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Evaluation of Seismic Design Values in the Taiwan Building Code by Using Artificial Neural Network

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Abstract: Taiwan frequently suffers from strong ground motion, and the current building code is essentially based on two seismic zones, A and B. The design value of horizontal acceleration for zone A is 0.33g, and the value for zone B is 0.23g. To check the suitability of these values, a series of actual earthquake records are considered for evaluating peak ground acceleration (PGA) for each of the zones by using neural network models. The input parameters are magnitude, epicenter distance, and focal depth for each of the checking stations, and the peak ground acceleration is calculated as the output with the use of spatial relationship in an averaged sense. The neural network model estimations showed that for 5 of the locations, out of the 24 locations considered, the design value recommended in the building code would be exceeded. In addition, a curve fitting model, PGA = 8.96/Df, is developed for the relationship between horizontal PGA and focal distance (Df), and reflecting the essential characteristics of strong motion in region investigated. The neural network model and the mathematical equation can provide useful information for both the relevant government agencies and practicing engineering designers.

Keyword: building code, design value criteria, neural network, peak ground acceleration, potential hazardous locations, curve fitting model.

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1 Introduction

Located in the circum-pacific seismic zone, the island of Taiwan is about 400 km long from tip to tip, 130 km wide at its broadest points and a total area of about 36000 km^2. There are about 54 earthquake faults existing around the whole island, and the occurrence of strong motion has a very high possibility in this region. According to the records from Central Weather Bureau Seismological Center (CWBSC), in the years between 1991 and 2004 [Central Weather Bureau (2005)], the average occurrence rate of strong motion is 18694 per year. Among these earthquakes, 1047 cases can be felt by human beings, where one of these cases has the possibility to cause property damages in each year. Seven earthquakes, capable of causing serious damage, with magnitudes over 6.5 on the Richter scale have been reported since 1906. Hence, the need for people living in this island to deal with the earthquake problems is inevitable.

From Figure 1 it can be seen that there are three major earthquake zones in the Taiwan region. The west seismic zone is about 80 km in width, the frequency of occurrence is low within this zone, but the resulting damage is serious as the earthquake in this zone often occurs at a shallow focal depth (less than 20 km). In the east seismic zone, the width is about 130 km, a much higher frequency of occurrence and a deeper focal depth than that of the west seismic zone, and thus less damage is reported for this zone. The northwest seismic zone is concentrated on a small area, and the characteristics of strong motion are similar to the one in west seismic zone. With these regional geophysical characteristics, the effects of strong motions have to be considered in setting up an adequate building code for the area.

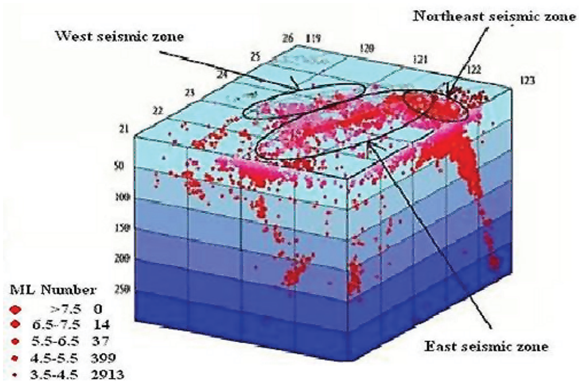

Figure 1: Major earthquake zones in Taiwan area (source: CWBSC, 09/1999 – 12/2004).

Each country has its own building code in accordance with regional characteristics and construction developing history. However, the content of the United States Uniform Building Code (UBC) is probably the most commonly used reference document for many of countries around the world. Based on this concept, the Construction and Planning Agency of Taiwan government started to consider the effect of strong ground motion for structural design in the year of 1974, and three seismic zones were identified in the building code at that time. In 1982, the design earthquake force was increased based on the 1976 version of the UBC. Then, a major code revision was done in 1997, and the original three zones were replaced by four zones (i.e. 0.33g, 0.28g, 0.23g, and 0.18g). But after the major earthquake, the so-called 921 earthquake with a magnitude 7.3 on the Richter scale in the year of 1999 [Ma (1999); Lee and Loh (2000)], it was found that the design codes were unable to reflect the actual situation. Thus, an adjustment to the building code was made, and two division zones (0.33g and 0.23g) became the present design standard [Construction and Planning Agency (2006)].

From academic point of view, whether the above mentioned revision in building code is suitable or not may become an interesting research topic, and may be checked by scientific methods. Previous research on earthquake problems can be found in several published literature [Conte and Peng (1997); Katayama (1982); Liang et al (2005); Luco and Wong (1987); Trifunac and Lee (1989); Trifunac (2005); Yeh and Wen (1990)], and recent research has used artificial intelligence techniques in this important engineering field [Der Kiureghian and Crempien (1989); Ghaboussi and Lin (1998); Lee and Han (2002); Lin and Yong (1987); Ozerdem et al (2006)]. In particular, researchers have used neural network to estimate peak ground acceleration (PGA), one of the key factors for evaluating the potential damage resulting from strong motion [Chu et al (2003); Kerh and Chu (2002); Kerh et al (1996); Kerh and Ting (2005)]. The results indicate that the use of three seismic parameters, i.e. magnitude (ML), epicentral distance (Di), and focal depth (De) in the neural network models can achieve the best PGA estimations. This research extends previous work to investigate the suitability of using two zones standard in Taiwan's building code.

Although conventional methods such as nonlinear regression analysis may be employed to analyze seismic records, this method needs to assume a function form in advance, and the result may not be able to correctly predict PGA at a particular site that is different from the checking station. In contrast, the neural networks are powerful pattern recognizers and classifiers, which are capable of estimating PGA not only at the checking point, but also at a specified point by inputting its spatial relationship. There is some argument about the lack of physical meaning in neural network black-box type of training [Benitez et al (1997)], but more and more researchers agree that this approach is a primary tool for analyzing random data sets due to its simplicity and effectiveness. Thus, the purpose of this study is to analyze seismic records collected at 209 checking stations, by using back-propagation neural network. The PGA at 24 geographical central locations, based on the data set at several checking stations around a specified location is estimated for each division zone (see sketch details in Figure 2). The estimated horizontal PGA is compared with the building code design value, and potentially hazardous areas are identified from the neural network calculations. Also, a curve fitting model is

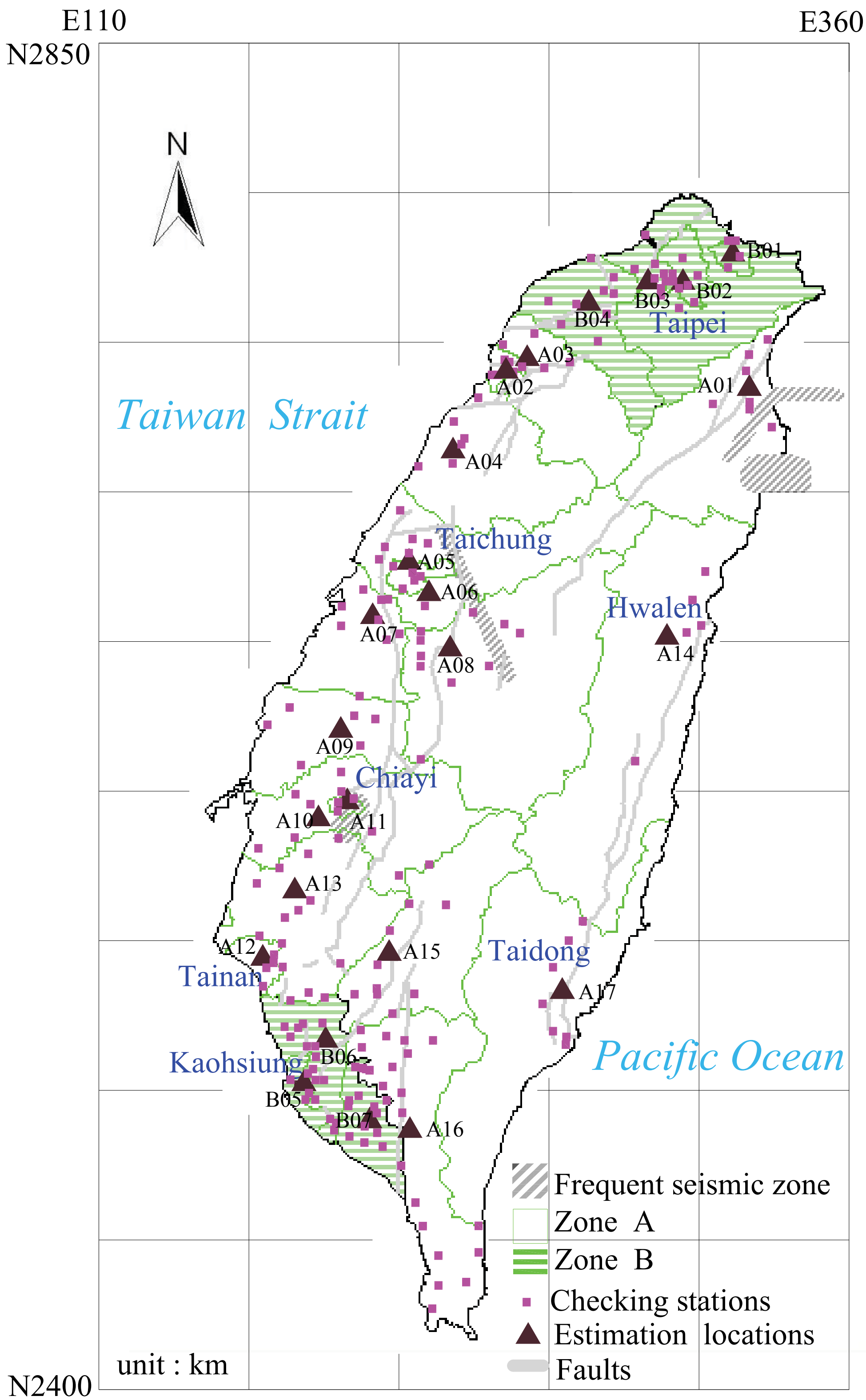

Figure 2: Sketch details of the investigation area.

developed based on the relationship between calculated horizontal PGA and focal distance. It is expected that the results from the present study will provide useful information for government agencies and designers working in this field.

2 Neural Network Model and Seismic Data Treatment

As mentioned in Wikipedia encyclopedia, the term information technology has ballooned to encompass many aspects of computing and technology [Wikipedia Encyclopedia (2008)], where artificial neural network is one of popular methods used in the recent academic and practical research fields. Since the pioneer work of artificial neural concept in the year of 1943, several types of neural network model have been developed up to the present time [McCulloch and Pitts (1943); Hagan et al (2004)]. But due to effectiveness and easy to implement in a computer code, the multi-layer neural network with its modification seems to attract more researchers (e.g. [Mandal et al (2005); Oishi and Yoshimura (2007); Noroozi et al (2006); Zhang and Subbarayan (2002)]). The basic structure of back-propagation neural network includes an input layer, a hidden layer, and an output layer. The application of the neural network approach can be found in various engineering fields, as this approach can be used to generate the required functions for parameter prediction and pattern recognition [Chang and Chang (2006); Kuźniar et al (2005); Lu (2005); Pu and Mesbahi (2006); Sarghini et al (2003); Shanga (2005)]. In this multi-layered neural network, the output of each layer becomes the input of the next layer, and a specific learning law updates the weights of each layer connections in accordance with the errors from the network output. The equation for each layer may be written as:

$$Y_j = F(\sum W_{ij} X_i - \theta_j) \tag{1}$$

where Y_j is the output of neuron j; W_{ij} represents the connection weight from neuron i to neuron j; X_i is the input signal generated for neuron i; θ_j is the bias term associated with neuron j; and F is the nonlinear activation function. There are several functions from which the activation function can be chosen, but the sigmoid function, of the form $F(x) = 1/(1+e^{-x})$, is commonly used to limit the output values to be between 0 and 1 for the input values ranging from negative to positive infinity. The sigmoid transfer function is used in this study to make the operating process continuous and differentiable.

Figure 3 shows the basic neural network model used in the present study, with the three seismic parameters, magnitude, epicentral distance, and focal depth forming the input layer. A single hidden layer is used and the output layer is the target PGA. In order to evaluate the performance of this neural network model, the coefficient of correlation (R) is used and defined as follows:

$$R = \frac{\sum_{i=1}^{m} (x_i - \overline{x})(y_i - \overline{y})}{\sqrt{\sum_{i=1}^{m} (x_i - \overline{x})^2 \sum_{i=1}^{m} (y_i - \overline{y})^2}} \tag{2}$$

where x_i and $\overline{x}$ are the recorded values and its average value respectively; y_i and $\overline{y}$ are the estimated values and its average value respectively; and m denotes the number of data points in the analysis. This coefficient may have a positive or negative value, so that its square value R^2 is also frequently taken to represent the degree of correlation between the recorded data and the estimation by the neural network model. In general, when $R^2 > 0.7$, it denotes a high degree of correlation; when $0.3 < R^2 \leq 0.7$, it denotes a medium degree of correlation; and when $R^2 \leq 0.3$, it represents a low degree of correlation.

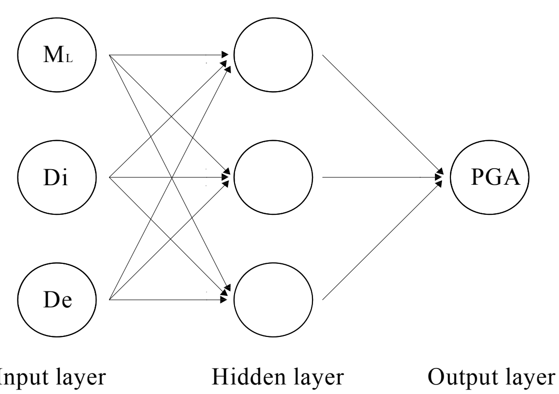

Figure 3: Three layers neural network model.

Furthermore, an error evaluation function is required to calculate the difference between the actual record values and neural network estimations. The root-mean-square error as defined in the following equation was used in this study:

$$\mathrm{R}MSE = \sqrt{\frac{\sum_{n}^{N}(T_n - Y_n)^2}{N}} \tag{3}$$

where N is the number of learning cases; T_n is the target value for case n; and Y_n is the output value for case n. The performance of neural network model was evaluated, using the above equations, to check its effectiveness.

Note that the seismic data sets used were collected from some of the checking stations in the entire Taiwan Island [Seismological Center (2007)]. Figure 4 shows a typical earthquake wave propagation, where the information such as time, location of hypocenter, magnitude (ML), epicentral distance (Di), focal depth (De), and acceleration in different directions, were obtained from seismometers installed in the checking stations. In this study, the data sets are taken from a total of 209 checking stations around the island recorded between the years from 1994 to 2005. Since the main objective of this study is to estimate the PGA value, only the earthquake data with magnitudes over 5.0 on the Richter scale were chosen, to decrease unwanted noise in neural network training. Each checking station basically provided 30 data sets, but in cases where there are insufficient actual records, as for some new stations, then at least 15 data sets were included. Because the useful seismic data cannot be obtained in a short period of time, the data sets for analysis in this study may be considered as a minimum requirement from a statistical standpoint.

Further, in order to minimize the effect of extreme values in the data sets, the input data were normalized using the following equation:

$$f_t = \frac{f_i}{\left(\sum_{i=1}^{n} f_i^2\right)^{1/2}} \tag{4}$$

where f_i is the input data obtained from each measuring record; and f_t is the new input data after transformation [Lin (2000)]. With this preprocessing of data, the input values will be within the range of 0 to 1, and this normalization will match with the transfer function used in the neural network.

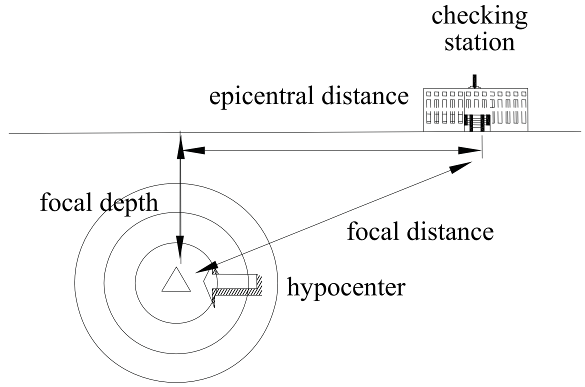

Figure 4: Definitions of parameters for a typical earthquake wave propagation.

3 Neural Network Training and Verification

In this study, the toolbox of MATLAB is used to develop the neural network models, the details of this software package and operating procedure can be found in the user manual or related books [Yeh (1997); Wun et al (2003)]. It should be mentioned that before the neural network training process, three data sets including the maximum earthquake magnitude, the shortest epicentral distance, and the shallowest focal depth are set aside from the whole seismic data sets for each station for verification of the model. The remaining seismic data sets are used to train the neural network.

By considering one of checking stations in the Taipei area as an example in the ANN training process, the rate of error convergence during training is shown in Figure 5. The curves show that the root mean square error converged after about 500 epochs for the three directions (V, NS, EW). Because there are three directions of PGA at each station, those result in a total of 627 sets of weight and bias values in the neural network models. A typical data set for weight and bias terms for the example station can be seen in Table 1. Once the training is completed, the verification data sets are used to validate the model.

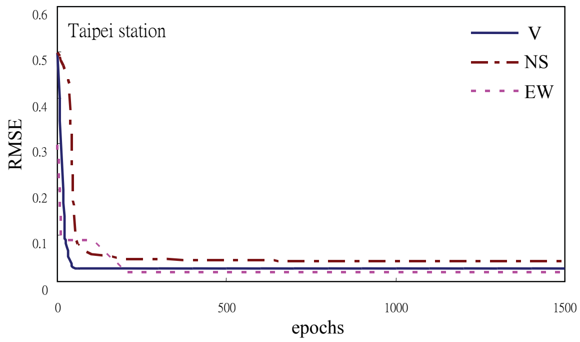

Figure 5: Rate of error convergence during ANN training.

By taking seven metropolitan areas: Taipei, Taichung, Chiayi, Tainan, Kaohsiung, Hwalen, and Taidong in the island as examples, the averaged square coefficients of correlation obtained from the trained neural network models are 0.9098, 0.8567, and 0.9032 for V, NS, and EW three directions, respectively. Table 2 shows the result of for the three verification data sets. It can be found that the square values of correlation coefficient range from 0.8146 to 0.8695, exhibiting a high degree of correlation. For all estimated locations, the performance of the ANN models compared to the actual seismic records for the three directions are shown in Figure 6. The squared values of correlation coefficient are 0.8244, 0.8519, and 0.8872 for three directions V, NS, and EW, respectively. The value is 0.8517 for all combined data sets, indicating that the estimations do have an acceptable high degree of correlation with records. Therefore, these neural network models at each station are ready to simulate PGA estimation values, and the work of post-analysis can be done from the output.

4 Evaluation of PGA Design Value by Neural Network Estimation

Based on the classification in the building code for Taiwan, there are 17 subdivisions in seismic zone A (i.e. A01 – A17), and 7 subdivisions in zone B (i.e. B01 – B07). In each subdivision, there exist several checking stations providing many sets of seismic data. In this study, the simplest way for determining the estimation location for each subdivision is by taking its average coordinate for checking stations. In case there is only one checking station in the subdivision, this checking station is considered as the estimation location for the whole subdivision. In accordance with the relationship between the coordinates of the two locations, the seismic data in each checking station is transferred to the estimation location. Then, by inputting these transferred data to the neural network model, the PGA is obtained from the neural network output.

Before evaluating the design values in building code, a comparison of neural network PGA estimation with available microtremor measurements at Kaohsiung city (B05) is shown in Figure 7 [Kerh and Chu (2002); Lermo and Chávez-Gaírcía (1994); Nakamura and Takizawa (1990)]. The experimental result is obtained from the three nearest checking stations in the neighborhood of the estimation location, by the use of weighting factors based on the distances between the estimation location and the checking stations. For the three directions, the result shows that the present neural network estimation is in reasonably good agreement with experimental measurement and previous ANN estimation. This comparison proves the effectiveness of using the present neural network model, and provides confidence in the use of this model for the further analysis.

By taking the PGA values in the NS and EW directions, the horizontal PGA can be calculated for each station, and the averaging value is then obtained for the estimation location at each subdivision zone. Figures 8 and 9 show the estimated horizontal PGA values compared to the design values of the building code for zones A and B respectively. Iit can be seen that the locations at A05 and A10, for zone A, have the horizontal PGA of 0.332g and 0.340g, which are slightly higher than that of the design value (0.33g). But at locations of A06, A08, and A11, the estimated horizontal PGA has the values 0.375g, 0.578g, and 0.404g, which are all significantly higher than the design value. For zone B, the estimated values all comply with the building code and have a lower horizon-

Table 1: Typical weight and bias values at one of the checking stations in Taipei.

Weights & Bias	W1(1,1)	W1(1,2)	W1(1,3)	W1(2,1)	W1(2,2)	W1(2,3)	W1(3,1)	W1(3,2)
V	-70.827	-1.971	-4.399	13.971	-2.001	-23.804	49.619	1.698
NS	4.970	1.048	37.240	-4.261	59.494	22.388	-94.580	1.111
EW	-63.791	2.044	-5.564	-67.839	-0.956	-30.315	25.283	-0.876
	W1(3,3)	W2(1,1)	W2(1,2)	W2(1,3)	B1(1,1)	B1(2,1)	B1(3,1)	B2(1,1)
V	9.668	14.916	11.581	25.891	13.550	2.125	-10.979	-27.878
NS	-25.668	-13.654	7.947	-13.961	-8.128	-27.642	22.682	11.164
EW	1.750	20.344	6.171	52.581	11.119	21.932	-4.320	-45.869

Table 2: Performance of trained neural network models on verification data sets.

Parameter Direction	V	NS	EW
ML (R^2)	0.8612	0.8371	0.8543
Di (R^2)	0.8311	0.8517	0.8673
De (R^2)	0.8146	0.8339	0.8695

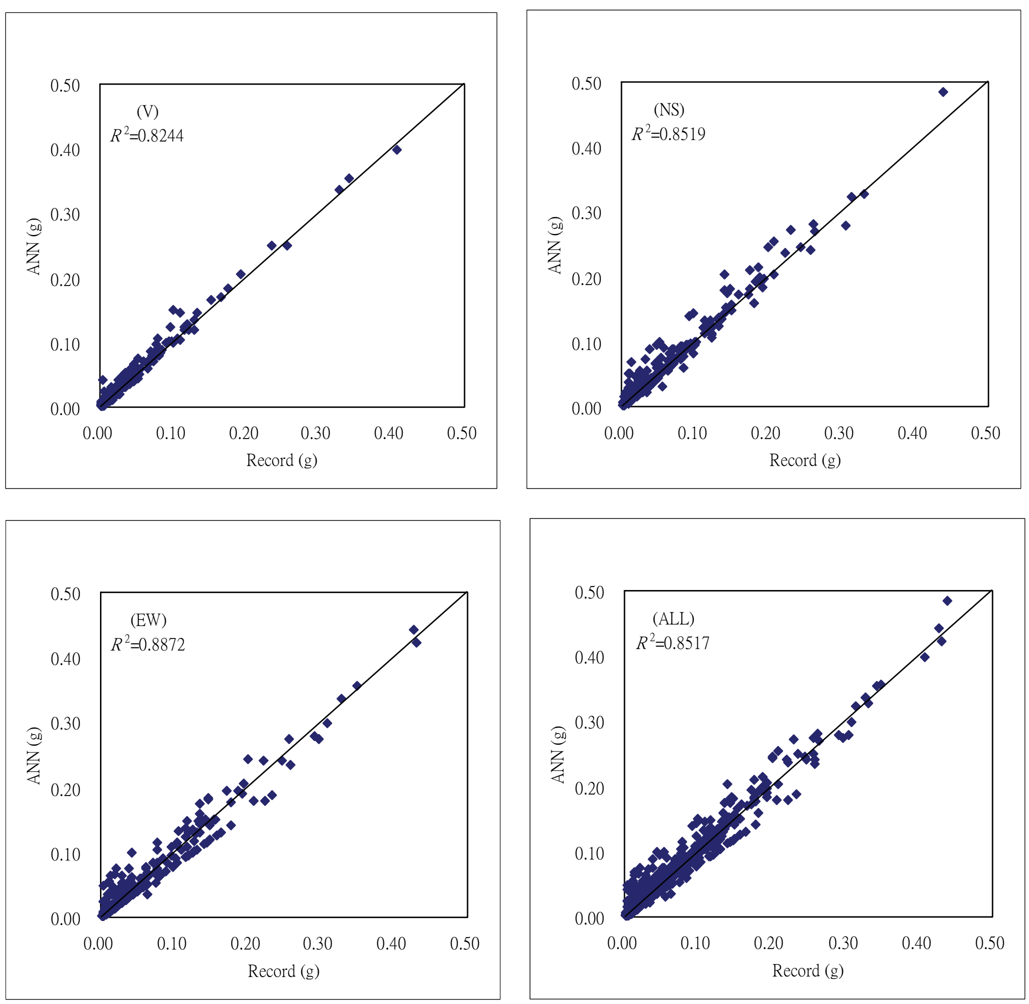

Figure 6: Comparison of neural network model estimations and records, (a) V direction, (b) NS direction, (c) EW direction, and (d) three combined directions.

tal PGA than the design value (0.23g). To be safe, the public should be made aware of these potential hazardous locations identified in zone A, to prevent excessive property damages and economical losses during unpredictable strong motions. Most importantly, those responsible for revising the building code should take the results of this study into consideration in the next revision of the building code.

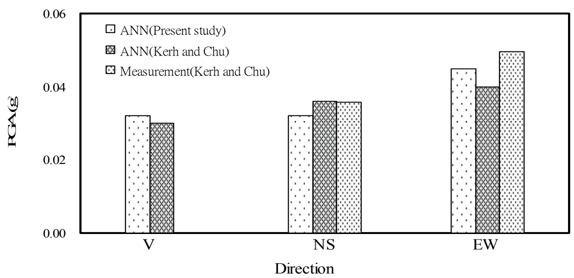

Figure 7: Comparison of ANN estimated PGAs with microtremor measurements (B05).

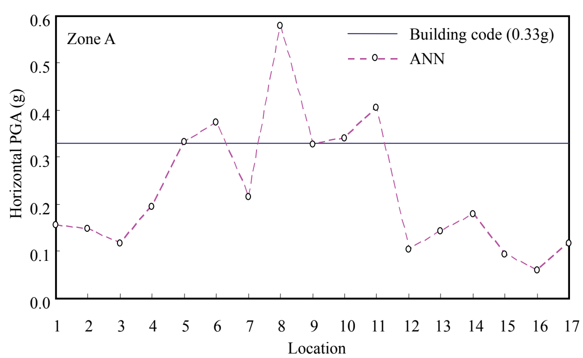

Figure 8: ANN estimated horizontal PGA vs. design value of building code (zone A).

To better illustrate the potential hazardous locations,, the three dimensional horizontal PGA plot for ANN estimations and design values are displayed in Figure 10. It is seen that the potential hazardous locations are in the vicinity of frequent seismic zones. In particular, the Nantou subdivision (A08) is near the fault which caused the 921 earthquake (Df = 20.1 km), hence a relatively very high estimated horizontal PGA is found in this region. Similar reasons may be found for Taichung

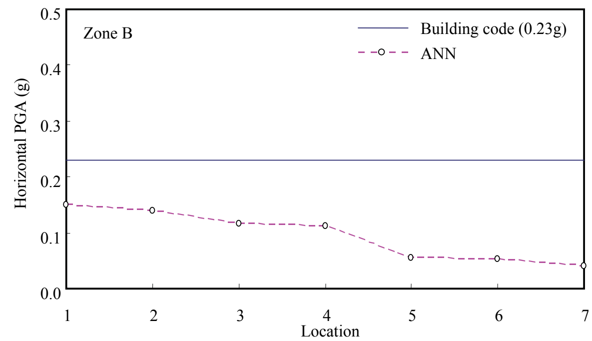

Figure 9: ANN estimated horizontal PGA vs. design value of building code (zone B).

city (A05), and Taichung county (A06), which have Df = 38.2 km, and Df = 28.4 km, respectively. For the subdivisions at Chiayi city (A10) and Chiayi county (A11), the higher horizontal PGA may be caused by the 921 after shock, which occurred on 22/10/1999 with a magnitude 6.4 on the Richter scale. The focal distances are considered short, and have the values Df = 20.6 km and Df = 17.1 km for the two regions.

From the ANN estimation results, it can be found that the focal distance, which represents two important earthquake parameters, i.e. the focal depth and the epicentral distance, seem to have a close relationship with the horizontal PGA. Therefore, a simple curve fitting model is developed based on the 24 estimation cases, and the result is shown in Figure 11. The curve fits the equation PGA = 8.96/Df with an acceptably high correlation coefficient of R^2 = 0.7739, and may be taken to describe the characteristics of strong motion in Taiwan. Because the present study used the actual seismic records from many checking stations as the data base, the ANN estimation results and the developed curve fitting model have an acceptable level of reliability. Thus, the identified potential hazard estimations and mathematical equation provide useful bases for the next revision of the building code and for practicing engineers for designing construction projects in this region.

5 Conclusion

Taiwan is under constant threat of earthquakes due to its location at the intermediate boundary

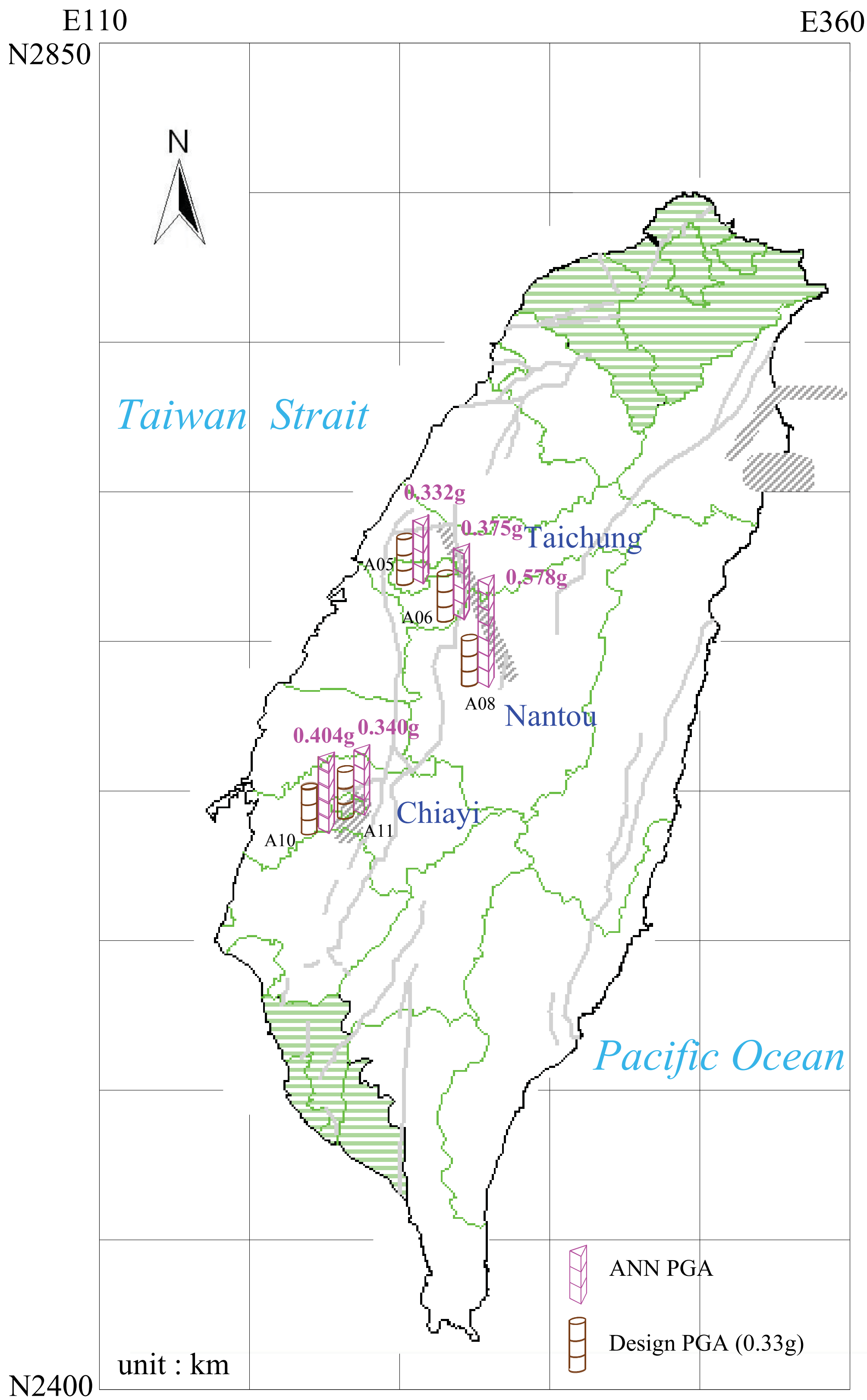

Figure 10: The ANN identified potential hazardous locations.

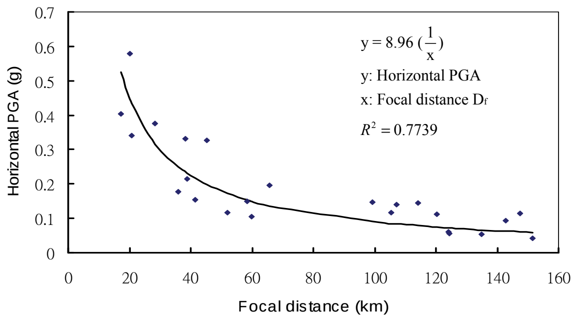

Figure 11: The curve fitting model between horizontal PGA and focal distance.

region of the Eurasia plate and the Philippine sea plate. It is thus essential to revise the building code in accordance with the actual strong motion characteristics. In this study, a back-propagation neural network model is employed to evaluate the suitability of code provisions for the current condition. The input seismic parameters are magnitude, epicentral distance, and focal depth and their values are based on the multi-year records collected from several checking stations in this region. After neural network training and verification, the PGA at the output layer is then calculated and compared with the design value. Thus the potential hazardous locations are identified and a curve fitting model is developed for the relationship between horizontal PGA and focal distance.

Following the development of technology for recording strong motions, some checking stations and measuring instruments may be installed in a new area, but some of the old stations may be closed for various reasons. At the present time, there are about 686 seismic checking stations functioning around the island of Taiwan, but only records of 209 checking stations are taken as the data for the present neural network computation. Nevertheless, because the chosen checking stations are as close to the cities or near as possible to areas with high population density, the estimated results should still represent to an acceptable approximation for the investigation area. That is, the present neural network PGA estimation should provide a reasonably reliable value in comparison to the design value of building code.

Although the occurrence of strong motions is unpredictable, the resulting damages may be reduced by using a suitable design value for the constructions in the applicable region. The division of seismic zone in building code is not the unique reason to decrease the property damage resulting from natural disaster, but it does have a long term influence on the people living in areas where earthquakes frequently occur. By balancing the economical concern and the potential for property damage, the hazardous locations identified by the neural network model, provides useful information for the next revision of the building code. Certainly, more advanced methods such as genetic algorithm and vibration analysis may be used to further explore this crucial topic and to provide an enhancement for the present research results.

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