## Response prediction of multistory building using backpropagation neural networks method

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### Response prediction of multi-story building using backpropagation neural networks method

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Abstract. The active ground motion in Indonesia might cause a catastrophic collapse of the building which leads to casualties and property damages. Therefore, it is imperative to design the structural response of building against seismic hazard correctly. Seismic-resistant building design process requires structural analysis to be performed to obtain the necessary building responses. However, the structural analysis could be difficult and time-consuming. This study aims to predict the structural response includes displacement, velocity, and acceleration of multi-story building with the fixed floor plan using Backpropagation Neural Network (BPNN) method. By varying the building height, soil condition, and seismic location in 47 cities in Indonesia, 6345 datasets were obtained and fed into the BPNN model for the learning process. The trained BPNN is capable of predicting the displacement, velocity, and acceleration responses with up to 96% of the expected rate.

#### 1 Introduction

Indonesia is one of the high-risk seismic-zone in the world, which refers to the geographical region with the most active tectonic plate and volcanic activities on earth as known as the Pacific Ring of Fire. Therefore, a high tendency of \$3 png ground motion to occur due to the earthquake in the Pacific Ring of Fire 3 egion. The spectral hazard maps for Sumatra and Java islands was developed by [1, 2]. Two hazard levels for representing 10% and 2% probability of exceedance (PE) in 50 years ground motions were analyzed for Sumatra and Java. The analysis implemented some improvements in seismic hazard by considering the lates 4 seismic activities around Java and Sumatra. The authors also proposed a revision of the seismic hazard map in Indonesian Seismic Code SNI 03-1726-2002 which partially adopts the concept of UBC 1997 [3].

The new revision Indonesian seismic code is as known as SNI 03-1726-2012. According to [4], before 2012, the seismic design criteria for 11 Idings in Indonesia is based on a map with ground motion spectral accelerations of 10% probability of being exceeded (PE) in 50 years. The seismic design criteria and the plan were hazard-based

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without considering uncertainty from the collapse capacity of building 12 includes. Otherwise, in the new seismic design criteria included 2% PE in 50 years, defined as Maximum Considered Earthquake (MCE). The new MCE ground motion parameter for 1.0 second spectral acceleration, site class B with 5% of critical damping as shown in Fig. 1.

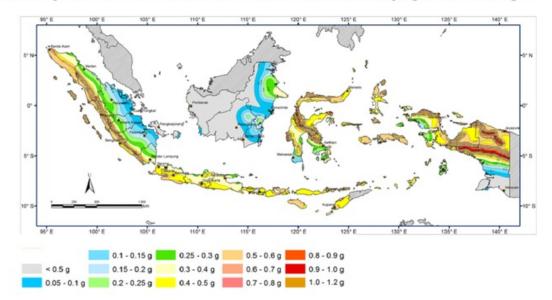


Fig. 1. Spectra design map of Indonesia for 1-second spectral acceleration with 5% [5].

One of the many factors that affect the aftermath of earthquake disaster is the resilience of the infrastructure building against the strong ground motion [6]. Critical infrastructure-structures such as a hospital, school, power plant office, and administrative structure are most likely multi-story buildings which are very prone to seismic loading. During strong ground motion, the multi-story building might collapse in a brittle way that endangers its occupants due to the massive dead weight, especially for Reinforced Cement Concrete (RCC) building. Furthermore, in case the tall building is not appropriately designed will experience excessive displacement (story-drift) that cause discomfort and might damage non-structural components such as partition wall, window, and a door which blocks evacuation passage. Due to these facts, the multi-story building shall be adequately designed to exhibit ductile behavior and controlled deformations during strong ground motion.

Seismic-resistant building design requires structural analysis to be performed first, to obtain some building response characteristics, such as story displacement (drift), velocity, and acceleration. However, such structural analysis could be complicated, especially for 3D building structural models. For complex building structure, the structural analysis will require the involvement of finite element structural analysis program which is very costly and time consuming to learn and operate.

This research aims to predict the structural response includes displacement, velocity, and acceleration of multi-story building in the region of seismic hazard maps of Indonesia using the Backpropagation Neural Network (BPNN) method. The previous study [7] discussed the prediction of structural response based on the seismic hazard maps of Sumatera. The study was successful to predict the story drift of multi-story building in all the capital cities of the provinces in Sumatera. The prediction capability of the BPNN-based system was achieved through a learning process with over 4000 of data sets. Meanwhile, other researchers have applied a Backpropagation Neural Networks to predict response spectra such as [8] and to generate the artificial earthquake such as [9], [10] and [11].

#### 2 Backpropagation Neural Networks

Backpropagation Neural Network (BPNN) is a mathematical model inspired by its biological neural network counterpart. The BPNN system comprises several processing layers and neurons. Just like the biological neural network, the connection and signal transfer between neurons and layers enable the BPNN system to transform the given input signal into appropriate outputs, which is later called prediction.

According to [12], the human neural network comprises billions of interconnecting neurons, which vary in shapes and functionalities depending on their locations in the human body. The neuron is defined as the smallest information processing unit which consists of the dendrite, cell body, axon, and synapse (Fig. 2). Dendrite receives an input signal (external or from other neurons) and transfers it to the cell body. Cell body further transfers the message to the axon, then from axon to synapse. The update signal generated from the synapse may vary in strength depending on the power of the synapse.

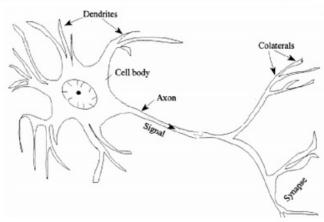


Fig. 2. Biological neural network [12].

The output layer is composed of the output neurons. BPNN neuron's functionality is analog to the biological neuron. The synapse strength in the biological neural network is represented by the weight factor in the BPNN system. The initial rank of the weight factors usually is random, which later modified through a process called BPNN training, iteration, or the learning process. The BPNN learning process requires a set of data to 'train' the BPNN before it is ready for testing. To customarily adopted criteria to evaluate the performance of the BPNN system are Mean-Squared-Error (MSE), and Coefficient of Correlation (R) is computed using (1) and (2), respectively.

$$MSE = 0.5 \left(T_i - Y_i\right)^2 \tag{1}$$

$$R = \frac{n\sum T_{i}Y_{i} - \left(\sum T_{i}\right)\left(\sum Y_{i}\right)}{\sqrt{n\left(\sum T_{i}^{2}\right) - \left(\sum T_{i}\right)^{2}}\sqrt{n\left(\sum Y_{i}^{2}\right) - \left(\sum Y_{i}\right)^{2}}}$$
(2)

where  $T_i$  = target value based on learning data set,  $Y_i$  = predicted output value, and n = the number of data sets.

#### 3 Methodology

The prediction system based on a BPNN analysis, which requires an amount of learning data sets to perform the training, validation, and testing process. In this research, the BPNN data sets were generated by performing structural analysis on several varieties of building the structure model, soil condition, and seismic location. In the following sub-sections, the methodology used in this research will be described in detail.

The multi-story building structure models are reinforced cement concrete (RCC) moment frames combined with shear-walls. In this research, three variations of building height are adopted: 10 stories (Model 1), 15 stories (Model 2), and 20 stories (Model 3), as tabulated in Table 1. The inter-story height is 4.5 m at the base and 4 m at other stories.

Geometry parameters	Model 1	Model 2	Model 3	
Number of bays in the X direction	7	7	7	
Number of bays in the Y direction	6	6	6	
Total floor length in the X direction (m)	42	42	42	
Total floor length in the Y direction (m)	36	36	36	
Number of stories	10	15	20	
Total building height (m)	40.5	60.5	80.5	

Table 1. Building structure model.

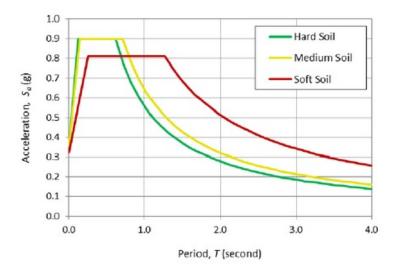


Fig. 3. Seismic response spectrum plot for Banda Aceh City [5].

The responses of the building structure models consist of story-displacement, velocity, and acceleration. The seismic load was included as a seismic response spectrum plot which shows the relationship between the design structure acceleration ( $S_a$ ) and the structure's period of free vibration (T). The  $S_a$  vs. T plot varies with soil condition and seismic location. In this research, 34 capital cities and 13 other cities in Indonesia were selected as a seismic location with three soil conditions (soft, medium, and hard soil). By adopting 47 cities in Indonesia with three possible soil conditions, 141 seismic response spectrum plots were obtained (e.g., Banda Aceh City is shown in Fig. 3). In the study, ten building responses data were generated from modal response spectrum analysis from Model 1, 15 data from Model 2, and 20 data from Model 3, which sums up to 45 data. Therefore, as many as 6345 data sets (141 x 45) were generated from the whole structural analysis process.

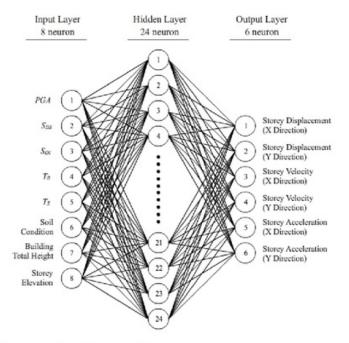


Fig. 4. Proposed backpropagation BPNN architecture.

The proposed BPNN architecture on the prediction of building structure 2 ponse in this research as shown in Fig. 4. The BPNN architecture consists of 3 layers: input layer with eight neurons, a hidden layer with 24 neurons, and an 6 tput layer with six neurons. The input parameters are peak ground acceleration (PGA), design spectral acceleration at short period ( $S_{DS}$ ), design spectral acceleration at 1 second of the period ( $S_{DI}$ ), the lower limit of period that results in maximum acceleration ( $T_0$ ), the upper limit of period that results in maximum acceleration ( $T_S$ ), soil condition, building total height, and storey elevation (base level was not included). Whereas the output parameters are story displacement, velocity, and acceleration in both orthogonal horizontal directions (X and Y).

#### 4 Results and discussion

Table 2. MSE after BPNN learning process.

D	Mean-Squared-Error (MSE)			
Parameters	Training Validation		Testing	
Displacement X	1.09 x 10 <sup>-4</sup>	1.01 x 10 <sup>-4</sup>	1.00 x 10 <sup>-4</sup>	
Displacement Y	1.05 x 10 <sup>-4</sup>	0.96 x 10 <sup>-4</sup>	0.96 x 10 <sup>-4</sup>	
Velocity X	2.05 x 10 <sup>-4</sup>	2.14 x 10 <sup>-4</sup>	1.96 x 10 <sup>-4</sup>	
Velocity Y	1.99 x 10 <sup>-4</sup>	1.99 x 10 <sup>-4</sup>	1.88 x 10 <sup>-4</sup>	
Acceleration X	4.04 x 10 <sup>-4</sup>	4.13 x 10 <sup>-4</sup>	3.80 x 10 <sup>-4</sup>	
Acceleration Y	3.80 x 10 <sup>-4</sup>	3.93 x 10 <sup>-4</sup>	3.43 x 10 <sup>-4</sup>	
Average	2.34 x 10 <sup>-4</sup>	2.36 x 10 <sup>-4</sup>	2.17 x 10 <sup>-4</sup>	

The details on the MSE and R values obtained through the BPNN learning process is tabulated in Table 2 and Table 3 after 1000 epochs during the BPNN learning process. Based on Table 2, the average MSE was calculated as  $2.34 \times 10^{-4}$  for the training phase,  $2.36 \times 10^{-4}$  for validation phase, and  $2.17 \times 10^{-4}$  for the testing phase. Meanwhile, Table 3 shows the best coefficient of correlation (R) was 0.961 for training phase, 0.949 for validation phase and 0.976 for the testing phase.

-	The Coefficient of correlation (R)			
Parameters	Training	Validation	Testing	
Displacement X	0.982	0.981	0.988	
Displacement Y	0.982	0.981	0.988	
Velocity X	0.972	0.964	0.982	
Velocity Y	0.972	0.965	0.983	
Acceleration X	0.928	0.901	0.957	
Acceleration Y	0.928	0.899	0.959	
Average	0.961	0.949	0.976	

Table 3. R details after the BPNN learning process.

#### 5 Conclusions

The comparison of displacement, velocity and acceleration data have been concluded based on MSE and coefficient of correlation (R) amount of the network model. According to the results, the neural networks' method based on the displacement data has the best performance rather than velocity and acceleration data in all process, training, validation, and testing. This is because the displacement is derived from the second time to generate the acceleration. The displacement has more straightforward physic quantity rather than acceleration, so the convergent is approached faster. Furthermore, the BPNN is a very promising tool to provide an early prediction on structural response such as story drift (displacement, velocity, and acceleration at the multi-story building in the region of Indonesia to assist further Finite Element Method analysis.

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