Inelastic Seismic Response of RC Buildings: an Artificial Neural Network Model

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***Abstract*—The current National Structural Code of the Philippines (NSCP) has been revised to address seismic excitation in building design. However, previous research demonstrates that strict adherence to the code may not provide adequate structural damage protection. To design resilient structures, it is necessary to consider the non-linear behavior of materials. However, the computational requirements of nonlinear time history analysis present a significant challenge. Despite efforts to revise the National Structural Code of the Philippines (NSCP) to address seismic excitation in building design, previous research shows that this may not provide sufficient structural damage protection. To address this challenge, this study presents a machine learning approach to predict the inelastic seismic response of reinforced concrete (RC) buildings in the Philippines through the implementation of an artificial neural network model. The study involved the development of 900 building models, which were subjected to both linear analyses using the equivalent lateral force (ELF) procedure and non-linear time history analysis (NLTHA). The resulting dataset was used to train an Artificial Neural Network (ANN) model to predict the maximum inter-story drift ratio (MIDR) and serve as the primary engineering demand parameter (EDP) to evaluate the damage and performance levels. A web-based application was also developed, leveraging the ANN model as the computational basis.**

Keywords—artificial neural network, reinforced concrete, structural damage, inelastic response, earthquake

I. Introduction

The Philippines is a country situated in the Pacific Ring of Fire where about 90 percent of all seismic activities in the world happens [1]. Because of this, the country experiences a lot of earthquakes resulting in significant damage to buildings [2]–[4]. The National Structural Code of the Philippines (NSCP) received multiple critical updates to address the design of buildings experiencing severe seismic excitation [5]. But several studies have shown that following the code provisions, although safe against collapse, may not protect the structure against structural damage [4], [6], [7].

Reinforced concrete (RC) is one of the most used building materials in the country. Following initiatives in sustainable construction [8], structural engineers are tasked to design RC structures with specified levels of performance [5], [9]–[12] when subjected to such hazards. Calculating the non-linear or inelastic response (e.g., inelastic displacements) of a building is a must to predict the amount of damage that a structure can withstand. In the calculation of the inelastic response, non-linear time history analysis (NLTHA) is often used. But such a calculation technique is computationally cumbersome and needs computers with fast computational capabilities. A faster method of analysis is needed to mitigate delays in the engineering process.

This study follows the development of a deep feed-forward artificial neural network (ANN) model to predict the inelastic seismic response of RC buildings. ANNs have been applied to numerous engineering problems [13], [14]. A web-based software application utilizing the ANN model was developed to assess the damage and performance level of buildings.

II. Methodology

A. *Definition of Model Parameters*

30 sets of structural parameters, together with 30 sets of seismic parameters were randomly generated from a typical range of values. A total of 900 building models will be generated for structural analysis.

The structure parameters considered in this study are number of spans in both directions, number of stories, span lengths, story height, ground floor height to typical story height ratio, concrete strength, main reinforcement strength, confinement strength, floor superimposed dead and live loads, roof dead and live loads, wall thickness, column steel ratio, beam steel ratio, confinement ratio for columns, and confinement ratio for beams. Also, derived parameters such as concrete elastic modulus, shear modulus, total building height, typical floor area, and approximate story stiffness were considered in the study.

The seismic parameters are seismic source type, seismic source distance, soil profile type, and seismic zones. Seven randomly selected earthquake ground motions [5], [9] are extracted from the PEER NGA-West2 strong ground motion database [15] for each set of data and spectrally matched to the design spectra using a wavelet transform algorithm [16].

The structural models are built using OpenSees [17] and the OpenSeesPy library [18]. The models were fully fixed to the ground and the effects of infill walls neglected. Only the frame members (columns and beams) were considered as members of the lateral force-resisting system (LFRS).

B. *Structural Analysis of Building Models*

Structural analysis was conducted to identify both the linear behavior and the non-linear behavior of the sample buildings. The code-based procedure (CBP) for the inelastic response is:

$$\Delta_M = 0.7R\Delta_S \tag{1}$$

where Δ_M is the maximum inelastic displacement, R is the response modification factor and Δ_S is the linear displacement [5], [9]. The linear behavior was analyzed using the equivalent lateral force (ELF) procedure. The seismic response in both directions were combined using the square root sum-of-squares (SRSS). The inelastic response of the models was determined by adopting a distributed plasticity model with five integration points. Fiber elements [19], [20] were used to set the non-linear properties of the sections. The material constitutive models were based on [21], [22] and [23]. The matched ground motions were applied in the two primary directions as transient loads. The average response from seven different ground motion [5], [9] time histories was recorded. The maximum inter-story drift ratio (MIDR) was calculated for each model and served as the main engineering demand parameter (EDP) to identify the performance and damage levels (Table I) [10].

TABLE I. MIDR VS DAMAGE AND PERFORMANCE LEVELS

MIDR, %	Damage Level	Performance Level
< 0.2	Negligible	Fully Operational
0.2 to 0.5	Light	Operational
0.5 to 1.5	Moderate	Life Safety
1.5 to 2.5	Severe	Near Collapse
> 2.5	Complete	Collapse

C. *Development of Artificial Neural Network Model*

The hyperparameters like network topology (number of hidden networks and number of neurons), activation functions [24], and training algorithms [25]–[27] were varied. The hyperparameters were optimized using the Hyperband search algorithm [28] using the mean squared error (MSE) as its scoring criteria [29].

Feature analysis [30] were employed to reduce the number of features. The outliers for the MIDR are removed, then transformed or scaled to get a normal distribution. Redundant features based on a 90% correlation were eliminated and wrapper method of feature elimination [31] was done to select the best features. One-hot encoding was used for the categorical features. The processed data was randomly assigned into three groups: 70% for training, 15% for validation, and 15% was reserved for evaluation. The permutation importance algorithm [32] was then utilized to rank the contribution of each input feature.

D. *Evaluation of the Model*

Using the evaluation data set, the best ANN model identified from the hyperband search was compared with the CBP. The correlation coefficient of both methods with the results of the NLTHA was compared.

E. *Software Application Development*

A static web-based application was programmed comprised of different input boxes for the different structural parameters and seismic parameters. The ANN model was used for the calculation of the predicted MIDR together with the performance level of the building.

III. RESULTS AND DISCUSSION

The main objective of this study is to develop a tool utilizing an artificial neural network model that will predict the structural damage on RC buildings expressed via the MIDR.

RC Building Models

900 different building models were produced. The generic geometry of the models is shown in Fig. 1. The natural periods of the models are shown in Fig 2. The distribution of fundamental periods indicates that the models have good variation. A wide variation is necessary for the ANN model to be representative of structures within the range of parameters considered.

A. *Structural Response*

Each model was analyzed and the MIDR computed (Table II). The outliers from this MIDR data were eliminated resulting in 854 rows of data remaining. The minimum MIDR is 0.03% and the maximum is 3.86%. The mean MIDR is 0.75% with a standard deviation of 0.73%.

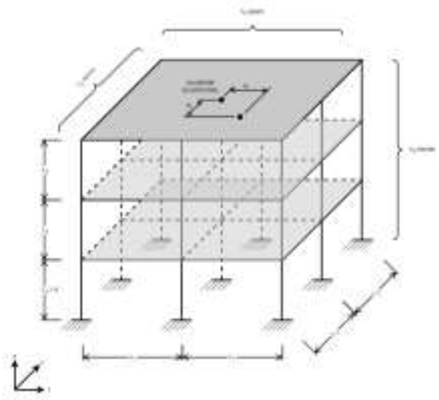

Fig. 1. Generic building model. The building models adopted in this study are of regular structure with equal spans and only accidental eccentricities considered

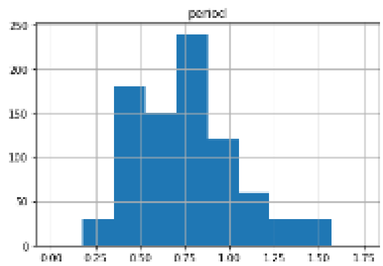

Fig. 2. Distribution of calculated natural periods for the building models

TABLE II. LINEAR AND NON-LINEAR MIDR RESULTS

Response	Min	Max	Mean	SD
Linear MIDR	0.02	0.89	0.18	0.12
Non-Linear MIDR	0.03	3.86	0.75	0.73

B. *Best ANN Model Parameter*

After feature analysis, the set of best features include story stiffness, column and beam steel ratios, floor area, roof live load, concrete compressive strength, building height, seismic source distance, seismic source type, soil profile, and seismic zone.

The Hyperband search yielded the following results as shown in Table III. The best ANN model topology is shown in Fig. 3.

TABLE III. RESULTS OF THE HYPERBAND SEARCH FOR HYPERPARAMETER OPTIMIZATION

Hyperparameter	Best Model	2nd Best Model	3rd Best Model
No. of Hidden Layers	8	4	3
No. of Neurons per Hidden Layer	90	90	50
	100	30	10
	50	60	90
	20	80	-
	50	-	-
	20	-	-
	10	-	-
	60	-	-
Activation Function	ReLU	ReLU	Sigmoid
Optimizer Algorithm	Adam	RMSProp	Adam
MSE	0.0295	0.0355	0.0371
Epochs	23	22	59

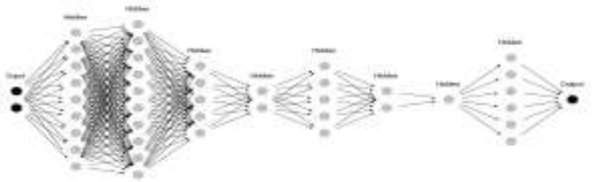

Fig. 3. Network topology schematic of the best ANN model. The number of neurons in the input layer and each hidden layer shown represents ten units

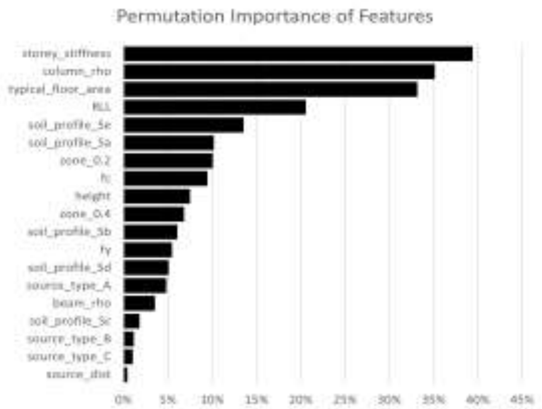

Fig. 4. Permutation feature importance scores

The models utilizing the ReLU activation function (best and 2nd best models) converged faster than the 3rd best model which uses a sigmoid activation function. This is expected since the ReLU was developed as an improvement to logistic type activation functions like the sigmoid and tanh functions.

The input features were ranked based on permutation importance algorithm. From Fig. 4, the most important features are the story stiffness, column steel ratio (column_rho), and typical floor area.

C. ANN Model vs CBP

It can be seen in Fig. 5 that the scatter of the ANN model is less than the CBP, especially in the lower drift range. However, the scatter of the results is higher in the larger drift range for both procedures. The correlation coefficients are 95.31% for ANN and 76.88% for code-based results.

D. Software Application

A custom software application was developed and deployed at https://sdpann.engrleir.com/. Sample calculation results are shown in Fig. 6.

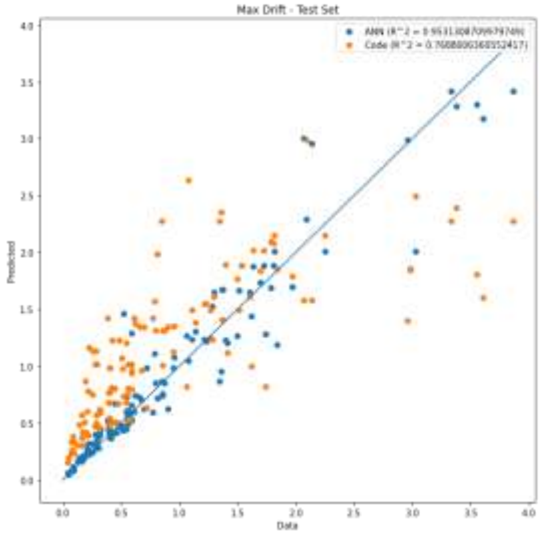

Fig. 5. Evaluation data from NLTHA vs Predicted MIDR of the ANN and CBP. The scatter plot shows a correlation of 95.31% for the ANN while 76.88% for the CBP

Fig. 6. Sample results of the software application

IV. CONCLUSIONS AND RECOMMENDATIONS

The ANN model showed a better performance than CBP. A web-based software application was developed to implement the model, which serves as a tool in predicting the MIDR, damage, and performance level of RC buildings during earthquakes. Additionally, it is recommended to consider the effects of masonry walls, other types of LFRS, higher mass eccentricities, other material constitutive models, and soil-structure interaction in future studies. Overall, this study provides a foundation for future research on utilizing ANNs to improve the understanding of structure response.

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