

Intelligent Monitoring System on Prediction of Building Damage Index using Neural-Network

Mardiyono*¹, Reni Suryanita², Azlan Adnan³

¹Informatic Engineering, Politeknik Negeri Semarang, Indonesia

²Civil Engineering Department, Faculty of Engineering University of Riau, Indonesia

³Faculty of Civil Engineering, Universiti Teknologi Malaysia, Johor Bahru, Malaysia

e-mail: m4rdiyono@yahoo.com, renisuryanita@yahoo.co.id, azlan_fka_utm@yahoo.com

Abstrak

Gempa bumi berpotensi menghancurkan gedung tinggi. Kerusakan bangunan dapat diindeks oleh FEMA menjadi tiga kategori yaitu immediate occupancy (IO), life safety (LS), dan collapse prevention (CP). Untuk menentukan indeks kerusakan, model bangunan telah disimulasikan ke dalam perangkat lunak analisis struktur. Data Percepatan telah dianalisis menggunakan metode non linier dalam program analisis struktur. Beban gempa adalah riwayat waktu di permukaan, PGA = 0105g. Karya ini mengusulkan sistem pemantauan cerdas memanfaatkan jaringan syaraf tiruan (JST) untuk memprediksi indeks kerusakan bangunan. Sistem ini juga menyediakan sistem peringatan dan pemberitahuan untuk menginformasikan status kerusakan. Data pembelajaran dilatih pada JST umpan maju dan menggunakan kembali algoritma propagasi. Sistem peringatan ini dirancang untuk dapat mengaktifkan suara alarm, melihat bar waspada atau teks, dan mengirimkan pemberitahuan melalui email untuk keamanan atau manajemen. Sistem ini diuji dengan menggunakan data sampel diwakili dalam tiga kondisi melibatkan IO, LS, dan CP. Hasil penelitian menunjukkan bahwa sistem pemantauan yang diusulkan cerdas bisa memberikan prediksi dengan akurasi 92% dan mengaktifkan sistem alarm. Penerapan sistem dalam pemantauan bangunan akan memungkinkan untuk prediksi cepat, cerdas dan akurat terhadap indeks kerusakan bangunan akibat gempa.

Kata kunci: bangunan, cerdas, indeks kerusakan, jaringan syaraf tiruan, monitoring

Abstract

An earthquake potentially destroys a tall building. The building damage can be indexed by FEMA into three categories namely immediate occupancy (IO), life safety (LS), and collapse prevention (CP). To determine the damage index, the building model has been simulated into structure analysis software. Acceleration data has been analyzed using non linear method in structure analysis program. The earthquake load is time history at surface, PGA=0105g. This work proposes an intelligent monitoring system utilizing artificial neural network to predict the building damage index. The system also provides an alert system and notification to inform the status of the damage. Data learning is trained on ANN utilizing feed forward and back propagation algorithm. The alert system is designed to be able to activate the alarm sound, view the alert bar or text, and send notification via email to the security or management. The system is tested using sample data represented in three conditions involving IO, LS, and CP. The results show that the proposed intelligent monitoring system could provide prediction of up to 92% rate of accuracy and activate the alert. Implementation of the system in building monitoring would allow for rapid, intelligent and accurate prediction of the building damage index due to earthquake.

Keywords: artificial neural network, building, damage index, intelligent, monitoring

1. Introduction

A tall building has an important function in relation to public services, state administration, telecommunication, center of business, etc. When earthquake occurs, the status of the building damage index should be determined to find out whether that building could be re-occupy. According to the Federal Emergency Management Agency (FEMA) 356 [1], the performance of the building structure consists of three categories; (a) Collapse Prevention (CP) or total damage level, (b) Life Safety (LS) or moderate/partial damage level, and (c) Immediate Occupancy (IO) or safety level. Damage index of building can be defined as a reference of building stability using structural analysis method. Acceleration data gathered from accelerometer are computed based on the equation of FEM and it carries out the damage

index. Since the collection of data from the accelerometer normally takes a long time, it triggers an idea to develop an intelligent monitoring system which would allow data collection from the accelerometer and prediction of the damage index to be carried out rapidly and accurately.

The application of artificial intelligent on civil engineering field has been performed in relation to building/structure [5], [12], [13], [14] management and control [2], [3], [10], [13], disaster [6], [7] and earthquake [4], [8], [9]. Mostly, the algorithm utilized in the training process is back propagation or otherwise, radial basis is used by [5] in the research of reducing earthquake effects on nonlinear base isolated building. The implementation of ANN results in the prediction rate of over 96 % [2] and 98 % [3], [13]. This indicates that ANN is feasible and reliable to be applied as intelligent engine for prediction in civil engineering fields. This research will also utilize ANN in other case study on the prediction of building condition after an earthquake event that is enhanced with monitoring and alert system. The aim of this research is to develop an intelligent monitoring for prediction the building damage index due to an earthquake.

This paper is organized as follows; Chapter 2 explains the overview of damage index of building structure. Chapter 3 describes the proposed BP-ANN Architecture while Chapter 4 discusses the research methodology used in this research. Design and development of intelligent monitoring is explained in Chapter 5. Furthermore the results and discussion are described in chapter 6 and concluded thereafter.

Table 1. The Structural Performance Levels Criteria

Elements	Type	Structural Performance Levels		
		Collapse Prevention S-5	Life Safety S-3	Immediate Occupancy S-1
Concrete Frames	Primary	Extensive cracking and hinge formation in ductile elements. Limited cracking and/or splice failure in some nonductile columns. Severe damage in short columns.	Extensive damage to beams. Spalling of cover and shear cracking (<1/8" width) for ductile columns. Minor spalling in nonductile columns. Joint cracks <1/8" wide.	Minor hairline cracking. Limited yielding possible at a few locations. No crushing (strains below 0.003).
	Secondary	Extensive spalling in columns (limited shortening) and beams. Severe joint damage. Some reinforcing buckled.	Extensive cracking and hinge formation in ductile elements. Limited cracking and/or splice failure in some nonductile columns. Severe damage in short columns.	Minor spalling in a few places in ductile columns and beams. Flexural cracking in beams and columns. Shear cracking in joints <1/16" width.
	Drift	4% transient or permanent	2% transient; 1% permanent	1% transient; negligible permanent
Steel Moment Frames	Primary	Extensive distortion of beams and column panels. Many fractures at moment connections, but shear connections remain intact.	Hinges form. Local buckling of some beam elements. Severe joint distortion; isolated moment connection fractures, but shear connections remain intact. A few elements may experience partial fracture.	Minor local yielding at a few places. No fractures. Minor buckling or observable permanent distortion of members.
	Secondary	Same as primary.	Extensive distortion of beams and column panels. Many fractures at moment connections, but shear connections remain intact.	Same as primary.
	Drift	5% transient or permanent	2.5% transient; 1% permanent	0.7% transient; negligible permanent
Braced Steel Frames	Primary	Extensive yielding and buckling of braces. Many braces and their connections may fail.	Many braces yield or buckle but do not totally fail. Many connections may fail.	Minor yielding or buckling of braces.
	Secondary	Same as primary.	Same as primary.	Same as primary.
	Drift	2% transient or permanent	1.5% transient; 0.5% permanent	0.5% transient; negligible permanent

2. Damage Index of Building Structure

Damage index of building structure based on structural performance levels in FEMA 356 [1]. Each level has a wide range which can be defined by individual building owners. In the system, IO, LS and CP are denoted by index 1, 2 and 3 respectively. The structural performance levels criteria of concrete and steel element of building are shown in Table 1 below.

Structural performance levels are the indicator to explain the damage of structure element in post-earthquake evaluation. In the structure monitoring, the indicator is shown as alert or warning system.

3. Proposed BP-ANN Architecture

The intelligent monitoring uses Back-Propagation Artificial Neural Network (BP-ANN) to predict the building damage index. An architecture has been proposed in the previous research which consists of three layers involving input, hidden, and output layer as shown in Figure 1. Input layer involves 16 input cells that fetch data from the accelerometer, whereas hidden layer comprises of 32 cells/neurons connected to all outputs of the input cells. In output layer, 1 neuron is provided where its input connects to all outputs of the hidden cells.

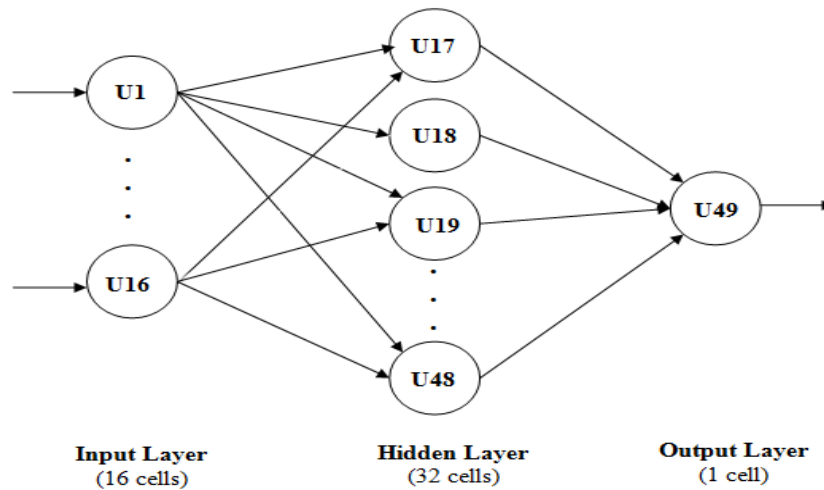


Figure 1. The Proposed Architecture of BP-ANN [16]

Several equations derived from BP-ANN algorithm are utilized in computing the output of each neuron, error, Mean Squared Error (MSE), and the weight. Sigmoid activation function is utilized in each neuron and the output is calculated based on the following equation:

$$\gamma = f(w_0 + \sum_{i=1}^n u_i w_i) \quad (1)$$

Where sigmoid function (f) is shown in equation (2):

$$\gamma \text{ sigmoid} = \frac{1}{1+e^{-x}} \quad (2)$$

The error of output cell can be determined as follows:

$$\text{Output cell: } \delta_o = (C_i - u_o)u_o(1 - u_o) \quad (3)$$

$$\text{Hidden cell: } \delta_i = (\sum_{m:m>i} w_{m,j} \delta_o)u_i(1 - u_i) \quad (4)$$

$$\text{Mean-squared error (MSE): } err = 0.5(O_{desired} - O_{target})^2 \quad (5)$$

The weights are updated as the following equations:

$$\text{Weights hidden to output: } w_{i,j}^* = w_{i,j} + \rho \delta_o u_i \quad (6)$$

$$\text{Weights input to hidden: } w_{i,j}^* = w_{i,j} + \rho \delta_i u_i \quad (7)$$

ρ : learning rate

Furthermore, the ANN architecture was trained and tested using the following steps:

- (a) Simulating the earthquake occurred in such building to get the accelerometer and damage index data using Finite Element Software Analysis.
- (b) Splitting the data into training and testing.
- (c) Training the ANN using the data shown in Table 2. This process is iterated up to 1000 times with ρ is 0.1.
- (d) Testing the ANN with the data explained in Table 3.
- (e) Save the weights to text file as the initial weight value for intelligent monitoring software.

Table 2. The Sample Learning Data

No	Sensors / Inputs								Output
	Sensor1Y	Sensor1X	Sensor2Y	Sensor2X	Sensor3Y	Sensor3X	Sensor4Y	Sensor4X	
1	0	0	0	0	0	0	0	0	IO
2	0.01148	-8.72E-04	-0.01188	0.00279	-0.01366	0.01593	-0.00344	-0.000256	IO
3	-0.00765	-0.00103	-0.04705	0.00698	-0.04765	0.01439	-0.04063	0.00371	IO
4	0.01188	0.00444	-0.02647	0.00827	-0.02671	0.00662	-0.02942	0.01012	IO
5	0.02149	0.01325	0.0083	0.00915	0.00882	-0.00628	-0.0128	0.02237	IO
6	0.08491	0.02406	0.0834	0.00776	0.08358	-0.01051	0.05932	0.0228	IO
7	0.01975	0.01608	0.00171	0.01555	0.00197	0.00176	-0.01733	0.02644	IO
8	0.06786	0.01352	0.02359	0.01741	0.02291	0.01858	0.02491	0.01705	IO
9	-0.00749	0.01333	-0.04961	0.02189	-0.04809	0.02186	-0.05011	0.02532	IO
10	-0.13283	0.019	-0.1851	0.02142	-0.18754	0.02982	-0.18074	0.02011	IO
....
....
32	-0.02672	0.09348	-0.06525	0.067	-0.06415	-0.01046	-0.17997	0.13314	LS
33	-1.01455	0.08722	-1.18172	0.07919	-1.17324	0.07389	-1.15905	0.07398	LS
34	0.13304	0.0274	-0.12698	0.11992	-0.13798	0.18371	-0.10578	0.11554	LS
....
833	0.14809	-0.0617	0.12603	-0.37281	0.11007	-0.39279	0.20461	-0.46633	CP
834	0.21406	-0.03131	0.37959	-0.40252	0.45846	-0.31759	0.37243	-0.25186	CP
835	0.08579	0.01996	0.09365	0.00454	-0.06886	-0.46194	-0.09436	-0.08765	CP

Based on the experiment conducted in previous research, the result of MSE obtained is $1.6 \text{ E-}10$ and the rate of prediction = 92%. Hence, the BP-ANN architecture is ready to be applied as an intelligent machine of building damage index monitoring system.

4. Research Methodology

To achieve the aim, this research is conducted in several steps depicted in Figure 2. The steps are explained as follows:

- (a) Designing ANN architecture including simulating the building damage index due to an earthquake, training and testing ANN, and obtaining the initial weights.
- (b) Designing and developing the intelligent monitoring software

Table 3. The Sample Testing Data

No	Sensors / Inputs								Output
	Sensor1Y	Sensor1X	Sensor2Y	Sensor2X	Sensor3Y	Sensor3X	Sensor4Y	Sensor4X	
1	0	0	0	0	0	0	0	0	IO
2	0.014	-8.72E-04	-0.00936	0.00279	-0.01114	0.01593	-9.18E-04	-2.56E-04	IO
3	-0.01329	-0.00103	-0.05271	0.00699	-0.05331	0.01439	-0.04627	3.71E-03	IO
4	0.01552	0.00441	-0.02294	0.00825	-0.02323	0.00672	-0.0259	1.01E-02	IO
5	0.03516	0.01341	2.31E-02	0.00922	2.36E-02	-0.00693	0.00129	2.27E-02	IO
6	0.12355	0.02448	0.12261	0.00751	0.12286	-0.0106	0.09897	2.24E-02	IO
7	0.03371	0.01502	0.01339	0.01612	0.01351	0.00402	-0.00405	2.62E-02	IO
8	0.09246	0.01322	0.04559	0.01769	0.0446	0.02025	0.04853	1.61E-02	IO
9	-0.00788	0.01372	-0.04681	0.02156	-0.04454	0.01758	-0.05108	2.74E-02	IO
10	-0.1788	0.0211	-0.22818	0.02019	-0.23116	0.02806	-0.22604	2.01E-02	IO
....
90	0.02086	0.07325	-0.07237	0.08811	-0.07333	0.09062	-0.0906	0.11632	LS
91	0.03517	0.08069	-0.16619	0.09481	-0.096	0.11093	-0.121	0.12003	LS
92	-0.0574	0.13524	-0.17086	0.10049	-0.11818	0.05812	-0.23251	0.15577	CP
93	-0.10365	0.16339	-0.15026	0.14706	-0.14032	0.06875	-0.28638	0.22109	CP
....
98	0.01318	9.75E-04	0.01694	-0.03709	0.01493	-0.03715	0.01878	-0.03998	IO
99	0.04583	-0.01932	0.04199	-0.03572	0.0287	-0.03548	0.05436	-0.05473	IO
100	0.11601	-0.03066	0.10189	-0.03402	0.08294	-0.03419	0.11749	-0.0601	IO

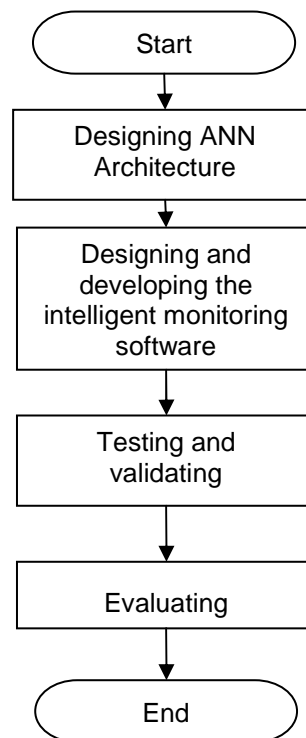


Figure 2. Steps of Research Methodology

- (c) Designing and developing the alert system
- (d) Testing and validating
- (e) Evaluating

Figure 2 shows the research methodology used in this study. Designing the ANN architecture is the core of prediction engine to determine the building damage index based on the fetched data from accelerometer. The architecture consists of 16 input cells, 32 hidden cells, and 1 output cell. The training and testing result [16] indicate that the ANN could predict the building damage index with the accuracy rate of up to 92%. The second step is designing and developing the intelligent monitoring software utilizing VB.NET. The software scope is defined to handle the following tasks; collecting the inputs from accelerometer, feeding forward the inputs to ANN, predicting the output as building damage index, and providing the alert if the result is LS or CP. To test and validate the software, the sample data, including three outputs; IO, LS, and CP are tested and the software has to show the input data in number and line chart, and the notification in text, color bar, and email alert. The last step is evaluation stage that collects the lacks of software found by the user and makes the necessary correction.

5. Design of Intelligent Monitoring

Building intelligent monitoring has a main function on the prediction of damage index when an earthquake occurred. Several components/modules that supported the main function include data acquisition module, intelligent engine module, alert system module, and monitoring module. The framework is illustrated in Figure 3.

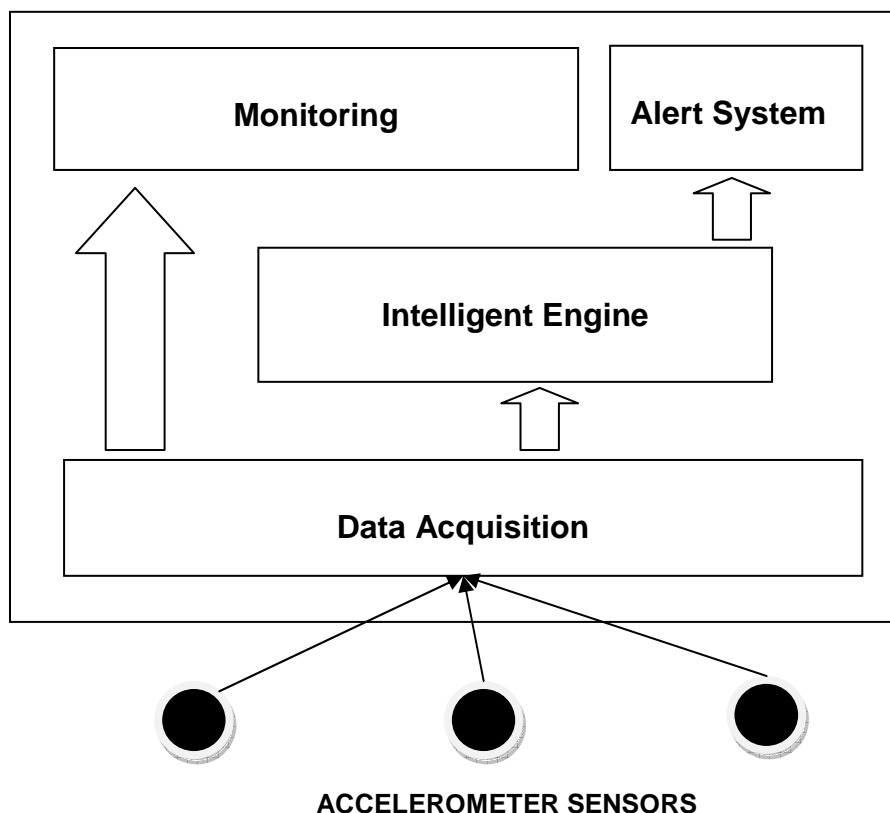


Figure 3. Intelligent Monitoring Framework

Figure 3 is a proposed framework of building intelligent monitoring that contains several modules or components. The descriptions of each module are discussed as follows:

- **Accelerometer Sensor:** vibration or acceleration of the building can be measured by accelerometer sensor. When an earthquake occurred, there is acceleration caused by gravity. The acceleration signals are identified into three-axis direction. Thus the sensors provide the acceleration data and transfer the signal to the data acquisition module.[Thesis Graham]
- **Data Acquisition:** The acceleration signals from many sensors are gathered in the data acquisition module. This module converts the electric signal fetched from sensor to the digital data that can be processed by the software into different data format transferred to intelligent engine and monitoring module. Data acquisition includes timestamp, acceleration data X, Y, and Z direction.
- **Intelligent Engine:** The prediction of building damage index is determined by inserting the acceleration data from data acquisition module to the input of intelligent engine. The core of this engine is the ANN that has 92% prediction rate through the training and testing process in the previous research []. All of the input data should be normalized before feeding forward to the ANN. The prediction output is presented in three levels namely IO (safe), LS (moderate safe), and CP (total damage).
- **Monitoring:** The acceleration data from data acquisition are shown in the monitoring screen. It enables the user to see the progress of reading data from the sensors. In this module the acceleration data are presented in line chart and numeric value.
- **Alert System:** When the prediction output indicated to LS and CP, alert system notifies the user that the condition of the building is not secure. The alerts are provided into three formats namely alert bars showing in different color (IO: green, LS:orange, and CP:Red), alert sound/alarm, and alert-mail sending to the user.

The modules that are mentioned above are developed utilizing VB.NET provided in two versions involving local and remote monitoring. The local monitoring is located in the building 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 illustration of the two accessed methods is shown in Figure 4.

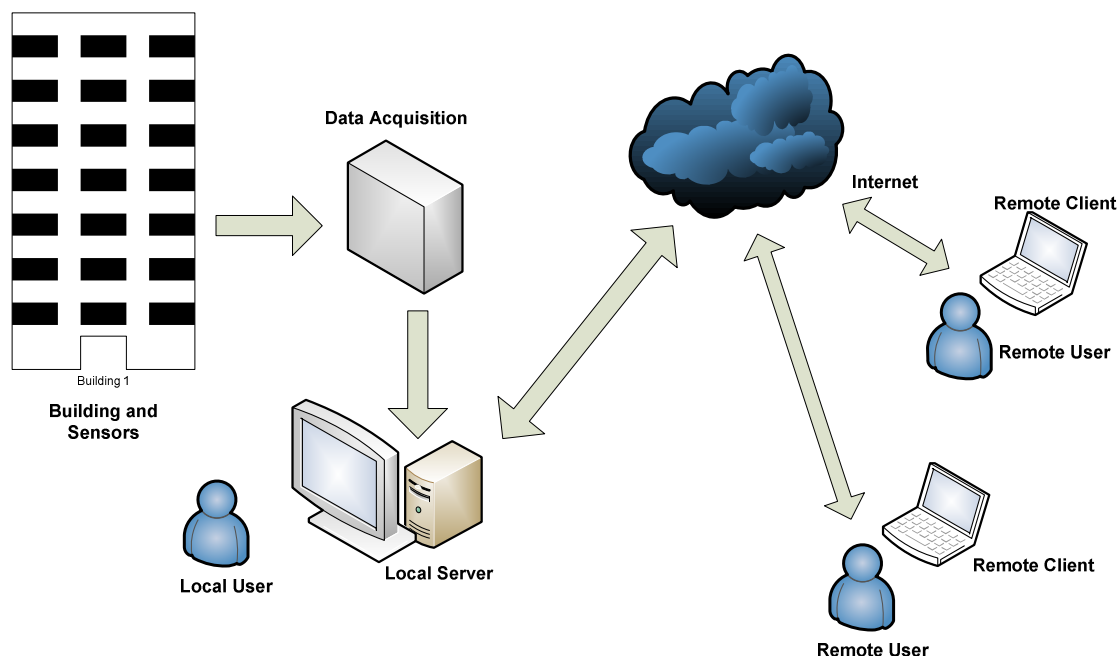


Figure 4. Intelligent Monitoring Architecture

Figure 4 shows the architecture of intelligent monitoring that includes two versions namely local and remote monitoring. In tall buildings, the acceleration sensors are installed in

specific points, generally located in the basement, middle, and roof of building. Data emerging from sensors are fetched by data acquisition module. Furthermore, the local server normalizes the acceleration data and carries out the prediction. Remote client is able to monitor the acceleration data using remote monitoring software that has the similar function with local server including intelligent engine, alert system and monitoring. The client can obtain the remote data from the server which could also convert acceleration data to HTML format.

6. Result and Analysis

The developed intelligent monitoring is tested with two types of data namely dummy and real data. The dummy data shown in Table 4 is the sample data obtained from the learning data that contains three outputs in IO, LS, and CP. The real data comes out from the sensors that represent the building acceleration either due to an earthquake or not.

Table 4. The Sample Data for Testing

Data	Sensors / Inputs								Output
	Sensor1Y	Sensor1X	Sensor2Y	Sensor2X	Sensor3Y	Sensor3X	Sensor4Y	Sensor4X	
1	0	0	0	0	0	0	0	0	IO
2	0.01148	-8.72E-04	-0.01188	0.00279	-0.01366	0.01593	-0.00344	-0.000256	IO
3	-0.00765	-0.00103	-0.04705	0.00698	-0.04765	0.01439	-0.04063	0.00371	IO
4	0.01188	0.00444	-0.02647	0.00827	-0.02671	0.00662	-0.02942	0.01012	IO
5	0.02149	0.01325	0.0083	0.00915	0.00882	-0.00628	-0.0128	0.02237	IO
6	-0.02672	0.09348	-0.06525	0.067	-0.06415	-0.01046	-0.17997	0.13314	LS
7	-1.01455	0.08722	-1.18172	0.07919	-1.17324	0.07389	-1.15905	0.07398	LS
8	0.08491	0.02406	0.0834	0.00776	0.08358	-0.01051	0.05932	0.0228	IO
9	0.01975	0.01608	0.00171	0.01555	0.00197	0.00176	-0.01733	0.02644	IO
10	0.06786	0.01352	0.02359	0.01741	0.02291	0.01858	0.02491	0.01705	IO
11	0.14809	-0.0617	0.12603	-0.37281	0.11007	-0.39279	0.20461	-0.46633	CP
12	0.21406	-0.03131	0.37959	-0.40252	0.45846	-0.31759	0.37243	-0.25186	CP

Table 5. The Check List Result

Data	Output Prediction	Monitoring		Alert Bar			Alert Sound			Alert Mail		
		Numeric	Line Chart	IO	LS	CP	IO	LS	CP	IO	LS	CP
1	IO	✓	✓	✓								
2	IO	✓	✓	✓								
3	IO	✓	✓	✓								
4	IO	✓	✓	✓								
5	IO	✓	✓	✓								
6	LS	✓	✓		✓			✓				✓
7	LS	✓	✓		✓			✓				✓
8	IO	✓	✓	✓								
9	IO	✓	✓	✓								
10	IO	✓	✓	✓								
11	CP	✓	✓			✓			✓			✓
12	CP	✓	✓			✓			✓			✓

The test carried out using dummy data indicates that the developed intelligent monitoring could perform its functionalities including monitoring, predicting, and alerting. To validate the testing result in order to deal with the functionalities, the check list method is used that describes the value of inputs and the behaviour of the software. Table 5 shows the testing result of its functionalities.

Based on the result shown in Table 5, the monitoring has successfully displayed all of the input data in numeric value and line chart. The alert system has triggered the alert bar, sound and mail if the output prediction goes to LS and CP. The results indicate that the functionalities of the intelligent monitoring have met system requirements. The real data have been tested too, but the output prediction always goes to IO/safe since there is no earthquake event occurrence when the testing was done.

7. Conclusion

This paper has described the intelligent monitoring to predict the building damage index using artificial neural network. The work has been done involving designing the ANN architecture including its learning and testing, designing and developing the intelligent monitoring software in two versions; local and remote monitoring, and testing and validating. According to the result, the developed software could predict the acceleration data and trigger the alert system if the output indicates to moderate safe (LS) and total damage (CP). Applying the system will help the user to determine the building status whenever an earth quake occurred.

Acknowledgment

The authors would like to thank to Politeknik Negeri Semarang, Universitas Riau and Structural Earthquake Engineering Research (SEER) Faculty of Civil Engineering Universiti Teknologi Malaysia for the support given throughout this study.

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