Early-Warning System in Bridge Monitoring Based on Acceleration and Displacement Data Domain

Reni Suryanita and Azlan Adnan

Abstract Bridges should be monitored periodically in order to assess the bridge health at any given time. The sensors send the acceleration and displacement data of a bridge response under earthquakes loading to the system server. This study aims to conduct the early-warning intelligent system based upon the performance of the acceleration and displacement data. The damage detection in the system applied the Neural Networks for prediction of a bridge condition at the real time. The architecture of Neural Networks' model used one input layer, which consists of acceleration and displacement data domain, two hidden layers and an output layer with four neurons consist of safety level, Immediate Occupancy (IO), Life Safety (LS) and Collapse Prevention (CP). The IO, LS and CP are the bridge condition which indicates the extent of bridge health condition ranging from the light damage until high-risk level during and after subject to six earthquakes data. The training activation used the Gradient Descent Back-propagation and activation transfer function used Log Sigmoid function. The early-warning system is applied on 3 spans of box girder bridge model which is monitored in the local and remote server. The result showed that the evaluation of bridge condition using alert-warning in the bridge monitoring system can help the bridge authorities to repair and maintain the bridge in the future.

Keywords Acceleration · Bridge healthy · Displacement · Early-warning system · Gradient descent back-propagation · Log sigmoid function

R. Suryanita (✉)
Civil Engineering Departement, University of Riau, Jl. HR Subrantas KM 12.5, Pekanbaru-Riau, Indonesia
e-mail: renisuryanita@yahoo.co.id

A. Adnan
Engineering Seismological and Earthquake Engineering Research (E-Seer), Faculty of Civil Engineering, Universiti Teknologi Malaysia, 81310 Skudai-Johor Bahru, Malaysia
e-mail: azlanadnan@utm.my

G.-C. Yang et al. (eds.), *Transactions on Engineering Technologies*,
Lecture Notes in Electrical Engineering 275, DOI: 10.1007/978-94-007-7684-5_12,

© Springer Science+Business Media Dordrecht 2014

1 Introduction

Bridge monitoring needs to be carried out regularly in order to maintain and evaluate bridge condition periodically. Currently, the information technology is capable to helping the bridge owner to supervise the bridge condition from remote area through the Internet connection. The installed sensors will sent the acceleration and displacement data to the acquisition tools. The prediction of a bridge damage uses the Neural Network for a bridge structure based on the acceleration and displacement data which has been conducted in the previous study [1].

Many researchers have discussed the application of Neural Network in the bridge engineering field such as [2, 3] and [4]. Other researchers have conducted study about the best performance of Neural Network for prediction of sensors' data for the axial bearing capacity by [5], and the strain of FBG sensors which are based on the time domain by [6]. However, there is limited discussion pertaining to the performance of acceleration and displacement data from sensors using the Neural Networks method, especially for early-warning system on the bridges monitoring.

This study aims to develop and apply the early-warning system on bridge management system based on the acceleration and displacement data domain for damage prediction due to earthquakes load. The system can detect even minor to major damage on the bridge structure. Thereby, the bridge authorities can provide appropriate assessment for maintenance, reparation and improvement the bridge function.

2 Bridge Monitoring Under the Earthquake Load

Regular monitoring of bridge can immensely help the bridge authorities to know and detect the bridge condition early through the sensors data reading. The sensors will sent the acceleration and displacement data to the server through the data acquisition. In structural dynamic, the response of the bridge structure due to earthquakes commonly is derived from (1)

$$[\mathrm{M}]\{\ddot{\mathrm{u}}\} + [\mathrm{C}]\{\dot{\mathrm{u}}\} + [\mathrm{K}]\{\mathrm{u}\} = -[\mathrm{M}]\{\ddot{\mathrm{u}}_{\mathrm{g}}\} \tag{1}$$

where [M], [C] and [K] are matrix of mass, damping and stiffness respectively. Meanwhile $\ddot{u}$, $\dot{u}$, and u are each the vector of acceleration, velocity, and displacement of a bridge response. Vector $\ddot{u}_g$ is acceleration of earthquake excitation. By using the uncoupling procedure, the modal equation of n^{th} mode can be written as (2).

$$\ddot{\mathrm{u}} + 2\xi_{\mathrm{n}}\omega_{\mathrm{n}}\dot{\mathrm{u}}_{\mathrm{n}} + \omega^2\mathrm{u}_{\mathrm{n}} = -1/_{\varphi\mathrm{n}}\ddot{\mathrm{u}}_{\mathrm{g}} \tag{2}$$

Displacement for each mode shown as (3)

$$\mathrm{u(t)} = \sum \varphi_{\mathrm{n}}\mathrm{u}_{\mathrm{n}}(\mathrm{t}) \tag{3}$$

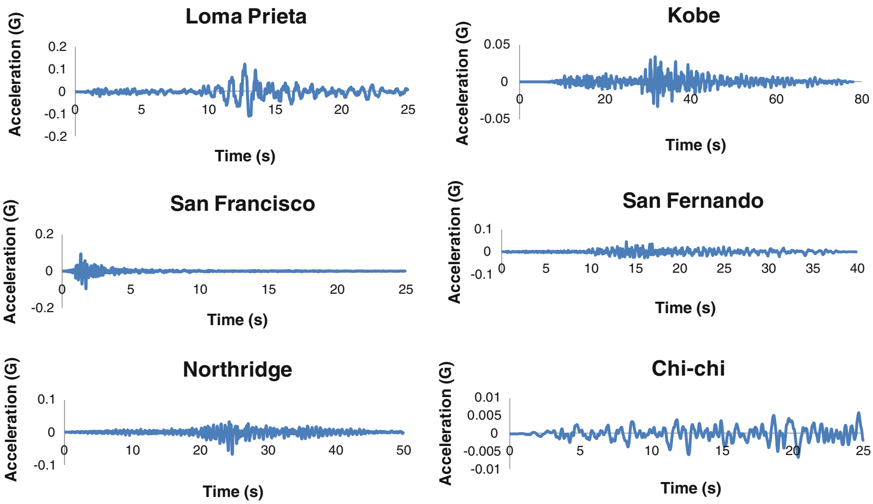

Fig. 1 Time history of six earthquakes data from PEER [9]

where ξ_n, ω, and φ_n are damping ratio, frequency and n number of mode shape respectively. The acceleration is generated by second time derivative of displacement function. The displacement values of a bridge response describe the performance of the bridge under an earthquake loading. In bridge monitoring, both of acceleration and displacement values can be obtained from measurement by sensors which are installed on the bridge. The acceleration and displacement values can be produced from finite-element analysis using a computer program [1].

According to [7], normally, damage of bridge structure is defined as the intentional or unintentional changes in material and geometric properties of the bridge, including changes in boundary or supporting conditions and structural connectivity, which adversely affect the current or future serviceability of the bridge. Damage can occur under large transient loads such as strong motion earthquakes and can also be accumulated incrementally over long periods of time due to factors such as fatigue and corrosion damage.

Time history analysis shall be performed with at least three time-histories data sets of ground motion. Since three time history data sets are used in the analysis of structure, the maximum value of each response parameter shall be used to determine design acceptability [8]. Time history data in this study is adopted from [9] as shown in Fig. 1. The Peak Ground Acceleration (PGA) of the earthquakes are 0.4731G (4.64 m/s^2) for Loma Prieta earthquake, 0.3051G (2.99 m/s^2) for San Francisco earthquake, 0.2363G (2.32 m/s^2) for Northridge earthquake, 0.122G (1.197 m/s^2) for Kobe earthquake, 0.1539G (1.51 m/s^2) for San Fernando earthquake, and 0.062G (0.61 m/s^2) for Chi-chi earthquake.

The acceptance criteria of piers damage are based on structural performance levels in Federal Emergency Management Agency (FEMA) 356. The damage criteria are divided into 3 categories, Immediate Occupancy (IO), Life Safety (LS) and Collapse Prevention (CP). The IO category describes the structure as still safe to be occupied after an earthquake has occurred. In the LS category, some structural elements and components are severely damaged but the risk of life-threatening injury is low. The CP category describes that the structure is on the verge of partial or total collapse and there is significant risk of injury.

3 Application of Neural Networks in Early-Warning System

Reference [3] has applied the Neural Networks in the study of a bridge under dynamic load, especially general traffic load. The objective of the research is to estimate the bridge displacement which corresponds to the strain of the bridge. The other researchers [10] studied the acceleration-based approach using Neural Networks to predict the displacement of building response under earthquake excitation. The inputs data are the acceleration, velocity and displacement at ground and several stories of building.

Early-warning system in this study adopted the Neural Network Back Propagation (BPNN) algorithm to predict the criteria of damage during and after earthquakes. The best performances of BPNN depend on the selection of suitable initial weight, learning rate, momentum, networks architecture model and activation function. The architecture model for this system has *n* number of input neurons, two hidden layers with *n* neurons and an output layer consists of damage levels IO, LS and CP. The input networks consist of time-acceleration domain and time-displacement domain of the bridge seismic response analysis. The numbers of input correspond to the numbers of sensor which are installed on the bridge monitored. Meanwhile the output layer is the level of a bridge health condition due to an earthquake, which is resulted by finite-element analysis software. The architecture model of Neural Networks for this study is illustrated in Fig. 2.

The study used Gradient Descent Back-propagation as training function to minimize the sum squared error (E) between the output value of Neural Network and the given target values. The total error is defined as (4).

$$\mathrm{E} = \frac{1}{2}\sum_{\mathrm{j}\in\mathrm{J}} (\mathrm{t_j} - \mathrm{a_j})^2 \tag{4}$$

where $\mathrm{t_j}$ defines target value, $\mathrm{a_j}$ denotes activation value of output layer, and J is set of training examples. The steps are repeated until the mean-squared error (MSE) of the output is sufficiently small [11].

The final output is generated by a non linear filter Φ caller activation function or transfer function. The transfer function for this model used Log Sigmoid function, which has a range of [0, 1] to obtain the output. This function is differentiable function and suitable to be used in BPNN multilayer as shown in (5).

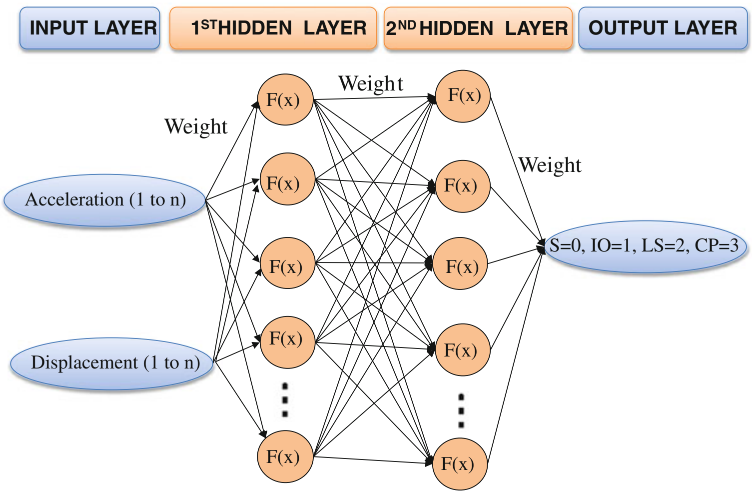

Fig. 2 The architecture model of neural networks with 2 hidden layers in the early-warning system

$$a_j = \frac{1}{(1 + e^{-a_{net,j}})} \tag{5}$$

where $a_{net,j} = [\sum_{i=1}^{l} w_{ij} a_i] + \theta_j$.

Each i represents one of the units of layer l connected to unit j and θ_j which represents the bias.

The weight, w_{ij} of networks has been adjusted to reduce the overall error. The updated weight on the link connected to the i^{th} and j^{th} neuron of two adjacent layers is defined as,

$$\Delta W_{ij} = \eta(\partial E/\partial W_{ij}) \tag{6}$$

where, η is the learning rate parameter with range 0–1 and $\partial E/\partial W_{ij}$ is the error gradient with reference to the weight.

The input data has been normalized by a linear normalization equation as follows:

$$z_i' = (z_i - z_{min})/(z_{max} - z_{min}) \tag{7}$$

where z_i' is the normalized input values, z_i the original data, z_{max} and z_{min} are the maximum and minimum values.

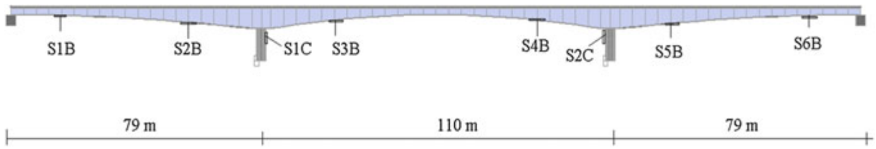

Fig. 3 Sensors location on the 3 spans of box girder bridge model

4 A Case Study

The previous study [1] has conducted the performance of displacement and acceleration data domain for a 3 spans box girder concrete bridge using 2 sensors on the piers. In this study the 8 sensors were assumed to be installed along the bridge as shown in Fig. 3. The sensors measured the acceleration and displacement values of the bridge response. The lengths of the bridge spans are 79, 110, and 79 m respectively.

The bridge model in Fig. 3 has been analyzed using the finite-element analysis software. The non linear time history analysis has been applied in the model so that the behavior and condition of the model due to earthquake can be known as a detail at the given time. The bridge model in this study has been simulated to receive six excitations of earthquake as shown in Fig. 1. Thereby, responses of bridge structure due to some earthquakes have been applied as input in the training process.

The damage of structural elements from finite-element analysis are described in Fig. 4. The criteria of bridge damage are based on standard of Federal Emergency Management Agency (FEMA)356 [8]. The operation level is described as B, which states transition from safe level to IO level. The level before damage is described as S (safe level). Figure 4 illustrates the point of high risk damage due to New Zealand earthquake occurred at bottom of piers (CP level).

Figures 5 and 6 show the response of the bridge model due to New Zealand earthquake. The acceleration and displacement responses of the bridge are measured during the 8 s at the point where S1C and S2C sensors are located. The damage level occurred after 4.70 s. This level consists of IO level (1st index), LS level (2nd index) and CP level (3rd index) at 4.70, 6.20, and 7.10 s respectively. The time before 4.70 s is categorized a safe level (zero index). The maximum acceleration values of bridge response are 1.57 m/s^2 at S1C sensor and 3.21 m/s^2 at S2C sensor as shown in Fig. 5.

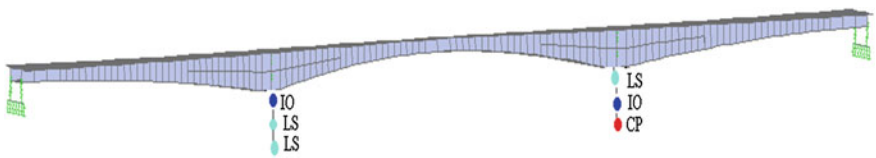

Fig. 4 Damage location of bridge model due to the New Zealand excitation earthquake

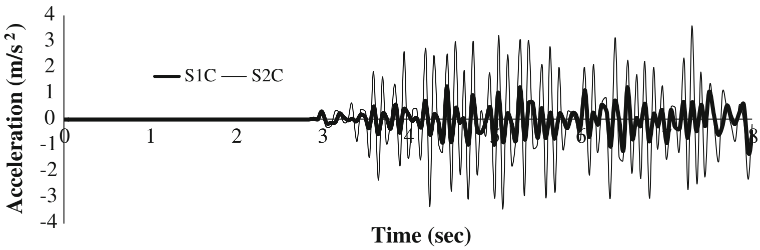

Fig. 5 The acceleration response of bridge model due to the excitation of New Zealand earthquake

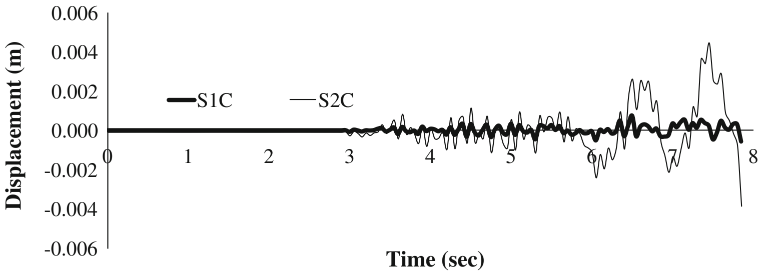

Fig. 6 The displacement response of bridge model due to the excitation of New Zealand earthquake

The maximum displacement value at S1C sensor is 0.0014 m whereas at S2C is 0.00457 m as shown in Fig. 6.

The study used two hidden layers to find the best result for prediction of bridge condition. The architecture model for 2 hidden layers has 17 neurons for input layer, 17 neurons for 1^{st} hidden and 17 neurons for 2^{nd} hidden layer and 4 neurons for output layer. The topology of neurons can be written as 17-17-17-4. The 17 neurons of input layer consist of 1 neuron for time domain, 8 neurons each for acceleration and displacement data domain. At the same time 4 neurons of output layer consist of the bridge damage levels which are categorized into 4 indexes. The indexes are 0 (zero) for safety level (S), 1 (one) for IO level, 2 (two) for LS level and 3 (three) for CP level.

The example of the input data Neural Networks from two sensors due to New Zealand earthquake is shown in Table 1. This data comes from Figs. 5 and 6. The ACC1 and ACC2 denote acceleration data domain for S1C and S2C sensors, whereas DISPL1 and DISPL2 denote displacement data domain for S1C and S2C sensor. The total data in Table 1 is 170 consist of the safety level has 159 data for time of occurrence 7.90 s, the IO level has 5 data for time of occurrence 2.0 s, the LS level has 2 data for time occurrence 0.05 s, and the CP level has 3 data for time of occurrence 0.15 s. The total numbers of input and output data are 5,891, which are obtained from six earthquakes excitation.

Table 1 The example of input data S1C and S2C sensors due to New Zealand earthquake

Data	Input					Output
	Time	S1C		S2C		
		ACC1	DISPL1	ACC2	DISPL2	
1	0	0	2.11E−02	0.00E+00	−9.77E−02	S = 0
2	0.05	1.23E−04	2.13E−02	−4.95E−04	−9.71E−02	S = 0
⋮	⋮	⋮	⋮	⋮	⋮	⋮
160	7.95	−1.29514	−1.72	−2.29747	−10.31	IO = 1
161	8	−4.73E−01	−3.39E+00	−1.75E−01	−1.70E+01	IO = 1
162	8.05	1.77E+00	−4.75E+00	3.01E+00	−2.35E+01	IO = 1
163	8.1	3.81E−01	−2.98E+00	−3.32E+01	−2.65E+01	IO = 1
164	8.15	−8.37E−01	−2.12E+00	2.67E+01	−4.57E+01	IO = 1
165	8.2	4.46E−01	−2.78E+00	−1.99E+01	−3.22E+01	LS = 2
166	8.25	−2.82E−01	−2.66E+00	1.43E+01	−4.05E+01	LS = 2
167	8.3	−1.70E−01	−2.67E+00	−9.72E+00	−3.31E+01	CP = 3
168	8.35	7.63E−01	−3.34E+00	6.85E+00	−3.68E+01	CP = 3
169	8.4	−4.05E+00	−2.62E+00	−2.80E+00	−3.14E+01	CP = 3
170	8.45	−6.48E+05	2.55E+01	−8.78E+01	−2.73E+01	CP = 3

The Neural Networks in the study used 70 % data for training, 15 % data for testing and 15 % data for validation process. The parameters to indicate the end of training are the mean square error (MSE), maximum of epochs and learning rate (Lr). The MSE with 0.001 performance goal has been used in the networks, whereas the maximum number of epoch used is 50,000, and learning rate used is 0.1. The networks have been examined by the computer with specification Intel Core i5-2410M, the power of processor is 2.30 GHz with turbo boost up to 2.90 GHz and memory 4 GB.

The MSE of Neural Network models based on acceleration data domain with two hidden layers is as in Fig. 7. The figure illustrates that all MSE models have the same trend after 20,000 iterations. The MSE values of testing process are higher than other MSE values. However, overall the error on all processes decreases along the iterations. The error due the testing process is not used during the training process, but it is used to compare with the different models.

Similar to the MSE of acceleration data domain, the MSE of displacement is also shown the same trend after 20,000 iterations. Figure 8 shows the MSE of the model based on displacement data domain for two hidden layers. The MSE of validation has the fluctuation along the iterations before 15,000 epochs. The fluctuation describes the networks have not been convergent yet if the runtime is less than 20,000 epochs.

The result indicates the architectures model for 2 hidden layers with more than 20,000 epochs can be accepted and used for predict the damage level based on the acceleration and displacement data domain.

The best performance of MSE value is the smallest of MSE, because it means the smallest of the error occurred in the calculation. However the best regression value is the highest value which is closes to 1. The regression with value close to 1 defines the

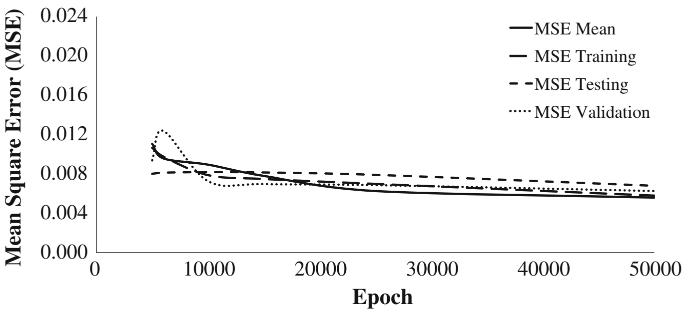

Fig. 7 The means square error of neural network model for 2 hidden layer of acceleration domain

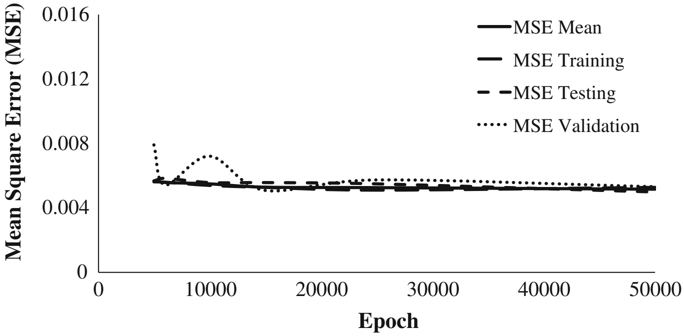

Fig. 8 The means square error of neural network model for 2 hidden layer of displacement domain

prediction value almost 100 % close to the actual one. The best performance of CPU time is defined as the shortest time to process the calculation in central processing unit (CPU). The CPU time is measured in seconds. The CPU time is dependent on the CPU's computational power and specification of the computer.

Table 2 shows the comparison of the acceleration and displacement data domain. The average of regressions (R-mean) for acceleration data domain is above 0.85 % whereas the Mean Square Error (MSE) is lower than 1 %. At the same time, the best of MSE and R-mean value of acceleration data domain are 0.0056 and 0.88689 at 50,000 epochs, whereas the best of MSE and R-mean value for displacement data domain are 0.0512 and 0.83001 at 50,000 epochs. The results shows acceleration data domain can produce higher R-mean values and smaller MSE rather than the displacement data domain for the bridge model which has 8 installed sensors.

The result shows that the Neural Networks model with 2 hidden layers is suitable for the prediction of damage level in bridges seismic monitoring system. Therefore the method can be applied to warn the bridge owner to evaluate the bridge condition early.

Table 2 Comparison of acceleration and displacement domain

Epochs	Acceleration			Displacement		
	MSE mean	R Mean	CPU time	MSE mean	R Mean	CPU time
5,000	0.0111	0.8532	357.4525	0.0565	0.81091	378.0502
6,000	0.00961	0.8543	387.2341	0.0555	0.81619	421.5607
10,000	0.00897	0.8566	405.1233	0.0546	0.81876	561.2712
15,000	0.00782	0.8589	587.8143	0.0525	0.8278	871.2349
25,000	0.00627	0.8678	778.4599	0.0522	0.82921	983.8231
50,000	0.0056	0.88689	1,298.3425	0.0512	0.83001	1,330.8237

5 Early-Warning System

The bridge monitoring system in the study has several components to support the main function which includes data acquisition module, intelligent engine module, alert system module, and monitoring module. The modules use the VB.NET which is provided in two versions involving local and remote monitoring from server. The local monitoring is located in the bridges whereas the remote monitoring accesses the data from any places via internet. HTTP server is utilized to provide the remote data that has a script converting acceleration data to HTML format. The testing using dummy data indicates that the developed intelligent monitoring could perform its

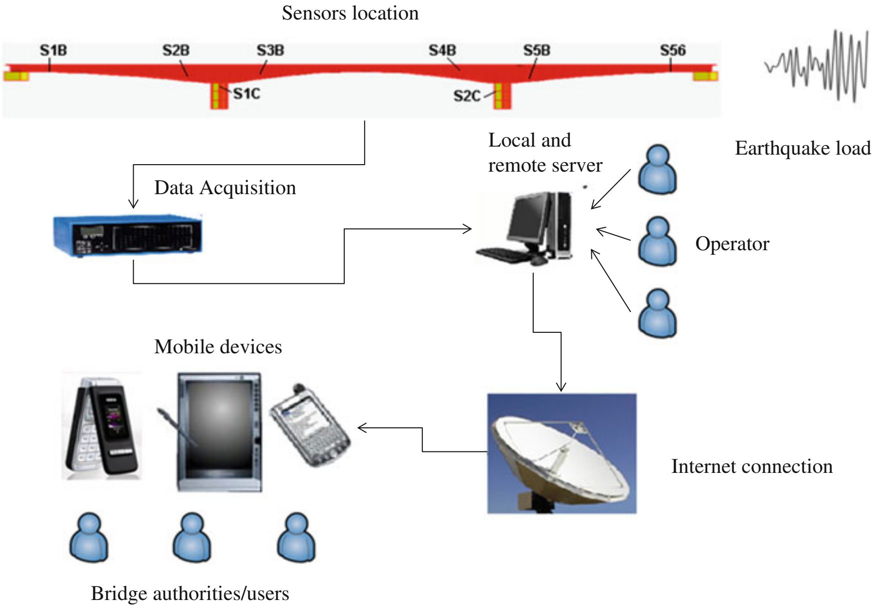

Fig. 9 The bridge monitoring system is developed in this study

functions including monitoring, predicting, and alerting. The monitoring system in the study is illustrated in Fig. 9.

The three steps of monitoring system are adopted from previous research [12]. First step is designing Neural Networks architecture including simulating the bridge damage level due to the earthquakes, training and testing neural, and obtaining the initial weights. The second step is designing and developing the intelligent monitoring software using VB.NET, namely SEER Monalisa. The last step is designing and developing the alert system. The early warning system is embedded in the SEER Monalisa software which is developed by Structural Earthquake Engineering Research at Universiti Teknologi Malaysia [13].

The software scopes are the data inputs from sensors such as accelerometers and strain gauges, feeding forward the inputs Neural Networks, predicting the output as bridges damage level and providing the alert warning as shown in Fig. 10.

The alerts are divided into four format namely the alert bars which are shown in different color (S: Green, IO: Yellow, LS: Orange, and CP: Red), alert sound/alarm, and alert-mail sent to the user. The software has a main function prediction of damage level when an earth quake occurred. After the prediction output indicated either IO, LS, or CP, the alert system will then notify the user that the condition of the bridge is not secure.

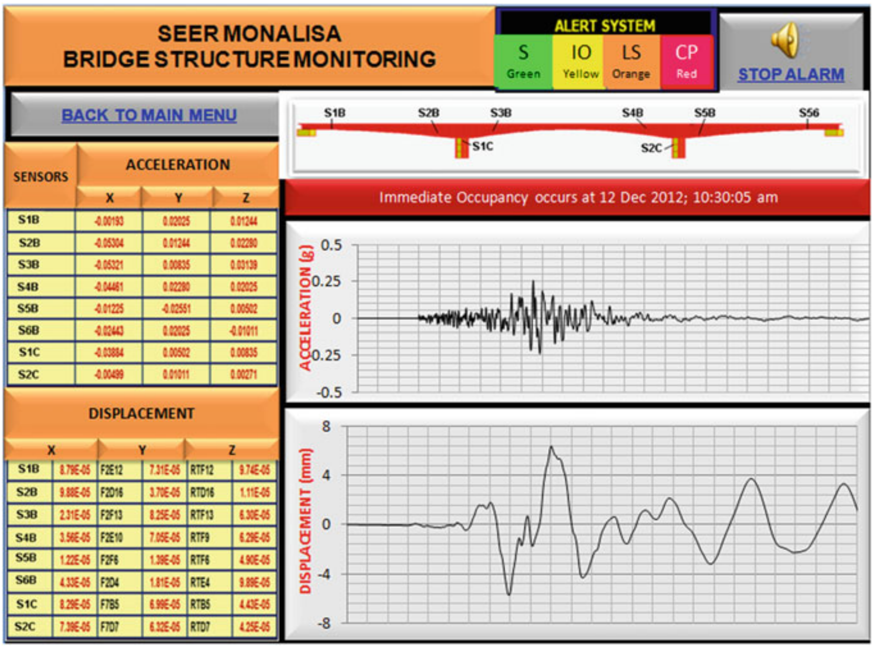

Fig. 10 Early warning system in the SEER-Monalisa bridge monitoring software (colour figure online)

6 Conclusion

The bridge health system used several sensors to detect the behavior of a bridge such as bridge deformation and damage. The sensors connected to the data logger and subsequently sent the information data such as displacement and acceleration to the server. The data is used as input by Neural Networks within the server system. The architecture of neural network method in this study is comprised of two hidden layers.

The Neural Network model which is based on acceleration and displacement data domain with two hidden layers, illustrated that all MSE models have the same trend after 20,000 iterations. The comparison of acceleration and displacement data domain for two hidden layers' model has been concluded based on MSE mean value, regression mean value and CPU time of the network model. Both comparisons showed that the MSE mean value decreased as the epoch increased.

Most bridge monitoring systems use the accelerometer sensors to measure the acceleration of bridge response, because the accelerometer sensor is simpler to install in the field. Furthermore, the acceleration from accelerometer sensors can be modified directly to conduct the displacement value before being entered into the Neural Networks system server. Consequently, the monitoring system is recommended to be used in the Neural Networks with two hidden layers based on displacement domain.

The implementation of an early-warning system in the intelligent Neural Network method for the bridge seismic monitoring system can help the bridge authorities to predict the stability and health condition of the bridge structure at any given time. The software is needed in order to disseminate the bridge health information to the public because it has a main function prediction of damage level when an earthquake occurred.

References

1. Suryanita R, Adnan A (2013) Application of neural networks in bridge health prediction based on acceleration and displacement data domain. In: Lecture notes in engineering and computer science: proceedings of the international multiconference of engineers and computer scientists 2013, vol 2202(1). Hong Kong, pp 42–47, 13–15 March 2013
2. Kerh T, Huang C, Gunaratnam D (2011) Neural network approach for analyzing seismic data to identify potentially hazardous bridges. Math Prob Eng 1–15
3. Ok S, Son W, Lim YM (2012) A study of the use of artificial neural networks to estimate dynamic displacements due to dynamic loads in bridges. J Phys: Conf Ser 382(1)
4. Cheng J, Li QS (2012) Artificial neural network-based response surface methods for reliability analysis of pre-stressed concrete bridges. Struct Infrastruct Eng 8(2):171–184
5. Maizir H, Kassim KA (2013) Neural network application in prediction of axial bearing capacity of driven piles. In: Proceedings of the international multiconference of engineers and computer scientists 2013, vol 2202(1). Hong Kong, pp 51–55, 13–15 March 2013
6. Kahandawa GC et al (2013) Use of fixed wavelength fibre-bragg grating (FBG) filters to capture time domain data from the distorted spectrum of an embedded FBG sensor to estimate strain with an artificial neural network. Sens Actuators, A 194:1–7

7. Wong K-Y (2007) Design of a structural health monitoring system for long-span bridges. Struct Infrastruct Eng 3(2):169–185
8. FEMA356 (2000) Prestandard and commentary for the seismic rehabilitation of buildings. Federal Emergency Management Agency
9. PEER (2012) Pacific earthquake engineering research ground motion database. 15 March 2011. Available from: http://www.peer.berkeley.edu/
10. Qian Y, Mita A (2008) Acceleration-based damage indicators for building structures using neural network emulators. Struct Control Health Monit 15(6):901–920
11. Jones MT (2005) In: Pallai D (ed) AI application programming. Boston, Charles River Media
12. Mardiyono M, Suryanita R, Adnan A (2012) Intelligent monitoring system on prediction of building damage index using artificial neural network. TELKOMNIKA Indonesian J Electr Eng 10(1):155–164
13. SEER-UTM (2007) Intelligent bridge health monitoring system software