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# Intelligent Bridge Seismic Monitoring System Based on Neuro Genetic Hybrid

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***Abstract***

*The natural disaster and design mistake can damage the bridge structure. The damage caused a severe safety problem to human.The study aims to develop the intelligent system for bridge health monitoring due to earthquake load. The Genetic Algorithm method in Neuro-Genetic hybrid has applied to optimize the acceptable Neural Network weight.The acceleration, displacement and time history of the bridge structural responses are used as the input, while the output is the damage level of the bridge. The system displays the alert warning of decks based on result prediction of Neural Network analysis. The best-predicted rate for the training, testing and validation process is 0.986, 0.99, and 0.975 respectively. The result shows the damage level prediction is agreeable to the damage actual values. Therefore, this method in the bridge monitoring system can help the bridge authorities to predict the health condition of the bridge rapidly at any given time.*

***Keywords***: *bridge monitoring, damage level, intelligent system, Neuro Genetic, predicted rate*



## 1. Introduction

Bridges are necessary structures to connect two places throughout the transportation system. The bridge should have enough strength capacity to withstand the self-weight and moving loadson the deck. Construction of the bridge shall be supervised by the bridge authoritiesto obtain long service life, ensure public safety, and reduce maintenance costs. One of the essential efforts to know the life cycle performances and management procedures of bridges is through Structural Health Monitoring (SHM). According to [1], SHM refers to the implementation of a damage identification strategy for Civil Engineering infrastructures. Application of SHM in Bridge Engineering aims to ensure long service life and improve the high-level service to the highway users. Meanwhile, [2] stated the objectives of bridge monitoring are to ensure bridge safety and provide a better maintenance planning continuously. The concept of health monitoring can be explainedregarding the goals of preventing health management in medical sciences. The diagnosis and precaution due to common ailments at a sufficiently early stage are the best options as the chances of curability are significantly higher. The potential in applying this concept in many aspects such as in Bridge Engineering to replace time-based maintenance with a symptom or health-based supportis well established [3]. In the past decade, traditional SHM combines visual observations and heuristic assumption with mathematical models of predicted behavior. Currently, the modern SHM system which includes the sensors, and automated reasoning techniques have been applied in bridge monitoring.SHM can also help the owners, builders, and designers of structures in rational decision making [4]. The variety of bridge data and information in bridge SHM should be recorded in real time so that the bridge structure can be observedin the monitoring room or remote area using internet connection. Therefore, theexpertsrationally should make the right decisions based on the bridge SHM results.

There are many uncertainties or factors in the bridge projects have the high impact for the stability of bridge structures. First, the low level of the engineers' knowledgeand experience inconstruction andmethod of implementation. The failure in the bridge construction can cause catastrophic damages in theelement of a bridgeand can lead to the collapse of bridge structures. One example is the I-35W Bridge in Minneapolis, Minnesota designed in 1964 and

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opened to traffic in 1967, which collapsed suddenly on August 1, 2007, as shown in Figure 1. The investigation by [5], reveals that bridge collapse is caused using undersized gusset plate in bridge construction.

Figure 1. One section of the I-35W Bridge collapse [6]

Another example is the collapse of the Kutai Kartanegara Bridge in East Kalimantan Indonesia on 26 November 2011, approximately ten years after construction completed, as shown in Figure 2. Touted as Golden Gate Bridge of Indonesia, the longest suspension bridge in the country at 710 m length, collapsed in less than 20 seconds. The evaluation and investigation team which is appointed by Indonesia's Ministry of Public Works announced that the cause was an accumulation of problems that included brittle bolts, lack of standards, fatigued materials, and improperly performed maintenance. At the time of monitoring on the bridge, a suspender cable brokeand caused the collapse of the bridge deck [7].These problems led to fatal stress to the bridge. The failure occurred when engineers were jacking underneath one side of the bridge deck at mid-span. Both the examples indicate that the lack of engineers' knowledge has been identified as the cause of the more significant problem in many aspects such as human safety, damages of public facilities and economics.

Figure 2. Kutai Kartanegara Bridge before and after collapse [7]

The second, natural disaster such as an earthquake can affect the stability of bridge structures. The proximity of the bridge to the fault and site conditions influence the intensity of ground acceleration along the length of the bridge. Even a well-designed bridge may face damage as a result of theincreased vulnerability of the bridge to non-structural modifications which may alter the imposed load as well as structural deterioration due to earthquake loads [6, 7]. Despite these uncertainties and variations, a lot can be learned from past earthquake damage, because the type of damage occurs repetitively. Stability and performance of bridge structure are important to ensure un-disrupted traffic without compromising the safety of its users. The bridge performance is revealed in the Eurocode 2 [10] by imposing stricter damage naturaldisasters such earthquake can affect the stability of bridge structures. Due to the presence of much uncertainty and variations caused by the complexity of the whole bridge system, a lot of predictable responses are only known from past incidents. However, post-earthquake inspection often takes time for the authorized assessor to perform specificchecks on the affected bridge. The condition bridge is essential to monitor and mitigate before the onset of problems.Bridge authorities should understand that to obtain long service lives and to reduce maintenance costs. Correct actions must be implemented right from the design and construction phases. The activities must also be performed with bridge management systems for service stage. This management system will assist in maintenance decision making by considering both structural safety and economy.

According to the problem background, the bridge structure is necessary to evaluate and monitor regularly. The study proposed the new method to bridge monitoring and evaluation using a combination of Genetic Algorithm and Artificial Neural Networks methods. Many researchers have succeeded to apply the Artificial Neural Networks in their research, such as [11] proposed Artificial Neural Networks to predict damage detection for an idealized model of a bridge which could detect the change of stiffness in an element. The study only focuses on numerical simulation. Therefore, the accuracy of the method on real bridge monitoring using this technique has not been proven. Meanwhile [12] observed the Time Neural Networks (TNN) and Time Delay Neural Networks (TDNN) architectures with Back-propagation learning algorithm on structural health monitoring and damage detection. The algorithm has been adopted for vibration signature analysis of a typical bridge truss with simulated damaged states. Kerh, Huang et al. in 2011 have discussed the application of the Neural Networks on twenty-one bridges with span length over 500m in Taiwan [13]. The inputs of Neural Networks datasets are focal depth, epicenter distance, and local magnitude while the output is Peak Ground Acceleration (PGA) for each of the bridge site.Other researchers, [14] and [15] estimated the dynamic displacement of bridges due to dynamic load using the Neural Networks. The progressivemovement of the bridges is accepted as the actual physical quantities because it can quickly generate strain as well as stress, velocity, and acceleration at the measurement point.

The application of Neuro-Genetic Hybrids method in Civil Engineering has been discussed by many researchers such as [16] who studied the technique to find the relationship between fatigue life of asphalt and fibers. The results show that the Neuro-Genetic Hybrids with two-hidden-layer can predict the fatigue life of fiber-reinforced asphaltic concrete with 96% accuracy. Meanwhile [17] studied the Neuro-Genetic Hybrids for prediction of pile bearing capacity with 99% accuracy, whereas [18] adopted the neuro-genetic algorithm to more effectively forecast and the best performance for the daily water demands. Other researchers, [19] has applied the hybrid of Artificial Neural Network with support vector machine method for detecting plagiarism, meanwhile [20] used the combination of Artificial Neural Network with Proportional Integral (PI) control technique for Doubly Fed Induction Generator (DFIG) based wind energy generation system. However, there has been little literature on the application of Neuro-Genetic Hybrids method in health monitoring of bridges based on displacement time series to predict the damage levels.The previous study about neural networks has applied to building astructure to predict the damage level of building [21] and on bridge monitoring to predict bridge health based on acceleration and displacement data domain [22]. Nevertheless, the previous study only focuses on structure response in x-direction only. Meanwhile, this study has been developed by using displacement and acceleration data in x, y, and z-direction. The monitoring system of bridges is designed to extend the lifetime of deficient bridgesstructure. Therefore, the study aims to develop the intelligent network for bridge health monitoring due to earthquake load using Neuro Genetic Hybrids.

## 2. The Proposed Method

Commonly, problems faced by a conventional bridge monitoring system include the errors to interpret monitoring data and submission database system (server). Meanwhile, human issues include inconsistency and subjective while reading data in the monitoring system, and also insufficient knowledge to analyze thelacking interaction between visible defects and invisible structural degradation. Therefore, the accuracy and reliability of the results are pretty much subjective of the engineer experiences. Thus, the young engineers require specialized trainingbefore theygo into the field. Theyshould understand thefundamental knowledge of bridge engineering not only in theory but also in application to project.

The errors occurred while performing analysis and interpreting data reading can be solved and minimized by Neuro-Genetic Hybrids methods. Neuro-Genetic hybrids consist of Neural Networks and Genetic Algorithms as numerical modeling techniques. The Neural Networks can model the non-linear relationship between a set of theinput and outputs without theneed to know the equations of mathematical. In addition to that, Neural Networks require noprior knowledge of the relationship between the inputs and corresponding outputs. Compared to traditional methods, Neural Networks tolerate the relatively imprecise, noisy or incomplete data. Meanwhile, the Genetic Algorithms use three basic operations: selection, crossover, and mutation. Theselection is the process of choosing the fitness string from the current population (parents) to the next generation (offspring). The Genetic Algorithm uses a community of candidate solutions as chromosomes. Computer programming-coding is used for a complete replacement for chromosome, crossover, mutation, and inversion at specific probabilities. Each parameter of the problem is a chromosome, which represents a unique independent parameter.Crossover is the process whereby new chromosomes are generated from existing individuals (each parent) by cutting each old string (chromosome) at a random location (crossover point) and replacing the tail of one series with the other. Mutation is a random process whereby the value of elements is changed such as 1's to 0's and vice versa in a binary string.

The Genetic Algorithms provide the initial population, which is done by creating chromosomes randomly or by seeding the community with known fit chromosomes. According to [23], the Genetic Algorithms consist of three fundamental steps, namely evaluation, selection, and recombination as shown in Figure 3.

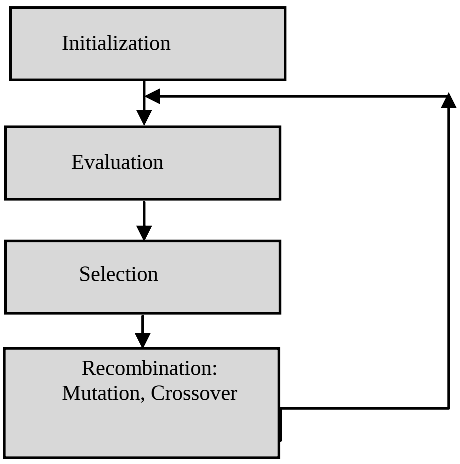


Figure. 3. The Genetic Algorithm process

The locations of observation points are determined according to modal identification function from the structural analysis results.

According to [24], Neuro-Genetic hybrids have provided efficient solutions to a wide-range of problems belonging to different domains. At the same time, various attempts have been successfully made to synergize the two or three different technologies in whole or in part, to solve problems for which these techniques could not find solution individually. This inventive method can be applied to the monitoring system for prediction of the bridge performances during and after the earthquake and getting the optimum weight more accurately and rapidly. Genetic Algorithm (GA) based on Back-Propagation Neural Network is a hybrid architecture in which a Back-Propagation Neural Network (BPNN) employs Genetic Algorithms for the determination of its weights. Several the researchers such as [25] have successfully used one hidden layer for their study. However, many researchers reported two hidden sheets are the best [12] and [14].

## 3. Research Method

### 3.1. Neuro-Genetic Hybrids Procedure

Genetic Algorithm (GA) based on Back-Propagation Neural Network is a hybrid architecture in which a Back-Propagation Neural Network (BPNN) employs Genetic Algorithms for the determination of its weights. In the study, the Neuro-Genetic Hybrid procedure has several steps. This process includes Back-Propagation Neural Networks and optimization of weight by Genetic Algorithms as shown in Figure 4.

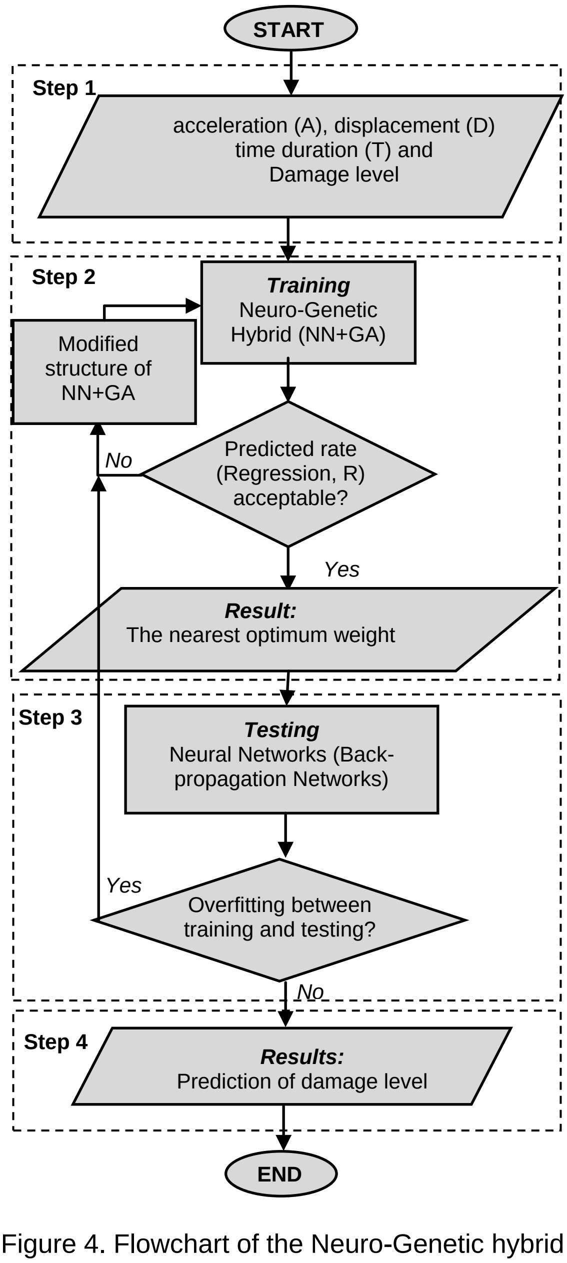


Figure 4. Flowchart of the Neuro-Genetic hybrid

Neuro-Genetic Hybrid consists of acceleration (A), displacement (D), and time (T) as input data, while output data are the damage levels (Step 1).The input data was conducted through the Nonlinear Finite Element Analysis under earthquake load using SAP 2000 Software. Meanwhile, the damage levels consist of minor-damage as Immediate Occupancy (IO), moderate-damage stated Life Safety (LS) and severe damage as Collapse Prevention (CP) level based on FEMA 356. In Step 2, input and output data are loaded for training BPNN. Every chromosome has several genes in an initial population of GA is definedas *A* chromosomes times *B* genes. B genes refer to the total of weight that involved in BPNN based on Neural Networks architecture. The configuration of a BPNN consists of *x, y, and z* where, *x* is the number of input neuron, *y* is a number of the hidden neuron, and *z* is some output neuron respectively. Therefore, the number of weights that are to be determined are *(x+z)y*. Selecting a gene length of *d*, the range of the chromosome string S comprising *(x+z)y* genes is *(x+z)y.d*. The Neuro-Genetic hybrid includes some hidden layers, iteration, mutation, and cross-over operator.

Initially, a population (*Po*) of chromosomes of size *N*is randomly generated. The weight sets for the BPNN are extracted from *Po*. For each weight set, the BPNN is trained for all the input instances of the given problem. The error in the training is utilized to compute the fitness value for each of the chromosomes.In the next phase, the worst-fit chromosomes are terminated and replaced by rest-fit chromosomes. The parent chromosomes are randomly selected in pairs, and a two-point crossover operator is applied to produce offspring. The new population P1 again has its fitness values computed after extraction of weights and computation of error. The generation progress is terminated until the population converges to the same fitness values. During the training of BPNN, Regression (R) and CPU time values are obtained and controlled by initial assumption (R > 0.80). The weights extracted from the 'converged' populations are the final weights of the BPNN.

The procedure of the testing is the same process with the BPNN training in Step 2, but without a weight optimization by GA. The process is done using the final weight in Step 2 and applies other data for testing. The control phase is over-fitting between training and testing of BPNN. If over-fitting occurred, then the structure of Neuro-Genetic hybrid should be modified (Step 3). The output of this method is the prediction of damage level of bridge structure (Step 4).

### 3.2. The Bridge Monitoring System Procedure

The bridge monitoring system in the study has several components to support the primary function which includes server system, Artificial Intelligence, and sensor system. The monitoring system in the study is illustrated in Figure 5.

The product of this intelligent monitoring system is an Intelligent Software. The software can be stated as a smart software because it can predict and analyze the damage level of a bridge due to the earthquake loads and also the other dynamic loading. The prediction based on the standard of FEMA 356 and analysis based on results of the forecast, which describes as green, orange, and red color of an alert system. The software is saved in the server system. The software uses the Visual Basic in the program coding which is provided in the local monitoring. The testing using dummy data indicates that the developed intelligent monitoring could perform its functions, including control, predicting, and alerting. Artificial Intelligence consists of a Neuro-Genetic Hybrid to obtain the optimum weight (updated weight) as an engine in the monitoring software. The process includes the training and testing of BPNN.

In this study, seven sensors such as LVDT and accelerometer are installed on the bridge. The sensors sent the signal to the data acquisition and passed data to the monitoringsoftware in the server system. The three steps of the monitoring system are adopted from previous research (Mardiyono et al., 2012). The 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 creating and developing the intelligent monitoring software using VB.NET. The last step is designing and developing the alert system. The bridge monitoring system in the study has several components to support the primary function which includes data acquisition module, intelligent engine module, an alert system module, and monitoring module. The modules use the VB.NET which is provided in two versions involving local and remote monitoring from the server. The local monitoring is located in the bridges whereas the remote tracking accesses the data from any places via the internet. The testing using dummy data indicates that the developed intelligent monitoring could perform its functions including monitoring, predicting, and alerting. The monitoring system in the study is illustrated in Figure 6.

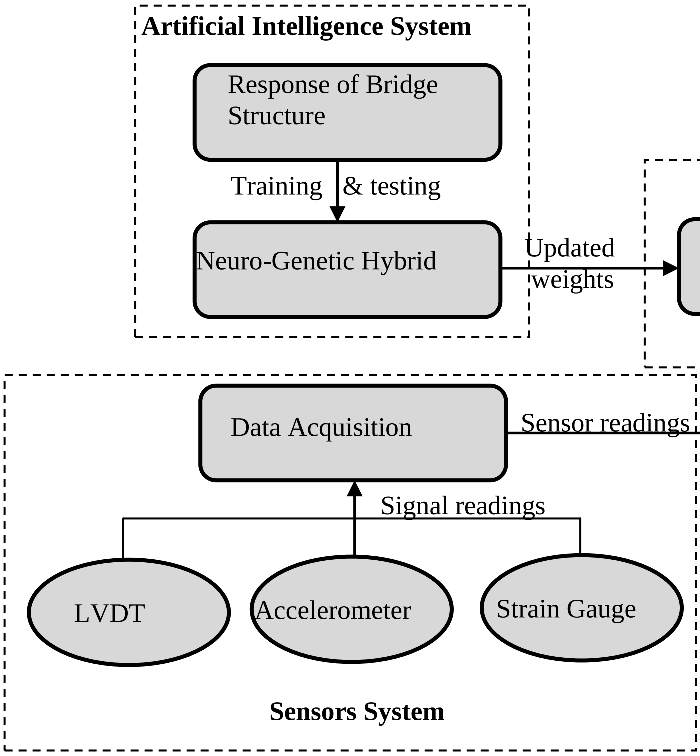


Figure 5. The procedure of a bridge monitoring system in the server

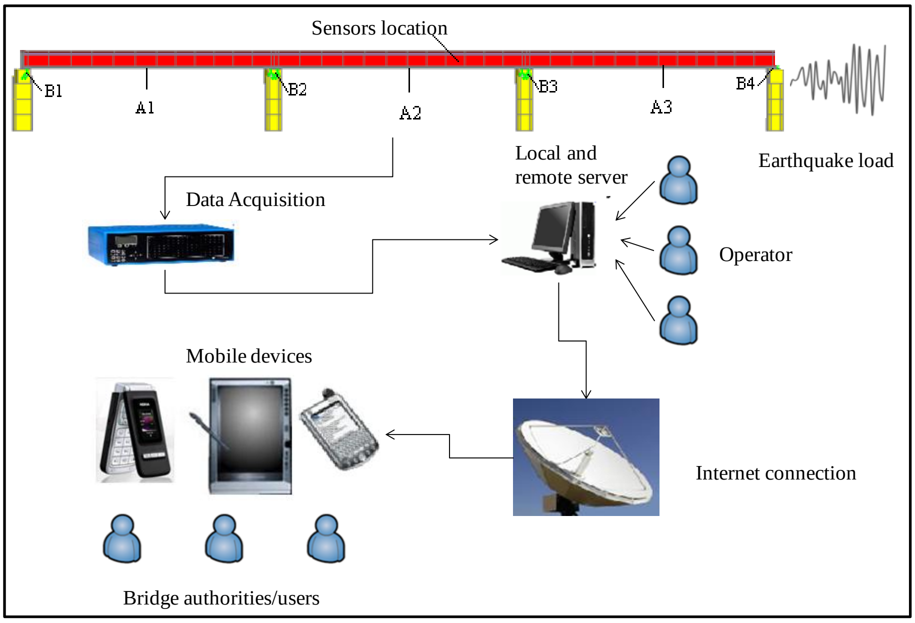


Figure 6. The bridge monitoring system is developed in this study

## 4. Results and Analysis

The neurons in input layer consist of time and displacement while the output layer is a damage levelinto four levels. The levels are 0 (zero) for safety level (B), 1-indexstate for IO, 2-index for LS and 3-index for CP level.The parameters of training to indicate the end of thetraining are the Mean Square Error (MSE). An acceptable MSE in this study has performance goal 0.005. The maximum number of epochs is 50000, and learning rate is 0.15. The training process used the Intel Core i5-2410M computer specification. The power of the processor is 2.30 GHz with turbo boost up to 2.90 GHz and memory 4 GB. Input data based on the time history of bridge response which, consists of the displacement on the top of the piers. The Neuro-Genetic Hybrid used 70% data for training, 15% data for testing and 15% data for the validation process. The performances of Neuro-Genetic Hybrids for damage level prediction based on Finite Element analysis dataare shown in Figure 7, Figure 8 and Figure 9. These figuresshowregression value (R) for training, testing, and validation process. Value (R) for training processis 0.986, the testing process is 0.989, and validation process is 0.975 on 50000$^{th}$ epoch. The best performances of Neuro-Genetic Hybrid depend on the selection of suitable initial weight, network architecture model, and activation functions. The R-value denoted the damage values from the data domain has been predicted more than 97% closer to the actual damage values.

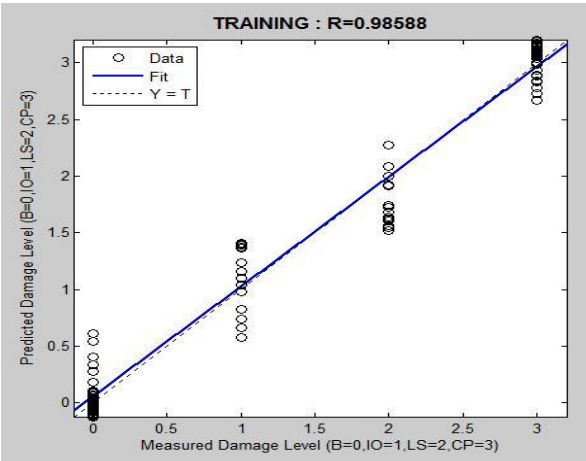


Figure 7. Regression (R) Training of damage level prediction through finite element analysis data

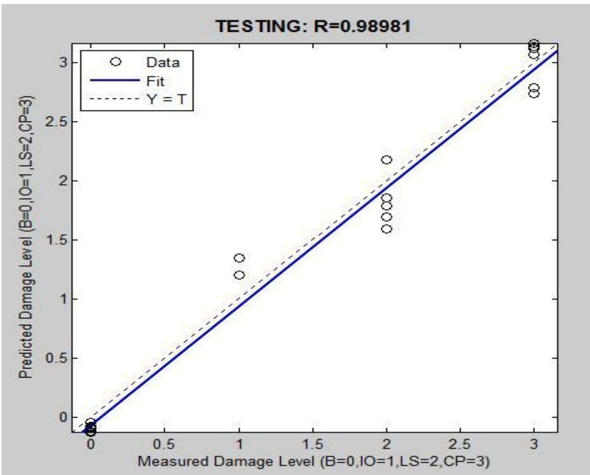


Figure 8. Regression (R) Testing of damage level prediction through finite element analysis data

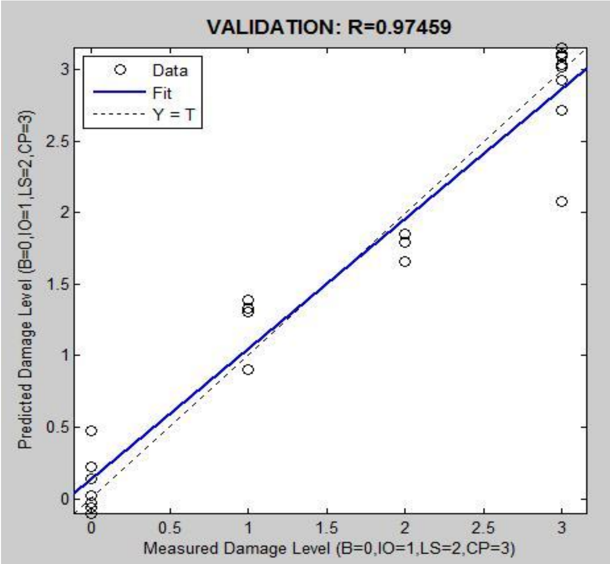


Figure 9. Regression (R) Validation of damage level prediction through finite element analysis data

The best performance of the Neuro-Genetic hybrids conducted the optimal weight of the system. The optimal-weightwas applied in the bridge monitoring system. This method can be used to predict the responses of bridges due to an earthquake load. The menus of the monitoring system consist of general monitoring and sensors monitoring. The public monitoring displays the global monitoring of bridge and the record of the acceleration graph in 3 directions, transversal (X), longitudinal (Y) and vertical (Z) direction respectively.

A neuro-genetic hybrid has embedded in the software with the alert system. The alert system denotes minor damage (IO), moderate (LS) andsevere damage (CP). If the sensors record the data over the reasonable limit, then the alert system will detect the damages.The alert system contains the reasonable prediction that predicts three such levels based on the accelerometer data. It will activate the blink color of IO, LS, and CP and also the alarm sound if the result of prediction indicating to IO, LS, and CP level.

The bridge structural monitoring system, including anaccelerometer data, displacement data, and alert system as shown in Figure 10. In general function, this software reads all the sensor data, display in numerical or charts and predicts the level of bridge damage showing in IO, LS, and CP. Toolbar sensor menus consist of the accelerometer and displacement datafrom a sensor which representing in numeric of X, Y, and Z axis. Figure 10 illustrates the bridge displacement sensor data. It shows the location of each sensor on the bridge, the sensor data, and the result of an alert indicator of safe representing as a green color, moderate (orange), and severe damage (red). Based on the data collected by displacement sensors.

The intelligent software has been resulted using VB.NET. Menus of software include the data inputs from sensors such as accelerometers, feeding forward the inputsNeural Networks, predicting the output as bridges damage level and providing the alert warning as shown in Figure 10. The alerts are divided into four formats 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 primary function prediction of damage level when an earthquake occurred. After the prediction output indicated, either IO, LS, or CP, the alert system would then notify the user that the condition of the bridge is not secure.

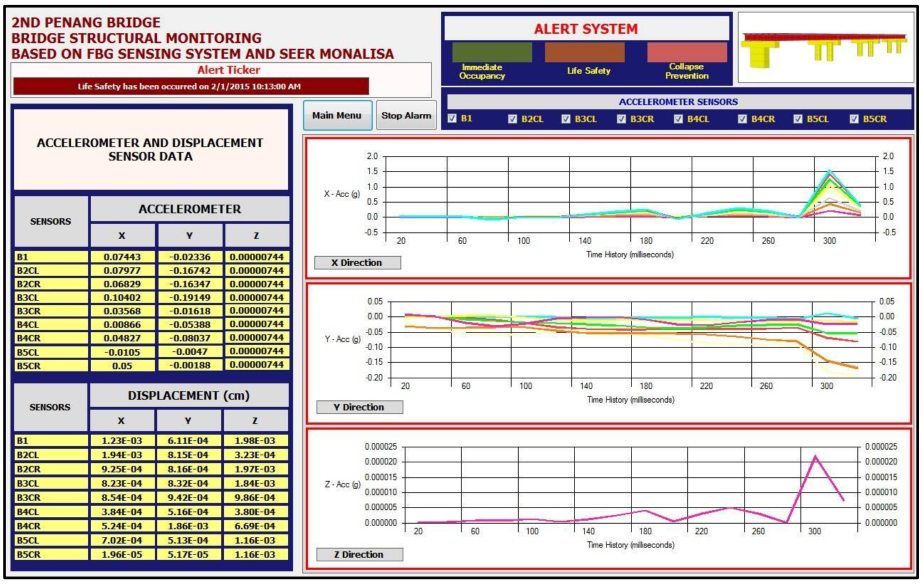


Figure 10. The structural bridge monitoring system

## 5. Conclusion

The best performances of Neuro-Genetic Hybrids (NGH) based on the initial weight and networks architecture model. The neurons of NGH for input layer consist of time, acceleration and displacement have been obtained from finite element software.The output layer is a damage level of the bridge which is categorized intofour indexes based on FEMA 356. This study used the Back Propagation Neural Network (BPNN) and Genetic Algorithms (GA) for prediction the optimum weight and damage levels. According to the results, the Neuro-Genetic Hybrids method based on the sensor recording data in the system can produce the best performance for prediction of damage level of bridge structure due to earthquake loads. The prediction rate value is 97% closer to the actual damage values.Therefore, this quick method can be applied to the monitoring system and predict bridge performances during and after the earthquakes.

## References

[1] H Wenzel. *Health Monitoring of Bridges*, 1st ed. John Wiley & Sons Ltd. United Kingdom. 2009.
[2] D Pearson-Kirk. "The benefits of bridge condition monitoring". in *Proceedings of the ICE - Bridge Engineering*. 2008; 161(3): 151-158.
[3] FK Chang. "Structural Health Monitoring, The Demands and Challenges". CRC Press. 2001.
[4] D Huston. *Structural Sensing, Health Monitoring, and Performance Evaluation*. United States of America: CRC Press. 2011.
[5] S Hao. "I-35W bridge collapse". *J. Bridg. Eng.* 2009; 15(5): 608–614.
[6] H Stambaugh, H Cohen. "I-35W Bridge Collapse and Response, Minneapolis, Minnesota, August 1, 2007". 2008.
[7] Nicolas Janberg. "Kutai Kertanegara Suspension Bridge". *Structurae International Database for Civil and Structural Engineering*. 2016. [Online]. Available: https://structurae.net/structures/kutai-kertanegara-suspension-bridge.
[8] N Shaban, A Caner, A Yakut, A Askan, A Karimzadeh Naghshineh, A Domanic, G Can. "Vehicle Effects On Seismic Response Of A Simple-Span Bridge During Shake Tests". *Earthq. Eng. Struct. Dyn.* 2015; 44(6): 889–905.
[9] Y Li, N Chen, K Zhao, H Liao. "Seismic Response Analysis Of Road Vehicle-Bridge System For Continuous Rigid Frame Bridges With High Piers". *Earthq. Eng. Eng. Vib.* 2012; 11(4): 593–602.
[10] CEN1992. *Eurocode 2: Design of Concrete Structures: Part 1-1: General Rules and Rules for Buildings*. British Standards Institution. 2004.
[11] J Shu, Z Zhang, I Gonzalez, R Karoumi. "The application of a damage detection method using Artificial Neural Network and train-induced vibrations on a simplified railway bridge model". *Eng. Struct.* 2013; 52: 408–421.

[12] N Lin, C Qun, Ieee. *Structural Health Monitoring and Damage Detection Using Neural Networks Technique*. 2013.
[13] T Kerh, C Huang, D Gunaratnam. “Neural Network Approach for Analyzing Seismic Data to Identify Potentially Hazardous Bridges”. *Math. Probl. Eng.* 2011; 2011.
[14] S Ok, W Son, YM Lim. “A study of the use of artificial neural networks to estimate dynamic displacements due to dynamic loads in bridges”. *J. Phys. Conf. Ser.* 2012; 382(1).
[15] R Suryanita, A Adnan. “Application of Neural Networks in Bridge Health Prediction based on Acceleration and Displacement Data Domain”. *Lect. Notes Eng. Comput. Sci. Proc. Int. MultiConference Eng. Comput. Sci. 2013, 13-15 March, 2013, Hong Kong*. 2013; 2202(1): 42-47.
[16] M Vadood, MS Johari, AR Rahai. “Relationship Between Fatigue Life Of Asphalt Concrete And Polypropylene/Polyester Fibers Using Artificial Neural Network And Genetic Algorithm”. *J. Cent. South Univ.* 2015; 22(5): 1937–1946.
[17] E Momeni, R Nazir, D Jahed Armaghani, H Maizir. “Prediction of pile bearing capacity using a hybrid genetic algorithm-based ANN”. *Measurement*. 2014; 57: 122–131.
[18] JH Kim, SH Hwang, HS Shin. “A neuro-genetic approach for daily water demand forecasting”. *KSCE J. Civ. Eng.* 2001; 5(3): 281–288.
[19] IMI Subroto, A Selamat. “Plagiarism Detection through Internet using Hybrid Artificial Neural Network and Support Vectors Machine”. *TELKOMNIKA (Telecommunication Comput. Electron. Control.* 2014; 12(1): 209.
[20] GV Madhav, YP Obulesu. “A New Hybrid Artificial Neural Network Based Control of Doubly Fed Induction Generator”. *Int. J. Electr. Comput. Eng.* 2015; 5(3).
[21] Mardiyono, R Suryanita, A Adnan. “Intelligent monitoring system on prediction of building damage index using neural-network”. *Telkomnika*. 2012; 10(1).
[22] R Suryanita, A Adnan. “Application of Neural Networks in Bridge Health Prediction based on Acceleration and Displacement Data Domain”. *IAENG International Conference on Artificial Intelligence and Applications (ICAIA’13)*. Hongkong, 13th – 15th March 2013. 2013.
[23] MT Jones. *AI Application Programming*. Boston, Massachusetts: Charles River Media. 2005.
[24] S Rajasekaran, GAV Pai. *Neural Network, Fuzzy logic, and Genetic Algorithms Syntesis and Applications*. New Delhi: Prentice Hall of India. 2007.
[25] J Cheng, QS Li. “Artificial neural network-based response surface methods for reliability analysis of pre-stressed concrete bridges”. *Struct. Infrastruct. Eng.* 2012; 8(2): 171–184.