A NEURAL NETWORK BASED METHODOLOGY FOR ESTIMATING BRIDGE DAMAGE AFTER MAJOR EARTHQUAKES

Tzu-Kang Lin, Chu-Chieh Jay Lin, and Kuo-Chun Chang*
Department of Civil Engineering
National Taiwan University
Taipei, Taiwan 106, R.O.C.

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ABSTRACT

A neural network based seismic bridge damage estimation system is proposed to estimate damage to the bridges in Taiwan after major earthquakes. The damage estimation system is composed of two parts: a peak ground acceleration (PGA) estimator and a bridge damage estimator. The PGA neural network estimator was first trained by the ground motion data recorded from the eight largest earthquakes in Taiwan over the past ten years. The magnitude, depth, and epicenter coordinates of the earthquake were used as the inputs in this neural network. The damage estimator was trained to learn the relationship among bridge coordinates, structure types, PGAs and damage levels to bridges based on the data collected from the 1999 Chi-Chi earthquake. Sixty-four sets of bridge data were used to train a 7-8-8-2 neural network. These two neural networks were then integrated into one system and were tested, using another twenty sets of bridge damage data. The result has demonstrated that the proposed method is able to successfully assess the damage of bridges due to major earthquakes in Taiwan.

I. INTRODUCTION

Over the last decade, plenty of research has been carried out on the application of artificial intelligence to civil engineering structures. Neural networks, one of the artificial intelligence paradigms, are composed of large numbers of interconnected processing nodes as well as parallel structures. Since the neural network has the advantages of parallel processing abilities, it can be used to deal with complicated problems in a more effective way and has been demonstrated in several research fields. (Ghaboussi and Lin, 1998; Hung *et al.*, 2000).

Recently, some research efforts have been devoted to developing structural monitoring systems using neural networks. (Elkordy *et al.*, 1994) successfully applied neural networks to structural damage diagnosis and condition monitoring applications. (Elkordy *et al.*, 1994). This provided a suitable framework for automatic structural monitoring. A structural state detection and damage assessment system was also introduced using optic fiber sensors and neural networks (Tu *et al.*, 1995). After that, many other types of artificial neural network systems were

*Correspondence addressee

established to monitor the safety of bridge structures. For example, Wong *et al.*, (1996) presented a method to assess the feasibility of using neural networks to predict and detect faults at early stages, in a power system. Nakamura *et al.* (1998) also proposed a method for detecting damage to a steel building, using neural networks.

In this paper, the neural network is trained by the data observed from the field. The learning capabilities of neural networks are used to develop a PGA estimation system responsive to major earthquakes, without any sensors in bridges. Furthermore, a neural network based system is developed to offer a reliable estimation of the bridge damage conditions subsequent to a major earthquake. After knowing the magnitude, the epicenter, the depth of the earthquake and the coordinates of the bridge location, possible damage to the bridge can be estimated by the proposed neural network within a few seconds.

II. NEURAL NETWORKS

Symbolic systems play an important role in traditional artificial intelligence. Since symbolic systems can only duplicate knowledge and have no capability of learning, neural networks become more and more important in the field of artificial intelligence. Neural networks are computational tools inspired by the structures and process of the biological brain and neural system (Hopfield, 1982). Using connections between the processing nodes, neural networks are able to simulate the human brain and reflect some basic characteristics. Comparing to the traditional computing methods, there are three characters in the neural networks: (1) adjustable and trainable functions: these two functions make it feasible to train the neural networks by using data and patterns. (2) The more training data used to train the neural networks, the better and more experienced results will be. However, traditional computing methods perform slowly for large scope programs. (3) Neural networks are huge parallel processing systems. High-speed calculations and tolerance of mistakes give neural networks the capability to filter noise from the training data. In other words, neural networks can reduce the influence of noise on accuracy. The above characteristics make it possible to solve problems that cannot be solved by traditional computing methods. (Fahlman and Lebiere, 1988)

In this study, Multi-Layer Feed-Forward (MLFF) neural networks (Rumelhart and McClelland, 1986) are used to develop the proposed system. MLFF neural networks process information in interconnecting processing units, which are organized into layers. There are three different types of layers in MLFF neural networks: the input layer, the hidden layer, and the output layer. The information was given to a neural network through the nodes of the input layer, then, it was distributed to the first hidden layer through the weighted connections. The nodes of the hidden layers process all incoming data and emit outgoing signals to the nodes in the next layer. All inputs to a node are weighted, combined and processed through a transfer function that controls the strength of the signal relayed through the output connection of the unit. Neural networks continue processing through each layer until the response is obtained at the output layer.

III. BRIDGE DAMAGE ESTIMATION SYSTEM

A major earthquake with the local magnitude of $M = 7.3$, due to the rupture of the Che-Lung-Pu fault struck the center of Taiwan in the early morning on September 21, 1999. Bridges near the fault and the epicenter along provincial and county routes in Taichung, Nantou, Changhua and Yunlin counties were severely damaged during this earthquake (Chang *et al.*, 2000). Various degrees of damage occurred to hundreds of bridges during this earthquake.

Traditionally, it is usually time consuming to investigate bridge damage conditions. In order to solve this problem, a new neural network based methodology is proposed to improve this situation. The proposed system is composed of two parts: a PGA estimator and a bridge damage estimator. Both estimators will be described as follows.

1. PGA Estimator

It's well accepted that the PGA value at the bridge site plays an important role in estimating the damage condition of the bridge. Nowadays, the seismic attenuation curves are the most common methods used to evaluate the approximate PGA values at the sites. However, one of the major weaknesses of using Taiwan's attenuation curve methods is that one PGA value may represent more than two sites the same distance from the epicenter, which is usually not true when compared to recorded ground motions. Under this situation, a system which can estimate a proper PGA value with better accuracy after a major earthquake is needed.

Thousands of earthquake records have been collected from the strong motion recording system in Taiwan for the last ten years. These records make great contributions to both academic research and professional applications of earthquake engineering and offer a proper database for developing the neural network system in this study.

In order to include a wide range of possible cases for the training patterns, eight large earthquakes that

Table 1 Characteristics of eight earthquakes for training

Earthquake Number	Year	Latitude	Longitude	Magnitude	Energy Ratio
1	9/21/1999	23.9	120.8	7.3	354
2	7/17/1998	23.5	120.7	6.2	7.95
3	6/25/1995	24.6	121.7	6.5	22.28
4	2/23/1995	24.2	121.7	5.8	1.94
5	6/5/1994	24.4	121.8	6.2	7.5
6	12/16/1993	23.2	120.5	5.9	2.81
7	4/20/1992	23.8	121.6	5.6	1
8	3/12/1991	23.2	120.1	5.9	2.8

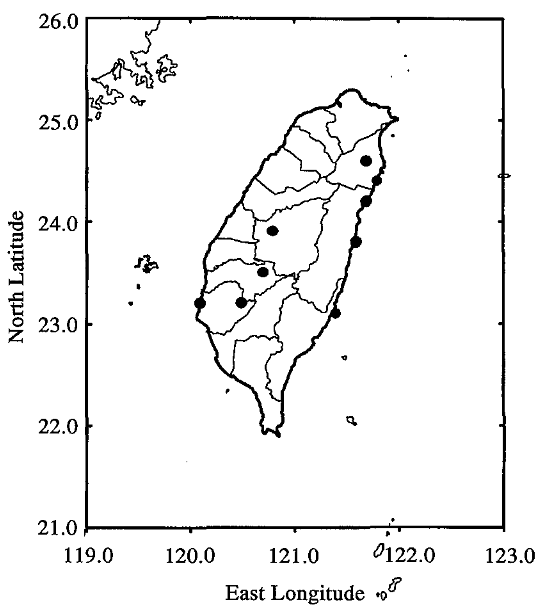

Fig. 1 The epicenters of eight earthquakes

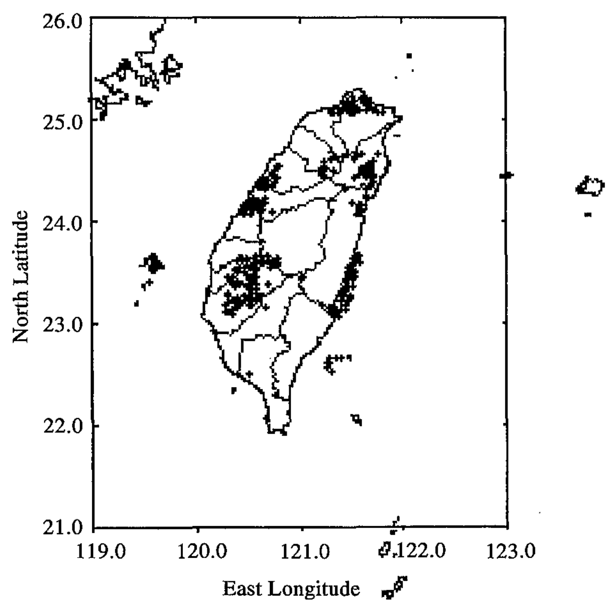

Fig. 2 The distribution of training sites

affected Taiwan during the last ten years were used to train the neural network. The descriptions of these earthquakes, including dates, magnitudes, epicenters, and normalized energy ratios, are listed in Table 1 and the epicenters of these eight earthquakes are shown in Fig. 1. Since the smallest magnitude among these earthquakes was 5.6, the PGA values used in the neural network would cross a certain level and the data used to train the neural network estimator may be less affected by noise.

Meanwhile, it is very important to choose proper sites for training if a successful neural network is to be established. In this study all the measuring stations that successfully recorded the Chi-Chi earthquake ground motions were used to offer the training data to the neural network. The distribution of these sites is shown in Fig. 2.

Since the purpose of the neural network is to estimate the PGA value at any specific location in Taiwan during an earthquake with magnitude greater than 5.6, the characteristic of the earthquake should be reflected by the input items of the neural network. Six parameters from the data collected in the strong motion recording system were used as inputs to the neural network. They are: the longitude and latitude coordinates of the epicenter, the longitude and latitude of the location where PGA values are estimated, the normalized energy ratio of the earthquake and the depth of the epicenter. The output nodes of the neural network are the PGA values of Up-Down (UD), East-West (EW) and North-South (NS) components. The basic structure of the neural network is shown in Fig. 3.

After determining the inputs, 1138 sets of training patterns, including the above-mentioned eight earthquakes, were picked to represent earthquake

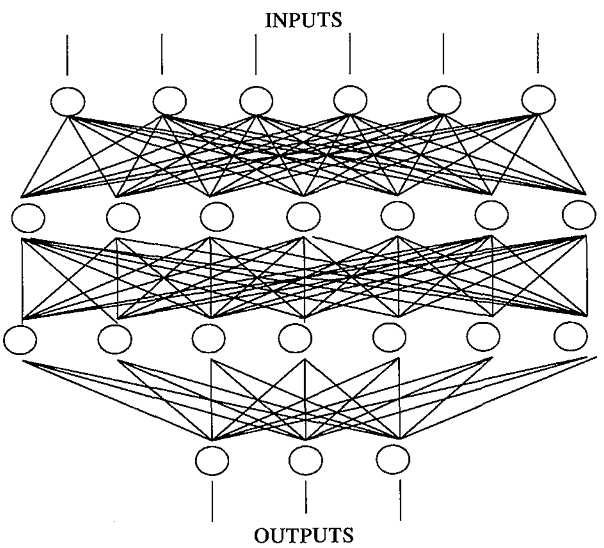

Fig. 3 The basic structure of PGA estimator

characteristics in Taiwan and input into the neural network. In order to determine the optimal number of hidden layers and nodes, the trial and error method was used. The transfer functions in this neural network were chosen the sigmoid and linear functions. A brief description of the neural network is listed in Table 2. Meanwhile, the correlation coefficient is used to represent the training result and is defined as

$$R=\frac{\sigma_{xy}}{\sqrt{\sigma_x^2\sigma_y^2}}$$

where x is the original data, y is the regression result, σ_{xy} is the cross covariance of x, y and σ_x, σ_y are the variance of x, y, respectively.

After many trials, the optimal structure for the PGA estimator was chosen to be 6-7-7-3 and the correlation coefficient between the output and target was 0.923. The result has demonstrated that the relationship between the input and output can be learned successfully by the PGA estimator.

To evaluate the performance of the PGA estimator, two different attenuation curve methods, the Taiwan Science Team Attenuation Function and the Campbell Function Form-NCREE Taiwan (Ku *et al.*, 1993) were used to offer the benchmark values for the neural network outputs. It should be noted that for sites that have the same parameters, the attenuation curve will generate identical results regardless of the difference in locations. However, the difference of site conditions may be learned by the neural network during the training procedure and reflected in the output PGA values. This is one of the advantages of using the neural network.

In order to demonstrate the feasibility of using the PGA estimator, the neural network was then tested to predict the PGA values of sites other than those used in the training procedure. The testing data were chosen from three different earthquakes other than the training samples. The comparisons among these three methods and the recorded data are shown in Fig. 4.

Table 2 Description of PGA estimator

Items	
Input node number	6
Transfer function	Linear
Hidden Layer 1 node number	7
Transfer function	Sigmoid
Hidden Layer 1 node number	7
Transfer function	Sigmoid
Output node number	3
Transfer function	Sigmoid

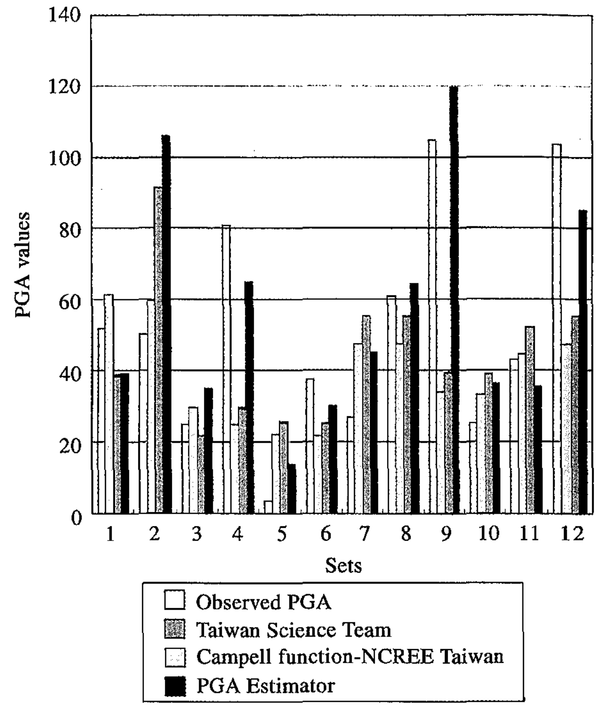

Fig. 4 Comparison of three different methods in the EW direction

It is clear from Fig. 4 that different site geology can be reflected by the neural network system, therefore, a more reasonable PGA distribution, due to strong earthquakes, can be predicted.

2. Bridge Damage Estimator

An extensive bridge damage investigation program was organized and carried out by the National Center for Research on Earthquake Engineering

Table 3 The classification of the superstructure

Group	Item		Hazard condition
Superstru cture	Bridge type	Beam bridge I prestress beam (I) B Box beam (2) R rigid frame bridge (3) T truss bridge (4) A arch bridge (5) C cable bridge (6) Suspension bridge (7) O other (8)	F: Collapsed superstructure (4) A: Severe hazard (3) Concrete bridge: Substantial spalling or fallen concrete on a concrete girder Steel bridge: Broken truss or other primary member Broken bottom flange or large local buckling of the web
	Support type	Simple support (1) Continued (2)	B: middle hazard (2) Concrete bridge: spalling or large cracking on a concrete girder
	Materials	R RC (1) P PC (2) S Steel (3)	Steel bridge: Buckled or deformed truss or other primary members Deformed bottom flange or localized bucking of the wab
	Plan shape	L Line bridge (1) G curvedbridge (2)	C: small hazard (1)
	Vertical shape	slope≤2% (1) 2%<slope≤6% (2) 6%<slope (3)	Concrete bridge: Minor cracking on a concrete girder Steel bridge: Localized light deformation or buckling of a member
	Slope	A 75<θ≤90 (1) B 60<θ≤75 (2) C θ≤60 (3)	D: No hazard (0) No damage, or if there is, extremely light damage that will not affect the load-resistant capacity

(NCREE) after the Chi-Chi earthquake (Chang *et al.*, 2000). A total number of 1094 bridges in the disaster area were investigated in detail and the collected data was classified into four groups with fifteen items. These four groups are superstructure, piers and foundations, bearing, and earthquake. Since the damage condition is not affected by the bearing factor seriously, the other three groups are used to train the neural network in this study and they are: the superstructure, piers and foundations, and earthquake. The classification of the superstructure as well as piers and foundations are shown in Tables 3 and 4. The parenthetical numbering after each item listed in the tables will be used for the neural network input nodes.

Two types of damage conditions are identified: superstructure damage and sub-structure damage. Each type is further divided into five categories according to the severity of damage. The statistical data have shown that more than 80% of the investigated bridges were not damaged in the 921 earthquake. In other words, among the 1094 bridges investigated, about 100 bridges experienced minor to severe damage. In order to analyze the damage conditions, only bridges with damage were chosen and accumulated. The damage percentages for the four conditions, excluding the undamaged condition, in the superstructure and the sub-structure are shown in Figs. 5 and 6, respectively.

Although more than one thousand bridges were investigated after the earthquake, how to properly choose the data to represent typical damage conditions is a critical issue for the proposed system. After carefully reviewing the available data, sixty-four sets of typical bridges were chosen to train the neural network and another twenty were reserved as testing samples. The training samples have been selected carefully to include the bridges constructed over the last few decades and damaged in various ways during earthquake so that all possible conditions may be covered.

One of the values needed by the damage estimator to evaluate the damage to bridges due to earthquakes is offered by the PGA estimator. Therefore, the bridge damage evaluation system is established

Table 4 The classification of piers and foundations

Group			Hazard condition
Piers and Foundation	Pier type	W Wall column (1) S Single column (2) M Multiple column (3) N No pier (4) O Other (5)	F: Collapsed columns, piers or abutments (4) A: Big hazard (3) Concrete: Fractured reinforcements, tiled columns or piers Overturned or tiled abutments Steel: Cracking or welding fracture
	Abutment	Gravity Abutment (1) Cantilever Abutment (2) Wall-type (3) Other (4)	B: Middle hazard (2) Concrete: partial buckling of reinforcements or deformation of members Partial bulging out of reinforcements and spalling of cover concrete
	Materials	R Rc (1) S Steel (2)	Massive fracture on abutments Steel: Residual deformation less than $0.03L_b$
	Shape	C Circular (1) R Rectangular (2) E Ellipse (3) P Polygon (4)	C: Small hazard (1) Concrete: Horizontal or bevelled cracks on columns or piers Minor cracks on abutments
	Body	Solid (1) Hollow (2)	Steel: residual deformation less than $0.01L_b$. D: No damage, or if there is, extremely light damage that will not affect the load-resistant capacity (0)
	Height	A $20\text{m}<h$ (1) B $10\text{m}<h<20\text{m}$ (2) C $h<10\text{m}$ (3)	

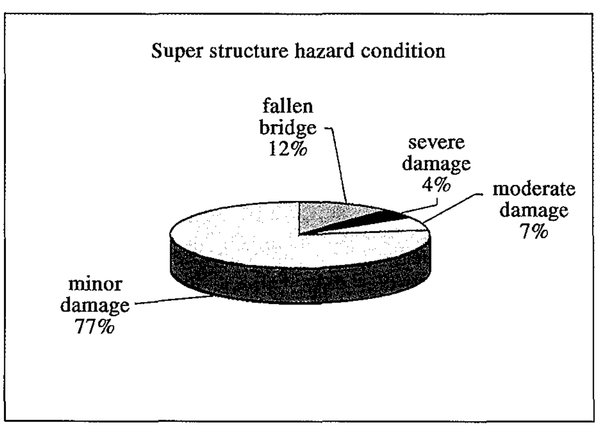

Fig. 5 Damage percentages in superstructure

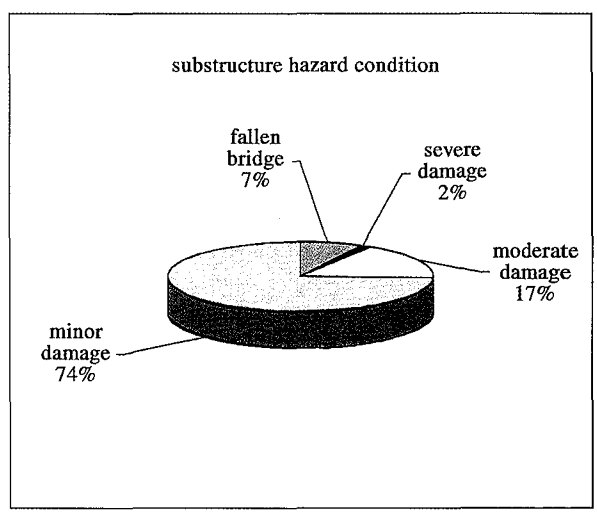

Fig. 6 Damage percentages in sub-structures

with the proposed PGA estimator. Since the neural network structure is usually case-dependent, a better way to construct the neural network structure is by trial and error. Meanwhile, the prediction results will be influenced by the input items.

The classification of PGA levels plays an important role in the neural network. After classifying PGA levels, using the standard described in Table 5, the damage estimator performs in a better way for practical situations. The main reason to use this classification is that the magnitude of the 921 Chi-Chi earthquake is much larger than earlier earthquakes, therefore it is not appropriate to use the standard

Table 5 Classification standard of PGA value

PGA	Classification
< 300	0
300-400	1
400-500	2
500-600	3
> 600	4

Table 6 Input and output of the damage estimator

Node Number	Itesm
Input 1	PGA
Input 2	Bridge type
Input 3	Materials
Input 4	Support
Input 5	Abutment
Input 6	Pier
Input 7	Height
Output 1	Super-structure damage condition
Output 2	Sub-structure damage condition

earthquake intensity classification.

Seven nodes shown in Table 6 were used as the input nodes and these nodes are the PGA value, bridge type, materials, support type, abutment type, height, and pier type. Meanwhile, the output nodes of the neural network are superstructure and substructure damage conditions. Two hidden layers were also chosen in the damage estimator. The training process was set to 10000 iterations and the automatic learning rate was used during the training. A brief description of the neural network information is shown in Table 7. After full training of the neural network, the correlation coefficient was 0.967 and the root mean square (RMS) was 0.01. The training results are shown in Figs. 7 and 8, and the RMS trend during the training procedure is depicted in Fig. 9. These results have shown that the whole of the information from the training data can be learned by the neural network and a precise prediction of the hazard condition of both super and sub structures may be offered.

The final neural network structure is shown in Fig. 10. After some trial-and-error effort, a 7-8-8-2 neural network was chosen and has given very good results in predicting damage conditions.

IV. ILLUSTRATIVE EXAMPLES

The feasibility of the individual neural networks has been demonstrated in the previous two sections. In order to build up an estimation system for bridge damage condition, these two neural networks were integrated and twenty testing patterns were input to the estimation system to verify its performance.

Table 7 Description of damage estimator

Neural network 2	
Number of layer	4
Input layer units	7
Transfer function	Linear
Hidden layer1 units	8
Transfer function	Sigmoid
Hidden layer2 units	8
Transfer function	Sigmoid
Out layer units	2
Transfer function	Sigmoid

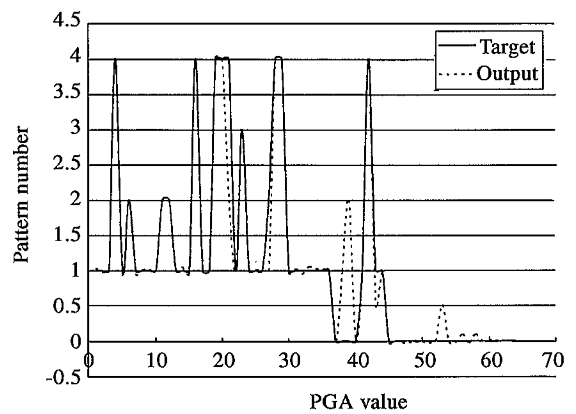

Fig. 7 Training results for superstructures

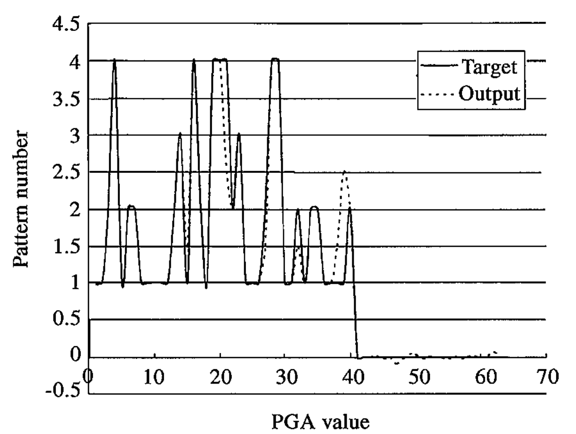

Fig. 8 Training results for sub-structures

Since there are no other strong earthquakes that caused as much bridge damage as the Chi-Chi earthquake, data other than the training patterns collected

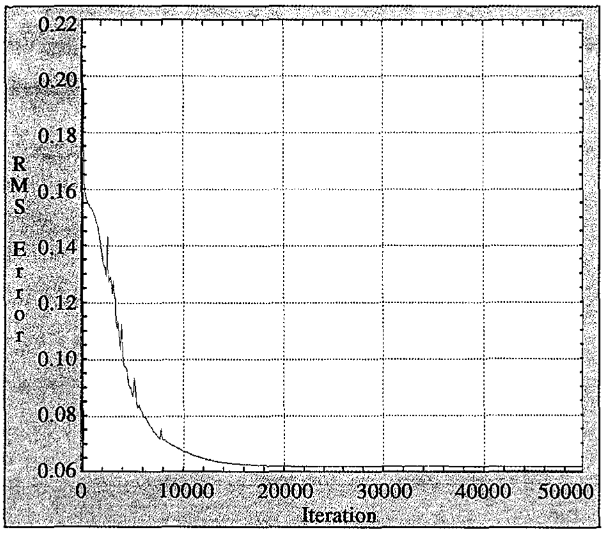

Fig. 9 The RMS time history diagram

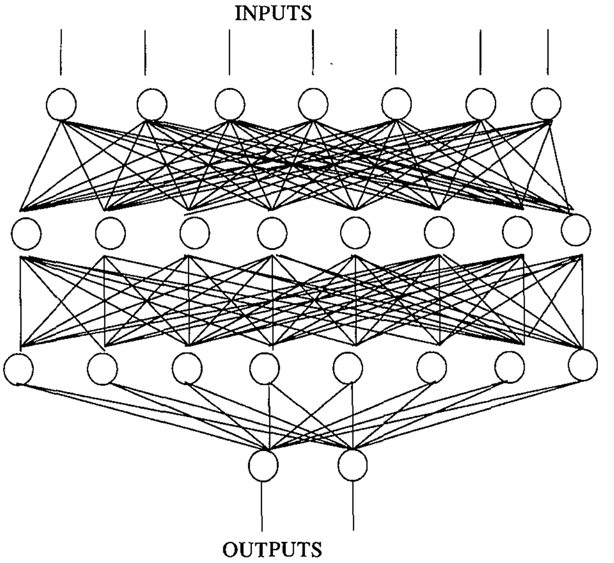

Fig.10 The neural network structure of damage estimator

from the Chi-Chi earthquake were used as testing samples to avoid the memory effect of the neural network. In order to evaluate the performance of the final system, the real conditions of bridge damage were also offered to the neural network.

The coordinates of the epicenter, coordinates of the bridges, magnitude and depth of the earthquake were input to the estimation system and the predicted results and observed conditions are shown in Figs. 11 and 12. It is shown that the first ten sets of the predicted results are quite close to the observed damage conditions. However, there is more discrepancy in the next ten bridges and the reason is discussed as follows.

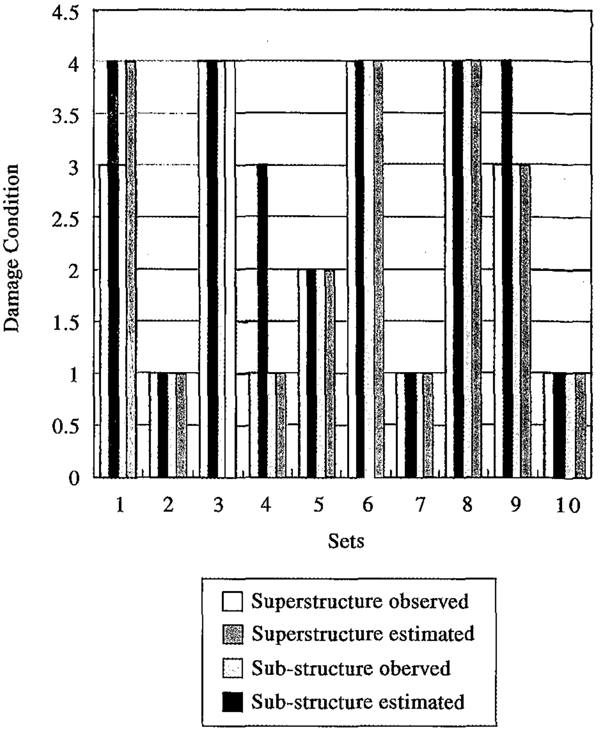

Fig. 11 Testing results from the first ten sets

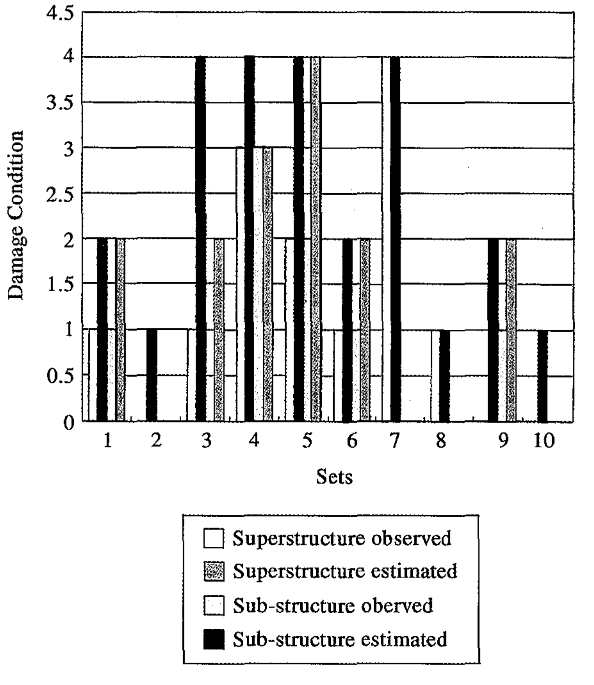

Fig. 12 Testing results of next ten sets

After analyzing the information on these bridges, it is realized that the main reason for the difference in prediction is the error accumulation between these two sub-neural networks. Although the best advantage of using the estimation system is that it can provide a rapid prediction about the bridge condition, the prediction error also accumulates during the procedure. In other words, the prediction error in the PGA estimator was propagated into the damage estimator and accumulated to the final output. However, the output of the estimation system is still in the conservative range.

V. SUMMARY AND CONCLUSION

A neural network based PGA prediction system is proposed to give a more reasonable estimation of PGA distribution after an earthquake. The PGA estimator is trained by the data collected from eight large earthquakes in Taiwan during the past ten years. After the full training procedure, this network is evaluated to ensure its robustness and accuracy. Furthermore, a damage estimator was proposed for bridge damage conditions after a major earthquake. Detailed damage data on bridges in Taiwan during the 921 Chi-Chi earthquake are collected and sixty-four sets of bridge data were used to train a 7-8-8-2 neural network. The damage estimator has been demonstrated to successfully assess the damage condition and provides an alternative way to predict the damage to bridges during earthquakes in Taiwan.

Finally, these two neural networks are integrated into an estimation system and are tested by observed data. Twenty sets of bridge damage conditions, other than the training samples picked from the Chi-Chi earthquake, are input to the system to evaluate the final performance of this system. The result has demonstrated that a quite good estimation of damage conditions to bridges can be obtained by the integrated system.

More research is needed to deal with the conditions of insufficient collected data. The first PGA estimator can be improved to be more robust by providing more earthquake data to the training database. There is a belief that the geological characteristic of Taiwan can be reflected more precisely by the PGA estimator than by the traditional attenuation curve method. In the second part, a possible study should be establishing a more robust neural network trained with data assumed insufficient. In this way, it may be possible to handle the problem with fewer terms of data collected and the practicability of this system can be upgraded once again.

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橋梁於遭受重大地震侵襲下的類神經網路震害評估系統

林子剛　林主潔　張國鎮

國立台灣大學土木工程學系

摘　要

本研究中提出一個以類神經網路爲基礎的橋梁震害評估系統以預估台灣地區的主要橋梁在遭受重大地震侵襲時所可能發生的破壞情形。此一類神經網路橋梁震害評估系統主要由兩個部分所構成，分別是地表最大加速度（PGA）類神經網路系統與橋梁震害神經網路系統。台灣地區在過去十年中所發生最大的八組地震測站紀錄首先被用來訓練地表最大加速度類神經網路系統以提供在橋梁震害神經網路系統中所需要的即時 PGA 值。另外一方面，利用在 921 地震中所調查到的橋梁基本資料、PGA 加速度以及橋梁實際破壞情形則作爲訓練類神經網路系統的資料。六十四組主要橋梁的調查資料被用來訓練一個7-8-8-2 的類神經網路系統。在整合了上述兩組類神經網路系統後，另外二十組測試資料被用來測試並評估整體系統之適用性。測試的結果顯示此一類神經網路震害評估系統能成功的評估台灣地區的橋梁在遭受重大地震侵襲下的破壞行爲並可進一步被整合爲一個震害預警系統。

關鍵詞：人工智慧，類神經網路，橋梁震害評估系統。