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A NEURAL NETWORK MODEL TO PREDICT STRUCTURAL DAMAGE DUE TO EARTHQUAKE GROUND MOTION

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INTRODUCTION: Neural networks are very powerful in classification problems and input to output mapping and have been used in the field of earthquake engineering [1,2]. However, the efficiency of the network depends largely on the training data used. Previous studies used actual real-world data to train the network, but such data are few and may not be favorably distributed within the range of values in which the network is expected to operate. This will result in a bias for the network to minimize errors in the range which has a lot of data rather than to minimize errors equally along the whole relevant range. In this study, simulated earthquake ground motions are used to generate training data that are well distributed within the range of values specified. With the use of simulated ground motions, a more unbiased neural network model can be achieved.

SIMULATION OF STRONG GROUND MOTION: The earthquake ground motion is simulated by first generating a stationary time series having the Kanai-Tajimi (K-T) power spectrum, $S(\omega)$, and random phase angles:

$$S(\omega) = S_0 \cdot \frac{1 + 4h_g^2\,\omega^2/\omega_g^2}{(1-\omega^2/\omega_g^2)^2 + 4h_g^2\,\omega^2/\omega_g^2} \qquad (1)$$

where $h_g = 0.4$ and ω_g is the dominant frequency of motion. The stationary time series is then multiplied with a trapezoidal envelope function to taper the start and end of the ground motion. A rise time and decay time of 2.5 s was used in this study. To have a well-distributed set of strong ground motion data, the parameters of the K-T spectrum and total time of simulation are randomly selected within the range of values (Table 1), assuming a uniform distribution for the parameters.

A total of 450 ground motion time series were generated. Figure 1 shows the distribution of the maximum acceleration and velocity for the set of simulated earthquakes.

Table 1. Parameters for earthquake simulation

Parameter	Lower Limit	Upper Limit
total time	7.5 s	30 s
S_o	10.0 cm^2/s^3	75.0 cm^2/s^3
ω_g	4.0 rad/s (0.64 Hz)	40.0 rad/s (6.34 Hz)

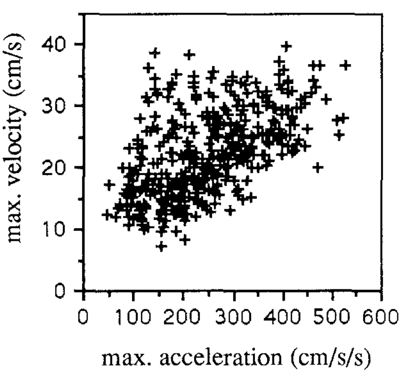

Fig. 1 Distribution of maximum acceleration and velocity for the 450 simulated earthquakes

STRUCTURE / DAMAGE MODEL: For this study, a single-degree-of-freedom model (T=0.55 s) representing two-story wooden houses commonly found in Japan was used. The model has a bi-linear stiffness with the secondary stiffness taken as 20% of the initial stiffness. The damping ratio is 0.05 and the restoring force at yielding is taken as

$$Q_y = mg \cdot C_y \quad \text{where } C_y = 0.25/\sqrt{T} \qquad (2)$$

Its response to the simulated earthquakes were calculated by a step-by-step nonlinear analysis. The ductility factor is then used to represent the damage level of the structure for that ground motion.

NEURAL NETWORK MODEL: A back-propagation neural network is used to estimate the damage level (i.e., ductility factor) from the indices of the input ground motion. The Normalized Cumulative-Delta-Rule learning algorithm was used together with the Hyperbolic Tangent transfer function. The ground motion indices (i.e., PGA, PGV, PGD, SI, mean square, and time duration [3]) were used as input to the network while the damage level was used as the output. The neural network has one hidden layer with four processing elements fully connected to the input and output layers and bias (Figure 2).

RESULTS AND DISCUSSION: Due to the large number of training data, 900,000 training counts were done. Since the relationship between input and output is very complex and highly nonlinear, the network cannot be expected to predict the output precisely. The learning process, however, will minimize the errors associated with the training data. In this respect, it is similar to a multivariate regression, although an *a priori* functional form is not required. A plot of the desired output and the network output shows that the neural network gives a good estimation of the damage (Figure 3). This implies that for any earthquake motion within the range of the training data, the probable damage can be immediately estimated without making use of numerical analysis methods. This makes the network ideal for very quick damage estimation as the ground motion is recorded by strong motion sensors.

A sensitivity analysis of the trained network shows that the output (i.e., damage) is most affected by the PGA, SI, and the mean square of the ground motion. It is least affected by the time duration of the motion. To see the effect of changing the input parameters, four cases are compared. Case A represents the network using 6 input parameters (i.e., PGA, PGV, PGD, SI, mean square, and time duration). Since SI and PGV are relatively correlated, 2 more cases without the PGV (Case B) and then without the SI value (Case C) are used. Case D uses only the PGA, SI, and mean square.

Figure 4 shows the convergence of the four cases from 10,000 learn counts to 90,000 learn counts in terms of the correlation between the desired output and the network output and in terms of the root-mean-square error of the training data. It can be seen that Case A gives the best estimation followed by Case B, Case D and Case C. This implies that the neural network model makes use of as much information as it can to arrive at an estimate of the damage.

CONCLUDING REMARKS: A neural network model is used to estimate the damage of a specific structure (T=0.55s) from basic indices of the ground motion. To have a well-distributed training data for the network, 450 artificial earthquakes were generated from parameters randomly chosen from a specified range of values. A sensitivity analysis of the network shows that the PGA, SI, and mean square have the most effect on the damage for the particular structural model studied. However, the network which uses all the ground motion indices provides the best estimation of the damage of the structure. Although this study only considers one specific structure, it can be easily repeated for other structures as well. It may also be important to include an input parameter which is a function of the predominant period of the structure and of the ground motion. These considerations will be included in future studies.

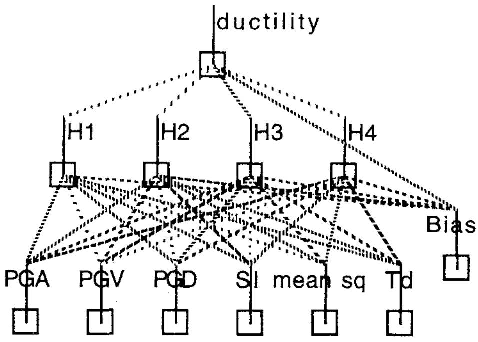

Fig. 2 Neural network structure

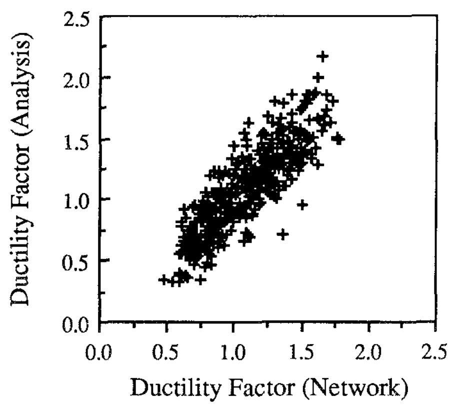

Fig 3 Plot of the neural network output vs the desired output

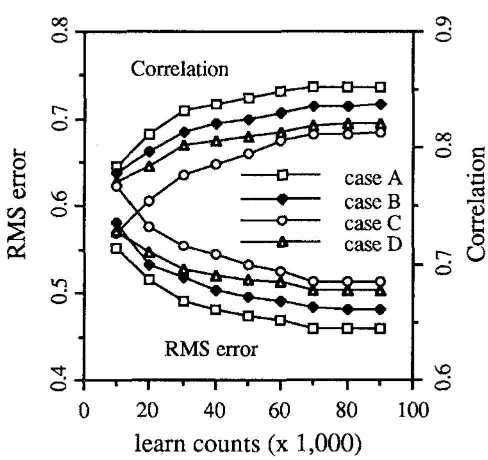

Fig 4 Convergence of the neural network in terms of the root-mean-square error and the correlation between the desired and network outputs

References:

[1] F.S. Wong, A.T.Y. Tung, and W. Dong (1992). Seismic hazard prediction using neural nets. *Proc. 10th World Conf. on Earthquake Engineering*, **1**, 339-343.

[2] M. Fatima, F. Yamazaki, and T. Katayama (1992). Neural networks for estimation of earthquake damage severity. *Proc. 47th Annual Meeting Japan Society of Civil Engineers*, 142-143.

[3] M.D. Trifunac and A.G. Brady (1973). A study of the duration of strong earthquake ground motion. *Bull. Seis. Soc. Am.*, **65**.