SSRG International Journal of Civil Engineering
ISSN: 2348-8352/ https://doi.org/10.14445/23488352/IJCE-V12I7P113

Volume 12 Issue 7, 145-158, July 2025

Original Article

Intelligent Prediction of Seismic Displacements Computed Using the Newmark-Beta Method: A Comparison Between Random Forests and Artificial Neural Networks

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Received: 10 May 2025 Revised: 15 June 2025 Accepted: 14 July 2025 Published: 31 July 2025

Abstract *- This research explores the application of Random Forest (RF) and Artificial Neural Networks (ANN) to determine the most effective method for predicting the displacement of ground-floor structures subjected to various seismic excitations, modeled using the Newmark-Beta method. The introduction first presents the Random Forest algorithm, which uses bagging (bootstrap aggregation) combined with variance-based splitting. Then, we introduce Artificial Neural Networks, detailing their structure and training steps. This is followed by a presentation of the Newmark-Beta method, which is used to compute the seismic response of the structures. In the results section, we analyze the range of variation in input parameters and the corresponding displacement outputs at the ground floor. Next, we apply both the Random Forest and ANN models using the results generated by the Newmark-Beta method. In the discussion, we compare the performance of both models using the Mean Squared Error (MSE). We also examine the sensitivity and non-linearity of each model to assess which method—Random Forest or ANN—provides more accurate predictions. Finally, we compare our results with similar studies in the literature and highlight our contribution as well as future research perspectives*.

Keywords *- Seismic Displacements, Newmark-Beta Method, Random Forest, Artificial Neural Network, Predictive Modeling.*

1. Introduction

1.1. Presentation of Earthquakes

Earthquakes are natural phenomena resulting from a sudden release of energy in the Earth's crust, generating seismic waves perceptible at the surface [1]. Understanding seismic processes and the resulting deformations is essential for assessing seismic risks in vulnerable areas [2]. The complexity of tectonic interactions, combined with local characteristics of the soil and urban structures, makes predicting the impacts of an earthquake particularly challenging [3].

Recent studies, such as that of Portillo & Moya [4], have highlighted that rapid urbanization without consideration of seismic risk can aggravate the consequences of seismic events. Furthermore, the analysis of spatio-temporal distribution patterns of earthquakes not only allows for the identification of risk areas, but also for the improvement of early warning systems and urban planning [5]. These efforts converge towards better management of natural disasters and a reduction of human and economic losses on a global scale.

However, for seismic analysis to be truly effective in disaster prevention and management, it must rely on precise and efficient digital tools capable of faithfully simulating the dynamic responses of structures subjected to seismic stress. This research, entitled Intelligent Prediction of Seismic Displacements Computed Using the Newmark-Beta Method: A Comparison Between Random Forests and Artificial Neural Networks, aims to improve the accuracy of seismic predictions using artificial intelligence.

However, the Newmark-Beta method still has several shortcomings in terms of

- Dependence on numerical parameters (β, γ) and data quality-The stability and accuracy of the Newmark Beta method are very sensitive to the choice of β and γ, as well as to the quality of the input data (acceleration, damping, mass). For example, Takács & Fülöp [6] demonstrate that compensation terms applied to modified matrices (mass, stiffness, damping) can improve accuracy, thus revealing the limitations of the original scheme without such adjustments.

- High computational time for complex structures- Applying Newmark Beta to complex structural systems (high degrees of freedom, nonlinear phenomena) is time-consuming. The study by Takács & Fülöp [6] highlights the increased computational cost and the loss of the sparse structure of matrices with more accurate compensated methods.
- Few studies combine Newmark-Beta and artificial intelligence; the use of Artificial Intelligence to directly predict Newmark-calculated movements is rare. One notable study by Wang et al [7] applies XGBoost to predict these movements, but neural networks and random forests remain largely underexplored.
- There is a lack of comparisons between different AI models for this type of problem. One study proposes an ANN (neural network) model for Newmark movement prediction [9], but it does not directly compare its performance to that of random forests or XGBoost. The lack of detailed comparative analyses between AI models limits our understanding of their specific advantages and disadvantages.

1.2. Novelty of This Research

This analysis highlights a real scientific interest in an in-depth comparative study on the use of Random Forest and neural networks in predicting Newmark-Beta movements: it will fill a methodological gap and potentially improve prediction performance in a practical setting.

1. Sequential Use of Newmark-Beta and Artificial Intelligence - The idea of using the results calculated by Newmark-Beta as a learning database to train AI models is an innovative hybrid approach. This allows:

- To preserve the rigor of the physical model,
- While accelerating future predictions by eliminating the need for cumbersome simulations.

2. Direct Comparison between RF and ANN- An explicit comparison between two AI algorithms—Random Forest and Artificial Neural Networks—applied to Newmark movement prediction represents a gap in the current literature. This comparison will allow:

- To identify the most suitable algorithm in different contexts (quantity of data, noise, complexity),
- To assess the robustness, accuracy, and generalizability of the models.

3. Contribution over existing approaches

- The majority of existing work is limited to a single algorithm (often XGBoost or ANN) without comparative evaluation.
- This approach proposes a complete and scalable architecture, combining deterministic methods (Newmark-Beta) and machine learning, with comparative and quantitative analysis.
- It can result in a fast, economically and time-efficient prediction tool for engineers.

In this context, we propose to explore the effectiveness of two artificial intelligence approaches: Artificial Neural Networks (ANN) and random forests. These algorithms will be applied to estimate the structural displacement induced by seismic excitations, based on the results provided by the Newmark-β numerical method, commonly used for the time integration of the equations of motion in the dynamic analysis of structures.

The objective of this study is to compare the predictive capacity of these two machine learning models, with a view to identifying the one offering the best accuracy and robustness in the context of seismic engineering.

1.3. Organization of the Paper

This paper is organized as shown in the Figure 1.

2. Methods

2.1. Random Forest

Random Forest is a machine learning algorithm based on an ensemble of decision trees, which improves the accuracy of predictions by combining the results of multiple trees built on random subsamples of the data [9]. Zeini et al. [10] applied the Random Forest algorithm for the strength prediction of geopolymer-stabilized clayey soil. Singh et al. [11] utilized Random Forest in combination with the M5P model tree approach to estimate the compressive strength of high-strength concrete.

Kumar et al. [12], conducted a comparative study between Random Forest, CART, and MLR-based predictive models for the unconfined compressive strength of cement-reinforced clayey soil. Aminpour et al. [13] applied Random Forest in a comparative study with other machine learning methods for slope stability prediction on spatially variable random fields. Geng et al. [14] used a Kriging–Random Forest hybrid model for real-time ground property prediction during earth pressure balance shield tunneling. Kaveh et al. [15], conducted an experimental study and developed a machine learning model using a Random Forest classifier for predicting the shear strength of RC beams with externally bonded GFRP composites.

Yang et al. [16] developed hybrid Random Forest-based models to predict ground settlement induced by earth pressure balance tunneling. Li et al. [17], conducted research on the application of the Random Forest algorithm for estimating the dynamic mechanical behavior of reinforced concrete column members. Dabous et al. [18] used a case-based reasoning and Random Forest framework to select preventive maintenance strategies for flexible pavement sections.

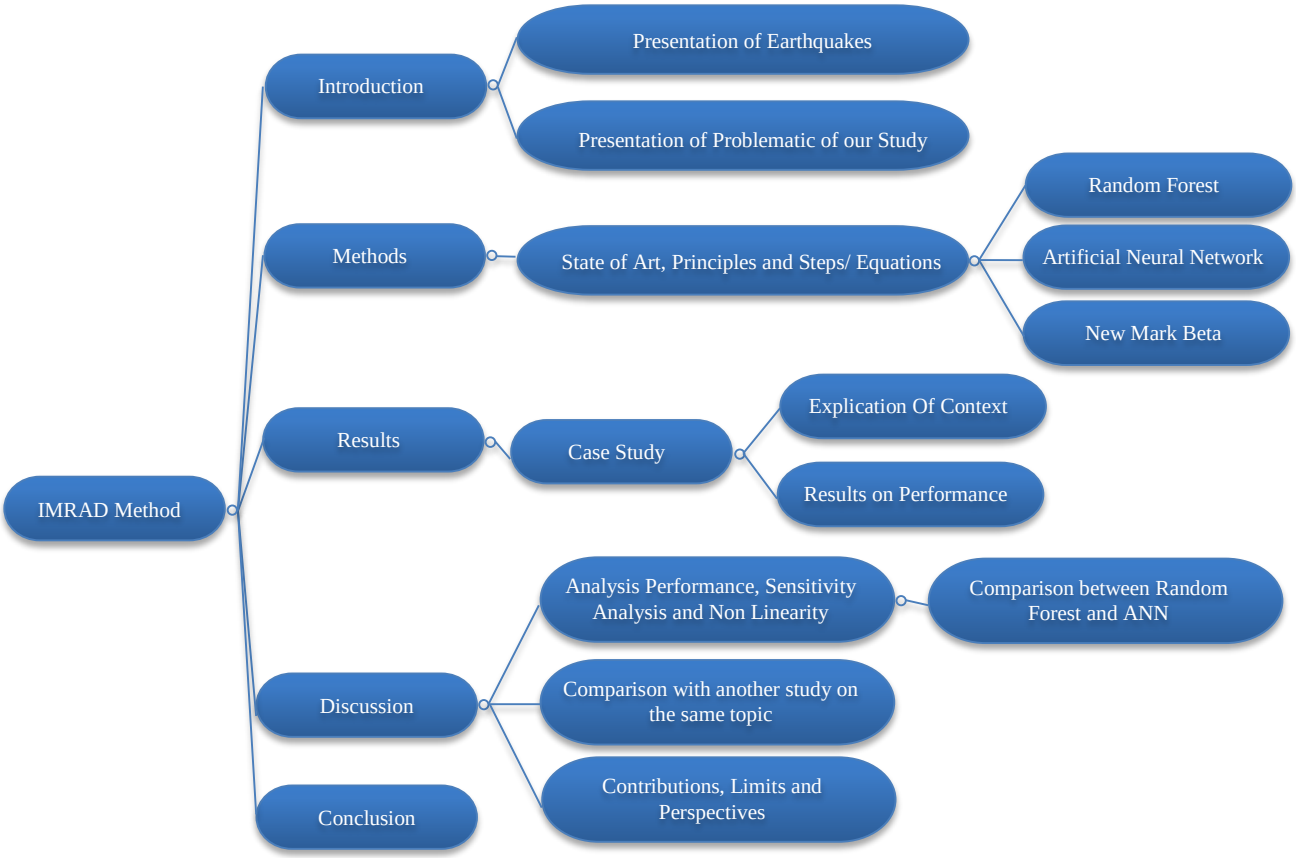

Fig. 1 Methodolgy conducted in our research

Over the past five years, the Random Forest (RF) algorithm has been widely used in earthquake engineering for various applications ranging from event detection to structural damage prediction. Ao et al [19] used an improved random forest algorithm to identify channel sand-body from multiple seismic attributes. The Random Forest algorithm was applied to automatically classify seismic signals into landslides, earthquakes or background noise, based on their temporal and frequency characteristics extracted from 642 recordings Lin et al [20]. The study conducted by Shi et al [21], using the Random Forest algorithm, demonstrates that a model based on distances and azimuths between the epicenter and the sites predicts co-seismic landslides more effectively than traditional PGA-based models, while being more accessible, faster to implement, and better suited to near-real-time and high spatial resolution applications. In their study, Kim et al [22] applied five machine learning-based prediction methods, highlighting the Random-Forest algorithm for tsunami prediction from seismic data. The results obtained indicate that Random Forest performs satisfactorily, compared to the XGBoost algorithm."

According to Breiman [6], we present the steps of the algorithm that we will use

Step 1. Bootstrap Sampling (Bagging)

From a training dataset, $D = \{(x_i, y_i)\}_{i=1}^{N}$ generate B bootstrap samples:

$$D^{(b)} = \{(x_i^{(b)}, y_i^{(b)})\}_{i=1}^{N}, \quad \text{for } b = 1,2,\dots,B \tag{1}$$

Each $D^{(b)}$ is sampled with replacement from D.

Step 2. Grow a Decision Tree on Each Bootstrap Sample

At each node of the tree, choose a feature X_j and a threshold that minimizes the weighted variance of the target variable after the split.

Variance Reduction Criterion:

$$\text{Var}_{\text{split}} = \frac{n_L}{n} \cdot \text{Var}(Y_L) + \frac{n_R}{n} \cdot \text{Var}(Y_R) \tag{2}$$

Where:

- n_L, n_R are the number of samples in the left and right child nodes,
- Y_L, Y_R are the response values in the left and right nodes,
- Var(Y) is the sample variance:

We choose the split that results in the lowest $\text{Var}_{\text{split}}$

Step 3. Repeat for All Trees
Train B separate regression trees:

$$T_1(x), T_2(x), \dots, T_B(x)$$

Each tree is trained independently on a different bootstrap sample.

Step 4. Aggregate Predictions (Ensemble Averaging)
For a new input x, the final prediction is the average of the predictions of all B trees:

$$\hat{y} = \frac{1}{B}\sum_{b=1}^{B} T_b\,(x) \qquad (3)$$

This aggregation step reduces variance and improves generalization.

Table 1 below shows the advantages and disadvantages of Random Forest.

Table 1. Advantages and disadvantages of random forest

Type	Element	Description	Reference
Advantages	High Accuracy	Multiple decision trees reduce prediction variance, leading to higher overall accuracy.	Biau & Scornet [23],
	Robust to Noise and Outliers	Random Forest minimizes the impact of outliers by averaging over many trees.	Marimuthu & Saroja [24]
	Handles Missing Data	The algorithm is capable of dealing with missing data through bootstrap sampling.	
	Variable Importance Estimation	It calculates the importance of each feature based on impurity reduction or variance.	Berk [25]
	High-Dimensional Data Handling	Effective for large datasets with many variables, even when the number of observations is smaller.	Biau & Scornet [23]
Disadvantages	Complexity and Limited Interpretability	Random Forest is often seen as a "black box", making it difficult to interpret individual tree decisions.	Louppe [26]
	Sensitive to Hyperparameters	Performance can be highly dependent on hyperparameter optimization, such as tree depth or the number of trees.	Zhu [27],
	High Computational Cost	Training many trees requires considerable memory and time, especially with large datasets.	Marimuthu & Saroja [24]
	Not Ideal for Time Series Data	Random Forest does not consider temporal dependencies, which makes it less suitable for time series tasks.	
	Less Effective for Imbalanced Data	Random Forest struggles with imbalanced datasets unless techniques like resampling are applied.	Zhu [27]

2.2. Artificial Neural Network

An Artificial Neural Network (ANN), a subset of machine learning, acts as the core framework for deep learning techniques. It functions in a manner akin to neurons in the human brain, handling data effectively [28]. According to [29] [30], Artificial neural network architecture (ANN i-h1-h2-hn-o).

Bao et al.[31] a deep transfer learning network was applied for structural condition identification with limited real-world training data. Muhammad [32] applied ensemble models and neural networks for an improved prediction of high-performance concrete compressive strength. Sahin et al [33] researched Towards a Hybrid Digital Twin: Physics-Informed Neural Networks as Surrogate Model of a Reinforced Concrete Beam. Nabizadeh et al [34] used artificial neural networks and machine learning models for predicting the lateral cyclic response of post-tensioned base rocking steel bridge piers.

Soleimani and Liu [35] developed a probabilistic seismic demand model for bridge components using Artificial Neural Networks (ANNs), improving prediction over traditional methods. Moseley et al [36] designed a deep neural network inspired by waveNet capable of rapidly simulating the behavior of seismic waves in layered media. Conte et al [37] used a backpropagation neural network to model the seismic response of multistory buildings, demonstrating the network's ability to learn elastic dynamic behaviors. Figure 2 below presents the design of the ANN architecture. The design of an ANN architecture entails specifying the number of input and output units, the number of hidden neurons, and the depth of hidden layers.

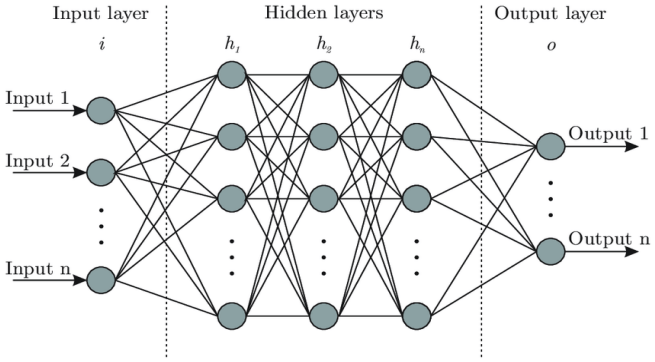

Fig. 2 The design of an ANN architecture [29] [30]

According to Rumelhart et al [38], Goodfellow et al [39] and LeCun et al. [40] we present the steps of the calculation of weight in ANN. In each layer, a neuron performs a weighted sum of its inputs, applies an activation function, and transmits the result to the next layer.

Step 1. Weight Calculation in Each Layer
Weights between the input layer and the first hidden layer

$$X = [x_1, x_2, \ldots, x_n] \quad \text{(inputs)}$$

$$W^{(1)} \quad \text{(weight matrix of the first hidden layer)}$$

$$b^{(1)} \quad \text{(bias)}$$

$$Z^{(1)} = W^{(1)}X + b^{(1)}$$

Activation Function Applied to the First Hidden Layer

$$A^{(1)} = f(Z^{(1)}) \tag{2}$$

Step 2. Weights between hidden layers

If a hidden layer has outputs $A^{(L)}$ and is connected to the next layer with weights $W^{(l+1)}$, then the weighted sum for the next layer is:
Weighted Sum in a Hidden Layer

$$Z^{(l+1)} = W^{(l+1)}A^{(l)} + b^{(l+1)} \tag{3}$$

Activation Function Applied to a Hidden Layer

$$A^{(l+1)} = f(Z^{(l+1)}) \tag{4}$$

Step 3. Weighted Sum in the Output Layer

If the last hidden layer has outputs $A^{(L)}$ and the output layer has weights $W^{(out)}$ and bias $b^{(out)}$, then:

$$Z^{(out)} = W^{(out)}A^{(L)} + b^{(out)} \tag{5}$$

Output Activation Function

$$\hat{y} = f_{out}(Z^{(out)})$$

f_{out} is typically Softmax for classification and identity for regression.

Step 4. Weight Update
Weights are adjusted using gradient descent:

$$W^{(l)} \leftarrow W^{(l)} - \eta \frac{\partial L}{\partial W^{(l)}} \tag{6}$$

- η is the learning rate,
- L is the loss function,
- $\eta \frac{\partial L}{\partial W^{(l)}}$ is the cost gradient with respect to the weights.

2.3. New Mark Beta Method

In the context of structural dynamic analysis, the Newmark-Beta method represents a widely used implicit time integration scheme for the numerical resolution of second-order differential equation systems. The New Mar Beta Method was applied in several research studies. Pourzeynali et al [41] applied an explicit Newmark-β-based method for moving load identification on bridges: Numerical and experimental studies. Ji et al [42] use a simplified nonlinear coupled displacement Newmark model with degraded yield acceleration for seismic stability analysis of slopes. Kumarci et al [43] conducted a study and developed a dynamic analysis of cable-stayed towers using the Newmark-β method. Xi et al [44] applied the performance of a Newmark-based sampling strategy for post-earthquake landslide susceptibility mapping using deep learning, SVM, and logistic regression. A dynamic analysis of bridge decks under high-speed train loads using the Newmark method. Abbas et al [45] use modified Newmark integration for seismic response analysis of soil–structure interaction systems. Several recent studies have proposed improvements to the Newmark model to better assess seismic displacements of slopes and earth dams. Li et al [46] developed a modified version of the Newmark block method, specifically adapted to slopes reinforced by prestressed anchors, allowing for a more accurate estimation of displacements under seismic loading. Similarly, Le et al [47] proposed a modified approach to the Newmark model to estimate earthquake-induced displacements in earth dams, introducing a sliding mass redivision to improve the representation of the failure mechanism. Yang et al. [48] combined the Newmark and runout models to build an integrated seismic landslide hazard identification tool, which was applied to a case study on the Eastern Tibetan Plateau. Furthermore, Ji et al [42] presented a simplified, nonlinear Newmark-based displacement model coupled with degrading limit acceleration to improve the analysis of seismic slope stability. These contributions illustrate the ongoing evolution of analytical approaches to better represent the complex mechanisms of slope instabilities in seismic contexts.

We present the steps of New Mark Beta according to [49]

Step 1. In the context of structural dynamic analysis, the Newmark-Beta method represents a widely used implicit time integration scheme for the numerical resolution of second-order differential equation systems. It is particularly applied to the equation of motion of a discretized dynamic system:

$$M\ddot{x}(t) + C\dot{x}(t) + Kx(t) = f(t) \quad (7)$$

In this expression:

- M, C, and K represent the mass, damping, and stiffness matrices.
- f(t) is the vector of external forces applied to the system;
- x(t), x˙(t) and x¨(t) denote the generalized displacement, velocity, and acceleration vectors at time t.

Step 2. The time domain is discretized into regular intervals of duration Δt such that $t_{n+1}=t_n+\Delta t$. The Newmark-Beta scheme is based on quadratic approximation formulas derived from a linear interpolation of the acceleration over each time step.

The approximated expressions for the generalized displacement and velocity at the next time step n+1 are given by the following Newmark-Beta formulas:

$$x_{n+1} = x_n + \Delta t\dot{x}_n + \frac{\Delta t^2}{2}[(1-2\beta)\ddot{x}_n + 2\beta\ddot{x}_{n+1}] \quad (8)$$

Velocity approximation:

$$\dot{x}_{n+1} = \dot{x}_n + \Delta t[(1-\gamma)\ddot{x}_n + \gamma\ddot{x}_{n+1}] \quad (9)$$

The parameters β and γ are numerical integration constants that control the scheme's stability and numerical damping characteristics. The commonly used values:

$$\beta = \frac{1}{4}, \quad \gamma = \frac{1}{2}$$

Step 3. Matrix Equation to Solve

By substituting the approximated expressions of displacement and velocity into the equation of motion, we obtain an algebraic system to solve for the generalized displacement vector at time step n+1:

Global equation

$$K_{\text{mod}}x_{n+1} = f_{\text{mod}} \quad (10)$$

Modified Stiffness Matrix:

$$K_{\text{mod}} = K + \frac{\gamma}{\beta\Delta t}C + \frac{1}{\beta\Delta t^2}M \quad (11)$$

Effective Load Vector:

$$f_{\text{mod}} = f_{n+1} + M\left(\frac{1}{\beta\Delta t^2}x_n + \frac{1}{\beta\Delta t}\dot{x}_n + \left(\frac{1}{2\beta}-1\right)\ddot{x}_n\right) + C\left(\frac{\gamma}{\beta\Delta t}x_n + \left(\frac{\gamma}{\beta}-1\right)\dot{x}_n + \Delta t\left(\frac{\gamma}{2\beta}-1\right)\ddot{x}_n\right) \quad (12)$$

In this formulation:

- Kmod is the effective (or modified) stiffness matrix.
- Fmod is the effective load vector, which includes contributions from previous displacement, velocity, and acceleration states.
- β and γ are the Newmark integration parameters;
- Δt is the time step.

This algebraic system is solved iteratively at each time step to determine the updated displacement x_{n+1} , which is then used to update velocity and acceleration.

Step 4. Update of Kinematic Variables

Once the displacement x_{n+1} is determined, the acceleration and velocity at the new time step can be updated using the following relations: Velocity -

$$\ddot{x}_{n+1} = \frac{1}{\beta\Delta t^2}(x_{n+1} - x_n - \Delta t\dot{x}_n) - \frac{1-2\beta}{2\beta}\ddot{x}_n \quad (13)$$

Acceleration

$$\dot{x}_{n+1} = \dot{x}_n + \Delta t[(1-\gamma)\ddot{x}_n + \gamma\ddot{x}_{n+1}] \quad (14)$$

3. Resluts

3.1. Context of Study

Since the building has only one level (ground floor), modeling it as a Single Degree of Freedom (SDOF) system is more straightforward.

A concentrated mass is considered at the center of gravity of the structure, with a dynamic behavior characterized by its mass, stiffness, and damping.

This study models the dynamic response of a Single-Degree-Of-Freedom (SDOF) system subjected to random seismic excitations. Ten seismic waves, generated with random frequencies and amplitudes, are applied to structures whose parameters (mass, stiffness, and damping) vary within defined margins.

The nodal displacement is first determined, followed by a time integration using the Newmark-Beta method (β = 1/4, γ = 1/2), allowing for the total combined displacement of the system.

$$M\ddot{u}(t) + C\dot{u}(t) + Ku(t) = -M\ddot{u}_g(t) \quad (15)$$

Table 2. Margin of variation of inputs and outputs of our study

	Category	Description	Variation Range (Moroccan Context)
Inputs	Equivalent Mass M	M=W/g, where W is the total weight of the building and g=9.81g m/s²	10^4 to 10^5 kg (depending on material and dimensions)
	Equivalent Stiffness K	K=Mω$_1^2$, with ω1=2πf1 and f1≈3−5f	10^7 to 10^9 N/m (depends on structure and materials)
	Damping Coefficient C	C=2ξMω1, with ξ≈0.05 for reinforced concrete	10^4 to 10^6 Ns/m (depends on damping ratio and mass)
	Seismic Excitation	10 seismic wave records $\ddot{u}_g(t)$ (ground acceleration)	0.1g to 0.6g (depends on seismic zone)
Output	Building displacement u(t)		

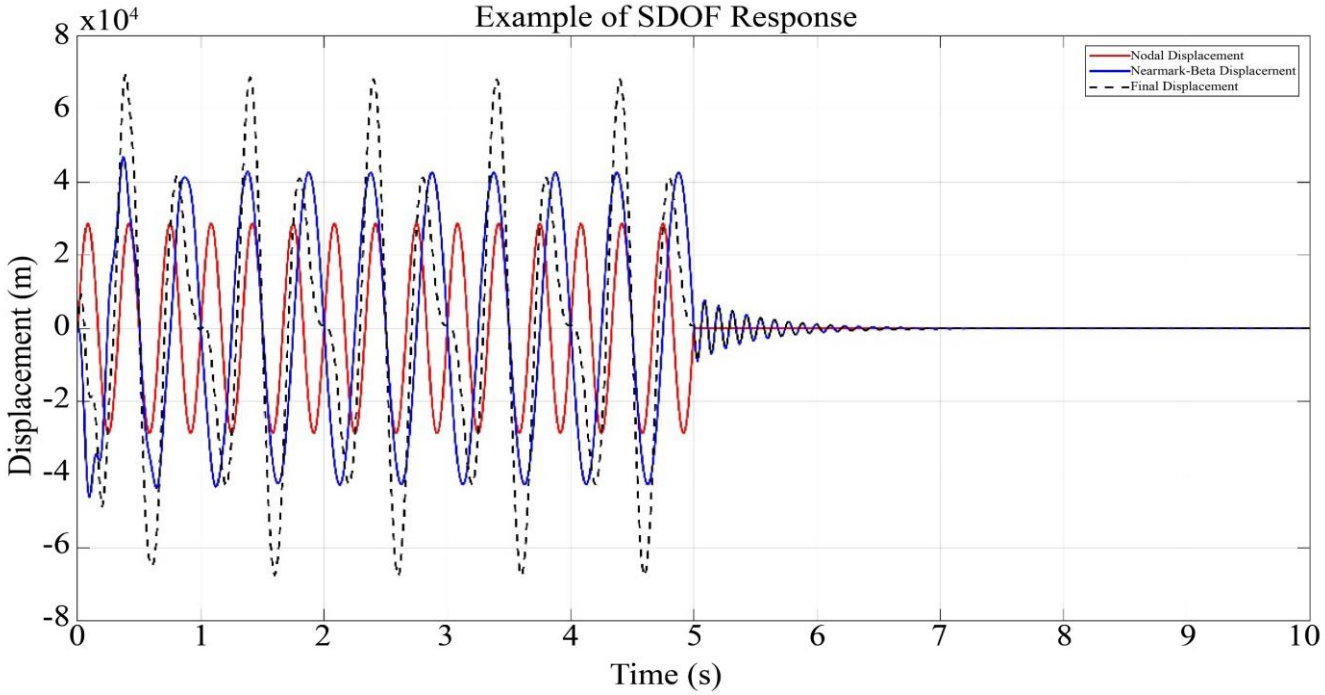

Fig. 3 Nodal, NewMArk Beta and Final displacement

3.2. Modeling and Simulation Procedure

3.2.1. System Modeling

The system under study is a Single Degree of Freedom (SDOF) oscillator, consisting of a mass M, a spring with stiffness K, and a viscous damper with damping coefficient C. The system is assumed to be isolated, meaning it is subjected solely to an external seismic excitation (ground acceleration), with no interaction with other structures.

3.2.2. Time Definition

The simulation is performed over a 10-second interval with a constant time step Δt=0.01 s.

The time vector is defined as t=0 : Δt: 10

3.2.3. Generation of Seismic Excitation

Ten synthetic seismic signals are generated, each in the form of a sinusoidal wave:

- Random frequency between 2 Hz and 6 Hz
- Random amplitude between 0 and 0.5 g
- Each wave is truncated at 5 seconds to simulate a transient excitation

These signals are stored in a matrix called waves, and their peak amplitudes are stored in waves_amplitudes.

3.2.4. Simulation Loop (100 Random Cases)

For each simulated case: Definition of dynamic Properties

- $M \in [10^4, 5 \times 10^4]$ kg

- $K \in [10^7, 10^9]$ N/m
- $\xi \in [0.02, 0.07]$
- $C = 2\xi\sqrt{KM}$

3.2.5. Selection of a Seismic Signal

One of the 10 generated seismic signals is randomly selected to serve as the input ground acceleration $\ddot{u}_g(t)$. Calculation of Nodal Displacement (Approximate) The nodal displacement (pseudo-static ground displacement) is calculated as:

$$u_{\text{nodal}}(t) = \frac{\ddot{u}_g(t)}{\omega_n^2} \quad \text{where} \quad \omega_n = \sqrt{\frac{K}{M}} \tag{18}$$

3.2.6. Calculation of the Relative Dynamic Response (Newmark-Beta Method)

Implicit Newmark-Beta integration

- $\beta = \frac{1}{4}$,
- $\gamma = \frac{1}{2}$
- $u(t) = M\ddot{u}(t) + C\dot{u}(t) + Ku(t) = -M\ddot{u}_g(t)$
- $u(t), \quad \dot{u}(t), \quad \ddot{u}(t)$ are calculated recursively.

3.2.7. Reconstruction of Absolute Displacement

The absolute displacement of the mass is obtained by superposition:

$$u_{\text{abs}}(t) = u_{\text{nodal}}(t) + u(t) \tag{19}$$

This represents the position of the mass with respect to a fixed reference frame.

3.2.8. Extraction of Key Results

For each simulation, the parameters M, K, C, and the maximum wave amplitude are stored. The following maximum displacements are recorded:

- max|u(t)|:relative displacement
- max|u_{nodal}(t)|: nodal displacement
- store max|u_{abs}(t)|.

3.2.9. Display and Visualization

A results table is displayed at the end of the simulation.

A graph illustrates, for the first simulation:

- The nodal displacement.
- The relative displacement obtained by Newmark.
- Their sum represents the absolute displacement of the mass.

3.3. Parameters of Random Forest and Neural Network

The Artificial neural network is used to model a relationship between 4 input variables and 1 output variable. The data is first normalized and then divided into training (70%) and test (30%) sets. The neural network is a feedforward network with Two Hidden Layers, each with 10 Neurons. The Training Function Used Is TrainLM (Levenberg-Marquardt), which is followed for regression problems. The data is transposed to fit the expected format by the MATLAB neural network. After training, the predictions are compared to linear and quadratic regression models using the Mean Squared Error (MSE) and the mean absolute deviation.

Random Forest regression is used to predict an output variable from 4 input variables. The model is structured in two successive levels: the first level predicts directly from the input data, and the second level learns to correct the predictions of the first. Each model uses 50 trees (decision trees), with bagging (bootstrap aggregating) to improve robustness and limit overfitting. The trees are built with the Mean Squared Error (MSE) minimization criterion as the splitting criterion. Using two successive levels is a simple form of stacking, which can improve the accuracy of the model.

Figure 4 below shows the structure of the Random forest that we use in our study.

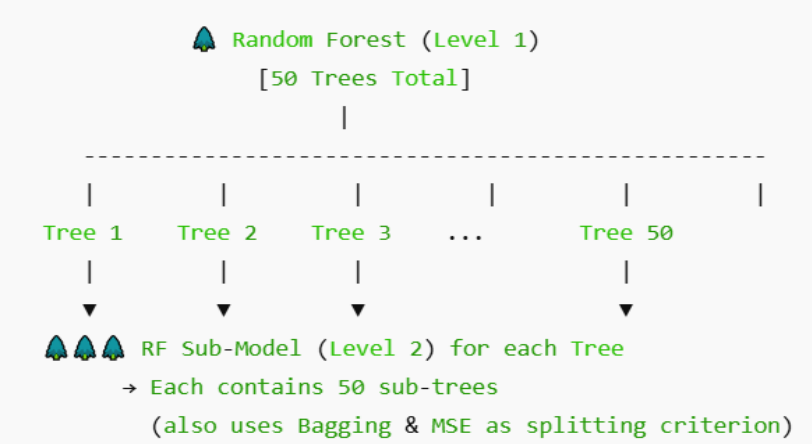

Fig. 4 Structure of random forest

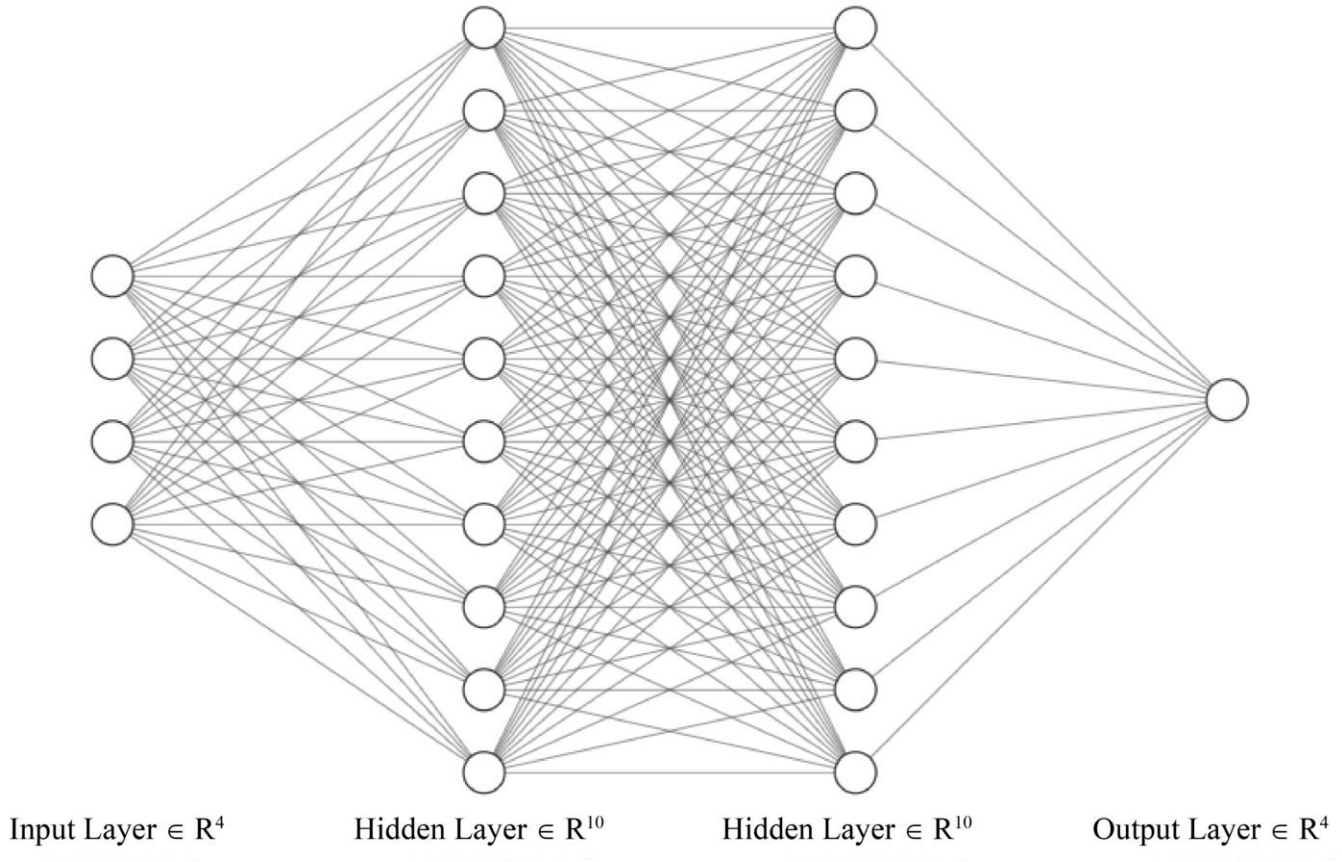

Fig. 5 Architecture of artificial neural network used in our study

3.4. Performance

After the application of both approaches, Table 3 below presents the results of performance. The random forest shows superior performance with near-zero error across all sets (training, testing, cross-validation), indicating strong generalization capability. In comparison, the neural network shows higher and unstable error, suggesting a less optimized model or one that is ill-suited to the data. Thus, the random forest is clearly the most reliable model in this context.

Table 3. Performance of results

	MSE training	MSE Test	Cross-Validation for 5 folds
Neural Network	0.49372	0.086594	0.30881
Random Forest	1.1779e-07	9.9081e-08	2.184e-07

4. Discussions

4.1. Sensitivity Analysis

Table 4 shows how the models' outputs react to a percentage change in the inputs. In other words, it measures the models' sensitivity or robustness to perturbations in the input data.

Table 4. Sensitivity analysis of random forest and artificial neural network

Percentage rate of change in inputs	Percentage rate of change in outputs for Artificial Neural Network	Percentage rate of change in outputs for Random-Forest
1 %	1.4455%	1.9793%
3 %	9.7857%	12.0062%
5 %	6.3957%	9.7382%
7 %	37.883%	3.5540%
9 %	36.141%	15.8805%

Up to 5% input variation: Both models react moderately, with output changes in relatively similar proportions (slightly more for the Random Forest).

From 7%: The artificial Neural Network (NN) becomes unstable, with very high output variations (up to 38% for only 7% input variation). The Random Forest (RF) remains much more stable, demonstrating greater robustness to perturbations.

The Random Forest model is more robust and stable in the face of variations in input data. The neural network, on the other hand, shows excessive sensitivity above a certain threshold, which can be problematic in real-life settings, especially if the data is noisy or subject to measurement errors.

4.2. Non-Linearity Capture

Table 5 compares the gap between the predictions of machine learning models (ANN and Random Forest) and two simpler reference models: linear regression and quadratic regression.

Table 5. Comparison between RF and ANN

Methods	ANN	Random-Forest
Linear Regression	0.36826	0.00027884
Quadratic Regression	0.38907	0.00037499

The Neural Network (ANN) exhibits a significant deviation from simple regression models, indicating that it produces very different, likely nonlinear and more complex, predictions. In contrast, the Random Forest generates predictions very similar to those of the regression models, with deviations close to zero, indicating that it follows a similar structure to these basic models.

Random Forest is consistent with linear or quadratic trends in the data, while maintaining high performance. Artificial Neural networks, on the other hand, deviate significantly from this, which may indicate a more flexible but potentially less interpretable model.

4.3. Comparison with Other Studies

Table 6 below shows the comparative study between our piece of work and other studies.

Table 6. Comparatives with other studies

Study	Application Domain	Context	Findings	Scientific Contribution / Added Value	Future Work / Perspectives
Our Study	Prediction of Seismic Displacements Computed Using the Newmark-Beta Method in Morocco country	Comparative analysis of ANN and Random Forest using multiple evaluation metrics	Random Forest consistently outperformed ANN in MSE, robustness, and alignment with traditional regression trends.	Highlights the robustness and generalization ability of Random Forest over ANN in noisy or nonlinear contexts	Application to more complex or real-world datasets; exploration of ensemble and hybrid models
Wani & Suthar [50]	Sustainable concrete / Recycled materials in civil engineering	Estimating the compressive strength of concrete using waste foundry sand with AI models (ANN, RF, etc.)	Random Forest model showed the best performance (R = 0.94, RMSE = 2.79)	Demonstrates the effectiveness of AI methods in evaluating the mechanical properties of recycled concrete	Integration into optimized and sustainable concrete mix design tools
Arokiaprakash & Selvan [51]	Concrete-Filled Steel Tube (CFST) structures	Predicting the axial compressive capacity of CFSTs using ANN and RF models	RF model outperformed MLP-ANN in predictive accuracy	Provides a robust approach for structural design without costly physical testing	Extend the study to other composite (steel-concrete) structural elements
Vyshnavi et al. [52]	Earthquake engineering / Non-structural components	Assessing the effects of soft stories on Non-Structural Components (NSCs) during seismic events	RF gave better predictive results than ANN for Dynamic Amplification Factors (DAFs)	First AI-based prediction of the dynamic behavior of NSCs	Application to seismic design and regulatory frameworks for safer buildings

4.4. Contribution

This study makes several notable scientific contributions. First, it demonstrates increased accuracy in predicting maximum displacements using artificial intelligence models (Random Forest and ANN), surpassing conventional deterministic methods used alone.

It then proposes an innovative hybrid model, combining the Newmark Beta scheme (a physical approach) with data-driven AI techniques, taking advantage of both paradigms.

Furthermore, the study is adapted to local Moroccan realities by using accelerograms from real earthquakes in the region. This allows for more accurate modeling of the dynamic behavior of structures in a seismic context specific to Morocco. This approach also offers significant savings in time and resources, reducing the need for intensive numerical simulations or experimental tests.

Furthermore, this research contributes to the creation of valuable local databases for training machine learning models. Finally, it opens up concrete prospects for improving earthquake-resistant standards by integrating more reliable predictive approaches into building design and rehabilitation processes.

4.5. Perspectives

Research Directions for a Multi-Degree-of-Freedom (MDOF) System:

- ✓ More Realistic Structural Modeling: Extend analysis to MDOF systems to capture realistic mass, stiffness, and damping distributions. Include mode shapes, mode coupling, and torsional effects.
- ✓ Dynamic Soil-Structure Interaction: Investigate how soil dynamics and seismic wave propagation affect the MDOF system, possibly using complex base models or non-rigid boundary conditions.
- ✓ Modal Analysis and Superposition: Apply modal decomposition to simplify numerical analysis and evaluate how each mode contributes to the overall structural response.
- ✓ Uncertainty and Probabilistic Analysis: Account for uncertainties in physical parameters and seismic inputs using stochastic methods or Monte Carlo simulations for more robust results.
- ✓ Non-linearities and Large Displacement Behavior: Incorporate nonlinear effects such as material plasticity, friction, and large deformations, which are critical in seismic dynamic analysis.

Artificial Intelligence and Hybrid Modeling for Seismic Assessment

- ✓ Develop a hybrid model combining RF/ANN with the Newmark Beta equations for rapid prediction of maximum displacements.
- ✓ Create a Moroccan seismic database integrating soil characteristics, historical accelerograms, and local structure types.
- ✓ Study the sensitivity of inputs (soil type, earthquake intensity, damping, etc.) on model accuracy.
- ✓ Compare the effectiveness of different AI models (SVM, XGBoost, LSTM, etc.) in addition to RF and ANN for the same purpose.
- ✓ Apply this approach to regional modeling of probable damage following a seismic scenario to aid in risk management.
- ✓ Integrate the results into a software tool or web platform for decision support in earthquake engineering.
- ✓ Extend the application to existing structures for rapid large-scale vulnerability assessments (e.g., in historic cities).

5. Conclusion

In conclusion, this study demonstrated the potential of both Random Forest (RF) and Artificial Neural Networks (ANN) in predicting the displacement of ground-floor structures subjected to seismic excitations, based on simulations from the Newmark-Beta method in Morocco. While both models provided valuable insights, the comparison based on Mean Squared Error (MSE) revealed distinct strengths: RF showed robustness in handling input variability, whereas ANN captured complex non-linear patterns with high predictive accuracy.

The sensitivity and non-linearity analyses further supported the suitability of each model depending on the characteristics of the seismic data and prediction goals. These findings highlight the importance of selecting the appropriate machine learning model based on the nature of the structural behavior and available data.

As a future perspective, the integration of hybrid models or the use of advanced deep learning architectures could enhance prediction accuracy and generalizability. Additionally, expanding the dataset to include multistory structures and real earthquake records would strengthen the reliability and applicability of these predictive approaches in real-world civil engineering scenarios.

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