Application of Backpropagation Neural Networks in Predicting Story Drift of Building

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Abstract— **This study utilizes Backpropagation Neural Network (BPNN) to predict the story drift of multi-story reinforced concrete building under earthquake load. Seismic-resistant building design process requires structural analysis to be performed to obtain the necessary building responses. Modal response spectrum analysis is performed to simulate earthquake loading and produce story drift data for further use in the Backpropagation Neural Networks. The BPNN architecture comprises of 3 layers: an input layer, a hidden layer, and an output layer. The input data consist of earthquake load parameters, soil condition, and building geometry, whereas story drift is selected as output parameter. The trained BPNN is capable of predicting story drift of building due to earthquake loading at 96% rate of prediction and the calculated Mean-Squared Errors (MSE) as low as $1.2.10^{-4}$. The high accuracy of story drift prediction can greatly assist the engineer to identify the building condition rapidly due to earthquake loads and plan the building maintenance routinely**

Index Terms—**Backpropogation Neural Networks, Earthquake load, Modal response spectrum, Story drift**

I. Introduction

ONE of the so many factors that affect the aftermath of earthquake disaster is the resilience of the infrastructure building against the strong ground motion. Critical infrastructure building such as hospital, school, power plant office, and governmental buildings are most likely multi-storey buildings which are very prone to seismic loading. During strong ground motion, multi-storey building might collapse in a brittle-way that endanger its occupants due to the massive dead weight, especially for reinforced cement concrete (RCC) building. Other than that, tall building if not designed properly will experience excessive displacement (storey-drift) that cause discomfort and might damage non-structural components such partition wall, window, and door which blocks evacuation passage. Due to these facts, multi-storey building shall be designed properly to exhibit ductile behavior and controlled deformations during strong ground motion.

Story drift is one of the most important limit states in multi-story building structure design. A Building shall not drift excessively to provide better performance and prevent damage to non-structural elements such as walls and doors. Provisions that limit story drift vary depending on which code is used. Frequently, story drift governs the design of structural elements rather than strength. According to [1], story drift can be solved with estimation of displacement modal responses, whereas [2] used the spectral displacement and beam-to-column ratio to determine the story drift of the building. The various methods can be useful for preliminary design of new structures or rapid assessment of existing buildings.

Finite Element Method (FEM) is currently the best available method to analytically calculate the story drift of multi-story buildings. Performing FEM for such complex buildings could be very tedious to be hand-calculated if not practically impossible. To help in faster and more accurate calculations, FEM software is developed and widely available in the market. However, precisely the modeling and running analysis of building structures in FEM software is indeed very time-consuming especially for nonlinear and dynamic analysis.

Though Finite Element Method for structural analysis is accurate, it is relatively slow. To provide an adequate early prediction of story drift building or displacement at a faster rate, Backpropagation Neural Network (BPNN) method may be used. BPNN method is a general prediction tool which is widely used in various fields of application. The BPNN is one of the Artificial Neural Network methods which simplified models of the biological nervous system and have drawn their motivation from the kind of computing performed by a human brain [3]. An Artificial Neural Network is organized into a sequence of layer with full or random connections between the layers. A typical Neural Network is fully connected, which means there is a connection between each neuron in any given layer to each neuron in the next layer. Backpropagation Neural Network is capable of modeling the nonlinear relationship between input and output parameters. BPNN works by processing weighted input data using certain algorithms to produce a desired output [4]. The relationship between neurons in BPNN is represented by weight factors that will be modified through a training process. If sufficient data sets are available and learning algorithm is correctly chosen, the training process will modify the weight factors, by each iteration performed and eventually the desired output will be achieved.

Many researchers have studied the application of Artificial Neural Networks in Civil Engineering such as [5] discussed the prediction of axial bearing capacity of driven piles and [6] for predicting shaft and tip resistances of concrete piles. Meanwhile, the studies about the multi-storey shear structure to predict the health of the building have been studied by [7] and [8]. The previous studies about the

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application of BPNN have been done to predict the damage level on bridges structure [9] and to alert in the bridge monitoring system [10]. In this study the BPNN is used to predict the story drift of reinforced concrete multi-story building under earthquake loading in 34 provinces of Indonesia. Indonesia is one of the highest-risk seismic zone in the world, where is crossed by the Pacific Ring of Fire, which refers to the geographical region with the most active tectonic plate and volcanic activities on earth, such as Krakatau Volcano. This condition causes a high tendency of strong ground motion to occur due to earthquake in the Pacific Ring of Fire region. In 2004, a whopping 9.3 richer-scale mega quake struck Aceh on the Western Coast of Sumatera Island, which then followed by a tsunami that travelled several kilometers inland. In all the aforementioned cases, the property damage was severe and the casualty was huge. The high accuracy of story drift prediction can greatly assist the engineer to identify the building condition rapidly due to earthquake loading and plan the building maintenance routinely.

II. Backpropagation Neural Networks

Artificial neural network (ANN) is a mathematical model inspired by its biological neural network counterpart. The ANN system comprises of several processing layers and neurons. Just like the biological neural network, the connection and signal transfer between neurons and layers enable the ANN system to process the given input signal into appropriate outputs, which is later called prediction. ANN possesses the capability to predict output based on any given input in which the mathematical relationship between the input and output parameter is nonlinear, complex, and often vague. Common multi-layer ANN system comprises of an input layer, hidden layer, and the output layer as shown in Fig. 1. Input layer consists of input neurons that receive external signals (input data). Hidden layer also consists of neurons that receive signals from input neurons and transfer it to the output layer. The number of neurons in hidden layer affects the prediction rate and the ability of the ANN system to cope with nonlinear relationship between variables. Finally, output layer consists of output neurons that represent the output parameters to be predicted. The difference between the predicted output value and the target value (the true value according to learning data set) is the error of the ANN system.

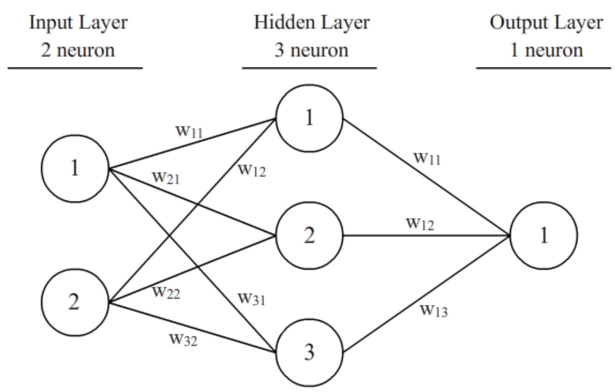

Fig.1. Simple Artificial Neural Network Scheme

ANN neuron's functionality is analogue to the biological neuron. The synapse strength in biological neural network is represented by the weight factor in the ANN system (for example: notated as w_{11} in Fig.1). The initial values of the weight factors are usually random, which later modified through a process called ANN training, iteration, or learning process. The ANN learning process requires a set of data to 'train' the ANN before it is ready for testing. The trained ANN system is expected to possess the capability to predict outputs based on any given inputs at decent accuracy. The commonly adopted criteria to evaluate the performance of the ANN system are Mean-Squared-Error (MSE) and Coefficient of Correlation (*R*).

Backpropagation Artificial Neural Network is one of the most widely used types of ANN. The Backpropagation ANN algorithm consists of two calculation phases: Feed-forward calculation and Backpropagation calculation. In Feed-forward processing, input data is fed into the input layer, then the calculation is continued until it reaches the output layer during the feed-forward calculation. The difference between the predicted output value and the target value is used to calculate the error value. Meanwhile, during the Backpropagation calculation, the error value obtained in the previous phase is used to modify the weight factors of each neuron in the output layer, then the hidden layer. The completion of one Feed-forward and Backpropagation calculation for each data set is called one epoch.

The feed-forward calculation uses (1) and (2) to compute the value of the neuron.

$$\xi_j^l = \sum_{i=1}^{N_{l-1}} w_{ji}^l x_i^{l-1} \tag{1}$$

$$\sigma_j^l(\xi) = \frac{1}{1+e^{-\xi_j^l}} \tag{2}$$

where:
ξ_j^l = net input of neuron *j* at layer *l*;
w_{ji}^l = weight factors between neuron *j* at layer *l* and neuron *i* at layer ($l-1$);
x_i^{l-1} = value of neuron *i* at layer ($l-1$);
N_{l-1} = number of neurons in layer ($l-1$); and
$\sigma_j^l(\xi)$ = Sigmoid transfer function to compute the final value of neuron *j* at layer *l*.

To evaluate the performance of the ANN system before proceeding to the Backpropagation calculation, Mean-Squared-Error (MSE) and Coefficient of Correlation (*R*) are computed using (3) and (4), respectively.

$$MSE = 0.5(T_i - Y_i)^2 \tag{3}$$

$$R = \frac{n\sum T_i Y_i - (\sum T_i)(\sum Y_i)}{\sqrt{n(\sum T_i^2) - (\sum T_i)^2}\sqrt{n(\sum Y_i^2) - (\sum Y_i)^2}} \tag{4}$$

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

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III. Methodology

Backpropagation analysis requires an amount of learning data sets to perform the training, validation, and testing process. In this study, 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.

A. *Building Structure Model*

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

TABLE I
MULTI-STOREY BUILDING STRUCTURE MODELS

Geometry Parameters	Model 1	Model 2	Model 3
Number of bays in X direction	7	7	7
Number of bays in Y direction	6	6	6
Total floor length in X direction	42 m	42 m	42 m
Total floor length in Y direction	36 m	36 m	36 m
Number of storeys	10	15	20
Total building height	40.5 m	60.5 m	80.5M

B. *Seismic Analysis: Modal Response Spectrum Analysis*

In this study, 34 capital cities and 13 other cities in Indonesia were selected as seismic location with 3 soil conditions (soft, medium, and hard soil). By adopting 47 cities in Indonesia with 3 possible soil conditions, 141 seismic response spectrum plots were obtained. One of the seismic response spectrum plots for Banda Aceh City is shown in Fig.2.

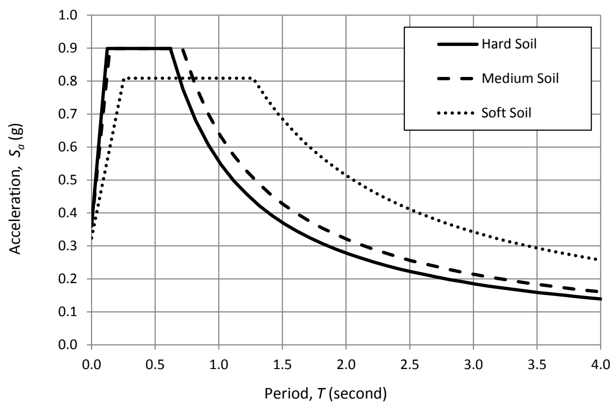

Fig 2. Seismic Response Spectrum Plot for Banda Aceh City

Modal response spectrum analysis was performed to obtain the responses of the building structure models such as storey displacement. The seismic load was included as 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.

For each seismic load, 10 building response 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.

C. *Backpropogation Neural Network Architecture*

The proposed Backpropagation Neural Network architecture on the prediction of building story drift due to seismic load in Indonesia is as shown in Fig.3.

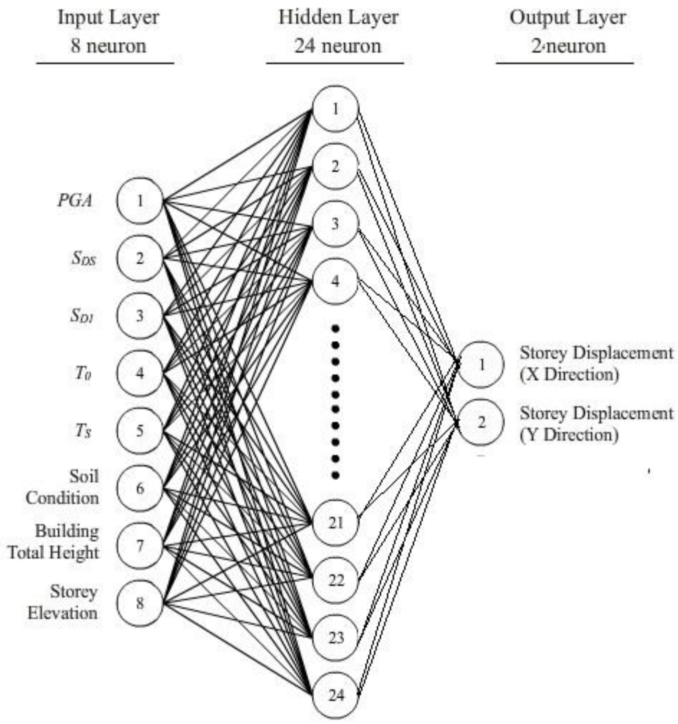

Fig.3. Proposed Backpropagation (BPNN) Architecture

D. *Learning Data Sets for the ANN System*

As stated in previous sub-section of this work, as many as 6345 learning data sets are obtained from the structural analysis and these data sets are fed into the BPNN system for training, validation, and testing process. From the overall data sets, 4590 data sets (72%) are used for training process, 877 data sets (14%) for the validation process, and 878 data sets (14%) for testing.

IV. Result and Discussion

The ANN learning process was conducted by using the following learning parameters:

1. Learning rate = 0.05
2. Number of epochs (iterations) = 1000
3. Momentum coefficient = 0
4. Variable normalization range = 0 – 0.5

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A. *Prediction Criteria: MSE and R*

The details on the Mean Squared Error (MSE) and Coefficient of Correlation (*R*) values obtained through the BPNN learning process is tabulated in Table II and Table III. After 1000 epochs during the BPNN learning process, the average MSE of displacement was calculated as $1.07E10^{4}$ for training phase, $0.985E10^{-4}$ for validation phase, and $0.98E10^{-4}$ for testing phase (Table II). Meanwhile the average R of displacement was calculated as 0.982 for training phase, 0.981 for validation phase and 0.988 for testing phase as shown in Table III.

TABLE II
MEAN SQUARED ERROR (MSE)

Parameters	Mean-Squared-Error (MSE)		
	Training	Validation	Testing
Displacement X	1.09E-4	1.01E-4	1.0E-4
Displacement Y	1.05E-4	0.96E-4	0.96E-4
Average	1.07E-4	0.985E-4	0.98E-4

TABLE III
COEFFICIENT OF CORRELATION (*R*)

Parameters	Coefficient of Correlation (*R*)		
	Training	Validation	Testing
Displacement X	0.982	0.981	0.988
Displacement Y	0.982	0.981	0.988
Average	0.982	0.981	0.988

B. *ANN Learning Process*

The results show that the prediction performance of the trained BPNN is sufficiently accurate, which can also be observed on the Target vs. Prediction Plots for all parameters and learning phase. The Coeffisien of Correlation (R) of Displacement X and Displacement Y were calculated as 0.988 for testing phase as shown in Fig. 4 and Fig.5

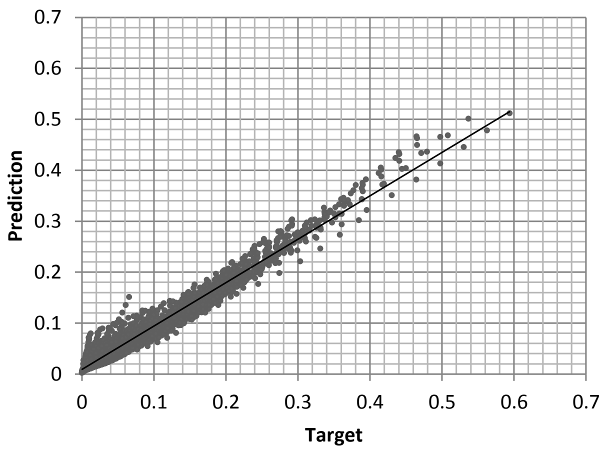

Fig. 4 Displacement X for Testing Phase

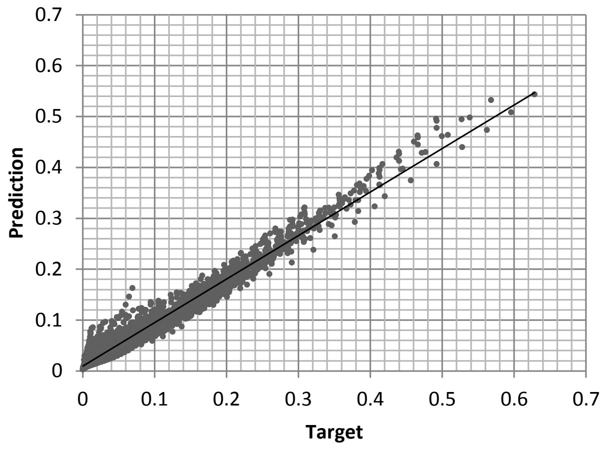

Fig. 5 Displacement Y for Testing Phase

V. CONCLUSIONS

The MSE was calculated as $1.09x10^{-4}$ for training phase, $0.985x10^{-4}$ for validation phase, and $0.98x10^{-4}$ for testing phase. Meanwhile, the coefficient of correlation (R) for testing phase results 0.988 for the testing phase. Both calculated MSE and R value indicate that the prediction performance of the trained BPNN is sufficiently accurate. The BPNN is a very promising tool to provide an early prediction of story drift (displacement) at multi-story building in the region of Indonesia to assist further Finite Element Method analysis.

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