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Artificial Neural Networks for seismic demand prediction of a single degree of freedom

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Abstract – This paper proposes using an artificial neural network (ANN) to estimate and predict the seismic demand of Single Degree of Freedom (SDOF) systems. Our methodology entails the production of a comprehensive dataset containing SDOF and earthquake characteristics. Nonlinear Time History Analysis (NL-THA) is performed on a randomly generated SDOF system using thirty-one artificial ground motions (GMs) matched to the EuroCode-8 (EC8) response spectrum to train the ANN model. To assess the performance of the ANN model, we compare the Incremental Dynamic Analysis (IDA) curves, the median IDA curve, and the 3D fragility surface in a case study. This analysis assists in determining the precision and dependability of the predicted maximum displacement of the SDOF system. The results showed a remarkable reduction in processing time without losing prediction accuracy. . It was concluded that the ANN-based method can be used as an alternative for the current method for estimating the performance points and the fragility assessment of buildings.

Keywords – Seismic Demand, Artificial Neural Network, Incremental Dynamic Analysis, Nonlinear Time History Analysis.

I. INTRODUCTION

The seismic vulnerability assessment represents a severe step to evaluate the buildings' state, especially for existing ones [1] [2]. Nonlinear time history analysis (NL-THA) is the most reliable and accurate method to calculate the seismic response under seismic excitation [3]. In addition, incremental dynamic analysis (IDA) is highly used to perform a fragility assessment, i.e., estimate the probability of exceeding a damaged state or a performance level [4]. However, both methods are time-consuming and require expertise to perform correctly.

For that reason, several methods have been proposed to determine the seismic demand or the performance point of buildings when subjected to earthquake excitation [5] [6], [7] [8] FEMA 356 [9] introduced two methods to calculate the performance or target points. The capacity spectrum method (CSM)[10] is based on transforming the obtained pushover curve that represents the base shear versus the roof displacement into another acceleration displacement response spectrum (ADRS) representation. The response spectrum will also be transformed into ADRS form to estimate the performance point using one of three algorithms. Conversely, the Displacement coefficient method (DCM) [11] uses modification coefficients (C0, C1, C2, and C3) to estimate the target displacement. In FEMA 440 [12], both methods were changed into equivalent linearization and modified coefficient methods. This improvement allowed the methods to estimate the performance points more quickly than the NL-THA results. However, when it comes to accuracy, these methods underestimate the seismic demand in some cases.

This work proposes an artificial neural network (ANN) to predict and estimate the seismic.

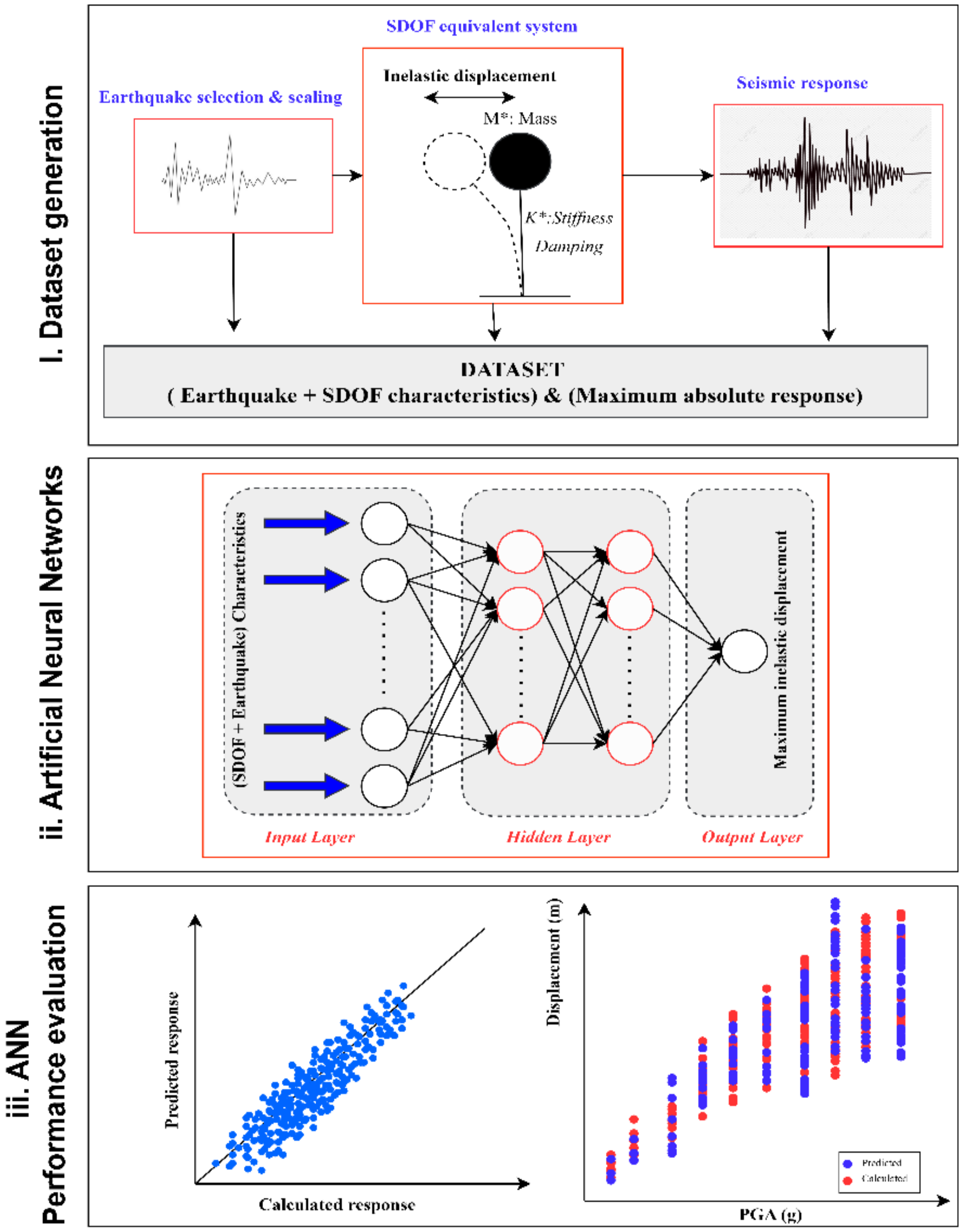

Figure 1 The proposed ANN-based methodology for the seismic demand prediction

demand of SDOF systems. The proposed methodology is based on generating a dataset that contains the SDOF characteristics (mass, stiffness, and yielding force) and the earthquake characteristics (peak ground acceleration (PGA), peak ground velocity (PGV), peak ground displacement (PGD), cumulative energy (Ecum), arias intensity (Ia), cumulative absolute velocity (CAV), spectral acceleration (Sa), spectral velocity (Sv), spectral displacement (Sd), Housner intensity (HI), acceleration spectrum intensity (ASI),

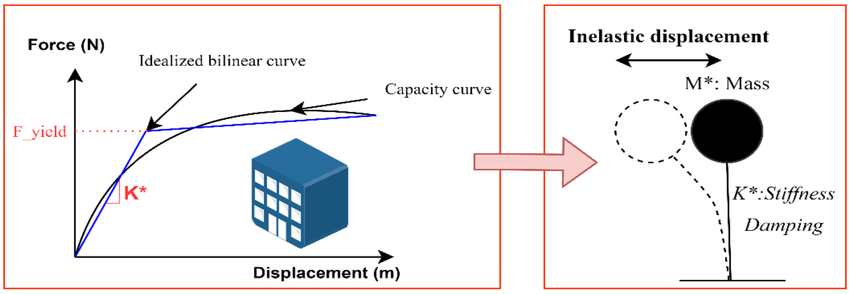

Figure 2 The SDOF equivalent system obtained from the idealization of the pushover curve.

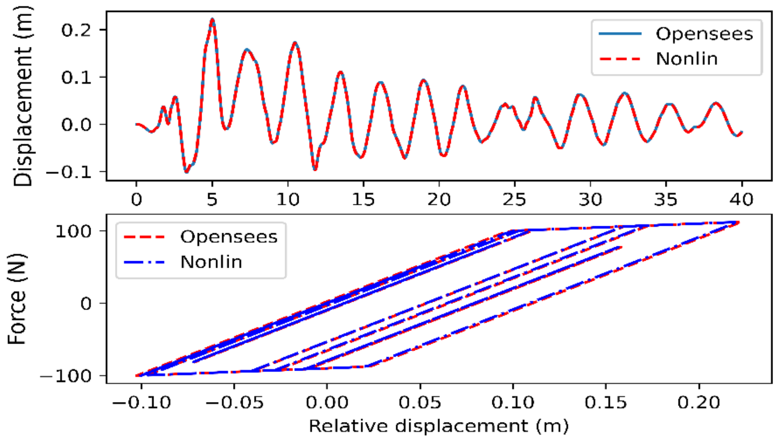

Figure 1 A comparison between the NL-THA using OpenSees and Nonlin software.

velocity spectrum intensity (VSI), displacement spectrum intensity (DSI), dominant frequency, bandwidth, and central frequency). The NL-THA will be performed on a randomly generated SDOF system. The used ground motions (GMs) are 31 artificial GMs generated and matched to the EuroCode-8 response spectrum. The generated dataset will be used to train the ANN after splitting the data into three datasets (training 80%, testing 10%, and validating 10%). A case study will check the ANN's performance by comparing the IDA curves, the median IDA curve, and the 3D fragility surface.

II. METHOD

Our proposed methodology as it is illustrated in Figure 1 aims to develop an Artificial Neural Network (ANN) model that can predict the maximum displacement of a Single Degree of Freedom (SDOF) system. This prediction can be used to create the fragility curves for any damage state. To get started, we need to create a dataset that contains all the necessary information to train the ANN model. This includes the SDOF characteristics (mass, fundamental period, and yielding force) and seismic characteristics (PGA, PGV, PGD, Ecum, arias intensity, CAV, Sa, Sv, Sd, Housner Intensity, ASI, VSI, DSI, SI, dominant frequency, bandwidth, and central frequency). We will then perform Nonlinear Time History Analysis (NL-THA) to capture the maximum inelastic displacement under 31 ground motions, which will represent the output of the ANN model. To select the hyperparameters of the ANN model, we will use a random selection

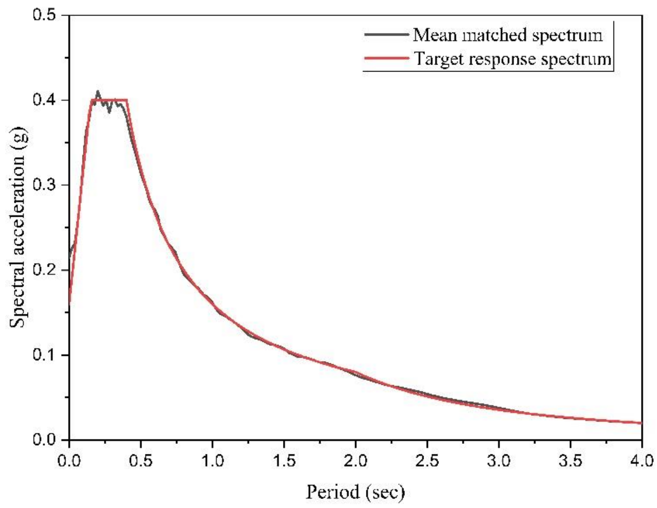

Figure 2 Response spectrum of the target and the mean matched spectra.

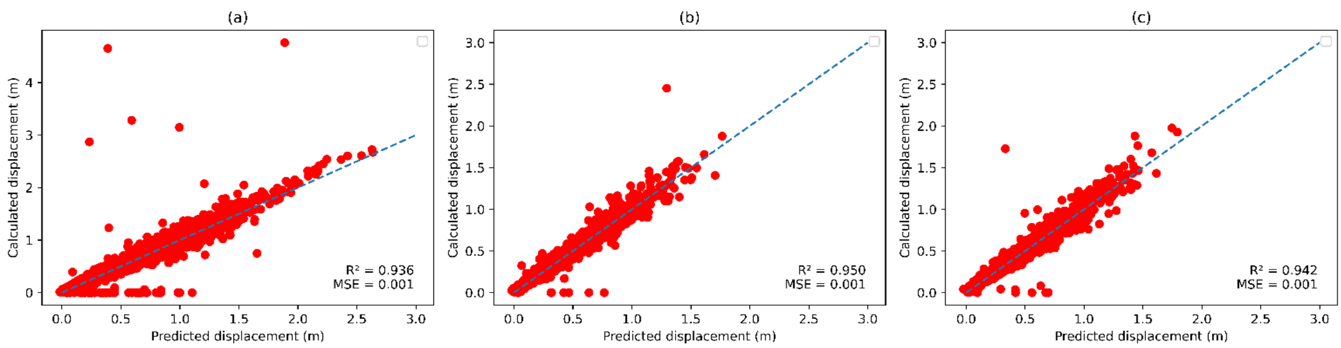

Figure 3 ANN performance (R^2 and MSE) for: a) Training, b) Testing and c) Validation

technique to determine the optimal number of hidden layers and neurons.

A. *Dataset generating*

The NL-THA method is a numerical method that resolves the differential equation of motion. It is more efficient and accurate for calculating elastic.

and inelastic seismic responses. Such an analysis was carried out using the OpenSees environment. The model is an SDOF with mass (m), period of vibration (T), and yielding force (fy) defined. The material behavior of the SDOF model is depicted in Figure 2. First, the OpenSees model was validated by comparing its output to that of the Nonlin software to ensure no programming error. Figure 3 depicts a comparison of the inelastic seismic response of an SDOF system and the Nonlin response under "El Centro 1940" ground motion. The Nonlin response can be observed to be identical to the inelastic displacement and hysteretic curves.

Second, The SDOF model will be subjected to 31 ground motions matched to a EuroCode-8 spectrum, and it is based on the following characteristics:

- PGA= 0.16 g.
- Spectrum type = Type 1.
- Ground type: A.
- Importance class: II.

Figure 4 illustrates the target response spectrum and the generated artificial and synthetic matched response spectra. Before the NL-THA, the mass, period of vibration, and yield force will be chosen from the interval ranges shown in Table 1.

Table 1. Selection interval of the SDOF parameters

Feature	Min	Max	Step
Mass (kg)	100	1000	100
Period (second)	0.1	3	0.1
Yielding Force (N)	100	1000	100

It is worth noting that the SDOF's material behavior is the elastic perfectly plastic (EPP) model, and more than 25,000 analyses were carried out and saved in the dataset.

B. *Artificial neural networks (ANN)*

The ANN algorithm is a type of supervised machine learning algorithm. It is widely used because it can accurately determine the relationship between inputs and outputs. This study used the ANN to determine the relationship between the SDOF and GM characteristics and the inelastic maximum displacement.

Before using the dataset, it should first be pre-processed, which means that the dataset may contain noise, undefined values, and infinite values, which can affect ANN performance during training and prediction accuracy. Furthermore, the dataset should be standardized, with all inputs and outputs having the same scale, i.e., all features having a zero mean and a standard deviation equal to one.

Second, define an optimization algorithm, learning rate, and activation functions. This work used the "Adam" algorithm as an optimizer, with a 0.01 learning rate and "Relu and Linear" activation functions for the hidden and output layers, respectively.

The number of hidden layers and neurons is chosen by repeatedly changing them and using the best combination corresponding to the highest correlation coefficient (R2) and the lowest mean squared error (MSE).

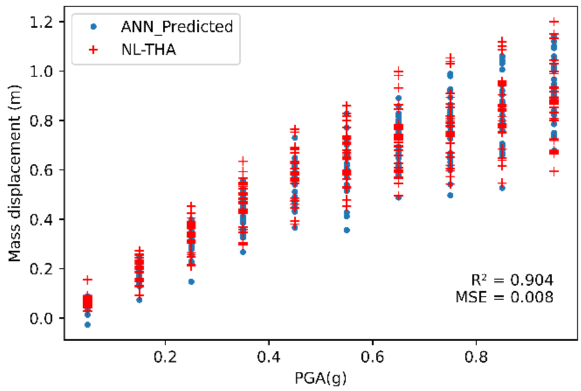

Figure 5 IDA points of the predicted response and the NL-THA response

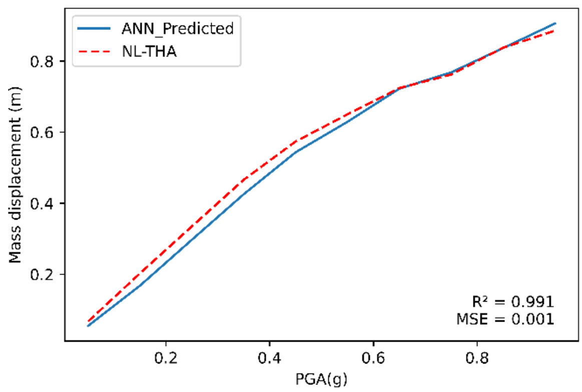

Figure 4 the median IDA curves of the predicted and the NL-THA responses

Following the execution of 25 ANN models using a random selection technique, it was found that [20:4] is the best number of neurons and hidden layers combination. Figure 5 shows the ANN's performance in terms of R2.

III. CASE STUDY

This section will use an SDOF system as a case study for evaluating the accuracy and quality of the ANN model's predicted results. The IDA points earned will be compared to the NL-THA points earned. The median IDA and fragility curves will be compared to calculate the error between the ANN prediction and the NL-THA values. The used SDOF has a mass of 200 kg, a vibration period of 0.7 seconds, and a yielding force of 1000 N. The SDOF model was subjected to 31 GMs matched to the same spectrum target.

Figures 6 and 7 display the obtained IDA points and their medians. The 3D fragility surfaces of the ANN-based and NL-THA-based models are depicted in Figure 5.

IV. RESULTS

Figure 5 shows the performance of the ANN in terms of R2 and MSE for training, testing, and validation to be (93.6%), (95.0%), and (94.2%), respectively. Figure 8 illustrates the predicted and calculated IDA points with R2=90.4% and MSE=0.008, whereas Figure 9 represents the median IDA curve from the case study with R2=99.1% and MSE=0.001.

Figure 10 depicts the R2 value of 98.6% and the MSE value of 0.0027 for the fragility assessment curves (surfaces).

The processing time was also examined, and it was determined that the IDA for an SDOF subject to a 31-ground motion required approximately 10 minutes, whereas the ANN-based prediction required only 4 seconds.

V. DISCUSSION

This work aimed to develop an ANN model that estimates the performance point of an SDOF system quickly and accurately. The SDOF system represents the equivalent single degree of freedom of a multi-degree of freedom. This type of simplification can only be performed for low- and mid-rise buildings where neither the torsional effect nor the higher mode effect is presented.

The results demonstrated that the ANN model predicted the maximum inelastic displacement of an equivalent SDOF system with remarkable accuracy. The ANN performance demonstrated a high correlation coefficient between predicted and calculated responses during training and testing. As a result, for the IDA point, median curve, and 3D fragility surface, the IDA also shows remarkable accuracy between the ANN-based and NL-THA results.

Finally, the time required to perform the IDA and build the fragility surface was reduced from 10 minutes to 4 seconds without losing much accuracy.

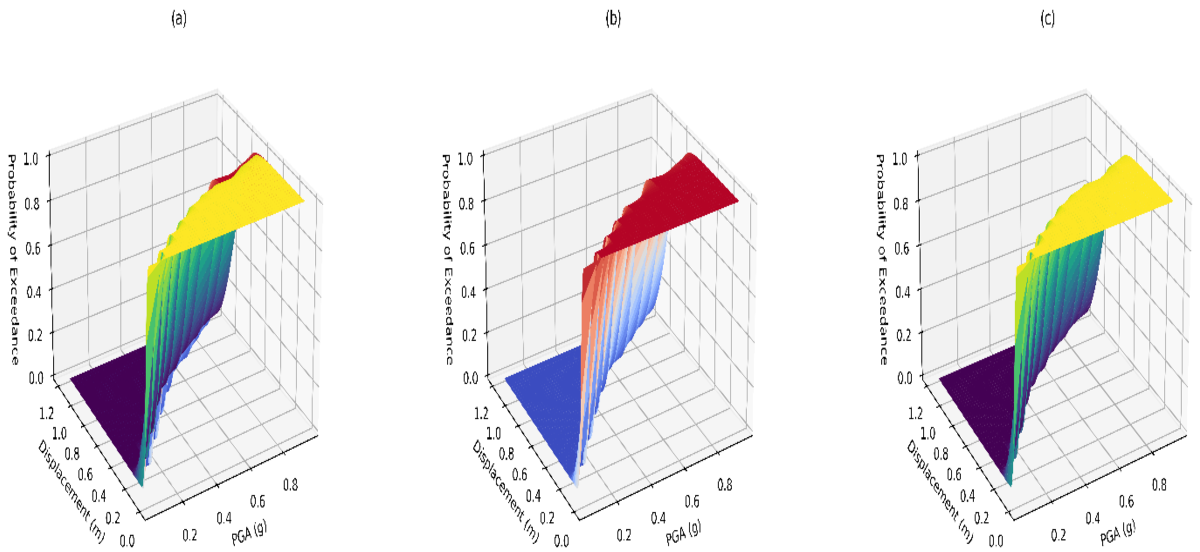

Figure 8 The fragility 3D surface of the predicted and the NL-THA responses: a) ANN-based, b) NL-THA-based and c) both fragility surfaces

VI. CONCLUSION

The proposed ANN-based method has shown promising results in predicting maximum inelastic displacements. The application of the ANN-based approach demonstrated in the research suggests that it can serve as a viable alternative to traditional analytical seismic evaluation and vulnerability assessment procedures. The study demonstrated that the ANN can accurately and quickly predict seismic response without the need for complex calculations. Furthermore, the proposed methodology has the potential to be extended to predict the behavior of complex structures. When performing Incremental Dynamic Analysis (IDA), the ANN-based method can provide a faster and more efficient solution. The methodology can overcome the limitations of artificial neural networks by using their computational power and pattern recognition capabilities.

Overall, the work presented emphasizes the effectiveness of the ANN-based method in predicting seismic response, emphasizing its potential as a valuable tool in seismic engineering for assessing structural behavior and assessing vulnerability. More research and development in this area may improve the applicability and reliability of the proposed methodology in a variety of structural analysis and design contexts.

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