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Research Article

Neural Network Approach for Analyzing Seismic Data to Identify Potentially Hazardous Bridges

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Examining the effect of strong ground motions on civil engineering structures is important as it concerns public safety. The present study initially selects twenty-one bridges with lengths over 500 m in the Formosa freeway of Taiwan and collects a series of recorded seismic data from checking stations near these bridges. Then, three seismic parameters including focal depth, epicenter distance, and local magnitude are used as the input data sets, and a model for estimating the key seismic parameter—peak ground acceleration—for each of bridge site is developed by using the neural network approach. This model is finally combined with a simple distribution method and a new weight-based method to estimate peak ground acceleration at each of the bridges along the freeway. Based on the seismic design value in the current building code as the evaluation criteria, the model identifies five bridges, out of all the bridges investigated, as having the potential to be subjected to significantly higher horizontal peak ground accelerations than that recommended for design in the building code. The method presented in this study hence provides a valuable reference for dealing with nonlinear seismic data by developing neural network model, and the approach presented is also applicable to other areas of interest around the world.

1. Introduction

Most of the economical activities in Taiwan are concentrated on the western side of the island, and rely heavily on the first ever built national highway (Jhongshan freeway in the north-south direction), which started operation of the full length (372.8 km) in 1978 [1]. Following the rapid development in many areas, a more complete transportation networks including rail system, mass rapid transit system, and high-speed rail system were required to link major cities and to fulfill all needs. Therefore, it is not difficult to find a variety of traffic engineering projects, including regional highways and large scale national freeways, being constructed or rebuilt around the island in recent years. Naturally, the topic of analyzing the environment and the structures in a road system by emerging scientific methods can contribute to increase the engineering quality and safety standard of these structures.

Mountains occupy about two-third of the total area of the island of Taiwan, thus most early highways and freeways were constructed basically along the coastline region. Whereas, in recent years, due to lack of sufficiently flat areas for planning, the second north-south freeway (Formosa freeway), wich was opened fully in the year of 2008, had to be built along the mountain region. This freeway has a total length of 430.5 km and includes about 200 km of bridges, which occupy almost half the length (45%) of the freeway [2–4]. Hence, it is crucial to understand the safety levels of bridges in this major freeway, and they must be examined from time to time to prevent economical losses caused by natural disasters, particularly potential damages resulting from strong ground motions.

The island of Taiwan is located within the Pacific ring of fire or sometimes called the circum-Pacific seismic belt, hence strong ground motions are frequently recorded due to the intrusion of Eurasia plate and Philippine plate. Therefore, the problems of engineering quality and antiearthquake design are often considered while dealing with construction projects in this area. In the current building code, there are two earthquake zones, A and B, that are classified into all the subregions, and the design values for the earthquake horizontal acceleration are 0.33 g and 0.23 g, respectively, for these two zones [5]. This zone classification and the corresponding design value and their underlying assumptions can be taken as an evaluation index for examining the safety of the bridges along the freeway.

The variables that need to be considered in developing models for the estimation of peak ground acceleration (PGA)—the key factor for evaluating the characteristics of strong motion at a specified region—can be classified into those arising from the source, travel path and the site [6]. Models for the prediction of PGA have been developed previously based on various combinations of these variables, and essentially fall into two categories: empirical equations developed through nonlinear regression analysis and more recently neural network models developed through supervised learning methods [7–9]. It has been demonstrated that just three variables—local magnitude (ML), focal depth (De), and focal distance (Di)—are adequate for developing acceptable models, and for this set of variables the neural network models have been shown to provide better estimations of PGA with much higher coefficients of correlations compared to the nonlinear regression analysis approach [10]. The superior performance of the neural network model is due to its ability to learn the underlying function using information available in the data rather than make assumptions about the form of the function, as in the nonlinear regression analysis.

The advantage of developing models using three independent variables is that the underlying function will be simpler. The site information, not represented explicitly as a variable, is embedded in the numerical values of the equations or the weights and biases of the neural network. Thus, these models are only applicable to the sites for which they are developed. This, however, is not an issue for the present work as separate neural network models are developed for each of the checking stations. It is also possible to use different neural network types to develop the model, but previous research indicates that the best results are obtained with feed-forward back-propagation networks [11]. Thus, this network type has been used for developing network models for all the checking stations.

Among the emerging scientific methods for data analysis, computational intelligence methods such as evolutionary algorithm, in addition to artificial neural network, find applications in solving a variety of engineering problems, including the problem of detecting or identifying seismic damage in various engineering structures [12–19]. It is also possible to use hybrid approaches—genetic algorithm and neural network—to develop better performing neural network models for PGA predictions [20]. Neural network models have also been used for earthquake forecasting [21], but this is not the objective of the present research. In comparing the predicted PGA values against those recommended in the appropriate design codes, the probability of occurrence of the earthquake that produced the PGA values should also be taken into consideration.

In the present investigation, neural network models are developed using the seismic data available for checking stations close to the bridges of interest, including the following stages: (1) selecting twenty-one bridges, with lengths over 500 m, along the Formosa freeway; (2) collecting a series of recorded seismic data from at least three checking stations in the neighborhood of each bridge; (3) using measuring tool in Google map to calculate the distance between a bridge and each of the checking stations; (4) developing a simple distribution model and a new weight-based model for the neural network approach to estimate PGA for each bridge, and (5) identifying potentially hazardous bridges based on the comparison of the neural network estimate and the design value required by building code. It is hoped that the results of the present study will provide useful information for improving the level of bridge safety along the freeway investigated.

2. Active Faults and Recorded Seismic Data

The central geological survey data of the ministry of economic affairs (MOEA) in Taiwan shows that there exists at least 42 active faults in the whole island (see Figure 1, [22]), with 5 major active faults located on the western side, near several areas with important engineering projects and very high population density [23, 24]. Specifically: (1) Sanyi fault, numbered 13, is 19 km long; (2) Chelungpu fault, numbered 19, is 50 km long; (3) Tamaopu-Shuangtung fault, numbered 20, is 55 km long; (4) Meishan fault, numbered 22, is 13 km long; (5) Chukou fault, numbered 26, is 67 km long. Historical records show that these major active faults did create destructive earthquakes that caused tremendous damages.

When the active faults trigger a strong ground motion, the released energy from hypocenter generates an elastic wave that propagates to the ground surface, and the vertical point is called epicenter. The characteristics of this seismic wave can be measured by seismometers installed in checking stations. A typical seismic data recorded usually include several items of information such as date and time, exact location, intensity, local magnitude in Richter scale, focal depth, epicentral distance, PGA in vertical (V), north-south (NS), and east-west (EW) directions, respectively. The distance between hypocenter to epicenter is defined as the focal depth, and epicentral distance is calculated from the epicenter to checking station.

It is necessary to further mention that the focal depth is an important factor as it relates to the degrees of damage caused by earthquakes. It is clear, even without considering other seismic parameters that a low focal depth, in general, will result in high damage. Therefore, earthquakes may be classified as shallow, intermediate, or deep depending on the value of the focal depth. For shallow earthquake, the focal depth is less than 70 km beneath the ground surface, while in the case of focal depth between 0–30 km, it is referred to as a very shallow earthquake. For intermediate earthquakes, the focal depth is between 70 km to 300 km. When the focal depth is more than 300 km, it is referred to as a deep earthquake [25]. In general, the intermediate earthquakes occur much more often than the other two categories. It occurs about 3 times the deep earthquake and about 10 times the shallow earthquake, but the occurrences of these earthquakes are not uniformly distributed around the world.

As mentioned previously, the Formosa freeway is mostly constructed in the mountain region, and thus some of active faults are mainly distributed in the neighborhood of bridges

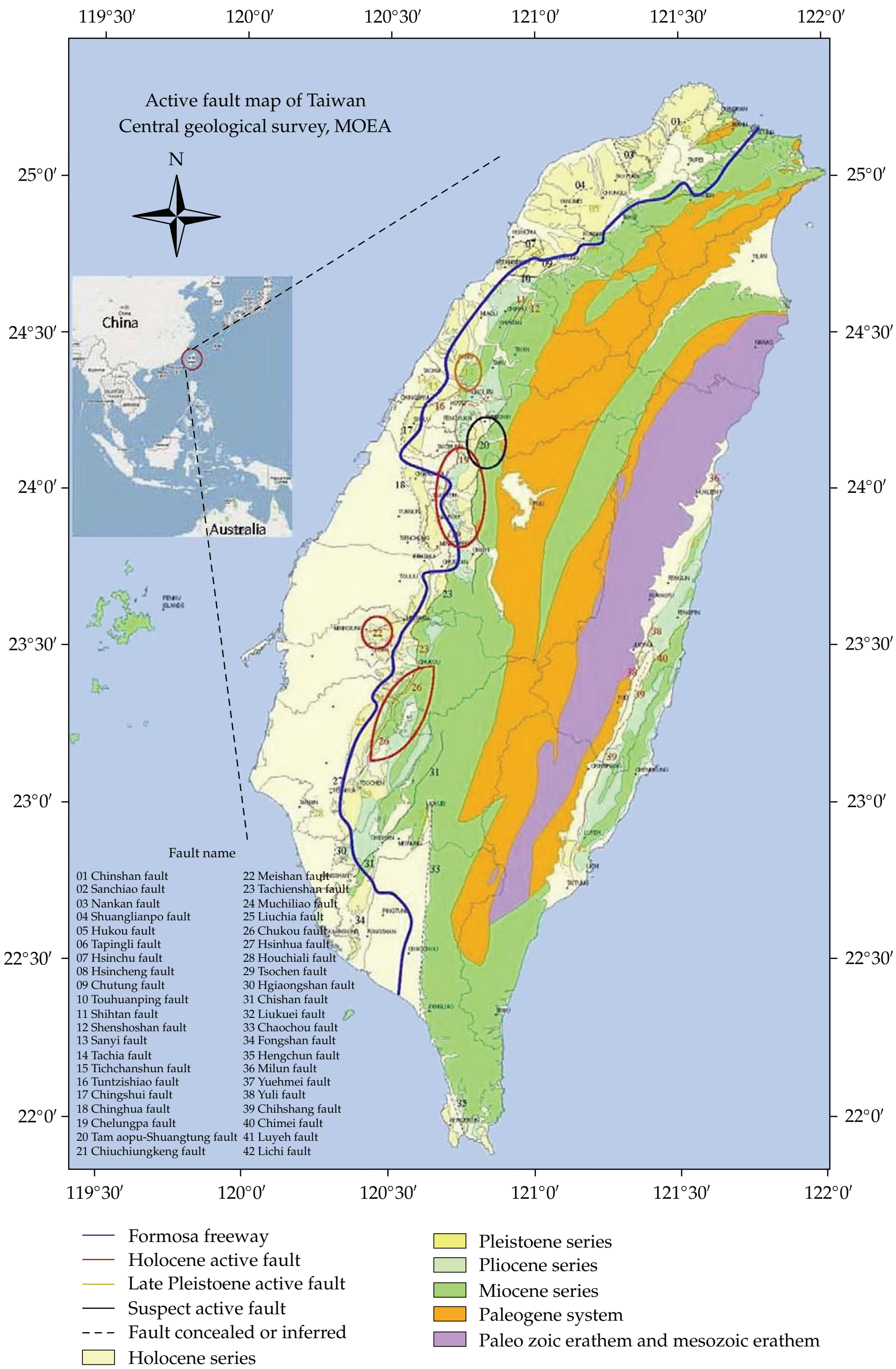


Figure 1: Formosa freeway and distribution of active faults in the island of Taiwan. (Map sources: MOEA and http://www.simcam.net/Personal-Website/taiwan-links.html).

along the freeway, particularly those in the central and southern parts of the freeway. Thus, the seismic effect on each of the bridges along the freeway is a crucial issue and can be examined by available scientific methods, including the neural network approach, which, in recent years, has been shown to have a wide range of applications. In the present study, a series of seismic data recorded at checking stations around the main bridges along the freeway is evaluated by neural network models, which take local magnitude, focal depth, and epicentral distance as the input, and PGA in each of three different directions as the output.

Shown in Figure 2 is the distribution of main bridges along the freeway, and the nearby seismic checking stations for each bridge. Before developing neural network models, the seismic records need to be processed to prevent the existence of extreme values in the input data set, which may affect the accuracy of neural network training. The following equation can be applied to normalize the input data:

$$V_n = \frac{(V_o - V_{\min})}{(V_{\max} - V_{\min})}, \tag{2.1}$$

where V_n is the normalized seismic data, V_o is the original record, $V_{\min}$ is the minimum value in the data set, and $V_{\max}$ is the maximum value in the data set [26]. With this preprocessing of data, the input values will be within the range of 0 to 1, and this normalization will match the transfer function used in the neural network.

3. Neural Network Approach and Evaluation Index

The concept of artificial neural networks first appeared in the study of McCulloch and Pitts in 1943, but the development of this method did not progress far until the appearance of Hopfield network in 1982 [27–29]. Now many different types of neural networks have been developed, and the back-propagation neural network, which uses supervised learning to obtain minimum error, is possibly the most commonly employed model in a variety of applications [30–35]. This multilayered network model includes an input layer, one or more hidden layers, and an output layer. The output of each layer becomes the input of the next layer, and a specific learning law updates the weights of each layer connections based on the errors in the network output.

The basic algebraic equation of each layer may be written as:

$$Y_j = F\left(\sum W_{ij} X_i - \theta_j\right), \tag{3.1}$$

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

Information regarding the use of neural network model to study the key element of seismic problems around the world can be found in recent research literature. For instance, Tselentis and Vladutu [36] developed a combination model of using artificial neural network and genetic algorithm to uncover relations between the engineering ground-motion

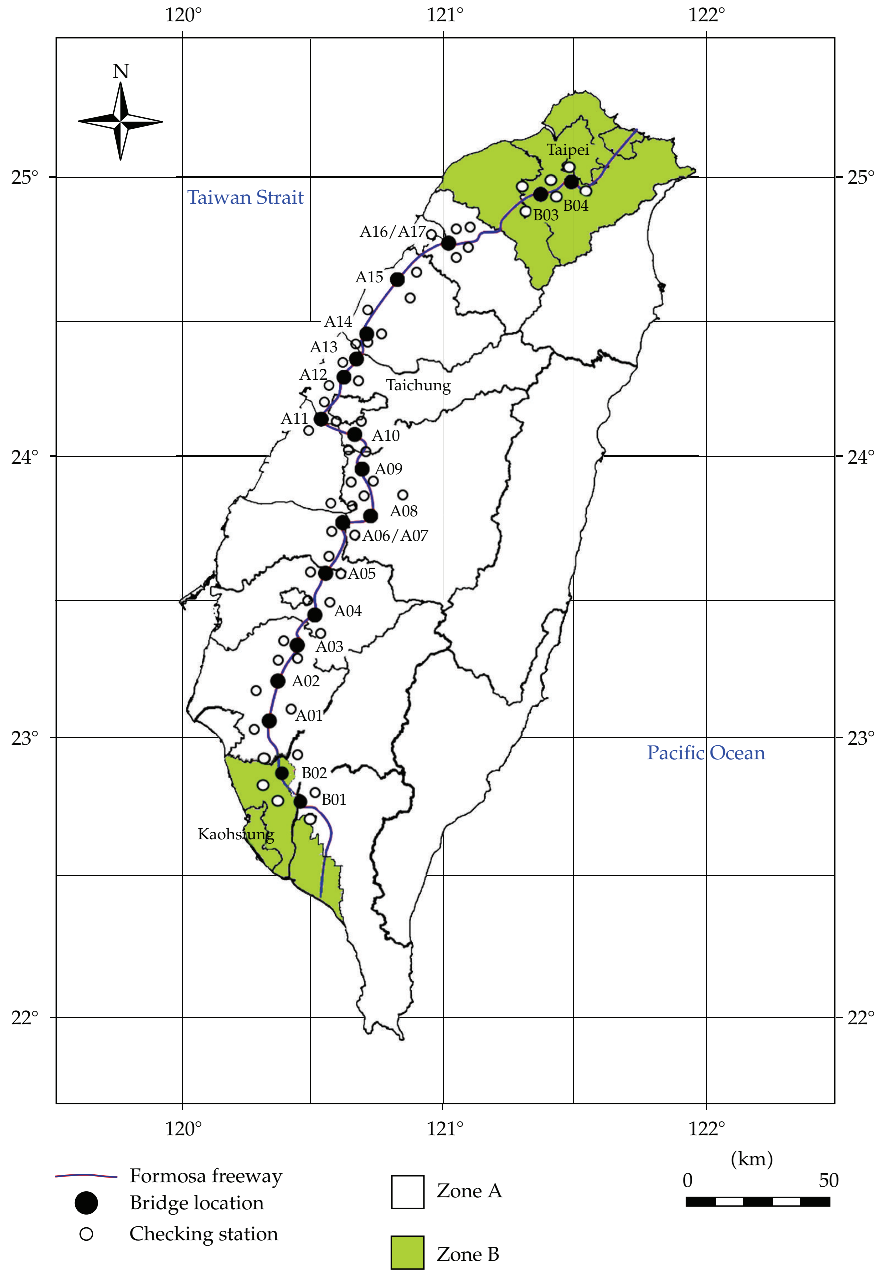


Figure 2: Bridges along Formosa freeway and the nearby seismic checking stations.

parameters and macroseismic intensity. The results concluded that the model can be satisfied by using Greek seismological database. Another example as reported by Derras [37], the neural network approach was able to predict peak ground acceleration with different input seismic parameters collected from a data base in Japan. More researches related to this topic, using regional seismic data bases, may also be found in Turkey [11] and in Mexico [38].

Since neural network method is widely applied in the computational intelligence community due to its simplicity and effectiveness; therefore, in this study, the neural network toolbox in the software package Matlab [39, 40] is used to analyze seismic data collected from checking stations around each of the chosen bridges along the Formosa freeway. For creating a network in the software data manager toolbox, the input range is set to between 0 and 1, and the Levenberg-Marquardt back-propagation algorithm is chosen in the training process. For the training parameters including epochs, goal, max_fail, mem_reduc, min_grad, mu, mu_dec, mu_inc, mu_max, show, and time are set to 1000, 0, 5, 1, $1e-010$, 0.001, 0.1, 10, $1e010$, 25, and infinite, respectively. With three neurons in the hidden layer, and one neuron in the output layer, the creating neural network model can then be trained, adapted, and simulated to obtain an estimation result for analysis.

The effectiveness of neural network model developed can be evaluated by using the coefficient of correlation (R or r) that is defined as:

$$R = \frac{\sum_{i=1}^{n} (x_i - \overline{x_i})(y_i - \overline{y_i})}{\left[\sum_{i=1}^{n} (x_i - \overline{x_i})^2 \sum_{i=1}^{n} (y_i - \overline{y_i})^2\right]^{1/2}}, \tag{3.2}$$

where x_i and $\overline{x}_i$ are the recorded data and its averaged values, respectively, y_i and $\overline{y}_i$ are the estimated and its averaged values, respectively, and n denotes the number of data items in the analysis. This coefficient may have a positive or negative value, so that its squared value, R^2, is also frequently taken to represent the degree of correlation between the recorded data and the estimation. In general case as seen in Wikipedia encyclopedia [41], $|R| > 0.5$ denotes a large level of correlation, $0.3 < |R| \leq 0.5$ denotes a medium level of correlation, and $|R| \leq 0.3$ represents a small level of correlation. However, the ranges $0.3 < |R| \leq 0.7$ and $|R| > 0.7$ may also be used to represent medium and large levels of correlation, respectively [42]. For more conservative manner, the present study takes $R^2 > 0.7$ as sufficient criterion for checking the neural network models developed.

Furthermore, an error evaluation function is required to calculate the difference between the actual records and estimations by neural network model. This is usually the root mean square error (RMSE) function [43], and the definition in this study is:

$$\mathrm{RMSE} = \left[\frac{\sum_{n}^{N} (T_n - Y_n)^2}{N}\right]^{1/2}, \tag{3.3}$$

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. In general, the smaller the root mean square error, the more accurate the estimation.

4. Evaluation Models and Illustrative Results

To develop an adequate neural network model for evaluating peak ground acceleration at each of bridge of interest, the seismic data sets are arranged into three groups. Initially, three sets of largest value for local magnitude, focal depth, and epicenter distance are withdrawn from seismic data base in each checking station for verification purpose. Then, the remaining parts are divided into 70% and 30% of the data sets, for training and adapting, respectively,

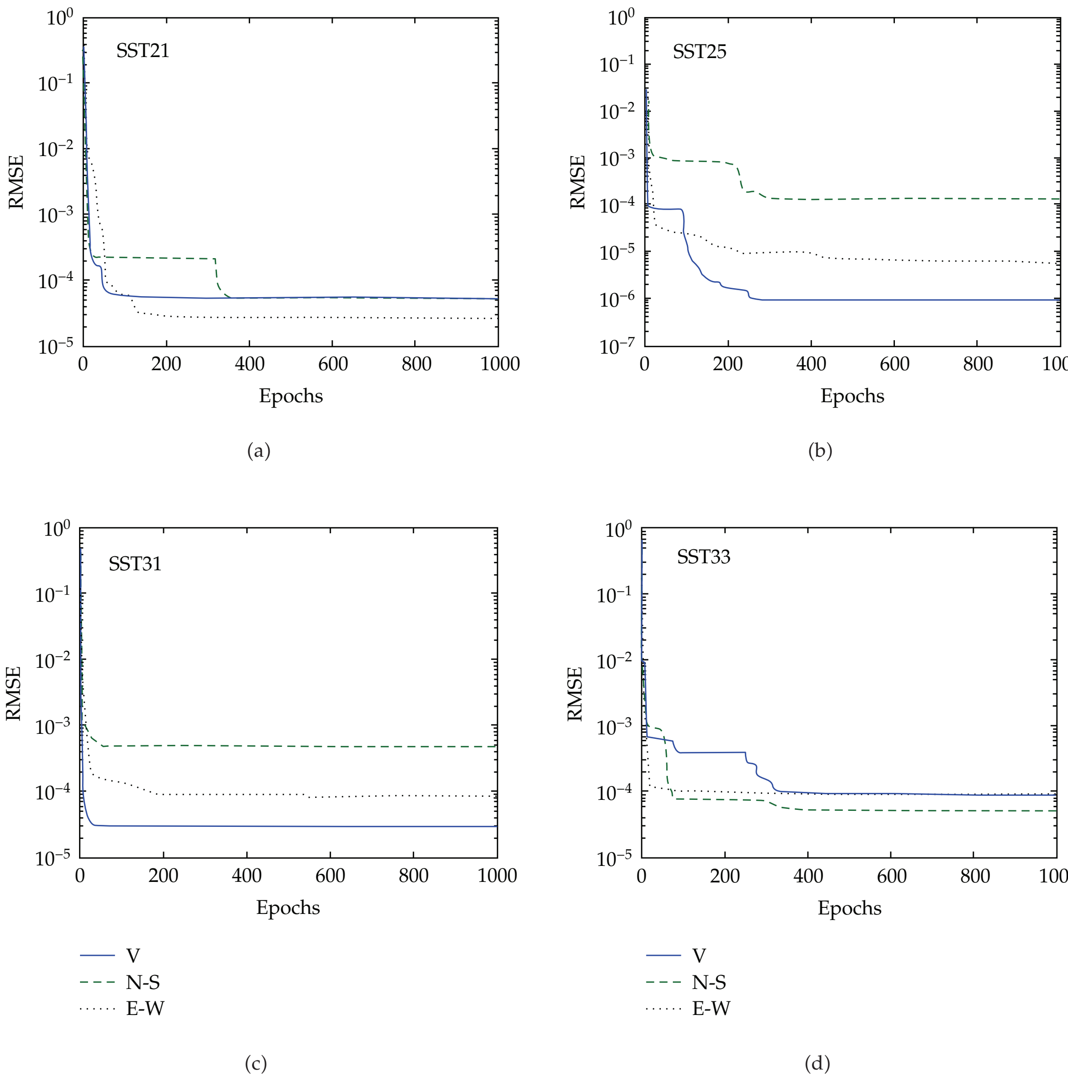


Figure 3: Convergence tendency of root mean square error versus epochs for each of checking station around bridge A09.

in the neural network model. For a total of 52 checking stations investigated, the seismic data sets with magnitude over 5.0 in Richter scale are only used in neural network modeling to prevent unwanted noise. For each of the checking station, the size of the data sets range from 25 to 120, this may be sufficient to meet the minimum requirement from statistical standpoint.

Now for the trained model, the averaged square values of correlation coefficient (R^2) for all checking stations are 0.912, 0.899, and 0.908, in V, N-S, and E-W directions, respectively. After the weights and bias terms of neural network model are adapted slightly, the verification result is finally shown in Table 1. It can be seen that the averaged square values of the correlation coefficients range from 0.821 to 0.964 for the checking stations around each of the bridge. That is, the correlation between seismic records and neural network estimations has a very high level. Besides, by taking bridge A09 as an example, the plot

Table 1: Averaged square values of correlation coefficient for all directions at each bridge.

A01	A02	A03	A04	A05	A06	A07
0.841	0.846	0.821	0.876	0.937	0.964	0.925
A08	A09	A10	A11	A12	A13	A14
0.878	0.901	0.914	0.964	0.865	0.897	0.901
A15	A16	A17	B01	B02	B03	B04
0.960	0.937	0.895	0.857	0.848	0.933	0.958

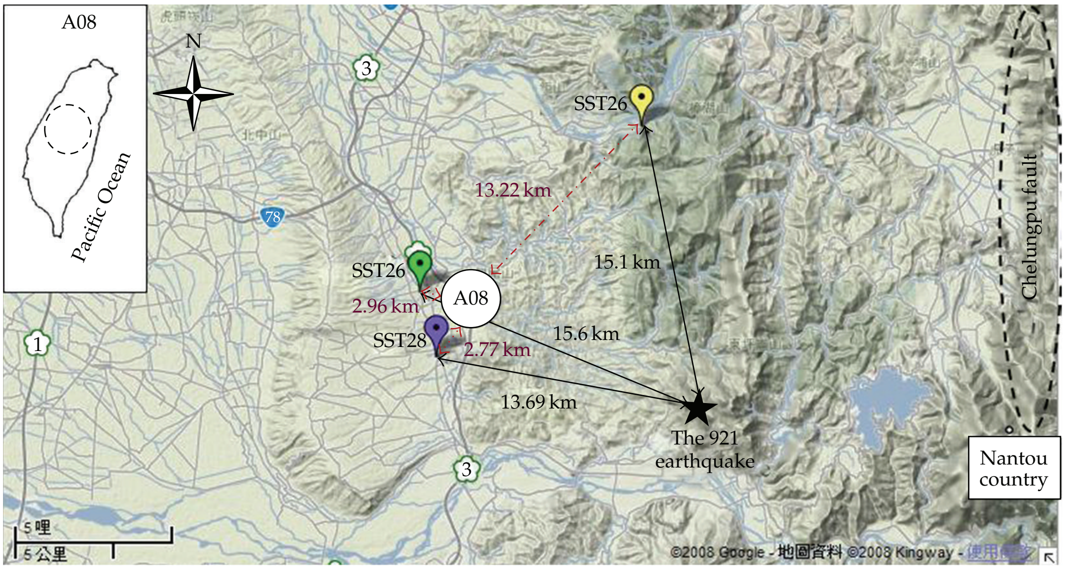
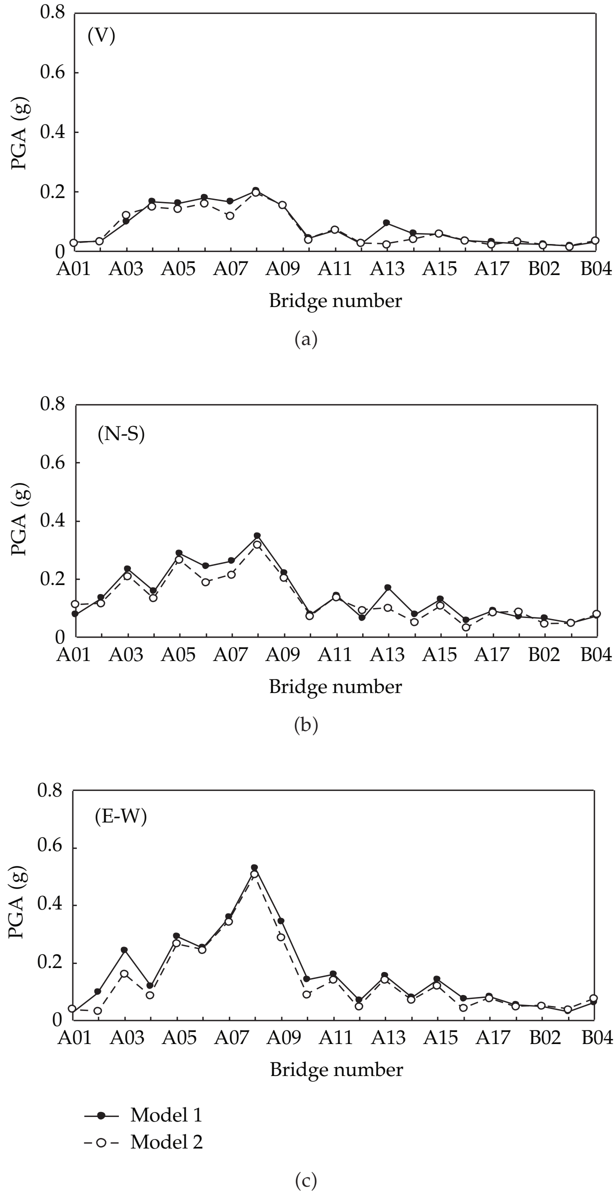


Figure 4: Spatial relationship between bridge (A08), checking stations and epicenter location of the 921 earthquake (Map source: http://maps.google.com/).

of root mean square error versus epochs for each of the checking stations (SST 21, SST 25, SST 31, SST 33) around the bridge is shown in Figure 3. For all plots, it can be seen that the root mean square errors are converged between 10^{-3} and 10^{-6} for the three directions. These results reflect that the neural network estimations already have a sufficient accuracy.

The objective of this study is to evaluate PGA at all 21 bridge locations, and to identify the potential for damage to each bridge resulting from strong ground motions. Since, there exists no checking station just right on the bridge site to record historical seismic data, a suitable method is required to calculate PGA for each bridge based on available neural network estimations from nearby checking stations. In the present study, the straightforward way to estimate PGA for each of the bridges is by simply distributing the estimated results from nearby checking stations in accordance with weighting factors.

By taking bridge A08 as an example, the distance between this bridge and checking stations can be calculated from their precise coordinates with Google map, as shown in Figure 4. The distances to the bridge A08 are 13.22 km, 2.96 km, and 2.77 km for checking stations SST24, SST26, and SST28, respectively. The weighting factor for each station is then



(a)

(b)

(c)

Figure 5: Comparison of PGA estimations in different directions.

calculated by the following formula:

$$W_i = \frac{\left(\sum_{j=1}^{n} d_j\right)/d_i}{\sum_{k=1}^{n}\left[\left(\sum_{j=1}^{n} d_j\right)/d_k\right]}; \quad i = 1, 2, 3, \ldots n, \tag{4.1}$$

where d_i, d_j, and d_x are the distances between the bridge and checking stations, n is the total number of seismic checking stations, and W_i denotes the weight of each checking station to

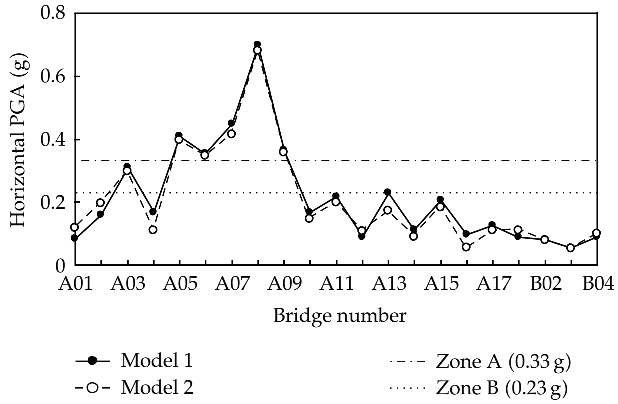


Figure 6: Comparison of horizontal PGA estimations versus seismic design values.

the specified bridge. For the bridge A08, the weighting factors can then be calculated as 0.098, 0.436, and 0.466 for the three checking stations SST24, SST26, and SST28, respectively.

Now by using the above method, PGA for each bridge can be obtained directly from the estimated results for the checking stations by the neural network models. That is, PGA for each bridge is simply aggregated from distributed results of checking stations around it, and the computing process of this simple distribution model is denoted as "Model 1 or NN1." For the other model, namely "Model 2 or NN2," the epicentral distance to the bridge is calculated for each strong motion, and then this new parameter with the other two inputs (same local magnitude and focal depth) is processed through the trained neural network models. After all available earthquake records are processed through the models, the output values are then modified by the weights and summed as shown in the following equation:

$$\mathrm{NN}_b = \sum_{i=1}^{n} (\mathrm{ANN}_i) W_i, \tag{4.2}$$

where NN_b is the final PGA estimation for each bridge; ANN_i is the estimation using neural network model for each checking station; W_i and n have the same definitions as in (4.1). This new approach of taking into account both the epicentral distance and the distance from the checking station appears more likely to represent the true PGA estimation for each bridge.

Figure 5 shows PGAs estimated for the 21 bridges in V, N-S, and E-W directions respectively, by the two neural network estimation models. From the plots, it can be seen that Model 1 has a slightly higher PGA estimation than that of Model 2 for most of the bridges, particularly for N-S and E-W directions. It can also be seen that PGA in V direction is slightly smaller than that of the other two directions. Because most of natural faults in the island of Taiwan are in the neighborhood of the central mountain region, which is basically distributed in north-south direction; therefore, it is not surprising that PGA estimations in E-W direction tend to have a higher value than that of the estimation in N-S direction for most of bridges due to the extrusion of Eurasia plate and Philippine plate.

By using the formula $\mathrm{PGA_h} = [(\mathrm{PGA_{N\text{-}S}})^2 + (\mathrm{PGA_{E\text{-}W}})^2]^{1/2}$, the calculated horizontal PGA for each bridge is displayed in Figure 6. It can be identified that there are five bridges (A05, A06, A07, A08, and A09) with higher horizontal PGA values than that in the seismic design standard for zone A (0.33 g). That is, these bridges have the potential to be damaged by

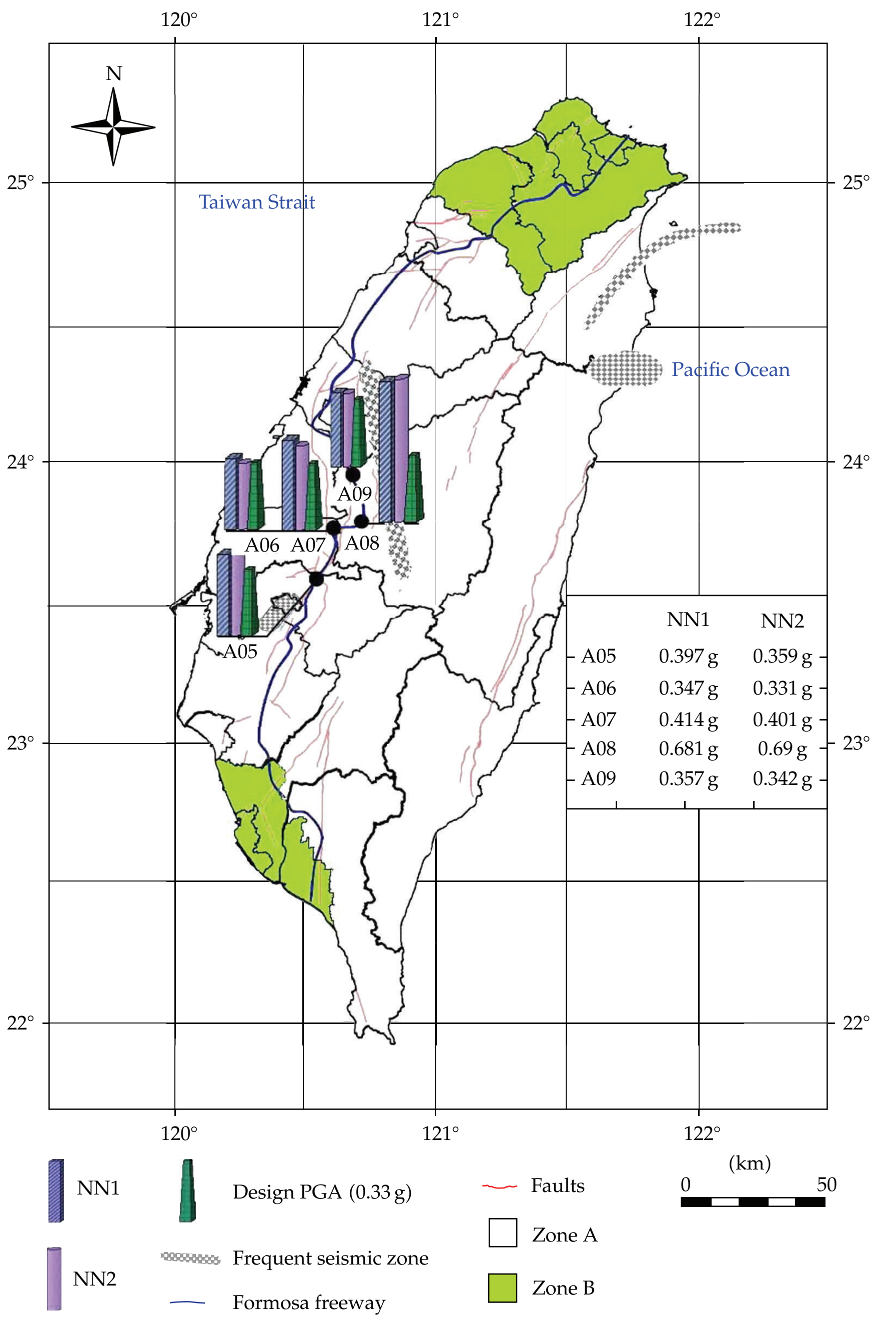


Figure 7: Location of potentially hazardous bridges and estimated horizontal PGAs.

strong ground motions, and thus public must be cautioned to prevent unnecessary economic losses. In zone B, all bridges comply with building code seismic requirement (0.23 g), and thus no further action is necessary at this stage, based on the present research results.

In order to see more clearly, bridges with horizontal PGA values in excess of the seismic design value are shown in Figure 7. It can be seen that the five bridges are mostly located in the west-central part of Taiwan, and in the neighborhood of two frequent seismic zones and six active faults, including the two major Chelungpu and Meishan faults, numbered 19 and 22 in Figure 1. The historical records showed that there exist several destructive earthquakes in this region with local magnitude over 7.0 in Richter scale including the recent big one (921 earthquake) with ML = 7.3 that occurred in the year 1999. From the plot and numerical results, it can also be seen that bridge A08 has significantly higher estimated horizontal PGAs than that of the other bridges and the design standard value, that is, 0.681 g obtained from Model 1 (NN1), and 0.690 g obtained from Model 2 (NN2). The reasons may be that this bridge is quite close to the major active faults, and it is only about 13 km from the epicenter of 921 earthquake, as shown in Figure 4. Anyway, it is better to pay more attention to these potentially hazardous bridges that have been identified and check their safety status as often as possible.

5. Summary and Conclusion

Seismic recorded parameters can be used to evaluate regional engineering safety level, and for establishing design values in the building code by applicable scientific methods. This study employed the neural network approach to train and adapt a series of recorded seismic data to estimate PGA in checking stations around 21 major bridges along the Formosa freeway in Taiwan. A total of three input seismic parameters: focal depth, epicenter distance, and local magnitude have been considered in developing the models for estimation.

By taking the developed neural network model for each of checking station around the specified bridge as the basis, two methods have been used to estimate PGA at each of the bridge locations along the freeway. Model 1 (NN1) simply takes the results of nearby checking stations with the use of weighting factors to obtain PGA for the bridge being investigated. Model 2 (NN2) calculates epicenter distance at first for each bridge in accordance with recorded seismic data. By inputting this new parameter to a weight-based neural network model, the final PGA estimation was then obtained for each bridge.

Based on the calculation results, five bridges out of 21 bridges have been identified as having a higher horizontal PGA than the seismic design value in the building code. This study has thus demonstrated that the neural network approach could be used to develop concise models of recorded nonlinear seismic data that can be used for prediction, and this approach may be applicable to other areas of interest around the world. Note that the seismic requirement in building code is applicable for bridge design, but it may no longer play an important role if the bridge code is revised in accordance with the actual site conditions.

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