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Use of neural networks for earthquake damage estimation

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ABSTRACT: This paper proposes an application of neural networks to damage estimation of structures subjected to strong earthquake motions. Since it is not so easy to correlate strong motion parameters and resultant structural damage using simple mathematical equations, neural networks are conveniently employed to construct such a relationship. The peak ground acceleration, the peak ground displacement and the spectrum intensity from 79 actual earthquake records are considered as input parameters of a neural network and the damage observations near the recording sites are used as desirable outputs of the network. After iterations of supervised learning, the network converges and can be used for future estimations. Although the input parameters and learning data are still preliminary, the methodology may be useful for an early damage detection of structures due to earthquakes.

1 INTRODUCTION

When an earthquake strikes large cities, it is important to estimate the resultant damage soon after the earthquake. Especially, for city gas networks, a decision of whether or not to shut off the supply is urgent otherwise secondary disasters may follow structural damage. However, this decision must be made carefully. If we shut off the gas supply without severe structural damage, recovery may take time and inconvenience to customers may be more serious. In order to make an early but accurate estimation of damage to customers' buildings and pipelines, an extensive monitoring system of earthquake intensities was developed in Japan (Nakane et al., 1992). This system measures the peak ground acceleration (PGA) and the spectrum intensity (SI) of many points within a service area. The monitored PGA and SI values are transmitted to the headquarters of the gas company, and the damage estimation is conducted.

To estimate structural damage from these earthquake indices, a large number of studies exist. Obviously, if we specify structures and specify the input motion in terms of time history, sophisticated response analyses can be conducted. However, if we must estimate overall damage of many types of structures from the measured earthquake ground motion indices, a quick and robust method is necessary. The PGA is the most commonly used index to describe the severity of earthquake ground motion. However, it is well known that a large PGA value is not necessarily followed by severe structural damage. Katayama et al. (1988) demonstrated that the SI value has a better correlation with structural damage than the PGA. Some other indices of earthquake ground motion, e.g., the peak ground velocity (PGV), the peak ground displacement (PGD), the duration of strong motion, and the spectral characteristics of various definitions, can also be considered in such a damage estimation. Ando et al. (1990) demonstrated that PGA, PGV and SI, and PGD are related to the damage of short-period, intermediate-period, and long-period structures, respectively.

However, to correlate these input parameters with observed damage in a mathematical form is not an easy task since a large number of uncertainties are involved and the relationship must be highly nonlinear. A conventional way to construct such a relationship from observed data is to use the multiple regression analysis. But in such a case, we must assume some functional forms to relate input and output parameters. To avoid this, the use of neural networks is proposed in this paper for the earthquake damage estimation problem.

Among several new techniques of computer science, neural networks or parallel distributed processing (PDP) recently has drawn considerable attention in various fields of science and technology. Along with the development of theories and computational algorithms (see e.g., Aleksander and Morton, 1990), the technique has been applied to fields like automation, character recognition, electro-communication and noise filtering, image processing, industrial control problems, etc. Several recent studies can also be found where the neural networks are applied to problems in earthquake engineering, e.g., active vibration control of structures (Nekomoto et al., 1991), seismic hazard prediction (Wong et al., 1992).

The use of neural networks for the earthquake damage estimation problem has several other advantages: adding new data to the network is quite easy; once the network has been set up, the damage estimation for new inputs is very fast. However, since the estimation is highly dependent on learning data, we must prepare well-examined data sets. In this paper, however, the learning data set is not so complete. But we can still demonstrate the usefulness of the technique for earthquake damage estimation problems. Collection of more extensive data is, of course, very important to make the relationship more reliable.

2 DATA

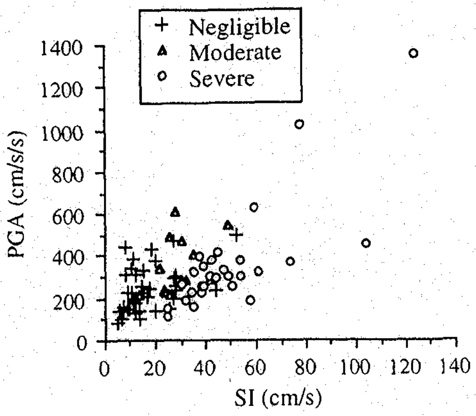
In order to construct a relationship between earthquake ground motion and structural damage using neural networks, a data set comprising inputs (strong ground motion parameters) and outputs (structural damage) must be prepared. There are basically two methods for doing this: one is collecting actual earthquake records and damage data near the recording site; the other is performing earthquake response analyses for given inputs and models and obtaining the resultant damage (outputs). The former is more convincing because it uses actual damage data. But good recordings obtained near structural damage are few. With the latter, it is easier to prepare well-distributed data. But, since it is not based on actual observations, a lot of care should be taken in selecting structural models and input motions. In this paper, we use the former approach as a first attempt although available data are rather limited. The latter approach was also used and the results were presented by the authors elsewhere (Molas and Yamazaki, 1993).

To prepare the data set consisting of earthquake recordings and structural damage information, an extensive literature survey was conducted for past earthquakes (Japan Gas Association, 1991). Among these records, 73 records from 11 earthquakes were selected. Structural damage around these recording sites was rather well-known. The records of two recent earthquakes in Japan; namely, the 1993 Kushiro-Oki (Nagata et al., 1993) and Noto Peninsula-Oki earthquakes, are also used. The number of records and damage are summarized in Table 1. At these locations, damage extent is given in three levels: negligible, moderate, and severe. The definition of these categories is given in the paper by Iwata et al. (1992), where damage to wooden houses and underground pipelines is primarily used to judge the damage extent. This judgement was mostly done based on the literature survey. But for three recent earthquakes, the 1987 Chibaken-Toho-Oki and the 1993 Kushiro-Oki earthquakes in Japan, and the 1989 Loma Prieta earthquake in California, site investigation was also performed to judge the degree of damage.

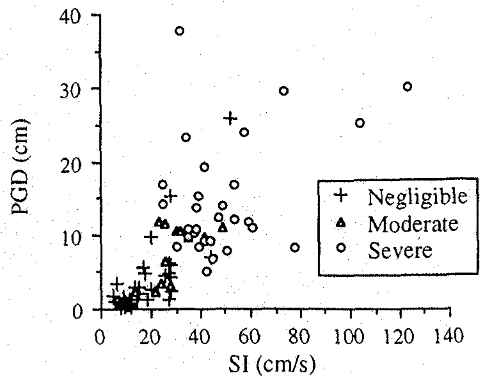
As simplest indices of the ground motion severity, the PGA, PGV, PGD and SI of the 79 records were

Table 1. List of earthquake records and their damage classification

Damage Category	Negligible	Moderate	Severe	Total
Niigata (1964)	0	0	1	1
Matsushiro (1965-66)	20	2	1	23
Tokachi-Oki (1968)	0	0	3	3
Miyagiken-Oki (1978)	2	0	2	4
Nihonkai-Chubu (1983)	0	0	2	2
Chibaken-Toho-Oki (1987)	7	2	0	9
Izu Pen. Toho-Oki (1989)	2	2	0	4
Kushiro-Oki (1993)	2	2	1	5
Noto Pen. Oki (1993)	1	0	0	1
Imperial Valley (1940)	0	0	1	1
San Fernando (1971)	0	2	3	5
Mexico (1985)	0	0	2	2
Loma Prieta (1989)	4	2	13	19
Total	38	12	29	79



(a) on SI-PGA plane



(b) on SI-PGD plane

Figure 1. Distribution of peak values of the 79 earthquake records used in the analysis

calculated from two horizontal components of the acceleration time histories. Note that in this study, the SI value is defined as the average velocity response spectrum of 20 % damped single-degree-of-freedom systems with natural period between 0.1 s to 2.5 s as (Katayama et al., 1988)

$$SI = \frac{1}{2.4} \int_{0.1}^{2.5} S_V(T,h{=}0.2)\, dT \qquad (1)$$

For the peak values of the ground motion, the maximum of the resultants of the two horizontal components is used. SI values are computed by rotating the axis from the East-West to the North-South axis in 9 degree intervals and the maximum is used in the analysis. Figure 1 shows the relationship between (a) SI and PGA, and (b) SI and PGD together with the damage category for the 79 records. Due to the difference in the waveform and frequency contents, the data points look quite scattered in the SI-PGA plane. But severe damage is only seen for SI values larger than 25. In the SI-PGD plane, damage looks to be proportional to both SI and PGD although some exceptions are found. The relationship between PGV and SI is not shown here, but they were found to be very similar values. Thus, we decided to use only SI instead of PGV in neural network analyses since SI value (and PGA) is actually observed by a new type of seismometer of a Japanese gas company (Nakane et al., 1992).

Other parameters showing severity (or characteristics) of ground motion, duration and dominant frequency contents of motion should be taken into account in damage estimation. But in this first trial using neural networks, we just considered three parameters; PGA, PGD and SI.

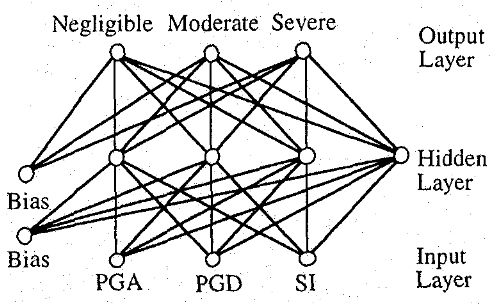


Figure 2. A neural network model for earthquake damage estimation

3 NEURAL NETWORK MODEL

A neural network is a collection of parallel processors connected together in a form of a directed graph. A network consists of neurons or Processing Elements (PEs) which are arranged in layers. In this study, a typical feed-forward network with supervised learning using the extended delta-bar-delta learning algorithm (Minai and Williams, 1990) is employed. Neural network analyses are run on Neural Works Professional II simulator (NeuralWare, Inc., 1991).

Figure 2 shows a three-layered network model used in this study. PGA, PGD and SI are considered as input parameters. To represent the three damage categories, three PEs are considered in the output layer. Each of the PEs represents one damage category. For a particular damage category, the corresponding PE is activated as 1 and the two other PEs are inhibited as 0.

Table 2 Mean output values and correctly estimated case ratios by recall tests for the 79 records

Input parameters	No. of PEs in hidden layer	Mean of network's estimation			Correctly estimated case (ratio)		
		negligible	moderate	severe	negligible	moderate	severe
PGA, PGD, and SI	4	0.855	0.557	0.870	0.92	0.50	0.97
	5	0.933	0.685	0.844	0.95	0.67	0.93
	6	0.944	0.502	0.931	0.95	0.50	0.97
PGA and SI	4	0.800	0.418	0.894	0.82	0.33	0.97
PGD and SI	4	0.836	0.439	0.822	0.92	0.33	0.97
PGA only	4	0.575	0.238	-0.002	0.55	0.33	0.10
SI only	4	0.763	0.249	0.797	0.74	0.00	0.86

An output vector of {1,0,0} represents negligible damage while moderate and severe damage categories are represented by {0,1,0} and {0,0,1}, respectively.

One hidden layer is considered between the input and output layers. The number of PEs in the hidden layer is usually determined by experience or trial and error. Several cases are tested in this study (see Table 2). The PEs between the input and hidden layers and between the hidden and output layers are fully interconnected. The relationship between connected PEs is represented by a hyperbolic tangent transfer function with connection weights and bias. The connection weights are updated to reduce the squares of errors between desired and actual outputs by supervised learning. The bias term is included to help the convergence of the weights in an expectable range. After thousands of iterations (learning), the network converges.

Similar neural network analyses are also performed for two input parameter cases (PGA and SI; and PGD and SI) and one input parameter cases (PGA only and SI only).

4 RESULTS AND DISCUSSIONS

The results of neural network analysis are summarized in Table 2 for the number of learning counts =79,000 (1000 iterations of the 79 records of the training data set). In this study, the connection weights are updated after one complete pass of the training data set. Figure 3 shows the convergence of the neural network with 5 hidden layer PEs using the PGA, PGD and SI as input. The convergence is based on the sum of the root-mean-square (RMS) errors of each of the three output PEs for the whole training data set. After the supervised learning, the converged network suggests three output values for a given set of input parameter values. Although the ideal output for a severe damage case is {0,0,1}, the network gives, for example, {0.03, 0.32, 0.89}. The numbers in the three left columns in Table 2 are the mean values of the network estimation for the recall test with the 79 data. Figure 4 plots these numbers for different input parameter combinations.

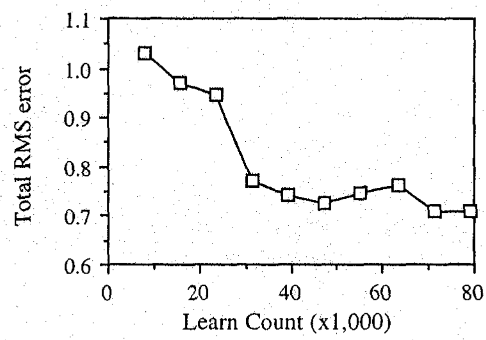
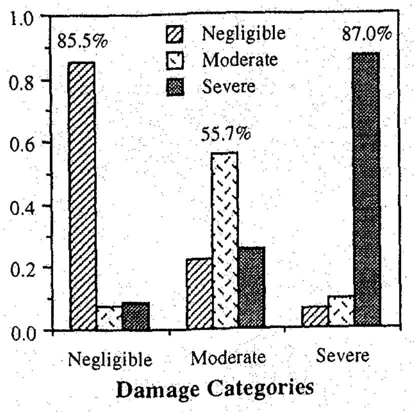


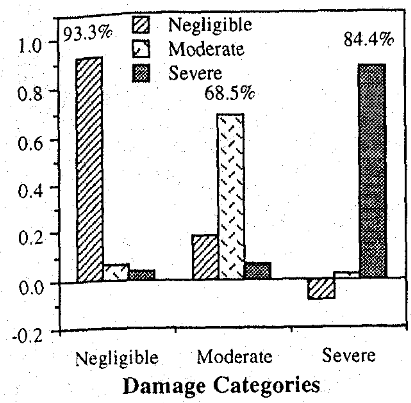
Figure 3. Convergence of neural network with 5 hidden layer PEs using PGA, PGD, and SI as input

It is observed that the estimated values corresponding to negligible damage and severe damage are high (mostly more than 0.8), except for the case that uses only PGA as input parameter. In fact, it can be seen that the PGA alone cannot adequately estimate the damage. The network that uses only SI gives a better estimation than the one using only PGA. This is consistent with the observations of other researchers (Katayama et al., 1988). The estimation using both the PGA and SI, however, gives a better estimation than PGA alone or SI alone.

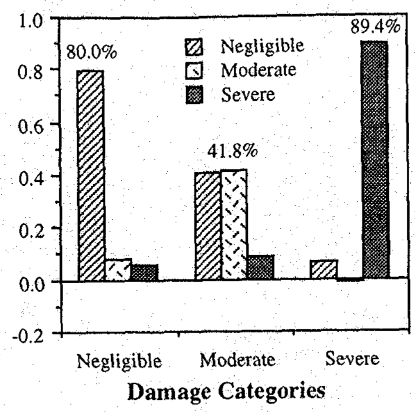
The values for moderate damage are not so high (often less than 0.5). This fact indicates that moderate damage is most difficult to identify. Actually, the criteria for this category are most uncertain and the number of data used for the learning is smallest (only 12 as shown in Table 1). Considering uncertainties



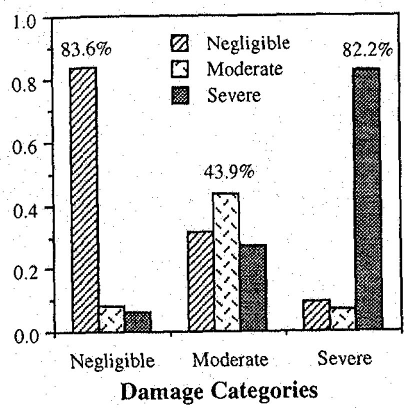
(a) PGA, PGD and SI input (4 hidden PEs)



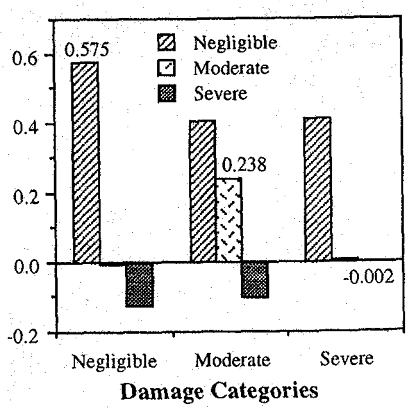
(b) PGA, PGD and SI (5 hidden PEs)



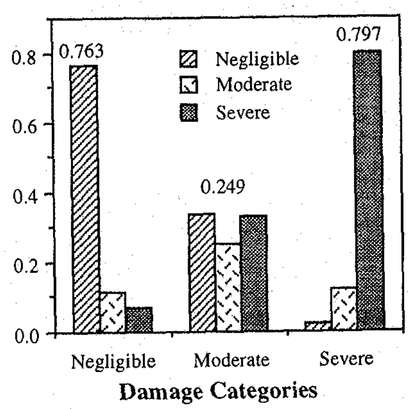
(c) PGA and SI input (4 hidden PEs)



(d) PGD and SI input (4 hidden PEs)

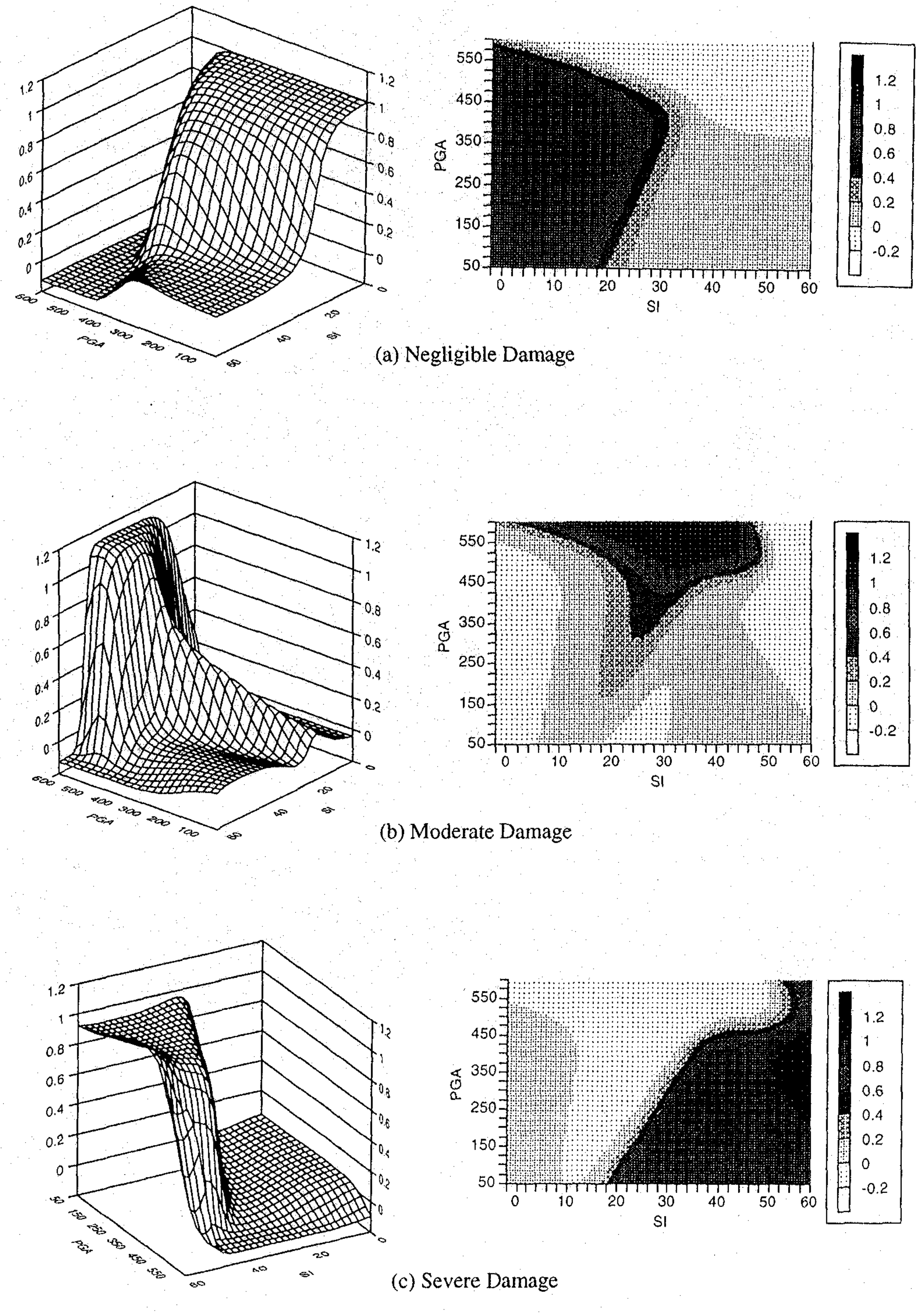


(e) PGA input (4 hidden PEs)



(f) SI input (4 hidden PEs)

Figure 4. Mean output values of networks by recall tests for the 79 records at 79,000 learning counts

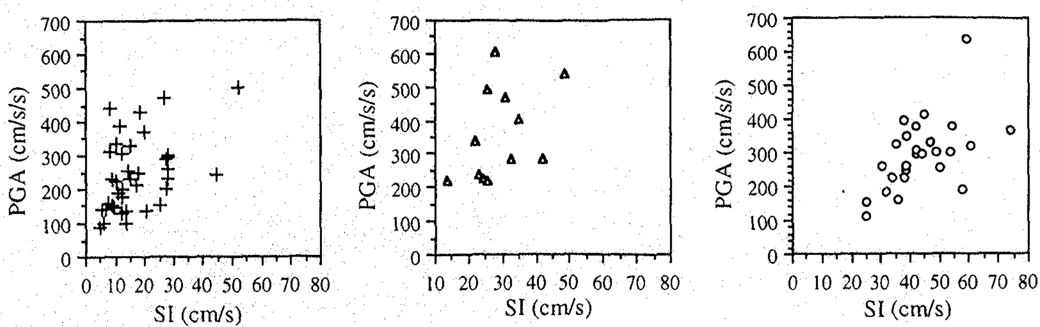


(a) Negligible Damage

(b) Moderate Damage

(c) Severe Damage

Figure 5. Output values by the converged network for various new inputs of PGA and SI



(a) Negligible Damage (b) Moderate Damage (c) Severe Damage

Figure 6. Distribution of training data using the PGA and SI as input

involved in the input-output relation, the estimation can be concluded to be fairly good.

The numbers in the three right columns in Table 2 indicate the ratio of correctly estimated cases, which means that if the maximum of the three output values is larger than 0.5 and it is the correct damage category, it is considered as a correct estimation. These ratios look also high.

Among three cases of input parameter combinations, the three parameter case (PGA, PGD and SI) gave the highest estimated values. However, the two parameter cases (PGA and SI; PGD and SI) also gave high values, indicating the feasibility of damage estimation based on observed SI and PGA by the new type of seismometer.

For the three input parameter case (PGA, PGD and SI), the appropriate number of elements in the hidden layer was sought. Among 4, 5 and 6 PEs' networks, the 5 and 6 hidden layer PEs gave the best estimation for negligible damage; the 5 hidden layer PEs gave the best estimation for moderate damage; and the 4 and 6 hidden layer PEs gave the best estimation for severe damage. The appropriate number of PEs in hidden layers seems to be problem (model)-dependent and data-dependent. Hence, a sensitivity analysis may be necessary for each problem.

The converged network is a kind of damage criterion in numerical sense. Figure 5 shows the estimated category values for various new input values of PGA and SI. The plot for negligible damage shows that this category is more dependent on SI than PGA: if SI is less than 20, the damage is negligible even when the PGA is high. The severe damage category seems to be affected by both PGA and SI although SI looks more influential. The range of SI and PGA for moderate damage lies between negligible and severe damage. But the estimated values are low, which indicates low confidence to assign this category, except for a small region where the training data distribution indicates moderate damage only.

By looking at the separate plots of the distribution of the damage categories with respect to the PGA and SI (Figure 6) and comparing with Figure 5, it can be seen that the regions for the neural networks damage category are very similar to the training data distribution. In the case of the regions where the damage data overlap, the network identified the damage as the one with the most number of cases in the training data. Since moderate damage has the least number of data in these regions, it will be considered by the network as "noise" and be disregarded.

In order to avoid this effect, the network was retrained using the moderate damage data twice. This means that the number of moderate damage data is increased by 12 and the number of training data becomes 91. Table 3 shows the results of the retrained neural networks. Compared with Table 2, the estimation for the moderate damage was improved, but this is accompanied by a decline in the estimation of negligible and severe damage. This demonstrates the dependence of the network on the training data used.

Although the examples shown here are highly data-dependent, the general tendency is close to the damage observations in previous studies (e.g., Katayama et al., 1988). It is also noted that since it is rather difficult to construct damage criterion of structures in terms of several strong motion parameters (e.g., PGA and SI), the method used in this paper may be conveniently applied to such cases. However, it must be emphasized that although a neural network can estimate damage extent, the estimation is learning data-dependent. Hence, to prepare a good data set for the learning is the most important thing in the practical use of neural networks in engineering problems.

Table 3. Mean output values and correctly estimated case ratios by recall tests for the 79 records for the network trained by doubling the data for moderate damage

Input parameters	No. of PEs in hidden layer	Mean of network's estimation			Correctly estimated case (ratio)		
		negligible	moderate	severe	negligible	moderate	severe
PGA, PGD,	4	0.814	0.612	0.819	0.92	0.67	0.90
and SI	5	0.934	0.686	0.835	0.97	0.67	0.90
	6	0.854	0.638	0.841	0.97	0.67	0.90
PGA and SI	4	0.712	0.604	0.841	0.74	0.75	0.93
PGD and SI	4	0.722	0.418	0.683	0.74	0.50	0.69

5 CONCLUSIONS

A use of neural networks for the damage estimation of structures subjected to strong earthquake motions was demonstrated. Since it is not so easy to correlate strong motion parameters and resultant structural damage using simple mathematical equations, neural networks were conveniently introduced to construct such a relationship based on given data. The peak ground acceleration, the peak ground displacement, and the spectrum intensity from 79 actual earthquake records were used as input parameters while the corresponding observed damage extent (e.g., negligible, moderate, and severe) was considered as a desired output. After iterations of supervised learning, the network converged. The recall tests using the learning data showed fairly good accuracy of estimation. Although the input parameters and data used are still preliminary, the method may be a useful tool for early damage estimation of structures based on observed strong motion parameters.

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