Hybrid backpropagation neural network-particle swarm optimization for seismic damage building prediction

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ABSTRACT

The evaluation of the vulnerability of buildings to earthquakes is of prime importance to ensure a good plan can be generated for the disaster preparedness to civilians. Most of the attempts are directed in calculating the damage index of buildings to determine and predict the vulnerability to certain scales of earthquakes. Most of the solutions used are traditional methods which are time consuming and complex. Some of initiatives have proven that the artificial neural network methods have the potential in solving earthquakes prediction problems. However, these methods have limitations in terms of suffering from local optima, premature convergence and overfitting. To overcome this challenging issue, this paper introduces a new solution to the prediction on the seismic damage index of buildings with the application of hybrid back propagation neural network and particle swarm optimization (BPNN-PSO) method. The prediction was based on damage indices of 35 buildings around Malaysia. The BPNN-PSO demonstrated a better result of 89% accuracy compared to the traditional backpropagation neural network with only 84%. The capability of PSO supports fast convergence method has shown good effort to improve the processing time and accuracy of the results.

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1. INTRODUCTION

Since long time ago, Malaysia was believed to be free from earthquakes [1]. An earthquake could do significant damages within 100-200km from the epicenter but in Mexico in the year 1985 the earthquake event occurred up to 700km. This damage has also happened in Malaysia due to the high intensity of the earthquake from neighboring countries. The recent event which were tremors are felt from time to time in Malaysia. The one that happened at Ranau, Sabah on the 5th of June 2015 affected many people including civilians and 187 climbers of Mount Kinabalu where 137 of them were stranded before eventually being rescued. The most catastrophic loss is 18 people from different nationalities who were confirmed dead. In addition, lots of properties, especially structural damages to residence, hotels, school buildings, hostels, and the Ranau Mosque [2-3]

Over the past century, researchers have done research to evaluate the vulnerability of buildings to earthquakes to prepare for any casualties if they are near civilians. They came up with damage models to calculate the damage index of buildings to determine their vulnerability to certain scales of earthquakes.

Damage index is defined as an indicator of structural damage of buildings related to base excitations. The scale ranges from one of unity, where undamaged state is represented by zero and the collapse damage state is represented by unity [4]. This helps in assessing the performance of buildings which are subjected to seismic activity. The damage models differ from each other, with some of them considering the variables that are not in other damage models. For example, Powell and Allahabadi's damage model (1988), Wang and Shah's damage model (1987), Mehanny and Deierlein's damage model (2001), Park-on damage model and many more. Examples of some of the models of damage indices can be referred in [4].

A lot of initiatives were done to find solutions to the seismic damage prediction including ground motion prediction [5-7], seismic assessment [6](Cotton, 2017), numerical seismic assessment [8] and earthquake magnitude prediction [9-10]. Computational methods such as Support Vector Machine, Neural Network [10-11]), Neural Dynamic Model of Adeli and Park Seismic Model [11], and Adaptive Neuro-Fuzzy Inference System [10] were implemented. Although, many methods were applied to assist seismic damage prediction in seismic in many countries, in Malaysia, the current practice of seismic inspection uses the rapid screening procedure survey using ATC-21 and ATC-22 survey [12]. This survey is to identify the building's capability to resist seismic threats and the application of neural network was employed to predict seismic damage index which provide less than 75% accuracy [12]. This article presents a solution to predict the seismic damage index of buildings using hybrid of back propagation neural network and particle swarm optimization (BPNN- PSO) method.

2. MATERIALS AND METHOD

a. Data Acquisition

Datasets were collected usingthe software IDARC-2D from 35 buildings around Malaysia. The buildings include the range of 1-storey building up to 35-storey building. The collection datasets were based on a few damage models, the damage model that was chosen to be integrated in the application of BPNN-PSO, the formula of the damage model, and the variables of a building that can potentially affect the seismic damage index. Seven variables namely age, number of bay, height, length seismic zone, natural period, ground acceleration and damage index of the buildings were used. Table 1 shows the sample of datasets

Table 1. Sample of datasets

Buildings	Year built	Age	Number of bay	Height (m)	Length (m)	Seismic Zone (gal)	Natural Period (sec)	Damage Index
1	1982	28	3	17.00	11.00	60	0.470	0.000
2	1999	11	6	7.40	36.00	40	0.290	0.015
3	1975	35	1	48.54	6.10	40	1.030	0.022
4	1980	30	3	39.90	20.10	150	0.830	0.035
5	2004	6	3	10.60	9.00	100	0.400	0.082

b. Data pre-processing

Data pre-processing isdefined as the initial process to transform raw data into viable datasets to be used as an input in neural networks [13-14]. Different variables will have different ranges for the classifications. The summaries of ranges for the classifications of all the variables are given in Table 2 to Table 8. There is no range for the number of bays as it is already in integer format and can be fed into thesystem directly. These datasets were used for the training, testing, and validation phases.

Table 2. Classifications of age variable

Age Class	Age Range (Year)
1	$0 < Yr \leq 10$
2	$10 < Yr \leq 20$
3	$20 < Yr \leq 30$
4	$30 < Yr \leq 40$
5	$40 < Yr \leq 50$
6	$50 < Yr \leq 60$

Table 3. Classifications of seismic zone variable

Seismic Zone Class	Seismic Intensity (gal)
1	31-50
2	51-70
3	71-90
4	91-110
5	111-130
6	131-150

Table 4. Classifications of height variable

Height Class	Overall height range (m)
1	$H \leq 10$
2	$10 < H \leq 20$
3	$20 < H \leq 30$
4	$30 < H \leq 40$
5	$40 < H \leq 50$
6	$50 < H \leq 60$
7	$60 < H \leq 70$
8	$70 < H \leq 80$

Table 5. Classifications of natural period variable

Natural Period Class	Range (sec)
1	$T_n \leq 0.5$
2	$0.5 < T_n \leq 1.0$
3	$1.0 < T_n \leq 1.5$
4	$1.5 < T_n \leq 2.0$
5	$2.0 < T_n \leq 2.5$

Table 6. Classification of length variable overall

Length Class	Length Range (m)
1	$0 < L \leq 10$
2	$10 < L \leq 20$
3	$20 < L \leq 30$
4	$30 < L \leq 40$
5	$40 < L \leq 50$
6	$50 < L \leq 60$
7	$60 < L \leq 70$
8	$70 < L \leq 80$

Table 7. Classifications of Peak Ground Acceleration variable

Peak Ground Acceleration Class	Acceleration Value (g)
1	0.01
2	0.03
3	0.05
4	0.10
5	0.15
6	0.20
7	0.50
8	0.70
9	0.90
10	1.00

Table 8.Classifications of damage index variable

Damage Class	Damage Index	Range
1 - None	0	
2 - Slight	0.001	– 0.009
3 - Light		0.01 – 0.1
4 - Moderate	0.101	– 0.3
5 - Heavy	0.301	– 0.6
6 - Major	0.601	– 0.999
7 - Collapse	1	

c. Designing the BPNN Structure

The implementation of BPNN requires a known output for each set of inputs to calculate the loss function gradient (weights). The number of nodes in the input layer was determined according to the number of inputs; in this case, seven input nodes. The output is based on the degree of damage index class; in this case, seven output nodes. Figure 1 shows BPNN architecture forseismic damage index prediction.

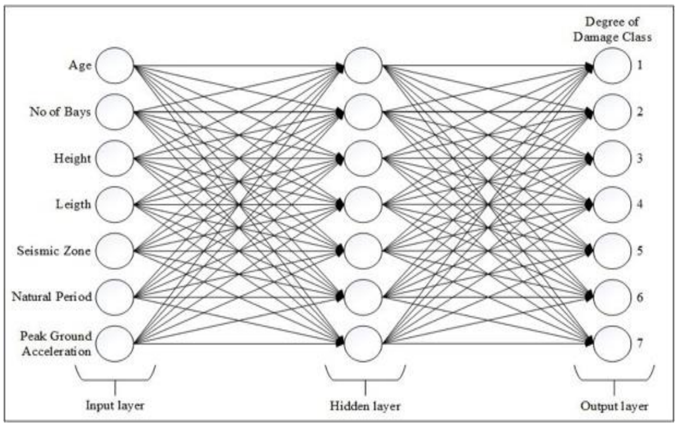

Figure 1. BPNN architecture forseismic damage index prediction

3. DESIGNING THE PARTICLE REPRESENTATION OF PSO AND A HYBRID BPNN-PSO

PSO is an optimization method that was introduced by Kennedy and Eberhart in 1995 [15-17]. PSO is hybridized with the BPNN to assist in finding optimal weights. The weights of the BPNN are the values that are used as a particle in PSO. The number of weights are very depended on the BPNN structure. For this study, there are 7 input neurons, 7 hidden neurons, and 7 output neurons. The number of weights in the system is 7 X 7 + 7 X 7 which equals to 98. Every particle in the swarm will have 98 values. The weights are in the range of - 0.5 to 0.5. These values will be assigned randomly. One particle in the swarm will contain all these values. Table 9. show a sample of random particle.

Table 9. Samples of values for aparticle

Particle Number	From	To	Weight
1	Input Node 1	Hidden Node 1	0.4123
2	Input Node 2	Hidden Node 1	0.3151
.	.	.	.
98	Hidden Node 7	Output	-0.4251

An idea of hybridizing BPNN-PSO procedure is illustrated in Figure 2. The process starts with splitting data randomly for training and testing, and validation. The data which consists of 350 instances are split into two groups. 250 instances will be used for training and testing, while the others will be used for the validation phase. Then, the initialize the network and parameters of BPNN and PSO. The next step is to initialize PSO parameters, particles in the swarm. Then, assign each particle’s weights into BPNN, train and test the network. The weights are then will be updated for every epoch. The next step is to calculate the accuracy, update the pbest and gbest as well as update particle’s velocity and position and finally set the stopping criteria.

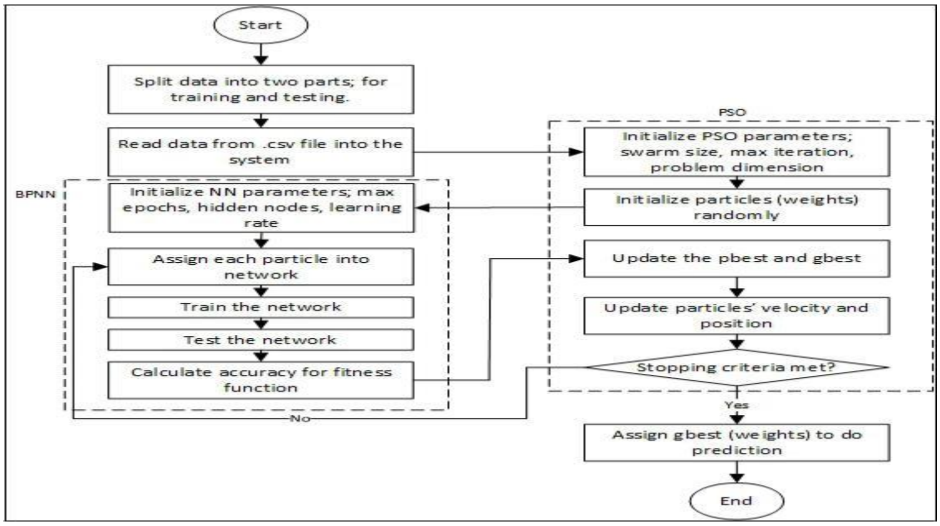

Figure 2. A hybrid BPNN-PSO procedure

4. COMPUTATIONAL RESULTS

a. Result using traditional BPNN

Several parameters for BPNN were applied to find the best hidden node and learning rate prior to the employment of BPNN. Parameter tuning and control were accordingly applied to the number of hidden nodes, learning rate, and epoch number. The results are shown in Table 10. It is discovered that the suitable parameters were 7 hidden nodes, and 0.2 learning rate which reach the highest accuracy of 84.810%. The results were mostly better than the result in [18] when using similar datasets for 4 - 10 hidden nodes. As can be seen in Table 10, the parameter settings for the implementation of BPNN give a good impact to the results using 500 epochs. However, the accuracy is still not good due to the overfitting problem. This can be seen from the results of all hidden nodes.

Table 10. Computational results for BPNN using learning rate ranging from 0.1 - 1.0 and hidden node from 4 – 10

Learning Rate	Accuracy (%) for each hidden layer						
	4	5	6	7	8	9	10
0.1	81.013	81.013	81.013	81.013	81.013	82.279	81.013
0.2	82.279	82.279	82.279	**84.810**	82.279	81.013	82.279
0.3	79.747	83.544	79.747	82.279	81.013	79.745	79.747
0.4	78.481	82.279	78.481	82.279	79.747	78.481	79.747
0.5	78.481	82.279	78.481	83.544	81.012	79.747	82.279
0.6	79.747	81.013	79.747	82.279	79.747	79.747	83.544
0.7	81.013	81.013	79.747	82.279	83.544	79.747	82.279
0.8	82.279	79.747	81.013	82.279	78.481	79.747	79.747
0.9	82.279	81.013	82.279	78.481	78.481	79.747	75.950
1	82.279	81.013	82.279	79.747	78.481	79.747	77.215

b. Experimental Result for a Hybrid BPNN-PSO

The computational experiments were conducted using a maximum of 50 iterations for each of the experimental variable with the swarm sizes (population numbers) of 10, 20, and 30 (Yusoff et al., 2015). An inertia weight of 0.9 is used (Eberhart et al., 2000). The average, maximum, minimum, and standard deviation of the fitness value (Gbest) and processing time were tabulated and analyzed. Each experiment was done 10 times and the highest accuracy is tabulated. In addition, computational time (seconds) of each experiment is also calculated. Table 11 shows the performance of BPNN-PSO in terms of fitness value and processing time. It is interesting to note that the highest accuracy achieved is 88.61% by using 30 as the swarm size, 26th iteration number and 168 seconds of computational time. It is known that larger swarm size managed to achieve better results. However, to the point where the swarm size was set to 30, the accuracy with max iteration set to 40 was higher thantheonesetin50.Thisshowsthatwithhigher number of iterations, better results might not be achieved. It is down to the ability of the particles to explore based on their velocity, which were partly determined by the pbest and gbest.

For example, from the accuracieswhenswarmsizewassetto30,andthe max iteration set to 20 and 30. Results were the same, but the iteration number that managed to get the highest accuracy were 9 and 6 respectively. This proves that exploration and exploitation of the PSO algorithm work to get better results, sometimes take a longer time and sometimes shorter. Another one noticeable result was when the swarm size set to 30 and the max iteration set to 40 and 50. The accuracy of the latter was lower and it achieved the accuracy later than when the maxiterationsetto40.Thisshowsthatforalarge dimensionofparticles,largerswarmsizeleadsto better accuracy but max iteration doesnot.

Table 11.The performance of BPNN-PSO in terms of accuracy and processing time

Swarm Size	Processing Time	Iteration Number at the highest accuracy	Accuracy (%)
10	14.656	10	78.48
	27.859	12	79.75
	41.407	9	81.01
	55.218	24	82.28
	68.708	41	86.08
20	29.492	8	82.28
	55.868	13	81.01
	80.846	27	86.08
	109.243	28	86.08
	133.648	49	86.08
30	43.177	7	83.54
	81.916	9	84.81
	123.105	6	84.81
	168.046	26	88.60
	208.301	40	87.34

Figure 3 Illustrates that for the computation time relativelyincrease as the number of iteration and swarm size. The iteration number that the swarms managed to increase.This is due to the high dimension of the particles the high estaccuracy was not consistent. Each particle contains 98 values (weights) which are means that the convergence can appear in any passed back and forth between BPNN-PSO algorithm.

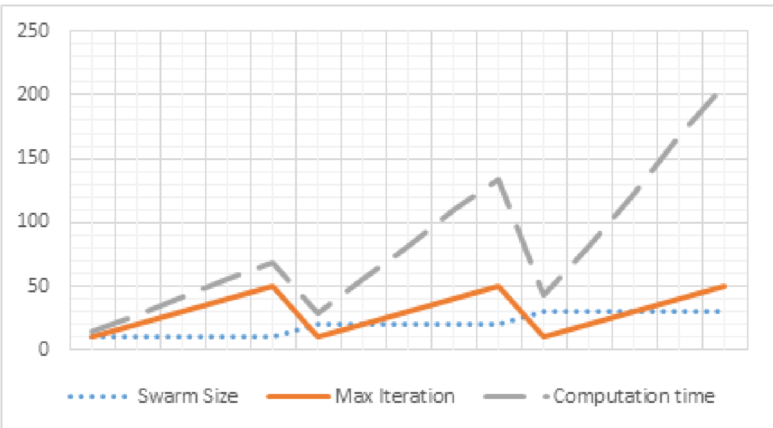

Figure 3. Computational time agains tswarm size and maxiteration

5. CONCLUSION

The paper analyses the use of BPNN and a hybrid BPNN-PSO for seismic damage prediction for buildings. This paper has proposed a weight optimization procedure that is embedded in PSO to obtain good accuracy. This study reveals that BPNN-PSO outperformed the BPNN with respect to the percentage of accuracy and computational time. The result is substantiated by using suitable velocity, coefficients and weight value. This parameter tuning can facilitate the optimal weight for neural networks. In addition, few experiments were conducted to determine the best parameters for the BPNN and design of the BPNN architecture. It is suggested that further research should consider the recent optimization algorithms such as cuckoo search and firefly and the applications of hybrid BPNN- PSO in various types of prediction as such as building collapses and landslide to improve the accuracy of the damage prediction.

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REFERENCES

[1] A. Marto,et al. “Universal correlation of shear wave velocity and standard penetration resistance”. *Electronic Journal of Geotechnical Engineering.*vol .18, pp.2727-2738. 2013.
[2] F. Nazri, et al., “Vulnerability Assessment of Building Frames Subjected to Progressive Collapse Caused by Earthquake*”, in MATECWeb of Conferences. EDP Sciences,* Vol. 103, 2017.
[3] S. Takano and T. Saito, “Analysis of a school building damaged by the 2015 Ranau earthquake Malaysia”, in *AIP Conference Proceedings,* Vol. 1892, No. 1, pp.120004), 2017.
[4] R. Sinha and S. R. Shiradhonkar, “Seismic Damage Index for Classification of Structural Damage-Closing The Loop”, *in 15th World Conference on Earthquake Engineering,* 2012.
[5] M. S. Liew et al., “Ground Motion Prediction Equations for Malaysia due toSubduction Zone Earthquakes in Sumatran Region. *In IEEE Acces,*Vol *5,* pp. 23920-23937, 2017.
[6] F. Cotton, “After the damages: Lessons learned from recent earthquakes for ground-motion prediction and seismic hazard assessment (CF Gauss Lecture),” *in EGU General Assembly Conference Abstracts*, Vol 19, pp 19183, 2017.
[7] S. Barani et al., “Empirical scoring of ground motion prediction equations for probabilistic seismic hazard analysis in Italy including site effects” *Bulletin of EarthquakeEngineering*, vol. 15(6), pp. 2547-2570, 2017.
[8] A. Ismail-Zadeh et al., “Numerical earthquake simulations for seismic hazard assessment,”. in *EGU General Assembly Conference Abstracts*, vol. 19, pp. 2648, 2017.
[9] G. Asencio-Cortés et al., “Medium–large earthquake magnitude prediction in Tokyo with artificial neural networks,” *Neural Computing and Applications*, vol. 28(5), pp.1043-1055, 2017.
[10] M. H. Rafiei et al., “A novel earthquake early warning model using neural dynamic classification and neural dynamic optimization,” *Soil Dynamics and Earthquake Engineering*, vol.100, pp. 417-427. 2017.
[11] I. Kaftan et al., “Processing of earthquake catalog data of Western Turkey with artificial neural networks and adaptive neuro-fuzzy inferencesystem,”. *Arabian Journal of Geosciences*, vol. 10(11), pp. 243. 2017.
[12] A. Adnan et al., “Artificial neural network application for predicting seismic damage index of buildings inMalaysia,” *Electronic Journal of Structural Engineering,* vol. 12(1), pp. 1-9, 2012.
[13] H Dai and C. MacBeth, “Automatic picking of seismic arrivals in local earthquake data using an artificial neuralnetwork,” *Geophysical journal international,* vol. 120(3), pp. 58-774. 1995.
[14] Samarasinghe, “Neural networks for applied sciences and engineering: from fundamentals to complex pattern recognition. *CRC Press.* 2016.
[15] Eberhart, R. C., Shi, Y. Comparing Inertia Weights and Constriction Factors in Particle SwarmOptimization. *in Proceedings of theCongressonEvolutionaryComputation*, vol. 1,pp. 84-88, 2000.
[16] R. Eberhart and j. Kennedy, “A New Optimizer Using Particle Swarm Theory,” *in Sixth International Symposium on Micro Machine and Human Science.* pp. 39-43, 1995.
[17] M. Yusoff et al., “DPSO based on a min-max approach and clamping strategy for the evacuation vehicle assignment problem,” *Neurocomputing.* vol. 148, pp. 30-38. 2015.
[18] A. Adnan et al., “Artificial neural network application for predicting seismic damage index of buildings in Malaysia”, *Electro J Struct Eng*, vol. *12*(1), pp. 1-9, 2012.

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