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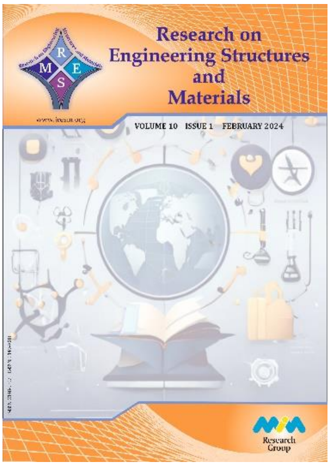

Dynamic response estimation of an equivalent single degree of freedom system using artificial neural network and nonlinear static procedure

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Research Article

Dynamic response estimation of an equivalent single degree of freedom system using artificial neural network and nonlinear static procedure

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Abstract

This paper introduces an innovative methodology for predicting the maximum dynamic response of structures using capacity curves and artificial neural networks (ANNs). This novel approach offers a quick and accurate procedure for estimating target displacements, obviating the need for intricate supplementary computations. The method generates a comprehensive dataset encompassing the bilinear representation of a single-degree-of-freedom (SDOF) characteristic, with ground motion parameters as inputs and maximum inelastic displacement as the corresponding output. This dataset is used to train an ANN model, with meticulous calibration of hyperparameters to ensure optimal model performance and predictive precision. The findings of this study demonstrate that the ANN model showed operational efficacy in approximating dynamic displacements. It is notably revealed that the size of the dataset significantly influences the ANN's performance and predictive accuracy. Through comparative analysis with established methodologies such as the displacement coefficient method and the modified coefficient method adopted by the Federal Emergency Management Agency (FEMA), the ANN model emerges as a fast tool for precisely predicting the dynamic response of single-degree-of-freedom systems, particularly those characterized by vibration periods exceeding 0.5 seconds. Consequently, this research culminates in the assertion that the ANN, owing to its inherent simplicity and impressive precision, is an alternative tool for estimating target displacements.

1. Introduction

The seismic response of buildings represents an essential factor in evaluating existing buildings' performance and seismic vulnerability (1–3). This response is known by engineering demand parameters (EDPs) such as roof drift ratio, inter-story drift ratio, base shear, etc. (4,5). Usually, the analyst is interested in capturing the maximum EDPs to evaluate the highest damage level during an earthquake. This valuable information can be used to justify the need to retrofit, strengthen, or demolish the assessed building (6–8).

The Nonlinear time history analysis is the most reliable procedure that can capture the response of the building in terms of displacement, velocity, acceleration, and forces (9–11).

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This method is based on solving a complicated equation of motion using numerical methodologies. However, the NL-THA is known for its complexity and the consumed processing time, which sometimes is inconvenient for performing a fast vulnerability and performance assessment. Therefore, the Nonlinear static procedure (NSP) was proposed as an alternative to the NL-THA due to its simplicity and less time-consuming feature (12–14). The NSP is based on finding the relationship between the base shear of the structure and the corresponding roof displacement, and the obtained curve is called the capacity curve. This curve illustrates the buildings' behavior when subjected to a static lateral loading that simulates the dynamic loading generated by the earthquake. It also shows the linear and nonlinear behavior of the building and the rupture point. The NSP is commonly used in performance analysis and performance-based design by calculating the performance point (15). It represents the intersection point between the capacity and the demand curves. The Federal Emergency Management Agency (FEMA) and the Applied Technology Council (ATC) (16) propose many procedures that allow us to estimate the performance point and the target displacement, which is the maximum displacement of a building. The Displacement coefficient method proposed by FEMA 356 (17) uses the four coefficients C0, C1, C2, and C3 to calculate the target displacement of a building. These coefficients are calculated and calibrated using empirical data. In FEMA-440 (18), they proposed to make some modifications to this method. C3, which considers the P-delta effect on displacement, was removed, and the formulas of C1 and C2 were changed. However, these two procedures sometimes provide a good and accurate estimation of the target displacement (19).

Artificial intelligence has recently become an exciting tool used in earthquake engineering, especially in seismic vulnerability assessment of existing buildings and damage prediction (20–28). Due to the simplicity and the high performance of the machine learning (ML) techniques, the analysis became much faster and less complex. Therefore, this work proposes a fast and accurate procedure that uses the NSP and artificial neural networks (ANNs) to estimate the maximum inelastic response of an SDOF system. The process is based on transforming the pushover curve into an idealized curve (transforming a multi-degree-of-freedom system (MDOF) into a single-degree-of-freedom system (SDOF)). Then, a dataset will be generated using the SDOF characteristics to perform NL-THA. The effective vibration period (Ti), the effective mass (M*), and the yielding force limit (fy) are the SDOF's characteristics. On the other hand, 31 artificial ground motions (AGM)parameters were selected to characterize the accelerogram of the earthquake: Peak Ground Acceleration, Peak ground velocity, Peak ground displacement, Arias intensity, Cumulative energy, Acceleration spectrum intensity, displacement spectrum intensity, cumulative absolute velocity, Uniform duration, predominant period, bracket duration, Housner intensity, Spectral acceleration, Spectral velocity, Spectral displacement, significant duration dominant frequency, Bandwidth, and central frequency. The output of the dataset is the maximum absolute inelastic displacement of the SDOF using the NL-THA. Two datasets will be used to train the ANN model (50,096) and (90,000). The investigation will be applied to 10 SDOF systems with various vibration periods (0.1 sec – 3 sec) and four yielding force limit (fy) (fy={100N, 400N, 700N, 1000N}). The comparison will be made between the mean response of each SDOF subjected to 31 artificial ground motions and the NL-THA's results.

2. The Proposed Artificial Neural Networks Model

The supervised ML techniques became a helpful tool in civil and earthquake engineering. Its ability to find the relationship between the input and output features makes it suitable for creating predictable models. The most used ANN technique is based on finding the best weights and biases corresponding to the lowest error between the predicted and the exact outputs.

The main idea of the proposed method is finding the relationship between the idealization parameters (equivalent SDOF) and the ground motions parameters with the maximum inelastic response, assuming that the dynamic response of the equivalent SDOF system is the same as the MDOF's. The procedure is illustrated in Figure 1 with the following steps.

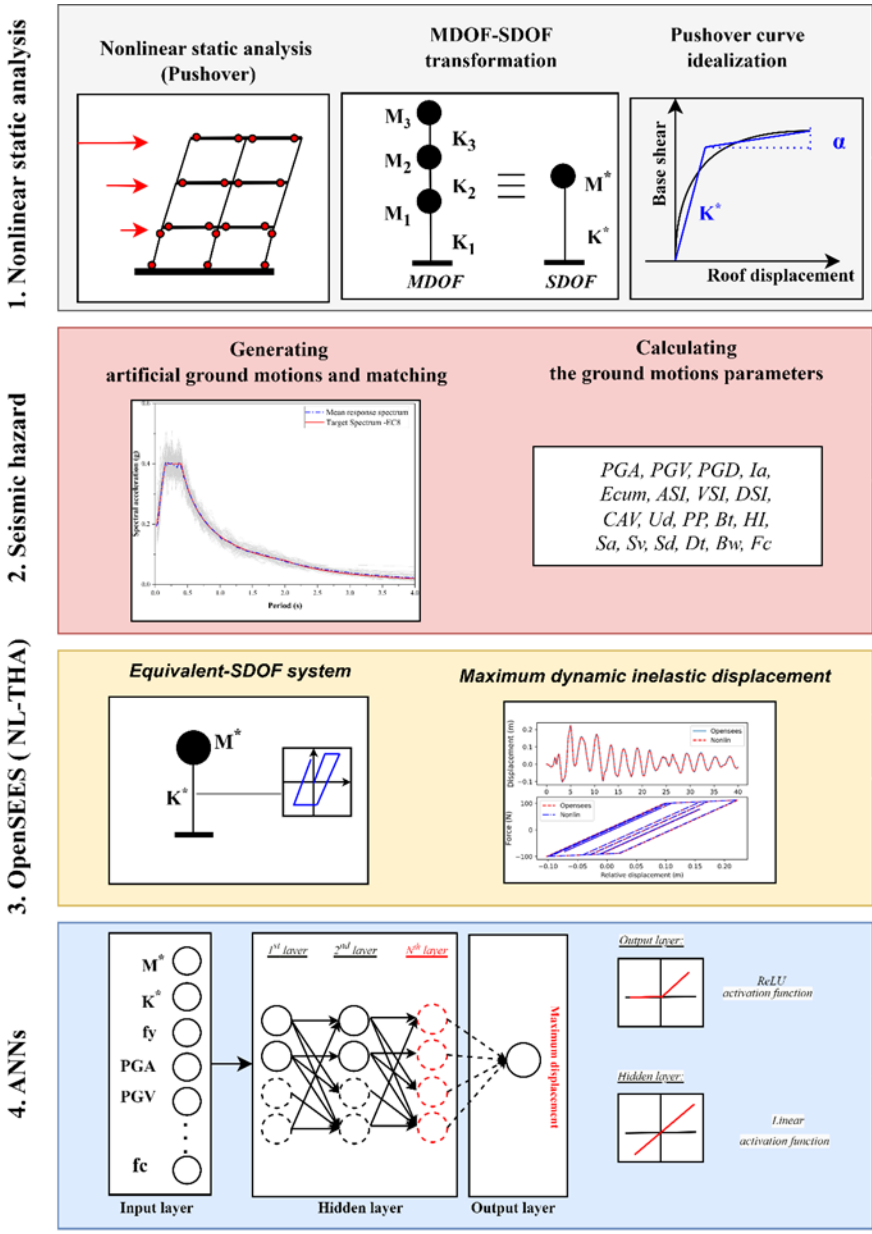


Fig. 1. The followed steps of the proposed ANN-based methodology

The ANN model needs enough datasets to be trained and to achieve high performance. The dataset will be generated by performing NL-THA analysis of equivalent SDOF systems and artificial ground motions. The output of the dataset will be the maximum inelastic displacement of the equivalent SDOF systems.

2.1. Ground Motion Selection

Earthquakes release energy in the form of waves and vibrations of different intensities. The acceleration records of a ground motion (GM) are the most used characteristics that describe and distinguish an earthquake from another. Each GM has specific characteristics like duration, location, peak ground acceleration, and frequency content that affect the building's response.

Table 1. The generated artificial ground motions and their parameters

	PGA	PGV	PGD	Ecum	Ia	CAV	HI	PP
AGM 1	0.16	0.89	1.27	128.75	20.61	35.75	3.47	0.40
AGM 2	0.19	0.72	0.33	84.47	13.52	28.42	3.06	0.15
AGM 3	0.16	0.81	0.59	123.71	19.81	37.01	3.49	0.40
AGM 4	0.19	0.88	1.08	78.82	12.62	28.95	3.10	0.15
AGM 5	0.19	0.75	0.48	86.92	13.92	28.56	3.00	0.15
AGM 6	0.16	0.87	0.59	120.48	19.29	36.75	3.53	0.30
AGM 7	0.16	0.91	0.34	143.74	23.01	40.08	3.74	0.25
AGM 8	0.18	0.73	0.47	95.91	15.36	31.91	3.26	0.15
AGM 9	0.20	0.76	0.69	93.61	14.99	29.93	3.03	0.15
AGM 10	0.17	0.70	0.48	83.22	13.33	29.78	3.24	0.15
AGM 11	0.17	1.07	0.69	109.57	17.54	34.69	3.46	0.20
AGM 12	0.19	0.74	0.66	68.98	11.05	26.99	2.87	0.25
AGM 13	0.15	1.54	3.65	124.17	19.88	33.46	3.73	0.40
AGM 14	0.15	0.99	0.29	107.16	17.16	30.53	3.76	0.15
AGM 15	0.18	1.41	1.81	92.68	14.81	29.65	3.24	0.30
AGM 16	0.19	0.78	0.74	89.12	14.27	29.09	3.16	0.15
AGM 17	0.24	0.70	0.31	47.51	7.61	20.38	2.36	0.40
AGM 18	0.18	0.66	0.45	80.31	12.86	25.63	3.30	0.15
AGM 19	0.18	1.67	2.38	74.50	11.93	25.20	3.17	0.30
AGM 20	0.20	0.99	1.21	62.50	10.01	23.51	2.87	0.40
AGM 21	0.24	0.62	0.27	55.29	8.85	23.29	2.34	0.40
AGM 22	0.19	0.84	0.53	54.72	8.76	21.38	2.84	0.40
AGM 23	0.16	0.81	0.43	97.59	15.63	35.30	3.33	0.35
AGM 24	0.17	5.98	17.29	130.20	20.85	45.11	3.05	0.30
AGM 25	0.18	0.72	0.51	84.89	13.59	33.06	2.91	0.20
AGM 26	0.17	0.76	0.69	101.06	16.18	36.42	3.15	0.15
AGM 27	0.22	0.83	0.69	64.96	10.40	24.70	2.55	0.25
AGM 28	0.15	2.22	6.03	120.99	19.37	39.59	3.57	0.20
AGM 29	0.21	0.73	1.48	65.88	10.55	25.08	2.58	0.15
AGM 30	0.18	0.78	0.51	104.86	16.79	31.72	3.27	0.20
AGM 31	0.19	0.66	0.81	79.15	12.6	24.63	3.21	0.30

Choosing the right GMs for the seismic vulnerability assessment is crucial for a reliable result. However, in some cases, the number of GMs selected for the study is insufficient due to the unavailability of real GMs. Therefore, using artificial ground motions is adequate to generate ground motions with the same spectral response of a target spectrum.

In this study, 31 artificial ground motions (AGM) have been generated and matched to a target response spectrum of the EuroCode-8, as shown in Figure 2. The AGMs were generated and matched using "SeismoArtif" (29), and the seismic parameters of the generated AGMs are shown in Table 1.

These AGMs are used in the NL-THA after scaling them using a scaling factor that increases and decreases the peak acceleration without changing the frequency content. The dataset will contain the GMs' characteristics that are illustrated as follows:

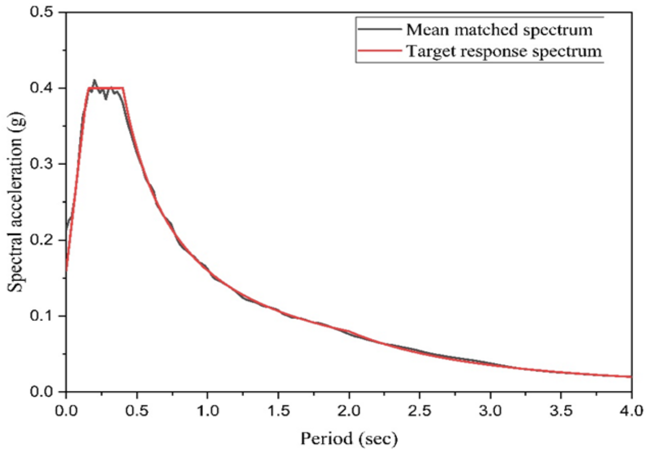


Fig. 2. The target response spectrum and the mean matched spectrum of the generated AGMs

- PGA: Peak Ground Acceleration
- PGV Peak ground velocity
- PGD Peak ground displacement
- Ia: Arias intensity
- Ecum: Cumulative energy
- ASI: Acceleration spectrum intensity
- VSI: velocity spectrum intensity
- DSI: displacement spectrum intensity
- CAV: cumulative absolute velocity
- Ud: Uniform duration
- PP: predominant period
- Bt: bracket duration
- HI: Housner intensity
- Sa: Spectral acceleration
- Sv: Spectral velocity
- Sd; Spectral displacement
- SD: significant duration
- Df: dominant frequency
- Bw: Bandwidth
- Fc: central frequency

2.2. Generating The Dataset

The performance of the ANN model depends on the size and quality of the dataset. It should contain enough information regarding variability and the number of input features. The inputs should describe the effective parameters of the problem and illuminate any unrelated features that may increase the training time and the complexity of the ANN model. This study aims to use the SDOF characteristics and the GM parameters to estimate the seismic response of an equivalent system. For that reason, 90,000 NL-THA are performed in OpenSees (30) using 31 AGMs that characterize the earthquake. OpenSees model's results are compared to Nonlin's (31) results to validate them, as shown in Figure 3. The maximum inelastic displacement of the SDOF is calculated and stored as an output of the dataset. This dataset contains 24 input parameters and one output. The SDOF characteristics are the fundamental effective vibration period (Ti), the effective mass (M*), and the yielding force (fy). Their variation range is represented in Table 2. The characteristics of the equivalent SDOF systems used to generate the dataset are selected randomly from a selection interval, as shown in Table 2. The random selection has to be uniform, i.e., the choice of each value from the SDOF characteristics (Mass, stiffness, etc.) has the same probability of being selected, and that way, the number of each value will be almost equal, as shown in Figure 4.

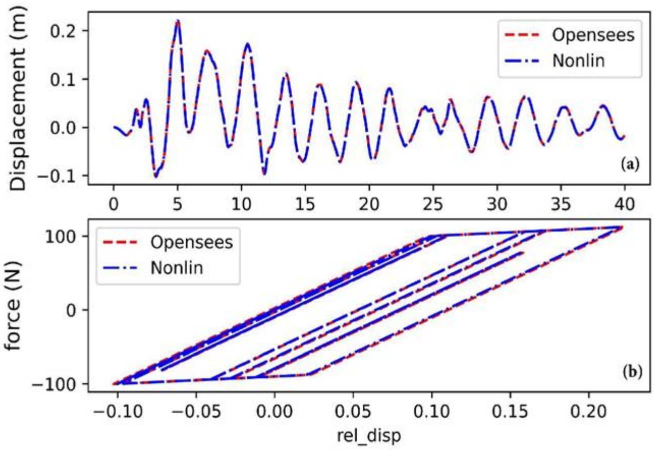


Fig. 3. NL-THA using OpenSees results and Nonlin software case of an SDOF (Mass= 200 Kg, Stiffness= 1000 N , fy= 100 N and El-Centro ground motion): a) Time versus dispalcement response, b) Displacement versus force response

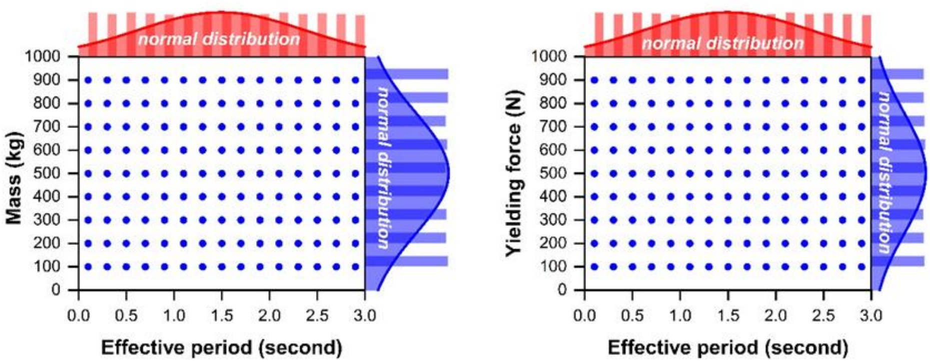


Fig. 4. the SDOF characteristics and their distribution in the generated dataset

The material behavior is considered elastic perfectly plastic (EPP), and no stiffness or strength degradation is considered in this study.

Table 2. Selection interval of the SDOF parameters

SDOF parameter	Minimum	Maximum	Step
Mass (Kg)	100	1000	100
Period (sec)	0.1	3	0.03
Yielding force (N)	100	1000	100

2.3. Training The ANN Model

The ANN is a supervised ML technique that requires inputs and outputs to find the relationship between them. The performance of the ANN model depends on various parameters and steps that will enhance its performance and reduce its complexity. Finding the best hyperparameters is a crucial step that decreases the training time and improves predictability. Activation functions, learning rate, number of epochs, number of hidden layers, and number of neurons are the principal hyperparameters that should be optimized by finding the best combination.

The training is divided into three phases. The first phase is the forward phase, where weights and biases of the hidden layers are initialized with adequate values, and it ends with calculating the outputs in the output layer. After finding the first predicted output, an error should be calculated between the data's and the ANN's output. The best weights and biases are computed using the gradient descent and the chain rule by finding the lowest error. This process should be repeated for all the hidden layers backward until the network is updated. This process is the back-propagation algorithm, which represents the second phase of the training. Lastly, as explained previously, the training dataset should be passed through the network, where weights and bias adjustments should be made. The testing and the validation datasets are used to compare the prediction of the updated network to the exact solution by calculating the correlation coefficient and the mean squared error (MSE) for each iteration. These datasets are an indicator of the performance of the ANN for predicting unseen cases and monitoring the performance of the ANN during the training process.

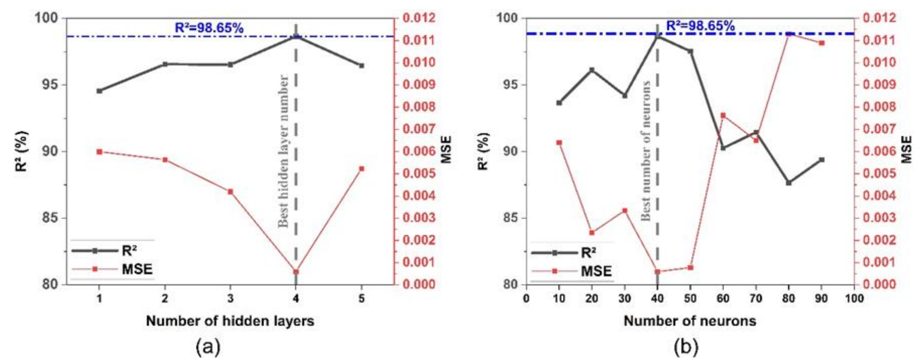


Fig. 5. Selection of best number of a) Hidden layers, b) Neurons

Figure 5 represents the selection of several neurons and hidden layers of the ANN and the corresponding performance criteria. "ReLU" and "Linear" activation functions are used for this ANN model of the hidden and output layers. To select the best number of the hidden layers HL and number of neurons NN, the HL was fixed, and the NN was varied from 10 to 90, calculating the R^2 and MSE each time, as shown in Figure 5 -b. The HL was also changed from 1 to 5; the best performance is illustrated in Figure 5 -a. It was found that four hidden layers and 40 neurons are the optimum selection that corresponds to the highest correlation coefficient (98.65%) and the lowest mean squared error (0.0007).

3. The Displacement Coefficient Method (FEMA-356) For Target Displacement Estimation

The NL-THA is the most reliable method to estimate the seismic response of structures. Since it is a time-consuming process, a nonlinear static analysis was proposed as an alternative. FEMA-365 proposes two ways to estimate the target displacement of an equivalent SDOF system: the capacity spectrum method (CSM) and the displacement coefficient method (DCM). The CSM is based on transforming the pushover curve (base shear versus top displacement) and the response spectrum (spectral acceleration versus period) into the acceleration displacement response spectrum. Then, a performance point should be determined using proposed algorithms by ATC-40 (19). However, this method represents some instabilities where the performance point cannot be calculated due to the absence of an intersection between demand and capacity curves. This study compares the proposed method to the NL-THA, DCM, and modified coefficient method MCM proposed by FEMA 356 (32) and FEMA 440. (33)

The DCM is expressed in the following equation to estimate the target displacement:

$$\delta_T = C_0 C_1 C_2 C_3 S_a \frac{T^2}{4\pi^2} g \tag{1}$$

Where:

- C_0: is a modification factor to relate the SDOF 's spectral displacement to the MDOF's response.
- C_1: is a modification factor that relates the inelastic expected response to the elastic response.
- C_2: is a modification factor representing the effect of strength and stiffness degradation on the maximum response.
- C_3: is a modification factor that relates the effect of the P-delta effect to the maximum response.
- S_a: is the spectral acceleration of the effective fundamental period of vibration.
- T: is the effective fundamental vibration of the building.

However, FEMA-440 (33) recommended some changes and improvements to the displacement coefficient method DCM. They recommended changing the C1 and C2 formulas and making them based on empirical data.

C1 improved to transform the maximum elastic displacement to an estimate for inelastic systems. C2 was recommended for structures with significant strength and stiffness degradation behaviors. C3 was recommended to be eliminated from equation (1) for strength limit favor.

4. A Comparative Study Between The ANN, DCM, MCM, and the NL-THA

This section aims to calculate the seismic response of various SDOF systems subjected to 31 unseen GMs using the ANN models and the FEMA's procedures, where the NL-THA's results will be used as exact solutions. Two ANN models will be used to study the effect of the dataset's size on the ANN's predictability.

Three statistical criteria will be used to evaluate the performance of each method to the NL-THA's results. 10 SDOF systems with different vibration periods and yielding force limits but fixed post-yielding ratio α=0% will be studied. These SDOFs' characteristics are illustrated in Table 1. The statistical criteria are shown in Table 2.

Table 2. The used statistical criteria to estimate the performance of each approach to the NL-THA results

Statistical criterion	Equation
Mean Relative Error (MRE)	$=\frac{1}{N}\sum_{i=1}\frac{\delta_{NLTHA,i}-\delta_{estimated,i}}{\delta_{NLTHA,i}}\times 100$
Mean Absolute Error (MAE)	$=\frac{1}{N}\sum_{i=1}\lvert\delta_{NLTHA,i}-\delta_{estimated,i}\rvert$

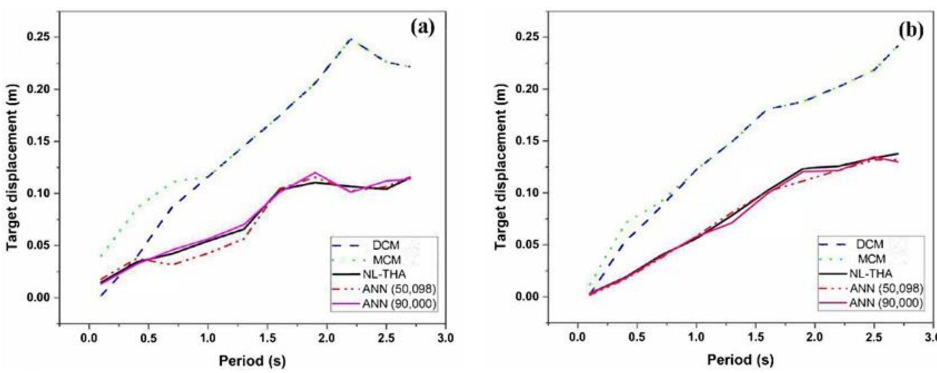
Where:

- $\delta_{NLTHA,i}$: is the maximum inelastic displacement of the mass under a ground motion 'I'.
- $\delta_{estimated,i}$: is the target displacement estimated using the ANN, DCM or MCM.
- N: is the total number of the used ground motions.

5. Results and Discussion

This paper proposed an ANN model that can predict the maximum inelastic displacement of an equivalent SDOF system using the nonlinear static procedure (pushover analysis). The study generated a dataset to train the model containing the SDOFs' characteristics and the GM parameters. Two datasets were generated containing 50,096 and 90,000 analyses. The aim of generating two datasets is to study the effect of dataset size on the performance of ANN. Then, these models will be compared to existing methods that estimate the target displacement. The NL-THA results have been used to compare the accuracy of prediction and estimation of the methods. The study is applied to 10 SDOF systems (0.1 sec to 3 sec) with different yielding force limits (fy).

Figure 6 represents the predicted, estimated target displacement and the dynamic inelastic response of the SDOF systems using DCM, MCM, ANN, and NL-THA for four yielding limit forces (fy =100 N, 400 N, 700 N, 1000 N) as illustrated in Figure 6-a, Figure 6-b, Figure 6-c and Figure 6-d respectively. The obtained results are the median response of each SDOF system using ANN, DCM, MCM, and NL-THA.



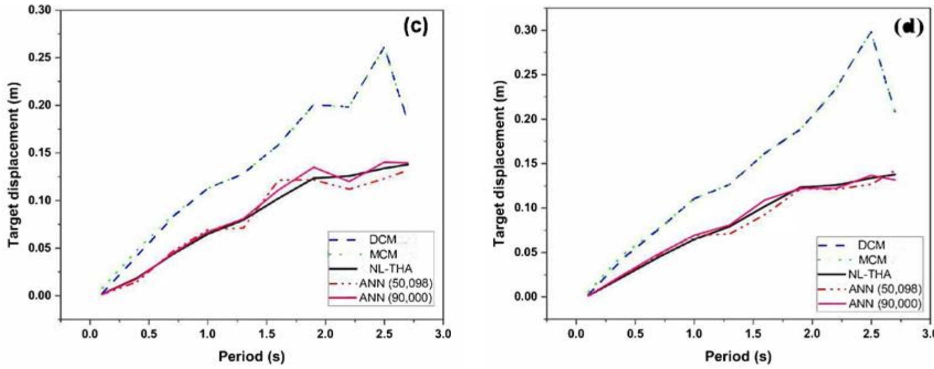


Fig. 6. Target displacement estimation using NL-THA, ANN, DCM and MCM for: a) fy=100 N, b) fy=400 N, c) fy=700N and d) fy= 1000N

Figures 7 and 8 illustrate the MRE and the MAE between the exact solution (NL-THA) and the estimated target displacements.

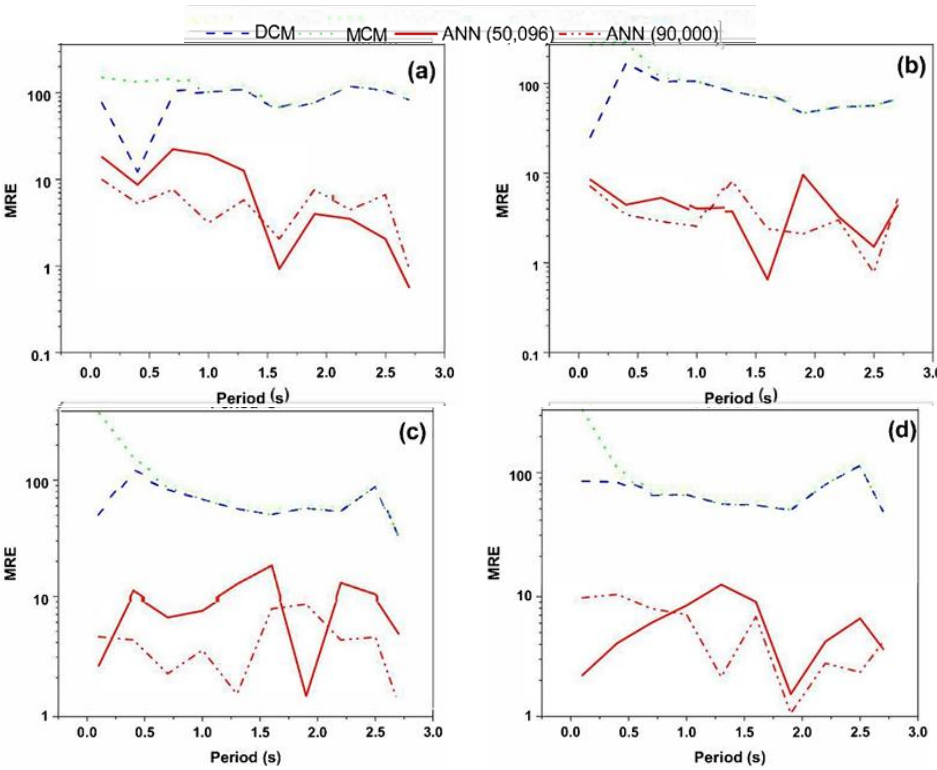


Fig. 7. Mean relative error of the predicted and the NL-THA seismic response of 10 SDOF systems: a) fy=100 N, b) fy=400 N, c) fy=700N and d) fy= 1000N

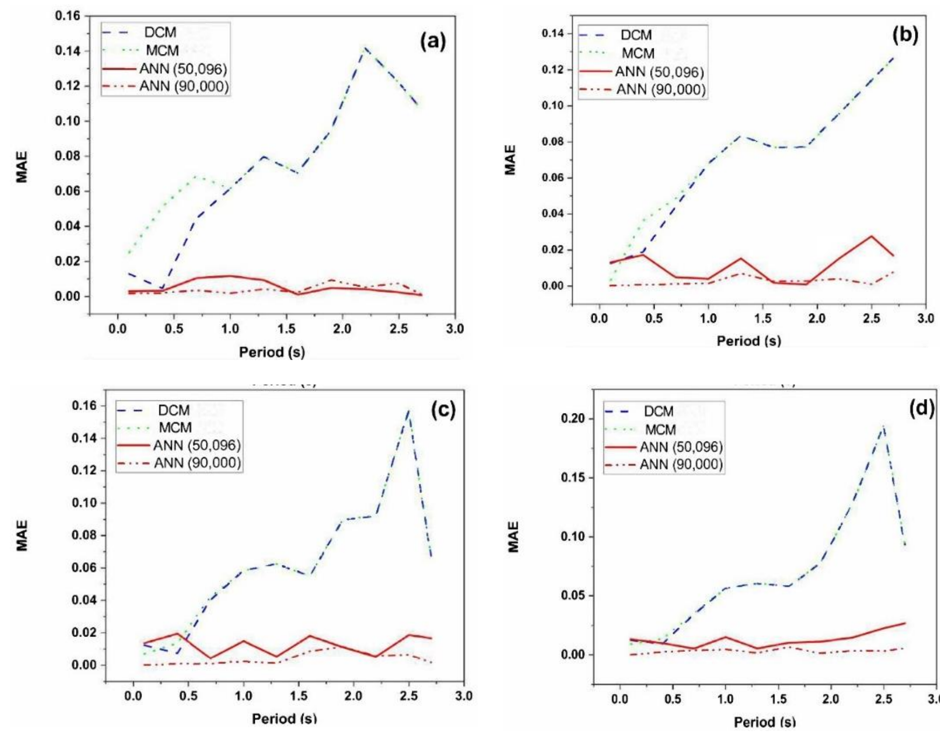


Fig. 8. Mean absolute error between the predicted and the NL-THA seismic response of 10 SDOF systems: a) fy=100 N, b) fy=400 N, c) fy=700N and d) fy= 1000N

The ANN-based method using 50,096 and 90,000 analysis is the nearest to the exact solutions calculated by the NL-THA. DCM and MCM overestimate the maximum inelastic displacement, especially for periods greater than 0.5 sec. Figure 7 shows the relative error between the mean dynamic inelastic response of the SDOFs subjected to 31 AGMs scaled to PGA=0.3 g. The results showed a high overestimation of the dynamic response (>100% in some cases), and the lowest relative error is 16% for the DCM and the MCM for all the cases. On the other hand, the ANN model shows a high predictability of the SDOFs' dynamic response for all the selected yielding limit forces (fy). It was also observed that the size of the used dataset enhanced the performance of the ANN model in terms of MRE. Figure 8 shows that the DCM and the MCM have the highest mean absolute error (>0.1) for all systems with vibration periods higher than 0.5 sec. These methods are promising approaches to estimating the target displacement of rigid and high-frequency buildings. On the other hand, the ANN showed a lower MAE than the DCM and MCM (0.02 was the highest MAE value for both the ANN models and for all the fy).

The ANN model could precisely predict the dynamic response using the SDOF and the ground motion characteristics. In addition, the obtained results were more accurate than the existing methodologies adopted by FEMA-356 and FEMA-440. Using the NSP with the ML showed remarkable predictability of dynamic responses, which makes it less complex and faster than the NL-THA. This hybrid procedure that uses the pushover curve and the ANN can be transformed into software that the analyst can use to estimate the dynamic response of any building without using the NL-THA. However, since the proposed procedure uses the equivalent bilinear curve of the pushover analysis, the higher mode effect can change the seismic response remarkably.

6. Conclusion

The seismic response estimation of structures is essential in assessing their performance and vulnerability. The NL-THA is considered the most reliable method to estimate the seismic demand. Many alternative methods have been developed to reduce the complexity and the computation time of the NL-THA, like Nonlinear static pushover (NSP). FEMA-356 and FEMA-440 proposed two equations to estimate the target displacement. However, their results remain inaccurate sometimes, and they overestimate or underestimate the seismic demand. For that reason, this study introduces a new approach that combines Nonlinear Static Pushover (NSP) analysis and Artificial Neural Networks (ANNs) to rapidly and accurately estimate the maximum inelastic displacement of an equivalent single degree of freedom (ESDOF) system subjected to a ground motion. This ESDOF represents the idealization of the pushover curve by transforming the MDOF system into an SDOF system, making the analysis much more effortless. The procedure is based on generating a dataset that contains various SDOF systems (Their characteristics: effective mass (M), effective stuffiness (K), and limit yielding force (fy)) and the parameters of the artificial ground motions (AGMs). The artificial neural networks were selected as a supervised machine learning algorithm to find the relationship between the ESDOF and the maximum inelastic displacement.

To evaluate the predictability of the ANN-based model, ten SDOF systems with variant vibration periods were selected to calculate the median seismic demand using the displacement coefficient method (DCM) proposed by FEMA-356, the modified coefficient method (MCM) proposed by FEMA-440 and the NL-THA using 31 AGMs. For limit yielding forces were selected fy= [100 N,400 N,700 N,1000 N]. The results were quite promising, showing that the model can predict deformations accurately. It has also been found that the size of the dataset used for training the model affects how well it performs.

This new ANN-based method shows a remarkable accuracy compared to existing alternative methods. The technique provides high accuracy for structures with a vibration period greater than 0.5 seconds, and the first mode is the predominant.

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