Suggested Reference

Omenzetter, P., Ramhormozian, S., Mangabhai, P., Singh, R., & Orense, R. (2013). A framework for rapid post-earthquake assessment of bridges and restoration of transportation network functionality using structural health monitoring. In J. P. Lynch, C. B. Yun, & K. W. Wang (Eds.), *Proceedings of SPIE* Vol. 8692, article number 86920J. San Diego, California, USA. doi:10.1117/12.2008875

A framework for rapid post-earthquake assessment of bridges and restoration of transportation network functionality using structural health monitoring

Piotr Omenzetter[*a], Shahab Ramhormozian[b], Poonam Mangabhai[c], Ravikash Singh[d], Rolando Orense[b]

[a]The LRF Centre for Safety and Reliability Engineering, University of Aberdeen, Aberdeen AB24 3UE, UK
[b]The University of Auckland, Private Bag 92018, Auckland, New Zealand
[c]Graduate Networks Engineer, Watercare, 2 Nuffield Street, Auckland, New Zealand
[d]Road Asset Management Engineer, Beca, 6 Garden Place, Hamilton, New Zealand

ABSTRACT

Quick and reliable assessment of the condition of bridges in a transportation network after an earthquake can greatly assist immediate post-disaster response and long-term recovery. However, experience shows that available resources, such as qualified inspectors and engineers, will typically be stretched for such tasks. Structural health monitoring (SHM) systems can therefore make a real difference in this context. SHM, however, needs to be deployed in a strategic manner and integrated into the overall disaster response plans and actions to maximize its benefits. This study presents, in its first part, a framework of how this can be achieved. Since it will not be feasible, or indeed necessary, to use SHM on every bridge, it is necessary to prioritize bridges within individual networks for SHM deployment. A methodology for such prioritization based on structural and geotechnical seismic risks affecting bridges and their importance within a network is proposed in the second part. An example using the methodology application to selected bridges in the medium-sized transportation network of Wellington, New Zealand is provided. The third part of the paper is concerned with using monitoring data for quick assessment of bridge condition and damage after an earthquake. Depending on the bridge risk profile, it is envisaged that data will be obtained from either local or national seismic monitoring arrays or SHM systems installed on bridges. A method using artificial neural networks is proposed for using data from a seismic array to infer key ground motion parameters at an arbitrary bridges site. The methodology is applied to seismic data collected in Christchurch, New Zealand. Finally, how such ground motion parameters can be used in bridge damage and condition assessment is outlined.

Keywords: Artificial neural networks, bridges, condition assessment, damage, risk, structural health monitoring

1. INTRODUCTION

The need to protect and maintain road assets and their functionality has become a necessity for any local authority or national road and highway operator to ensure the needs of communities and economy are adequately met. Bridges are critical and expensive components within the transportation network providing essential infrastructure, services and interconnections between various road networks that underpin the life of communities. Bridges are subject to various natural hazards, of which earthquakes are one of the most important. It is required that all lifelines (including the road network) be able to function to the fullest possible extent during and after an emergency[1]. Complex topography often dictates transportation networks lacking in redundancy and failure of a small number of bridges may have significant negative consequences at the time of natural disaster. Following an earthquake, bridges may be closed due to safety concerns, and may only be re-opened for use once site investigations have been carried out. Due to the large number of

[*] piotr.omenzetter@abdn.ac.uk; phone 44 1224 272529; fax 44 1224 272497; www.abdn.ac.uk

Sensors and Smart Structures Technologies for Civil, Mechanical, and Aerospace Systems 2013,
edited by Jerome Peter Lynch, Chung-Bang Yun, Kon-Well Wang, Proc. of SPIE Vol. 8692,
86920J · © 2013 SPIE · CCC code: 0277-786X/13/$18 · doi: 10.1117/12.2008875

bridges within any network and limited resources for inspections, this can be a time consuming process and may lead to traffic delays and congestion thus hampering quick post-disaster recovery and rebuilt. Furthermore, adequate functionality of the critical links within the transportation network of the affected area is necessary immediately in the aftermath of an event to ensure access to such services as hospitals, evacuations centers and airports, and operation of search and rescue, fire and emergency supply services and others. To exacerbate the challenges brought about by limited resources, judging the soundness of a bridge stroke by an earthquake is difficult because of the subjective and qualitative nature of visual inspections[2].

Research into strategies, tools and technologies that will assists in quick post-earthquake assessment of bridge damage, condition and performance and overcome, or at least lessen the aforementioned problems, is urgently required. Monitoring systems can collect real time data and, with appropriate and careful data interpretation, provide information about the condition and performance of bridges. This will provide asset managers and emergency response centers with valuable information to assist decision making following a seismic event. While it is not expected, or necessary, or practical to completely replace visual inspections by monitoring systems, the latter can be a useful supplement to the more traditional assessment methods. However, to achieve the maximum benefit from monitoring systems they need to be implemented in a strategic, planned and targeted way, and well-integrated into the entire post-disaster response plans and practices.

This paper reports on a part of a larger research effort to develop strategies and tools that will enable quick post-earthquake assessment of bridge damage, condition and performance using data collected by monitoring systems. The full set of tasks leading to that end is as follows:

- Developing a methodology for prioritization of bridges for application of quick assessment and sensing technologies. This will take into account bridge importance in the network and seismic risks, including structural and geological risks.
- Developing methodologies for using existing wide-area free-field seismic data for post-earthquake bridge condition and damage assessment. This assessment will take into account both structural and geotechnical failures affecting bridges. The focus will be on correlating simple measures extracted from the strong motion data with structural, foundation and soil performance and damage.
- Developing guidelines for instrumentation to be installed on bridge structures and in their vicinity for measuring seismic responses (bridge specific instrumentation). This instrumentation will record structural, foundation and soil responses as appropriate. The focus will be on optimal, affordable hardware and simple measurements, such as accelerations and tilts, that can help in assessment of seismic damage.
- Developing a methodology for quick condition and damage assessment based on correlating simple measures extracted from data collected by bridge specific instrumentation with structural and foundation performance and damage.
- Developing guidelines for integration of monitoring and quick assessment results into the emergency planning and response practices of organizations responsible for post-disaster functionality of transportation networks.

This paper reports on the research related to the first two tasks, i.e. i) the development of a prioritization methodology for selection of bridges for strategic application of monitoring systems and quick assessment using monitoring data, and ii) using data from strong motion arrays to infer damage to bridges. The need for such a methodology stems from the fact that due to the cost of monitoring systems it is unrealistic, if ever necessary, to instrument all, or even the majority, of bridges on a network. Furthermore, immediate information about post-earthquake condition is not necessarily required for all bridges but only these that are more critical for network functioning. The question then arises as to which bridge structures should be monitored and quickly assessed. Considering seismic risk of each bridge at a network level provides a useful basis for selection and underpins the proposed methodology.

The outline of the reminder of the paper is as follows. The next section contains a short review of representative approaches to assessment of seismic risk to bridges. This is followed by the presentation of the developed risk-based prioritization methodology that enables informed selection of bridges for monitoring and quick post-earthquake condition assessment. An example of methodology application to the road network of Wellington, New Zealand is provided and discussed. In the next part, an approach based on using artificial neural networks (ANNs) to interpolate key ground motion parameters from recorded free-filed data to an arbitrary bridge site is presented. The methodology is applied to seismic data collected in Christchurch, New Zealand. Finally, an approach is outlined that will be investigated to correlate damage to bridges to ground motion metrics.

2. TIERED, RISK-BASED APPROACH TO MONITORING AND QUICK CONDITION ASSESSMENT OF BRIDGES

From the point of view of organizations responsible for post-disaster functioning of transportation networks, monitoring offers a useful tool as it addresses their key challenges, i.e., the need for advanced knowledge about bridge condition and performance, and reliable data for ensuring that bridges can perform to the expected level. Monitoring systems can collect data in real time and can help detect damage to the structure, which can be in the form of changes to the material and/or geometric properties of the system. They can aid decision making immediately following a seismic event. They can also be used for long term condition monitoring. It is important to recognize that the term 'monitoring systems' is used herein in a broad sense and includes not only sensors installed on individual bridges: another source of quantitative data for inferring likely seismic loading and post-earthquake structural condition are wide-area free-field seismic arrays.

However, monitoring has only made limited transition from the research domain into widespread practical applications. In order to achieve a widespread, planned and proactive integration of monitoring into post-disaster response and realize its potential benefits it is necessary to establish a sound philosophy guiding the implementation of monitoring systems to bridges. By doing so, monitoring systems can be strategically deployed to enhance the post-disaster response processes and help alleviate its current limitations in a cost effective way.

This paper argues that such a philosophy should be based on considering the risk that failures of individual bridges present to the entire transportation system and presents a risk-based method for prioritization of bridges for implementation of monitoring systems and quick condition assessment methods of increasing sophistication and complexity. The adopted risk-based philosophy assumes that some bridges, i.e. those that pose more risk to the operation of the transportation system, will be selected for monitoring and quick post-disaster assessment of their condition. Omenzetter et al[3] considered uncertainties related to the available information about structural and functional capacity and loads and other demands imposed on the structure. To account for these uncertainties and errors, conservative assumptions must be made that increase the apparent risk. More data, and more importantly better quality and more reliable data, and information inferred from the data can reduce uncertainties and eliminate erroneous assumptions. Thus, better estimation of risk factors in most cases reduces the risk in the first place. In some cases, when previously unknown and unexpected problems not covered by the conservativeness of less refined risk estimations surface, the risk may actually increase, but this increase is then underpinned by evidence. Monitoring systems can provide such additional data for improved risk assessment. Omenzetter et al[3] also demonstrated that the overall network level-aggregated risk reduction is most efficient when efforts to collect better quality data focus mostly on those structures that already present the highest risks, while not ignoring totally the less-at-risk ones.

The whole spectrum of approaches to bridge condition evaluation is presented in Table 1.

Table 1. Risk-based approaches to bridge monitoring and quick post-earthquake condition assessment.

Seismic risk level	**Data collection/monitoring system use**	**Condition assessment techniques**
Low	Data collected only via visual inspections No quantitative data collected via monitoring	'Slow' assessment based only on inspectors' reports from visual inspections
Intermediate	Monitoring data from wide area strong motion arrays Additional data collected via visual inspections	'Quick', less accurate assessment based on wide area strong motion data interpolated to the bridge site Follow-up assessment based on visual inspections and technical analyses as required
High	Monitoring data from bridge specific monitoring systems Additional data collected via visual inspections	'Quick', accurate assessment based on monitoring data collected on the bridge Follow-up assessment based on visual inspections and in-depth technical analyses as required

In the proposed framework, bridges with low seismic risk will be evaluated post-earthquake using the currently prevailing approach based mostly on visual inspections scheduled depending on the availability of inspectors and need. Bridges in the intermediate risk category will not have dedicated instrumentation installed on them or in their proximity.

Instead, data recorded by wide area free field arrays will be used. However, this will require interpolation of such data so that ground motion parameters can be estimated at the bridge site. Work is underway, and is reported later in this paper, to develop a suitable approach to predict basic ground motion metrics such as peak ground acceleration (PGA) using ANNs. This will be complemented by quick and simple methods for translating the hazard metrics into damage estimates. The outcome will allow declaring a bridge as safe for immediate continuous use, or requiring traffic restrictions, or closure. If required, further assessment supplemented by data from visual inspections and technical analyses can be conducted at a suitable time.

Bridges in the high risk category will receive special consideration. They will have dedicated monitoring systems with sensors measuring their responses, including super, substructure and foundation, and those of nearby soil. The amount, type and locations of instrumentation will be individually tailored to the need of each bridge as determined by a prior structural vulnerability study. Using the bridge specific monitoring data will enable much more detailed and accurate assessment of bridge condition.

3. RISK-BASED BRIDGE PRIORITIZATION METHODOLOGY

The commonly accepted definition of risk, R, is the probability of failure multiplied by the expected impacts (or consequences) of failure. Failure probability itself is a function of hazard occurrence probability and structural vulnerability to the given hazard[4]. In many real life applications of risk analysis to bridges detailed and refined probabilistic information about both failure probability and consequences is often unavailable. Many simple, yet practical, risk assessment schemes circumvent these limitations by assigning numerical scores for hazard, H, vulnerability, V, and impacts, I, and risk R can then be succinctly expressed in the following form:

$$R = H \times V \times I \tag{1}$$

However, even those scores can only be reasonably determined if enough information is available. For example, if vulnerability is judged using only simple desktop revisions of as-designed documentation there is considerably more uncertainty involved compared to a situation when more information is available such as as-built documentation, non-destructive testing and/or monitoring results, structural analysis results etc. To address such uncertainties resulting from different data quality and assessment practices, Moon et al.[5] presented an extension of the above risk formula:

$$R = H \times V \times I \times U \tag{2}$$

where U is the uncertainty premium penalizing relative lack of data and information used for, and simplifications in, risk assessment. Applying an uncertainty factor brings further insights into the risk analysis as it accounts for data and assessment techniques which will likely differ between bridges.

In this research it was felt, based on inspection of available information that further differentiation of uncertainty levels and premiums is required, and individual premiums related to the assessment of hazards, U_H, vulnerabilities, U_V, and impacts, U_I, were introduced. Furthermore, several different aspects of vulnerability and impacts may receive different scores and to combine, or aggregate those, root-mean-squares (RMS) is used. The adapted formula for the total risk for a bridge thus becomes:

$$R = \left(U_{H,i} \times H_i\right) \times \mathrm{RMS}\left(U_{V,i} \times V_i\right) \times \mathrm{RMS}\left(U_{I,i} \times I_i\right) \tag{3}$$

where subscript i refers to individual vulnerabilities and impacts. (Note, in the proposed hazard scoring method there is only one hazard score.)

Moon et al.[5] developed tables to determine hazard, vulnerability, impacts and uncertainty premium scores. Their concepts are the foundation upon which further developments have been undertaken in this study. However, the methodology presented here differs in several aspects. While Moon et al.[5] considered a wide spectrum of hazards facing bridges, here only the seismic hazard is taken into account. Also, scoring criteria were better aligned to the local New Zealand context where this research was conducted using the tables recently developed for multiple hazards by Omenzetter et al.[6] These have been further developed and specified in this project for seismic hazards and vulnerabilities. Furthermore, geotechnical and structural aspects have been combined to determine the overall seismic vulnerability, treating the structure, foundation and soil as a whole. Available space prohibits showing the whole developed tables but they can be found in Omenzetter et al.[7]

The flow of the methodology developed to evaluate risk for each bridge site is summarized in Figure 1. The procedural steps are also enumerated below and are as follows:

1. Data collection, archiving and/or retrieval.
2. Determination of uncertainty premium scores.
3. Determination of raw seismic hazard score.
4. Determination of individual raw structural vulnerability scores and geotechnical vulnerability scores.
5. Determination of individual raw impact scores.
6. Determination of individual scores taking into account uncertainty.
7. Calculation of aggregated vulnerability and impact score by root-mean-square (RMS) of individual scores.
8. Calculation of overall bridge risk using Equation (3).
9. Re-evaluation step, involving additional data collection and/or analyses, is recommended to reduce the uncertainty at important bridge sites that might have led to high risk as data used in the assessment could have been of poor quality.

Determination of the uncertainty premium, hazard, vulnerability and impact scores is based on a discrete scoring system. Key areas and indicators of hazard, vulnerability and impacts have been identified and ranked depending on their level. Table 2 shows the basic philosophy of ranking and score assignment for hazard, vulnerabilities and impacts. Following the original ideas of Moon et al.[5] it was felt that a more refined uncertainty premium scoring system was required and five scores between 1.0 and 1.4 were adopted for that purpose, as shown in Table 3.

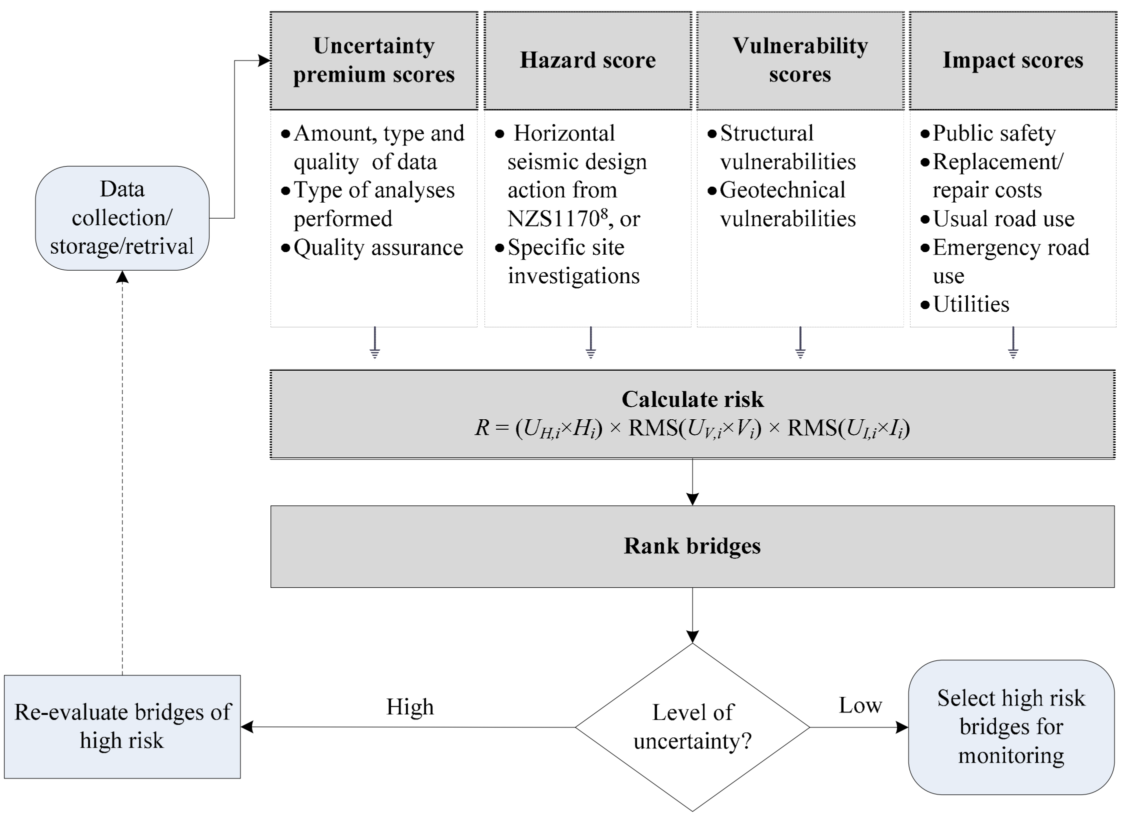


Figure 1. Flow of risk scoring methodology.

Table 2. Discrete scoring system for hazard, vulnerabilities and impacts.

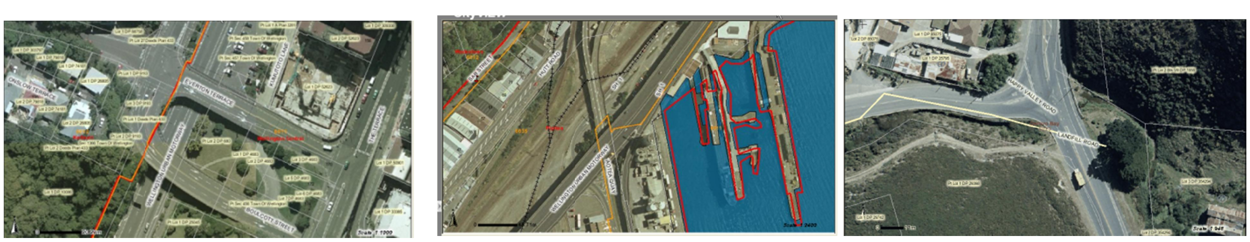
Hazard/vulnerability/impact level	Low	Moderate	High
Score	1	2	3

Table 3. Risk assessment levels and associated uncertainty premium scores.

Level	Data included and assessment techniques	Quality assurance	Uncertainty premium score
1	Very limited data/no data, aerial photos, site photos, GIS data, non-site specific reports, document reviews	Minimum standards	1.4
2	Aerial photos, site photos, as-built plans, visual inspections, maintenance history, traffic data, document reviews	Adequate practice	1.3
3	Aerial photos, site photos, as-built plans, visual inspections, maintenance history, site specific soil data, traffic data, analytical techniques	Adequate practice	1.2
4	Aerial photos, site photos, as-built plans, visual inspections, maintenance history, traffic data, site specific soil data, in-depth analytical techniques	Best practice	1.1
5	Aerial photos, site photos, as-built plans, visual inspections, maintenance history, traffic data, non-destructive testing, structural monitoring, site specific soil data, in-depth analytical techniques	Best practice	1.0

3.1 Example of risk-based bridge prioritization

This section demonstrates the application of the proposed prioritization methodology to three real bridges located within the transportation network of New Zealand's capital Wellington: Boulcott Street, Aotea Quay North and Happy Valley Road. The bridges are shown in Figure 2. Table 4 provides a brief description of the bridges and associated hazards, vulnerabilities and impacts. Only those aspects were mentioned that resulted in scores larger than one. Seismic hazard was estimated using the approach outlined in Omenzetter et al.[7] that calculates peak ground accelerations based on the seismic horizontal design action formula from NZS1170.5:2004[8], and converted to scores. Soil type and liquefaction potential at bridge sites were determined using maps available in Semmens et al.[9] To assess the vulnerabilities data from Wellington City Council Bride Database was used that consisted mainly of general bridge descriptions, site photos, description of defects and simple condition rating, maintenance plans and estimates of replacement cost. Given the rather general nature of data and risk assessment methods adopted, the uncertainty premium scores were assumed to be 1.2 for hazard, 1.3 for structural vulnerabilities, 1.3 for geotechnical vulnerabilities, and 1.2 for impacts, respectively. Table 5 provides, as an example, detailed risk assessment for Boulcott St. bridge, while Table 6 a summary of the final total risk scores of the three bridges. It is not an intension to provide here any absolute risk score thresholds to judge if monitoring and quick assessment should be used but based on the results, Aotea Quay North bridge would be the first bridge of the three to consider for application of monitoring and quick assessment, followed by Boulcott St. bridge, and Happy Valley Rd. bridge would have the lowest priority.



a) b) c)

Figure 2. Aerial photos of analyzed bridges: a) Boulcott St., b) Aotea Quay North, and c) Happy Valley Rd.

Table 4. Description of analyzed bridges.

Bridge #	Description
Boulcott St.	2-span, 58m long RC structure Overall good condition of substructure and superstructure Situated on reclaimed land with fill consisting of domestic waste, sand, boulders and rock Soil class C[8] High susceptibility for liquefaction Less than 2km to the active Wellington fault Over road of national significance Moderate replacement cost Significant numbers of vehicle per day
Aotea Quay North	15-span, 211m long RC structure Overall good condition of substructure and superstructure Situated on reclaimed land with fill consisting of domestic waste, sand, boulders and rock Soil class E[8] High susceptibility for liquefaction Less than 2km to the active Wellington fault Over road of national significance and important railway line Significant replacement cost Significant numbers of vehicle per day
Happy Valley Rd.	6.1m long double RC culvert Significant corrosion and spalling of superstructure Soil class B[8] 3km to the active Wellington fault Some scour vulnerability

4. PREDICTION OF PGA AT BRIDGE SITES USING STRONG MOTION DATA

This section is concerned with the approaches applicable to bridges falling into the intermediate risk category. Data collected by wide-area strong motion arrays and simple metrics extracted from them will be used for estimating seismic loading sustained by the structures and its effects. To estimate ground motion metrics at bridge sites simple artificial intelligence models are proposed.

ANNs are one of the most powerful learning approaches that find functional relationships between the input and output data. They are simplified models of the human brain made of a number of nodes and connections between them. They have proved their capabilities to infer solutions to different types of problems such as prediction, interpolation and pattern recognition which include nonlinear and complex interactions among the variables. The basic idea of modeling the human brain's activities numerically was first proposed by McCulloch and Pitts[10] and the starting point of developing ANN appears in Hopfield[11].

In this research, three different approaches using ANNs to predict PGA at any arbitrary bridge site by using PGAs recorded by strong motion stations distributed over a wide area are developed and evaluated. The city of Christchurch in New Zealand was selected the study and PGA records were collected from GeoNet data center (www.geonet.org.nz). This strong motion network uses Kinemetrics Etna high dynamic range strong motion accelerographs and CSI CUSP-3 strong motion accelerographs.

All three ANNs developed in this research are feed-forward back propagation networks which have three components: an input layer, a hidden layer, and an output layer. In a network, all input nodes are multiplied by weights and collected at each node of the hidden layer and a bias is added to this sum. The sum is later transformed through a sigmoid transfer function and transferred to the output layer which has one node and uses the linear transfer function. The overall error between the network output and the desired value is calculated and propagates backwards to the input layer to adjust the weights such that finally the minimum error between network output and desired values is achieved. Figure 3 shows a diagram of the networks used in this research where NOI is the number of input neurons and NOH is the number of hidden neurons.

Table 5. Detailed risk assessment and scoring for Boulcott. St bridge.

Row no.	Hazard/vulnerability/impact				Raw score, S	Uncertainty premium, U	S × U
1	Hazard				2	1.2	2.4
2	Vulnerability	Structural	Substructure	Columns	1	1.3	1.3
3				Abutments	1	1.3	1.3
4				Retaining walls	1	1.3	1.3
5				Spalling	1	1.3	1.3
6			Superstructure	Spalling	1	1.3	1.3
7				Fatigue cracks in girders	1	1.3	1.3
8				Bearing failures	1	1.3	1.3
9				Expansion joints	1	1.3	1.3
10				Holding down bolts	1	1.3	1.3
11			Deck	Deck	1	1.3	1.3
12				Deck reinforcement	1	1.3	1.3
13				Deck joints	1	1.3	1.3
14				Linkages and shear keys	1	1.3	1.3
15		Geotechnical	Soil	Soil homogeneity	1	1.3	1.3
16				Liquefaction Potential	3	1.3	3.9
17				Lateral spreading	2	1.3	2.6
18				Bearing capacity, settlement	1	1.3	1.3
19				Fault rupture	3	1.3	3.9
20				Ground improvement	2	1.3	2.6
21				Slope stability	1	1.3	1.3
22			Foundation	Foundation and soil type	1	1.3	1.3
23				Piles	1	1.3	1.3
24				Foundation settlement	1	1.3	1.3
25				Scour	1	1.3	1.3
26	RMS vulnerability (2-25)						1.32
27	Impact			Public safety	2	1.2	2.4
28				Replacement/ repair cost	2	1.2	2.4
29				Typical road use	2	1.2	2.4
30				Emergency road use	1	1.2	1.2
31				Utilities	1	1.2	1.2
32	RMS impact (27-32)						1.39
33	Risk						4.38

Table 6. Summary of risk assessment and scoring for the three analyzed bridges.

Bridge	Boulcott St.	Aotea Quay North	Happy Valley Rd.
$(U_{H,i} \times H_i)$	2.4	3.6	2.4
$\mathrm{RMS}(U_{V,i} \times V_i)$	1.32	1.25	1.21
$\mathrm{RMS}(U_{I,i} \times I_i)$	1.39	1.55	1.10
R	4.38	6.99	3.18

In this study, PGAs recorded by 15 stations distributed over the whole city of Christchurch have been used to develop and test the networks. The stations are located on four different seismic soil classes. Local soil properties are known to influence strongly the PGAs. The seismic soil classes are according to the current New Zealand seismic loading standard NZ1170.5:2004[8] and are obtained from Wood et al.[12] and Bradley and Cubrinovski[13]. Table 7 provides the basic information of these 15 stations and Figure 4 shows graphically their locations and the corresponding seismic soil classes. Four stations located on each one of the seismic soil classes were put aside and after training the networks were asked to predict the PGAs recorded by those stations to test the predictive power of the networks. In Table 7 these appear as shaded.

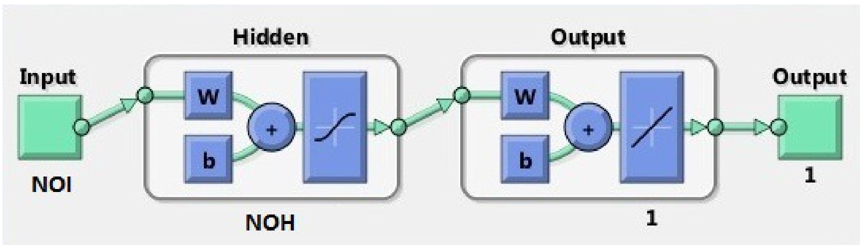


Figure 3. ANN architecture used.

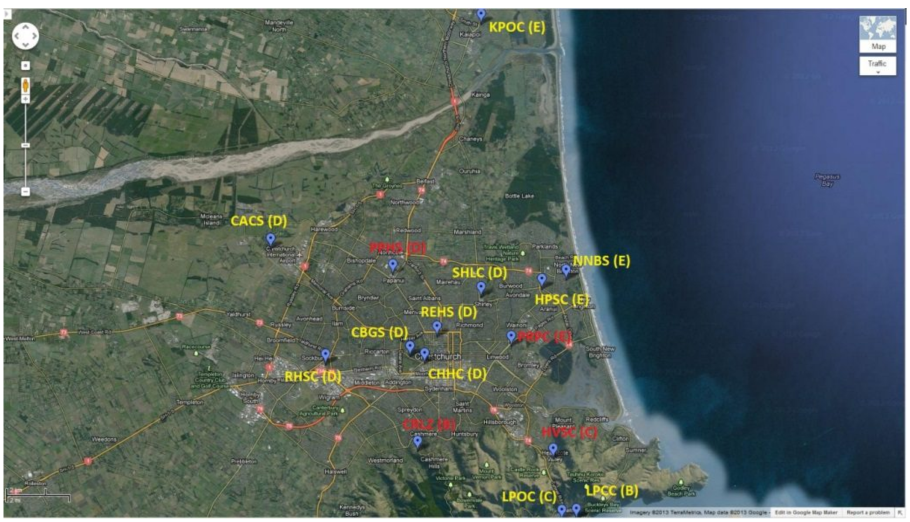


Figure 4. Location and corresponding seismic soil classes of strong motion recorders in Christchurch.

Three different ANNs, denoted as ANN1, ANN2 and ANN3, respectively, were developed in this research using the PGAs recorded during seven selected earthquakes that occurred in 2011 and 2012. Table 8 shows the information on the earthquakes used in this research.

ANN1 is a single ANN. The number of hidden neurons, NOH, was 7. The earthquake magnitude, hypocentral depth, seismic soil class of the stations, epicentral distances to the stations, and distances between the stations were considered as the influential parameters as selected as input data. PGA at the target station was the only output of the network. It is worth noting that the seismic soil classes were presented to the network using numerical codes. All the data used to train, validate and test the networks were normalized using the following equation to prevent any unwanted effects on the accuracy of the networks[14]:

$$D_n = \frac{(D_o - D_{min})}{(D_{max} - D_{min})} \tag{4}$$

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. Considering the above-mentioned parameters related to 11 stations, ANN1 was trained and validated using a 47×77 input matrix (7×11=77 samples of 3+4×11=47 elements). The number of input neurons, NOI, was therefore 47.

The second network, ANN2, was in fact a committee of eleven networks where each of the participating networks was developed using the data of ten stations other than the testing stations. By assembling eleven input matrixes, a 47×770 input matrix was obtained to train ANN2. The numbers of input neurons, NOI, and hidden neurons, NOH, were 47 and 5, respectively.

The third network, ANN3, considered the stations individually to train the network. There are previous studies in the literature that used the similar approach considering different influential parameters[15]. The earthquake local magnitude, hypocentral depth, seismic soil classes of each station, and epicentral distances to each station were considered to develop ANN3. A 4×77 input matrix was used for training and validating this network. The numbers of input neurons, NOI, and hidden neurons, NOH, were both 4.

To train each network, 80% randomly selected input data were used. The rest of the data were used for validation. The purpose of validation is to stop training before overfitting occurs. After training of the networks, mean squared errors (MSEs) for training and validation were 0.00124 and 0.0160 for ANN1, 0.00358 and 0.00347 for ANN2, and 0.00332 and 0.00527 for ANN3, respectively. These errors are close to zero and show very small differences between the networks' outputs and the targets. The regression coefficients, R, for training and validation were 0.976 and 0.909 for ANN1, 0.948 and 0.936 for ANN2, and 0.941 and 0.958 for ANN3, respectively. They are very close to 1 showing again a very close correlation between targets and networks' outputs. Figures 5-7 show comparisons of measured target and ANN-generated PGA values for training and validation for ANN1-ANN3.

Table 7. Strong motion stations in Christchurch used in the research.

Number	Name	Code	Latitude (°)	Longitude (°)	Seismic Site Class
1	ChCh Canterbury Aero Club	CACS	-43.48484	172.52989	D
2	ChCh Botanic Gardens	CBGS	-43.53101	172.61975	D
3	ChCh Hospital	CHHC	-43.535929	172.627523	D
4	Hulverstone Drive Pumping Station	HPSC	-43.50157547	172.702194214	E
5	Kaiapoi North School	KPOC	-43.37813	172.66364	E
6	Lyttelton Port Company	LPCC	-43.60785	172.724778	B
7	Lyttleton Port Oil Wharf	LPOC	-43.608378	172.714823	C
8	ChCh North New Brighton School	NNBS	-43.49709	172.71787	E
9	ChCh Resthaven	REHS	-43.52361	172.63502	D
10	Riccarton High School	RHSC	-43.536172	172.564404	D
11	Shirley Library	SHLC	-43.505336761	172.663391113	D
-	Canterbury Ring Laser	CRLZ	-43.57641	172.6231	B
-	Heathcote Valley Primary School	HVSC	-43.579787	172.709423	C
-	ChCh Papanui High School	PPHS	-43.49451	172.60679	D
-	Pages Road Pumping Station	PRPC	-43.527476	172.682644	E

Table 8. Earthquake records used by ANNs.

Earthquake Date yyyy-mm-dd	Time (UT) hh:mm:ss	Magnitude (Ml) Local (Richter)	Hypocentral Depth (km)
2011-04-16	5:49:19	5.34	33
2011-06-05	21:09:55	5.54	8
2012-01-02	5:59:00	5.36	100
2012-01-04	19:28:54	4.79	13
2012-01-06	1:20:58	5.03	5
2012-01-06	7:04:16	4.66	11
2012-01-14	13:47:52	4.99	9

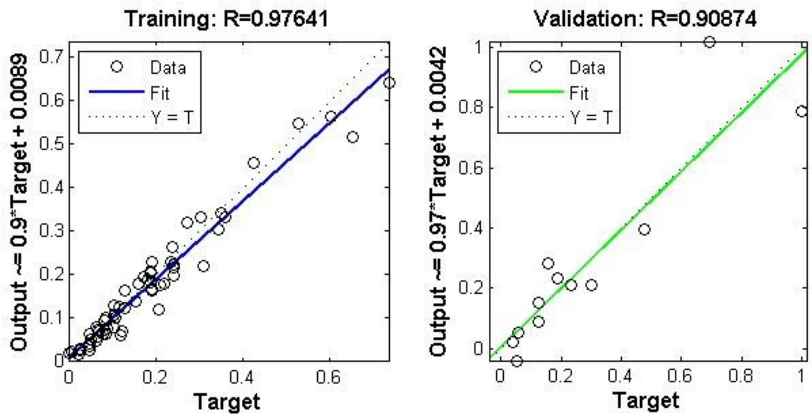


Figure 5. Regression of ANN1 outputs on training (left) and validation (right) data.

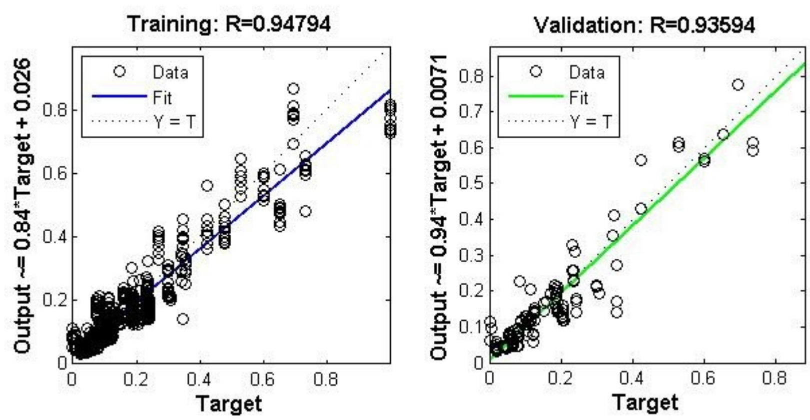


Figure 6. Regression of ANN2 outputs on training (left) and validation (right) data.

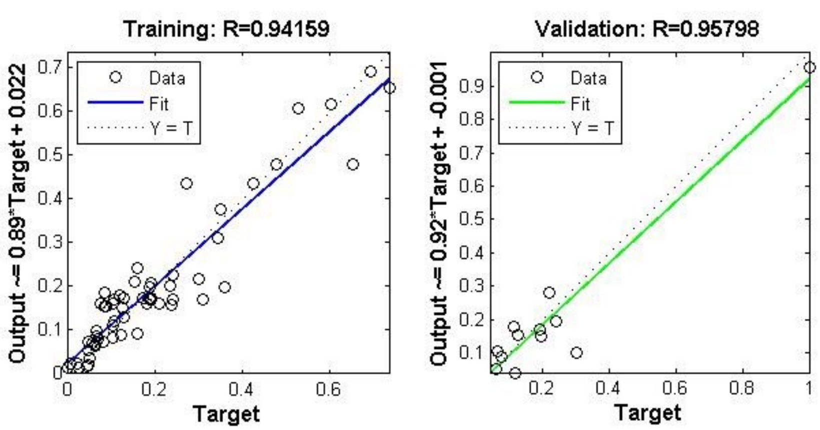
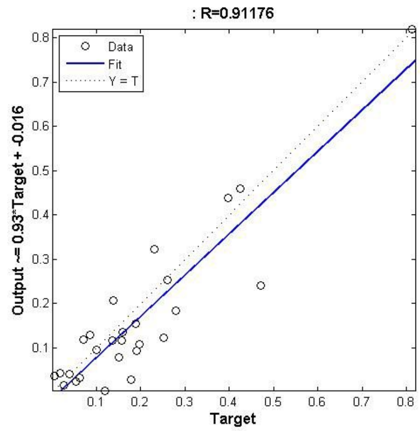
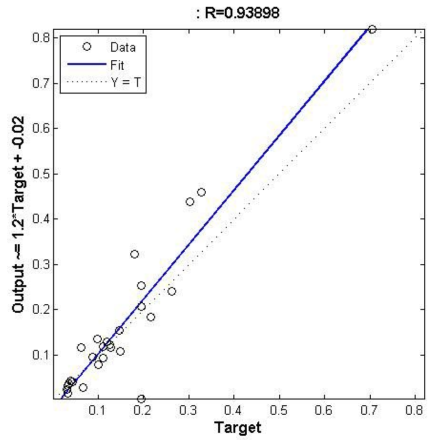


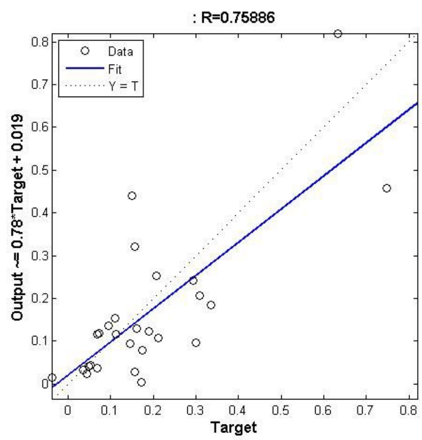
Figure 7. Regression of ANN3 outputs on training (left) and validation (right) data.



a)



b)



c)

Figure 8. Regression of network outputs on testing data: a) ANN1, b) ANN2, and c) ANN3.

The predictive power of the developed networks for an arbitrary point was tested by asking them to predict the PGAs recorded by the four stations located on four different seismic soil classes which were not used for training or validation. The MSEs for such testing were 0.00608, 0.00448, and 0.0147 for ANN1, ANN2 and ANN3, respectively. The *R* values were 0.912, 0.939, and 0.759. Figure 8 shows the match between the network-predicted values and targets for testing ANN1, ANN2 and ANN3. As it can be seen, ANN1 and ANN2 have considerably better predictive power compared to ANN3 based on using the same data set. ANN2 showed a better capability still compared to ANN1.

5. INFERING BRIDGE CONDITION AND DAMAGE USING SIMPLE GROPUND MOTION METRICS

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. Simple seismic design of bridges uses SDOF models and design actions determined from elastic design spectra which 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. NZS1170.5:2004[8]). Comparing the design actions (expressed as pseudo acceleration) and the predicted PGA at the site 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 SDOF structural models, gas distribution networks and multi-story buildings respectively[16-18].

6. CONCLUSIONS

A framework for systematic and planned application of monitoring to quick post-earthquake assessment of bridge condition and damage has been proposed. The framework consist of prioritization of bridges for monitoring based on their risk, tiered approach to implementation of monitoring systems, and integration of monitoring-assisted condition assessment results into post-disaster response and recovery activities.

The risk-based prioritization methodology takes into account the seismic hazard, both structural and geotechnical vulnerabilities and impacts of bridge failure. A discrete scoring system for hazard, vulnerabilities and impacts has been proposed enabling quantifying relative seismic risk for each bridge. The methodology has been applied to a few bridges taken from the road network of Wellington, New Zealand and successful validation achieved.

For intermediate risk bridges, for which data from wide-area seismic arrays will be used, three different ANN-based approaches were proposed to predict PGA at an arbitrary bridge site. The networks were developed and tested using the PGAs recorded by strong motion recorders distributed over the city of Christchurch. The first two networks, ANN1 and ANN2, were developed considering multiple recording stations and the influential parameters such as seismic soil class, hypocentral depth, epicentral distance, and the distances between the stations while the third approach, ANN3, considered the stations individually. It was observed that the networks which consider multiple stations have considerably better predictive power than the network which considers the stations individually. In addition, the second approach, ANN2, which is a committee of networks, showed a better predictive power than the single ANN. A simple approach based on design concepts was proposed to predict the likelihood of damage to bridges using the predicted PGA. Another method to relate a larger number of seismic and structural parameters to structural damage was also outlined.

ACKNOWLEDGMENTS

The authors would like to express their gratitude to their supporters. Piotr Omenzetter's work within The LRF Centre for Safety and Reliability Engineering at the University of Aberdeen is supported by The Lloyd's Register Foundation (The LRF). The LRF supports the advancement of engineering-related education, and funds research and development that enhances safety of life at sea, on land and in the air. Wellington City Council provided access to their bridge stock database for the case study. Research work at the University of Auckland was supported by the Natural Hazards Platform grant UAOM11/15-4.3.

REFERENCES

1. Seville, E. and Metcalfe, J. Developing a hazard risk assessment framework for the New Zealand state highway network, Land Transport New Zealand, Wellington (2005).
2. Phares, B. M., Graybeal, B. A., Rolander, D. D., Moore, M. E. and Washer G.A. "Reliability and accuracy of routine inspection of highway bridges," Transportation Research Record: Journal of the Transportation Research Board 1749 82–92 (2007).
3. Omenzetter P., Bush, S., Henning, T., and McCarten, P. "Risk based bridge data collection and asset management and the role of structural health monitoring," Proceedings of SPIE's Smart Structures and Materials/Nondestructive Evaluation and Health Monitoring Conference, SPIE: San Diego, 79830K1-13 (2011).
4. Standards New Zealand, Risk management guidelines companion to AS/NZS4360:2004, Standards New Zealand, Wellington (2004).
5. Moon, F. L., Laning, J., Lowdermilk, D. S., Chase, S., Hooks, J. and Aktan, A. E. "A pragmatic risk-based approach to prioritizing bridges," Proceedings of SPIE Conference on Nondestructive Characterization for Composite Materials, Aerospace Engineering, Civil Infrastructure, and Homeland Security, SPIE: San Diego, 72940M1-11 (2009).
6. Omenzetter, P., S. Bush, and P. McCarten, Guidelines for data collection and monitoring for asset management of New Zealand road bridges, Ingenium, Wellington, (in review).

7. Omenzetter, P., Mangabhai, P., Singh, R. “Prioritisation methodology for application of bridge monitoring systems for quick post-earthquake assessment,” Bulletin of New Zealand Society of Earthquake Engineering (in preparation).
8. Standards New Zealand, NZS1170.5:2004 - Structural design actions. Part 5: Earthquake actions, Standards New Zealand, Wellington (2004).
9. Semmens, S., Perrin, N. D., Dellow, G., Van Dissen, R. “NZS1170.5: 2004 Site subsoil classification of Wellington City,” Proceedings of the Ninth Pacific Conference on Earthquake Engineering, Auckland, New Zealand, 1-8, (2011).
10. Hopfield, J. J. "Neural networks and physical systems with emergent collective computational abilities." Proceedings of the National Academy of Sciences 79, 2554-2558, (1982).
11. McCulloch, W. S., Pitts, W. H. "A logical calculus of the ideas immanent in nervous activity," Bulletin of Mathematical Biophysics 5, 115-133 (1943).
12. Wood, C. M., Cox, B. R., Wotherspoon, L. M., Green, R. A. "Dynamic site characterization of Christchurch strong motion stations," Bulletin of the New Zealand Society for Earthquake Engineering 44, 195-204 (2011).
13. Bradley, B. A., Cubrinovski, M. "Near-source strong ground motions observed in the 22 February 2011 Christchurch earthquake," Bulletin of the New Zealand Society for Earthquake Engineering 44, 181-194, (2011).
14. Yeh, Y. C. (2009). Application and practice of neural networks, Rulin, Taipei, Taiwan.
15. Guyanda, K. Gunaydin, A. "Peak ground acceleration prediction by artificial neural networks for Northwestern Turkey," Mathematical Problems in Engineering 2008 1-20 (2008).
16. de Lautour, O. R., Omenzetter, P. "Prediction of seismic-induced structural damage using artificial neural networks," Engineering Structures 31 600-606, (2009).
17. Hadzima-Nyarko, M., Nyarko, E. K., Moric, D. "A neural network based modelling and sensitivity analysis of damage ratio coefficient," Expert Systems with Applications 38 13405-13413 (2011).
18. Molas, G. L., Yamazaki, F. "Neural networks for quick earthquake damage estimation," Earthquake Engineering & Structural Dynamics 24 505-516 (1995).