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Original Research Article

Implementation of AI for The Prediction of Failures of Reinforced Concrete Frames

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Abstract

Reinforced concrete tall building failure, in residual areas, can cause catastrophic disaster if they can't survive during the destructive earthquakes. Hence, determining the damage of these buildings in the earthquake and detecting the probable mechanism formation are necessary for insurance purposes in urban areas. This paper aims to determine the failure modes of the moment resisting concrete frames (MRFs) according to the damage of the beam and column. To achieve this goal, a 15-storey moment resisting reinforced concrete frame is modeled via IDARC software, and nonlinear dynamic time history analysis is performed through 60 seismic accelerograms. Then the collapse and non-collapse vectors are constructed obtaining the results of dynamic analysis in both modes. The artificial neural network is used for the classification of the obtained modes. The results show good agreement in failures classes. Hence it is possible to introduce the simple weight factor for frame status identification.

Keywords: Reinforced Concrete Building; Plastic Hinge; Peak Ground Acceleration; Artificial Intelligence.

1. Introduction

Seismic prone regions have frequently suffered from injuries and financial losses, especially in the densely populated urban and industrial areas. In these areas, the only possible choice is to make the buildings safe against this phenomenon. Despite the application of different criteria and factors in the design and construction of a structure, different modes of damage and loss are possible during an earthquake. Hence, fully trusted structures can't be designed. The seismic damage evaluation of a structure is the first step in building strengthening [1-3]. The results can determine all plausible failure modes. Providing the criteria for avoiding failure modes can, to some extent, ensure structural safety [4]. In this method, we will look for structural modes of collapse when earthquakes occur [5]. Also, it is important to determine the main earthquake damage to the structure which can bring it to the brink of destruction in aftershocks [6,7]. Along with these issues, it is also important to pay attention to uncertainties [8].

Haselton et al. evaluated the Safety of Reinforced Concrete buildings in seismic zones [9]. They conclude that the code provisions delay, but do not prevent, column yielding and the formation of story collapse mechanisms. Goulet et al. considered seismic hazards to collapse safety and economic losses for this type of structures [10].

Classification of failure mode and prediction of strength for reinforced concrete structures based on machine learning techniques is considered in many researches [11]. Nguyen et al. used an evolutionary algorithm to optimize artificial intelligence for predicting of the axial capacity of rectangular concrete filled steel tubes under compression [12]. Ly, Hai-Bang, et al hired computational hybrid machine learning to predict the shear capacity of steel fiber reinforced concrete beams [13].

In this research, the damage of the tall frames, on the verge of collapse, will be evaluated by IDARC software through the nonlinear dynamic time history analysis. The results of these analyses were used to train a neural network to improve the possibility of decision making and to state structural conditions and modes of failure based on nodes' status.

2. Review of Artificial Intelligence and Machine Learning in Earthquake Engineering

The topic area of damage detection is broadly defined as a group of studies that develop AI and ML models to recognize, classify, and assess seismic damage to civil structures. The existing literature in this area possesses a large range of attributes in ML method, data resources, and analysis scale. To be consistent, data resource is used as the main trait to subdivide the relevant studies herein. First, several studies relied on post-earthquake linguistic or photographic records to predict seismic damage. A major challenge in this area lies in addressing the damage information in linguistic forms. To this end, De Stefano et al. [14] used ANN and Bayesian classification to predict seismic damage mechanisms of historic churches. Fuzzy logic models have been utilized in a collection of studies that transform physical descriptions of seismic damage into mathematical model parameters [15-20]. Recently, the linguistic damage records from the 2014 South Napa earthquake have been used to develop a DL-based method that classifies the building damage [21]. On the contrary, the damaged RC column images collected after the 2010 Haiti earthquake have been used by German et al. [22] to develop a procedure that automatically detects spalled regions on the column surface and measures the properties of the spalling. The multi-step procedure measures the area of spalled concrete, the area of the reinforcement, as well as the sizes of exposed reinforcing bars. This damage detection procedure was further incorporated into a comprehensive framework that links the column damage with the residual drift capacity and post-earthquake fragility curves of RC structures [23, 24]. Besides, ML methods have been implemented in dealing with satellite imagery and digital maps to detect and classify building damage [25, 26]. Gao and Mosalam [27] have also constructed an image database called ''Structural ImageNet,'' from which two DL technologies such as transfer learning (TL) and visual geometry group (VGGNet) were applied to recognize structural damage caused by earthquakes and other natural hazards.

A large part of the existing literature uses simulated and test data to detect the seismic damage of building structures. In particular, an ANN model is first trained with respect to the reference system in its undamaged state, whereas the response data from the damaged state of the same system are fed into the same model. As a result, the variation in the level of prediction error between the two states can serve as a reference to quantify the structural damage in a nonparametric manner [28, 29]. Similar studies have considered using innovative metrics such as Bayes factors, natural modes, and coefficients of autoregressive models for damage detection [30-35. Following the same logic, a couple of studies have improved the approach to enable parametric quantification of structural damage (e.g. damage quantified through the change of stiffness values) [36, 37]. In a broader context, ANN models have been developed to predict the seismic response for a variety of structures so as to infer their damage conditions. Related studies in this area include (1) quick earthquake damage estimation on ordinary wooden framed houses in Japan [38]; (2) seismic vulnerability assessment of chemical industrial plants with various topologies [39]; (3) damage index prediction of RC frames [40-42]); (4) seismic damage evaluation of concrete shear walls [43] and cantilever structures [44]; and (5) global damage classification of RC slab-column frames by combining ANN with SVM [45]. ML has also been utilized by Burton and his coworkers [46-48] to link the seismic damage patterns of buildings to the residual structural capacity indices (i.e. the median capacity ratio between the intact and damaged buildings). Their proposed framework integrates seismic demand analysis, component damage simulation, and residual collapse capacity estimation on both intact and damaged structures. The applied ML algorithms involve CART and RF for safety classification, LASSO and SVM for capacity index prediction.

3. Structural Modeling

The fifteen-story / four-bay frames are modeled according to the ACI code based on the median ductility [49, 50]. We assume that the building is located in a high risk seismic area with soil type 2 [51, 52]. According to UBC Code, concrete pressure strength and steel yield stress in beams and columns are 25 MPa and 400 MPa respectively. Frame geometrical properties are shown in figures 1 and 2 and Tables 1 and 2.

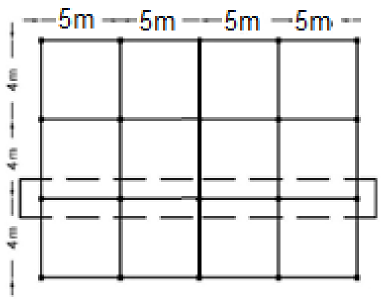

Figure 1. building plan

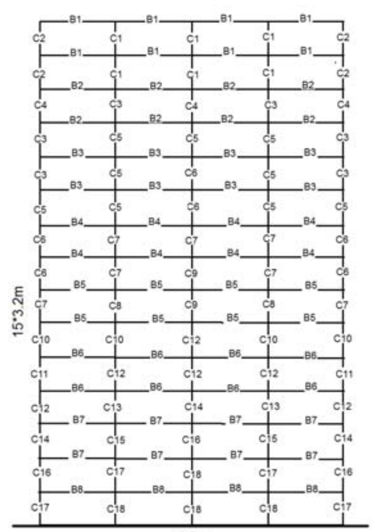

Figure 2. Frame Elevation

Frame analysis is performed using IDARC software which can model RC frames and conduct nonlinear dynamic time history analysis [50-52].

Table 1. beams details

Group	Width (cm)	Depth (cm)	top bars	bottom bars
B1	30	30	4Φ16, 1Φ12	3Φ14
B2	30	35	4Φ18, 1Φ12	3Φ16
B3	30	40	4Φ18, 1Φ12	2Φ16, 1Φ18
B3	30	40	4Φ18, 1Φ14	2Φ16, 1Φ18
B4	35	40	4Φ18, 1Φ12	2Φ16, 1Φ18
B5	40	40	4Φ20, 1Φ12	4Φ16, 1Φ12
B6	40	45	4Φ20, 1Φ12	4Φ16, 1Φ12
B7	40	50	4Φ20, 1Φ16	4Φ16, 1Φ12
B8	40	50	4Φ20, 1Φ18	4Φ16, 1Φ12

Table 2. Columns details

column	Dimensions	bars	column	Dimensions	bars
C1	30X30	8Φ14	C10	40X40	8Φ18
C2	30X30	10Φ14	C11	40X40	10Φ8
C3	30X30	12Φ14	C12	45X45	8Φ18
C4	30X30	14Φ14	C13	45X45	8Φ18
C5	35X35	8Φ14	C14	45X45	10Φ18
C6	35X35	10Φ14	C15	45X45	14Φ18
C7	35X35	12Φ14	C16	50X50	8Φ20
C8	35X35	16Φ14	C17	50X50	10Φ20
C9	40X40	6Φ18	C18	50X50	12Φ20

Experience from past earthquakes shows that the behavior of reinforced concrete structures during an earthquake is not elastic, but is nonlinear and follows the hysteresis model (figure 3). According to different experimental concrete hysteresis behaviour, different models have been proposed, such as bilinear models, models with no loss of strength, stiffness reduction model, the model based on energy reduction and tri-linear model [50-53]. In this paper, the tri-linear model was selected, which is the most complete model for the hysteresis and nonlinear behaviour of concrete. In this model, the degradation in stiffness and strength, pinching, and asymmetric slip for different values of model parameters is applicable. The values of the parameters of this model are selected empirically [54-56].

After the frame analysis, different response parameters such as period, story shear, relative displacement, displacement, velocity, acceleration, and overall structural damage index can be used, some of which have been used in previous research [54, 55].

4. Earthquake Database

Earthquakes are selected from peer databases in such a way that is compatible with the building site condition. Table 3 shows the names and Peak Ground Accelerations (PGA) of the selected earthquakes.

Table 3. Earthquakes pga

seismic	pga
A41-2BZ000_AT2	0.188
A42-2BZ270_AT2	0.143
A43-2BZ-UP_AT2	0.207
A44-2IZT090_AT2	0.219
A45-2IZT180_AT2	0.176
A46-2IZT-UP_AT2	0.154
A47-2LCN000_AT2	0.777
A51-2LCN275_AT2	0.677
A52-2LCN-UP_AT2	0.678
A53-2TCU046-N_AT2	0.111
A54-2TCU046-V_AT2	0.119
A85-TAP103-W_AT2	0.128
A86-TCU046-N_AT2	0.111
A87-TCU046-V_AT2	0.119
A88-TCU046-W_AT2	0.128
A91-A-RN180_AT2	0.316
A92-A-RN180_AT2-1	0.316
A93-A-RN180_AT2-2	0.304
A94-A-RN270_AT2	0.205
A95-A-RN270_AT2-1	0.205
A55-2TCU046-W_AT2	0.128
A56-2TCU046-W_AT2	0.208
A57-2TCU046-W_AT2	0.443
A61-ABY000_AT2	0.119
A62-ABY090_AT2	0.148
A63-ABY-UP_AT2	0.089
A64-01-UP_AT2	0.068
A65-01090_AT2	0.51
A66-01230_AT2	0.104
A67-01320_AT2	0.143
A71-BZ000_AT2	0.188
A96-A-RN270_AT2-2	0.205
A97-A-RN270_AT2-2	0.226
A101-A-RN-UP_AT2-1	0.226
A102-A-RN-UP_AT2-	0.226
A103-A-MTW000_AT2	0.122
A104-A-TW000_AT2-1	0.122
A105-A-TW000_AT2-2	0.122
A106-A-MTW090_AT2	0.179
A107-A-TW090_AT2-1	0.179
A72-BZ270_AT2	0.143
A73-BZ-UP_AT2	0.207
A74-IZT090_AT2	0.219
A75-IZT180_AT2	0.176
A76-IZT-UP_AT2	0.154
A77-LCN000_AT2	0.777
A81-LCN275_AT2	0.677
A82-LCN-UP_AT2	0.678
A83-TAP103-N_AT2	0.182
A84-TAP103-V_AT2	0.027
A111-A-TW090_AT	0.179
A112-A-MTW-_AT2	0.113
A113-A-MTW-AT2-	0.113
A114-A-MTW-AT2-	0.113
A115-ARM270_AT2	0.111
A116-ARM270_AT2-	0.111
A117-ARM360_AT2	0.128
A121-ARM360_AT2-	0.128
A122-ARM-UP_AT2	0.07
A123-ARM-P_AT2-1	0.07

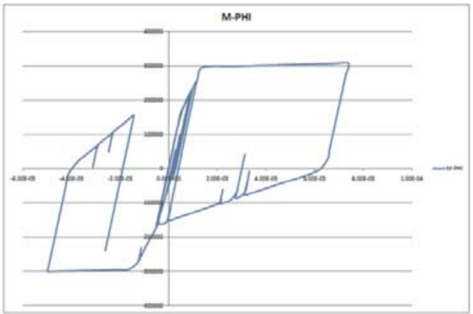

Figure 3. Sample of hysteresis pattern

5. Data processing and results

After non-linear dynamic analysis, the output data including the damage status at the ends of members will be displayed in the vector format. The number of members of this vector will be equal to 2m, for a frame with m members. For example, in the above frame which contains 75 columns and 60 beams, the array will have 90 members.

For each end, four states are considered, namely, no damage (0), cracking (1), the plastic hinge (2), and local failure (3). It can be seen that the total number of possible collapse – non-collapse scenarios are equal to, which would constitute the sample space.

An artificial neural network (ANN) is a parallel-structured information processing system that has certain functionality similar to the biological neural networks of the human brain, in that knowledge is the product of a learning process and finding the best weights for different connections between cells of a separate nerve. The neural network is characterized by its architecture, which represents the pattern of communication between nodes, as well as by its method for determining the relationships of weights and their active function. ANN consists of several nodes that are positioned according to a specific order.

ANNs are divided into single-layer, double-layer, and multi-layer based on the number of layers. ANN The network is divided into forward and backward movements based on the direction of data entry and processing. Among these combinations, the multilayer forward motion networks known as multilayer perceptrons (MLPs) with the training post-diffusion learning algorithm provide the best performance with respect to the approximation of the input-output function as predictions. An MLP can have multiple layers. A typical MLP with a hidden layer used in this research is shown in Figure 4.

The processor elements in each layer are called nodes or units or neurons. The first layer communicates between input variables called the input layer, and its constituent elements are called information-receiving neurons. The last layer communicates between the output variables, which are called the output layer, and its constituent elements are called output information neurons. The layer between these two layers is called the hidden layer, in which we may have more than one hidden layer in an MLP. Each node is associated with neighboring layer nodes. The parameters associated with each of these relationships are called weights [57]. The inputs in the neural network move from the input layer to the middle layer (hidden layer) and then to the output layer. When the network modifies its connection weights, the correction process begins with the output units and spreads back through the middle layers, and this process is repeated over and over again. The term post-release has been chosen according to this modification process [58]. Analysis of the frame, containing 60 analyses of the failure mode and 60 analyses of the non-failure mode, 60 seismic acceleration time series has been used to train an artificial neural network.

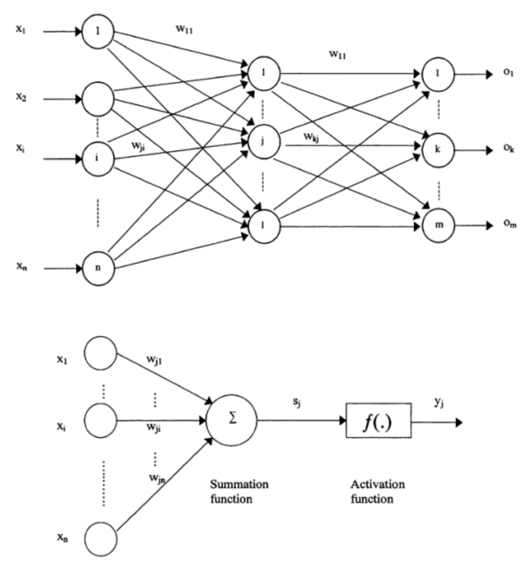

Figure 4. Sample of tree layer artificial neural network

Therefore, we have 60 vectors for failure mode and 60 vectors for the non - failure mode. The number of vectors increases for training the neural network using the Taguchi method [49]. The accuracy of predictions is shown in Table (3) in terms of the number of training samples. As can be seen, with 100 samples an acceptable precision is achieved. The precision values for different sets of 100 data are shown in Table (4).

Table 3. Results of failure prediction

num	Number of train and test samples (70% to 30%)	precision
1	100	87.6
2	500	98.45
3	1000	98.70
4	1500	98.90
5	2000	99.40
6	2500	99.60

Table 4. Prediction results for 100 data samples

num	Number of train and test samples (70% to 30%)	precision
1	100	88.3
2	100	90.01
3	100	88.65

It is clear that with about 500 data samples 15-storey concrete structures condition can be predicted accurately [59].

Regarding to each of the categories of damage which Consists of no damage, cracking, hinge formation, and local collapse the weights 0, 1, 2, and 3 are assigned respectively. The total weight $w_{collaps}$ of the collapse mode is equal to:

$$w_{ave.collaps} = \frac{w_{collaps}}{2m}$$

The weight of the above mentioned frame is obtained as follows. It should be noted that this weight means a collapse of the building.

$$w_{collaps} = 270$$

$$wave.collaps = \frac{583}{270} = 2.16$$

Thus a very simple model is achieved, which determines the status of the structure and can be generalized to other frames. The frame is stable if its weight is lower than this number, and the structure will collapse otherwise.

6. Conclusion

This study proposes utilizing artificial intelligence for the prediction of failure in high-rise buildings. The existence of numerous structural elements in tall buildings results in inefficient and time-consuming nonlinear dynamic analyses using various seismic records to determine structural failure. The proposed method can rapidly predict the failure state of a structure using the results of dynamic analysis. According to the results of nonlinear dynamic analysis processing in the neural network algorithm, the following points can be concluded:

1. Reinforced concrete frames are subject to certain patterns of failure. It means that certain compounds of the no-damage, cracking formation and local collapse can be used to determine the structural condition, as is shown in [59]. This finding is compatible with the previous work [55].
2. Processing the results in a neural network showed that the average weight of the structural failure can be obtained and used for all the cases.
3. Using the Methods or algorithms like a neural network, models can be produced for engineers to identify the structural condition.

Prediction of failure modes is one of the critical components in seismic design and rehabilitation of engineering structures. However, in order to achieve a general framework, it is necessary to consider portfolios of structures with significant variations in the structural parameters. Thus, this study must be diversified by considering the analysis of archetype structures or groups of representative structures to derive general conclusions. The following work may include regional portfolios of structures with multiple predictors that reflect the variation across a portfolio and consequently multidimensional prediction models. Namely, the proposed method can be tailored to structures across a region since they are dependent on not only earthquake characteristics, but also other significant uncertain parameters such as material, geometry, and aging parameters of the structure.

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