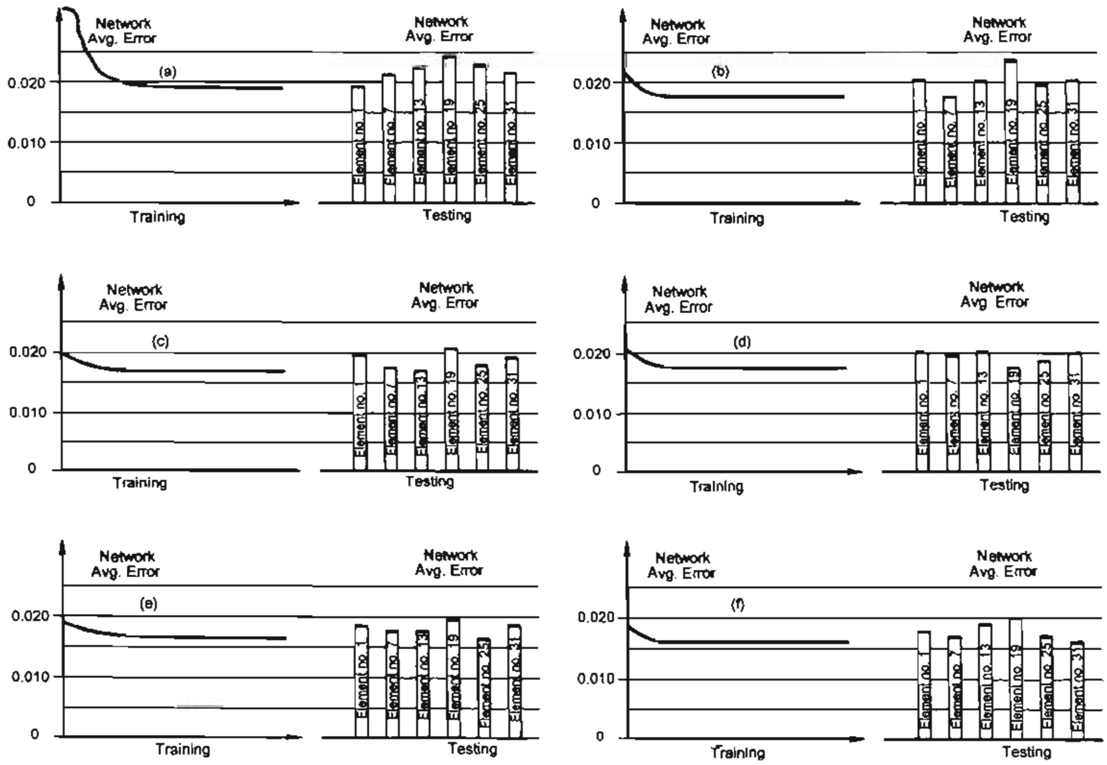


Figure 17. Network average simulation error.

4.1.4. Test (IV): Linear Braced Space Frame

To further show the flexibility of the proposed method, the damage in a linear braced spaee frame has been detected. Properties and geometry of the model used for this test are shown in Figure 18.

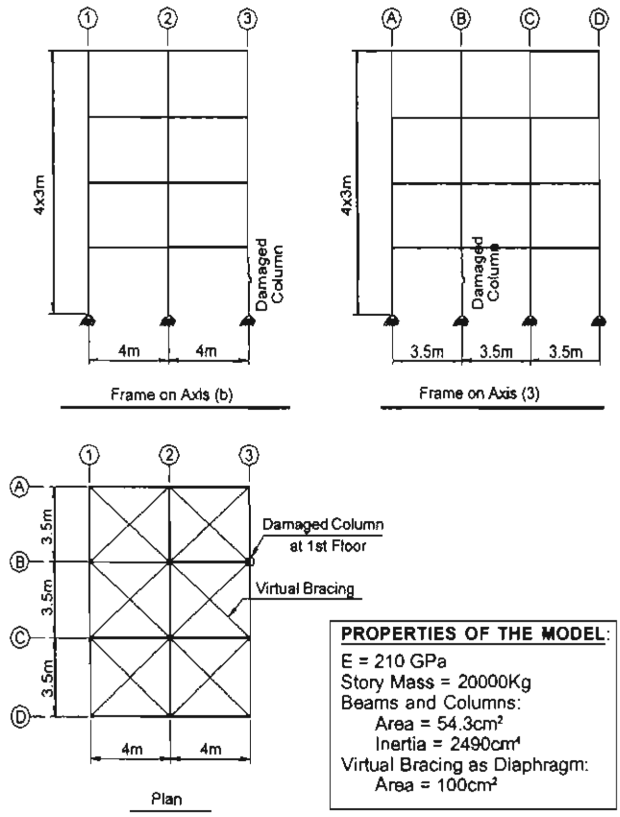


Figure 18. Model of test (IV).

In this test, damage is simulated by reducing by half, the modulus of elasticity of column on axis 'B3, at first floor. The response of the system due to a recorded ambient excitation is computed. Same as before, NN has been applied to detect the location of damage. As it can be seen in Figure 19, damage in frame on axis (B) is apparent.

Next, only the damaged frame, which has been detected on axis (B), is considered. Applying the same procedure, the damaged column is detected and its modulus of elasticity has been estimated.

- ❑ Damaged column: E = 109400MPa.
- ❑ Undamaged columns: E = 194400MPa.

4.2. Sensitivity Analysis of the Procedure

In order to survey the sensitivity of the procedure in conjunction with the change in the geometry of the model, state of damage and noise in acquired data, several computer-simulation tests were performed. Two and three dimensional frames with 1 to 6 spans and 4, 6, 10, 15 stories are modeled and the behavior of each has been analyzed for a total of about 200 tests. The results of these tests are presented in this section.

4.2.1. Effect of Geometry of the Model

To investigate the effect of number of spans and stories of a plane frame on the amount of error in evaluating the degree of damage, models with the following variations are analyzed:

Number of spans: 1, 2, 3, 4, 5, 6
Number of stories: 4, 6, 10, 15
Damage location: at middle stories

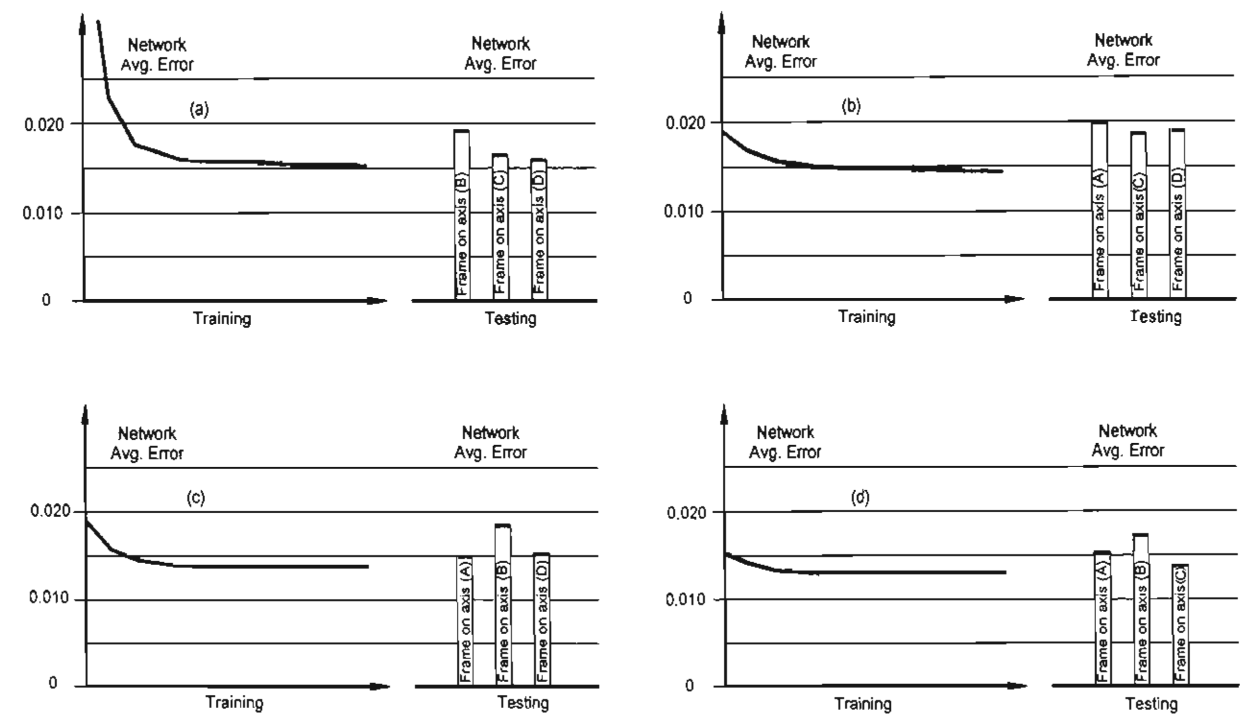


Figure 19. Network average simulation error.

Damaged part: one column in one story
Degree of damage: 50%
Noise amplitude: 5%

As it can be seen from the results shown in Figure 20, by increasing the number of spans or stories, error in evaluating the degree of damage increases.

When the above tests are repeated assuming the damage extent in all columns of one of the stories, the results are somewhat different. As shown in Figure 21 although, same as before, increase in number of stories, increases the error but increasing the number of spans results in decreasing the error.

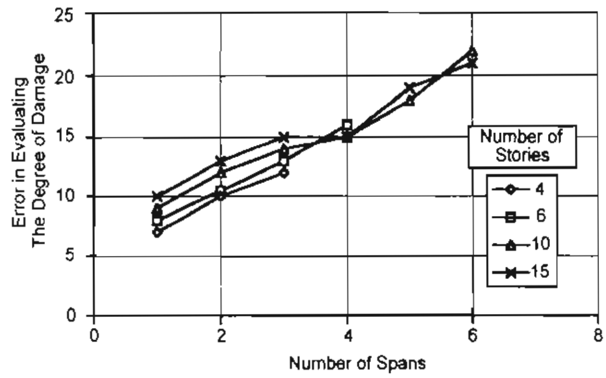


Figure 20. Effect of geometry of the model on performance of the procedure.

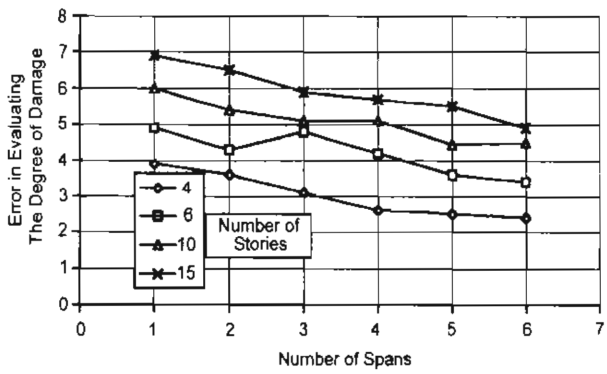


Figure 21. Effect of geometry of the model on performance of the procedure.

4.2.2. Effect of the Degree of Damage

To investigate the effect of the degree of damage on the amount of error in evaluating the damage, the following two-dimensional models of frames are analyzed:

Number of spans: 3
Number of stories: 4, 6, 10, 15
Damage location: at middle stories
Damaged part: one column in one story
Degree of damage: 10, 25, 50, 75%
Noise amplitude: 5%

Results obtained from these tests are shown in Figure 22.

When the damage is assumed to be in all columns of one story instead of being in one column, the results in terms of error is shown in Figure 23. At it can be seen, for both cases, increase in degree of damage results in decrease in damage evaluation error, as it could be expected.

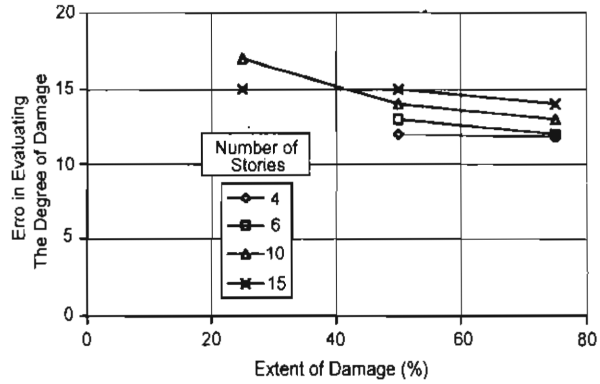


Figure 22. Effect of degree of damage on performance of the procedure.

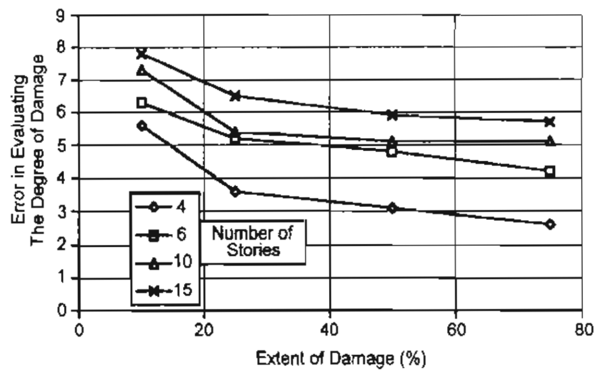


Figure 23. Effect of degree of damage on performance of the procedure.

4.2.3. Effect of Damage Location

To investigate the effect of the location of damage on the amount of error in evaluating the degree of damage, the following plane frame models are analyzed:

Number of spans: 3
Number of stories: 4, 6, 10, 15
Damage location: at lower, middle and upper stories
Damaged part: all columns in one story
Degree of damage: 50%
Noise amplitude: 5%

The obtained results shown in Figure 24 indicate that, evaluation error for middle stories is less than lowers or upper stories, which is due to the effect of boundary conditions on the behavior of the models.

4.2.4. Effect of the Noise in the Data

In order to investigate the effect of noise on the accuracy of the proposed method, the following plane frame models have been analyzed:

Number of spans: 3
Number of stories: 4, 6, 10, 15

Damage location: at middle stories
Damaged part: all columns in one story
Degree of damage: 50%
Noise amplitude: 5, 10, 15, 20%

Obtained results shown in Figure 25, indicate increase in noise amplitude results in increase in the damage evaluation error, but the procedure is still stable even for significant amplitude of noise in acquired data.

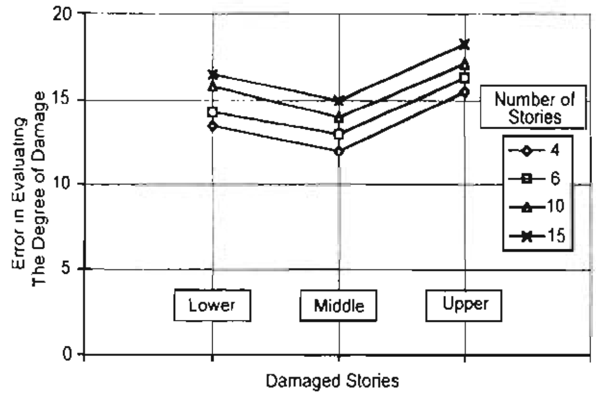


Figure 24. Effect of location on performance of the procedure.

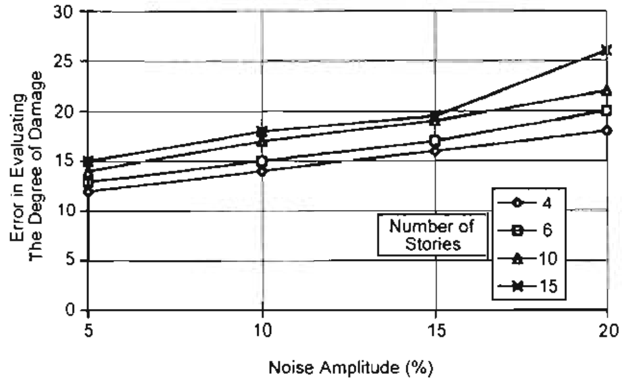


Figure 25. Effect of noise on performance of the procedure.

4.2.5. *Effect of Distance between Damaged Locations*

To investigate the effect of distance between damaged locations on the amount of error in evaluating the degree of damage, the following models of plane frames are analyzed:

Number of spans: 3
Number of stories: 4, 6, 10, 15
Damage location: at middle stories
Damaged part: all columns in two stories
Degree of damage: 50%
Noise amplitude: 5%

Results obtained from these tests are shown in Figure 26. It can be seen that for the cases, in which the damaged stories are far apart, the error is smaller.

4.3. *Experimental Verification of the Proposed Procedure*

To investigate the performance of the proposed damage

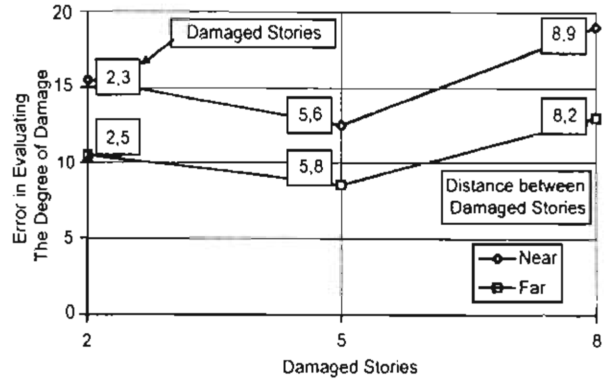


Figure 26. Effect of distance between damaged locations on performance of the procedure.

detection procedure in conjunction with real data, experiments on a $\frac{1}{2}$ scale model of a typical four-story steel structure in Iran have been performed. Geometry of this model is shown in Figure 27.

The model is made up of three longitudinal frames on axes (1), (2), and (3). In these frames the beams are connected to columns through Khorjeeni (satchel) connection. The beam profiles are attached to the columns by top and seat angles placed on the sides of the columns. Columns are built up of two UNP 50x25 and beams on axes (1) and (3) consist of one IPE 80 and on axis (2) consist of two IPE 80. Longitudinal frames are connected to each other by the roof beams, spaced at approximately 450mm [30].

In longitudinal direction the connection of beams to columns are semi-rigid, so stability is attained. In addition, gusset plates are welded to frames on axes (1) and (3) in order to add bracing to the frames. On these plates holes are provided to configure different type of bracings, using angle profiles and friction type bolts. In this way, damage to one diagonal element may be simulated by removing

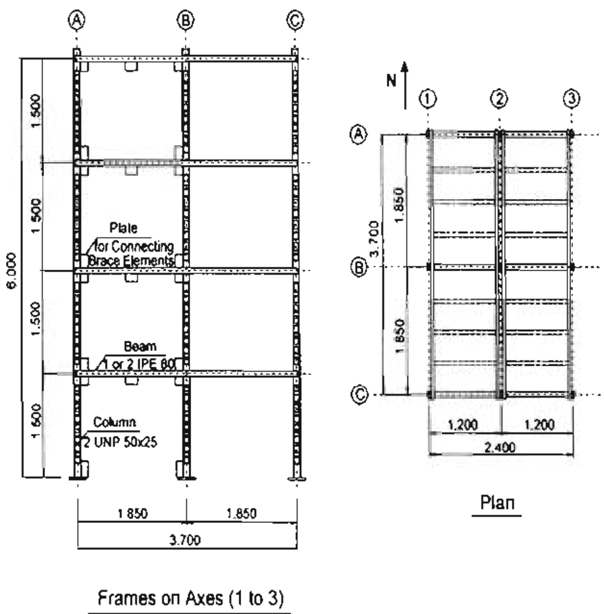


Figure 27. Half scale four-story steel structure model.

associated element in the model. In transverse direction stability against lateral loads is attained by "X" bracings on axes (A) and (C). The mass of 1st, 2nd and 3rd floors is about 8100 kg and 5500Kg at the 4th floor.

The response of the model is recorded using three SS-1 Velocity meters. These devices are arranged in three different configurations shown in Figure 28. For each configuration, the response of the model due to ambient excitation is recorded.

Similar to previous tests on computer-simulated models, here the measured responses of the model are fed to NN to detect the location of damage. In this test, damage is simulated by removing bracing elements of second floor (Figure 29). The architecture of NN used for this test is the same as for test in section 4.1.1. Figure 30 shows the network average error. As it can be seen, simulation error for second story is slightly greater than other stories, which indicates that there may be a type of damage in the second floor.

After detecting the location of damage, GA is applied to estimate the stiffness of the braces in the second floor. The following result is obtained:

- Damaged brace area = 0.12cm^2.
- Undamaged brace area = 12.3cm^2.

These theoretical and operational results from various simulated damage conditions indicate the reliability of the proposed procedure.

5. CONCLUSION

In this paper new damage assessment procedure is presented using the pattern recognition capability of backpropagating NNs and the global optimization power of GA-based algorithm. The procedure is performed in two steps. In the first step, NNs are utilized to locate possible

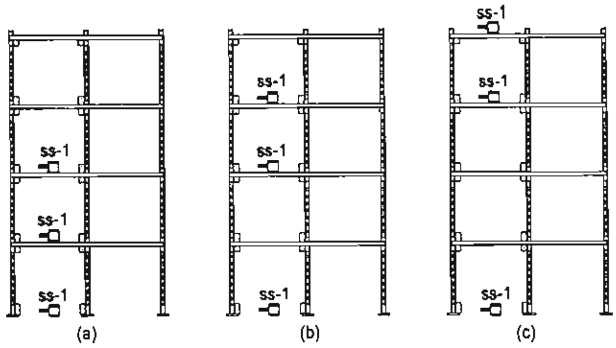


Figure 28. Three different configurations for measurements.

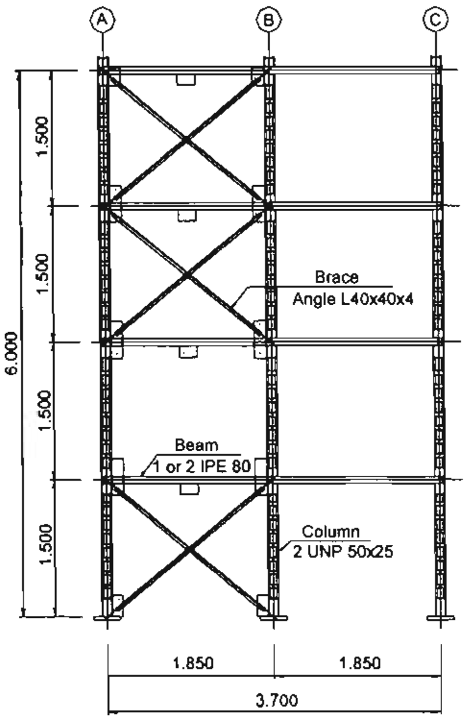


Figure 29. West view of model under test.

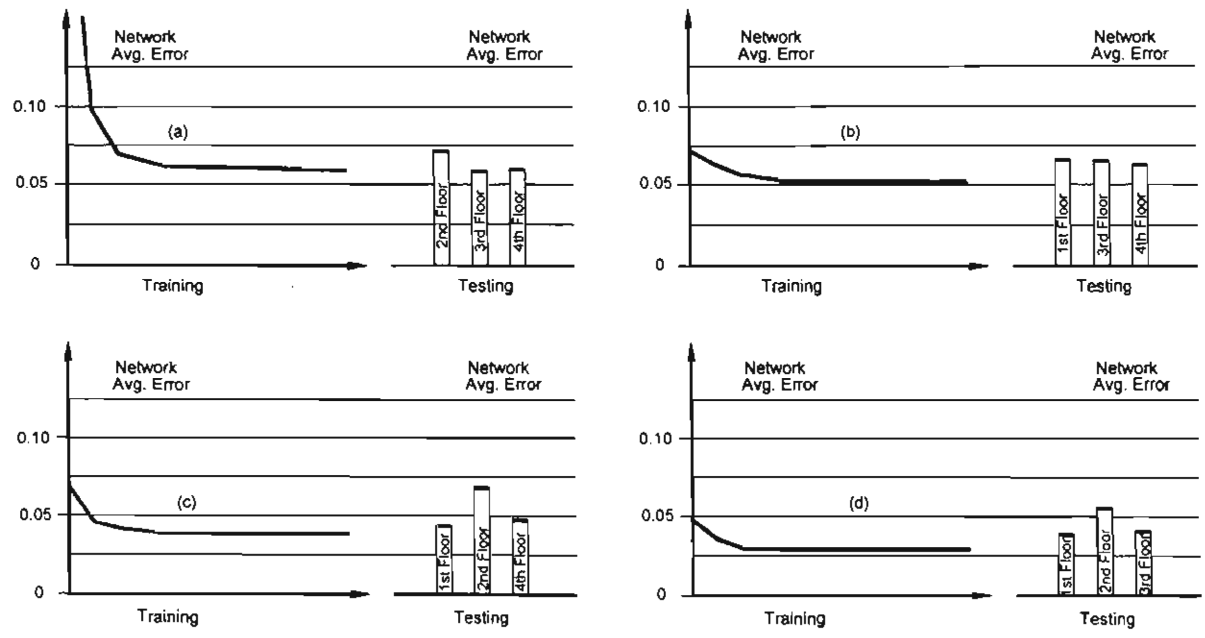


Figure 30. Network average simulation error.

damage states associated with the changes in vibration signature. Second, genetic based identification procedure has been applied to evaluate the dynamic parameters of the structure at damaged locations. The stiffness of the damaged parts of the structure has been identified by the GA such that the difference between analytically predicted and experimentally observed response is minimized throughout the response time history. The amount of stiffness reduction is considered as the degree of damage. Since the location of damage is detected in the previous step, in this step only the stiffness of the damaged parts has to be estimated. This feature reduces the search space by utilizing substructure approach and results in unique outcomes.

To verify the performance of the proposed scheme, several tests were performed on computer-simulated linear and nonlinear, plane and space frames. Also the effect of some vital parameters on the performance of the procedure is investigated. In order to investigate the performance of the proposed method in conjunction with real data, experiments on a $\frac{1}{2}$ scale model of a four-story steel structure has been performed. The results obtained from these tests are promising. Although presence of nonlinearity and/or noise may degrade the accuracy of the results, it is shown that the proposed approach is still a robust method for detecting and evaluating the damage. Concluding remarks resulting from this study are listed as follows:

- In procedures, which are based on non-destructive evaluation tests, stiffness reduction is the best criterion for estimating the degree of damage.
- Utilizing NNs, any changes in the behavior of structure can be studied, and consequently, the location of damage may be detected.
- GA is a reliable algorithm for system identification.
- Detecting the damage location separately from damage degree, reduces the computational time for evaluating the degree of damage, rejects the trivial solutions and also enables the analyst to apply substructure approach to eliminate the number of DOF of the model. It is also possible to apply Neuro-substructure approach for nonlinear dynamic systems [13].
- Investigating the effect of change in geometry of the model, state of damage and noise in acquired data on accuracy of the procedure, results in following issues:
  - Increase in number of structural elements decreases the accuracy of thc procedure.
  - Increase in degree of damagc increases the accuracy of the procedure.
  - Increase in distance between damaged locations or distance from boundaries of the model increases the accuracy of the procedure.
  - Increase in noise amplitude in acquired data decreases the accuracy of the procedure, but the procedure will be stable even for great noise amplitude.

Following issues remain to be resolved before the proposed approach becomes an applicable method for structural damage assessment:

- The performance of the procedure in conjunction with different combination of damage locations and extent has to be investigated.
- The performance of the method in conjunction with real data acquired from real structures and the effect of nonstructural elements has to be examined.
- It will be useful to investigate if it is possible to reduce the number of measurements for damage assessment.

The procedure may be incorporated in an integrated general software for damage assessment. The major modules of such a software are shown in Figure 31. In this study only the shaded modules were considered.

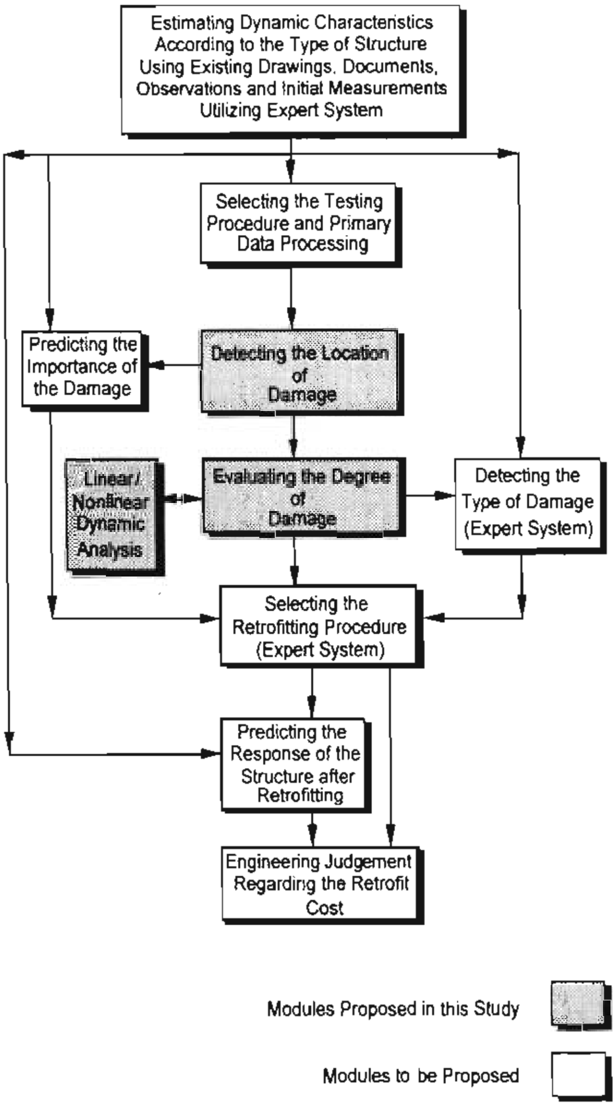


Figure 31. Damage assessment modules.

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