Development of a Novel ANN Model for Earthquake Resistant Design of RC Buildings in Hilly Terrain

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**Abstract.** Structural engineers encounter significant challenges in planning, designing, and constructing safe buildings in hilly areas. Time history analysis of structure utilizing real-time ground motion data is the most accurate analysis for earthquake resistant design. Currently, artificial intelligence models are being used to solve difficult real-world problems like earthquake analysis and structural design. The use of AI models can significantly reduce the time and effort required to efficiently create earthquake-resistant designs. Data generation was performed using the ETABS software, incorporating earthquake typical ground motions producing critical response to the typical structure. To develop an AI model for earthquake-resistant design, it is essential to consider key parameters of real earthquake ground motions, such as Peak Ground Acceleration, Peak Ground Velocity, Peak Ground Displacement, and the duration of the event and frequency of the ground motion which are in line with structural frequency. Additionally, building parameters, including maximum displacement, base shear, story drift and overturning moment were considered as essential factors as output in the AI model development process. The developed back propagation feed forward ANN model correctly predicts the design parameters of a typical target structure in hilly region which is computationally efficient. This meta-heuristic approach offers great research interest and possible applications in the design of earthquake-resistant structures due to its reduction in computational time and effort particularly for hilly region.

**Keywords:** Earthquake resistant design; Non-linear dynamic analysis; Time history analysis; Finite element software(ETABS); R C Building; Hilly Terrain; ANN Model..

# Introduction

The appearance of slopes is often attractive and soothing to the eye, structural engineers face significant challenges when planning, designing, and constructing buildings in such areas. The steep gradients, difficult terrain, and susceptibility to natural disasters like earthquakes make building design in hilly regions complex. Due to the mountainous terrain, structures in these areas should be designed with asymmetrical mass distribution and irregular shapes. When subjected to various stresses, especially seismic forces and loads, these structures behave differently compared to those built on flat land.

The study of earthquake-resistant building design has long been a significant field of civil engineering research. With the increasing frequency of earthquakes worldwide, particularly in hilly regions, it is crucial to build structures capable of withstanding such environmental disasters. Designing effective earthquake-resistant buildings is a challenging task for earthquake engineers in the hilly regions. Currently earthquake-resistant design techniques are complex, and the analytical models used for dynamic analysis must accurately represent the irregularities present in building configurations, especially in structures with unusual designs in hilly regions.

There is a pressing need for further studies, as structural failures due to earthquakes have led to significant loss of property and life. This investigation looks at using Artificial Neural Networks as an effective tool for enhancing and optimizing the efficiency of earthquake-resistant building designs, particularly in hilly areas. Traditionally, seismic-resistant design methods have based on empirical data and complex mathematical models to predict a structure’s response during an ground motion. However, the use of artificial neural networks (ANN) offers a practical way to revolutionize this field. ANNs, which are modelled after the neural network found in the human brain, are very good at learning, predicting, and recognizing patterns.

For designing earthquake-resistant buildings, several Finite Element softwares such as ETABS, STAAD-Pro, and others, are available. However, using Finite Element software requires significant computational resources and often demands expert knowledge, along with numerous approximations and assumptions. To address issues such as excessive time consumption and high computational demands, alternative approaches like ANN models, can be employed. In recent years, researchers have increasingly utilized ANN models in various civil engineering applications to improve and streamline the design process.

(Carlo et all., 2021) explains an innovative approach to optimize the seismic design of earthquake-resistant buildings utilizing an optimization approach and inversion of artificial neural networks. By applying an inversion algorithm, the method identifies a collection of design specifications that adhere to specified code-based seismic performance constraints. This approach is demonstrated through a multi-story reinforced concrete building's design, resulting in a cost-effective seismic-resistant design solution. The findings suggest that the suggested approach can greatly enhance the efficiency and effectiveness of earthquake-resistant building designs, offering a promising alternative to traditional design techniques.

(Berrais et all.,2005) tells earthquake-resistant design demands a comprehensive understanding of conceptual design, mathematical modeling, analytical assumptions, and precise structural detailing. The methodology outlined involves two key phases: the preliminary design, which includes conceptual design, elastic analysis, and reinforcement allocation, and the detailed design, which encompasses non-linear time history analysis, ductility review, and refinement of reinforcement. This structured approach ensures that the final design is both robust and compliant with seismic performance requirements, ultimately enhancing the safety and resilience of the building.

(behera et all.,2024) explains the trained ANN model could forecast the design specifications accurately and in significantly less time (around 0.5-0.9 seconds) compared to detailed finite element analysis (around 2-2.5 minutes) for the same ground motions.

(Narayanan et all.,2012) explains RC buildings in hilly regions are often non-engineered and constructed without proper planning on steep hill slopes. During earthquakes, these buildings experience severe damage and collapse due to factors such as varying column heights on slopes, irregular infill wall distribution, and inadequate foundations. This paper highlights the urgent need to improve seismic robust architecture and construction practices for buildings in hilly regions in high seismic areas, to enhance their safety and resilience.

(Moller et al., 2009) explored the use of neural networks for structural optimization in performance-based seismic engineering design. The primary goal of this approach is to optimize structural costs while ensuring compliance with specific performance criteria. This strategy aims to create cost-effective and resilient buildings capable of withstanding seismic events. To achieve this, the design must meet the minimum target reliability for various limit states, ensuring that the structure performs adequately under seismic loading conditions.

(conte et al., 1994) used neural networks to develop a method for modeling the seismic response of multi-storey frame buildings. This method accurately simulates the seismic response of individual building frames by combining a backpropagation learning technique with multi-layer feedforward neural networks.

(Shao & Andrawes, 2022) employed real-world seismic accelerograms and corresponding structural responses from analytical building models to train neural networks. Their study evaluated the performance of neural networks in predicting structural behavior by analyzing building frames subjected to seismic base excitations across varying heights (ranging from one to six stories). The findings demonstrated the effectiveness of the neural network model in capturing the dynamic responses of buildings under seismic loading conditions.

(Jafarzadeh et al., 2014) employed an Artificial Neural Network (ANN) model to predict the cost of seismic retrofitting for buildings. Their research demonstrated the effectiveness of this advanced modelling technique in accurately forecasting retrofit costs. By applying the ANN approach, they developed several non-parametric models based on key predictors of net retrofit costs, providing valuable insights into the financial planning of seismic retrofits.

(Nguyen et al., 2021) utilized Extreme Gradient Boosting and Artificial Neural Networks to predict the seismic drift responses of planar steel moment frames. The study aimed to develop machine learning models capable of forecasting how these frames would behave during seismic events caused by ground motion. By applying these advanced machine learning techniques, the researchers sought to enhance the accuracy of predictions regarding the seismic performance of planar steel moment-resisting frames.

(De Lautour & Omen- zetter, 2009) employed Artificial Neural Networks (ANNs) to predict seismic-induced structural damage. Traditionally, methods such as seismic vulnerability curves and the nonlinear finite element method (FEM) are used to assess the extent of damage caused by seismic events. However, to address some of the limitations of these conventional approaches, the authors used ANNs to improve the accuracy of damage predictions.

(Hansapinyo et al.,2020) employed Geographic Information System (GIS)-based building data in conjunction with an Artificial Intelligence system to forecast seismic damage to buildings.

(Bandara et al.,2013) The results indicate that, in comparison to other computational methods, ANN-based predictions offer more accurate forecasts and generally align better with experimental data.

Artificial neural networks (ANNs) and conventional regression models were evaluated by (Cho et al.,2022) in order to forecast the displacement of slopes due to earthquakes. Their research showed that although the ANN model offered clear benefits in collecting more intricate patterns in the data, the classical regression model produced smoother predictions based on input parameters.

(Ozkam et al., 2023) aimed to develop an efficient and rapid evaluation method for reinforced concrete buildings using artificial neural networks (ANNs) with minimal input data. Their results demonstrated that ANNs can accurately predict the behavior of reinforced concrete structures during earthquakes, highlighting the potential for quick and reliable seismic assessments.

(Vafaei et al.,2014) proposed a method combining wavelet transform and artificial neural networks to evaluate seismic damage in cantilever structures. The technique involves measuring response accelerations at strategically selected locations. The recorded signals are then analyzed using continuous wavelet transform to detect sudden changes indicative of damage.

(Sreenivas et al., 2008) aimed to examine the relationship between ground motion characteristics and ductility demands using a neural network approach. The study focused on predicting peak ground acceleration, ductility, and peak ground velocity based on factors such as the epicentral distance of the ground motion and its frequency.

(Sheikh et al.,2022) emphasized the need for a comprehensive fragility assessment, incorporating iterative nonlinear dynamic analysis (NDA), to measure the seismic resilience of buildings. However, the high computational cost of traditional methods based on finite element (FE) analysis can make this approach impractical. To address this, the study explores the use of soft computing techniques to reduce the computational expense of seismic fragility analysis. Specifically, it presents methods for analyzing the fragility of multistory structures using nonlinear autoregressive neural networks with external input.

(Tsikas et al., 2024) conducted several tests to assess the performance of their developed model using a regression diagram. They evaluated various strategies, including different configurations and sizes of artificial neural networks (ANNs). The results revealed that well-designed ANN approaches can achieve high precision and consistent outcomes across diverse datasets for training, testing, and validation. The study also suggests that similar techniques could be used to model seismic risk assessments using real data from past earthquakes, specifically for evaluating seismic damage to highways and bridges using soft computing methods.

(Kaveh et al.,2023) used Artificial Neural Networks (ANNs) trained with metaheuristic optimization techniques to accurately predict the maximum load-bearing capacity of high-strength steel columns under buckling conditions. Their method surpasses the conservative estimates provided by traditional theories. By employing advanced algorithms such as Particle Swarm Optimization, Genetic Algorithms, and Colliding Body Optimization, their models achieved an impressive accuracy rate of 99.8%. This highlights the effectiveness and precision of AI-driven approaches in structural engineering applications.

# Methodology

In this paper, a 3D five-story set-back RC building frame is studied for validation and the development of an Artificial Neural Network (ANN) model. For validation, the Fast Fourier Transform (FFT) of the structural response of a five-story set-back rc building is computed using MATLAB software and compared with the natural frequency of the five-story set back rc building. Subsequently, an ANN model for the five-story set-back building is developed using input and output data as shown in Table 2 and Table 3 respectively.

The input data includes Peak Ground Acceleration (PGA), Peak Ground Velocity (PGV), Peak Ground Displacement (PGD),the time duration and frequency of real earthquake ground motion (EQGM) data. The output data comprises structural design parameters such as displacement, maximum inter storey drift, base shear, and overturning moment. By using this input and output data from Table 2 and Table 3 respectively, the ANN model is trained. The trained ANN model is then used to predict the structural design parameters for a five-story set-back building using new real EQGM data.

**Table -1** Earthquake ground motion data

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| S.N. | Earthquake Name | Year | Station Name | Earthquake Magnitude | Latitude (deg) | Longitude (deg) |
| 1 | Helena, Montana-01 | 1935 | Carroll College | 6.00 | 46.61 | -111.96 |
| 2 | Parkfield | 1966 | Cholame - Shandon Array #5 | 6.19 | 35.955 | -120.4983 |
| 3 | Managua, Nicaragua-01 | 1972 | Managua, ESSO | 6.24 | 12.15 | -86.27 |
| 4 | Coyote Lake | 1979 | Gilroy Array #1 | 5.74 | 37.065 | -121.49 |
| 5 | Imperial Valley-07 | 1979 | El Centro Array #7 | 5.01 | 32.7667 | -115.4413 |
| 6 | Trinidad | 1980 | Rio Dell Overpass, E Ground | 7.2 | 41.074 | -124.61 |
| 7 | Whittier Narrows-01 | 1987 | Brea Dam (Downstream) | 5.99 | 34.0493 | -118.081 |
| 8 | Whittier Narrows-01 | 1987 | LA - Wonderland Ave | 5.99 | 34.0493 | -118.081 |
| 9 | Whittier Narrows-01 | 1987 | Mt Wilson - CIT Seis Sta | 5.99 | 34.093 | -118.081 |
| 10 | Loma Prieta | 1989 | Gilroy Array #1 | 6.93 | 37.0407 | -121.8829 |
| 11 | Northridge-01 | 1994 | Terminal Island - S Seaside | 6.69 | 34.2057 | -118.5539 |
| 12 | Kocaeli, Turkey | 1999 | Izmit | 7.51 | 40.748 | 29.99 |
| 13 | Caldiran, Turkey | 1976 | Maku | 7.21 | 39.015 | 44 |
| 14 | Whittier Narrows-02 | 1987 | Brea - S Flower Av | 5.27 | 34.06 | -118.1035 |
| 15 | Landers | 1992 | Big Bear Lake - Civic Center | 7.28 | 34.2 | -116.436 |
| 16 | San Simeon, CA | 2003 | Castaic - Old Ridge Route | 6.5 | 35.697 | -121.085 |
| 17 | Niigata, Japan | 2004 | FKIH01 | 6.63 | 37.307 | 138.839 |

The aim of this paper is to develop a novel ANN model capable of efficiently predicting the structural design parameters of earthquake-resistant real-type buildings, specifically for typical hilly buildings. After performing Time History Analysis (THA) of the five-storey set-back RC building, structural design parameters collected from ETABS software are used as output data for ANN training. The input data for training includes PGA, PGV, PGD, time duration, and frequency. Once trained, the ANN model can efficiently predict structural design parameters for new EQGM data in a very short amount of time.

**Table -2**  Input data

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| S.N. | Earthquake Name | Year | Earthquake Magnitude | PGA  (g) | PGD  (cm) | PGV  (cm/sec) | Time Duration(sec) | Frequency  (Hz) |
| 1 | Helena, Montana-01 | 1935 | 6.00 | 0.161 | 1.354 | 5.873 | 50.930 | 2.474 |
| 2 | Parkfield | 1966 | 6.19 | 0.146 | 2.178 | 7.100 | 44.000 | 5.455 |
| 3 | Managua, Nicaragua-01 | 1972 | 6.24 | 0.372 | 6.278 | 29.043 | 45.695 | 3.458 |
| 4 | Coyote Lake | 1979 | 5.74 | 0.063 | 0.661 | 2.558 | 26.860 | 3.611 |
| 5 | Imperial Valley-07 | 1979 | 5.01 | 0.058 | 0.059 | 0.900 | 17.310 | 20.046 |
| 6 | Trinidad | 1980 | 7.2 | 0.151 | 3.598 | 8.862 | 22.000 | 3.182 |
| 7 | Whittier Narrows-01 | 1987 | 5.99 | 0.171 | 1.476 | 8.115 | 29.94 | 4.542 |
| 8 | Whittier Narrows-01 | 1987 | 5.99 | 0.041 | 0.154 | 1.627 | 18.150 | 6.997 |
| 9 | Whittier Narrows-01 | 1987 | 5.99 | 0.123 | 0.727 | 4.569 | 39.995 | 6.476 |
| 10 | Loma Prieta | 1989 | 6.93 | 0.215 | 7.558 | 15.486 | 39.985 | 3.126 |
| 11 | Northridge-01 | 1994 | 6.69 | 0.148 | 2.284 | 16.472 | 34.990 | 2.144 |
| 12 | Kocaeli, Turkey | 1999 | 7.51 | 0.230 | 24.278 | 38.271 | 30.000 | 3.300 |
| 13 | Caldiran, Turkey | 1976 | 7.21 | 0.055 | 1.280 | 2.888 | 28.250 | 6.159 |
| 14 | Whittier Narrows-02 | 1987 | 5.27 | 0.073 | 0.564 | 4.699 | 24.235 | 2.104 |
| 15 | Landers | 1992 | 7.28 | 0.165 | 3.498 | 7.608 | 60.010 | 6.899 |
| 16 | San Simeon, CA | 2003 | 6.5 | 0.011 | 0.803 | 1.361 | 71.000 | 2.127 |
| 17 | Niigata, Japan | 2004 | 6.63 | 0.000773 | 0.19593 | 0.121764 | 120 | 4.0083 |

**Table -3** Output data

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| S.N. | Earthquake Name | Year | Earthquake Magnitude | Displacement (mm) | MISD (mm/mm) | Base Shar (kN) | Over-turning moment (kn/m) |
| 1 | Helena, Montana-01 | 1935 | 6.00 | 2.496 | 0.000799 | 372.871 | 747.6171 |
| 2 | Parkfield | 1966 | 6.19 | 4.841 | 0.001506 | 675.9512 | 1450.5185 |
| 3 | Managua, Nicaragua-01 | 1972 | 6.24 | 10.489 | 0.003262 | 1449.8165 | 3143.0801 |
| 4 | Coyote Lake | 1979 | 5.74 | 1.46 | 0.000487 | 230.394 | 437.3937 |
| 5 | Imperial Valley-07 | 1979 | 5.01 | 0.443 | 0.000138 | 65.2595 | 132.8698 |
| 6 | Trinidad | 1980 | 7.2 | 3.967 | 0.001234 | 559.1289 | 1188.7281 |
| 7 | Whittier Narrows-01 | 1987 | 5.99 | 7.291 | 0.002367 | 1120.2388 | 2184.895 |
| 8 | Whittier Narrows-01 | 1987 | 5.99 | 1.269 | 0.000419 | 198.1708 | 380.209 |
| 9 | Whittier Narrows-01 | 1987 | 5.99 | 3.373 | 0.001049 | 481.8713 | 1010.7951 |
| 10 | Loma Prieta | 1989 | 6.93 | 3.414 | 0.001093 | 517.3343 | 1022.927 |
| 11 | Northridge-01 | 1994 | 6.69 | 3.512 | 0.001092 | 480.2124 | 1052.4412 |
| 12 | Kocaeli, Turkey | 1999 | 7.51 | 5.767 | 0.002678 | 1267.354 | 1728.2257 |
| 13 | Caldiran, Turkey | 1976 | 7.21 | 1.008 | 0.000342 | 161.7107 | 302.0243 |
| 14 | Whittier Narrows-02 | 1987 | 5.27 | 1.668 | 0.000519 | 132.9365 | 499.779 |
| 15 | Landers | 1992 | 7.28 | 0.0004301 | 1.338E-07 | 0.0592 | 0.1289 |
| 16 | San Simeon, CA | 2003 | 6.5 | 0.196 | 0.000062 | 29.5375 | 58.6084 |
| 17 | Niigata, Japan | 2004 | 6.63 | 0.03 | 0.000009 | 4.0861 | 8.9751 |

# Finite element description

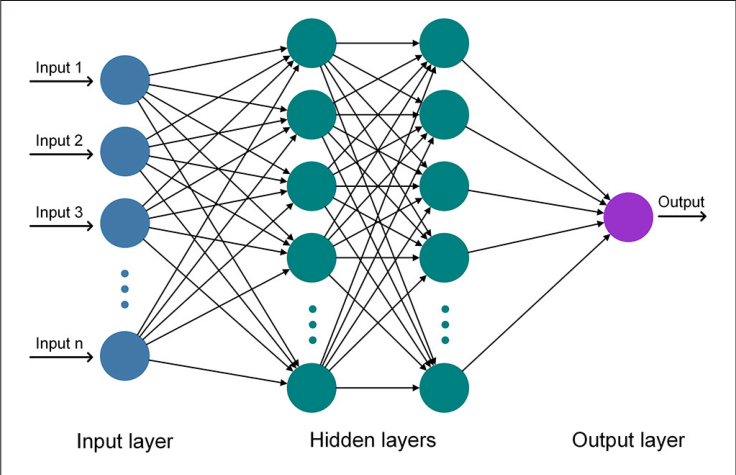
The Finite Element Method (FEM) is a popular numerical method for resolving intricate physics and engineering problems, such as those involving fluid dynamics, heat, and structures. In order to create a mesh that depicts the complete structure, it splits a bigger, more complicated geometry into smaller, simpler elements known as finite elements. These elements are joined at nodes. This method divides an issue into digestible chunks that are easily studied using mathematical models, enabling efficient analysis and optimization of designs. Many different fields of engineering, including aerospace, automotive, biomedical, structural, mechanical, and civil, heavily rely on FEM. Numerous finite element software packages are available, such as Abaqus, ETABS, ANSYS, and STAAD-Pro, each with specific functions for various kinds of analysis. This work uses ETABS.

# Artificial Neural Network

Artificial Neural Networks (ANNs) are computational systems designed to replicate the structure and function of biological neural networks in the human brain. They consist of interconnected units known as artificial neurons, organized into layers: input, hidden, and output. Each input can send signals to multiple neurons, and each neuron can receive signals from various inputs. During training, ANNs adjust the weights of these connections to learn from data, identify patterns, and make predictions. This training process enables ANNs to handle tasks like classification, regression, and pattern recognition effectively.

The performance of an ANN is influenced by the number of neurons in the hidden layers, which affects the network's ability to manage complex, nonlinear interactions between variables. Neurons in the output layer represent the predicted values. The difference between the predicted output and the actual target value is known as the error. Before testing, the ANN must be trained on a dataset to ensure accurate predictions for new inputs.

To evaluate an ANN model's performance, metrics such as the Coefficient of Correlation (R) and Mean-Squared Error (MSE) are commonly used. A typical application of ANNs involves using a feedforward multilayer neural network, which is well-suited for modelling complex, non-linear relationships. ANNs are widely applied in fields such as image recognition, natural language processing, and financial forecasting. In this context, MATLAB version 2019a is used for developing ANN models. The general schematic network diagram, shown in Fig. 1, illustrates the input, hidden, and output layers of the network.



**Fig.-1** Diagram of ANNs

# Data generation

ANN models necessitate large amounts of input and output data for development. For instance, input data from PEER ground motion includes the total time duration of various earthquake ground motion (EQGM) events, as well as peak values of acceleration, velocity, and displacement.

In relation to output data Non-linear dynamic analysis i.e Time history analysis has been carried out using finite element software ETABS version 2019.Key parameters for output data are displacement, maximum inter-storey drift, base shear and over-turning moment.

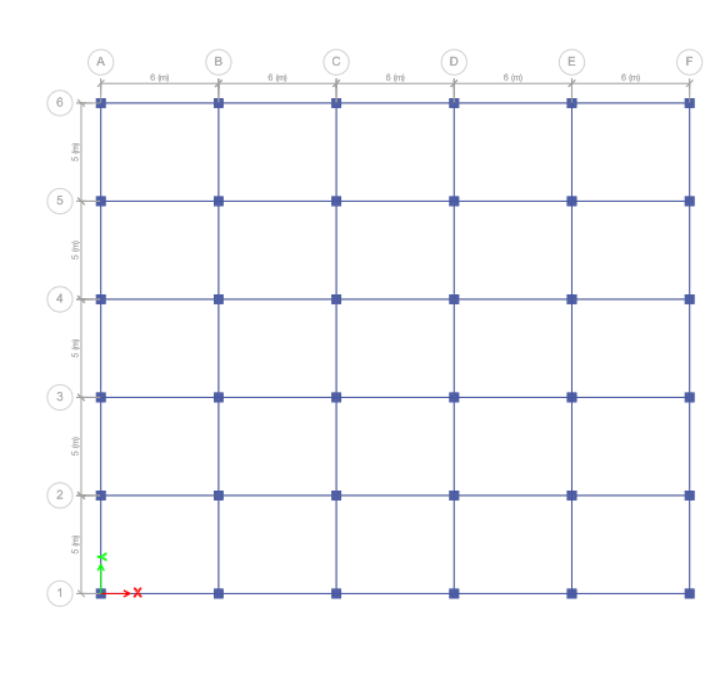
# Building data

**Table -4** Building details

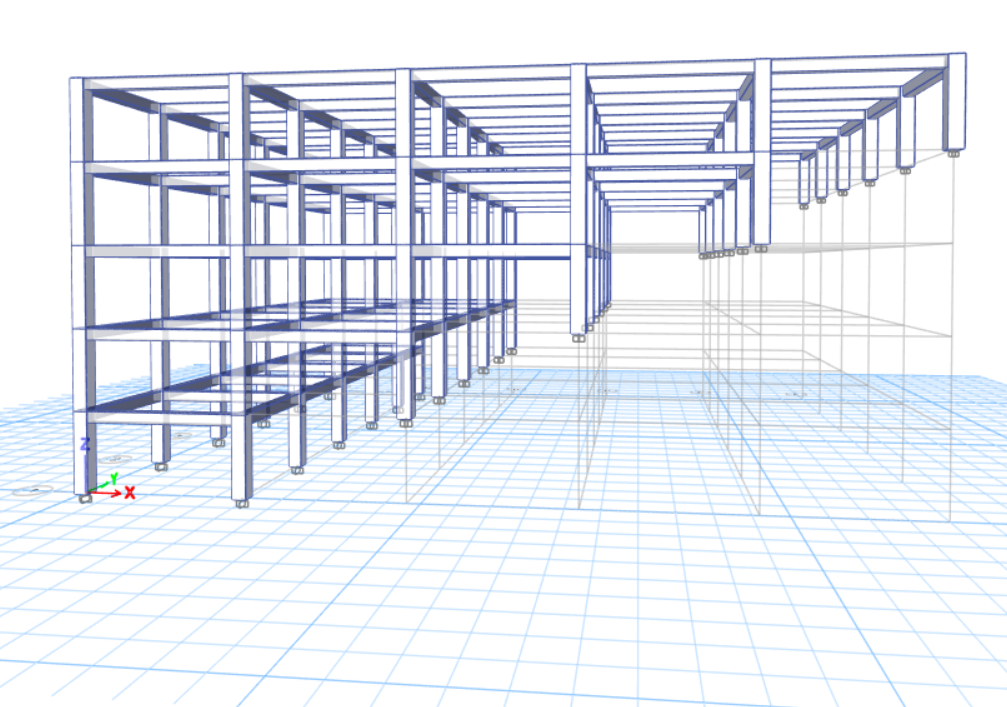
|  |  |  |  |
| --- | --- | --- | --- |
| Designation | Range | Designation | Range |
| Building height | 15m | Grade of concrete | M30 |
| Each Floor height | 3m | Grade of steel | FE415 |
| Damping | 5% | Importance Factor, I | 1 |
| Support conditions | fixed | Zone | 5 |
| Beam dimension | 350\*400(mm) | Column dimension | 500\*500(mm) |

**Table -5** Modal period and frequency of set-back building

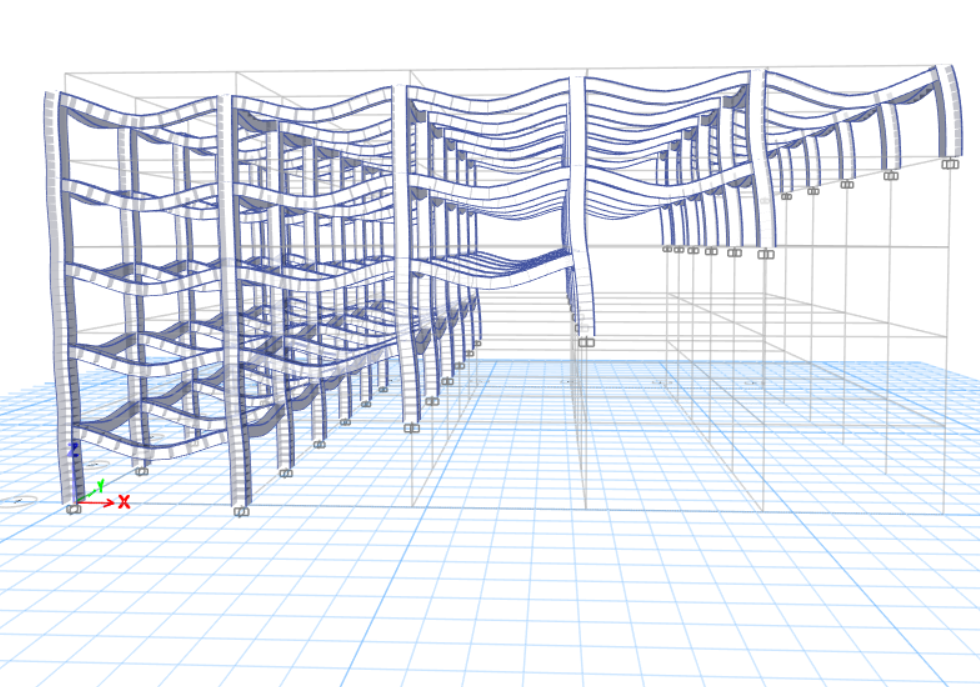
|  |  |  |  |
| --- | --- | --- | --- |
| Case | Mode | Period(sec) | Frequency(cycle/sec) |
| Modal | 1 | 0.365 | 2.743 |
| Modal | 2 | 0.239 | 4.185 |
| Modal | 3 | 0.181 | 5.515 |
| Modal | 4 | 0.181 | 5.538 |
| Modal | 5 | 0.168 | 5.958 |
| Modal | 6 | 0.149 | 6.702 |



(a)



(b)



**(c)**

**Fig.-2 a,b.c**  Simulated G+5 set-back building

The frame structure that was simulated using the ETABS 2019 version is displayed in Fig.-2 a,b,c

# Selection of ground motion

In this study, the nonlinear time history analysis of set-back rc framed structures was performed using seismic ground vibrations obtained from the PEER ground motion database. The ETABS software was used to conduct the time history analysis, which helped determine the inherent frequencies and response characteristics of the RC frames. These inherent frequencies are critical, as they serve as a reference for identifying potential ground motions that could damage the building's structure. The Fourier Transform method was applied to analyze the frequency domain of ground motions from various earthquakes, and these were then compared with the structure's inherent frequencies to identify any coincidences. It is crucial for these frequencies to coincide, as the structure is most vulnerable to damage when the ground motion frequency in line its modal frequency.

|  |  |
| --- | --- |
|  |  |
| a) Parkfield Earthquake ground motion acceleration | b) loma-prieta earthquake ground motion acceleration |
|  |  |
| c) Managua Nicaragua-01Earthquake ground acceleration | d) Imperial valley-07 Earthquake ground acceleration |

**Fig.-3 a,b,c,d** are earthquake ground motion data

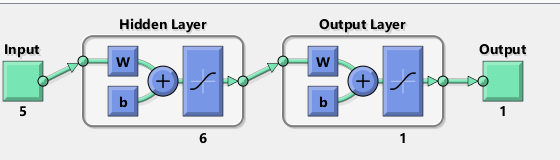
# Input and Output data

For a 5-story set-back RC frame building, 17 earthquake ground motion (EQGM) records were used for training and testing the ANN model. During ANN training, the peak values from 17 EQGM records were used as input, and the corresponding structural design parameters, calculated using time history analysis with ETABS, were used as output. These input and output data are shown in Tables 2 and 3 respectively. First, the EQGM files are converted into peak values of acceleration, velocity, displacement. For the ANN training, these peak values of PGA, PGV, PGD, along with the time duration and frequency are taken as inputs.

The output data are obtained after performing nonlinear dynamic analysis (Time History Analysis). The maximum values of each structural design parameter, such as displacement,maximum inter-storey drift, base shear, overturning moment are taken for each EQGM are taken as output. These results are shown in Table-3

# Development of ANN model

A feed-forward multilayer neural network with one hidden layer having 6 neurons used in this paper for ANN training as well as testing. The Levenberg-Marquardt method is employed in this paper to minimize error. All ANN applications were performed using the MATLAB Neural Network Toolbox. For ANN training Sl. No. 1 to 17 from Table 1. and Table 2. taken as input and output respectively. After training the ANN model, the comparison of structural design parameter from ETABS and ANN model takes place for a EQGM data from input and output Table.



**Fig.-4** Framework of ANN

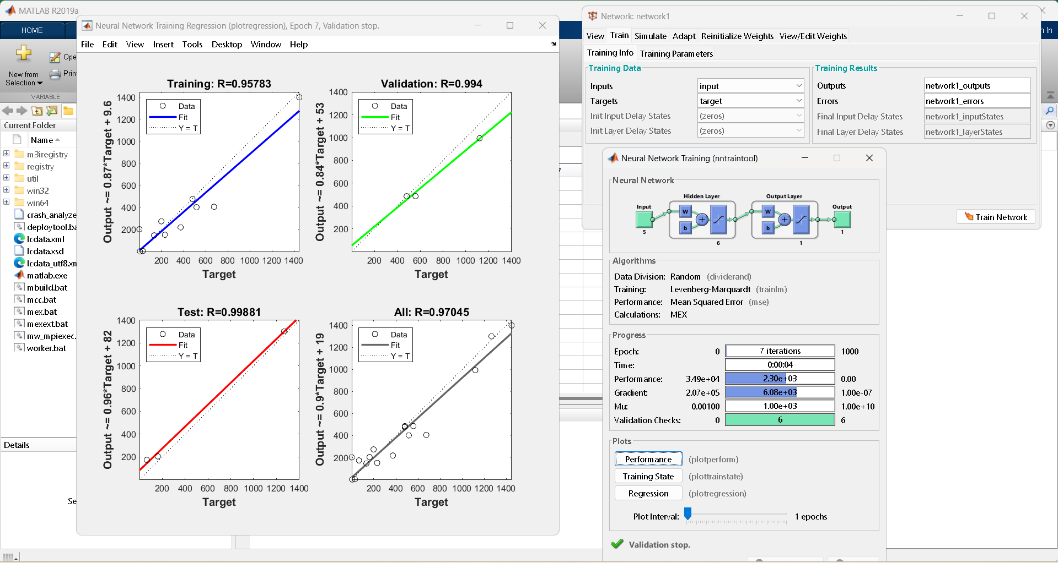
After training of ANN model using input and output data, the test of another earthquake ground motion named whitter narrows-02 is done , input data is taken from Table 1 and after time history analysis we have structural responses in Table 2. After that we will go to compare the results after finite element analysis i.e Time history and ANN modelling in MATLAB.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Table for Input data | | | | |
| Earthquake name | PGA | PGD | PGV | Time duration |
| Whittier Narrows-02 | 0.073 | 0.564 | 4.699 | 24.235 |

**Table -6** Structural parameter from ETABS and ANN modal

|  |  |  |  |
| --- | --- | --- | --- |
|  | Story drift | Base shear(kn) | Over-turning moment(kn-m) |
| From ETABS | .000519 | 132.9365 | 499.779 |
| From ANN | .000049 | 135.865 | 503.856 |

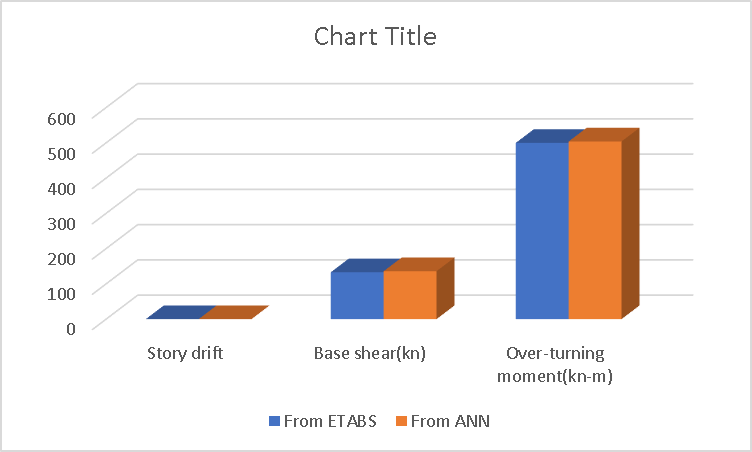
Three structural design parameters—story drift, base shear, and overturning moment—from the ETABS and ANN models for the identical earthquake ground motion data are compared in this study. The created ANN model and the anticipated design outcome have been compared to the most recent and sophisticated EQ resistant design technique, THA. The model performs well and requires a significant reduction in processing time.



**Fig.-5** Regression plot of trained ANN model considering input and output data

# Results and discussion

After training of ANN model with the help of input and output data, training of other earthquake ground motion data named whittier Narrows-02 takes place. Input data is taken from Table-2 and after Time history analysis data i.e. output data is taken from Table -3. Now we have to analogize between ETABS results and ANN modelling results. Using the same seismic ground motion data, ETABS and ANN models were used in this study to compare three structural design parameters: story drift, base shear and over-turning moment.



**Fig.-6** Difference of results from ETABS and ANN model

# Conclusion

The study's conclusion is deemed encouraging since the metaheuristic ANN model can be used to verify the design parameter without requiring a new EQ zone to undergo in-depth physical model investigation. By implementing the idea outlined in the paper, we can save a significant amount of time and money. The study's significant conclusions are included in below.

* + - We noticed that the Time History Analysis method took a long time when we used the Finite Element program (ETABS) with different seismic ground motion data. In order to tackle this problem, we created a unique Artificial Neural Network (ANN) model that can forecast RC building design characteristics more accurately, cutting down on the amount of time needed for the entire analysis.
    - While the Finite Element program (ETABS) 3-3.5 minutes to analyzed the RC building for the identical EQGM, the trained ANN model was able to predict the structural design parameter of the 5 storey three-dimensional Set-back RC building in just 0.5 seconds.

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