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# A SIMPLE AND RAPID APPROACH TO POST-EARTHQUAKE ASSESSMENT OF BRIDGE CONDITION AND DAMAGE

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## ABSTRACT

The paper proposes a simple method for quick post-earthquake assessment of damage and condition of a stock of bridges in a transportation network using seismic data recorded by a strong motion array. The first part of the paper is concerned with using existing free field strong motion recorders to predict peak ground acceleration (PGA) at an arbitrary bridge site. Two methods are developed using artificial neural networks (a single network and a committee of neural networks) considering influential parameters, such as seismic magnitude, hypocentral depth and epicentral distance. The efficiency of the proposed method is explored using actual strong motion records from the devastating 2010 Darfield and 2011 Christchurch earthquakes in New Zealand. In the second part, two simple ideas are outlined how to infer the likely damage to a bridge using either the predicted PGA and seismic design spectrum, or a broader set of seismic metrics, structural parameters and damage indices.

**Keywords:** bridges, structural health monitoring, condition assessment, damage assessment, peak ground acceleration, artificial neural networks.

## INTRODUCTION

Rapid and reliable assessment of bridge condition and damage is an important but challenging task required to ensure efficient operation of transportation networks in the aftermath of an earthquake. Existing previous experience indicates that the responsible organizations usually show bewilderment in performing such tasks. Having a simple and reliable approach to using data recorded during the earthquake with the aim of assessing quickly bridge condition and damage will be useful in such situations. These data can be obtained from either structural health monitoring systems (SHM) installed on individual bridges or wide-area seismic monitoring arrays. It is only realistic to assume that the number of bridges equipped with individual SHM systems will always be small and for the remaining structures it is beneficial to harness data from the wide-area seismic monitoring arrays often installed in earthquake prone cities. The task of these strong motion recorders is to capture the time history of the ground acceleration during an earthquake. The peak value of this time history is called peak ground acceleration (PGA) and is a key parameter in structural design as well as damage assessment.

It is necessary to know the ground motion's parameters, such as PGA, at a bridge site during an earthquake to be able to perform an assessment of the bridge condition immediately after that earthquake. Despite large numbers of strong motion recorders in earthquake prone cities there are still large numbers of bridges which are located in places which are remote from any of those strong motion stations. For the assessment of these structures it is therefore necessary to predict the ground motion parameters at their locations using data available from remote strong motion recorders. In the present paper, two artificial neural network (ANN) based approaches are first proposed which make it possible to predict the maximum horizontal PGA at any arbitrary point, e.g. a bridge site, using PGAs recorded by arrays of strong motion recorders distributed over a large area. The first approach uses a single ANN, whereas the second approach an ANN committee (ANNC). The array in the city of Christchurch, New Zealand and the data recorded during the devastating 2010 Darfield and 2011 Christchurch earthquakes and their aftershocks are used as a case study. The proposed approaches showed reliable capability to do intended task.

In the second part of this paper simple ideas are introduced which are intended to predict the likelihood of damage to bridge structures using the predicted ground motion metrics at the bridge site. The first idea is to use the predicted PGA and compare to that assumed in design using a design spectrum.

## ANN-BASED APPROACH TO PGA PREDICTION

Artificial neural networks are one of the most powerful mathematical approaches to find the governing relation between a set of inputs and outputs. There are many studies in the literature that have used artificial neural network for problems such as seismic damage prediction for multistory buildings (de Lautour and Omenzetter, 2009), estimating bridge damage after major earthquakes (Lin et al., 2002), sensitivity analysis of damage ratio (Hadzima-Nyarko et al., 2011), earthquake forecasting (Alves, 2006) and PGA estimation (Kerth et al., 2011).

In this study, the earthquake records from GeoNet data center (www.geonet.org.nz) have been used for training, validating and testing the neural networks. The data are related to the 2010 Darfield and 2011 Christchurch earthquakes and their aftershocks. Five recording stations located around the center of Christchurch were considered to develop the networks and another recording station (CBGS) was considered to test the predictive power of the proposed approaches. Figure 1 and Table 1 show the locations and additional information of these six stations.

While the output of the ANN, i.e. PGA, is determined, it is important to include as many as possible influencing factors as inputs. All of the stations used in this research are located on the same seismic soil class D (deep or soft soil) as defined by the New Zealand Loading Standard NZ1170.5:2004 (Standards New Zealand, 2004). Therefore, the influence of soil type on PGA could not be studied. With the aim of choosing other influential parameters, the magnitudes and hypocentral depths of the 2011 Christchurch earthquake and its aftershocks were plotted versus the maximum horizontal PGAs for five stations in Figure 2 and Figure 3, respectively, to explore their relationships.

As expected, PGA is generally increasing with the magnitude (Figure 2). The points that show sharp fluctuations are corresponding to very high or low epicentral distances and/or hypocentral depths. The PGA value is generally decreasing as the hypocentral depth is increasing (Figure. 3) and in this case sharp fluctuations are corresponding to very high or low magnitudes and/or epicentral distances. However, the general behavior of these two sets of graphs for all the considered stations is the same which shows a correlation between the magnitude and hypocentral depth and PGA. The correlations suggest including these parameters in the input data for developing the network. Furthermore, epicentral distances to each station were also included in the input data.

All the maximum horizontal PGAs that were recorded at the same times by all the six considered stations during the 2010 Darfield and 2011 Christchurch earthquakes and their 22 aftershocks were selected (the total number of records available is therefore 24). The lowest magnitude is 4.55 and the highest is 7.1. Table 2 shows the information on the earthquakes used in the subsequent analysis.

The full set of input parameters included magnitude of each earthquake, hypocentral depth of each earthquake, PGAs recorded at the stations, distances between the stations, and epicentral distances to each station. All the data used to train, validate and test the networks were normalized using the following equation to prevent any unwanted effect on the accuracy of the networks:

$$D_n = \frac{(D_o - D_{min})}{(D_{max} - D_{min})} \quad (1)$$

where $D_n$ is the normalized data, $D_o$ is the original data, $D_{min}$ is the minimum data value and $D_{max}$ is the maximum data value. After the normalization all of the data were within the range from 0 to 1.

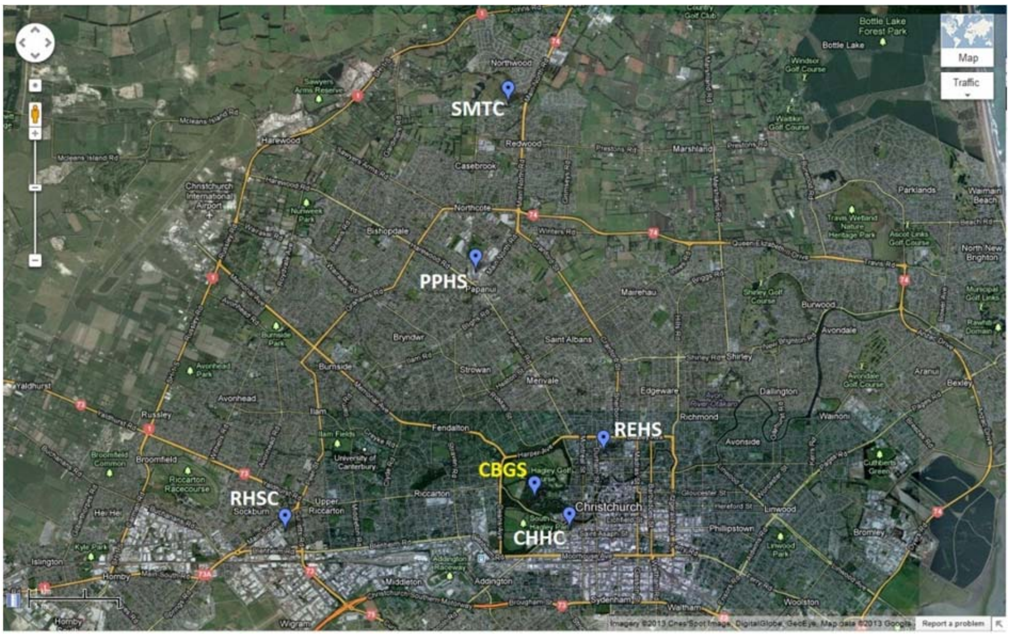



Fig. 1 Location of recording stations in Christchurch

Table 1 Information about strong motion recorders in Christchurch

| Station Name | Code | Latitude (°) | Longitude (°) | Seismic Site Class |
|---|---|---|---|---|
| ChCh Hospital | CHHC | -43.535929 | 172.627523 | D |
| ChCh Papanui High School | PPHS | -43.49451 | 172.60679 | D |
| ChCh Resthaven | REHS | -43.52361 | 172.63502 | D |
| Riccarton High School | RHSC | -43.536172 | 172.564404 | D |
| Styx Mill Transfer Station | SMTC | -43.4675293 | 172.613861 | D |
| ChCh Botanic Gardens | CBGS | -43.53101 | 172.61975 | D |

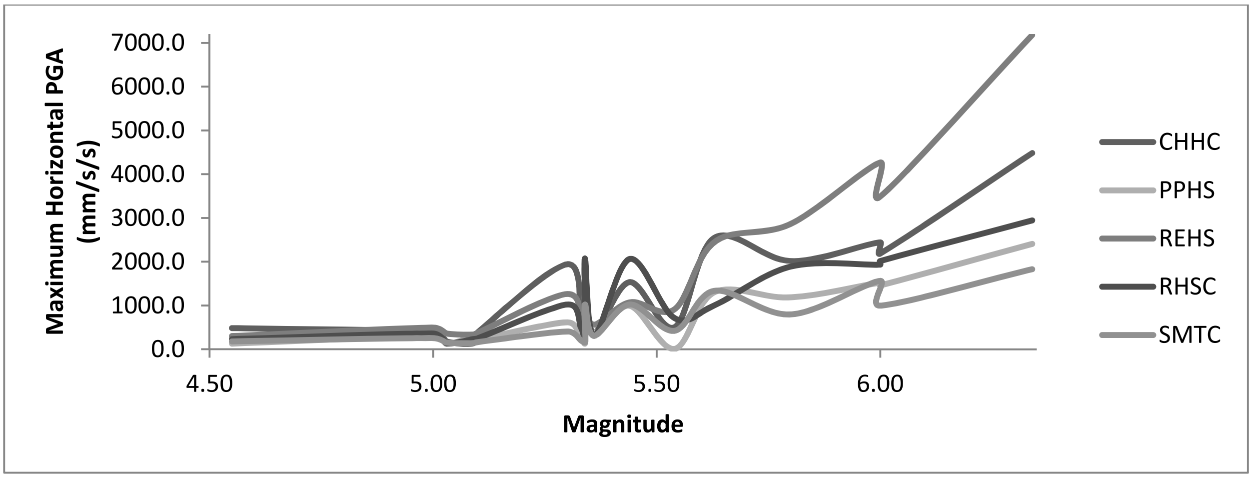



Fig. 2 Relation between magnitude and maximum horizontal PGAs recorded by five stations during the 2011 Christchurch earthquake and its aftershocks

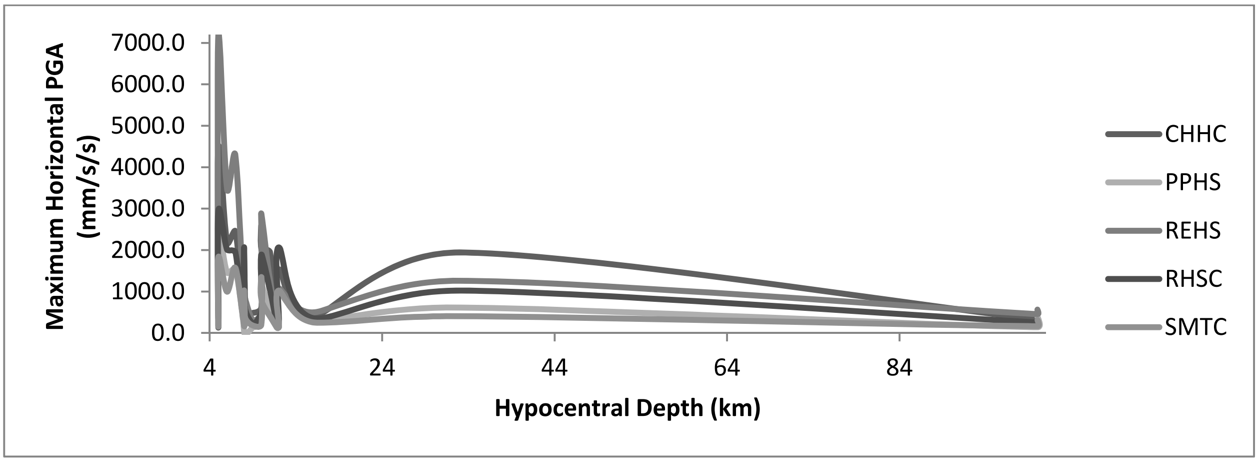



Fig. 3 Relation between hypocentral depth and maximum horizontal PGAs recorded by five stations during the 2011 Christchurch earthquake and its aftershocks

The first approach for PGA prediction used a single ANN. This ANN had a sigmoid transfer function in its one hidden layer and a linear transfer function in the output layer. The hidden layer contained 15 neurons and the network was trained with the Levenberg-Marquardt backpropagation algorithm. Figure 4 shows the diagram of the network used for the first approach. The first approach used the data of five stations, so a 17×120 input matrix (24×5=120 samples of 2+3×5=17 elements) was used to develop the network.

The second approach used an ANNC comprising five networks that were developed each using four stations' data as input and one station other than CBGS. The motivation was to remove a possible bias present in ANN caused by excluding only the CBGS station. The input data matrix had 17×600 elements. The characteristics of each network in the ANNC are the same as the single network except the number of hidden layer neurons which is 20. Figure 5 shows the diagram of a network used for the second approach.

To train each network, 75% randomnly selected input data were used, i.e. 90 and 450 input vectors for ANN and ANNC, respectively. The rest of the data were used for validation. The purpose of validation is to stop training before overfiting occures. After training of the networks, mean squared errors (MSEs) for training and validation were 0.00001 and 0.007 for the single ANN, and 0.0004 and 0.002 for ANNC, respectively. These errors are very close to zero and show a very small differences between the networks' outputs and the targets. The regression coefficient (R) values for training and validation were 0.999 and 0.969 for ANN, and 0.990 and 0.946 for ANNC, respectively. They are very close to 1 showing a very close corelation between targets and networks' outputs. Figure 6 and Figure 7 shows the R values for training and validation.

Table 2 Date, time, magnitude and hypocentral depth of earthquakes and aftershocks in chronological order (Darfield and Christchurch main shocks highlighted)

| **Earthquake Date yyyy-mm-dd** | **Time (UT) hh:mm:ss** | **Magnitude** | **Hypocentral Depth (km)** |
|---|---|---|---|
| 2010-09-03 | 16:35:41 | 7.10 | 11 |
| 2010-09-07 | 19:49:57 | 5.13 | 6 |
| 2010-10-15 | 9:31:40 | 4.56 | 7 |
| 2010-10-18 | 22:32:15 | 5.03 | 9 |
| 2010-10-24 | 2:13:28 | 4.78 | 9 |
| 2010-11-13 | 12:34:06 | 4.68 | 7 |
| 2011-02-21 | 23:51:42 | 6.34 | 5 |
| 2011-04-16 | 5:49:19 | 5.34 | 33 |
| 2011-04-16 | 5:49:22 | 5.30 | 11 |
| 2011-06-05 | 21:09:55 | 5.54 | 8 |
| 2011-06-13 | 1:01:00 | 5.63 | 10 |
| 2011-06-13 | 2:20:49 | 6.00 | 6 |
| 2011-06-17 | 4:21:57 | 4.55 | 9 |
| 2011-06-21 | 10:34:19 | 5.34 | 12 |
| 2011-06-21 | 10:34:23 | 5.44 | 8 |
| 2011-07-21 | 17:39:32 | 5.09 | 12 |
| 2011-12-23 | 0:58:38 | 5.80 | 10 |
| 2011-12-23 | 1:06:25 | 5.33 | 10 |
| 2011-12-23 | 2:18:03 | 6.00 | 7 |
| 2011-12-23 | 17:37:30 | 5.10 | 8 |
| 2011-12-31 | 0:43:00 | 5.34 | 100 |
| 2012-01-01 | 12:27:44 | 5.00 | 16 |
| 2012-01-02 | 5:59:00 | 5.36 | 100 |
| 2012-01-06 | 1:20:58 | 5.03 | 5 |

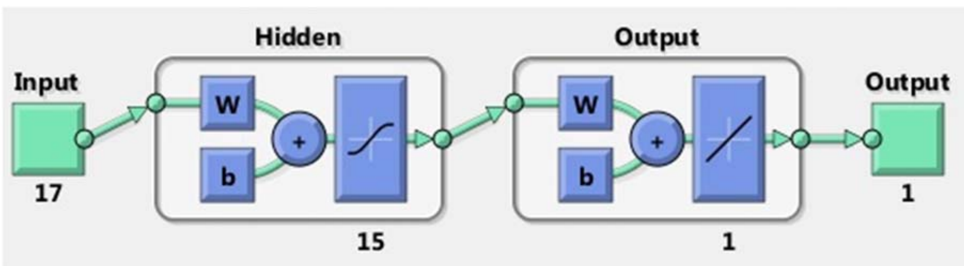



Fig. 4 Diagram of the ANN used in the single network approach

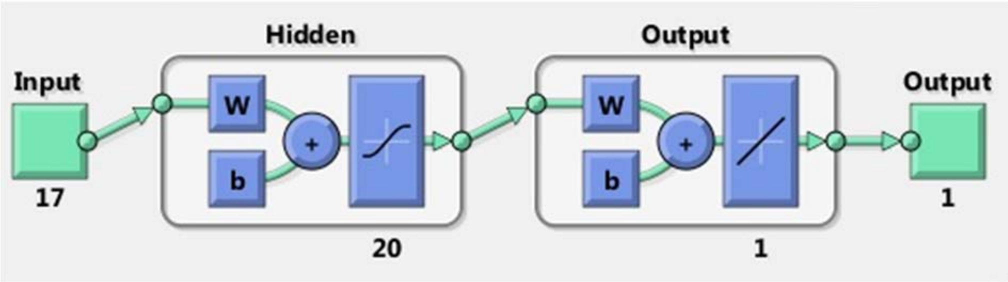



Fig. 5 Diagram of a network used in the ANNC approach

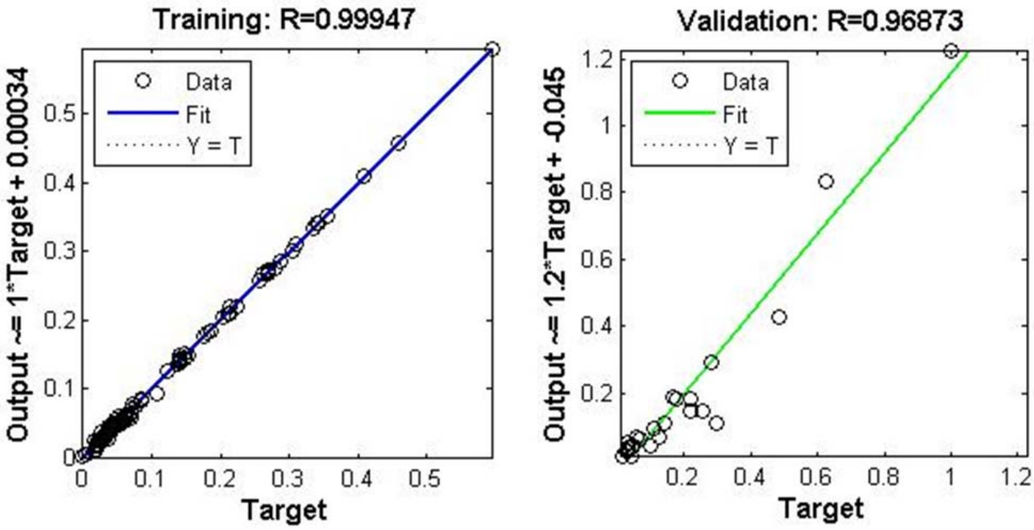



Figure 6 Reggresion of single ANN outputs on training (left) and validation (right) data

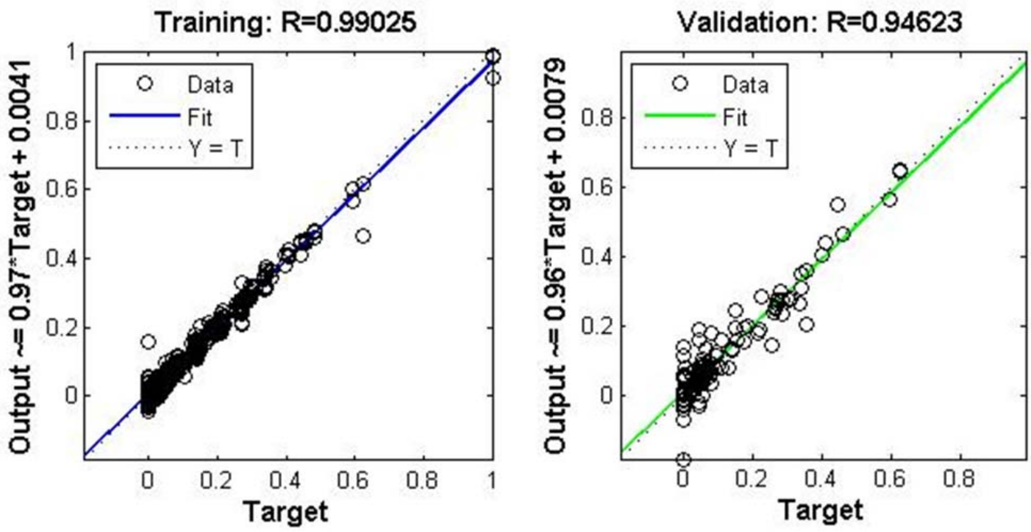
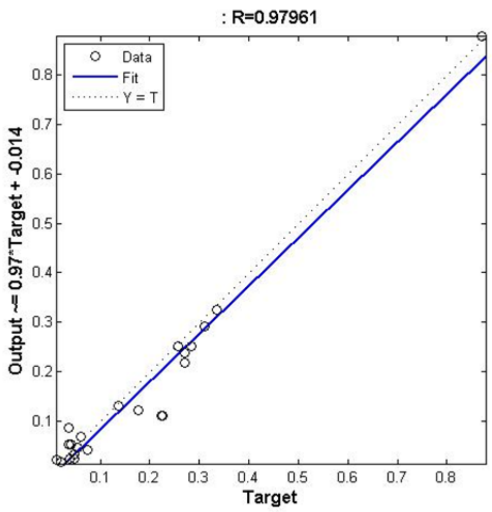
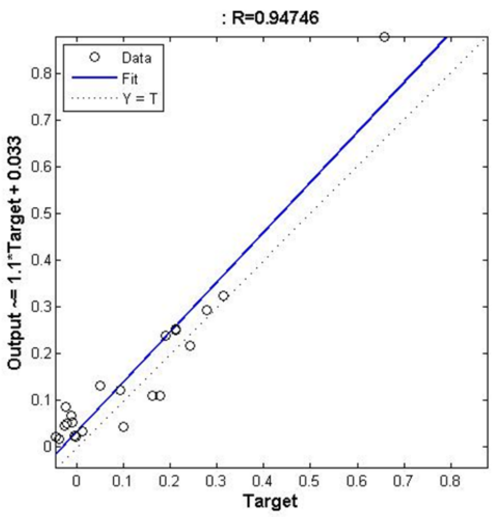



Figure 7 Reggresion of ANNC outputs on training (left) and validation (right) data

To test the predictive power of the developed networks for an arbitrary point, the networks were asked to predict the 22 PGAs recorded by the recording station CBGS which was not used for traing or validation. Earthquake magnitude, hypocentral depth, epicentral distance to each one of five stations, recorded PGAs by each station and the distances between the input stations and the CBGS station formed the input data for testing the networks in predicting the PGA. The MSEs for such testings were 0.0018 and 0.0052 for the single ANN and ANNC, respectively, which are both close to zero. The R values were 0.98 and 0.95 which are close to 1. Figure 8 shows the match between the network-predicted values and targets for testing the single ANN and ANNC. It is noted that the ANNC gave slightly less accurate predictions. This can be attributed to the fact that it had less (four) input PGAs compred to five input PGAs available to the single ANN.




a)




b)

Figure 8 Reggresion of network outputs on testing data: a) single ANN, and b) ANNC

## USING PREDICTED PGA TO INFER STRUCTURAL DAMAGE

Based on the recommendations commonly included in design codes, typical bridges (excluding cable stayed, suspension or arch bridges) can be modeled as a single degree of freedom (SDOF) system. Figure 9 schematically shows this idealization, where $k$ is the stiffness, $M$ is the mass and $c$ is the damping coefficient.

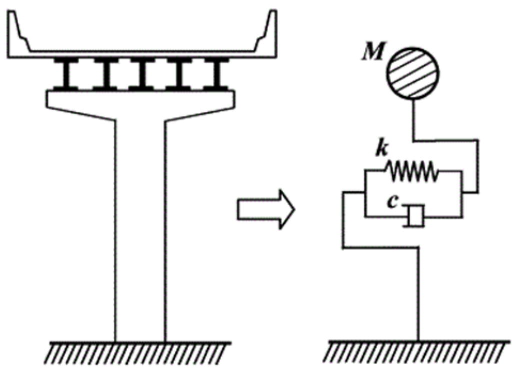



Figure 9 Using idealized SDOF system to model bridge structure

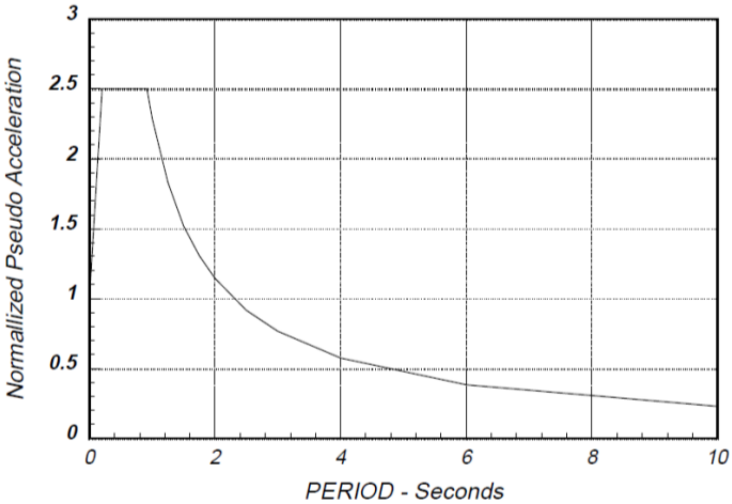



Figure 10 Typical design spectrum (Wilson, nd)

Simple seismic design of bridges uses SDOF models and design actions determined from elastic design spectra such as the one shown in Figure 10. Such design spectra also take into account general geotechnical and structural properties such as soil class, structural period and damping. Further provisions for inelastic response and ductility are also included (see e.g. Standards New Zealand (2004)). Comparing the design actions (expressed as pseudo acceleration) and the predicted PGA at the site using the approach proposed in this study offers a quick way of judging structural performance. The validity and reliability of this approach relies on the validity and reliability of the designing methods that were used to design the bridge since all of the assumptions came from the designing concepts.

Another approach can be based on correlating PGA, and other ground motion and structural metrics such as peak ground velocity (PGV) and displacement (PGD), spectral intensity (SI), structural period, to damage quantified using a damage index. This was done in the past for gas distribution networks and multi-story buildings respectively by Molas and Yamazaki (1995) and de Lautour and Omenzetter (2009).

## CONCLUSIONS AND FUTURE WORK

Two different artificial neural network based approaches for predicting PGA at an arbitrary bridge site were developed and examined using the data recorded by arrays of strong motion recorders over the city of Christchurch during the 2010 Darfield and 2011 Christchurch earthquakes and their aftershocks. The first approach used a single network, while the second a committee of five networks. Influential parameters of the domain of study were considered and both networks' testing results confirmed the feasibility of the approaches to predict reliably PGA at bridge sites. A simple approach based on design concepts was outlined to predict the probability of damage to bridges using the predicted PGA. Another method to explore will relate several ground motion metrics and structural parameters to a damage index.

It is intended in the future to expand the proposed methods to a wider area including more stations covering different seismic soil classes. It is also planned to develop methods for predicting other ground motion parameters such as PGV, PGD, SI and finally correlate them to damage to bridges.

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**REFERENCES**

Alves, E. 2006. Earthquake forecasting using neural networks: Results and future work. *Nonlinear Dynamics,* 44**,** 341-349.

Chopra, A. K. 2001. *Dynamics of structures: theory and applications to earthquake engineering*, Upper Saddle River, NJ: Prentice Hall.

de Lautour, O. R. & Omenzetter, P. 2009. Prediction of seismic-induced structural damage using artificial neural networks. *Engineering Structures,* 31**,** 600-606.

Hadzima-Nyarko, M., Nyarko, E. K. & Moric, D. 2011. A neural network based modelling and sensitivity analysis of damage ratio coefficient. *Expert Systems with Applications,* 38**,** 13405-13413.

Kerth, T., Huang, C. & Gunaratman, D. 2011. Neural network approach for analyzing seismic data to identify potentially hazardous bridges. *Mathematical Problems in Engineering,* 2011, 1-15.

Lin, T. K., Lin, C. C. J. & Chang, K. C. 2002. Neural network based methodology for estimating bridge damage after major earthquakes. *Journal of the Chinese Institute of Engineers,* 25, 415-424.

Molas, G. L. & Yamazaki, F. 1995. Neural networks for quick earthquake damage estimation. *Earthquake Engineering and Structural Dynamics*, 24, 505-516.

Standards New Zealand (2004). *NZS 1170.5:2004. Structural design actions. Part 5: Earthquake actions – New Zealand*. Wellington, New Zealand: Standards New Zealand.

Wilson, E. (nd). Dynamic analysis using response spectrum seismic curves. *CSI Technical Papers*, 1-24.