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Predicting the Seismic Response of Reinforced Concrete Structures Using Artificial Neural Networks

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ABSTRACT

The implementation of Artificial Neural Networks (ANNs) in the prediction of seismic behavior of Reinforced Concrete (RC) structures once revealed to seismic events is described. An ANN system is developed trained and validated leveraging the existing evaluation details obtained from the relevant documentation on the RC structural elements. Studies pertaining to measure the magnitude of vibration-induced structural damages involve using the Finite Element Method (FEM) model [1]. FEM is appropriate while evaluating a limited number of defined structural elements while is ineffective for wider assets. Influenced by these limitations, the model employed Artificial Neural Networks to introduce a specific model for estimating earthquake-induced damages. Modeling earthquakes technology is a compute complex domain whereby ANNs could be employed during stationary or adaptive loads to simulate the architectural response. Performance Based Design (PBD) is the latest concept in structured framework earthquake engineering wherein structural efficiency is evaluated for numerous risk scales, demanding considerable computational requirements. ANNs' projected structural contribution could be included in the PBD model while conducting comprehensive analyzes with a view to minimizing unnecessary computational costs [2]. The ANN's efficiency was tested utilizing multiple scenarios, and thus the ANN was determined to be equipped to predict damages effectively.

Keywords – Artificial neural network, Structural damages, Earthquakes, Finite element method, Performance based design

1. INTRODUCTION

In construction applications, Reinforcing Concrete (RC) is deemed among the most commonly utilized construction materials with a prominent element in the construction of the structure. Estimating the seismic hazard of these buildings on a regional spectrum mostly as significant aspect in any damage assessment is an expensive, time consumption, and challenging process, especially in moderately advanced nations. Many historic structures in earthquake zones would not meet the criteria of contemporary architecture codes, and therefore have to be updated to an acceptable standard [3]. The Performance Based seismology Designs (PBSD) has been the main valuable development principle for engineers to intentionally monitor structural damages scales under reasonable limits throughout massive earthquake which requires theoretical and practical structural risk evaluation. Many hazard simulations also sought to address the discrepancy among architectural efficiency and damages rates [4]. A tool for predicting earthquakes-induced damages using ANNs is investigated in this work which can be extended to a broader category of infrastructure susceptible to modifying floor vibrations. [5] The method would be to define both the architecture and field movement that used a combination of structure and grounds momentum attributes, thereby enabling for representation of a diverse variety of circumstances [6]. By using outcomes of the computational models, an optimization between the structural and floor movement features and the indexes of damages were therefore developed with an ANN [7].

2. LITERATURE SURVEY

The neural network has evolved during the past two decades as a versatile method which might be employed in several technology implementations to substitute time-consuming mathematical operations. In the previous several research findings have tried to analyze the non-linear seismic behavior subjected to various loading situations of surrogate modeling techniques of the category of neural network models. Neural network applications for smart system recognition and controlling were explored [8] wherein piezoelectric actuators were used to inhibit the movements of a construct with girder board [9] addressed experiments exploring modeling and controlling strategies through the implementation of soft computational approaches to inhibit movement of two-dimensional elastic surface structures. A complex time-delay fuzzy logic wavelet neural network concept was established in [10] of nonparametric system recognition, whereas the primary focus of the project was to analyze the capacity of multi - dimensional neural networks to predict the non - linear correlation between structural, grounds movement variables and the hysteretic energy needs in frame-resistant steel moments.[11] presented triple wavelet-dependent Damages Sensitive Features (DSFs) that are classified as wavelet energy functions over specific frequencies as well as periods. Such DSFs may be considered for seismic vulnerability evaluation

3. PERFORMANCE BASED DESIGN

Most earthquake model standards follow the procedural conceptual design that draws into account sites specification, initial and ultimate development phases. The durability of the system is assessed at one limitation condition as per a procedural model definition involving living-safety that uses a response spectrum-based loads contributing to single degree of seismic risk. Additionally, the level of dependability limitation is generally tested to guarantee that the system does not shift or pulsate excessive. At the another extreme, PBD is a specific methodology to the earthquake analysis of building structures, that involves the reliability of the structure following construction, besides the location of the sites and evaluation of the designing process, in attempt to guarantee a robust and consistent structural performance to earthquake forces throughout its lifespan.

4. STRUCTURE OF ARTIFICIAL NEURAL NETWORKS

The segment describes conceptual and analytical features of the Artificial Neural Networks (ANNs). Specific attention is provided to a probabilistic algorithms suggested for the implementation of an accurate and stable ANN that could predict RC architectures' seismic performance. ANNs are designs of pattern recognition, designed via a training method for a particular task. Trained ANN traces input information quickly into the desired output quantity and can therefore be included as met models that enhance the computation time of a mathematical analysis phase

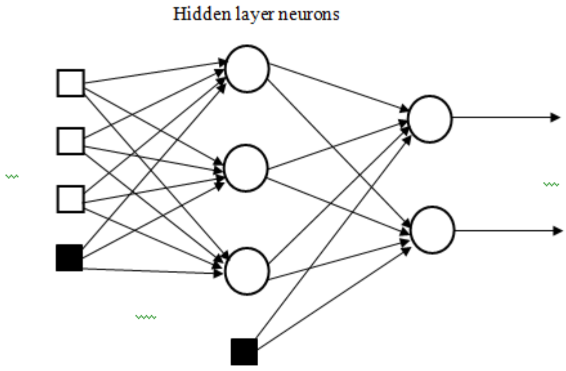

Fig.1 Layout of ANN using Back-Propagation Algorithm

In back-propagation algorithm, the revised loads could be recursively determined employing the corresponding equations:

$$W_{k+1} = w_k - [J^T(w_k)\,J(w_k) + \lambda_k I]^{-1} J^T(w_k)\,e(w_k) \ldots (1)$$

Here subset 'k' signifies the stage for iteration, and 'λk' is a scalar which regulates the features of convergence. The Leven berg Marquardt algorithm is the Gauss Newton process when λk is equivalent to 0. For this research work, all BP neural networks are trained using the Leven berg Marquardt methodology, with the authentication statistics of early-stop criteria. That barred the network from over-fitting its data on training. Entire computations for ANN have been carried out using the Mat lab Neural Network toolset (Mat lab, 2013)

5. SELECTION OF STIMULATION MODEL

Remotely, ground surveys were undertaken to examine historic structures and to discover about architectural sketches, descriptions as well as other relevant information to comprehend the structural features. Individuals residing in high elevated apartments will suffer enormous economic losses from prospective seismic. On the alternative, investors will not be financially stable sufficiently to solve currency losses besides low-rise residential buildings. In addition, in India the demographic is growing with each day. In India, high-rise apartments have been the sole choice for accommodating the rapidly growing community increase, spatial constraints related to population urbanization. Four story dwellings are thus important to construct following careful but also precise inspection of the major failure.

6. ANALYTICAL MODELING

The process consists of identifying a series of appropriate variables which represented the characteristics of the Structural members and floor movements. Next, nonlinear RC framed structure FEM analyzes was performed utilizing a set of seismic surface history records and risk indexes estimated to measure the degree of damages incurred during the earthquakes.

6.1 Factors for structures and ground motion

The architectural features included the count of stories, quantity of bays, Initial storey elevation, inter - storey length for the subsequent stories, bay width, beam thickness for first two stories, columns size for initial two stories, beam thickness for the subsequent stories, columns size for the subsequent stories, column strengthening proportion, columns reinforcement ratio, strength of concrete and damping ratio. The endorsed quantities for variables also including framework geometry beam and columns reinforcement ratios, concrete strength as well as damping ratios are shown in Table 1 and therefore Table 2 requires the two beams/columns dimensions to be identical. For structures of 5 stories or more it was deemed quite probable that the dimensions of the bottom and top beams or columns could vary widely.

Table 1: Variables employed for numerical simulations

Variables	Ranges
Height of first storey (m)	3.0 - 4.5
Height of subsequent storey (m)	3.0 - 4.0
Strength of concrete (M Pa)	30 – 40
Reinforcing ratio of beams	0.008 – 0.020
Reinforcing ratio of columns	0.010 – 0.050
Damping ratio (%)	2 - 5
Width of bays (m)	5.0 - 7.0

Table 2: Design Specifications for the structural elements

Variables	Number of storey/ No. of bay		
	3/2,3/3,3/4,4/4	5/3,5/4	6/3,7/4
d1 (m)	0.4 – 0.55	0.5 – 0.65	0.55 – 0.70
c1 (m)	d1+0.1	d1+0.1	d1+0.1
d2 (m)	d1/d1-0.05	d1-0.05/d1-0.075	d1-0.05/d1-0.075
c2 (m)	d2+0.1	d2+0.1	d2+0.1

6.2 Engineering Demand Parameters (EDPs)

The commonly regarded EDPs are presented in Table 3 these were widely implemented when designing and evaluating systems dependent on results.

Table 3: Selected EDPs

Type	EDPs
Structural EDP	Maximum Inter-Story Drift Ratio. (MIDR)
Non-structural EDP	Maximum Floor Acceleration. (MFA)

6.3 Damage Index

Damage Index (DI) of reinforced concrete structures was being analyzed employing multiple techniques suggested by various investigators for reinforcement material components to determine DI. The structures extend of damages as seen in Table 4 have been examined in both x and y directions. In addition, comprehensive risk evaluation of the single-degree freedom method (SDOF) and also the multiple-degree freedom method (MDOF) of reinforced concrete structures has been conducted on to create a correlation among sustaining and disruptive damages as a factor of strength and extent of ground shaking. Numerous techniques were being approximated by many investigators to predict structural DI of structures utilizing single or multiple EDPs as predictor factors. Capacity planning suggests layout theory and practice for some structural elements that are permitted to fall in the similar expected manner and other elements stay unscathed.

Table 4: Damage indexing

Damage index	Level of damage	Condition of structure	Structural look
>1.0	Collapse	Damage	Total collapse
0.4-1.0	Severe	Past Restoration	Extensive crushing of concrete reinforcements
<0.4	Moderate	Repairable	Large fracture and spalling of concrete elements

6.4 Predictive model constructed on ANN

A predictive method centered on ANN was established which has Inter-Storey Drift (IDR) (percent), joint spinning(radian), ductility, maximum roof movement (m),hardness (kN/m) and degenerated hysteretic energies (kN m) as input variables gathered through various normal and unconventional Rc structures. ANN simulation using neural network toolbox was performed in MATLAB (2013) framework. The software distribution of ANN system training and validation were conducted according to [12]. The system was built of data of 75percent and validated with data of 25 percent. The neural network based design has been configured customized trial and error methods with nine figures of neurons in hidden layer. Five estimated coefficients indicated the efficiency of the proposed algorithm: Mean Absolute Deviation (MAD), Mean Square Error (MSE), Rooted MSE (RMSE), and Mean Absolute Percent Error (MAPE) including linear correlation coefficient (R). Optimization of Levenberg–Marquardt and weighted processing method of back propagation are used for prediction analysis of the training effectiveness.

Table 5: Statistical variables of ANN model

Datasets	Variables			
	MAD	MSE	MAPE	R
Training	0.026	0.004	5.27	0.94
Testing	0.051	0.007	10.04	0.92

Table 6: Rating of response variable

Variable	IDR	Joint spin	Ductility	Roof movements	Hardness	Degenerated hysteretic energies
correlation	2	1	4	3	5	6
connection weighted strategy	5	1	2	3	4	6

Table 5 describes numerical analysis of prospective ANN model. Table 5 empirical measures propose a good estimate of DI by the ANN method. In addition, the comparative value or rating of response variable was also identified from the correlation sequences and connection weighted strategy as seen in Table 6. From Table 6 it can be perceived that joint movement is by far the key important variables on DI as per the connection weighted strategy. The comparative rating of the input variables is the joint spin, ductility, maximum roof movement, rigidity, IDR and degenerated hysteretic energies as per the connection weighted strategy. From Table 6 it is concluded that joints spinning is the main crucial consideration, and the least relevant hysteretic energies degenerated. Of the various EDPs, only hardness seems to have a negative correlation with DI as illustrated in the Neural Interpretation Diagrams in Figure 2 that is a physically supported depiction of the function of damages. Whenever a building vibrates while earthquake tremor, it disperses hysteretic energies by forming small to large fractures dependent on the architectural potential and requirement of the occurrence. When fracture occurs in a system it lacks its durability leading to hardness deterioration.

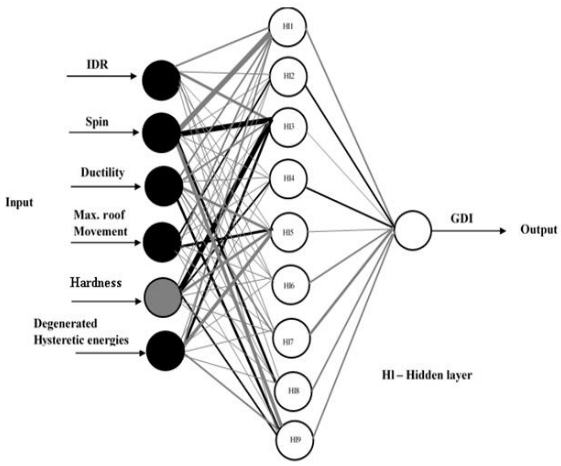

Figure 2: ANN model neural interpretation

7. CONCLUSION

For the building's performance-oriented development strategy, damaged status evaluation through its present condition is important because it relates to the building's established residual capacity from where the required restoration or servicing effort to enhance efficiency in its prolonged expected lifespan may be rendered. In this analysis, regarding highest fragile members, a creative methodology was suggested which predominantly decreases operational period and commitment of both static and dynamic architectures. A novel empirical formula has been introduced utilizing numerous EDPs which contribute concurrently in the DI to represent the resulting dynamic features which offer important information in this analysis. This method is simple to apply, as the formulated model predicts the DI of any structure, including certain framed structure and panel shear frame construction, explicitly of higher precision.

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REFERENCES

[1] El Alami, S. O., Tadili, B., Brahim, L. A., & Mouayn, I., "Seismicity of Morocco for the period 1987–1994" *Pure and Applied Geophysics*, 161(5–6), 2004, 969–982.

[2] Ruggieri, S.; Porco, F.; Uva, G. "A practical approach for estimating the floor deformability in existing RC buildings: Evaluation of the effects in the structural response and seismic fragility." *Bull. Earthq. Eng.* 2020, 18, 2083–2113.

[3] Kapetana, P.; Dritsos, S. "Seismic assessment of buildings by rapid visual screening procedures. WIT Trans." *Built Environ.* 2007, 93, 409–418. Doi: 10.2495/ERES070391

[4] Tomas, A.; Ródenas, J.; García-Ayllón, S. "Proposal for new values of behaviour modifiers for seismic vulnerability evaluation of reinforced concrete buildings applied to Lorca (Spain) using damage data from the 2011 earthquake." *Bull. Earthq. Eng.* 2017, 15, 3943–3962.

[5] Cerovecki, A.; Gharahjeh, S.; Harirchian, E.; Ilin, D.; Okhotnikova, K.; Kersten, J. "Evaluation of Change Detection Techniques using Very High Resolution Optical Satellite Imagery." *In Preface 2 Summer Course 2015; Bauhaus-Universitätsverlag: Weimar, Germany*, 2018; p. 20.

[6] Harirchian, E. "Constructability Comparison between IBS and Conventional Construction." *Ph.D. Thesis, Universiti Teknologi Malaysia: Skudai, Malaysia,* 2015.

[7] De Lautour OR, Omenzetter P. "Prediction of seismic-induced structural damage using artificial neural networks." *Eng Struct* 2009; 31(2):600–6.

[8] Jha R, Rower J. "Experimental investigation of active vibration control using neural networks and piezoelectric actuators.", *Smart Mater Struct* 2002; 11:115–21.

[9] Darus IZM, Tokhi MO. "Soft computing-based active vibration control of a flexible structure." *Eng Appl Artif Intell* 2005; 18(1):93–114

[10] Adeli H, Jiang X. "Dynamic fuzzy wavelet neural network model for structural system identification." *J Struct Eng* 2006; 132(1):102–11

[11] Noh HY, Lignos DG, Nair K, Kiremidjian AS "Development of fragility functions as a damage classification method for steel moment-resisting frames using a wavelet-based damage sensitive feature." *Earthq Eng Struct Dyn*, 2012, 41(4):681–696.

[12] Shahin, M. A., Maier, H. R., & Jaksa, M. B. "Data division for developing neural networks applied to geotechnical engineering." *Journal of Computing in Civil Engineering*, 18(2), 2004, 105–114