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Application of Artificial Neural Network for Prediction of Story Drift in High-Rise Buildings

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Abstract

The difficulties arising from growing population expansion and extensive urbanization are driving up the demand for high-rise structures. Comprehending the symmetry and composition of structural components correspondingly is becoming more and more important in light of current developments in computer technology, novel materials, and unique structures. The structural responses of multistory buildings predicted by Artificial Neural Networks (ANN) briefly outlined in a systematic manner. This review enhances the application of ANN for the prediction of story drift in multistory buildings with greater level accuracy. A multistory structure might fall because of the intense movement of the ground, resulting in fatalities and economic loss. As a result, it is imperative that the multistory structure be appropriately constructed to minimize the earthquake hazards. Based on a literature analysis, it can be concluded that artificial neural networks are widely used in simulating and predicting story drift in high-rise building systems. The objective of the current investigation is to present a comprehensive overview of the many approaches and uses of artificial neural network modeling research in the domain of structural engineering. Accordingly, the articles were categorized in this way based on author, year, algorithm used, software application and description of findings and conclusions. Here, the most influential parameter (input vector) is also rigorously reviewed. This information may be taken into account when creating a neural network model that operates more effectively. The review's conclusions might prove beneficial for structural and/or civil engineering problems. The approaches described here assist the structural practitioner in understanding the limitations and advantages of ANN in comparison to other traditional mathematical modelling. This review contributes a body of knowledge for the ANN modelling approach to forecast the story drift evaluation within the field of structural engineering.

Keywords: *Artificial Neural Network (ANN), Story Drift, Response Spectrum, Prediction, Etc.*

1. Introduction

Numerous elements influence the aftermath of an earthquake, one of which is the ability of high-rise building structures to withstand powerful movements of the earth. The avoidance of neglecting the dynamics loads may sometime become cause of disaster. As a result, there is increased interest these days in the process of constructing civil structures that can endure

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dynamic loads in the events of disasters. Several essential facilities, including educational institutions, healthcare facilities, power plants, offices, and government agencies, are high-rise buildings which make them particularly vulnerable to seismic activity. Because of their enormous inert loads, multiple stories buildings especially those made of reinforced cement concrete (RCC) may fail badly under significant surface momentum, posing a risk regarding the safety of their residents. However, poorly constructed tall buildings can suffer significant lateral movement, or "story-drift," and these makes residents uncomfortable as well as can lead to injuries to non-structural elements like doors, windows, and dividing walls may obstruct escape routes. The aforementioned variables mean that high-rise structures need to be carefully built to exhibit predictable deflections including flexible response under substantial ground instability. Using various ANN model-related structures, clustering, classification, and simulation are carried out in ANN models. Three categories exist for ANN models: (i) Statistical ANN, (ii) Dynamic ANN and (iii) Static ANN. The layers of an artificial neural network are connected to one another either completely or randomly. A typical neural network has all of its connections intact, meaning that every neuron in a layer has a link to every other layer's neuron. The mathematical representation of complicated relationships amongst input and output variables may be accomplished using Artificial Neural Networks. The sort of computation that occurs in a human brain served as the inspiration for artificial neural networks, which are essentially abridged representations of the naturally produced neurological mechanism. An ANN system is made up of several neurons and processing layers. Similar to a biological neural network, an artificial neural network (ANN) converts an input signal into appropriate outputs, or predictions, by means of connections and signal transmission between neurons and layers. An artificial neural network (ANN) can forecast an outcome according to every input provided that exists a complex, multidimensional scientific relationship involving an input and an output variable. A common multi-layer ANN architecture includes three layers: input, hidden, and output highlighted in figure 1. The input layer is made up of input neurons that receives external data or signals. Neurons in the hidden layer also get information by the input synapses and forward them to the output layer. The prediction rate and the capacity of a hidden layer are affected by the number of neurons and the artificial neural network technique's capacity to manage parameters using stochastic relationships. The output layer comprises the neuron which indicate the variables of the outcome to be anticipated, which is the last component. The precision of the ANN modelling analysis is represented by the difference between the goal value (the expected outcome based on the training sample sets) and the anticipated output.

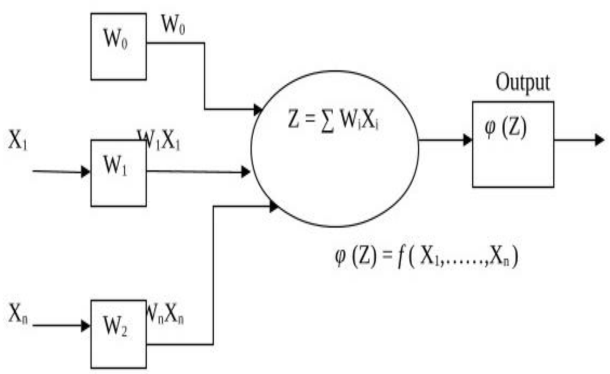

Figure 1 **Mathematical Model of ANN**

Figure 1 represents a typical mathematical model includes the input variables (x1, x2, x3…… xn), weights and biases, activation function and the output variable. The information is received from the input variables which includes the input neurons and forwarded to activation function with the help of synapses. The information is waited and biased in the activation function and summarizes according to learning. The three basic elements of neuron model are distinguished as follows:

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Every input neuron's information is associated with weights wi, i= 1, ...n. A series of information (input) xi, i, = 1, ...n, at the ith input is assigned (weighted) by the weight wi. A typical artificial neuron incorporated with sets of synapses which play interlinkage between the input neurons. In the activation function, the weighted input series of information are summarized. The resulting linear combination of the input sums is w1x1 +…. + wnxn. The linear equation is multiplied by a free weight (also known as a bias) w0, which does not relate to any input. This ends up resulting in a weighted sum Z = w0 + w1x1 +... + wnxn. To the weighted sum, a nonlinear activation function ϐ is applied. The activation function has a value of Y = φ (Z), which represents the neuron's output. The following equivalence is true if any function f (x1, ... xn) describes the activation function surveying,

$$\varphi(Z) = \varphi\ (w0 + w1x1 + \dots\dots\dots + wnxn)$$

2. Application of an Artificial Neural Network (ANN) In Story Drift Prediction

Among those highest significant limit states while constructing a high-rise structure is story drift. That structure must not sag too much in order to function effectively and protect non-structural components like doors and walls from damages. Rather than strength, area drift often determines how structural components are designed. The most effective technique for analytically calculating the story drift of the high-rise structures at the moment is the Finite Element Method (FEM). But for some complicated constructions, doing FEM by hand might be very time-consuming, if not virtually impossible. Several Finite Element software programs intended for use within the areas of structural engineering have been produced and are generally accessible in the market to help in quicker and more accurate calculations. However, it takes countless efforts to correctly model and analyze building structures using FEM software, particularly for nonlinear and dynamic analyses. The Finite Element Method is rather slow for structural analysis dynamic as well as quadratic computations is its accuracy. In order to offer a sufficient early prediction of structural reactions like displacement, acceleration and velocity. There are wide range of applications of ANN in civil engineering which includes the pattern recognition, classification, time series and prediction problems. In this section applications of ANN in story drift prediction are briefly described. The articles from the well reputed journals and recently published were considered. Suryanita R. and Jingga H. (2017) developed Backpropagation Neural Network (BPNN) model to forecast the story drift in building construction project. The developed neural network architecture consists of 3 layers: input layer, hidden layer, and output layer. The input layer has 8 neurons which represent 8 input parameters: 5 earthquake response spectrum function parameters (PGA, SDS, $SD1$, T0, Ts), ground or soil condition, and 2 geometric characteristics (total building height and ith story elevation) [1]. Total of 1080 data sets obtained from Modal response spectrum (MRS) analysis performed for 8 capital cities of Sumatra Island. They developed BPNN model as 96% accuracy in prediction with minimum mean square error (MSE) of 1.2*10-4. Furthermore, they concluded that BPNN was robust tool in prediction of story drift as well as helpful to the Finite Element Method analysis. Morfidis K. and Kostinakis K. (2017) proposed neural network modelling approach for the prediction of damage state of r/c buildings using 14 seismic variables. They used various ground motion parameters like Peak Ground Acceleration: PGA, Peak Ground Velocity (PGV), Peak Ground Displacement (PGD), Arias Intensity (Ia), Specific Energy Density (SED), Cumulative Absolute Velocity (CAV) as input variables of neural network model. [2-5] They implemented the Levenberg–Marquardt algorithm and the Scaled Conjugate Gradient algorithm for the effective generalization of BPNN. Furthermore, they performed sensitivity analysis to identify the prediction performance and effectiveness of input variables. Mallarapu P. and Tarangini D. (2022) developed a model that uses ANN to forecast actions of high-rise building structures. The reinforced concrete (RC) framed structures were developed by considering structural members like beam size, column size, story height, thickness of slabs and clear cover and various properties related to steel and concrete [51-56]. Two RC framed structures of 20 and 40 storied are planned and modelled in ETABS using equivalent lateral force approach as well as response spectrum method. In order to create a neural network model, the story drift data sets from both analyses were used. The created model of the ANN illustrates the Coefficient of Correlation (R) value for 20 story model in Y direction is 0.4204 and Min Correlation Coefficient (R) in Y direction is 0.9999. [3] Kim S. (2020) developed a Recurrent Neural network (RNN) model to perform Time History response stimulation for building structures using a semi-active control system. The input parameters were considered such as Sequence length, RNN cell number, Dropout rate, Hidden layer dimension, learning rate, RNN, Activation function, Optimizer. [4] A 26-story structure with a semi-active mid-story isolation system and an 11-story building with a semi-active tuned mass damper (TMD) were both installed using RNN models in relation to those data sets. Hakim S. et al. (2023) proposed comprehensive review study on development of Artificial Neural Networks for earthquake-prone structure damage prediction. The paper reviewed the latest research on using artificial neural networks (ANNs) to anticipate earthquake damage. According to the analysis of the literature, ANNs have been used due to the fact that they are far less computationally expensive than the conventional, labor-intensive methods. Additionally, they have advised putting together a thorough analysis of current research on the use of the fuzzy logic approach to anticipate seismic injury to buildings [5]. Vafaei R. et al. (2013) developed an ANN modal Pushover Analysis for Real-time Seismic Damage Detection of Concrete Shear Walls to resist lateral loads. This study introduced a technique based on artificial neural networks and analyzed dynamic responses for the current time earthquake harm identification of concrete shear wall structures. Finite element model of five story building was created and to prepare well-distributed input and output, modal pushover analysis was utilized for training a multilayer feed-forward neural network. In this study the inter story drifts are the input data sets and plastic hinges rotations of concrete shear walls are output data sets. They used four distinct methods to assess the trained neural network's resilience. In the first method, nine distinct NTH Analyses, findings were compared with the trained neural network's predictions [20 -25]. The rotations of the plastic hinges were found to be correctly predicted by the trained neural network. In the second method, after altering the PGAs of the chosen earthquake records, the outcomes were contrasted. It was noted that the trained neural network produced accurate forecasts and was insensitive to the parity of the chosen recordings PGA. In the third method, the outcomes of the NTH Analysis in the time domain were compared with the predictions made by the neural network. In this case, the anticipated designs for plastic hinges. The fourth method classified the damage based on three distinct damage levels that were established [57]. The network was able to determine the extent of damage to the concrete shear walls in all but four of the cases. [6] Some of the other ANN techniques used for prediction of story drift during earthquakes are listed in Table 1.

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Page No: 629 - 640
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Table 1 ANN Applications in Story Drift Prediction

Author	Algorithm	Input variables	Findings and conclusions
Dahiya et al. (2021) [7]	Deep Neural Networks (DNN) Keras model, Back propagation neural network (BPNN)	No of story, No. of bays, Building Height, Time Period, Displacement, Story acceleration	As compared with the robust BPNN, indicates Coefficient of correlation 0.8905, Root Mean Square Error of 0.00193, and Mean absolute Percentage Error of 0.4379. the developed DNN Keras model generated superior results with Coefficient of correlation 0.9598, Root Mean Square Error of 0.00120, and Mean absolute Percentage Error of 0.1385. The findings show that DNN Keras outperforms robust BPNN in story drift prediction by around 8%.
Moller et al. (2009) [8]	A multi-layer neural network	Geometric and structural parameters: Number of stories (N_S), number of bays (N_B), span (X_L) of each bay, mass (m) per unit length associated with each story, characteristic strength of concrete(fc), width of beams (b_b) depth of beams (h_b), width of columns (b_c), depth of columns (h_c), steel reinforcement ratios in beams and columns.	It is possible to calculate the chance of non-performance using a typical Monte Carlo simulation when neural networks are utilized to represent the response needs [26].
DeLautour O. and Omenzetter P. (2009) [9]	Backpropagation ANN, nonlinear FEM analyses.	1st Story height (m), Remaining story height (m), Bay width (m), Beam reinforcement ratio, Column reinforcement ratio, Concrete strength (MPa), Damping ratio (%), PGA, PGV, PGD, SI.	The paper suggests a novel approach to evaluating structural deterioration by modeling the link between ground motion parameters and structure using Artificial Neural Networks (ANNs). [58] The 2D RC frames that were exposed to a variety of ground movements and had different topologies, stiffness, strengths, and damping were the class of structures that were analyzed.
Suryanita R.et al. (2019) [1]	Backpropagation ANN	Peak ground acceleration, design spectral acceleration at short period, design spectral acceleration at 1 second of period, the lower limit of period that results in maximum acceleration (T_0), the upper limit of period that results in maximum acceleration (T_S), soil condition, building total height, story elevation (base level was not included)	The developed ANN model has average MSE of 2.34×10^{-4}, 2.36×10^{-4} and 2.17×10^{-4} for the [59] generalization of ANN model. The ANN model possesses the coefficient of correlation (R) 0.961, 0.976 and 0.949 during the training, testing and validation phase respectively.
Papadrakakis M. and Lagaros N. (2002) [10]	Backpropagation ANN	Random variables: ry, E, Design variables, Loads	(i) When severely non-linear structural behavior was present, the forecasting efficiency outperformed the non-adaptive technique [27]. (ii) It makes it possible to anticipate output standards, or forces and distortions, for every degree of freedom in the system of structure.

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Shokri M. and Tavakoli k. (2019) [11]	Artificial Neural Network (ANN) and Finite Element Model (FEM).	Bridge length (Lb), Bridge width (Wb), No. of columns (Nc), No. of beams (NB), Minimum dimension of column along X direction (Wcmin), Maximum dimension of column along X direction (Wcmax), Bridge height (Hb), Story height (Hs), No. of floors (Nf), Min. dimension of column in Y direction (Dcmin), Max. dimension of column in Y direction (Dcmax) Peak acceleration (Ap), Shear wall (Sw), Total moment of inertia (in x direction) (Ix), Total moment of inertia (in y direction) (Iy), Story height (Hn), Story height of base floor (Hb), Max width of bay in x direction (Lx), Max width of bay in y direction (Ly), Widths of building in plan in x direction (Bx), Widths of building in plan in y direction (By), Number of stories(N), Number of bays in x direction (Nbx), Number of bays in y direction (Nby), Pulse period (Np).	The results showed that, for both training and testing, the ANNs could estimate the degree of damage with an average percentage error of 6.8% and 8.25%, respectively. Based on statistical values and correct comparison with FEA findings, [30] the recommended ANNs model is adequate for forecasting the dynamic response of structures, accounting for base shear pressures, base bending moments, and roof displacement. The developed ANN model shown the correlation of R^2 and they are in order 0.999689, 0.99057, 0.97895, and 0.942561in different categories.

3. Machine Learning Models

A widely utilized machine learning approach is an Artificial Neural Network (ANN). As of late, majority of earthquake engineering applications have been using the ANN approach. Machine learning (ML) has advanced quickly in the last few years, and it could handle greatly [50] the modification and improvisation way of data science works across a range of industries [42]. Machine learning (ML) offers advantages over traditional approaches in handling complex problems, improving computing efficiency, handling and addressing uncertainties, and expediting decision-making. Furthermore, significant progress has been achieved in various scientific and technical domains like transportation engineering, structural engineering, material research, and building management, in addition to mainstream AI research, as machine learning (ML) has grown. The Additionally, maximum inter story drift was anticipated using ML models that were developed. [12] Sun H. et al. (2021) proposed comprehensive review study on application of machine learning algorithms in the prophecy of building structural design and performance assessment. In this study they highlighted the theoretical background of various machine learning algorithms which includes; Linear regression, Kernel regression, Decision Trees, random forests, Logistic regression, K - Nearest Neighbors, Discriminant analysis and ANN. [13] Gholizadeh S. (2015) carried out a comparative analysis between modified firefly algorithm and neural network for the purpose of forecasting the ideal steel structure seismic design. Total of 8 different network architectures of neural networks were developed along with different transfer function. [44-49] The Wavelet cascade-forward back-propagation (WCF-BP) neural network performs better as compared to other developed ANN models. The WCF-BP neural network model has MAPE value 2.3151, RRMSE value 0.0305, RSQUARE value 0.9987 and training time of 2.5 min. The optimal weights found by FA-Pushover and FA-WCFBP-RB are 2.11% and 2.29% lighter than the optimum weights found by the MFA-Pushover and MFA-WCFBP-RB techniques, respectively. [14] Yao J. et al. (2014) developed a Train-induced vibration model for forecasting the active motion in multi-story buildings, [43] which can effectively show the effect of vibrations on buildings. In this research, support vector machines (SVM) are utilized to predict train-induced vibrations in multistory structures with high accuracy. The Shuffled Frog-Leaping Algorithm (SFLA) is used to improve the SVM parameters as they are essential for prediction accuracy. They used Some common kernel functions to generate different support vector machines such as linear kernel, polynomial kernel, RBF kernel, sigmoid kernel. Additionally, it has been determined through vibration studies that a variety of factors influence the ground vibration caused by trains and those are such as the quality of the ground, which is the greatest significant factor and the others are such as kind of train, the railroad tracks, and the elevation layout, railway speed, structure type, base design, and the route between the building and the railway way track which is closest to the receiver [60]. Using data from assessments of over 160 trains of various kinds, speeds, and directions, the suggested SVM was successfully trained and evaluated [40]. First, it makes an effort to create models utilizing actual data to forecast vibration caused by rain in multi-story structures. Second, the shuffling frog-leaping approach is used to adjust the support vector machine's parameters, hence increasing prediction accuracy. [15]

Table 2 Summary of Integrated Approach of Artificial Intelligence (AI) Techniques

Author	Algorithm	Input variables	Findings and Conclusions
Sipos T. and Strukar K. (2019) [16]	Artificial neural Network, Bilinear Approximation, Experimental Database of Infilled Frames (EDIF).	Seven input layer units are present. Number of units for hidden layers: 3, 5, 8, Number of hidden layers: 1. There is only one output layer unit. Rate of learning = 0.01 Objective of performance = 0. 10,000 is the max number of epochs.	The primary fundamental of this research was to establish the role of infill in the reaction of framed structure. The developed optimum ANN model shows an average accuracy of 92%.
Kohrangi M. et al. (2016) [17]	Open Sees. (McKenna, 2000)	Modes, PMR, PMRX, PMRY, PMRZ	An ideal model builder (IM) for three-dimensional (3D) constructions should be capable of accurately forecasting reactions at every level. They believed that the most prominent feature of the ground motion was the spectral form.
LI J. (2021) [18]	1)The architecture of ANN models. (MIDSFP: MIDS of a certain fundamental period).	Peak ground displacement, peak ground acceleration, and peak ground velocity Arias Intensity, Vmax, Amax, Specific Energy Density, total absolute [41]velocity over time, Housner intensity, dominant period, acceleration spectrum intensity, effective design acceleration, and dominant period There are three types of time intervals: Bracketed, Significant, and Uniform.	Further developments of this research will include the deep learning model's evaluation of more complicated building structure models, more forms of structures, and additional field situations. During earthquakes, an extensive number of other technical factors, such as acceleration, residual displacement, and fundamental frequencies are also vital. Accurate deep learning networks research should examine the possibility of designing networks with the ability to predict these engineering factors.

Huu-Tai Thai (2022) [19]	1)Artificial Neural Network a) Convolutional Neural Network (CNN) b) ANFIS 2) Support Vector Machine.	Lateral confinement coefficient, Shear strength, Backbone curve parameters (e.g., yield and maximum shear force), Drift capacity Reinforcement - concrete ultimate bond strength, Punching shear capacity, Shear strength and failure mode, In - plane failure mode.	An overview of machine learning (ML) techniques in the creation of building design and effectiveness evaluation is given in this article (SDPA). Due to an intricacy of contemporary construction systems necessitates the use of reliable and efficient frameworks for risk-informed decision-making, condition monitoring, and performance assessment. The increased computational capacity in recent years has improved machine learning's applicability in complex applications.
Moscoso E. et al. (2021) [20]	Convolutional Neural Network.	Shear force (Qi), Story stiffness (ki), Number of story, ductility ratio, Story drift ratio, and Acceleration	With this technique, an accelerometer records from building's upper floors may be used to determine the extent of a building's damage right after an earthquake. The results will be helpful for preventative actions following an earthquake, including options about the building's lasting utilization and evacuation.
Nguyen H. et al. (2021) [12]	Artificial neural network (ANN) and Extreme gradient boosting (XG Boost)	Group 1: F1-Peak ground acceleration, F2- Peak ground velocity, F3- Peak ground displacement, F4-Dominant frequency, Group 2: F5- Magnitude of earthquake, F6- Joyner-Boore distance, F7 - Soil type classification according to EC8 Group 3: F8 SA (T1, 5%) (g) Spectral acceleration at T1with a damping ratio of 5%, F9- SA (T2, 5%) (g) Spectral acceleration at T2 with a damping ratio of 5%, F10- SA (T3, 5%) (g) Spectral acceleration at T3 with a damping ratio of 5%, Group 4: F11- Ns Number of stories, F12- Number of bays.	The article explores the use of machine learning methods to anticipate planar steel moment-resisting frames' tectonic drift reactions. In this work, two ANN and XG Boost models were constructed for comparison. 22,464 nonlinear dynamic assessments were performed using the Open Sees software for 36 steel frames that underwent 624 ground motions. Four types of input factors were identified by the study, with an emphasis on maximum top and inter story drifts: ground motion intensity, earthquake and soil properties, 5%-critical-damped spectral accelerations, and structural geometry configurations.

This Table 2 presents a solid understanding of the Artificial Neural Network technique from the state-of-the-art research and discussion made above. [61-66] The applications of ANN technique is widely used in the area of image processing, pattern recognition, prediction, classification, and control, among other fields. This thorough study included the theoretical background of ANN along with applications of some recent ANN developments in the field of structural engineering [28-32]. In order to estimate the damage that earthquakes would inflict, this report reviewed recent research. using ANN modelling approach. The major input parameters which include; strong ground acceleration, wind forces, wind velocity, terrain category and soil condition, responsible for lateral

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displacement of stories in high- rise building structure. Additionally, the applications of artificial intelligence techniques such as Support Vector Machine, Open sees, Firefly algorithm, etc. are briefly discussed in the prediction of story drift. Many researchers and practitioners found that artificial neural network performed better as compared to other AI applications. The accuracy level in the story drift prediction is better along with minimalistic error criteria. Such applications of modern soft computing tools will provide futuristic and robust solutions in the prediction problems [33-39]. This review study suggests the applications of ANN modelling approach and other AI tools in the story drift prediction problems as well as other problems of structural engineering [67]. By reviewing existing literature, this study adds to the body of knowledge about the application ANN in structural engineering to anticipate story drift.

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