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Prediction of earthquake-induced damage in structural components using artificial neural networks

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Abstract

Traditional damage detection methods can be costly, error-prone and labor-intensive inspections. Artificial neural networks have been applied broadly over recent years because of their outstanding pattern recognition capability, which is suitable for structural damage detection purposes. In this research, artificial neural networks were developed to predict structural damage resulting from earthquakes. This study investigates structural defects caused by earthquake loading in structural components using an inclusive dataset that covers a variety of structural factors. Different networks were trained to detect patterns engaged with structural faults. These networks included a database of general feature sets containing structural height, different types of material, number of floors, severity of earthquake, damping ratio, and source of cracks for predicting damage index. The results of this study indicate that, an ANN with a configuration of 6-14-7-1 possesses great potential to estimate the damage index, as evidenced by the low error and high correlation values. The performance and efficiency of such network was investigated, demonstrating both improved accuracy and efficiency. The ANN model obtained a correlation coefficient of 0.987 for the training set, 0.969 for the testing set, and 0.975 for the validation set, indicating considerable potential in expressing the non-linear behavior of damage to structures.

1. Introduction

It is very important for the security and life of buildings to detect damage in civil structures. Traditional damage detection methods use visual inspection, and these criteria are expensive and not very reliable [1-3]. Recently, scientists have developed advanced methods such as non-destructive testing (NDT) and computer-based approaches in search of more accurate structural assessments [4-5]. Damage in structures is an intricate problem and can be affected by certain parameters causing reduction in structural stiffness and strength. In nature, residential buildings are most vulnerable to catastrophic natural disasters such as typhoons, landslides and floods, especially earthquakes [6-9]. These hazards continually threaten buildings with robust forces like seismic excitation, wind pressures, and soil deformation. Because the interaction between seismic parameters and ground motion responses is complex and delicate, current conservative methods often produce ambiguous results. Artificial Neural Networks (ANNs) offer a promising option employing their ability to learn from historic earthquake records and detect hidden patterns within large-scale datasets [10-11].

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Through historical earthquakes and structural response data, ANNs make it possible to perform fast and reliable damage assessments and improve post-earthquake assessment techniques. ANNs are broadly used in pattern identification to match pattern features, mainly due to their superior generalization capabilities [12-15]. ANNs can learn complex patterns and relationships from input data, containing structural parameters, environmental conditions, and damage information from the past [16-17]. Recent research findings have suggested that neural network models significantly outperform linear models in terms of performance [18-20]. Thus, for damage prediction, they are more precise and reliable than classical models. Through dataset training that takes in many factors affecting damage, including material properties, structural loading and environmental conditions, ANNs can find patterns indicative of potential damage. In addition, ANNs can continuously update their predictions by integrating new data. Therefore, they can always move forward to improve their predicting capability.

ANNs have been shown by several research to be effective in predicting seismic defects. For instance, Aloisio et al. [21] applied an ANN to evaluate seismic weakness index with a database of approximately 300 building structures. ANN achieved the best performance and over 85% accuracy in case of enough data. This study showed that the ANN can be used to detect patterns and to reliably classify levels of deterioration. Its strong focus on masonry structures, however, limits its model to be adopted for other structural forms such as bridges and high-rise buildings. Shehzad et al. [22] presented an innovative machine learning-based method to improve the seismic performance of tall buildings. The proposed model incorporated ANNs and Support Vector Machines (SVM) for seismic response prediction. The recommended model demonstrated a substantial advancement in intelligent structural design for earthquake-prone regions. In another study Belhadj et al. [23] established a novel ANN model as an alternative for rapid building seismic defect evaluation using seismic, building, and soil parameters. The results of this research demonstrated the remarkable accuracy of this model, placing it as a successful predictive tool and quick decision support system for structures affected by earthquake impacts. This novel method served as a pre-disaster tool for evaluating possible damage and appeared as a practical asset for ensuring the safety and durability of structures during earthquakes.

Then, Xu et al. [24] established an ANN model capable of predicting the nonlinear seismic responses of various buildings enclosed in a group subjected to several different earthquake inputs. The implemented model was in an area with 2,788 buildings and 3,798 ground motions. Overall, compared to time history analysis, ANN demonstrated much quicker computation time and showed high efficiency, with errors less than 3% in a range of response measures. Jia and Wu [25] meanwhile proposed an ANNs-based probabilistic seismic risk assessment. They generated a set of data for structural defects through incremental dynamic analysis and trained an ANN to predict failure. By incorporating the uncertainties relating to both structural mechanics and earthquake action gradually into the process, they presented vulnerability curves embodying failure possibility limits. The results of research indicate that the proposed ANN has excellent stability and robustness, with a small range for the probability of structural failure.

In a different study, Abdellatif et al. [26] presented an ANN to predict seismic response of 3D reinforced concrete frame buildings. In this study, the Maximum Base Shear (MBS), the Maximum Inter-story Drift (MIDR) and the Maximum Roof Drift Ratio (RDR) as the critical engineering demand parameters were predicted. Over 192,000 buildings are analyzed using the nonlinear time history analysis and eighty artificial ground motions to generate the dataset. The results of ANN model could quickly and precisely predict the seismic responses of unseen ground motions using the building's characteristics and ground motions without using any finite element software. Moving on, Yuan et al. [27] aims to establish a seismic classifier using ANNs to enhance the accuracy of damage prediction and fault classification. By training the ANN, the model attempts to capture complex relationships between seismic inputs and structural responses, offering a more inclusive evaluation of possible damage. The research emphasizes the necessity for effective ANN layouts that balance predictive precision with computational proficiency.

Recent investigations highlight the potential of ANNs in predicting earthquake-induced structural damage while dealing with critical problems related to uncertainty and generalizability of the model [28-33]. Damage resulting from the earthquake is fundamentally uncertain due to alterations in ground motion, material characteristics, and construction quality, and existing ANN models struggle to directly determine these uncertainties, compromising their reliability.

Furthermore, extensive research focuses on specific structural elements, such as reinforced concrete or masonry structures, restricting their applicability to other structural types like steel, timber, or composite structures [34-37]. While ANNs have shown quite satisfactory results in predicting damage, further research has to be carried out to assess comprehensively their effectiveness. This study seeks to address these gaps by developing models that can cope with a variety of structural types to improve the predictability of ANN-based predictions. The research includes implementing ANNs to identify damage in various structural types, such as reinforced concrete buildings, steel frame buildings and timber frame structures. Training data for the ANN was generated by computer programming. This facilitates greater and efficient generation of data and preprocessing. It generates damage indices by pulling together such parameters as building height, damage of materials, number of stories in a building, earthquake intensity, damping ratio and crack location. These parameters are examined for damage indications.

2. Materials and Methods

This section highlights the methodology of the research, which includes the application of ANNs for predicting damage caused by earthquakes in structural components. ANNs represent computational frameworks that draw inspiration from the structure and functionality of biological neurons, specifically the human brain [38-39]. Various types of ANNS exist with differences in how their neurons are connected, the computations they execute, how patterns of activity are transmitted, and how they learn. ANNs consist of interconnected nodes, or artificial neurons, organized into layers. Among the various types of neural networks, multilayer perception stands out as the most employed one in structural engineering. It typically comprises an input layer with a neuron count equivalent to the number of parameters relevant to the given problem, while an output layer is presented with a neuron count matching the desired number of quantities obtained from the inputs. The intermediate layers are referred to as hidden layers. Figure 1 illustrates a sample of an ANN architecture which shows the signals from the input layer passing through the hidden layer and arriving at the output layer.

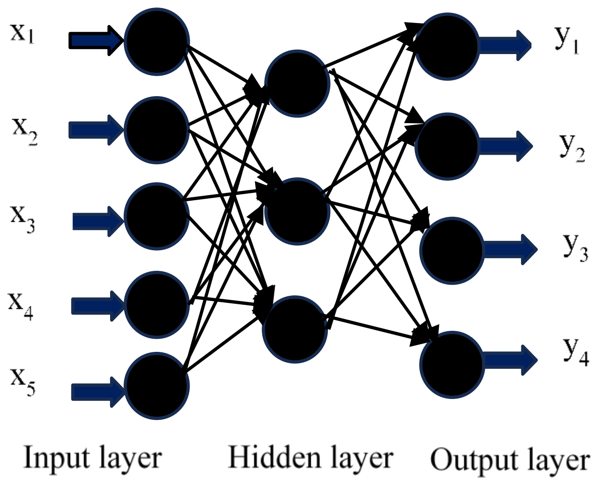

Fig. 1. An example of the architecture of three-layer ANN model

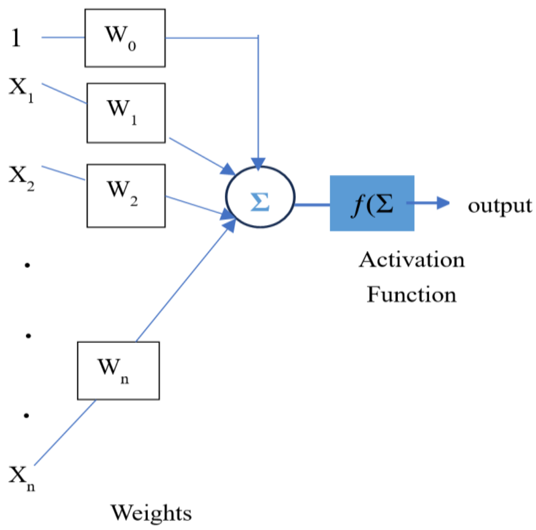

Fig. 2. Structure of an artificial neuron [5]

In layers beyond the input layer, each neuron performs a computation by taking a combination of the outputs from the preceding layer's neurons. The structure of an artificial neuron is shown in Figure 2. Each input is multiplied by its respective weight before being processed at the summing node. Following this, neurons within the hidden layer perform calculations using a non-linear function applied to their input. The sigmoid function is typically chosen for this purpose, which exhibits a range between 0 and 1. In accordance with the conditions of sigmoid function, the datasets have been scaled to fit within the range of 0 to 1 [40-41]. Since the sigmoid function constrains outputs to this range, it is a suitable to interpret in regression tasks with limited target domains.

The Backpropagation (BP) algorithm is broadly applied in ANNs due to its ability to describe complicated nonlinear relationships in mathematical terms. Its functionality is evaluated based on a performance metric intended to reduce the Mean Square Error (MSE). This algorithm progressively reduces the difference between the predicted by network and actual outputs until a satisfactory level of accuracy is attained with the training dataset. The MSE calculates this error by contrasting the goal output with the output generated by network. This algorithm adjusts the weights and biases of the ANN to reduce the average error between predicted and actual values. The refining process continues until the error is decreased to a satisfactory level. When the network is trained, it is tested with new datasets, and the outcomes are compared with actual results for validation. In this study, the backpropagation algorithm is employed to optimize the connection weights of neural network.

Figure 3 shows the workflow of the proposed research demonstrating both the development and validation of the ANN model and its application for emergency earthquake damage response. The flowchart is separated into two main phases. Phase A is model development and validation. This phase demonstrates the offline process of preparing and validating the ANN model. The dataset is first collected and pre-processed. To ensure the strength and reliability of the ANN predictions, 10-fold cross-validation is employed. The dataset is split into ten folds, with nine folds used for training and one for validation in each iteration. Performance metrics such as MSE, RMSE, AE, and R^2 are calculated for each fold. This step validates the stability and generalization capability of the ANN before implementation. The final trained ANN model (architecture 6–14–7–1) is saved for later use in real-time applications. In phase B, the emergency damage response application is considered. This phase establishes how the validated ANN can be combined into a practical earthquake response framework. The ANN model predicts the damage index for structural components, which is then converted into categorical damage levels. These predictions inform decision support processes for emergency response, including highlighting inspections, and proper maintenances.

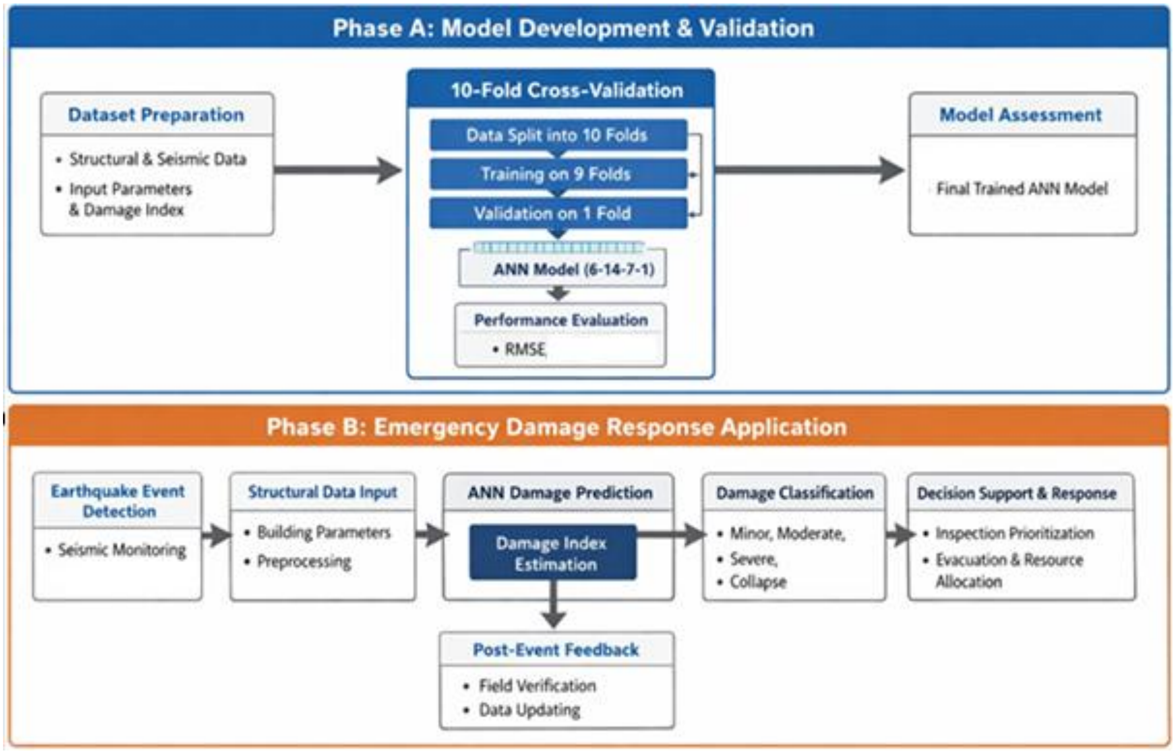

Fig. 3. Flowchart of the proposed ANN framework for earthquake damage prediction

3. Results and Discussions

The shaking of the ground during an earthquake transmits dynamic stress to structures, this can cause structural damage or even entire collapse. The way structures respond to seismic loads is determined by their design, construction standards and what they are made from. Observing how structural elements behave under earthquake loads is key to improving safety and reducing damage. Implementation of appropriate construction methods, adherence to the latest seismic codes, and regular maintenance can significantly improve a building's quake resistance. There are several factors affecting the degree of damage to structural components during an earthquake. The intensity and duration of the earthquake are two significant factors. More powerful and longer duration earthquakes lead to more damage because the structure must withstand under stress for a long time. Ground acceleration and frequency characteristics are very important to determining how a building will react. Structural systems play an essential role in determining how much damage is suffered by structural members during an earthquake. Structures with earthquake-resistant elements such as bracing, shear walls and moment-resisting frames perform exceptionally to reduce damage due to the earthquakes.

The overall symmetry of a building, both in plan and elevation, will influence its seismic behavior. Irregular not only means less economy in construction, but also larger vulnerability. Poor construction standards such as weak connections, insufficient reinforcement, or low-quality materials significantly raise earthquake vulnerability. Also, foundation and soil conditions, are influences on how buildings get hit by an earthquake. For instance, buildings built on unstable soils face a high risk of collapse. The interaction between soil and structure influences how seismic forces are transmitted to the building.

Various structural materials influence earthquake damage differently. Properly designed reinforced concrete (RC) buildings can effectively resist seismic forces, but poor detailing may lead to brittle failure. Common damages include column shear failure, beam-column joint failure, and cracks in infill walls. Steel structures, known for their ductility, efficiently absorb seismic energy, reducing collapse risk. However, weak connections, excessive deformations, and buckling of slender elements can cause failures. Timber buildings, being lightweight and flexible, generally perform well in earthquakes, but structural integrity can be compromised over time due to inadequate connections, decay, or termite damage. Using composite structures that combine materials like steel and concrete can improve both strength and ductility, though their effectiveness depends on the quality of material connections.

In this study, six independent variables that significantly impact the earthquake-induced damage were employed to develop ANN models. These parameters are building height, number of floors, earthquake intensity, damping ratio, crack location, and material properties. The output of the ANN was designated as damage index. Table 1 provides statistical details on the variation of parameters included in the database. In this study, training data for the ANN was generated through computer programming, resulting in 500 data sets that were collected and prepared for model development. These data samples were generated using a computer program developed in Python based on analytical relationships between seismic parameters and structural response. Each dataset represents a structural configuration subjected to simulated earthquake loading. An entire of 500 samples was selected as a balanced dataset size that permits suitable training and validation of the ANN model while minimizing overfitting risk. Primary trials showed that beyond 500 samples, enhancements in performance metrics (MSE, RMSE, AE, R^2) were insignificant, signifying that the model had reached adequate learning capacity for the given input range.

A measure, the Damage Index (DI), ranges from 0 to 1, signifying the level of structural damage. Higher numbers mean more damage has occurred. The corresponding Damage Index (DI) values were computed using analytical relationships that relate structural response parameters to the extent of damage. In this study the DI formulation followed the general concept proposed by Park and Ang [42-43], where the index ranges between 0 (no or negligible damage) and 1 (collapse). In this study, the DI thresholds for different materials (concrete, steel, and wood) were adjusted based on their distinct mechanical behavior and energy absorption capacity under seismic loading. This ensured that the dataset reflects the realistic variation of seismic damage across material types [44-47].

Table 1. Statistical information of datasets

Parameter	Remark
Building Height (m)	10 to 55m
Material types	Concrete/ Steel/ Timber
Number of floors	3 to 20 floors
Earthquake intensity (g)	0.1 to 1g
Damping ratio (%)	2 to 10%
Crack location	Column/Beam/Slab
Damage Index	0 to 1

Table 2. Damage index classification for reinforced concrete structures

Damage Index (DI)	Damage Level	Remarks
0-0.2	Low	Hairline cracks in beams, columns and slabs, no reinforcement yielding.
0.21-0.40	Moderate	Wider cracks and reinforcement start to yield.
0.41-0.70	High	Severe cracks, cover spalling, reinforcement buckling, potential joint failure.
0.71- 1	Very High	Structural instability, major rebar exposure, shear failure, collapse possible.

Table 3. Damage index classification for steel structures

Damage Index (DI)	Damage Level	Remarks
0-0.2	Low	Minor yielding, local deformations, no loss of load-bearing capacity.
0.21-0.40	Moderate	Noticeable plastic hinges, slight connection loosening, no global instability.
0.41-0.70	High	Significant yielding, local buckling, some connection failures.
0.71- 1	Very High	Extensive buckling, fractured connections, overall collapse risk.

Table 4. Damage index classification for timber structures

Damage Index (DI)	Damage Level	Remarks
0-0.2	Low	Slight deformation, minor cracks in connections, no loss of strength.
0.21-0.40	Moderate	Some loosened joints, moderate cracking, still stable.
0.41-0.70	High	Major joint failures, significant tilting, partial collapse risk.
0.71- 1	Very High	Structural collapse or near-collapse, widespread connection failure.

Furthermore, by classifying damage types for reinforced concrete, timber, and steel structures, the model will benefit from enhanced generality. This classification supports decisions on retrofitting, making it easier to bring the worst damage under control first. It also enhances risk assessments for earthquake zones, thus offering extra possibilities of mitigating disaster in advance. That there is a degree of commonality in how different materials may fail makes for lack clarity in classification, mainly in structures which have component parts made from composite material. Consequently, in this study, since the ANN predicts earthquake-induced damage for structural components composed of various materials, the Damage Index (DI) classification has been adjusted based on the material type. Given that materials such as concrete, steel and wood absorb seismic forces differently, the thresholds for classifications such as "High" or "Very High" damage may differ accordingly. A separate classification has been established for each material, as shown in Tables 2 to 4 for RC [42,43,48-50], steel [51] and timber materials [52], respectively. This classification enables the ANN model to interpret damage levels uniquely for different material types. The ANN's effectiveness relies on data availability, and materials with limited earthquake damage records may introduce bias in training, requiring additional data.

The process of evaluating the accuracy of predictions for damage through the utilization of ANNs includes a series of steps. The entire dataset covered a wide range of scenarios to capture the variability in real-world conditions. The data were pre-processed, and then they were divided into training, validation, and testing subsets. Each subset contained a representative distribution of different scenarios to prevent bias. Out of the total 500 datasets, 350 (70%) were assigned as training sets, whereas the remaining 150 datasets (30%) were used for the validation and testing phase. The division was conducted randomly among the three sets, and each set experienced statistical analysis to ensure that it covered a range of input parameters. Initially, the ANN was trained utilizing the training dataset. This training procedure was monitored using the validation dataset, and early stopping techniques were employed to avoid overfitting.

In this research, backpropagation algorithm was applied for ANN training. This algorithm was selected due to its simplicity, consistency, and appropriateness for problems containing moderate dataset sizes and regression-based damage prediction. While Adam and RMSProp are adaptive optimizers that may converge quicker, they can sometimes lead to overfitting convergence in small datasets. This algorithm allowed better control of learning rate, stable convergence, and reliable generalization performance during multiple trials. The error, calculated as the difference between the obtained output and the intended target output, is then propagated in a backward manner through the network. Throughout this procedure, the MSE is minimized, leading to the ANN's output closely aligning with the target output. A properly trained ANN can predict damage when presented with a new input sample. The datasets were normalized by scaling their values to a range between 0 and 1 before being provided as inputs to the network. The training process continues, constantly adjusting and refining the weights of the ANN, until the network can produce outputs that correspond to the target values.

In this study, numerous neural network architectures were considered, each with separate conditions such as connectivity weights, neuron counts per layer, the number of hidden layers, and the activation functions used in both hidden and output layers. The training of these networks was conducted using available datasets. Based on the results, a network with two hidden layers proved acceptable convergence. Therefore, the architecture of the ANN in this study was constrained to include two hidden layers, resulting in a total of four layers in the network configuration. As a result, the chosen network architecture adopts a configuration of 6-14-7-1, comprising a total of four layers, as shown in Figure 4.

The first layer consists of 6 neurons representing the six most influential parameters related to the earthquake-induced damage in structural components. The subsequent layer, referred to as the hidden layer, comprises fourteen neurons. Additionally, there is another hidden layer, the third layer, which consists of seven neurons. Finally, the output layer has a single neuron, corresponding to the damage index. It should be emphasized that employing a larger number of neurons in the network increases computational complexity and time consumption. In conclusion, the 6-14-7-1 architecture of the ANN was chosen to attain a balance between minimizing compatibility cost and maximizing precision.

Additionally, the findings indicated that the developed ANN achieved the lowest error when utilizing a learning rate of 0.3 and a momentum of 0.7. The momentum and learning rates were chosen through a series of primary experiments intended at reaching optimum convergence and minimizing validation error. The learning rate was adjusted within the range of [e.g., 0.01–0.1] to balance training speed and stability, while the momentum factor was tuned to accelerate gradient descent and prevent local minima. The final values were selected based on the configuration that provided the greatest performance in terms of precision and convergence. Training continued until the rate of error reached the smallest possible and the network became steady.

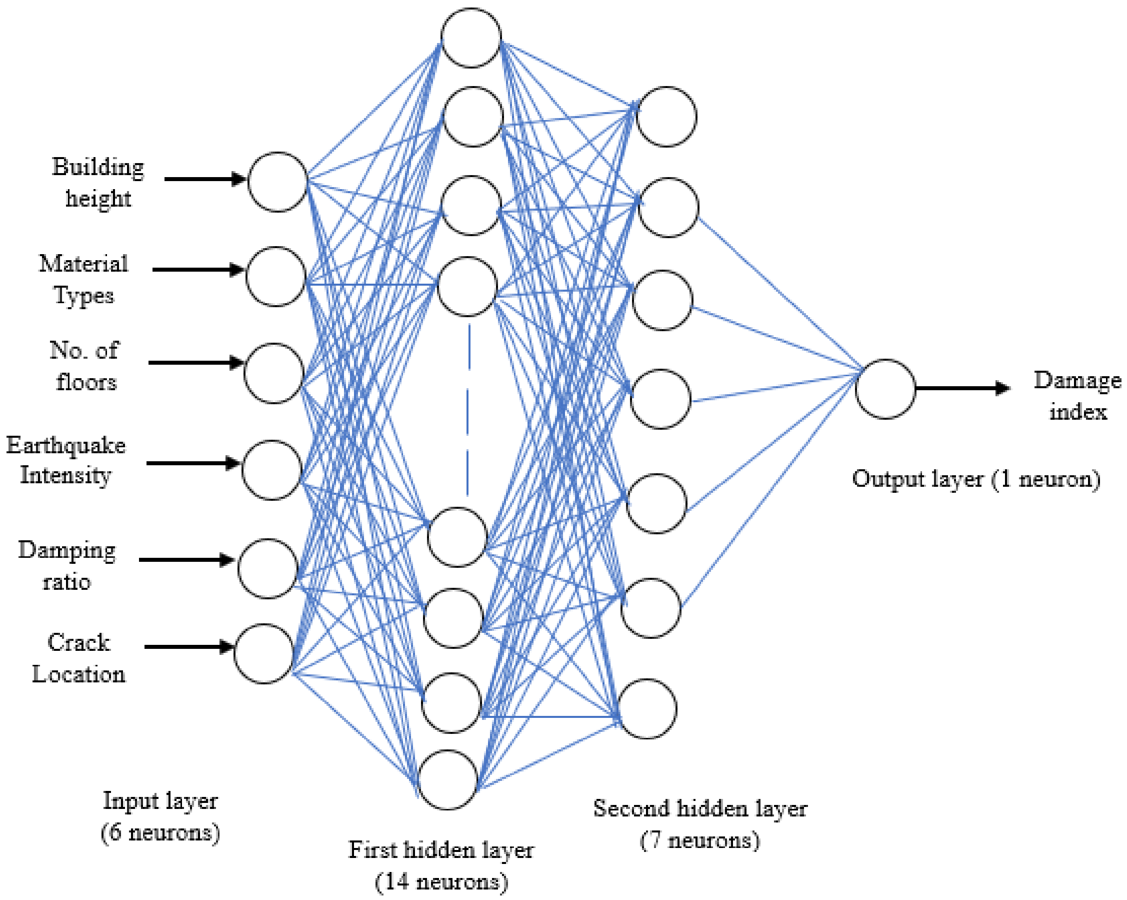

Fig. 4. Optimal ANN structure for predicting earthquake-induced damage in structures

All numerical input features were normalized using the min–max scaling method to a range of 0–1. Importantly, normalization parameters were computed only on the training set, and the same scaling factors were applied to the validation and testing sets to avoid data leakage. Adam optimizer was employed for efficient convergence. Sigmoid function was used for both the hidden and output layers to ensure the damage index output remain between 0 and 1. Number of epochs considered 30000, based on convergence behavior. Early stopping was applied to prevent overfitting when the validation loss did not improve for 50 consecutive epochs. The number of neurons, learning rate and momentum were tuned through trial and error and cross validation to achieve optimal performance and generalization.

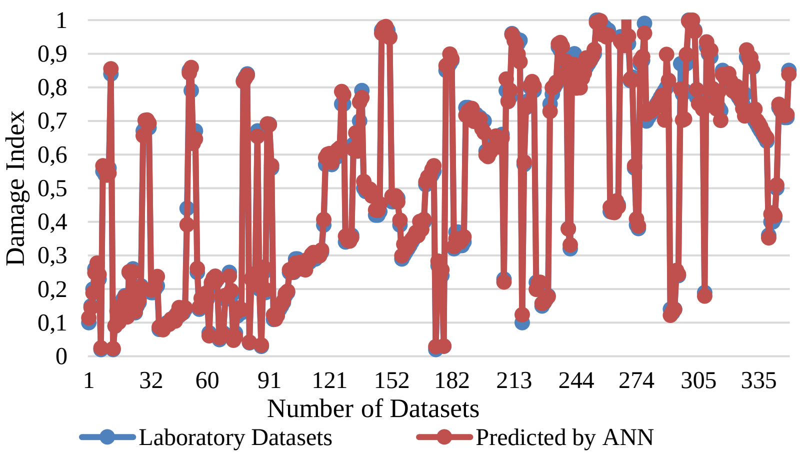

Fig. 5. Comparison of damage indices predicted by the ANN model with the actual values from the training dataset

The MSE and absolute error (AE) for this network were computed as 0.000232 and 0.632% respectively. Figure 5 shows the comparison between the predicted damage index values produced by the ANN and the actual values for the training datasets, which include 350 datasets. According to the results, the correlation coefficient for training data was 0.987. After the training process, the network has acquired knowledge from the samples, allowing it to make damage predictions with an acceptable level of error when tested on new data. Once trained, the ANN model is used to predict the damage index using datasets that were not part of the training sets. Therefore, following the training, the testing set was used to assess the accuracy of the chosen architecture. The correlation between the predicted damage index values generated by the ANN and the actual datasets is shown in Figure 6.

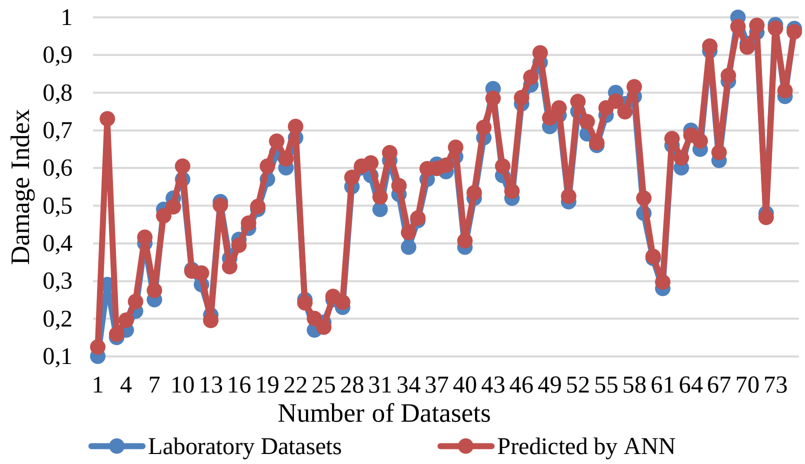

Fig. 6. Comparison of damage indices predicted by the ANN model with the actual values from the testing dataset

This evaluation was performed on 75 new datasets that were used as testing sets for the network's ability to predict damage index. The ANN achieved accurate damage predictions, yielding an absolute error of 0.6955% and a MSE of 0.000276 for the testing sets, demonstrating a strong approximation with the actual outputs. The correlation coefficient is 0.975 for the test data. From the results, the 6-14-7-1 network architecture was so accurate at identifying damage indicator with low error occurred and there was strong correlation value. Then the validation data was used to assess how well this network could generalize, in order to remain within bounds and not get stuck at any local point during the training. In validation, it is demonstrated that the ANN has effectively established the relationship between input and output data, achieving an absolute error of 0.717%, MSE of 0.000289, and correlation coefficient of 0.969.

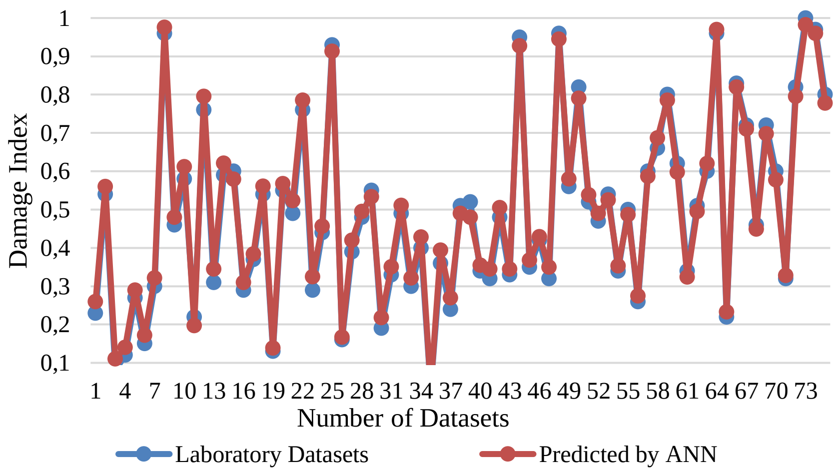

Fig. 7. Comparison of damage indices predicted by the ANN model with the actual values from the validation training dataset

As can be seen from Figure 7, the predicted damage index value generated by the ANN was compared with actual results for validation data sets. The validation dataset was conducted to ensure that the ANN's predictive performance was not dependent on a particular data split. The results of validation have demonstrated in Figure 7. The reported performance metrics (MSE, RMSE, AE, and R^2) for validation set have shown in Table 5. To provide additional evidence for the model's strength, the training procedure was repeated ten times with diverse random initializations of network weights. The results exhibited minimal differences, representing steady generalization capability. Also, to minimize overfitting, early stopping was used based on validation loss monitoring. This technique helped avoid the model from memorizing training data. From the results shown in Figure 7, it is clear that the selected network matched inputs to outputs well, which means it has predictive value, demonstrating its ability to precisely capture the relationship between the variables. Table 5 provides a summary of the statistics for all three datasets.

Table 5. Statistic results for three different datasets

Datasets	No. of Data	MSE	RMSE	AE (%)	Correlation
Training	350	0.000232	0.0152	0.632	0.987
Testing	75	0.000276	0.0166	0.695	0.975
Validation	75	0.000289	0.0170	0.717	0.969

To highlight the strength and generalization ability of the suggested ANN for predicting earthquake-induced damage in structural components, a 10-fold cross-validation (CV) approach was implemented in this research. Cross-validation is extensively recognized as an efficient method for mitigating overfitting and reducing bias connected with testing and training datasets, mainly in data-driven models where prediction precision may strongly depend on how the dataset is divided. By utilizing k-fold CV, the predictive performance of the ANN can be assessed more consistently across various subsets of the available data, thus providing robust proof for the stability and robustness of the ANN model.

In this study, the complete dataset was first randomly partitioned into 10 equal-sized folds. During each cross-validation iteration, nine folds were utilized for training, while the remaining fold was kept for validation. This process was repeated ten times so that each fold achieved as the validation set exactly once. Essentially, the ANN architecture was kept fixed throughout the entire cross-validation procedure, using the optimal configuration identified earlier (6 input neurons, two hidden layers with 14 and 7 neurons, and one output neuron). This confirmed that alterations in performance were differences in data partitioning rather than changes in network structure or hyperparameters. Before training in each fold, data preprocessing steps, including normalization of continuous variables were consistently applied to maintain uniformity across all folds. The ANN was then trained separately in each iteration using the same learning settings, stopping criteria, and activation functions. By repeating the training–validation cycle across all folds, the model was exposed to diverse combinations of training and validation data, thereby allowing a more comprehensive assessment of its predictive behavior under unseen conditions.

The predictive performance of the ANN was evaluated for each fold using standard regression-based performance indicators suitable for damage index prediction, such as the root mean square error (RMSE), absolute error (AE), and the coefficient of determination (R^2). After completing all ten folds, the performance metrics were accumulated, and the mean and standard deviation of each metric were calculated. Reporting both central tendency and dispersion is essential, as the mean values reflect the overall predictive accuracy of the model, while the standard deviations provide quantitative insight into the stability and sensitivity to data variations.

The cross-validation results proved that the proposed ANN model presents consistent predictive performance across all folds. This consistency indicates that the model is not overly dependent on a specific subset of the data and retains strong generalization capability. Additionally, the average performance gained from the 10-fold CV was found to be in close agreement with the results from the initial hold-out testing approach, confirming that the earlier reported accuracy was not an artifact of a favourable data split.

Overall, the integration of 10-fold cross-validation substantially improves the methodological accuracy of this research. It presents robust evidence supporting the consistency of the ANN model for predicting earthquake-induced damage in structural components across a large range of structural and seismic input conditions. According to the results of this research, among the six input parameters that are considered, earthquake intensity is likely to have the most significant impact on the predicted damage, as it directly determines the force exerted on the structure. This is the most critical factor since stronger and longer-duration earthquakes cause greater structural stress. Higher intensity leads to increased lateral forces, affecting deformation, cracking, and potential collapse. The internal functioning of the proposed ANN (6–14–7–1) was analyzed through weight distributions and error propagation. As shown in Figure 8 weight distributions across all layers reveal how the network balances contributions from different inputs, providing insight into learning behavior and stability. Hidden layer activations show that the first hidden layer with 14 neurons captures diverse features from the inputs, while the second hidden layer with 7 neurons produces more concentrated responses.

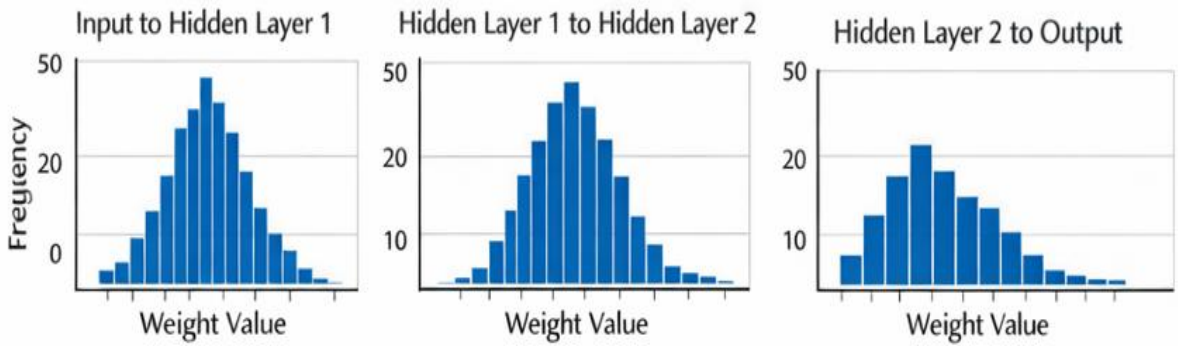

Fig. 8. Weight distributions of the proposed ANN (6-14-7-1) for network layers

From Figure 9, error propagation analysis shows how perturbations in input features influence the predicted damage index, emphasizing which inputs and layers contribute most to output variability. Together, these analyses improve precision, interpretability, and reliability of the ANN, indicating how the network transforms input data through succeeding layers to correctly predict earthquake-induced damage.

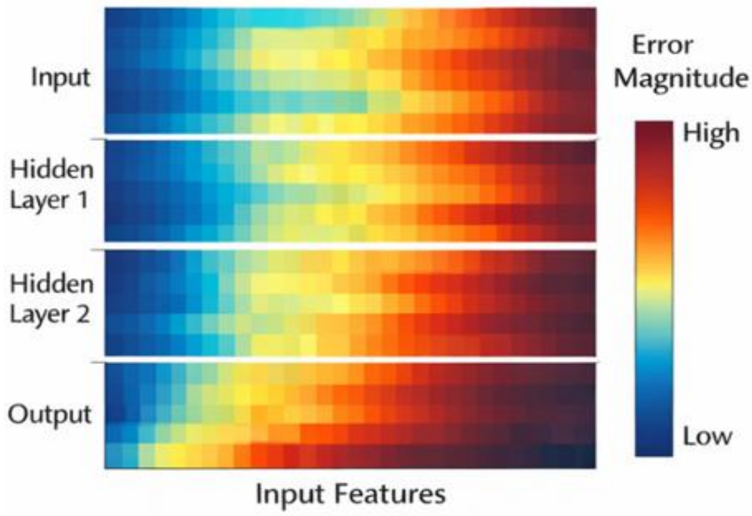

Fig. 9. Error propagation of input perturbations through the network output

From this study, taller buildings experience higher lateral displacements and are more prone to resonance effects, increasing the risk of severe damage in upper floors. Shorter buildings, on the other hand, may be stiffer but still susceptible to high intensity shaking. Closely related to building height, the number of floors affects the distribution of mass and stiffness. More floors increase the total mass, which can magnify seismic forces, especially if the building lacks suitable ductility.

A higher damping ratio helps dissipate seismic energy, reducing vibrations and damage. Buildings with good damp properties tend to perform better during earthquakes. Damping ratio represents the extent to which vibrations are reduced after an external disturbance. Structures with higher damping ratios absorb more seismic energy, reducing excessive vibrations and stress on structural components. In well-damped structures, earthquake-induced cracks and deformations are less severe, reducing the risk of structural failure. Cracks in structural components can significantly impact a building's performance during an earthquake. The location of cracks determines how seismic forces redistribute through the structure and whether they lead to failure. The position of existing cracks influences how damage propagates. Cracks in critical load-bearing areas such as columns or beam-column joints make the structure more vulnerable to failure under seismic loading.

Columns are the primary load-carrying elements, transferring loads from the beams and slabs to the foundation. Shear failure, crushing, or buckling in columns can lead to collapse. If cracks form at the base of columns or at beam-column joints, the structure becomes highly vulnerable to collapse. Cracks in beams have moderate impacts. Beams mainly resist bending and shear forces, so cracks affect their load-bearing capacity. Flexural cracks typically occur at mid-span, shear cracks are observed near the supports, and cracking may also be present at the beam-column joints.

Beams with severe cracking lose stiffness, affecting load distribution and may cause partial collapse. Cracks in slabs have a lower influence compared to beams and columns. Slabs primarily support gravity loads, but they can sustain damage as a result of lateral movements. Flexural cracks in flat slabs and punching shear cracks around columns in flat-plate systems are critical structural concerns affecting the performance and safety of structures. The location of cracks determines the severity of earthquake-induced damage. Cracks in columns are the most critical, as they directly affect the building's stability. Beams and slabs also play a role, but their failure is generally less catastrophic unless it triggers progressive collapse. Strengthening vulnerable areas before an earthquake is essential for improving structural resilience.

According to the results of this study, the choice of structural material plays a critical role in how a building responds to seismic forces. Each material has strengths and weaknesses in resisting earthquakes. Different materials exhibit diverse mechanical properties, such as ductility, stiffness, strength, and energy dissipation capacity, all of which influence their performance during earthquakes. Ductile materials like steel perform better due to their energy absorption capacity, while brittle materials like unreinforced masonry are more prone to catastrophic failure. Timber structures perform well due to their flexibility but require strong connections. If the training dataset does not fully capture these variations, ANNs may struggle to accurately predict material failure or overgeneralize results, leading to less reliable damage assessments. Therefore, material properties pose a challenge for ANN-based damage prediction due to their complex and nonlinear behavior under seismic loading.

In this study, the developed ANN model is planned for post-event damage evaluation rather than only pre-event prediction. In this framework, crack location is not a predetermined design variable but an observed structural response parameter that emerges following a seismic event. By incorporating it, the model can evaluate the severity and distribution of damage using structural attributes and recorded response data. From this research, the testing results exhibited accurate damage predictions for nearly all the datasets. However, crack location was one of the most challenging parameters for ANNs to predict accurately because crack formation and propagation are highly random and nonlinear. Even under identical structural and seismic conditions, small differences in material defects and stress concentrations can result in significantly different crack patterns. Moreover, crack formation is affected by various factors, such as changes in load path, stress redistribution, and localized weak areas, which may not be fully represented in training datasets. Because a neural network relies on recognized patterns in the original data, the variability in crack locations poses a challenge for the network to generalize predictions correctly. Although an ANN can capture overall damage trends, predicting the precise location and severity of cracks remains highly uncertain. The cause may be due to the ANN not having sufficient datasets to learn from within this range, in which case this reduced accuracy can be understood. It is widely recognized that the performance of an ANN is directly proportional to the variety and quantity of input data it processes.

The suggested ANN framework has apparent pre-event and post-event applications. In the pre-event phase, the model is developed and validated using datasets, with 10-fold cross-validation ensuring robustness and reliable prediction performance before application. This phase focuses on training the ANN with structural and seismic input parameters to create a validated predictive model. In contrast, the post-event phase applies to the trained ANN in real-time following an earthquake event, using actual seismic measurements and structural data to predict damage indices and classify damage levels to support emergency decision-making such as inspection prioritization and necessary maintenances. This proposed ANN model can be applied in real world scenarios such as fast post-earthquake damage detection, prioritizing structural inspections and incorporation into decision support systems for disaster management. One of the limitations of this model is that it may not fully represent real structural behavior under complex seismic loading. Incorporating really experimental or field data to validate and enhance the model's realism can increase its validity.

4. Conclusions

In this study, ANNs are used to explore complex relationships among six input variables including building height, number of floors, earthquake intensity, damping ratio, crack position and material properties. It then predicts the severity of structural damage under seismic forces. The findings reveal that among these indicators, earthquake intensity and material properties have a great influence over other factors, as they directly affect the loads applied on the structure and its resistance capability. While earthquake magnitude remains the most important parameter, material properties also play a significant role in damage of structures.

This study highlights that the seismic performance of structures is different regarding their material properties. Reinforced concrete buildings perform well under seismic forces when appropriately detailed. However, just one misplacement of a single bar can result in a brittle failure such as column shear failure, beam-column connection failure and cracks in infill walls. Steel structures have excellent ductility and can also take a serious earthquake without collapse. But weak connections, large deformations, or the buckling of a slender member endanger their stability. Timber structures, generally lightweight and flexible, could well survive under seismic loads, but their long-term effectiveness depends on joints and embedment that are secure, connections that provide the necessary strength in relation to wood quality and protection against decay or termite damage.

Damping ratio is very important for energy absorption, while crack location affects structural integrity. From the results, having cracks introduces significant uncertainties, potentially reducing the accuracy of ANN-based damage predictions. The height of a building and how many floors are in it determine how it interacts with seismic earthquake waves, affecting its dynamic response and deformation features. According to this study’s findings, ANNs demonstrate strong capabilities to predict earthquake-induced damage by identifying complicated patterns in structural response. Analyzing seismic data allows for precise damage predictions and strengthens the structural integrity. While ANNs are able to accurately capture overall damage trends, explicitly detecting localized failures remains a challenge. Enhancing model efficiency requires larger, various datasets and additional input parameters, such as real-time structural health monitoring data, to improve predictive accuracy.

A limitation of the present research is that the proposed ANN model was not benchmarked against simpler machine learning models, such as linear regression or support vector machines (SVM) approaches. Future work should therefore include comparative assessments of these baseline models using the same datasets and performance metrics. Such analyses would clarify the ANN’s benefits in precision, strength, and consistency for earthquake damage prediction.

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