Damage Level Prediction of Pier using Neuro-Genetic Hybrid

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Damage Level Prediction of Pier using Neuro-Genetic Hybrid

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***Abstract*— Generally, long span bridges have multiple columns as known as piers to support the stability of the bridge. The pier is the most vulnerable part of the deck against the earthquake load. The study aims to predict the performance of the pier on the bridge structure subject to earthquake loads using a Neuro-Genetic Hybrid. The mix design of the Back Propagation Neural Networks (BPNN) and Genetic Algorithm (GA) method obtained the optimum-weight factors to predict the damage level of a pier. The input of Neuro-Genetic hybrid consists of 17750 acceleration-data of bridge responses. The outputs are the bridge-damage levels based on FEMA 356. The categorize of a damage level was divided into four performance levels of the structure such as safe, immediate occupancy, life safety, and collapse prevention. Bridge responses and performances have resulted through analysis of Nonlinear Time History. The best of Mean Squared Error and Regression value for the Neuro-Genetic hybrids method are 0.0041 and 0.9496 respectively at 50000 epochs for the testing process. The Regression value denotes the predicted damage values more than 90% closer to the actual damage values. Thus, the damage level prediction of the pier in this study offers as an alternative to structural control and monitor of bridges.**

***Keywords*— acceleration; damage level; neuro genetic; mean squared error; regression.**

I. INTRODUCTION

Stability and performance of bridge structure are essential to ensure un-disrupted traffic without compromising the safety of its users. Natural disaster such as an earthquake can affect the stability of bridge structures. The problem is revealed in the Euro Code 2 [1] by imposing stricter damage natural disasters such as quake can affect the stability of bridge structures. Even a well-designed bridge may face damage as a result of the increased vulnerability of the bridge to non-structural modifications which may alter the imposed load as well as structural deterioration due to earthquake loads [2].

The pier is the most vulnerable element of a bridge due to earthquake load. The complexity of the whole bridge system caused the presence of much uncertainty and variations to predict the bridge responses. Commonly, seismic responses of the bridge only known from past incidents. However, post-earthquake inspection often takes time for the authorized assessor to perform specific checks on the affected bridge. Fig.1 shows the failure of the piers that caused by shear failures under earthquake loads [3]. Therefore, the bridge should be supervised to obtain the service life, ensure public safety, and reduce maintenance costs.

Fig.1 Higashi-Nada Viaduct collapse in 1995 due to Kobe earthquake [3]

The maintenance of bridges become complicated by the increased age of the bridges. One of the essential efforts to know the life cycle performances and management procedures of bridges is through Structural Health Monitoring (SHM). According to [4], 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. Moreover, the objectives of bridge monitoring are to ensure bridge safety and provide better maintenance planning. Commonly, bridge evaluation used any aspect of the condition of a bridge proactively, through the measured data from wireless sensors and the finite element method [5].

The bridge authorities should establish the systems and existing technologies for bridge monitoring system. Commonly in developing countries, the engineers use the conventional method such as Non-Destructive Test (NDT) and Visual Inspection (VI) for bridge evaluation and maintenance. On the other hand, modern technology such as the recording data SHM used the various sensors along the bridge in real time. The observation is in the monitoring room or remote area using internet connection. So, the experts rationally should make the right decisions based on the bridge SHM results.

According to FEMA 365 [6], the structural performance indicated the stability of structure that consists of operational and damage states as minor damage (Immediate Occupancy, IO), moderate damage (Life Safety, LS) and severe damage (Collapse Prevention, CP). The structural performance can be analyzed using static load (pushover analysis) such as has studied by [7] and dynamic load (non-linear time history analysis). Pushover analysis is used by researchers to analyze the structure due to static load while the material in the plastic stage. Meanwhile, the bridge structure analysis in this study used the nonlinear time history analysis due to dynamic load such as the earthquake load.

Commonly, problems faced by a conventional bridge monitoring system include the errors to interpret monitoring data and submission database system (server). Back-Propagation Neural Network (BPNN) can solve the issue of the existing system to unite bridge monitoring and analysis. One of the solutions is to interpret and predict the damage level of bridge structure due to earthquake loads. The BPNN links non-linear input and output data regardless of the specified mathematical equations. In addition to that, Neural Networks require no prior knowledge of the correlation between the data and target. Although the BPNN has its limitations, the use of this method has solved many cases in Civil Engineering.

The Artificial-Intelligent (AI) technologies include Neural Networks, Fuzzy Logic, and Genetic Algorithm technology. According to [8] and [9], many cases cannot be solved using each AI technology separately; then the solution can adopt a combination of two or three AI technologies to provide a more accurate and efficient solution.

The Genetic Algorithms use three basic operations: selection, crossover, and mutation. The selection process is the process of choosing the fitness string from the current population (parents) to the next generation (offspring). Crossover process generates the new child from existing individuals (each parent) by cutting each old string (chromosome) at a random location (crossover point) and replacing the tail of one line 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. A complete replacement for chromosome, crossover, mutation, and inversion at specific probabilities used computer programming-coding. The locations of observation points are determined according to modal identification function from the structural analysis results. Genetic Algorithm (GA) with Back-Propagation Neural Network (BPNN) is a hybrid architecture in which a BPNN employs Genetic Algorithms for the determination of its weights.

The Genetic Algorithm is an optimization technique that simulates the phenomenon of natural evolution. The basis of a Genetic Algorithm is survival of the fittest, means survival and the passing on of the characteristics of future children. The Genetic Algorithm has also defined a population of candidate generation. The encoded as known as a chromosome. Within the chromosome is a separate gene that represents the independent variables for the problem at hand. Each parameter of the problem is a chromosome, which represents a unique independent setting. This condition could represent bit strings, floating-point variables, or simple binary-encoded integers. The Genetic Algorithms provide the initial population, which is done by creating chromosomes randomly or by seeding the community with known fit chromosomes [10].

According to [11], the Genetic Algorithms consist of three fundamental steps, namely evaluation, selection, and recombination. The evaluation process accessed each chromosome to solve the problem. The stage used decoding the candidate solution into the cases. Next step is verification of the result using the parameters. The last is the calculation of fitness. After this step, a subset of the population is selected based on a predefined selection criterion.

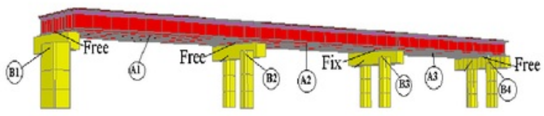
Many researchers have studied the application of the BPNN and GA methods. One of them is [12] who applied the Neuro-Genetic Hybrids for prediction of pile bearing capacity with 99% accuracy, and adopted the Neuro-Genetic algorithm to more effectively forecast and the best performance for the daily water demands. Meanwhile [13] who considered the optimization of the neural networks parameters. The results of the studies show that the method can predict with 96% accuracy. The other researchers have developed the hybrid of Artificial Intelligent (AI) using the Particle Swarm Optimization (PSO) to result in the highly accurate in numerical optimization such as [14] who studied fiber reinforced optimization, [15] who studied soil stability optimization, and [16] who studied structural failure optimization.

The previous study about Neuro Genetic Hybrid has applied to the intelligent system monitoring for bridge structure [17], [18]. The result indicates the Neuro Genetic Hybrid method can solve the problem to predict the condition of the bridge after the earthquake. This study continues the previous research, but input data is scaled on three classifications, low until high ground acceleration. Meanwhile, the target (output) data are damage level of bridge structure based on FEMA 356. Therefore, this paper aims to predict the bridge condition after earthquakes using the Neuro-Genetic hybrids.

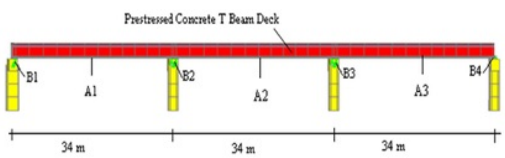
II. MATERIAL AND METHOD

A. Bridge Model

This study used the prestress bridge model with 102 m length. The bridge model has four piers and three spans. Each span is 34 m-long as shown in Fig. 2. The height of the piers is 9 m. The supports between the decks and the piers are free in both translation and rotation. Meanwhile, the support at the base of all piers is fixed in both translation and rotation. The points of observation for the bridge deformation are at the top of Pier B1, Pier B2, Pier B3, Pier B4 pier and the middle of spans such as Span A1, Span A2, and Span A3. The directional properties of the supports for Pier B1, Pier B2, and Pier B4 are free on x, y, and z-direction while Pier B3 is fixed for all the directions.



(a) 3D view



(b) 2D view

Fig. 2. The geometry of Bridge Model in 3D and 2D view

The bridge consists of concrete with reinforcing steels. The compressive design strength for the concrete is 40 MPa, and 50 MPa for the superstructure. Primary reinforcement bars in this study have the characteristic yield strength of 290 MPa. Frame element was assigned for the pier while the deck was represented by a shell element with a thickness of 12 mm. The damping of the bridge model was assumed to be 5 % of the critical damping. Nonlinear hinges element was assigned at top, middle and base of among the piers.

B. Earthquake load data

The seismic designs for the bridge model used five ground motion accelerations from Pacific Earthquake Engineering Research (PEER) database [19] as shown in Table. I. The finite-element analysis used SAP2000 Software for Nonlinear Time History analysis. The loading on the bridge structure is dead load, live load, and five earthquake loads. The earthquakes have been scaled to Peak Ground Acceleration (PGA) values: 0.5g (low acceleration), 0.75g (moderate acceleration) and 1.0g (high acceleration).

TABLE I
DESCRIPTION OF THE EARTHQUAKE DATA RECORDS

No	Name of Earthquake	Year	Magnitude (M_w)	PGV m/s	PGA (g)
1.	San Francisco, NA	1957	5.28	0.0391	0.095
2.	New Zealand	1987	6.6	0.2167	0.255
3.	Cape Mendocino	1992	7.01	0.2014	0.150
4.	Landers, NA	1992	7.28	0.097	0.104
5.	Loma Prieta	1989	6.93	0.1735	0.120

C. The procedure of Neuro-Genetic Hybrids

The study used Neuro Genetic Hybrid for prediction of the optimum weight and damage levels of the bridge structure. The Neuro-Genetic hybrid is a combination of Back Propagation Neural Networks (BPNN) and Genetic method in the design of the network, especially for the optimum design of the Neural Networks. The total error in Back Propagation Neural Network output is defined as,

$$Er_l = \frac{1}{2}\sum_{j\ J}(T_j \quad O_j)^2 \qquad (1)$$

where T_j is the target output, while Oj is the activation rate of output, and J is some training iteration.

Mean-Squared Error (MSE) should be convergent until the last iteration to get the sufficiently small output error (near to null). Error (Er_i) in Equation (2) can be calculated using Equation (1) previously. The root-mean-square, E; for N number of the Error can be rewritten as shown in Equation (2),

$$E = \sqrt{\frac{\sum_i Er_i}{N}} \qquad (2)$$

The fitness value FV_i for each of the chromosome (individual parameter) can be stated as

$$FV_i = \frac{1}{E} \qquad (3)$$

In the study, the Neuro-Genetic Hybrid requires acceleration, and time as input data, while output data are damage levels based on FEMA 356. In the training process used 75% of bridge acceleration response data while in the testing and validation process used 15% of the data respectively. Neuro-genetic calculations begin with the determination of the population number of chromosomes (Po) with N size randomly. The Po data determines the set of BPNN weight. The errors in the training process are used to calculate the value of fitness for each chromosome. The option of appropriate initial weight, learning rate, and activation function resulted in the best performances of Neuro-Genetic Hybrid (NGH). The weight of Neuro-Genetic method showed the acceleration or retardation of the input signals.

The architectural model has n number of input neurons, one hidden layers with $2n$+1 neurons and an output layer with some neurons. Time and acceleration data are used as input neuron while the target is the bridge damage data. The damage level consists of the safe level until the minor

(Immediate Occupancy, IO), moderate (Life Safety, LS) and severe damage (Collapse Prevention, CP). This study has chosen eight neurons in input layer consist of time history, four accelerations on top of Pier B1, Pier B2, Pier B3, and Pier B4, three accelerations on the middle of Span A1, Span A2 and Span A3. Meanwhile, the hidden layer has 17 neurons, and the output layer has four neurons such as safe, IO, LS and CP.

In the next stage, the worst chromosome is replaced by the best chromosome. The chromosomes of parent are randomly chosen in pairs and resulted in the best offspring through the crossover process. The first derivative (P1) of the population has the fitness after error calculation and weight extraction. Progress generation is ended since the community integrates with the same fitness value. The weight factor of BPNN is extracted from the best result of the population.

The procedure of testing is the same process with the BPNN training in the previous step, but without a weight optimization by Genetic Algorithm. The method uses the final weight and uses 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. The structure includes some hidden layers, iteration, mutation, and crossover operator. The last step is writing the results such as the prediction of damage level, Mean Squared Error and Regression values as an indicator of the duration of the run-time process.

III. Results and Discussion

The observation points for monitoring are on the top of Pier B1, Pier B2, Pier B3, and Pier B4. Meanwhile, the observation points on the span of the bridge are in the middle of Span A1, Span A2, and Span A3 individually. This study used 40 modes in the analysis of the finite element method which captured more than 90% mass participation in Ux and Uy direction.

The acceleration of an earthquake is required for the function input in Finite Element Nonlinear Time History analysis using SAP2000 Program. The results stated the location of critical parts of the bridge structure failure due to 5 earthquakes in Table I with three scaled PGAs (0.5g, 0.75g, and 1g). Bridge performance due to the earthquakes scaled PGA 0.75g are shown in Fig. 3 to Fig. 7.

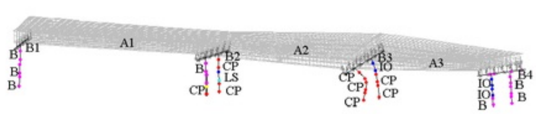


Fig. 3 Bridge performance due to San Fransisco NA Earthquake 0.75g.

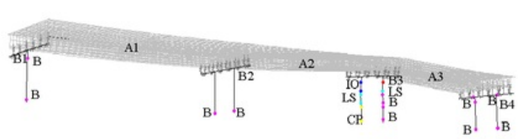


Fig. 4 Bridge performance due to the New Zealand Earthquake 0.75g.

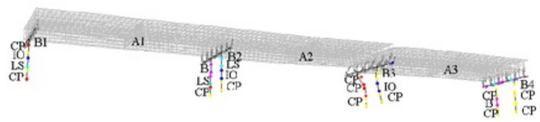


Fig. 5 Bridge performance due to Cape Mendocino Earthquake 0.75g.

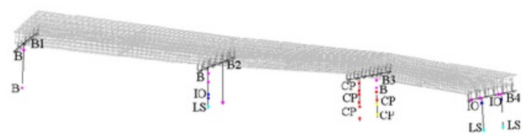


Fig. 6 Bridge performance due to Landers Earthquake 0.75g.

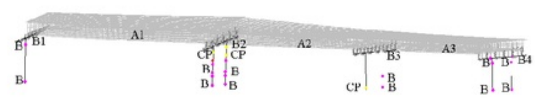


Fig. 7 Bridge performance due to the Loma Prieta Earthquake 0.75g.

The critical damage level of the bridge model during the time history of 0.75g scaled earthquake loads occurred on Pier B3. The support of Pier B3 has been designed fixed in all direction (x, y, and z-direction). Damage level occurred at IO, LS and CP level, while B level is a condition before first damage.

Bridge responses consist of acceleration at the piers and spans of the bridge such as are shown in Fig. 8 to Fig. 12. The bridge acceleration due to the San Francisco earthquake 0.75g is shown in Fig 8 and Fig 9.

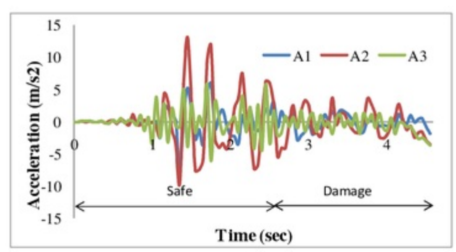


Fig. 8 The acceleration occurred in the middle of span due to San Fransisco NA Earthquake 0.75g.

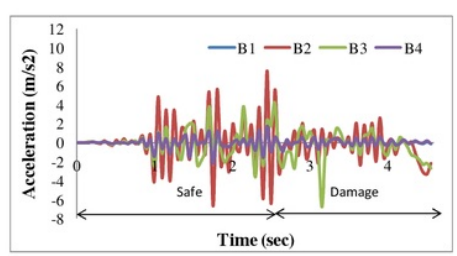


Fig. 9 The acceleration occurred in the top of the pier due to San Fransisco NA Earthquake 0.75g.

Fig 10 and Fig 11 show the acceleration of the bridge model due to the New Zealand earthquake 0.75g. The analysis results stated the maximum acceleration for the span is occurred at the middle span A2 (12.596 m/s^2) and for the piers is happened at the Pier B3 (7.845 m/s^2).

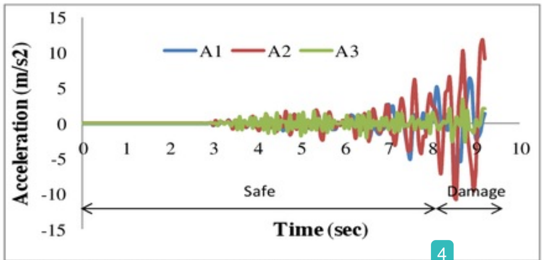


Fig. 10 The acceleration occurred in the middle of the span due to the New Zealand Earthquake 0.75g.

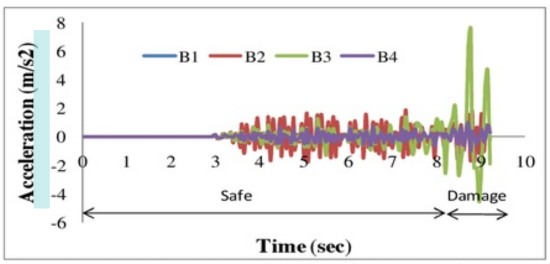


Fig. 11 The acceleration occurred in the top of pier due to New Zealand Earthquake 0.75g

The analysis results of bridge model due to Cape Mendocino earthquake 0.75g are shown in Fig 12 and Fig 13.

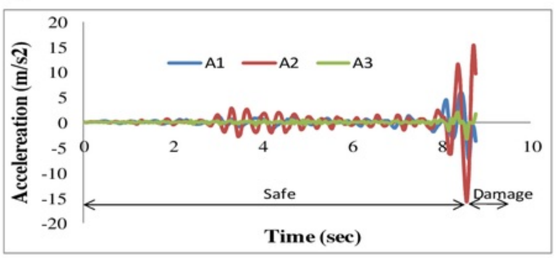


Fig. 12 The acceleration occurred in the middle of span due to Cape Mendocino Earthquake 0.75g.

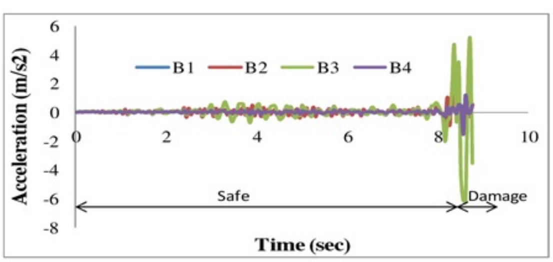


Fig. 13 The acceleration occurred in the top of pier due to Cape Mendocino Earthquake 0.75g.

The maximum acceleration for the span occurs at the middle span A2 (15.692 m/s^2) and for the piers is occurred at the Pier B3 (6.255 m/s^2).

Fig 14 and Fig 15 show the finite element result analysis of the bridge model due to the Landers earthquake 0.75g. The analysis results show the maximum acceleration for the span occurs at the middle span A2 (9.898 m/s^2) and for the piers occurs at the Pier B3 (19.755 m/s^2).

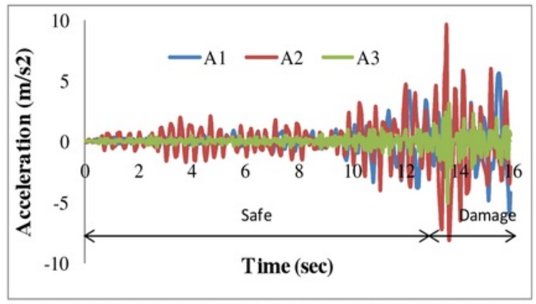


Fig. 14 The acceleration occurred in the middle of the span due to Landers Earthquake 0.75g.

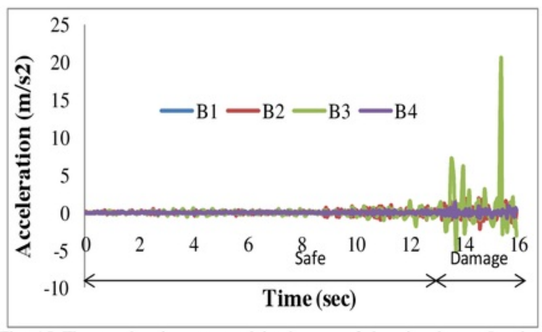


Fig. 15 The acceleration occurred in the top of the pier due to Landers Earthquake 0.75g.

The analysis results of bridge model due to the Loma Prieta earthquake 0.75g are shown in Fig 16 and Fig 17. The maximum acceleration for the span occurs at the middle span A1 (13.592 m/s^2) and for the piers is occurred at the Pier B2 (10.289 m/s^2).

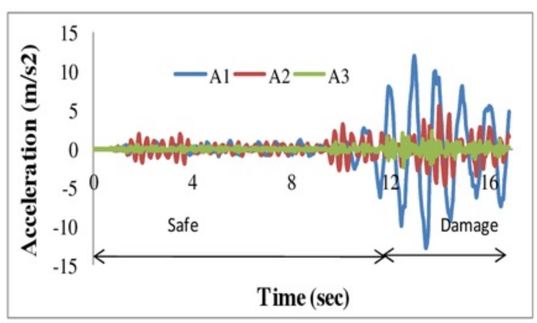


Fig. 16 The acceleration occurred in the middle of span due to Loma Prieta Earthquake 0.75g.

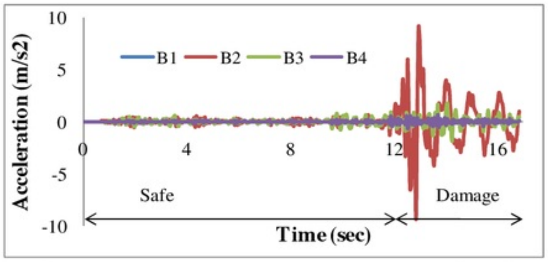


Fig. 17 The acceleration occurred in the top of the pier due to Loma Prieta Earthquake 0.75g.

The resume of Nonlinear Time History analysis with damage level which is used in the training and testing of the Neural Networks process is shown in Table II.

TABLE II
DAMAGE LEVEL OF BRIDGE MODEL FOR TRAINING AND TESTING DATA

NO	TIME HISTORY	NO. OF DATA	DAMAGE DETECTION TIME (Sec)				
			B	IO	LS	CP	END
1.	San Francisco 0.5g	1040	6.80	8.50	9.8	10.4	10.40
2.	San Francisco 0.75g	455	1.05	2.65	2.8	3.0	4.55
3.	San Francisco 1.0g	420	1.00	2.50	2.6	3.0	4.20
4.	New Zealand 0.5g	980	6.4	8.0	8.7	8.8	9.8
5.	New Zealand 0.75g	920	4.4	7.95	8.15	8.25	9.2
6.	New Zealand 1.0g	845	4.35	7.95	8.00	8.05	8.45
7.	Cape Mendocino 0.5g	940	8.30	8.50	8.90	9.05	9.40
8.	Cape Mendocino 0.75g	875	8.1	8.35	8.55	8.65	8.75
9.	Cape Mendocino 1.0g	875	7.90	8.30	8.55	8.20	8.70
10	Landers 0.5g	1640	13.20	14.20	15.10	15.4	16.40
11.	Landers 0.75g	1580	12.8	13.60	14.80	15.1	15.8
12.	Landers 1.0g	1050	0.85	7.05	7.85	8.25	10.50
13.	Loma Prieta 0.5g	3710	11.40	12.00	12.30	12.5	37.10
14.	Loma Prieta 0.75g	1255	10.1	11.5	12.1	12.3	12.55
15.	Loma Prieta 1.0g	1165	9.75	11.05	11.45	11.5	11.65
	Total of data	17750					

The NGH method in this study used seven number of input neurons, one hidden layers with 17 neurons and one output layer. The neurons for input layer consist of time, four accelerations on the top of the bridge model and three accelerations on the middle of the span. The output layer in this study consists of four indexes such as 0 (zero) states safety (S), 1 (one) states IO, 2 (two) states LS and 3 (three) for CP level. The total numbers of input and output data are 17750, which is resulted from finite-element analysis due to 15 earthquake excitations. The NGH used 70% data for training, 15% data for testing and 15% data for the validation process. The results of NGH are shown in Fig 18 and Fig 19.

The figure illustrates MSE for the training and testing process declined from the 5000th epoch to 50000th iterations. The error on all operations decreases along the iterations. The best result of NGH based on the suitable option of the first weight, the system architecture model, and activation functions. The best performances of Neuro-Genetic Hybrids (NGH) is determined by the selection of initial weights, the architecture model of networks and appropriate activation functions. The NGH neurons applied to this study had an input layer comprising time and acceleration which are obtained through the analysis of the finite element software SAP2000. The research used the Back-Propagation Neural Network (BPNN) and Genetic Algorithms (GA) to estimate the optimum weight and damage level of the bridge model. The MSE for one hidden layer is 0.0041, and the R-rate has resulted in more than 94% closer to the actual damage values.

The results proved the Neuro-Genetic Hybrids method based on the bridge acceleration data domain could produce the best performance for estimation the damage level due to earthquake loads on 94% accuracy. Therefore, this inventive method can be applied to monitor and predict bridge performances during and after the earthquakes. Furthermore, the engineers can use the bridge health monitoring results as a guide to a reasonable decision.

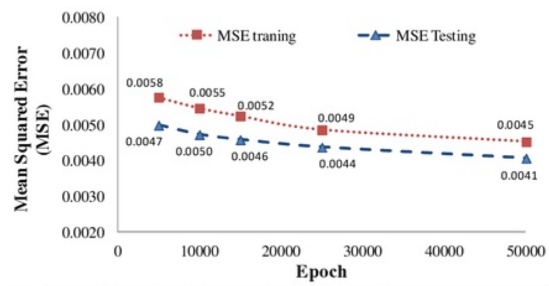


Fig. 18. The Mean Squared Error (MSE) of the acceleration domain input of Neuro-Genetic Hybrids

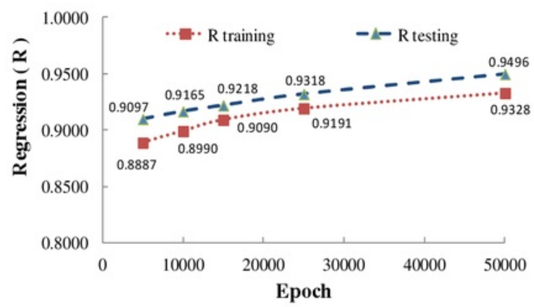


Fig. 19. The Regression (R) of acceleration domain input of Neuro-Genetic Hybrids

The calculation NGH stopped when the Mean Squared Error (MSE) indicated the small errors at the maximum of 50000 iterations. The performance goal of training and testing in this study is 0.05, and the learning rate parameter is 0.15. That means an acceptable MSE is reachable. The best performance of MSE value is the smallest of MSE. It indicates the lowest of the error occurred in the calculation. Meanwhile, the best Regression (R) value is the highest one close to 1. When the regression value is close to 1, then the prediction value is almost 100% close to the actual one.

The best performance of Central Processing Unit (CPU) time indicates the shortest time to process the training calculation in CPU. The CPU time is dependent on the CPU's computational power and specification of the computer. In this study, the training and testing process used the computer specification Intel Core i5-2410M with 2.30 GHz turbo boost up to 2.90 GHz. The CPU time for every iteration shown in Fig 20.

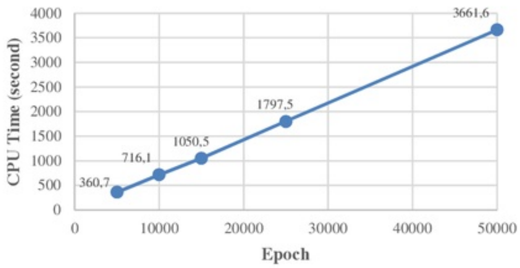


Fig. 20. The CPU time of training process of Neuro-Genetic Hybrids system.

IV. Conclusion

The best performances of Neuro-Genetic Hybrids (NGH) is determined by the selection of initial weights, the architecture model of networks and appropriate activation functions. The NGH neurons applied to this study had an input layer comprising time and acceleration obtained through the analysis of the finite element software SAP2000. The research has used the Back Propagation Neural Network (BPNN) and Genetic Algorithms (GA) to estimate the optimum weight and damage level. The results proved the Neuro-Genetic Hybrids method based on the bridge acceleration data domain could produce the best performance for estimation the damage level due to earthquake loads. Therefore, this inventive method can be applied to the monitoring system and predict bridge performances during and after the earthquakes. Furthermore, the engineers can use the bridge health monitoring results as a guide to a reasonable decision.

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