Artificial neural networks approach to predict principal ground motion parameters for quick post-earthquake damage assessment of bridges

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ABSTRACT: Having a quick but reliable insight into the likelihood of damage to bridges immediately after an earthquake is an important concern especially in the earthquake prone countries such as New Zealand for ensuring emergency transportation network operations. A set of primary indicators necessary to perform damage likelihood assessment are ground motion parameters such as peak ground acceleration (PGA) at each bridge site. Organizations, such as GNS in New Zealand, record these parameters using distributed arrays of sensors. The challenge is that those sensors are not installed at, or close to, bridge sites and so bridge site specific data are not readily available. This study proposes a method to predict ground motion parameters for each bridge site based on remote seismic array recordings. Because of the existing abundant source of data related to two recent strong earthquakes that occurred in 2010 and 2011 and their aftershocks, the city of Christchurch is considered to develop and examine the method. Artificial neural networks have been considered for this research. Accelerations recorded by the GeoNet seismic array were considered to develop a functional relationship enabling the prediction of PGAs.

1 INTRODUCTION

Road networks are one of the most important parts of each modern society's facilities. They link all different locations in a human society. Consequently, any damage sustained by one or more links in a network due to a natural disaster such as an earthquake, will most likely result in some undesirable repercussions. Furthermore, one of the most important parts of each transportation network, whose failure will have great impact on the whole system, are definitely bridges. Therefore, these structures deserve special consideration in natural hazard assessment studies, especially in countries that are strongly prone to damaging earthquakes such as New Zealand. One of the most important issues and research challenges is to develop quick and reliable methodologies to assess the condition and damage to bridge structures after an earthquake.

For any post-earthquake emergency response, a reliable insight into the structural integrity of bridges in a transportation network is required. In order to have such a reliable insight and performing an adequate risk evaluation, it is important at first to know the ground motion metrics at the base of each bridge experienced during the earthquake. One of the most important ground seismic parameters which can help structural engineers to evaluate structural integrity of a bridge after an earthquake is peak ground acceleration (PGA). However, currently only a very limited number of important bridges are instrumented to collect such data even in places where structural monitoring has made more decisive strides into practice. In New Zealand, despite the obvious seismic hazard risks, this number can be assumed as nil for all practical considerations. Hence, the aim of this paper is to propose an artificial neural network (ANN) based approach to predict this key seismic parameter at the bridge site immediately after an earthquake by using the data recorded by an array of free field strong motion recorders located at some distance from the bridge.

2 DESCRIPTION OF THE SENSOR ARRAYS

GeoNet is a project to build and operate a modern geological hazard monitoring system in New Zealand. It comprises a network of geophysical instruments, automated software applications and skilled staff to detect, analyse and respond to natural hazards such as earthquakes. The GeoNet data centre (www.geonet.org.nz) is responsible for collecting and processing the data recorded by strong-motion accelerographs which are located in major centres of population and near significant faults.

New Zealand's current strong motion network consists of the national strong ground motion network and the Canterbury regional strong motion network which are instrumented respectively with Kinemetrics Etna high dynamic range strong motion accelerographs and CSI CUSP-3 strong motion accelerographs.

The data used in this research containing information of accelerographs as well as accelerations and other parameters of the earthquakes and aftershocks are all collected from GeoNet.

3 ARTIFICIAL NEURAL NETWORKS

An efficient way of solving and understanding complicated problems, relationships and systems is decomposing them into simpler elements which are easier to understand. An approach which makes this possible is using networks. A network is made of a number of computational units, which are called nodes, and connections between nodes. The nodes receive inputs to process and generate outputs.

AANs are a kind of network that considers the nodes made of artificial neurons which are inspired by the natural neurons in human brain. ANNs are simplified models of the human brain and have been widely and successfully used in different fields of science and engineering to solve different types of problems such as pattern recognition, prediction and interpolation. The basic concept of modelling the activity of the human brain numerically has a history of over half a century and was first presented by McCulloch and Pitts (1943). The starting point of developing ANN appeared in Hopfield (1982) and abundant applications of ANNs can be found in the recent 20 years.

Figure 1 shows the way an artificial neuron generates an output from received inputs. The numerical inputs p_i are multiplied by the related numerical weights w_i, while they are being transmitted through the connections. A summation then will be imposed on all weighted inputs $w_i p_i$ and added to the numerical bias b to be used as an argument for transfer function f which generates the output $a = f(\sum w_i p_i + b)$. The bias is in fact a weight which multiplies a constant input of 1. There are three types of transfer functions which are most commonly used. These functions are the step (or hard-limit), the linear and the logistic (or sigmoid); they are shown in Figure 2.

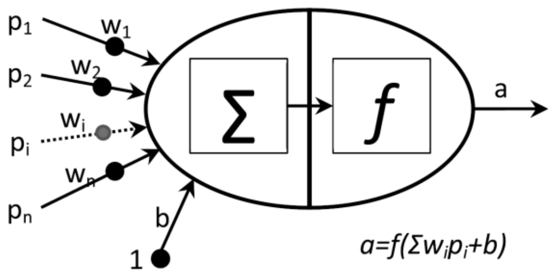

Figure 1. An artificial neuron

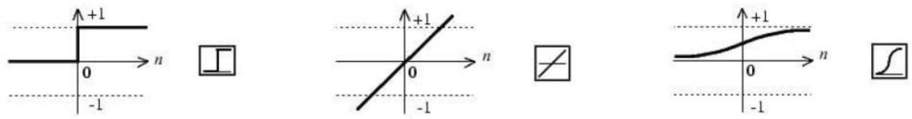

Figure 2. Commonly used transfer functions: step (left), linear (middle) and logistic (right).

One of the most important characteristics of ANNs which makes them suitable for solving a wide range of problems is the ability of being trained. All of the aforesaid numerical weights and biases are adjustable parameters of the neuron which are tuned during a procedure called training to make the network fit for doing a particular job. The common structure of ANN consists of neurons which are organized in layers and each neuron of a layer is connected to all the neurons in the previous and next layer. There is one input, one output and one or more hidden layers in each ANN.

There are several examples in the literature that have used ANNs for earthquake related research, such as earthquake forecasting (Alves, 2006) and seismic structural damage prediction (de Lautour & Omenzetter, 2009). Notably, Kerh et al. (2011) used an ANN to estimate PGA at selected checking stations and then distributed the estimated PGAs from nearby stations to bridge sites using weighting factors. However, the objective of this research is to propose an ANN-based approach that makes it possible to predict directly the PGA of any arbitrary point after an earthquake using PGAs recorded by accelerographs.

4 **METHODOLOGY**

In this research, an ANN model is developed using the maximum horizontal PGAs related to 21 February 2011 M6.34 Christchurch earthquake and its aftershocks which were recorded by the accelerographs installed over Christchurch.

Google Maps (http://maps.google.com) consider as the centre of the city of Christchurch the following coordinates: Latitude=-43.5° and Longitude=172.6°. With respect to these coordinates, all of the recording stations which are located within a radius of 5 km from the centre of the city were considered. However, amongst the 39 stations located in that area, just six stations were operational and had recorded accurate and reliable data that could be used. Figure 3 and Table 1 show the locations and additional information of these six stations. By using the measuring tool in Google Maps, the distances between all the six recording stations were calculated and are shown in Table 2.

For a total of six recording stations considered, only maximum horizontal PGAs were selected which were related to events of a magnitude greater or equal to 5.0 to prevent probable unwanted noise. The selected data came from a period of time shown in Table 3, starting from the main shock of 21st February 2011 at 23:51:42 and ending with an aftershock on 6th January 2012 at 12:27:44. The number of records available is 15.

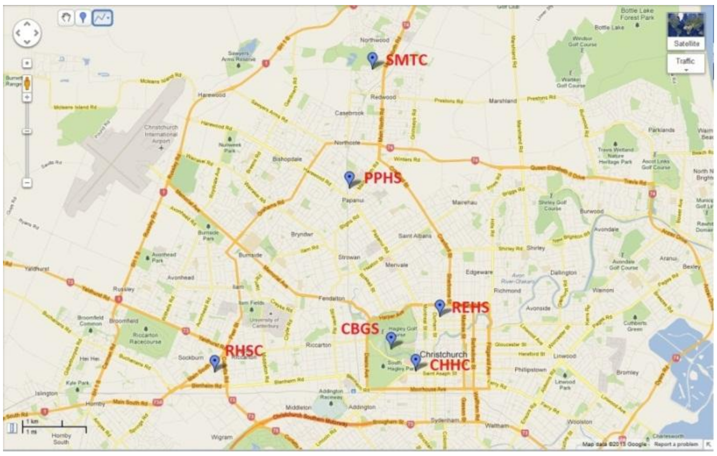

Figure 3. Location of accelerographs in Christchurch

Table 1. Information about accelerographs in Christchurch

Number	Name	Abbreviation	Latitude (°)	Longitude (°)
1	ChCh Botanic Gardens	CBGS	-43.53101	172.61975
2	ChCh Hospital	CHHC	-43.535929	172.627523
3	ChCh Papanui High School	PPHS	-43.49451	172.60679
4	ChCh Resthaven	REHS	-43.52361	172.63502
5	Riccarton High School	RHSC	-43.536172	172.564404
6	Styx Mill Transfer Station	SMTC	-43.4675293	172.6138611

Table 2. Distances between accelerographs (km)

	CBGS	CHHC	PPHS	REHS	RHSC	SMTC
CBGS	0	0.832	4.195	1.482	4.503	7.082
CHHC	0.832	0	4.905	1.498	5.094	7.694
PPHS	4.195	4.905	0	3.960	5.763	3.057
REHS	1.482	1.498	3.960	0	5.868	6.473
RHSC	4.503	5.094	5.763	5.868	0	8.621
SMTC	7.082	7.694	3.057	6.473	8.621	0

Table 3. Date, time and magnitude of earthquake and aftershocks (in order of increasing magnitude)

Earthquake Date yyyy-mm-dd	Time (UT) hh:mm:ss	Magnitude
2012-01-01	12:27:44	5.00
2012-01-06	1:20:58	5.03
2011-07-21	17:39:32	5.09
2011-12-23	17:37:30	5.10
2011-04-16	5:49:22	5.30
2011-12-23	1:06:25	5.33
2011-04-16	5:49:19	5.34
2011-12-31	0:43:00	5.34
2012-01-02	5:59:00	5.36
2011-06-21	10:34:23	5.44
2011-06-05	21:09:55	5.54
2011-06-13	1:01:00	5.63
2011-12-23	0:58:38	5.80
2011-12-23	2:18:03	6.00
2011-02-21	23:51:42	6.34

The objective of this research is to develop an ANN to predict PGA (as the output) at any desired point, particularly a bridge site, located in the circular domain of study within the radius of 5 km from the centre of Christchurch. There are, however, no recording stations installed right at the bridge sites that would supply the relevant data to be used for training the ANN. To overcome this challenge, the following approach is proposed and used in this research to obtain suitable inputs and outputs for ANN development.

- A single station is excluded and its PGAs set aside for evaluation of the network after it has been developed. This station is treated as if it were located at a bridge site where PGA prediction is desired.
- PGAs recorded at the remaining five stations and distances between them are used as the data to develop an ANN, i.e. to train, validate and test it.

This procedure results in a 10×75 input matrix (15×5=75 samples of 2×5=10 elements) for developing the ANN.

To prevent the existence of extreme values that can considerably affect the accuracy of the ANN, as observed in this study, all the PGAs are normalized using the following equation (Yeh, 2009):

$$PGA_n = \frac{(PGA_o - PGA_{min})}{(PGA_{max} - PGA_{min})} \quad (1)$$

where PGA_n is the normalized PGA, PGA_o is the original PGA, PGA_{min} is the minimum PGA in the data set, and PGA_{max} is the maximum PGA in the data set. After normalization, all of the PGAs in input and output data are within the range of 0 to 1.

Two feed-forward artificial neural networks are created in this study. Each network used a sigmoid transfer function in its one hidden layer and a linear transfer function in the output layer. The hidden layer contains eight neurons and the networks are trained with the Levenberg-Marquardt backpropagation algorithm. Figure 4 shows the diagram of the networks used in this study.

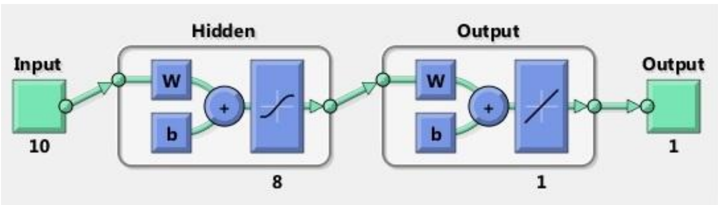

Figure 4. Diagram of the ANNs used

5 **RESULTS**

5.1 **Training, validating and testing the networks**

Two examples of artificial neural networks, ANN1 and ANN6, are created by excluding Station 1 and Station 6, respectively. The portions of the data used for training, validation and testing were in each case 70%, 15% and 15%, respectively, i.e. 53, 11 and 11 out of 75 samples. Training data are used to adjust the weights in the network and testing data are used to provide an independent measure of network performance after training. In this research, ANN testing is different from ANN evaluation as the latter uses data from a station entirely missing from the data used to develop the ANN. Validation data are used to stop training if the accuracy over the training data increases while the accuracy over the validation data stays the same or decreases for six consecutive epochs (iterations). This is to avoid overfitting.

After training the networks, mean squared errors (MSEs) for training, validation and testing were 0, 0.004 and 0.001 for ANN1, and 0.001, 0.001 and 0.001 for ANN6, respectively. These are all small values close to zero and show very small errors between the targets and actual ANN outputs. Figure 5 shows MSEs for training, validation and testing versus epochs for both networks. As can be seen, the best validation performance for ANN1occurs at epoch 72, where the training is stopped, and the error of the validation remains constant for the subsequent six epochs. The best validation performance for ANN6 occurs at epoch 3 and the training is stopped at epoch 9 after the validation error has not decreased during the next six iterations. The regression coefficient (R) values for training, validation and testing were ≈1, 0.94 and 0.94 for ANN1, and 0.99, 0.97 and 0.96 for ANN6, respectively. They are all close to 1 showing a very close correlation between outputs and targets. Figure 6 and Figure 7 demonstrate the R values for training, validation and testing, and all three combined for ANN1 and ANN6, respectively.

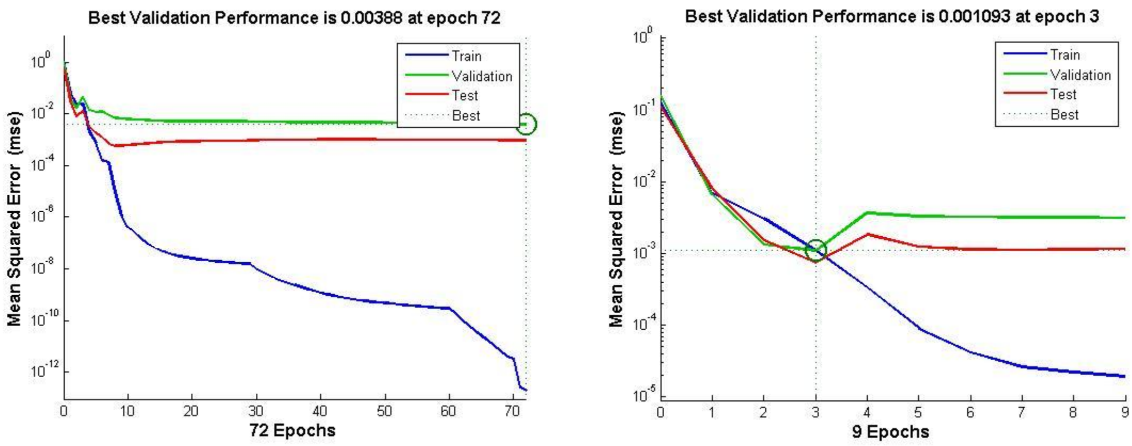

Figure 5. MSEs for training, validation and testing: ANN1 (left) and ANN6 (right).

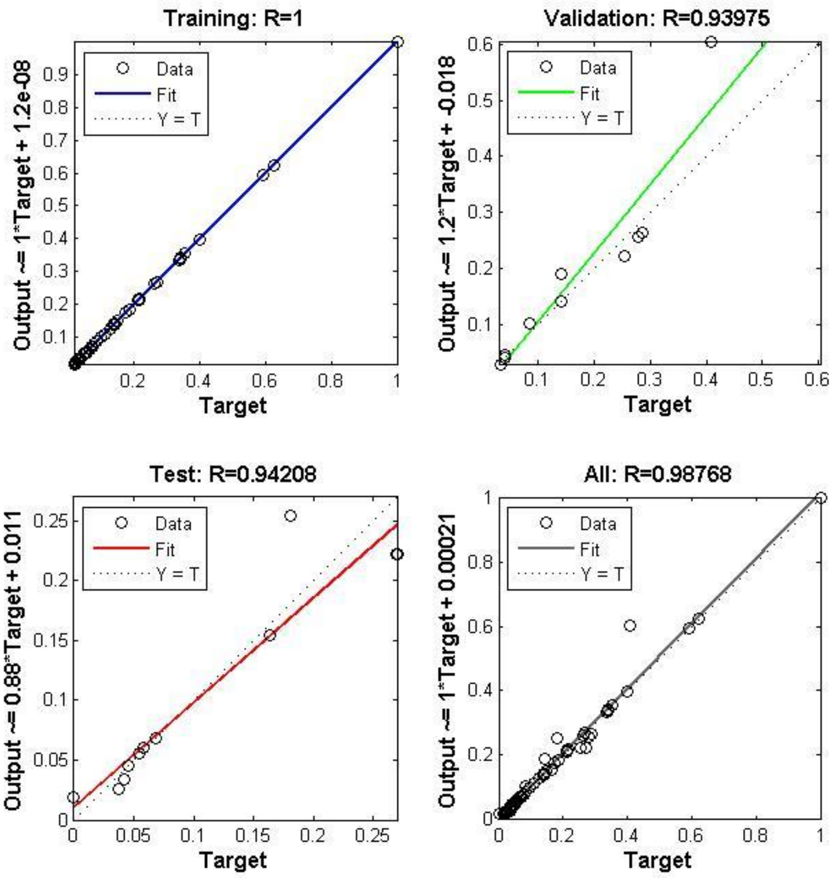

Figure 6. Regression of ANN1 outputs on training, validation, testing and all data

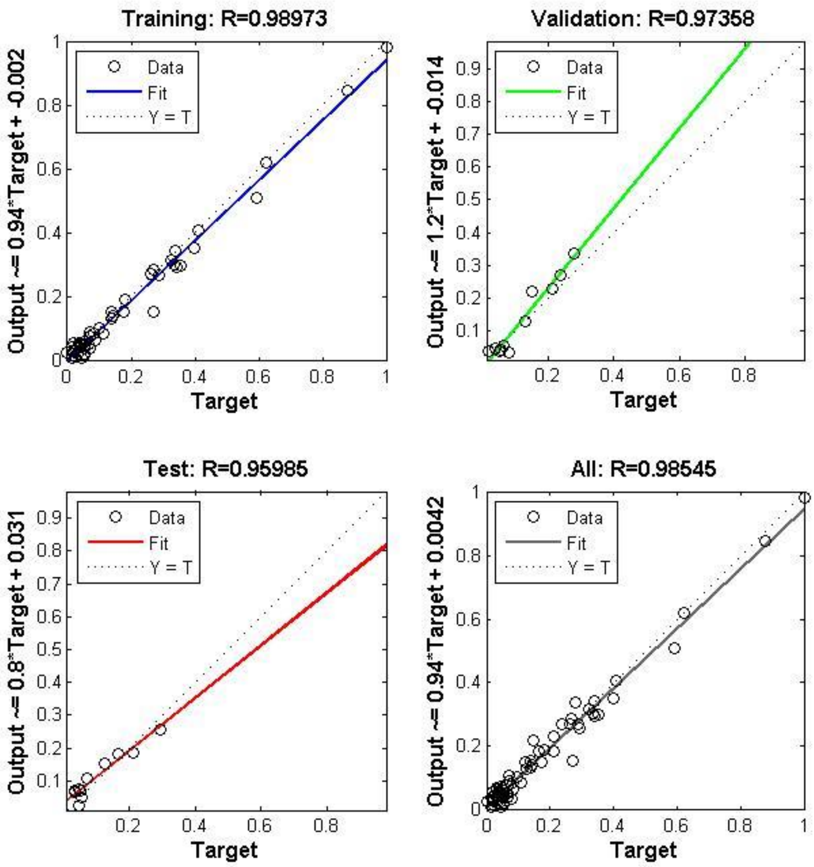

Figure 7. Regression of ANN6 outputs on training, validation, testing and all data

5.2 **Evaluating the networks**

The final goal of this research is to have an ANN which will be able to predict the PGAs at any arbitrary bridge site located in the domain of study, if it is given an input vector of PGAs recorded by the stations and associated distances between each recording station and the desired bridge. Therefore, it is necessary to evaluate the capability of the approach to predict the PGA at a point which has the certain value of PGA but had not been included in the process of developing the network. For this reason, the following evaluation of ANN's fit-for-purpose is performed: The station which has not been used in the process of generating the network is used to provide target PGAs for the ANN to predict. In the present study, those stations are Station 1 (CBGS) and Station 6 (SMTC) for ANN1 and ANN6, respectively.

Networks ANN1 and ANN2 were asked to predict the values of 15 PGAs at their respective evaluation station. The MSEs for such evaluations were 0.003 and 0.001 for ANN1 and ANN6, respectively, which are small values close to zero, and the R values were 0.97 and 0.90 which are close to 1. Figure 8 demonstrates the match between target and ANN-predicted values for evaluating ANN1 and ANN6. These results confirm the feasibility of the proposed approach to predict reliably PGA at an arbitrary point in the domain of study.

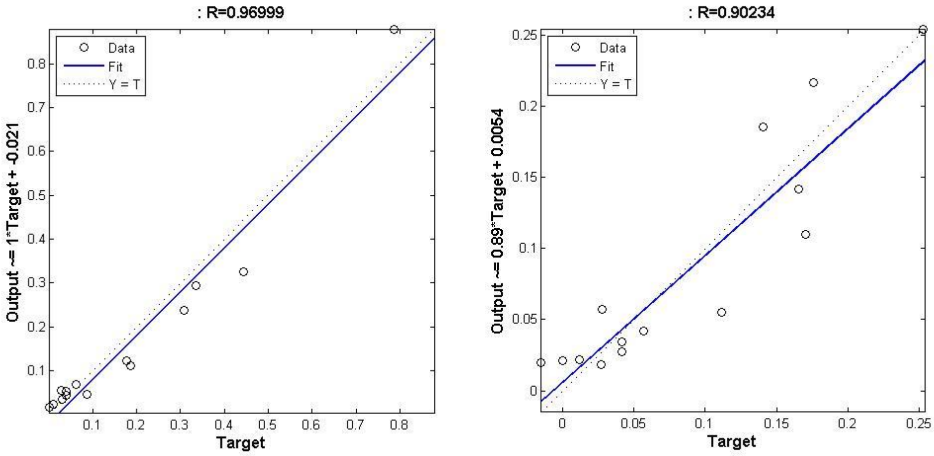

Figure 8. Regression of ANNs outputs on evaluation data: ANN1 (left) and ANN6 (right).

6 **CONCLUSIONS AND FUTURE WORK**

An ANN based approach has been proposed in this study to predict PGAs at any arbitrary point (e.g. bridge site) immediately after an earthquake, based on PGAs recorded by a distributed array of sensors. An area of study was considered within 5 km from the centre of Christchurch to develop the method. The only additional parameter considered except the recorded PGAs was the distance between the recording station and the target point. The results were promising and showed very small errors.

Based on this research, it is planned in the future to consider wider areas and more parameters such as seismic soil class, hypocentral depth and epicentral distance to reach a general approach that could be used for the whole city or large parts of the city. It is also planned to expand the method for predicting other ground-motion parameters such as peak ground velocity (PGV) and peak ground displacement (PGD). In addition, to use the predicted seismic parameters at the bridge site for the quick post-earthquake damage assessment, it is intended to develop a method using a simplified structural model of the bridge and estimated seismic parameters to compare with the design criteria for damage assessment.

7 **ACKNOWLEDGEMENTS**

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