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ANN-Based Prediction of Earthquake Damage in Steel Frame Structures

M.N.M. Dzulhazmi[1], S.J.S. Hakim[1]*, A.M. Mhaya[1], N. Jamaluddin[1], Z. M. Jaini[1], A.F. Kamarudin[1], S.N Mokhatar[1], H. Tami[1]

[1] *Department of Civil Engineering, Faculty of Civil Engineering and Built Environment, Universiti Tun Hussein Onn Malaysia, MALAYSIA*

*Corresponding Author: seyedhakim@uthm.edu.my
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Abstract

Rapid, reliable, and precise evaluation of earthquake-induced damage in steel frame structures is essential for ensuring structural safety and aiding post-earthquake decision-making. Although dependable, traditional evaluation techniques such as finite element analysis and experimental testing can be labor-intensive and computationally demanding, which makes them unsuitable for rapid damage assessment. This paper highlights the development of an Artificial Neural Network (ANN) model for classifying seismic damage levels in steel frame structures using a data-driven method. A dataset of 500 numerically generated samples was used, which included important structural and seismic parameters such as building height, number of stories, peak ground acceleration, fundamental period, inter-story drift ratio, steel yield strength, damping ratio, beam depth, column depth, and ground motion duration. The damage index was treated as a categorical output with five damage classes ranging from no damage to collapse. To assess the performance of the model, subsets of the dataset were divided into training, testing, and validation. Supervised learning implemented using Orange Data Mining Software was employed to train the ANN model, and classification performance metrics such as Area Under Characteristic Curve (AUC), Matthews Correlation Coefficient (MCC), and F1-score were used to evaluate the model. The optimal ANN identified in this study had two hidden layers with 18 and 9 neurons (10–18–9–1). Testing and validation results showed F1-scores of 0.922 and 0.934, AUCs of 0.964 and 0.972, and MCCs of 0.937 and 0.949. This architecture was used for damage prediction and classification, demonstrating that ANNs are a fast and reliable tool for assessing seismic damage in steel frame structures.

1. Introduction

Seismic damage assessment of steel frame structures is essential for ensuring structural safety and serviceability following earthquake events. Conventional assessment methods, such as nonlinear time-history analysis, pushover analysis and post-earthquake visual inspection can provide reliable results but are often time-consuming and impractical for rapid decision-making immediately after seismic events [1–5]. These limitations have motivated the development of alternative approaches that can provide faster damage evaluation with acceptable accuracy [6-8]. In recent years, data-driven techniques have gained increasing attention in structural engineering applications, particularly for damage identification and condition assessment problems [9–12]. Machine learning methods offer the ability to model complex and highly nonlinear relationships between seismic demand parameters and structural response without requiring explicit physical modelling assumptions [13-16]. Among these methods, Artificial Neural Networks (ANNs) have been widely adopted due to their strong pattern recognition capability and flexibility in handling multivariate input data [17-21]. Previous studies have successfully applied ANN-based approaches to predict structural damage indices, inter-storey drift ratios, and performance levels under seismic loading [22-24]. Applications have been reported for various structural systems, including reinforced concrete frames, steel frame buildings, and bridge structures [25–28]. These studies demonstrate that ANN models are capable of capturing nonlinear seismic–structural interactions that are difficult to represent using conventional analytical methods.

Despite these advances, several limitations remain in existing literature. Many studies focus on regression-based damage prediction or binary classification, which may not adequately represent the multiple damage states required for practical engineering decision-making [29-34]. In addition, the influence of ANN architecture configuration, particularly network depth, on classification performance and generalization capability has not been systematically investigated in some studies [35-37]. Another important limitation is the reliance on classification accuracy as the primary performance indicator. Accuracy alone may provide misleading conclusions when damage datasets are imbalanced across different damage classes. To overcome this issue, alternative performance metrics such as the F1-score, Area Under the Receiver Operating Characteristic Curve (AUC), and Matthews Correlation Coefficient (MCC) have been recommended for evaluating multiclass classification models [38–39]. These metrics provide a more balanced assessment of model performance by accounting for both correct and incorrect classifications across all classes. In view of these research gaps, this study develops an ANN-based framework for multiclass seismic damage classification of steel frame structures and evaluates the effect of network depth on predictive performance using robust classification metrics.

2. Materials and Methods

2.1 Artificial Neural Networks

Artificial Neural Networks (ANNs) are simplified models of the human brain and have evolved into one of the most useful mathematical concepts. They consist of many simple processing elements, called neurons, which are highly interconnected. ANNs have the ability to learn from experience, enabling them to improve their performance and adapt to changes in the environment [40]. They process information and establish complex, non-linear relationships by applying specific rules to large datasets in order to produce reliable results. This capability makes ANNs a powerful tool for solving complex engineering problems. Moreover, ANNs can provide meaningful outputs even when the input data contain errors or are incomplete, and they can process information extremely rapidly when applied to real-world problems [41-42]. As illustrated in Figure 1, the architecture of an ANN consists of an input layer, an output layer, and at least one hidden layer. Signals are received at the input layer, propagated through the hidden layer(s), and finally reach the output layer. Neurons in each layer are connected to neurons in the subsequent layer through weighted connections. Feed-forward neural networks were adopted in this study due to their proven effectiveness in classification and pattern recognition tasks in structural engineering applications. Feed-forward architecture is particularly suitable for damage classification problems, as they enable efficient mapping between seismic input parameters and discrete damage states.

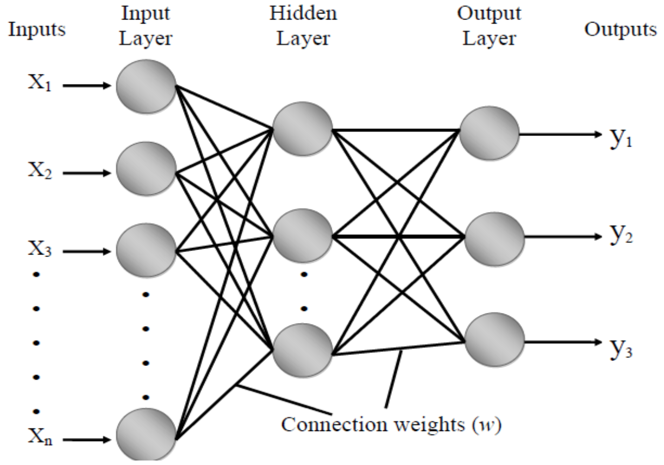

Fig. 1 *Schematic architecture of the feed-forward neural network*

J. of Struct. Monit. and Built Environ. Vol. 6 No. 1 (2026) p. 49-57

The Rectified Linear Unit (ReLU) activation function was employed in the hidden layers to improve training efficiency and reduce the risk of vanishing gradient problems commonly associated with sigmoid-based activation functions [38]. ReLU has been widely used in deep learning applications due to its computational simplicity and ability to accelerate convergence during training. Model optimization was performed using the Adaptive Moment Estimation (Adam) algorithm, which combines the advantages of momentum-based and adaptive learning rate optimisation methods [38]. Adam has been shown to provide stable convergence and improved training performance in machine learning models applied to civil and structural engineering problems.

2.2 ANN Parameters and Dataset Description

In this study, the dataset was generated to represent a wide range of structural configurations and seismic demand conditions, ensuring sufficient variability for effective model training and validation. Each sample corresponds to a structural response under earthquake excitation and is associated with a categorical damage state used as the target output. Structural responses were quantified using engineering demand parameters commonly associated with seismic damage. Based on predefined performance criteria, each simulation case was assigned to a discrete damage state, enabling the formulation of a supervised learning framework for seismic damage assessment.
The input parameters were selected based on their relevance to seismic response and damage behaviour of steel frame structures. A total of ten input variables were considered, including structural, material, and ground motion characteristics. These parameters include building height, number of storeys, peak ground acceleration, inter-storey drift ratio, fundamental period, damping ratio, steel yield strength, beam depth, column depth, and ground motion duration. The output variable is the damage index, which represents the structural damage state following seismic loading. To facilitate multiclass classification, the damage index was converted into categorical damage levels. This classification approach enables the ANN models to distinguish between different degrees of structural damage rather than predicting a continuous damage value.

In this study, a dataset consisting of 500 samples was used to develop and evaluate the ANN models for seismic damage classification of steel frame structures. The dataset was divided into three subsets to evaluate the model performance and generalization capability of the proposed ANN framework. Specifically, 70% of the data was used for training, while 15% were allocated for testing and the remaining 15% for validation. This data partitioning strategy allows the ANN to learn underlying patterns during training, while the testing and validation datasets are used to assess predictive accuracy and robustness on previously unseen data. The training dataset was used to update network weights through back-propagation, while the testing dataset was reserved exclusively for performance evaluation.

An iterative training process was adopted until convergence was achieved based on predefined stopping criteria. This strategy ensured that the developed model achieved an optimal balance between learning accuracy and generalization performance, while minimizing the risk of overfitting. In this study, Orange Data Mining Software is employed to train the ANN model, and classification performance metrics such as accuracy, confusion matrix, precision, recall, and F1-score were used to evaluate the model. To evaluate classification performance, the F1-score, Area Under the Receiver Operating Characteristic Curve (AUC), and Matthews Correlation Coefficient (MCC) were selected as the primary performance metrics. These indicators have been recommended for multiclass classification problems with imbalanced datasets, as they provide a comprehensive evaluation of prediction accuracy, class separability, and correlation between predicted and actual damage states [42-43]. The F1-score represents the harmonic meaning of precision and recall, and it is defined as Equation (1):

$$F_1\,Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{1}$$

Where precision and recall are given by Equations (2) and (3).

$$Precision = \frac{True\ Positives}{True\ Positives + False\ Positive} \tag{2}$$

$$Recall = \frac{True\ Positives}{True\ Positives + False\ Negative} \tag{3}$$

In the Orange Data Mining Software, the AUC metric measures the classifier's ability to distinguish between damage states by calculating the area under the Receiver Operating Characteristic (ROC) curve. Higher AUC values indicate stronger discriminative capability across different classification thresholds [38]. The Matthews Correlation Coefficient (MCC) provides a balanced evaluation of classification performance and is particularly suitable for imbalanced datasets. MCC is defined as shown in Equation (4).

$$MCC = \frac{TP \times TN - FP \times FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}} \tag{4}$$

In Equation (4), TP, TN, FP and FN denoting true positives, true negatives, false positives, and false negatives, respectively. MCC values range from −1 to +1, where +1 indicates perfect prediction, 0 corresponds to random classification, and −1 indicates complete disagreement between predicted and observed classes [40]. The combined use of F1-score, AUC, and MCC enables a more reliable and robust assessment of ANN performance compared to reliance on a single evaluation measure, particularly in seismic damage classification applications where accurate identification of damage states is critical.

3. Results and Discussion

The reliability of the proposed ANN models was assessed using feed-forward ANN architectures with one and two hidden layers. This study intends to assess the impact of the network depth on seismic damage classification performance in steel frame structures. The classification performance of the one hidden layer ANN is summarized in Table 1, which presents the testing and validation results in terms of classification accuracy (CA), F1-score, Area Under the Receiver Operating Characteristic Curve (AUC), and Matthews Correlation Coefficient (MCC). The findings indicate that the network with two hidden layers performs satisfactorily in classification, demonstrating its capacity to capture the key relationships between seismic input parameters and damage states. The model does not show significant overfitting and appears to generalize very well, based on the close comparison of testing and validation scores.

Table 1 *Test and score evaluation of test data for one hidden layer feed-forward ANN*

Data	F1	AUC	MCC
Training	0.946	0.994	0.923
Testing	0.805	0.968	0.816
Verification	0.843	0.952	0.860

The classification behaviour of one hidden layer is further illustrated using confusion matrices for the testing and validation datasets, as shown in Figures 2 and 3, respectively. The confusion matrices indicate that most predictions are correctly classified along the main diagonal. Misclassifications are most common between neighboring damage states, such as between modest and moderate damage categories, which is expected given the gradual process of damage progression under seismic stress. However, considerable confusion is detected in greater damage levels, indicating that the shallower network has limited representational ability.

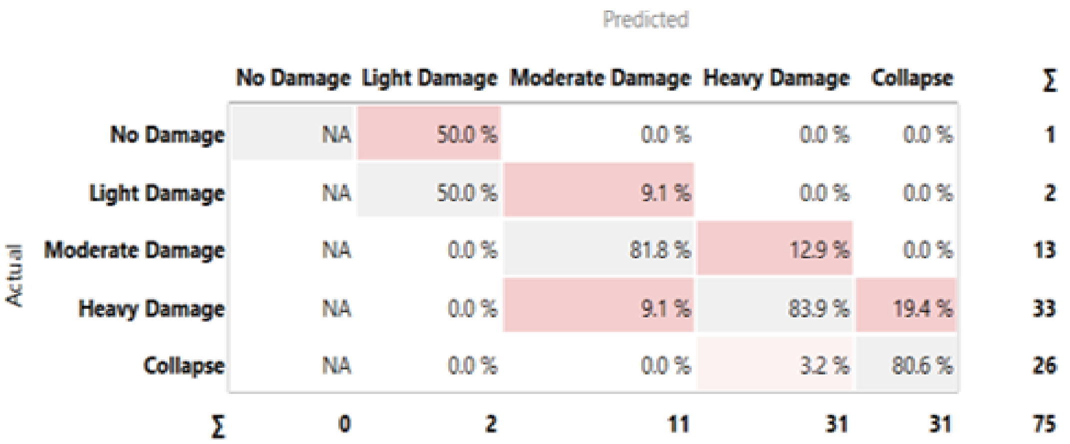

Fig. 2 *Normalized confusion matrix of the one hidden layer neural network for the testing dataset*

Predicted

Actual	No Damage	Light Damage	Moderate Damage	Heavy Damage	Collapse	∑
No Damage	NA	20.0 %	0.0 %	0.0 %	0.0 %	1
Light Damage	NA	80.0 %	16.7 %	0.0 %	0.0 %	5
Moderate Damage	NA	0.0 %	83.3 %	9.5 %	0.0 %	9
Heavy Damage	NA	0.0 %	0.0 %	88.1 %	18.2 %	41
Collapse	NA	0.0 %	0.0 %	2.4 %	81.8 %	19
∑	0	5	6	42	22	75

Fig. 3 *Normalized confusion matrix of the one hidden layer neural network for the verification dataset*

Using the same dataset a two hidden layer feed-forward ANN was created and tested to enhance classification performance. Table 2 summarizes the two hidden layer model's testing and validation performance. The two hidden layers for ANN outperform the one hidden layer design in all assessment metrics, including F1-score, AUC, and MCC values. This improvement shows that adding a hidden layer improves the model's ability to learn more complex nonlinear correlations between seismic demand parameters and structural reaction.

Table 2 *Test and score evaluation of test data for two-layer feed-forward ANN*

Data	F1	AUC	MCC
Training	0.963	0.996	0.949
Testing	0.922	0.964	0.937
Verification	0.934	0.972	0.949

The improved classification behaviour is further supported by the confusion matrix for the two hidden layer ANN shown in Figures 4 and 5 for the testing and validation datasets. In comparison to the one hidden layer model, there is a higher concentration of predictions along the principal diagonal, indicating enhanced classification accuracy. Severe damage states are more frequently diagnosed, whereas misclassifications are mostly restricted to nearby damage states. From the standpoint of engineering safety, this behaviour is especially crucial because it lessens the possibility of underestimating critical damage situations.

Predicted

Actual	No Damage	Light Damage	Moderate Damage	Heavy Damage	Collapse	∑
No Damage	NA	33.3 %	0.0 %	0.0 %	0.0 %	1
Light Damage	NA	66.7 %	0.0 %	0.0 %	0.0 %	2
Moderate Damage	NA	0.0 %	90.9 %	9.7 %	0.0 %	13
Heavy Damage	NA	0.0 %	9.1 %	83.9 %	20.0 %	33
Collapse	NA	0.0 %	0.0 %	6.5 %	80.0 %	26
∑	0	3	11	31	30	75

Fig. 4 *Normalized confusion matrix of the two hidden layers neural network for the testing dataset*

Predicted

Actual	No Damage	Light Damage	Moderate Damage	Heavy Damage	Collapse	Σ
No Damage	NA	20.0 %	0.0 %	0.0 %	0.0 %	1
Light Damage	NA	80.0 %	11.1 %	0.0 %	0.0 %	5
Moderate Damage	NA	0.0 %	88.9 %	2.6 %	0.0 %	9
Heavy Damage	NA	0.0 %	0.0 %	97.4 %	13.6 %	41
Collapse	NA	0.0 %	0.0 %	0.0 %	86.4 %	19
Σ	0	5	9	39	22	75

Fig. 5 *Normalized confusion matrix of the two hidden layers neural network for the verification dataset*

Investigations of ANN architectures with one and two hidden layers revealed that increasing the depth of the network leads to improved damage state classification accuracy and greater reliability when dealing with class imbalance. A stronger correlation between the expected and actual damage states is suggested by higher MCC values in the three-layer model. In summary, based on the training, testing, and validation results, the optimal ANN structure was identified as having two hidden layers with 18 and 9 neurons in the first and second hidden layers, respectively. This architecture (denoted as 10–18–9–1) was adopted for damage prediction and classification in this study. Nevertheless, the performance gain diminishes with increasing complexity, suggesting that profound networks may not offer significantly more value relative to their computational cost.

Overall, the findings show that an architecture with two hidden layers delivers better performance and more dependable damage level detection. These findings emphasize the importance of choosing an optimal network depth that strikes a compromise between prediction accuracy and modelling complexity. The findings of this study demonstrate that ANNs possess strong potential as a rapid and reliable approach for evaluating seismic damage in steel frame structures, thereby supporting post-earthquake decision-making and damage screening.

4. Conclusion

This study focused on the use of ANNs for multiclass seismic damage classification of steel frame structures utilizing structural and ground motion parameters. The predictive power and generalization performance of two different ANN designs with varying network depths were created and compared. A dataset composed of 500 samples was utilized to train and evaluate the models, with damage levels represented as categorical output classes. The findings indicate that both of the ANN models are capable of predicting seismic damage levels with reasonable accuracy. However, based on the training, testing, and validation results, the optimal ANN architecture for this study consisted of two hidden layers with 18 and 9 neurons, respectively (10–18–9–1). Performance metrics for the testing and validation datasets were as follows: F1-scores of 0.922 and 0.934, AUC values of 0.964 and 0.972, and MCC values of 0.937 and 0.949. This network structure was employed for damage prediction and classification, demonstrating that ANNs offer a rapid, reliable, and effective approach for evaluating seismic damage in steel frame structures. The more complicated network produced fewer misclassifications, especially in the categories of moderate to severe damage, as indicated by confusion matrix analysis. The results presented indicate that the capability of ANN models to accurately represent complex nonlinear relationships between structural reaction and seismic demand parameters is enhanced by network expansion. The proposed ANN framework, therefore, provides a computationally efficient alternative to conventional analysis-based approaches for rapid seismic damage assessment of steel frame structures. Despite the promising results, this study is limited by the size of the dataset and the use of numerical simulation data. For further improvement of prediction accuracy and reliability, future studies may concentrate on growing the dataset, adding experimental or field-recorded data, and investigating different machine learning approaches or hybrid models.

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J. of Struct. Monit. and Built Environ. Vol. 6 No. 1 (2026) p. 49-57

Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of the paper.

Author Contribution

The authors are responsible for the study conception, research design, data collection, data analysis, result interpretation and manuscript drafting.

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