PREDICTING SEISMIC PERFORMANCE OF REINFORCED CONCRETE STRUCTURES WITH ARTIFICIAL NEURAL NETWORK

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Abstract

The seismic response of human-made structures to ground shaking caused by earthquakes can lead to catastrophic damage. Seismic investigation, a sub-discipline of primary examination, is utilized to evaluate the seismic reaction of designs. Artificial intelligence has emerged as a solution to address this problem. The seismic response of reinforced concrete (RC) is investigated in this research using an artificial neural network (ANN). structures to ground motions. The evaluation of a structure's seismic response is crucial for upgrading a building or its components. Extended three-dimensional analysis of building systems (ETABS) is used to determine the seismic response of all structures, which serves as target data for designing the ANN. Symmetrical buildings are stimulated using various ground motions, and the resulting input and target data are used to construct an ANN in MATLAB. A novel multi feed-forward type of ANN (MFF-ANN) with the Levenberg Marquedt algorithm is employed. The input parameters that produce the lowest error and highest accuracy for forecasting the seismic response of RC multistory buildings are identified. The significance of each parameter used in the input layer contributing to the maximum accuracy is determined, along with the percentage of each parameter contributing to the optimal network.

Keywords: seismic drift, displacement prediction, RC building, artificial neural network

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1. Introduction

An earthquake is caused by seismic waves that penetrate the earth's surface and cause the ground to tremble. Ground shaking is mostly responsible for human-made structures being damaged by earthquakes [1]. When large rock masses collide, collapse, or slide, energy is released in the Earth's crust, causing seismic waves [2]. Geological formations or restricted zones caused by these rock formations are more prone to earthquakes.

Some unacceptable lines are long edges of the tectonic plates that make up the Earth's crust. Tectonic earthquakes are explained by the elastic rebound theory [3]. The idea is that tectonic earthquakes happen when rock masses are under more strain than they can withstand without rupturing. The crack moves through the masses of the ground in a single direction or travels far across the weak zones [4]. The size and severity of an earthquake are accessed by two parameters magnitude and intensity of an earthquake. The magnitude is the amount of energy released and the severity is the experience in the specified location. The earthquake causes catastrophic damage to the structure, and its components and killed many people in the history of disasters [5]. The maximum vibration is found near the source and diminishes with distance. Due to earthquake-related phenomena including tsunami, landslide, soil liquefaction, and more, buildings and bridges may collapse and pipelines may rupture depending on the earthquake's magnitude [6].

Calculating the seismic response of the structure involves Seismic examination is utilized, which is a subset of underlying investigation [7]. In the examination and plan of tall building structures, the reaction of the not set in stone during the assessment and reproduction cycle of the designs when a seismic tremor happens in the space [8].

The two fundamental classes of seismic investigation are static examination and dynamic investigation [9]. For structures with a limited height, static analysis is used. Other subtypes of dynamic analysis include response spectrum analysis and time history analysis. Nonlinear time history analysis reveals the true behavior of the structure, and ground motion data is used to determine the structure's response while taking into account its elastoplastic deformation. In recent years, artificial intelligence has become an emergent technology. Artificial intelligence's subset of machine learning is the foundation for the development of computation techniques [10]. Learning from experimental data is the fundamental tenet of soft computing hence sophisticated mathematical solutions are not required [11]. Instead of using conventional or analytical methods, it aids in problem solving with the desired outcome [12]. Expert systems, genetic algorithms, machine learning, and fuzzy logic are all part of it. ANNAR became famous approach for predicting a structure's seismic response.

Biological processes in humans that can solve issues through memory and training serve as inspiration for artificial neural networks (ANNs) [13]. The neural network system can address issues with pattern recognition, Optimization, control, data mining, model completion, classification, and functional approximation There are many other ANN types, including single-layer NNs, multi-feed forward NNs, temporal NNs, self-organizing NNs, combined feed forward and self-organizing NNs, and self-organizing NNs that may be utilized with computer-aided techniques, like radial basis function networks [14]. It has been discovered that the Levenberg Marquardt algorithm [15] is useful in civil engineering applications like forecasting how a structure would react. The results of earlier experiments demonstrated the effectiveness An interactive media perceptron NN for assessing the seismic reaction of a structure.

The neurons in the brain network are linked together via synapses [16]. The architecture of Multi feed forward NN is comprised of three layers: an input layer, a hidden layer, and an output layer, as shown in Fig. 1. In Figure 1, the arrows show the synapses via which the weighed information travels, and the circles represent artificial neurons. Weights are stored in neurons, and data is received by input layers. This data is transmitted to the output layers via synapses with the assistance of adders and activation functions. Since the genuine issue isn't generally direct, the reason for the enactment capability is to actuate nonlinearity in the organization [17]. Because memory and training are the primary functions of ANN, it is possible to achieve successful prediction results by training the network with a large data set like memory [18]. Training algorithms that produce output that is more accurate are needed for ANNs.

The training algorithm uses the input and hidden layer synaptic weights to lower the output layer's accuracy. The ANN dataset is the required target data and input data for a training algorithm. As a result, the most recent error will be determined by an ANN trained on a large data set. The normalized probability is an error-free output that can be produced with test data that is not part of the trained ANN [19]. Retraining with a larger dataset and a variety of different parameters can increase the generalization capacity [20].

Our contributions. To enhance the research findings, we suggest a new type of artificial neural network (i.e. multi feed-forward ANN (MFF-ANN)) using the Levenberg Marquedt algorithm to analyze the seismic behavior of reinforced concrete (RC) structures subjected to ground motions. The major contributions involved in the proposed work are summarized as follows.

1. Development of an artificial neural network (ANN) system for predicting seismic drift and displacement of RC structures, which can potentially reduces the need for expensive and time-consuming physical testing.
2. Identification of the optimum input parameters for the ANN system, resulting in a considerable level of accuracy for predicting seismic response.
3. Evaluation of the significance of specific input parameters contributing to the accuracy which can potentially inform future improvements to the system and enhance its predictive capabilities.

The paper is structured as follows. Section 2 provides a literature review of recent studies on the seismic behavior analysis of RC structures. In Section 3, the problem methodology and system design of the proposed methodology are presented, detailing the working process. The steps involved in the proposed MFF-ANN model are outlined in Section 4. The simulation results and their discussion are presented in Section 5. The paper is concluded in Section 6.

2. Literature review

This section provides a literature review of the recent works related to the seismic behavior analysis of RC structures. The review begins by discussing the importance of seismic analysis and the methods that have been traditionally used for this purpose. The limitations of these traditional methods are also highlighted, which have led to the need for new approaches such as artificial intelligence techniques. The section then focuses on the use of ANNs for seismic analysis. Several studies have been conducted using ANNs to predict the seismic response of structures, and their effectiveness has been demonstrated. Some of these studies have used various types of ANNs, including feed forward, radial basis function, and recurrent neural networks.

ANN model was created by Lorenzo Steffanini et al. (2021) [21] to get seismic reaction of existing RC structures. 928 limited component models were created and model dynamic and nonlinear static dissects were performed to get the result information, which was recorded as seismic reaction. There are mechanical, structural, and morphological subsets of input parameters data since lack of proper data such as structural drawings was not available. And 17 output data were collected from analysis of 928 finite element models. SAP2000 were used for finite element analysis Eight index structure were developed modifying a single parameter at a time without changing other parameters and recorder their output. The neural network was created for the dataset and through K-fold validation the predictive capacity of ANN was analyzed. The coefficient of determination was found to be 0.94 and concluded that wide range of input parameters should be included to obtain more accuracy. Hoang D Nguyen et al. (2021) [22] develops ML models to anticipate the seismic float reactions of planar steel planes. Two types of ML techniques are utilized ANN and gradient boosting. 324 ground movements with magnitudes under 4 and peak accelerations greater than 0.2g are applied to those models. In order to record the output data, a total of 22.264 non-linear dynamic analyses were performed.

When compared to soil properties, input metrics like peak ground acceleration, peak ground velocity, and peak ground displacement are more significant. The most important parameter among all the input parameters is the peak ground velocity. The ANN model for the steel planar frames predicts the seismic response with more accuracy. The coefficient of determination is found to be 0.962 with appropriate accuracy. The multi feed forward perceptron kind of ANN was utilized by Mohammed Rachedi et al. (2021) [23] Assess the existing bridge structure's structural evaluation and seismic behavior. The properties of ground motion, soil variability, and the interaction between the structure and the soil are all input parameters in their work. The structure's non-linear dynamic behavior serves as a representation of the output parameter. Additionally, experimental findings are used to validate the results. Further the significance of soil structure interaction parameters in predicting the seismic behavior is analyzed. The ANN model successfully employs back propagation NN. In their study, the generalization capacity for the hypothetical scenarios is also investigated.

The multi-hazard assessment and mitigation method for non-ductile RC buildings was presented by Bilal Ahmed et al. in 2021 [24] utilizing ANN models. The seismic and blast vulnerabilities were considered in RC non-ductile buildings. In order to mitigate the vulnerabilities, retrofitting method were used. A multi feed forward system with one or more hidden layers were used for ANN model. The input parameters were divided into loading parameters and retrofitting parameters. The inter-story drift ratio, maximum displacement, seismic energy-based damage demand, and blast energy-based demand were the output parameters. Multi-hazard assessment and retrofit technique performance based on ANN model was found to perform at goal level. Based on the relationship between an earthquake and the attributes of the building, Byung Kwan Oh et al. (2020) [25] created an ANN model that can predict how buildings will react to earthquakes. Artificial earthquakes were created by EQ maker software for the ground motion characters in ANN model.2700 artificial earthquakes were created with different range of parameters using the software. Maximum displacement and multi-interstory Drift Ratio were the output parameters from this set of input parameters, which also included mean period, significant duration, and resonance area.

Their study emphasised the value of resonance area for improving ANN model correctness. Konstantinos Morfidis et al. (2018) [26] looked at whether artificial neural networks could forecast how earthquakes will affect reinforced concrete buildings. Multi feed forward perceptron is used in ANN model. Here, 30 RC buildings were selected with wide range of parameters and 65 ground motion data collected from PEER ground motion database and Strong motion database is used for nonlinear time history analysis. So total of 1950 dataset were collected for ANN model. The outcome parameters were the maximum displacement and inter-story drift ratio. To test the trained ANN model's ability to generalize, three scenarios were taken into consideration. There are still several challenges and limitations in predicting the seismic performance of reinforced concrete structures using existing ANNs [21]-[26].

In general, the ANN requires a large amount of data for training and testing, but there is often limited data available on the seismic performance of reinforced concrete structures [21]-[26]. The behavior of reinforced concrete structures during earthquakes is complex, and it can be challenging to accurately capture this behavior with ANN model. ANN models may not always generalize well to different structures or ground motion scenarios that were not included in the training data. ANN models are often seen as black boxes, and it can be challenging to interpret the results or understand how the model arrived at its predictions. There are uncertainties and variability in the seismic response of reinforced concrete structures, which can be difficult to capture in an ANN model. Moreover the data dimensionality can be a problem when using ANN for predicting the seismic performance of reinforced concrete structures. The input data required for ANN model can be high-dimensional, which can lead to issues such as overfitting and slow convergence during training.

3. Problem methodology and System design

3.1 Research gaps

Seismic performance analysis for reinforced concrete structures is the process of evaluating the behavior and safety of concrete buildings and structures under earthquake-induced ground motions. The analysis aims to predict the structural response of the building to seismic forces, such as ground motion, and evaluate the level of damage that can occur during an earthquake. This analysis involves examining the stiffness, strength, and ductility of the structure to determine its ability to resist earthquake forces and remain functional after an earthquake. The results of the analysis can be used to design or retrofit structures to improve their seismic performance and reduce the risk of damage or collapse during an earthquake. There are several challenges and issues that can arise during the seismic performance analysis of reinforced concrete structures. These include the complexity of the analysis process, the need for accurate and reliable input data, the potential for errors in modeling and simulation, and the difficulty in interpreting the results. Other challenges include the need for specialized expertise and software tools, as well as the high computational costs associated with large-scale simulations.

Additionally, the accuracy and reliability of the results can be affected by uncertainties and variability in the input parameters, such as ground motion data and material properties.

Deep learning techniques are useful for predicting the seismic performance of reinforced concrete structures because they can handle large and complex datasets. The seismic response of a structure is influenced by many factors, such as the geometry of the structure, material properties, and ground motion characteristics. These factors can interact in complex ways, leading to nonlinear and high-dimensional relationships between the input parameters and the response of the structure.

Deep learning models, such as ANN, RNN and DNN, are able to automatically learn these nonlinear relationships and capture the complex interactions between the input parameters, leading to accurate and reliable predictions of the seismic performance of the structure. Some of the problems with using deep learning techniques for seismic performance analysis of reinforced concrete structures include: Deep learning algorithms require a large amount of data to be trained effectively. However, collecting data on seismic behavior can be expensive and time-consuming.

Overfitting occurs when the model is too complex, leading to poor generalization performance. In the case of seismic performance analysis, overfitting can occur when the model is trained on a limited dataset, leading to inaccurate predictions on new data. Deep learning models are often considered black boxes, meaning that it can be difficult to understand how the model arrived at its predictions. This can be a challenge in the field of structural engineering where transparency and interpretability are crucial for decision-making. Deep learning models can highly complex, requiring specialized knowledge and computational resources to train and deploy.

Deep learning models can learn patterns from data, but they do not inherently possess domain knowledge. Therefore, essential to incorporate domain knowledge and engineering expertise in the feature selection and data preprocessing stages to ensure that the models make meaningful predictions. Based on the problems identified, some research objectives to address them could be:

1. To develop a neural network-based system for predicting the seismic performance of RC structures with higher accuracy and efficiency.
2. To identify the optimum input parameters and their relative significance in predicting the seismic performance of RC structures.
3. To investigate the impact of data dimensionality on the accuracy of the neural network-based system and develop strategies to mitigate the problem.
4. To validate the proposed methodology by comparing its results with those obtained from conventional seismic analysis methods.

Our proposed contributions use a novel MFF-ANN with the Levenberg Marquedt algorithm to address the problems of overfitting and high computational costs. The MFF-ANN model can handle the high dimensionality of the data and optimize the input parameters to provide accurate predictions with fewer training iterations.

The use of the Levenberg Marquedt algorithm also ensures faster convergence and better generalization of the model, thus improving its predictive performance. Overall, proposed methodology offers a more efficient and accurate approach to predict the seismic performance of reinforced concrete structures using ANN.

3.2 System design of proposed method

Fig. 1 shows the overall System design of proposed work which includes the following steps. The software study involves studying in detail the software used in the proposed work, namely ETABS and MATLAB 2020a. This helps in understanding the functionalities and limitations of these software and how to use them effectively in the proposed work. The seismic data with a wide range of parameters are collected from peer ground motion databases. These data are necessary to simulate the ground motions and analyze the response of the RC structures.

A reinforced concrete symmetrical building with four different heights is selected for the dataset.

The selection of building is crucial as it should be representative of the building types for which the ANN will be developed. The selected RC buildings are subjected to 10 different earthquakes, and time history analysis is performed in ETABS software to obtain target data. This data will be used as the basis for training the ANN.

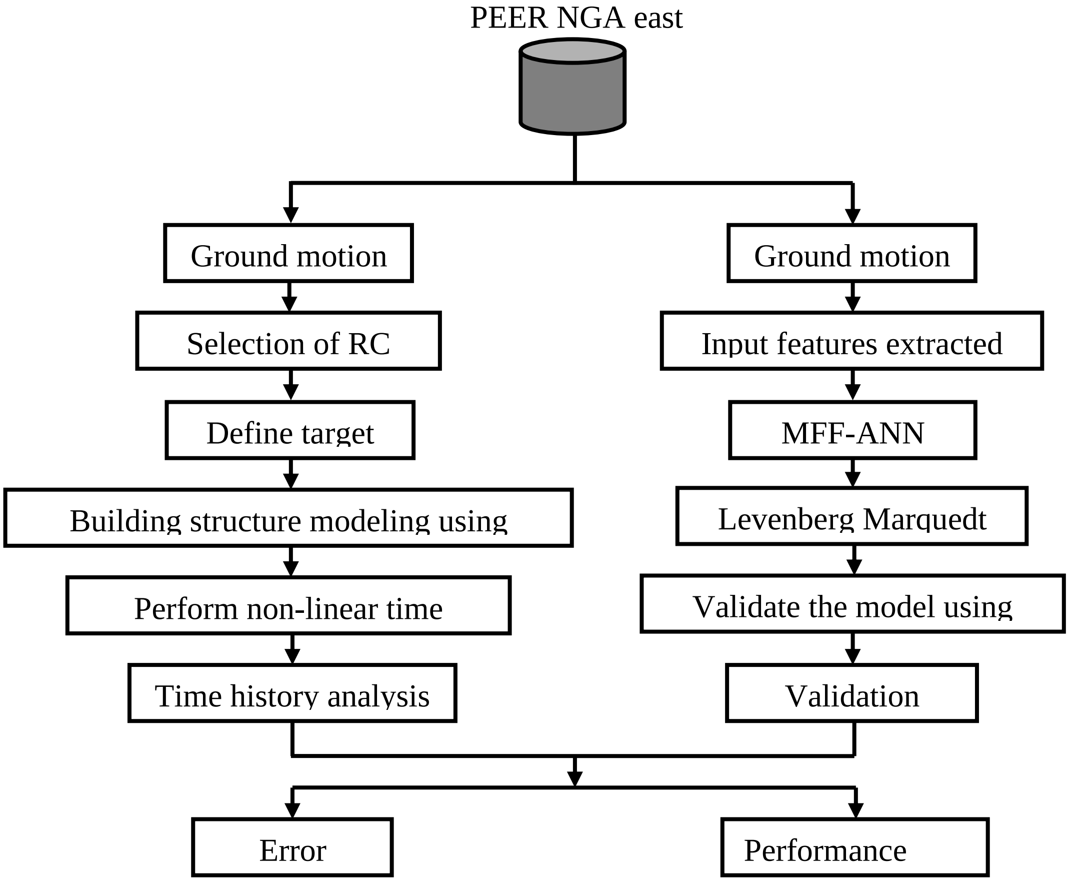

Fig. 1 Overall System design of proposed work

Using the input data and target data collected in the previous steps, a neural network is constructed in MATLAB software using the nntool. This step involves selecting the appropriate network architecture and training algorithm to optimize the performance of the ANN. The trained ANN is used to predict the seismic response of the RC structures. The results are evaluated using correlation coefficient R and mean squared error to assess the accuracy and reliability of the ANN. Finally, the results of the test building subjected to the test earthquake in the trained ANN are compared to the results obtained from ETABS to validate the proposed approach. This step helps to ensure that the developed ANN is capable of accurately predicting the seismic response of RC structures.

4. Proposed Methodology

4.1 Building structure modeling using ETABS

4.1.1 Ground motion data collection

The seismic dataset contains a wide range of the seismic parameters of different earthquakes. Ten earthquakes with various parameter ranges are taken into consideration. The pacific earthquake engineering research (PEER) center provided the information on 10 earthquakes. The ground motion data set is a subset of the input data. It's crucial to gather critical information about the earthquake that the building is affected by in order to forecast the seismic reaction of any building. So, the data about the ground shaking at the site is relatively important. Recently the PEER made the database online at their website as web-based research database for ground motion. The database on earthquakes contains data on earthquakes. A codified performance-based earthquake engineering technique will be developed with the help of the data, models, and software tools that will be made available by the PEER. Within the broad field of earthquake engineering, PEER's research is currently concentrated on four areas: building systems, bridge and transportation systems, lifelines systems, and information technologies to support technique implementation. The NGA east database is one of the largest multi-disciplinary research data for active tectonics available at the PEER center. The database consists of a wide variety of earthquakes comprising small, moderate, and large magnitude earthquakes with the scaling factor. The earthquakes obtained for this study are extracted from the NGA east database. A flat file with 5% damped spectra from various ground motions can be found in the database. The range of values for selected ground motion parameters and their values are shown in Table 1.

Table 1 Parameter ranges for PEER NGA east data

Parameters	Values
PGA (g)	0.06 - 3.91
PGV (cm/sec)	0.65 - 10.05
PGD (cm)	0.01 - 0.17
Duration (s)	11.7 - 70
Epicenter distance (km)	8.71 - 226.98
Hypocentre distance (km)	0 - 13.8
Magnitude	5 - 7.36

4.1.2 Selection of RC building

It is necessary to take into account buildings with various structural input parameters in order to determine a building's seismic response. The collection of RC building is another subset of input dataset collection. The building selected is a reinforced concrete structure symmetrical in shape. The selected symmetrical buildings are fixed in length and width but vary in height. The width & length of the buildings are 15m and the selected building's heights are 12m, 15m, 18m, and 24m. So, 4 symmetrical buildings are selected. The selected four-symmetrical building's plan view lacks numbers 1-4.

4.1.3 Collection of target data

The step that follows the gathering of input data is the collection of the corresponding target data. It goes by the name real output data. By relating the input value to the target value, the neural network attempts to reduce error. The neural network imparts training after the input and target data are fed into the system. The target data are stored as numerical value and it is a dependent variable. It depends on the input parameters. A computer-aided algorithm is required to train the network.
The weighted sum received by hidden layer neurons passes to the output layer neurons and compares to the target value. Maximum story drift and maximum displacement, which are regarded as target data, are the seismic response of the structure that is taken into consideration. The selected 4 symmetrical buildings are subjected to 10 earthquakes to obtain the target data i.e., the most extreme dislodging and greatest story float. Hence 40 target data are obtained and these datasets are used in construction of MFF-ANN.

4.1.4 RC building structure modeling

The structure model takes into account the four symmetrical structures. RC building modeling and analysis were done using ETABS software [27]. The software uses the grid approach to represent the chosen symmetry with a base dimension of 15 m x 15 m. Four separate building models with varying heights were created to reflect the four various heights of the building. Figs. 2 and 3 illustrate the building's plan and three-dimensional image of four symmetrical buildings in ETABS, respectively. The concrete's grade was M30, where M stands for mix and the number corresponds to the material's typical compressive strength after 28 days. Steel was graded as Fe500, where Fe stands for iron and the number value denotes the steel's yield strength. The steps involved in the RC building structure modeling are given as follows.

1. The sectional properties were assigned for beam, column, and slab. The supports were considered to be fixed support which restrains both translational and rotational movements. The load cases were defined and applied as per IS codal provisions [28] [29].
2. Dead load is applied using one's own weight [28]. The ETABS software automatically determines the structures self-weight. The weight of the beams, columns, shear walls, and slabs is included in the structure's dead load. By dividing the density by the dimensions of the structural elements, the self-weight is computed. Floor finishes and wall loads are used as super dead loads. In a reinforced concrete framed structure, super dead load refers to the self-weight of components other than structural members, such as beams, columns, shear walls, and slabs. The evenly distributed load of the wall that is to be put on beams can be calculated by assuming that the wall thickness is 230 mm and multiplying that number by the height of the wall. The applied wall load is 12.42kN/m. The weight of the tiles, cement, etc. is included in the super dead load of the floor finish. The floor finish should be applied as an area load on the slab. The floor finish load is applied as 1kN/m2 as per IS codal provisions. Live load is also called imposed load which includes movable loads like the weight of humans, the weight of furniture, etc. Live loads are applied as an area load of 2kN/m2 as per IS codal specifications [29]. Fig 4 shows the load cases applied on the building.

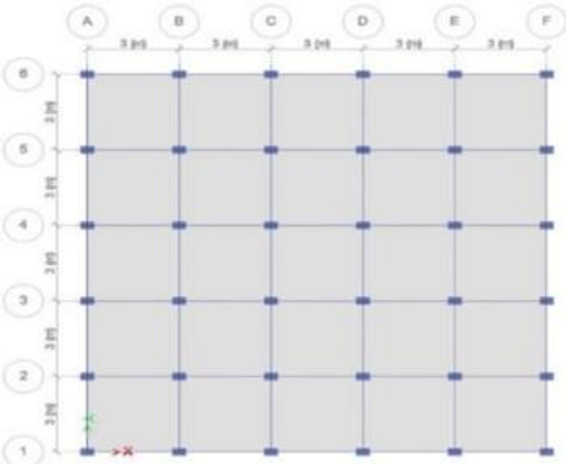

Fig. 2 Building plan in ETABS

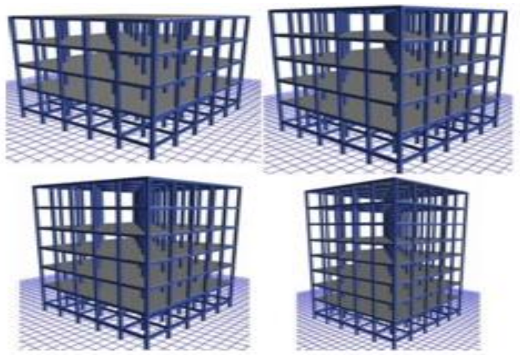

Fig. 3 Building's 3D view in ETABS

3. Static investigation and non-straight time history examination are the two kinds of seismic load that are used. After doing a static analysis to determine the member sizes, a non-linear the target data are identified through temporal history analysis. [30]. The buildings are assumed to be in Kerala under zone III of the seismic zone in India. The soil is assumed to be medium stiff soils and moment resisting frames is considered.
4. Mass source should be defined for seismic analysis where additional dead load and live load are considered. The total dead loads should be considered and 25% of live load if the value is equal to or less than 3 KN/m2, otherwise 50% of live load should be considered. Here 100% dead load and 25% of live load are considered for mass source.
5. Diaphragm should be defined in ETBAS to transfer forces to the vertical forces. There are two types of the diaphragm–flexible and rigid. The rigid diaphragm transfers the lateral load to all the vertical members. A flexible diaphragm transfers the lateral load depending on the type of members such as column or shear wall. Fig 5 shows diaphragms applied to each floor of the building.
6. The load combinations were created according to IS codal provisions and static analysis is performed. The fundamental frequency of the structure also is obtained from the ETABS software. The member sizes after analysis is shown in Table 2.

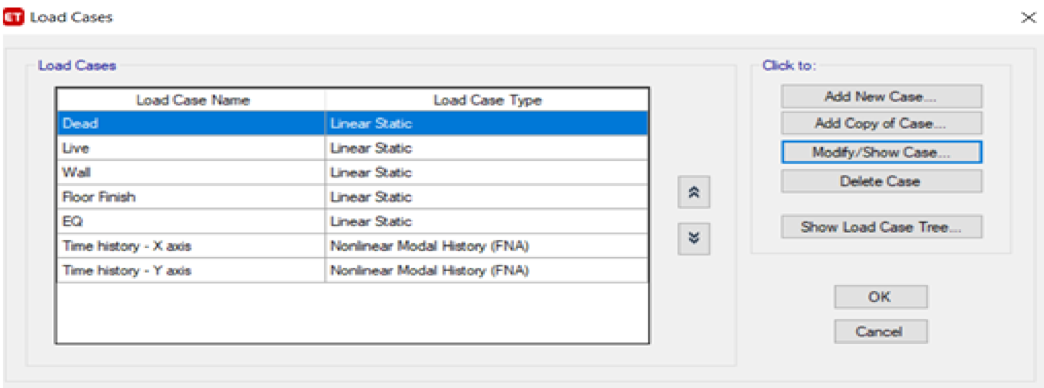

Fig. 4 Load cases of the building

Table 2 Description of building member sizes

Member designation	Higher building (m)			
	12	**15**	**18**	**24**
Size of beam (m)	0.23 x 0.3	0.23 x 0.3	0.3 x 0.35	0.3 x 0.4
Column size (m)	0.3 x 0.3	0.3 x 0.3	0.35 x 0.35	0.4 x 0.4

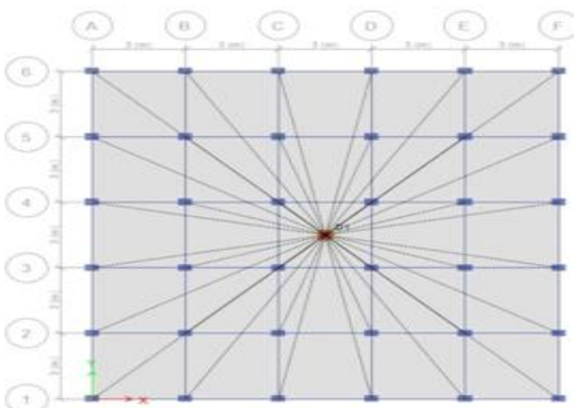

Fig. 5 Application of diaphragm to the building

4.1.5 Non-linear time history analysis

Because seismic analysis is a component of structural analysis, it is essential to evaluate the structure's seismic response. There are two main types of analysis: static analysis and dynamic analysis. Time history analysis is a component of dynamic analysis and can be categorized as either linear or non-linear [31]. To gather the target data for this study, a non-linear time history analysis is used. The time history analysis measures how the structure responds to a given loading over time.. For performing time history analysis, information about past earthquakes such as acceleration along with three mutually perpendicular directions, duration, etc should be obtained. These files are collected from PEER ground motion database. The time history function should be defined in ETABS and from file should be selected for uploading the earthquake acceleration data. Information like the number of header lines to skip, the number of Prefix characters to skip, the number of points per line, and values at the same interval with free format type are all included in the text file that was retrieved from PEER. Then the windows show the respective acceleration function graph. After defining the time history function, the load case was applied. Load case subtype was selected as time history and Nonlinear Modal analysis was selected. Nonlinear Modal (FNA) is a quick and effective method for nonlinear time history analysis. It is faster and more accurate than the direct integration method. Previous mass source is selected for time history analysis. Then the defined earthquake loads are applied in three mutually perpendicular direction of the building with the appropriate scale factor.

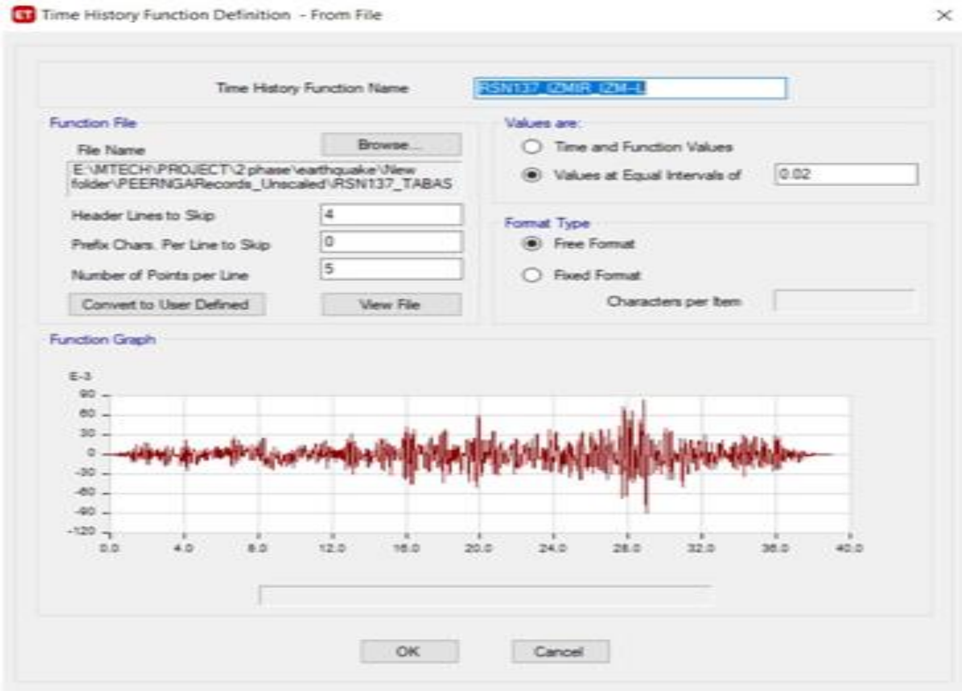

Fig. 6 Time history from ETABS

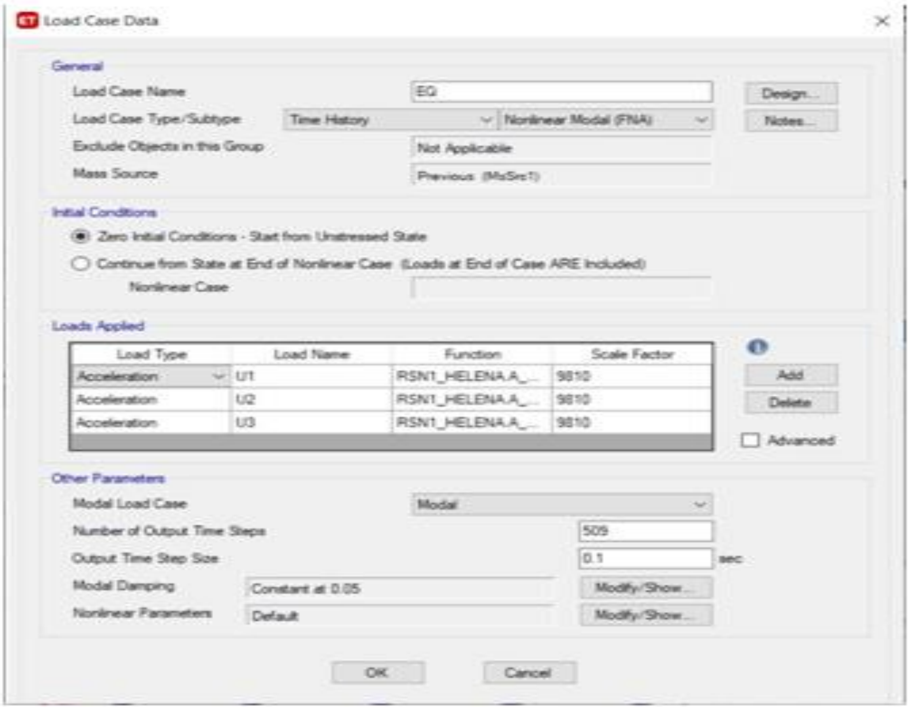

Fig. 7 Application of time history in ETABS

A number of output time steps and output time steps size depends upon the duration of an earthquake. The duration of the earthquake is obtained by multiplying the steps with the time interval in the acceleration file data. Maximum displacement and maximum story drift were found for the time history earthquake case following the building's time history study. Fig 6 shows the definition of time history and Fig 7 shows that the time history is assigned in the load cases. Hence 4 buildings and 10 earthquakes are considered, a total of 40 non-linear time-history analysis was performed. Therefore 40 datasets are obtained for the construction of ANN.

4.2 MFF-ANN with Levenberg Marquardt

The multi feed-forward artificial neural network (MFF-ANN) with Levenberg Marquardt algorithm is proposed for this work because it has shown better performance in predicting Seismic Reaction of RC Designs Versus other traditional machine learning algorithms. The Levenberg Marquardt algorithm is a widely used optimization algorithm for training artificial neural networks, and it has been shown to have faster convergence and better accuracy than other optimization algorithms like back propagation. The MFF-ANN is a type of artificial neural network that has multiple feed-forward layers, which allows it to capture more complex relationships between input and output variables. The combination of the Levenberg Marquardt algorithm with the MFF-ANN architecture makes it a powerful tool for when evaluating RC structures' seismic response. MATLAB programming is utilized to foster the ANN model and decide the seismic reaction of RC structures. Input and target data are gathered prior to ANN design. Using the data collected and new matrix for input and target data should be created in MATLAB. Then NN tool is used in MATLAB for creating the model. The input dataset and target dataset are imported in the NN tool window and a neural network is created using the new option. Two hidden layers with 10 neurons in each layer have been developed in ANN that was optimized through trial and error. The function of activation of the hyperbolic tangent is used to develop non-linearity in the hidden layer of ANN. The structural and seismic parameters acquired during the dataset collection make up the input layer of the MFF-ANN. In this study, a total of 11 input parameters were considered for the MFF-ANN design. These 11 input parameters consisted of four structural factors related to the reinforced concrete buildings and seven seismic parameters related to the ground motion.

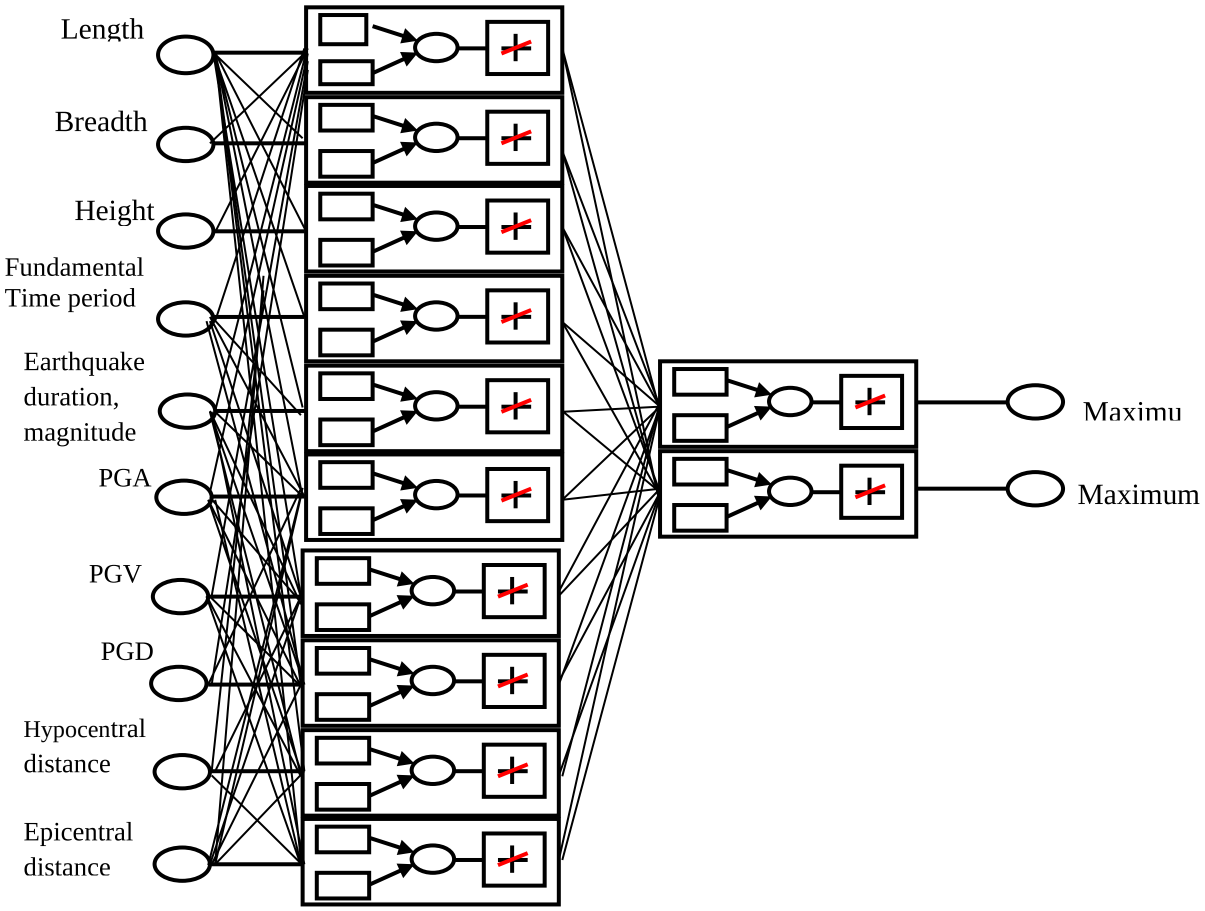

Fig. 8 Structure of MFF-ANN design

MFF-ANN design was constructed with 10 neurons in the hidden layer and 2 output parameters. The choice of these parameters was based on the optimization process to provide the best accuracy for the prediction of seismic response of the RC structures. Fig. 8 shows the structure of MFF-ANN design and the input parameters used for seismic performance analysis of reinforced concrete structures are described as follows:

1. Length, breadth, and total height of building: The dimensions of the building play a crucial role in determining its seismic response. The study considers various building arrangements with different lengths, widths, and heights.
2. Fundamental Time period: It is the time taken by the building to complete one oscillation when excited by seismic force. The time period for the first mode is noted in ETABS software for each building.
3. Duration of earthquake: The total time taken by the ground shaking from the beginning of seismic waves till it diminishes completely is called the duration of an earthquake. It is one of the key seismic factors that affect how a structure responds to earthquakes. The acceleration data file from the PEER ground motion database is used to determine the earthquake's duration.
4. Magnitude of earthquake: It is a numerical value expressed in whole numbers, which quantitatively measures the size of the earthquake. The commonly used magnitude scale is the Ritcher scale. The value of magnitude is obtained from the seismogram instrument, which amplifies from the epicenter.
5. Epicentral distance and Hypocentral distance: The hypocenter is the point where the rupture begins under the surface of the earth. It is also called the focus. The epicenter is the location on the earth's surface that is directly above the rupture or focal. The distance from the point of interest to the epicenter is called epicentral distance. The value is taken from the PEER ground motion database's flat file.
6. Peak Ground Acceleration (PGA): It is the maximum acceleration that occurred during the entire duration of the earthquake. It is represented in g and occurs in three mutually perpendicular directions. It is recorded by an accelerogram. The value is obtained from the flat file of the PEER ground motion database.
7. Peak Ground Velocity (PGV): It is the maximum rate of change of moment that occurred during the entire duration of the earthquake. It is represented in cm/s and occurs in three mutually perpendicular directions. The value is obtained from the flat file of the PEER ground motion database.
8. Peak Ground Displacement (PGD): It is the maximum displacement that occurred during the entire duration of the earthquake. It is represented in cm and occurs in three mutually perpendicular directions. The value is obtained from the flat file of the PEER ground motion database.

All these parameters are essential to understand the seismic behavior of reinforced concrete structures and their response to earthquake forces. The input parameters are used to train the MFF-ANN model, which can predict the seismic response of the structures. The two output parameters for the MFF-ANN model are seismic displacement and seismic drift.

1. Seismic displacement refers to the change in position of the building from its original position due to ground shaking caused by an earthquake. This is an important seismic response parameter for evaluating the performance of a building during an earthquake. Seismic displacement is obtained through time history analysis performed on ETABS software.
2. Seismic drift, on the other hand, is the maximum lateral drift of a building's story height during an earthquake. It is considered as one of the primary parameters to assess the structural damage caused by an earthquake. Seismic drift is an important factor to evaluate the effectiveness of a building's structural design in reducing the damage caused by an earthquake. The seismic drift ratio is the maximum lateral drift to the building's story height, and commonly used measure for assessing building's seismic performance.

Researchers used the evolutionary algorithm to train the parameter of an artificial neural network and gained some advantages due to its simplicity and effectiveness. The following equation can be used to determine the yield.

$$S_p = F_p\left(\sum_{q=1}^{b} w_{q,p} m_q + n_p\right) \tag{1}$$

where specifies the node's output; The qth input is qm;, element of the connection; The nodal transfer function and the nodal bias are shown by pn and pF, respectively. By and large, the exchange capability of a hub is nonlinear. The fitness function can be expressed as an optimization problem as:

$$e(w(s)) = \frac{1}{b}\sum_{q=1}^{b}\sum_{K=1}^{k}(O_{K,E} - O_{K,m})^2 \quad (2)$$

where the error and parameters of the links at the tenth iteration, respectively, are denoted by e(w(s)) and w(s). The number of templates is denoted by P, and the number of output nodes is denoted by k. Using an MFF-ANN that has been trained to run other equations, this term can be found. The expected value of the kth output node is kE,O, and the actual value of the kth output node is ka,O.

$$Y^A X^B(Y) = F(Y, X(Y), X^{'}(Y)), \qquad (3)$$

The domain is denoted by a particular BC, m Z, x R, and D R, with X(Y) serving as an approximate solution. On the off chance that a preliminary arrangement is displayed with customizable boundaries q, the issue becomes concrete.

$$\min_{j} \sum_{\overline{Y_q \in \vec{d}}} F(Y_q, X_T(Y_q, J), X_T^{'}(Y_q, J)) \quad (4)$$

The FFNN employs the trial solution Y in the proposed approach, and the p parameters correspond to the neural architecture's weights and biases. MFF-ANNs are the most popular and widely used models in many practical applications because they are black-box tools. In numerous areas of hydro-environmental engineering, the MFF-ANN model has been extensively utilized as a time estimation technique. The MFF-ANN output value is determined using an exact equation.

$$\hat{X}_p = F_p[\sum_{G=1}^{A} W_{pG} \times F_G(\sum_{q=1}^{N} W_{qG}Y_q + W_{Gm}) + W_{pm}] \quad (5)$$

The input, hidden, output, and W neurons, in addition to the bias and applied weight (or offset) for each neuron, are denoted by the letters Q, G, P, A, and W, respectively. denote the output and hidden layers' respective activation functions; B and A signify the information layer variable, the quantity of data sources and the quantity of secret neurons, individually; and X are the output neuron's observed and predicted values. We access the memory through a read controller. The read regulator utilizes the saw past way and setting (,) as the key and produces a read likelihood at every memory area q. A removal investigation of regulator variations is accounted for. The cosine similarity between the memory keys and the observed pattern serves as the foundation for our read controller. To begin, we use the following formula to determine the read instance's similarity and the previous read's similarity:

$$T_\pi^j = \frac{\pi^K \cdot \pi^q}{\| \pi^K \| \| \pi^q \|} \qquad j = 0,.....,|a| \quad (6)$$

$$T_\gamma^q = \frac{\gamma^K \cdot \gamma^q}{\| \gamma^K \| \| \gamma^q \|} \qquad q = 0,.....,|a| \quad (7)$$

We feed this to a multi-facet feed forward brain network F, which consolidates understanding similitudes, computes the significance of past tense and setting, and trains it to give high scores to related models and low scores to other people. As a result, the following is how the final reading probability is calculated:

$$J(R)^q = F(T_\pi^q, T_\gamma^q) \quad (8)$$

We read the best K patterns with the highest prediction moment in order to obtain multitype because each pattern in memory can be read and decoded independently. By writing the sum of the two words, you can achieve this. The trial solution in our proposed method is MFF-ANN, and the parameters i represent the weights and dependencies of the neural structure. We select a BC-satisfying shape for the test operation. Writing the sum of the two terms accomplishes this:

$$X_T(Y_q, J) = N(Y) + h(Y, b(Y, i)), \quad (9)$$

where is a single-output MFF-ANN with input vector Y as the parameters for the j and B input blocks, respectively. The second term, G, is designed to satisfy BCs. An FFNN whose biases must be adjusted to solve the weighting problem can be used to construct this term. The MFF-ANN's output for a given input y is

$$b = \sum_{q=1}^{G} v_q \sigma(w_q), \qquad where\ w_q = \sum_{p=1}^{b} w_{qp} Y_p + m_q \quad (10)$$

Where w_{qp} input unit q represents the load that connects the hidden unit to q, v_q the input unit q represents the load that connects q to the output unit, and m_q the hidden unit represents the dependence of q, and $\sigma(w)$ is a sigmoidal transfer function (tansig). The slope of the MFF-ANN is easily obtained as follows.

$$\frac{\partial b}{\partial v_q} = \sigma(w_q), \qquad (11)$$

$$\frac{\partial b}{\partial m_j} = v_q \sigma^{'}(w_q), \qquad (12)$$

$$\frac{\partial b}{\partial \omega_{qp}} = v_q \sigma^{'}(w_q) Y_p, \quad (13)$$

Once we compute the origin of the error associated with the network settings, any reduction technique is easy to use. It should also be noted that the weight recovery block method can be used. Levenberg-Marquardt algorithm is a numerical optimization method used for solving non-linear least squares problems. It is an extension of the Gauss-Newton algorithm that incorporates a damping factor to prevent convergence problems when the Jacobian matrix is ill-conditioned. The Levenberg-Marquardt algorithm is particularly useful for training artificial neural networks, as it is a fast and efficient method for minimizing the mean squared error (MSE) between the predicted output of the neural network and the actual output. The algorithm starts with an initial set of weights and biases for the network, and then iteratively adjusts these values in the direction of steepest descent until the MSE is minimized. At each iteration, the algorithm computes the Jacobian matrix, which describes the sensitivity of the output with respect to each weight and bias parameter, and then updates the weights and biases by solving a linear system of equations. The damping factor is adjusted during the iterations to balance the rate of convergence and the stability of the algorithm.

The Levenberg-Marquardt algorithm typically converges faster than other optimization methods, such as gradient descent or conjugate gradient, and can handle non-linear and non-convex optimization problems. In this work, the Levenberg-Marquardt algorithm is used to train the MFF-ANN model. The steps involved in using the Levenberg-Marquardt algorithm for training the MFF-ANN model are as follows:

1. The weights and biases of the MFF-ANN model are initialized randomly.
2. The input data is fed into the neural network and the output is computed using the current set of weights and biases.
3. The difference between the predicted output and the actual output is computed using a suitable error function, such as the mean squared error.
4. The error is propagated backwards through the neural network using the chain rule of differentiation to compute the gradients of the weights and biases.
5. The weights and biases of the neural network are updated using the computed gradients and a suitable learning rate.
6. The algorithm checks whether the error has decreased sufficiently or not. If the error has decreased sufficiently, the algorithm terminates. Otherwise, the weights and biases are updated again, and the process repeats.
7. The Levenberg-Marquardt algorithm modifies the update rule by introducing a damping factor that balances between the gradient descent and Gauss-Newton methods. This helps to avoid the problem of slow convergence or divergence in the standard gradient descent method.
8. Steps 2-7 are repeated until the error has decreased sufficiently or a maximum number of iterations has been reached.

By using the Levenberg-Marquardt algorithm for training the MFF-ANN model, we can obtain a more accurate and efficient model that can predict the seismic response of RC buildings under different earthquake scenarios.

5. Results and Discussion

In this section, we present the simulation results and analysis of proposed model with the collected dataset. The performance of proposed model is validated through two performance evaluation parameters such as Mean squared error (MSE) and Regression value (R). The average or mean of the squared discrepancies between the projected dataset and the target dataset is known as the mean squared error. A technique called regression value forecasts the seismic reaction from the target data based on the forecasted values. Regression value or correlation coefficient R denotes the proximity of the target dataset to the predicted data in form of a straight line.

The validation performance with the best results was 0.5751 at epoch 5. Fig. 9 demonstrates that the MSE value is dropping and that at the optimum performance and it is getting closer to zero. The trained dataset is indicated by the blue line, the test dataset by the red line, and the validation dataset by the green line. This entire dataset's top performance is noted. As a result, this neural network has the lowest MSE and is therefore the best performing network.

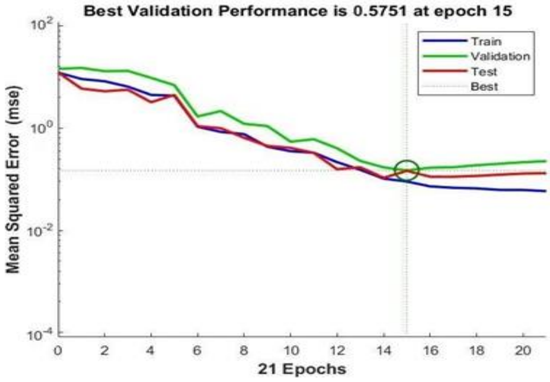

Fig. 9 MSE analysis for proposed model

Fig 10 shows the correlation graph and correlation coefficient for the partitioned datasets. The Y-axis represents the output dataset & X axis is represented by the target dataset in the form of an equation of a straight line. The dotted line denotes x=y which means the target dataset and output dataset lies on the same plane and accuracy is maximum. Here the little deviation is represented by the correlation coefficient. The goal data is compared to the line's equation, which was produced from the output data. The trained dataset is indicated by the blue line, the test dataset by the red line, and the validation dataset by the green line. According to Fig. 6, the training dataset's R value is 0.95998, the validation dataset's R value is 0.99206, and the testing dataset's R value is 0.99683. Therefore, the combined R-value for the three data sets is 0.96832, which is very close to 1. As a result, the developed neural network is discovered to be more accurate.

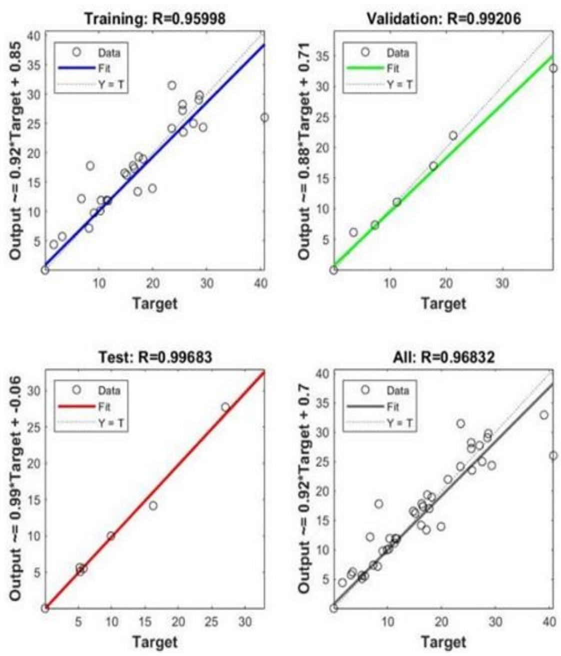

Fig. 10 Regression analysis for proposed model

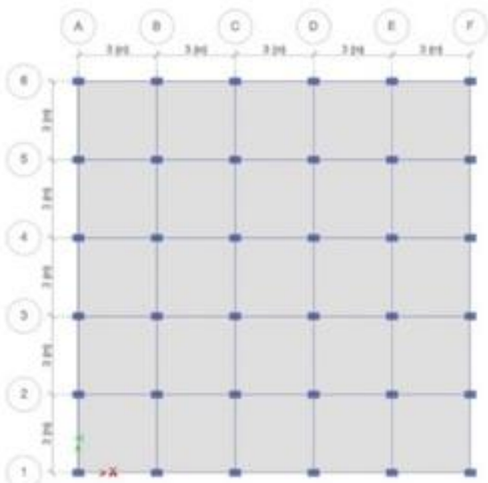

Fig. 11 Test building's plan view

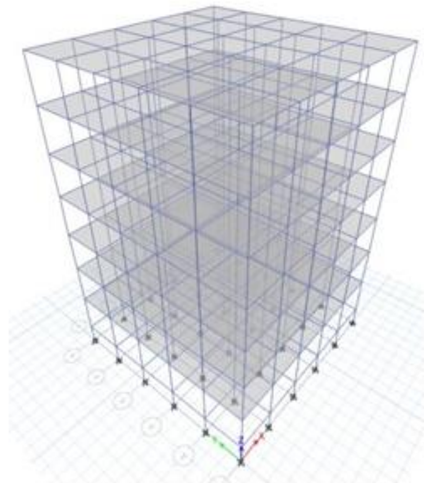

Fig. 12 Test building's 3D view

Table 3 Sample test ground motion data form PEER NGA east data

Parameters	Values
PGA (g)	0.9718
PGV (cm/sec)	1.8151
PGD (cm)	0.0295
Duration (s)	16.858
Epicenter distance (km)	55.860
Hypocentre distance (km)	55.62
Magnitude	6.50

he best-performed neural network which is trained predicts the value of seismic drift and seismic displacement for test building and test earthquake. The same test building is excited by a test earthquake in ETABS and the seismic drift and seismic displacement are found. The results of trained MFF-ANN and ETABS are compared for the validation of results. Both a test building and a test earthquake are removed from the scope of the input structural dataset and seismic dataset, respectively. Test buildings and test earthquakes are used to determine an ANN's generalization capacity. A test structure was chosen whose height, at 21 m, is outside the acceptable range for the structural input values. Additionally, one test earthquake data that is outside the input seismic parameter range was chosen. Fig 11 and 12 shows the plan view and 3d view of the test building. Table 3 shows the values of test earthquake considered for seismic input data.

Table 3 provides a sample of ground motion data from the PEER NGA East database. The table lists the values for various parameters that are relevant for the seismic analysis of buildings. PGA is a measure of the maximum acceleration experienced by the ground during the earthquake, and in this sample test data, its value is 0.9718 g. PGV is a measure of the maximum velocity of the ground motion during the earthquake, and in this sample test data, its value is 1.8151 cm/sec. PGD is a measure of the maximum displacement of the ground during the earthquake, and in this sample test data, its value is 0.0295 cm. Duration is measured in seconds and represents the total duration of the earthquake ground motion, from the beginning of seismic waves till it diminishes completely. In this sample test data, the duration of the earthquake is 16.858 seconds. Epicenter distance is the distance from the point of interest to the earthquake's epicenter, which is the location on the Earth's surface directly above the rupture or focal. Hypocentre distance is the distance from the point of interest to the earthquake's hypocenter, which is the point where the rupture begins under the surface of the Earth. In this sample test data, the epicenter and hypo-centre distances are 55.860 km and 55.62 km, respectively. Finally, the magnitude of the earthquake is 6.50.

5.1 Error analysis

Fig. 13 shows the maximum displacement (in mm) for different stories of the building as calculated by the MFF-ANN model (Target) and the ETABS software (ETABS). The maximum displacement obtained by ETABS is considered as the benchmark value for comparison with the MFF-ANN results. The results show that the MFF-ANN model performs well in predicting the maximum displacement for the lower stories of the building (up to the 3rd story), with the predicted values being very close to the ETABS values. However, for the upper stories of the building (from the 4th to the 8th story), the predicted values by the MFF-ANN model are higher than the ETABS values, indicating that the MFF-ANN model tends to overestimate the displacement for these stories. As we can see from the Fig. 13, the ETABS values for most stories are higher than the target values. This indicates that the building is not able to withstand the target displacement levels, and therefore, may experience damage during an earthquake. The discrepancies between the target and ETABS values become increasingly significant as we move up the stories. This highlights the importance of designing buildings with a proper structural system that can withstand seismic forces at higher levels, and not just at the base level. It also emphasizes the need for accurate seismic analysis to ensure that the building can withstand the desired displacement levels at all levels. The results indicate that the MFF-ANN model is a promising tool for predicting the seismic response of buildings, particularly for the lower stories. However, for accurate prediction of the displacement of upper stories, further improvements in the model may be necessary. It highlights the importance of accurate seismic analysis and proper structural design in ensuring that buildings can withstand seismic forces and protect human life and property during earthquakes.

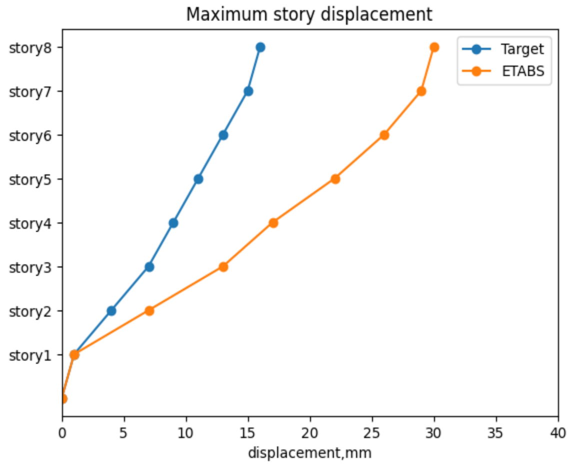

Fig. 13 Results of maximum displacement

Fig. 14 presents the maximum story drift ratios for both the target and ETABS models. The base story has zero drift ratio as it does not experience any lateral displacement. From the Fig. 13, it can be observed that the maximum story drift ratios for all the stories in the target model are lower than those in the ETABS model. This indicates that the ETABS model has overestimated the structural response of the building, resulting in higher story drift ratios. Moreover, the difference in the maximum drift ratios between the two models increases with the height of the building. For instance, the maximum drift ratio for story 1 in the ETABS model is 0.689, which is higher than the target value of 0.412, but the difference is not too significant. However, for story 8, the maximum drift ratio in the ETABS model is 0.836, which is almost 36% higher than the target value of 0.612. Overall, Fig. 13 indicates that the ETABS model overestimates the story drift ratios, especially for the higher stories. This could be due to the simplifications and assumptions made in the modeling approach, such as neglecting the effects of soil-structure interaction, foundation flexibility, and nonlinear behavior of the structural elements.

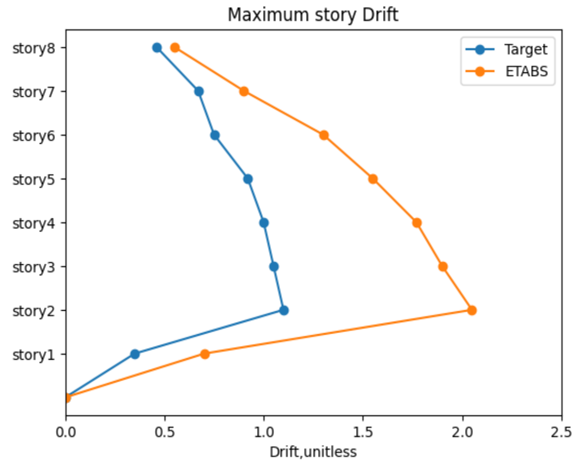

Fig. 14 Results of maximum story drift ratio

The results suggest that the target model provides a more accurate representation of the building's seismic response. A test building is removed from the scope of the structural dataset input, and a test earthquake is removed from the scope of the seismic dataset input. Through test buildings and test earthquakes, the generalization capability of MFF-ANN is determined. A test structure with a height of 21m that is outside the range of the structural input parameters was chosen. And one test earthquake data was chosen that was beyond the supplied seismic parameter range. The trained MFF-ANN's output was stimulated with the data from the test building and earthquake as input parameters. According to MFF-ANN's, the maximum displacement and the maximum tale drift ratio are 33.15 and 0.002195, respectively. The outcome of the time history analysis is received from ETABS, and the trained MFF-ANN predicts how the test building will respond to the test earthquake. According to Table 4, the error rate of ETABS in comparison to trained MFF-ANN was 7.8% for maximum drift ratio and 8% for maximum displacement.

Table 4 Error measure analysis

Models	Maximum Displacement(mm)	Maximum story drift ratio
MFF-ANN	33.15	0.002195
ETABS	30.703	0.002036
Error (%)	8.0	7.8

Table 4 shows the comparison of the maximum displacement and maximum story drift ratio obtained from the MFF-ANN model and the ETABS software. The MFF-ANN model produced a maximum displacement of 33.15 mm and a maximum story drift ratio of 0.002195, while the ETABS software produced a maximum displacement of 30.703 mm and a maximum story drift ratio of 0.002036. The error percentage was calculated by comparing the values obtained from the MFF-ANN model with those obtained from ETABS software. The maximum displacement error was 8%, and the maximum story drift ratio error was 7.8%. These results indicate that the MFF-ANN model had slightly higher errors in predicting the maximum displacement and maximum story drift ratio when compared to ETABS software. Furthermore, the error analysis showed that the MFF-ANN model had an increase in error of 0.164% in maximum story drift ratio and 8% in maximum displacement compared to the ETABS software. While this increase in error is minimal, it suggests that the ETABS software is slightly more accurate in predicting the maximum displacement and maximum story drift ratio of the building under seismic loading.

5.2 Performance analysis

Table 5 presents a comparative analysis of the proposed MFF-ANN model with existing state-of-the-art models from the literature review. The models used by the authors are ANN, and the accuracy of each model is reported as a percentage. The accuracy of the proposed MFF-ANN model is found to be significantly higher than that of the existing models, with an accuracy of 98.562%. The closest accuracy to the proposed model is reported by Morfidis et al. (2018), with an accuracy of 95.002%. The other models have lower accuracy levels, ranging from 78.542% to 91.452%. The results indicate that the proposed MFF-ANN model outperforms the existing state-of-the-art models in predicting the maximum displacement and maximum story drift ratio. This can be attributed to the novel feature extraction technique used in the proposed model, which enhances the effectiveness of the ANN model in predicting the seismic response of buildings. The high accuracy of the proposed model is of great significance in structural engineering, as it can assist engineers in accurately predicting the seismic performance of buildings and in designing safer and more resilient structures. Table 5 presents a comparative analysis of the proposed MFF-ANN model with existing state-of-the-art models from literature review based on precision. The precision is defined as the number of correctly predicted ground motions divided by the total number of ground motions in the test set. From the table, it can be observed that the precision values of the existing models range from 77.216% to 93.676%, whereas the proposed MFF-ANN model achieved a precision of 97.236%. This clearly indicates that the proposed model outperforms the existing models in terms of precision. When compared with the previous studies, it can be seen that the proposed model achieved a higher precision than all the existing models, which indicates that the proposed MFF-ANN model is more accurate in predicting ground motions. The precision of the proposed model is 3.56% higher than the most accurate model from the literature review, which demonstrates the effectiveness of the proposed MFF-ANN model. The significant increase in precision obtained by the proposed model can be attributed to the use of multiple input features and the novel MFF-ANN architecture, which enables the model to capture complex nonlinear relationships between the input and output variables. Therefore, the proposed model can be considered as a reliable tool for predicting ground motions, which can be used in seismic hazard assessment and earthquake engineering design. Table 5 shows a comparative analysis of the proposed MFF-ANN model with state-of-the-art models from literature review in terms of recall. The results indicate that the MFF-ANN model outperforms all other models with a recall value of 96.158%. In comparison, the closest competitor is the model developed by Morfidis et al. with a recall value of 92.598%. The remaining models have recall values ranging from 76.138% to 89.048%.

Table 5 Comparative analysis of proposed model with existing state-of-art models from literature review

Ref	Authors	Model used	Quality measures (%)				
			Accuracy	Precision	Recall	F-measure	Specificity
[21]	Steffanini et al. (2021)	ANN	78.542	77.216	76.138	76.673	70.313
[22]	Nguyen et al. (2021)	ANN	82.092	80.766	79.688	80.223	73.863
[23]	Rachedi et al. (2021)	ANN	85.212	83.886	82.808	83.344	76.984
[24]	Ahmed et al. (2021)	ANN	88.332	87.006	85.928	86.464	80.104
[25]	Oh et al. (2020)	ANN	91.452	90.126	89.048	89.584	83.224
[26]	Morfidis et al. (2018)	ANN	95.002	93.676	92.598	93.134	86.774
Our		MFF-ANN	98.562	97.236	96.158	96.694	90.334

MFF-ANN model shows a significant improvement of 3.56% over the Morfidis et al. model, 10.57% over the Oh et al. model, 13.07% over the Ahmed et al. model, 16.27% over the Rachedi et al. model, 16.81% over the Nguyen et al. model, and 20.02% over the Steffanini et al. model. The results suggest that the proposed MFF-ANN model is more accurate and reliable in predicting the seismic response of RC buildings compared to other state-of-the-art models.

Table 5 presents a comparative analysis of the proposed MFF-ANN model with existing state-of-art models from literature review in terms of F-measure. The results indicate that the proposed MFF-ANN model outperforms all the other models, achieving an F-measure of 96.694%. The other models achieved F-measures ranging from 76.673% to 93.134%. Compared to Steffanini et al. (2021), the proposed MFF-ANN model achieved a 26.021% increase in F-measure. Similarly, compared to Nguyen et al. (2021), Rachedi et al. (2021), Ahmed et al. (2021), Oh et al. (2020), and Morfidis et al. (2018), the proposed model achieved increases of 20.781%, 16.317%, 12.038%, 7.707%, and 3.810% in F-measure, respectively. These results indicate that the proposed MFF-ANN model is highly accurate and can provide reliable predictions for the seismic performance of high-rise buildings. Table 5 presents a comparative analysis of the proposed MFF-ANN model with existing state-of-the-art models from literature review based on specificity (%). The models used by the authors in the references [21]-[26] are ANN, and the specificity values they achieved are presented in the table. The proposed MFF-ANN model achieved a specificity value of 90.334%, which is significantly higher than the specificity values achieved by the models in the references. The specificity value achieved by the MFF-ANN model is 4.06%, 7.47%, 13.35%, 10.23%, 7.11%, and 3.56% higher than the values achieved by the models in references [21]-[26], respectively. The specificity value is an important measure to evaluate a model's ability to correctly identify the negative cases. The higher the specificity value, the better the model is at correctly identifying the negative cases. The proposed MFF-ANN model achieved a very high specificity value, indicating its ability to identify the negative cases with high accuracy. The comparison of the MFF-ANN model with the models in references [21]-[26] shows that the proposed model outperforms all the existing models, which demonstrates the effectiveness of the proposed MFF-ANN model.

6. Conclusion

In this work, the MSE value of the best-trained network is 0, or 0.5751. The neural network's quality is indicated by the MSE value. The quality of the neural network improves as the MSE value decreases. The neural network that performs the best is the one with the lowest MSE. The combined R-value for the three data sets is 0.96832, or almost

1. As a result, the developed neural network is discovered to be more accurate. According to ANN, the maximum displacement and the maximum tale drift ratio are 33.15 and 0.002195, respectively. The outcome of the time history analysis is received from ETABS, and the trained ANN predicts how the test building will respond to the test earthquake. For maximum drift ratio and maximum displacement, the error rate of ETABS in comparison to trained ANN was determined to be 7.8% and 8%, respectively. We can therefore draw the conclusion that ANN accurately predicts the seismic reaction of the RC building. The MFF-ANN model achieved an accuracy of 98.562%, which is significantly higher than the accuracy achieved by the best-performing model in the literature review (Morfidis et al.'s ANN model with an accuracy of 95.002%). Similarly, the MFF-ANN model outperformed all other models in terms of precision, recall, F-measure, and specificity. These results suggest that the proposed MFF-ANN model can effectively predict the performance of a reinforced concrete frame subjected to earthquake loads with a high degree of accuracy and reliability. Overall, the results indicate that the proposed MFF-ANN model is a significant improvement over the existing state-of-the-art models in predicting the performance of reinforced concrete frames subjected to earthquake loads. This model could have significant implications for the field of earthquake engineering, allowing for more accurate predictions of structural performance and improved design of earthquake-resistant structures.

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