MODELLING SEISMIC RECORD AND SOIL TEST RESULT BY NEURAL COMPUTING WITH GENETIC ALGORITHM

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Keywords: Neural Network, Genetic Algorithm, Peak Ground Acceleration, Unchecked Site, Prediction

Earthquakes are natural hazards which occur quite often worldwide every year, particularly in the region of "ring of fire" (USGS, 2012). To reduce various negative impacts from this natural disaster, a wide range of relating research topics, such as earthquake mechanism and potency investigation, prediction and warning system development, instrumental measurement and data analysis, have been extensively reported (Bailey et al., 2009; Wu and Kanamori, 2008; Zobin et al., 2014). In regard to seismic data analysis, this study focuses on developing a genetic algorithm based neural network model (NN+GA) to improve the reliability of predicting peak ground acceleration (PGA), the key element to evaluate earthquake response and to setup seismic design standard.

In addition to three seismic parameters: local magnitude (Mg), epicentre distance (Di), and epicenter depth (De), this study includes two geological conditions: standard penetration test value (SPT-N) and shear wave velocity (Vs), in the input to reflect the site response more adequately. Based on the earthquake records and soil test data from 86 checking stations within 24 seismic subdivision zones in Taiwan area, the computational results show that the combination of using neural network and genetic algorithm can achieve a better performance than that of using neural network model (NN) solely (see Table 1). This preferred model will be applied to predict PGA at 24 unchecked sites to represent each of the subdivision zones.

To estimate the PGA at an unchecked site, it can be performed by taking a new set of seismic data (same Mg and De, but new Di for each of seismic records) and a new set of geological conditions (weight-based soil test results of SPT-N and Vs) from known checking stations nearby. Then, insert the data set in a NN+GA model developed for each known checking station. By summing the results with weighting factors, the final estimation is obtained for the unmeasured site.

Figure 1 shows the comparison results of predicting horizontal PGA at the unchecked sites with design values for both of seismic zone A and zone B in Taiwan area. For the seismic zone A, it can be found that there are 6 subdivision zones exhibit to have a higher horizontal PGA than that of the design value (0.33g). However, a modified result by using square root of the sum of the square shows that there are 3 subdivision zones exhibit a higher horizontal PGA than the design value, and the tendency is also similar to previous researches (Kerh et al., 2009, 2013) Therefore, this modified result is believed to have a more reliability for the case studied herein. For the seismic zone B, as the PGAs obtained from both NN+GA and NN models are lower than that of the design value (0.23g), so all of prediction results comply with design standard in building code.

This study combines genetic algorithm with neural network, and by inputting both seismic parameters and soil test data to develop a model for predicting PGA at unchecked sites, may provide a new approach to solve this type of earthquake related nonlinear problem, and may be applied to other areas of interest around the world.

Table 1. Comparison and performance of NN model and NN+GA model

Model		NN		NN+GA	
Input parameter / Performance		trained	simulate	trained	simulate
Seismic (Mg, Di, De)	R^2	0.65614	0.46806	0.74626	0.53744
	RMSE	0.26482	0.35815	0.18427	0.18659
Seismic + Geological (Mg, Di, De, SPT-N, V_s)	R^2	0.64505	0.47678	0.83365	0.55943
	RMSE	0.29995	0.41748	0.16640	0.20245

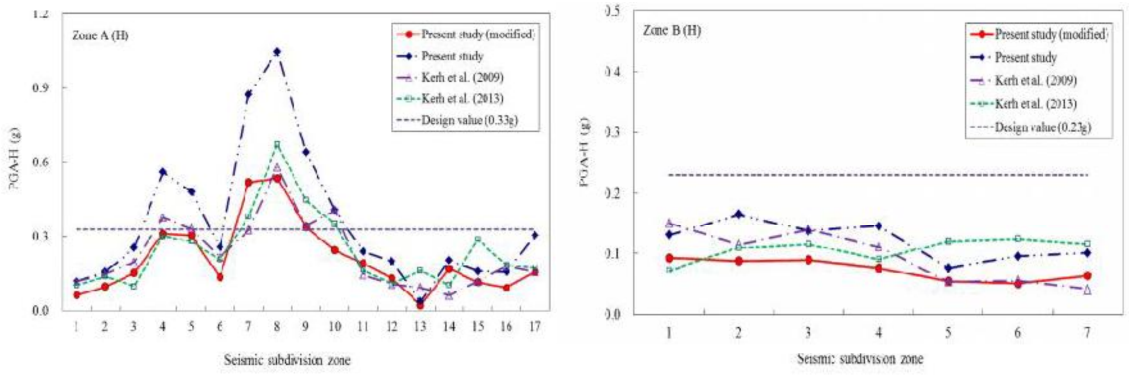

Figure 1. Comparison of PGA prediction result with design standard at 24 subdivision zones

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