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Development of a FAHP Algorithm Based Performance Measurement System for Lean Manufacturing Company

Anita Susilawati and John Tan

7 pages, DOI 10.18502/keg.v1i1.527

Preface

The 1st Conference on Science and Engineering for Instrumentation, Environment and Renewable Energy (ICoSE) 2015 was held at the Hotel Pangeran Pekanbaru, Indonesia, September 28-29, 2015.

This is a forum for more than 200 researchers, scientists and students from around 9 countries to share the latest research findings and exchange ideas regarding the innovations in measurement systems, and improvements to instrumentation for environmental analysis as well as selected topics in renewable energy. It also provides a medium for direct contacts among researchers and scientists for new international relationships and spark future collaborative research projects. The conference is jointly organized by the University of Riau (UNRI) Indonesia, cellasys GmbH R&D, Institute of Microengineering and Nanoelectronics (IMEN) Universiti Kebangsaan Malaysia and the Technische Universitaet Muenchen (TUM) Germany.

We have received approximately 160 abstracts to be presented in the seminar and around 108 papers are going to a peer-review process by at least two expert referees for a publication in this periodical and 70 papers have been accepted under rigorous and through revisions by editors and reviewers in respected fields. The accepted papers are organized into 7 chapters:

Chapter 1: Measurements, Sensors and Control Systems

Chapter 2: Materials for Electronics, Energy Conversion and Photocatalysts

Chapter 3: Renewable Energy Utilization

Chapter 4: Optoelectronics and Photonics

Chapter 5: Composites

Chapter 6: Environmental Monitoring

Chapter 7: Computational and Modelling

We are grateful to Kementerian Riset, Teknologi, dan Pendidikan Tinggi, Direktorat Jenderal Pembelajaran dan Kemahasiswaan Indonesia, Universitas Riau, Cellasys GmbH, FMIPA UR, Jurusan Fisika FMIPA UR, IMEN Universiti Kebangsaan Malaysia, Indonesian Physical Society (HFI) for providing financing and technical supports to this seminar.

Finally, we would like to take this opportunity to thank also all the members of the organizing committee, all the authors, all the reviewers, and all the local volunteers for their effort and valuable support to make ICoSE 2015 a reality. Special thanks go to the ICoSE staff for their outstanding service.

Conference Paper

The Application of Artificial Neural Networks in Predicting Structural Response of Multistory Building in The Region of Sumatra Island

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Abstract

Artificial Neural Network (ANN) method is a prediction tool which is widely used in various fields of application. This study utilizes ANN to predict structural response (story drift) of multi-story reinforced concrete building under earthquake load in the region of Sumatera Island. Modal response spectrum analysis is performed to simulate earthquake loading and produce structural response data for further use in the ANN. The ANN architecture comprises of 3 layers: an input layer, a hidden layer, and an output layer. Earthquake load parameters from 11 locations in Sumatra Island, soil condition, and building geometry are selected as input parameters, whereas story drift is selected as output parameter for the ANN. As many as 1080 data sets are used to train the ANN and 405 data sets for testing. The trained ANN is capable of predicting story drift under earthquake loading at 95% rate of prediction and the calculated Mean-Squared Errors (MSE) as low as $1.6.10^{-4}$. The high accuracy of story drift prediction is more than 90% can greatly assist the engineer to identify the building condition rapidly due to earthquake loads and plan the building maintenance routinely.

Keywords: Artificial Neural Networks, earthquake load, Mean-Squared Error, response spectrum, story drift

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1. Introduction

Story drift is one of the most important limit states in multi-story building structure design. 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 [1-3]. Frequently, story drift governs the design of structural elements rather than strength.

Finite Element Mehod (FEM) is currently the best available method to analyticaly 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, many FEM softwares specialized for Civil Engineering application are developed and widely available in the market. However, precisely modeling and running analysis for building structures in FEM softwares 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 on story drift at faster rate, Artificial Neural Network (ANN) method may be used. ANN method is a general prediction tool which is widely used in various fields of application, including Civil Engineering. Many researchers have studied the application of ANN in multystorey shear structure to predict the health of building, such as [4] and [5]. In this study, the ANN is used to predict story drift of reinforced concrete multi-story building under earthquake loading in the region of Sumatra Island. The Sumatra Island is located between the Indo-Australian and Southeastern Eurasian plates. This region has fault slip up to 15 meters occurred near Banda Aceh, Sumatra [6].

Artificial Neural Networks are simplified models of the biological nervous system and have drawn their motivation from the kind of computing performed by a human brain [7]. An Artificial Neural Network is organized into a sequence of layer with full or random connections between the layers. A typical Neural Networks is fully connected, which means there is a connection between each neuron in any given layer to each neuron in the next layer. Artificial Neural Network (ANN) is capable of modeling nonlinear relationship between input and output parameters. ANN works by processing weighted input data using certain algorithm to produce a desired output [8]. The relationship between neurons in ANN 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. The high accuracy of story drift prediction can greatly assist the engineer to identify the building condition rapidly due to earthquake loading in the region of Sumatra Island and plan the building maintenance routinely.

2. Methodology

2.1. Modal Response Spectrum Analysis

The data sets to be fed into the ANN are collected through a Modal Response Spectrum (MRS) analysis. The MRS analysis is performed using Finite Element Method software. The selected reinforced concrete (RC) building models are: Model 1 (10 stories or 40.5 m in total height), Model 2 (15 stories or 60.5 m in total height), and Model 3 (20 stories or 80.5 m in total height) as shown in Fig. 1. For all models, the floor plan is identical (Fig. 2).

The reinforced concrete building models are already proportioned to satisfy the dynamic requirements provided in SNI 1726-2012 [3]. The RC building models are subject to earthquake loading. The design response spectrum functions are obtained from the lastest Seismic Hazard Map for Indonesia. Eight capital cities and three other cities in Sumatera Island are selected as seismic location (eleven in total). By taking three ground conditions (hard, medium, and soft) into account, 33 response spectrum functions are obtained. Then for 3 building models, a total of 1485 story drift data sets are generated from all stories in MRS analysis.

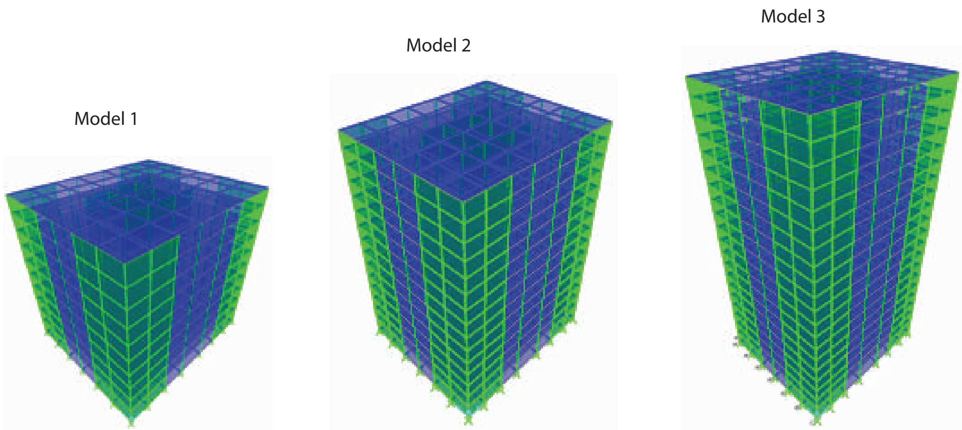

Figure 1: Reinforced Concrete Building Models.

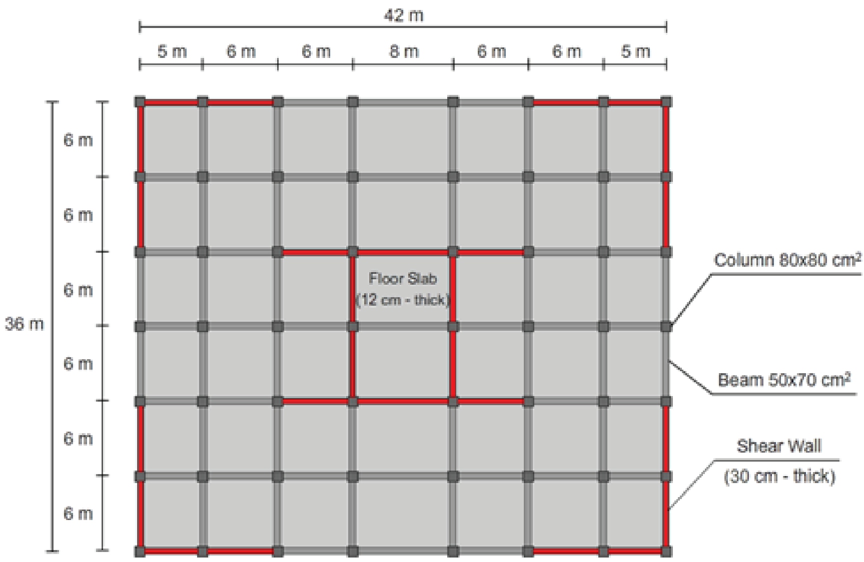

Figure 2: Floor Plan of Reinforced Concrete Building Model.

2.1.1. ANN Architecture

The Neural Network used in this study is Backpropagation ANN (algorithm details can be found at [9]). The ANN architecture consists of 3 layers: input layer, hidden layer, and output layer (Fig. 3). Input layer contains 8 neurons which represent 8 input parameters: 5 earthquake response spectrum function parameters (*PGA*, S_{DS}, S_{D1}, T_0, *Ts*), ground or soil condition, and 2 geometric characteristics (total building height and *i*-th story elevation). Whereas output layer has 2 neurons, that is, to represent story drift in both X and Y horizontal direction. The target story drift data obtained from modal response spectrum analysis is fed into the ANN, and then errors and rate of predictions are calculated. The number of neurons in hidden layer and training parameters such as learning rate, momentum coefficient, and variable normalization range are selected by trial and error to achieve highest rate of prediction. With this architecture, the neural network is intended to learn the capability to predict story drift for any given elevation of the RC building models.

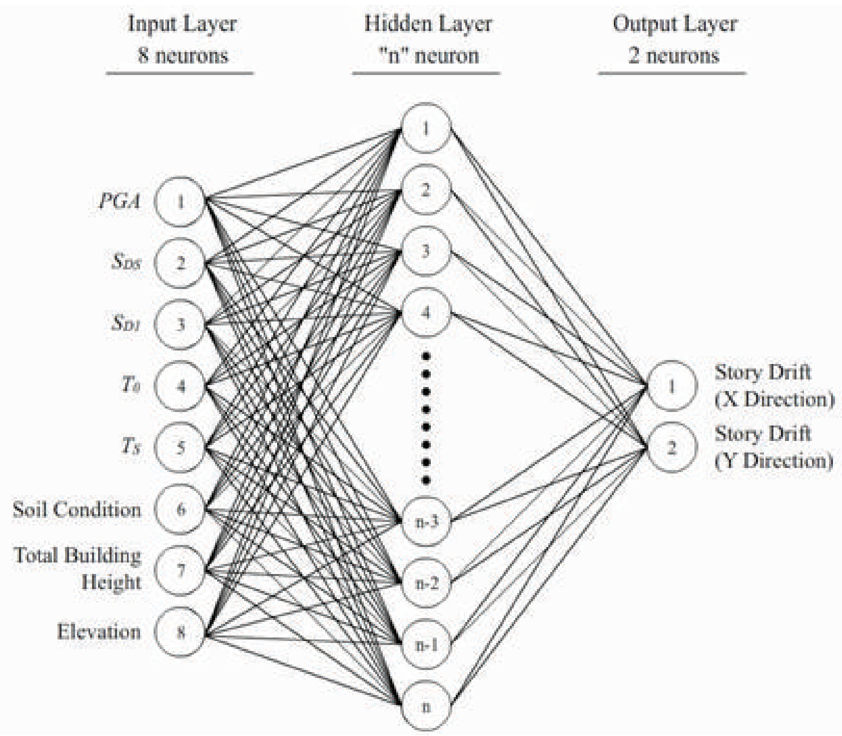

Figure 3: ANN Architecture to Predict Story Drift.

Num.	Seismic Location	Input Parameters								Output Parameters	
		PGA (g)	S_{DS} (g)	S_{D1} (g)	T_0 (sec)	T_s (sec)	Soil Con-dition	Building Height (m)	Eleva-tion (m)	Target Story Drift (X Direction)	Target Story Drift (Y Direction)
1.	B. Aceh	0.621	0.899	0.557	0.124	0.619	0	40.5	4.5	0.0067	0.0075
2.	B. Aceh	0.621	0.899	0.557	0.124	0.619	0	40.5	8.5	0.0146	0.0161
3.	B. Aceh	0.621	0.899	0.557	0.124	0.619	0	40.5	12.5	0.0237	0.0260
4.	B. Aceh	0.621	0.899	0.557	0.124	0.619	0	40.5	16.5	0.0338	0.0368
5.	B. Aceh	0.621	0.899	0.557	0.124	0.619	0	40.5	20.5	0.0442	0.0480
6.	B. Aceh	0.621	0.899	0.557	0.124	0.619	0	40.5	24.5	0.0548	0.0594
...	...	...	...	...	...	...	...	...	...	...	...
1077.	B. Lampung	0.369	0.604	0.587	0.195	0.973	2	80.5	68.5	0.2385	0.2526
1078.	B. Lampung	0.369	0.604	0.587	0.195	0.973	2	80.5	72.5	0.2542	0.2691
1079.	B. Lampung	0.369	0.604	0.587	0.195	0.973	2	80.5	76.5	0.2695	0.2852
1080.	B. Lampung	0.369	0.604	0.587	0.195	0.973	2	80.5	80.5	0.2846	0.3009

Table 1: Story Drift Data Sets for ANN Training Process.

3. Discussion

The story drift data sets obtained from MRS analysis is tabulated in Table 1 and Table 2. The 1080 data sets in Table 1 is related to 8 capital cities in Sumatera Island as seismic location, whereas another 405 data sets in Table 2 is related to 3 other cities in Sumatera Island as seismic location. Table 1 and Table 2 is used for ANN training and testing process respectively.

Based on trial and error process, the ANN achieve the lowest error with 24 neuron at hidden layer and the following training parameters; learning rate 0.1, momentum coefficient 0.1, variable normalization range 0 ~ 0.5.

Num.	Seismic Location	Input Parameters								Output Parameters	
		PGA (g)	S_{DS} (g)	S_{D1} (g)	T_0 (sec)	T_s (sec)	Soil Con-dition	Building Height (m)	Eleva-tion (m)	Target Story Drift (X Direction)	Target Story Drift (Y Direction)
1.	Dumai	0.143	0.221	0.22	0.2	0.998	0	40.5	4.5	0.0017	0.0019
2.	Dumai	0.143	0.221	0.22	0.2	0.998	0	40.5	8.5	0.0036	0.0042
3.	Dumai	0.143	0.221	0.22	0.2	0.998	0	40.5	12.5	0.0058	0.0067
4.	Dumai	0.143	0.221	0.22	0.2	0.998	0	40.5	16.5	0.0083	0.0095
5.	Dumai	0.143	0.221	0.22	0.2	0.998	0	40.5	20.5	0.0109	0.0124
6.	Dumai	0.143	0.221	0.22	0.2	0.998	0	40.5	24.5	0.0135	0.0153
...	...	...	...	...	...	...	...	...	...	...	...
402.	Bukittinggi	0.611	0.915	0.969	0.212	1.059	2	80.5	68.5	0.3936	0.4172
403.	Bukittinggi	0.611	0.915	0.969	0.212	1.059	2	80.5	72.5	0.4195	0.4444
404.	Bukittinggi	0.611	0.915	0.969	0.212	1.059	2	80.5	76.5	0.4448	0.4710
405.	Bukittinggi	0.611	0.915	0.969	0.212	1.059	2	80.5	80.5	0.4697	0.4970

Table 2: Story Drift Data Sets for ANN Testing Process.

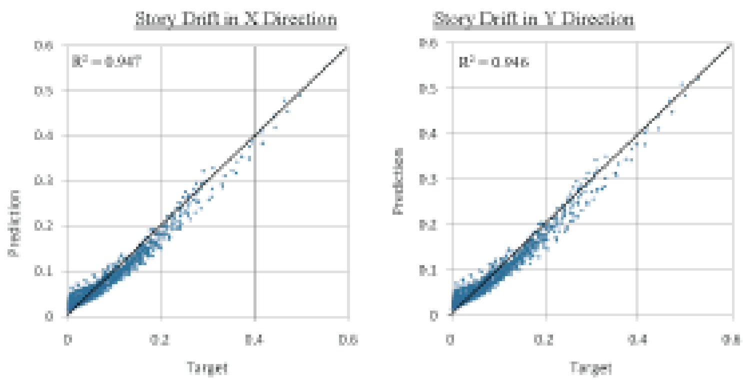

Figure 4: Target vs. Prediction Plot for Story Drift at Training Process.

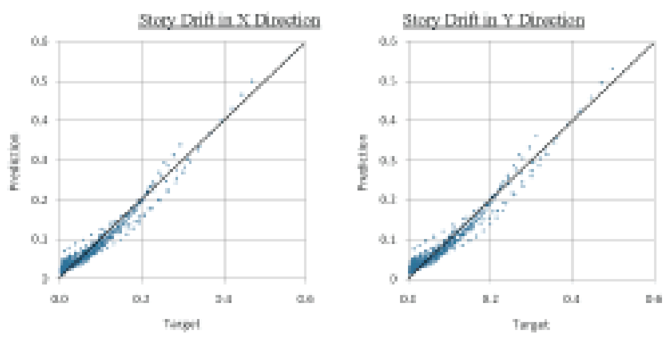

Figure 5: Target vs. Prediction Plot for Story Drift at Testing Process.

After 5000 iterations with the configurations stated above, the calculated MSE at training and testing process is 1.7x10^{-4} and 1.9x10^{-4}, respectively. Fig. 4 and Fig. 5 shows the target vs. prediction plot for story drift at training and testing process. From the plots, it can also be seen that the trained ANN has 95% of prediction rate, which indicates that the trained ANN is capable of predicting story drift at adequate accuracy especially at higher elevation on the building.

4. Summary

After 5000 iterations during ANN training with 1080 data sets, the rate of prediction is calculated as high as 95 percent and MSE is $1.6\text{x}10^{-4}$. From this study, it can be concluded that ANN is a very promising tool to provide early prediction on structural response such as story drift at multi-story building in the region of Sumatra Island to assist further FEM analysis.

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