Seismic Performance Evaluation of High-Rise RC Building with Shear Wall Using AI

Rohit Patel1\* and Aloke Kumar Datta 1

1\* National Institute of Technology Durgapur, West Bengal, India

[rp.23ce4110@nitdgp.ac.in](mailto:rp.23ce4110@nitdgp.ac.in)

1National Institute of Technology Durgapur, West Bengal, India

[akdatta.ce@nitdgp.ac.in](mailto:akdatta.ce@nitdgp.ac.in.com)

**Abstract.** The increasing frequency and impact of strong earthquakes on urban areas have prompted researchers to develop rapid seismic health monitoring techniques. Urban apartment-type multistorey buildings often feature shear walls for earthquake resistance. Health monitoring is crucial in these structures, as they house many people and differ from structures without shear walls. This research introduces an artificial intelligence (AI)-based method for identifying seismic damage in RC buildings. When developing an AI model, it is critical to incorporate key parameters of real earthquake ground motions (EQGM) such as Peak Ground displacement (PGD), Peak Ground Velocity (PGV), Peak Ground Acceleration (PGA), and time duration. Additionally, building parameters like maximum displacement, story drift, and base shear are also taken into account. The finite element software ETABS is utilized to generate simulation data for AI model development. MATLAB software is employed to develop the AI model, which is trained using the Levenberg-Marquardt (LM) algorithm. This proposed method can be effectively applied to monitor the post-earthquake condition of reinforced concrete (RC) structures.

**Keywords:** Earthquake ground motion, Finite element software (ETABS), Time history analysis, Artificial neural network, Structural health monitoring, Shear wall.

# Introduction

The development of a country's infrastructure has a major influence on overall progress and development and is crucial in elevating its economic standing. As infrastructure expands, a country's potential for growth and prosperity increases. In countries with large democracies, like India, the economy's functionality heavily relies on public infrastructure. Unfortunately, after such infrastructure is constructed and made available to the public, it often suffers from neglect and inadequate monitoring related to performance evaluation. Neglecting this issue can result in the collapse of structures, loss of lives, and disruption of critical services that support economic development. In earthquake-prone regions, the seismic performance evaluation of high-rise reinforced concrete (RC) buildings with shear walls is crucial for ensuring structural safety. Traditionally, this evaluation has relied on finite element methods (FEM) and empirical models. However, integrating Artificial Intelligence (AI) into this domain offers significant potential for improving prediction accuracy, computational efficiency, and the management of complex structural behaviour. High-rise RC buildings are particularly vulnerable to seismic activities. To mitigate these risks, shear walls are commonly implemented to enhance the structural integrity and resilience of such buildings under seismic loads (Paulay & Priestley, 1992). While traditional methods for evaluating seismic performance involve detailed computational modelling and simulations, these approaches are often time-consuming and complex. Shear walls play a critical role in providing lateral stiffness and strength in RC buildings, effectively reducing the lateral displacements and minimizing damage during earthquakes but modelling of shear for dynamic analysis is more challenging therefore inaccurate design may lead to some failure after earthquake which needs to be monitored for checking its future performance (Fintel, 1995). Research has consistently demonstrated that incorporating shear walls substantially improves the seismic performance of high-rise buildings, especially in regions prone to seismic activity (Chopra, 2017). Traditional seismic analysis methods, including linear and nonlinear static procedures, dynamic response analysis, and finite element modelling, have proven effective but require substantial computational resources and expertise in structural dynamics (Krawinkler, 1996). Recent advancements in AI have introduced new opportunities for optimizing and predicting the seismic performance of structures. Machine learning (ML) algorithms, in particular, have been applied to model complex structural behaviours under seismic loads with high accuracy and efficiency (Ghaboussi et al., 1998). AI techniques such as artificial neural networks, support vector machines (SVM), and genetic algorithms have been used to predict seismic responses and optimize the design of RC buildings with shear walls (Khoshnevisan et al., 2014). These AI-driven approaches have demonstrated improved accuracy and reduced computation time compared to traditional methods. Numerous case studies have validated the effectiveness of AI-based models in predicting the seismic performance of high-rise RC buildings. For example, an AI-driven model successfully predicted the nonlinear behaviour of shear walls under seismic loading, showing a strong correlation with experimental results (Goulet et al., 2007). Comparative studies between AI-based methods and traditional seismic analysis techniques reveal that AI models can achieve comparable or superior accuracy while significantly reducing the time required for analysis (Naderpour et al., 2019). This efficiency makes AI a valuable tool in seismic performance evaluation, particularly in the early stages of design. However, integrating AI into structural engineering practices presents challenges, including data availability, model interpretability, and the need for domain-specific knowledge in AI model development (Sun et al., 2020). Future research should focus on addressing these challenges by exploring hybrid models that combine AI with traditional methods and developing more robust datasets for training AI models. In this study, a 5-story reinforced concrete (RC) frame building with shear walls taken from SP:22 -1982 is examined for seismic damage using an artificial neural network (ANN) based method.

# Methodology

## Overview of finite element analysis (FEA) / finite element method (FEM)

The Finite Element Method (FEM) or Finite Element Analysis (FEA) is a numerical approach for solving the complex engineering problems by dividing a large complex domain into number of smaller sub-domains called finite elements. ETABS is a widely used FEM software in structural engineering, especially for analysing how structures behave under dynamic loads like earthquakes. It supports both linear and non-linear time history analysis, allowing engineers to create detailed 3D models of buildings, including beams, columns, walls, shear walls, slabs, and foundations. The software is user friendly and offers powerful tools for designing both simple and complex structures. It enables the definition of material properties such as elasticity, density, and damping, which are crucial for dynamic analysis. For more detailed assessments, it can simulate response of the structure to specific earthquake records over time, capturing the effects of real ground motion. Additionally, it can produce animations that visualize how a building responds to dynamic loads, aiding in the understanding of its behaviour.

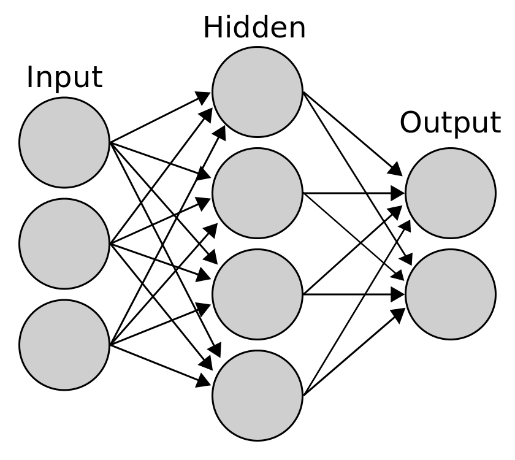
## Data generation

**Selecting Earthquake Ground Motion Data.** In this study, earthquake ground motions taken from the PEER ground motion database are employed to conduct a non-linear time history analysis of reinforced concrete (RC) framed structure. ETABS software is used to calculate the natural frequencies and time periods of the RC framed structures. These natural frequencies help to identify the critical earthquake ground motions that may cause severe damage to the structures. The Fast Fourier Transformation (FFT) method is applied to examine the frequency domain of various earthquake ground motions, comparing it with the natural frequency of the structure to identify potential matches. If the ground motion frequency aligns with the natural frequency of the structure, resonance may occur, increasing the risk of damage. After selecting a suitable earthquake ground motion, a nonlinear dynamic analysis is performed to determine the structural parameters.

**Building response data.** This study begins by using a 5-storey reinforced concrete (RC) framed building with shear walls to validate the development of an Artificial Neural Network (ANN) model. The structural response of this 5-Storey RC frame building with shear walls was analysed using Non-Linear Time History Analysis in ETABS software. Data from this analysis, including peak ground acceleration (PGA), peak ground displacement (PGD), peak ground velocity (PGV), ground motion frequency, and time duration of earthquake were used to develop the ANN model. The model was trained with these inputs to predict structural parameters such as maximum displacement, base shear, maximum inner-storey drift and structural frequency.

The objective of this study is to develop a robust ANN model capable of accurately predicting the structural responses of real buildings. To achieve this, a 5-story RC framed building with shear walls were analysed and modelled in ETABS. The non-linear time history analysis was performed with ground motion data to determine the structural responses, while input data for training the ANN model included ground motion parameters and structural details. After training, the ANN model efficiently predicted the structural parameters for new ground motion data.

## Artificial neural networks (ANN)

An artificial neural network (ANN) is a computational model designed to analyse and interpret complicated data patterns. It is inspired by the neural structure of the human brain. It consists of several main components: an input layer that receives the data, one or more hidden layers where processing and feature extraction take place, and an output layer that produces predictions or classifications. The network processes input data by passing it through each neuron, which applies a weight and an activation function to the data. During training, the model adjusts these weights to reduce errors by comparing the predicted outcomes with the actual results. The effectiveness of an ANN model is measured using metrics like Mean Squared Error (MSE) and the Coefficient of Correlation (R), which assess how accurately the predictions of the network align with the true values. Enhanced performance is achieved through iterative learning and optimization. The general schematic representation of ANN model having one input layer, one hidden layer and one output layer is shown in Fig. 1.

**Fig. 1.** General schematic representation of ANN model

## Validation of ANN model

**Simulating building response data: a numerical approach.** In this study, the non-linear time history analysis is performed using finite element analysis software ETABS to analyse a 5-storey RC framed building with shear walls. The earthquake ground motions used in the time history analysis are detailed in Table 1, with corresponding time history graphs shown in Figure 2.

The study evaluates the maximum allowable displacement, base shear, and inter-story drift and structural frequency for a 5-storey RC framed building with shear walls. The analysis and modelling of the entire structure are performed using ETABS software, following the seismic guidelines specified in IS 1893 (Part-1):2016 for different seismic zones in India. The load cases considered include Dead Load (the self-weight of beams and columns) and Earthquake Load in both the x and y directions. Details of the 5-storey RC framed building with shear walls are provided in Table 2.

The paper examines a 5-storey RC framed building with shear walls as a case study for dynamic analysis using Time History Analysis. The analysis is conducted with ETABS software, which calculates the natural frequencies or modal frequencies and time periods of the structure, as detailed in Table 3. These natural frequencies help to identify the critical earthquake ground motions that could cause damage to the structure. The Fast Fourier Transformation method is used to analyse the frequency domain of various earthquake ground motions. By comparing these frequencies with the natural frequencies of the structure, it is determined if they match, as matching frequencies can lead to resonance and significant damage. After selecting an appropriate earthquake ground motion, a nonlinear dynamic analysis is carried out to determine key design parameters such as acceleration, displacement, and velocity at different nodes.

The analysis involves selecting the top and bottom floors of the structure and using the Fast Fourier Transformation technique to convert acceleration data into frequency data. By analysing the frequencies of various nodes, a critical node for seismic performance evaluation can be identified. Since structural damage correlates with frequency, it is essential to evaluate the appropriate frequency range to effectively assess the performance of the structure. This process helps in pinpointing the critical nodes for the seismic performance evaluation.

For time history analysis, different types of earthquake ground motion data are collected from peer ground motion database. Every dataset undergoes Fast Fourier Transformation (FFT) to convert it from the time domain to the frequency domain. Utilizing the MATLAB software, this analysis is carried out.

**Table 1.** Earthquakes ground motions used for time history analysis

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| S.N. | RSN | Earthquake Name | Year | Station Name | Earthquake Magnitude | PGA(g) |
| 1 | 1 | Helena, Montana-01 | 1935 | Carroll College | 6.00 | 0.161 |
| 2 | 3 | Humbolt Bay | 1937 | Ferndale City Hall | 5.80 | 0.036 |
| 3 | 6 | Imperial Valley-02 | 1940 | El Centro Array #9 | 6.95 | 0.281 |
| 4 | 15 | Kern County | 1952 | Taft Lincoln School | 7.36 | 0.159 |
| 5 | 20 | Northern Calif-03 | 1954 | Ferndale City Hall | 6.5 | 0.163 |
| 6 | 30 | Parkfield | 1966 | Cholame - Shandon Array #5 | 6.19 | 0.146 |
| 7 | 68 | San Fernando | 1971 | LA - Hollywood Stor FF | 6.61 | 0.225 |
| 8 | 95 | Managua, Nicaragua-01 | 1972 | Managua, ESSO | 6.24 | 0.372 |
| 9 | 121 | Friuli, Italy-01 | 1976 | Barcis | 6.5 | 0.029 |
| 10 | 144 | Dursunbey, Turkey | 1979 | Dursunbey | 5.34 | 0.224 |
| 11 | 145 | Coyote Lake | 1979 | Coyote Lake Dam - Southwest Abutment | 5.74 | 0.141 |
| 12 | 146 | Coyote Lake | 1979 | Gilroy Array #1 | 5.74 | 0.063 |
| 13 | 158 | Imperial Valley-06 | 1979 | Aeropuerto Mexicali | 6.53 | 0.307 |
| 14 | 205 | Imperial Valley-07 | 1979 | El Centro Array #7 | 5.01 | 0.058 |
| 15 | 213 | Livermore-01 | 1980 | Fremont - Mission San Jose | 5.8 | 0.045 |
| 16 | 282 | Trinidad | 1980 | Rio Dell Overpass, E Ground | 7.2 | 0.151 |
| 17 | 577 | Taiwan SMART1(45) | 1986 | SMART1 M07 | 7.3 | 0.063 |
| 18 | 600 | Whittier Narrows-01 | 1987 | Brea Dam (Downstream) | 5.99 | 0.171 |
| 19 | 643 | Whittier Narrows-01 | 1987 | LA - Wonderland Ave | 5.99 | 0.041 |
| 20 | 663 | Whittier Narrows-01 | 1987 | Mt Wilson - CIT Seis Sta | 5.99 | 0.123 |
| 21 | 680 | Whittier Narrows-01 | 1987 | Pasadena - CIT Keck Lab | 5.99 | 0.112 |
| 22 | 747 | Loma Prieta | 1989 | Bear Valley #5, Callens Ranch | 6.93 | 0.026 |
| 23 | 765 | Loma Prieta | 1989 | Gilroy Array #1 | 6.93 | 0.215 |
| 24 | 957 | Northridge-01 | 1994 | Burbank - Howard Rd. | 6.69 | 0.112 |
| 25 | 1011 | Northridge-01 | 1994 | LA - Wonderland Ave | 6.69 | 0.103 |
| 26 | 1088 | Northridge-01 | 1994 | Terminal Island - S Seaside | 6.69 | 0.148 |
| 27 | 1108 | Kobe, Japan | 1995 | Kobe University | 6.9 | 0.276 |
| 28 | 1120 | Kobe, Japan | 1995 | Takatori | 6.9 | 0.618 |
| 29 | 1165 | Kocaeli, Turkey | 1999 | Izmit | 7.51 | 0.230 |
| 30 | 1200 | Chi-Chi, Taiwan | 1999 | CHY033 | 7.62 | 0.069 |

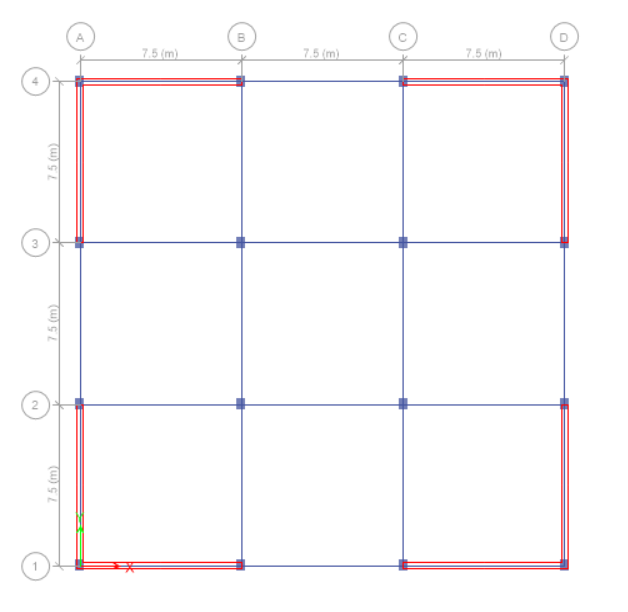
|  |  |
| --- | --- |
|  |  |
| (a) Helena Montana-01 Earthquake Ground Acceleration | (b) Humbolt Bay Earthquake Ground Acceleration |
|  |  |
| (c) Imperial Valley-02 Earthquake Ground Acceleration | (d) Kern County Earthquake Ground Acceleration |
|  |  |
| (e) Northern Calif-03 Earthquake Ground Acceleration | (f) Parkfield Earthquake Ground Acceleration |
| **Fig. 2.** Time history of earthquake ground motion acceleration | |

**Table 2.** Details of the building

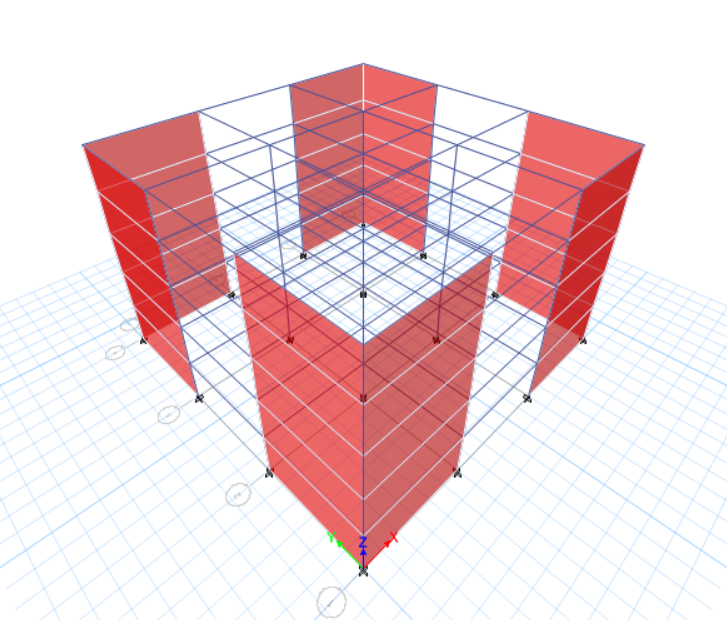
|  |  |
| --- | --- |
| Designation | Range |
| Total height of the building | 15 m |
| Storey to storey height (GF, FF) | 3 m |
| Plan area | 506.25 m2 |
| Concrete grade | M 30 |
| Steel grade | Fe 415 |
| Size of cross-section of beam | 250 x 400 (mm) |
| Size of cross-section of column | 400 x 500 (mm) |
| Thickness of shear wall | 300 mm |
| Support conditions | Fixed |
| Importance factor (I) | 1 |
| Damping constant (C) | 5% |

**Table 3.** Modal periods and natural frequencies of the structure

|  |  |  |
| --- | --- | --- |
| Mode Number | Modal Period (sec) | Natural Frequency (cyc/sec) |
| 1 | 0.421 | 2.378 |
| 2 | 0.416 | 2.406 |
| 3 | 0.294 | 3.402 |
| 4 | 0.236 | 4.234 |
| 5 | 0.193 | 5.188 |
| 6 | 0.183 | 5.461 |
| 7 | 0.168 | 5.955 |
| 8 | 0.155 | 6.458 |

****

**Fig. 3. (a)** Plan view of building in ETABS

****

**Fig. 3. (b)** 3D view of building in ETABS

**Development of artificial neural networks (ANN).** This study proposes the use of an Artificial Neural Network (ANN) to analyse a 5-storey reinforced concrete (RC) framed building with shear walls subjected to various earthquake ground motions. To develop the ANN model, a set of input and output data is required. In this study, the ANN model incorporates nine parameters: five related to ground motion and four to structural design. The ground motion parameters include: (i) Peak Ground Acceleration (PGA), (ii) Peak Ground Velocity (PGV), (iii) Peak Ground Displacement (PGD), (iv) Ground Motion Frequency, and (v) Time Duration of the Earthquake.

In this study, the ground motion parameters (PGA, PGD, PGV, Time Duration, and Ground Motion Frequency) are used as inputs, while structural parameters (maximum displacement, maximum inter-storey drift, base shear, and structural frequency) serve as outputs. Earthquake ground motion data is sourced from the PEER Ground Motion Database.

To derive the ground motion parameters (PGA, PGD, PGV and Ground Motion Frequency) from the ground motion data, Fast Fourier Transformation (FFT) is performed using MATLAB. Structural parameters such as maximum displacement, maximum inter-storey drift, base shear and structural frequency are analysed using FEM software (ETABS) through time history analysis.

During the training process, the network is trained using known input-output pairs, with the Levenberg-Marquardt method employed to minimize errors. All ANN modelling is conducted using the MATLAB Neural Network Toolbox. The ground motion data from 30 earthquakes is utilized for training, validation, and testing of the ANN model. The details of these ground motion and structural parameters are provided in Tables 4 and 5, respectively. The architecture of the ANN model is depicted in Figure 4.

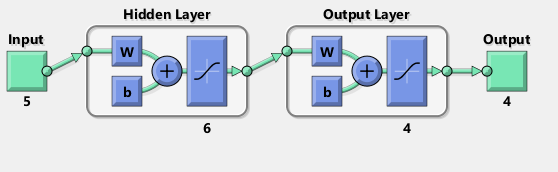
**Table 4.** Earthquake ground motion parameters and ANN model inputs

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Earthquake Name | PGA (g) | PGD (cm) | PGV (cm/sec) | Time Duration  (sec) | Frequency  (Hz) |
| Helena, Montana-01 | 0.161 | 1.354 | 5.873 | 50.930 | 2.474 |
| Humbolt Bay | 0.036 | 0.346 | 2.363 | 40.000 | 1.725 |
| Imperial Valley-02 | 0.281 | 8.660 | 30.923 | 53.720 | 1.471 |
| Kern County | 0.159 | 6.102 | 15.222 | 54.350 | 1.362 |
| Northern Calif-03 | 0.163 | 14.618 | 36.054 | 40.000 | 0.625 |
| Parkfield | 0.146 | 2.178 | 7.100 | 44.000 | 5.455 |
| San Fernando | 0.225 | 15.906 | 21.707 | 79.450 | 0.743 |
| Managua, Nicaragua-01 | 0.372 | 6.278 | 29.043 | 45.695 | 3.458 |
| Friuli, Italy-01 | 0.029 | 1.257 | 2.329 | 16.585 | 1.266 |
| Dursunbey, Turkey | 0.224 | 0.553 | 8.606 | 7.160 | 2.374 |
| Coyote Lake | 0.141 | 1.170 | 11.752 | 28.835 | 1.803 |
| Coyote Lake | 0.063 | 0.661 | 2.558 | 26.860 | 3.611 |
| Imperial Valley-06 | 0.307 | 10.546 | 42.769 | 14.770 | 0.677 |
| Imperial Valley-07 | 0.058 | 0.059 | 0.900 | 17.310 | 20.046 |
| Livermore-01 | 0.045 | 0.971 | 4.313 | 17.995 | 0.778 |
| Trinidad | 0.151 | 3.598 | 8.862 | 22.000 | 3.182 |
| Taiwan SMART1(45) | 0.063 | 3.655 | 6.854 | 72.940 | 0.357 |
| Whittier Narrows-01 | 0.171 | 1.476 | 8.115 | 29.940 | 4.542 |
| Whittier Narrows-01 | 0.041 | 0.154 | 1.627 | 18.150 | 6.997 |
| Whittier Narrows-01 | 0.123 | 0.727 | 4.569 | 39.995 | 6.476 |
| Whittier Narrows-01 | 0.112 | 1.391 | 10.317 | 39.995 | 1.425 |
| Loma Prieta | 0.026 | 0.437 | 1.839 | 29.815 | 0.805 |
| Loma Prieta | 0.215 | 7.558 | 15.486 | 39.985 | 3.126 |
| Northridge-01 | 0.112 | 2.974 | 10.704 | 29.990 | 1.567 |
| Northridge-01 | 0.103 | 1.840 | 7.896 | 29.990 | 1.267 |
| Northridge-01 | 0.148 | 2.284 | 16.472 | 34.990 | 2.144 |
| Kobe, Japan | 0.276 | 15.150 | 55.270 | 32.000 | 0.813 |
| Kobe, Japan | 0.618 | 39.924 | 120.615 | 40.960 | 0.806 |
| Kocaeli, Turkey | 0.230 | 24.278 | 38.271 | 30.000 | 3.300 |
| Chi-Chi, Taiwan | 0.069 | 15.007 | 19.429 | 90.000 | 0.278 |

**Table 5.** Structure response parameters and ANN model outputs

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Earthquake Name | Displacement (mm) | MISD (mm/mm) | Base Shear (kN) | Frequency (Hz) |
| Helena, Montana-01 | 11.909 | 0.001028 | 1565.289 | 15.217 |
| Humbolt Bay | 4.382 | 0.000377 | 245.950 | 15.575 |
| Imperial Valley-02 | 29.522 | 0.0031 | 2632.391 | 15.767 |
| Kern County | 21.167 | 0.00184 | 1221.053 | 16.118 |
| Northern Calif-03 | 19.414 | 0.002373 | 1891.961 | 16.200 |
| Parkfield | 11.881 | 0.001187 | 1704.964 | 16.182 |
| San Fernando | 23.973 | 0.002272 | 1671.483 | 15.758 |
| Managua, Nicaragua-01 | 32.113 | 0.003078 | 2452.469 | 15.844 |
| Friuli, Italy-01 | 0.968 | 0.000099 | 230.061 | 15.134 |
| Dursunbey, Turkey | 31.965 | 0.002779 | 2177.354 | 15.922 |
| Coyote Lake | 21.328 | 0.00186 | 1148.010 | 16.889 |
| Coyote Lake | 3.687 | 0.000354 | 670.132 | 15.488 |
| Imperial Valley-06 | 32.228 | 0.003087 | 2380.703 | 15.708 |
| Imperial Valley-07 | 1.480 | 0.000136 | 473.128 | 15.251 |
| Livermore-01 | 6.138 | 0.000538 | 234.831 | 16.004 |
| Trinidad | 14.894 | 0.001679 | 904.454 | 15.818 |
| Taiwan SMART1(45) | 9.123 | 0.000778 | 660.455 | 15.369 |
| Whittier Narrows-01 | 13.500 | 0.001405 | 896.583 | 15.999 |
| Whittier Narrows-01 | 2.842 | 0.000271 | 492.799 | 16.033 |
| Whittier Narrows-01 | 4.357 | 0.000573 | 1170.130 | 16.202 |
| Whittier Narrows-01 | 14.787 | 0.001354 | 1126.011 | 15.752 |
| Loma Prieta | 2.678 | 0.000266 | 217.316 | 16.066 |
| Loma Prieta | 18.941 | 0.001834 | 2378.187 | 16.606 |
| Northridge-01 | 122.298 | 0.018704 | 22269.113 | 2.367 |
| Northridge-01 | 11.729 | 0.00105 | 1002.479 | 15.605 |
| Northridge-01 | 28.802 | 0.002483 | 1578.101 | 16.147 |
| Kobe, Japan | 22.765 | 0.002651 | 2113.932 | 15.688 |
| Kobe, Japan | 77.510 | 0.00793 | 5429.650 | 15.527 |
| Kocaeli, Turkey | 25.242 | 0.002148 | 1401.887 | 16.100 |
| Chi-Chi, Taiwan | 7.981 | 0.000678 | 544.528 | 15.867 |

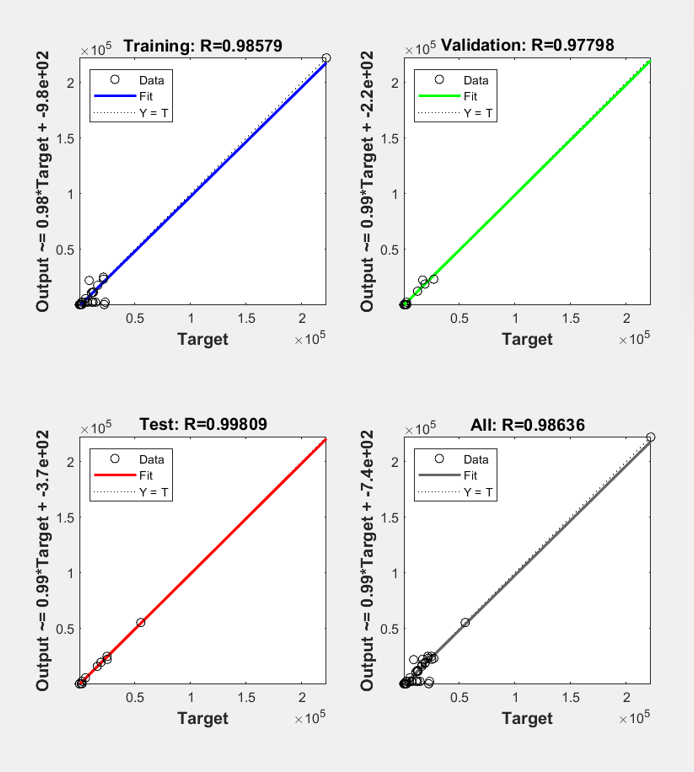
**Training of ANN Model.** In this study, the input and output data were randomly split, allocating 70% for training, 15% for validation, and 15% for testing the Artificial Neural Network (ANN) model. A two-layer feed-forward network will be utilized, featuring sigmoid neurons in the hidden layer and linear neurons in the output layer. The network will be trained using the Levenberg-Marquardt backpropagation algorithm, employing a sigmoid activation function. The performance of the model will be gauged through the Regression Analysis.

For training purposes, 30 samples of 5 items were taken from the input layer, along with 30 samples of 4 items from the output layer. A method of trial and error was used to identify a single hidden layer with six neurons.

**Fig. 4.** Architecture of ANN Model

**Efficiency of ANN Model.** Regression analysis gauges the efficiency of the ANN model by measuring how well the predicted outputs align with the actual targets. A high correlation coefficient (close to 1) indicates strong predictive accuracy, signifying that the model has successfully captured the underlying trends in the data. This analysis helps in determining the effectiveness of the ANN model in generalising to unseen data. Ultimately, it provides a quantitative measure of the predictive capacity of ANN model.

In this study, the trained ANN model achieved an R value of 0.98636 (as shown in Fig. 5), demonstrating superior predictive performance and the ability to deliver highly accurate results.



**Fig. 5.** Regression analysis

# Comparing results of ETABS and ANN model in predicting structural responses

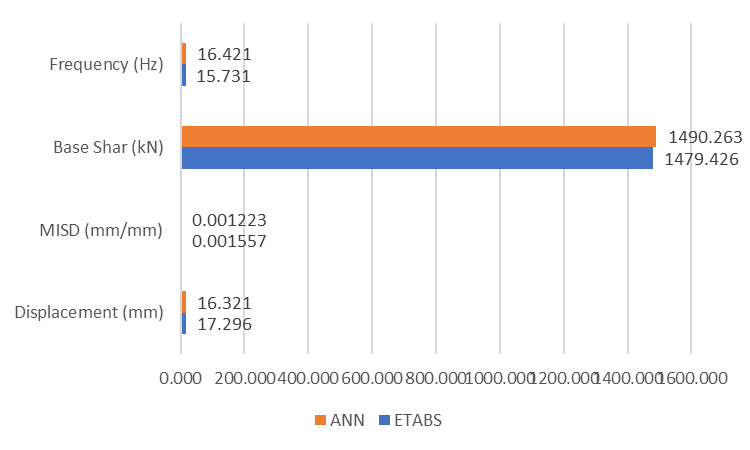
In this study, the ANN model was trained using input and output data from 30 earthquake events taken from peer ground motion database. The trained ANN model was then employed to predict the structural parameters such as maximum displacement, maximum inter-story drift (MISD), base shear and structural frequency of a 5-storey reinforced concrete (RC) framed structure with shear walls using new ground motion data from the 1992 Landers earthquake, which had a magnitude of 7.28, as presented in Table 6. The predicted structural parameters from the ANN model were compared with the results obtained from FEA software (ETABS) for the same 5-storey RC framed structure with shear walls. This comparison, detailed in Table 7, is further explored through a comparative analysis between the ANN model and FEA software (ETAB), with insights illustrated graphically in Fig. 6.

**Table 6.** New earthquake ground motion data

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Earthquake Name | PGA  (g) | PGD  (cm) | PGV  (cm/sec) | Time Duration  (sec) | Frequency  (Hz) |
| Landers | 0.165 | 3.498 | 7.608 | 60.010 | 6.899 |

**Table 7.** Comparison of structural parameters obtained from ETABS and trained ANN model

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Displacement (mm) | MISD (mm/mm) | Base Shear (kN) | Frequency  (Hz) |
| ETABS | 17.296 | 0.001557 | 1479.426 | 15.731 |
| ANN | 16.321 | 0.001223 | 1490.263 | 16.421 |



**Fig. 6.** Comparison of structural parameters from ANN model and FEA software (ETABS)

# Conclusions

A comprehensive numerical simulation study was conducted to evaluate the effectiveness of an ANN model within the scope of Artificial Intelligence (AI) for Seismic Performance Evaluation of a 5-storey RC framed structure with shear walls. The key findings from this research are as follows:

* To develop the ANN model, real-time earthquake ground motion data was utilized to obtain acceleration response records at key locations, particularly at the top level of the structure. This data was used to analyse Maximum Displacement and Maximum Inter-Story Drift (MISD).
* Key parameters from Earthquake Ground Motion data such as PGA, PGV, PGD, Time Duration of Earthquake and Ground Motion Frequency were used as inputs for seismic performance evaluation. The outputs included essential design parameters like Maximum Displacement, Base Shear, Maximum Inter-Story Drift and Structural Frequency.
* Regression values for the ANN modelling of 5-storey RC framed structure with a shear wall are 0.98579, 0.97798, and 0.99809 for training, validation, and testing respectively.
* The ANN model developed in this study is highly efficient, as it can predict design parameters much faster than the computations performed using FEM software (ETABS). Consequently, the findings of this research can be effectively applied to both design processes and future studies.
* An ANN model-based approach offers significant efficiency in Seismic Performance Evaluation, as it eliminates the need for a physical model-based approach, which is efficient for disaster mitigation just after the occurrence of earthquake.
* This ANN Model may be used for similar type of buildings at any locations. We can take some more structures for further research.

# References

1. Ekambaram, T., Datta, A. K., & Pal, A. (2024). Seismic structural health monitoring of RC framed building using artificial neural network model: a study. Asian Journal of Civil Engineering, 1-16.
2. Adeli, H., & Park, H. S. (1998). Neural networks in structural engineering. CRC Press.
3. Chopra, A. K. (2017). Dynamics of Structures: Theory and Applications to Earthquake Engineering (5th ed.). Prentice Hall.
4. Fintel, M. (1995). Performance of buildings with shear walls in earthquakes of the last thirty years. PCI Journal, 40(3), 62-80.
5. Ghaboussi, J., Garrett Jr, J. H., & Wu, X. (1991). Knowledge-based modeling of material behavior with neural networks. *Journal of engineering mechanics*, *117*(1), 132-153.
6. Goulet, C., Lee, J., Der Kiureghian, A., & Kiremidjian, A. (2007). Bayesian network model for post-earthquake infrastructure management. Earthquake Engineering & Structural Dynamics, 36(9), 1295-1313.
7. Khoshnevisan, S., Kaveh, A., & Raeisi, H. (2014). Optimal design of reinforced concrete shear walls using a hybrid of ant colony optimization and particle swarm optimization. Computers and Concrete, 13(2), 239-259.
8. Krawinkler, H. (1996). Seismic design and performance of steel moment-resisting frame structures. Structural Engineers Association of California (SEAOC) Vision 2000 Committee.
9. Naderpour, H., Fakharian, P., & Khodayari, A. (2019). Seismic performance assessment of concrete shear walls using soft computing techniques. Engineering Structures, 199, 109613.
10. Paulay, T., & Priestley, M. J. N. (1992). Seismic design of reinforced concrete and masonry buildings. Wiley-Interscience.
11. Sun, L., Gu, Q., & Li, Z. (2020). AI-based framework for structural health monitoring and damage detection: Case studies and applications. Structural Health Monitoring, 19(5), 1453-1474.
12. SP:22 -1982, “Explanatory Handbook on Codes, for Earthquake Engineering”, Published by Bureau of Indian Standards, New Delhi 110002.
13. Behfarnia, K., & Houshmandi, S. (2022). Application of deep learning in seismic performance evaluation of RC buildings with shear walls. Engineering Structures, 240, 112361.
14. PEER (Pacific Earthquake Engineering Research Centre). Strong motion database http://peer.berkeley.edu/smcat/.