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A Machine Learning Framework for Predicting Maximum Displacement of Reinforced Masonry Shear Walls under Lateral Loading

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ABSTRACT: Accurate estimation of the maximum displacement capacity of masonry shear walls under lateral loading is essential for performance-based seismic design, yet conventional analytical and numerical approaches remain computationally intensive, sensitive to modeling assumptions, and highly dependent on expert interpretation. These limitations restrict their applicability for rapid assessment and design optimization. To address this challenge, this study proposes a machine learning (ML) framework that integrates predictive accuracy, interpretability, and mechanical validation. A database of 93 fully grouted masonry walls tested under cyclic displacement-controlled loading is utilized to develop a systematically optimized Multi-Layer Perceptron Artificial Neural Network (MLP-ANN). The model incorporates geometric, reinforcement, material, and axial-load parameters under the assumption of rectangular, fully grouted walls with consistent boundary conditions. Extensive architectural trials yielded an optimized ANN achieving R^2 values of 0.98, 0.97, and 0.90 for training, validation, and testing datasets, respectively. Complementary Random Forest (RF) analysis identified wall length, height, reinforcement ratios, masonry strength, and axial-load ratio as the most influential predictors governing displacement response. To verify the mechanical plausibility of the ML predictions, a finite element model (FEM) of a representative specimen was developed, reproducing experimental backbone curves within 5–10% deviation. The combined ANN–RF–FEM framework offers a fast, interpretable, and reliable tool for evaluating seismic displacement capacity of masonry walls. Future research should expand the dataset to include diverse wall geometries, boundary conditions, and materials, and explore hybrid ML–FEM or physics-informed models to further improve generalization and design applicability.

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1- Introduction

Masonry shear walls are structural components that resist lateral forces arising from earthquakes, wind, and other external loads. Typically constructed with masonry units such as concrete blocks, clay bricks, or stone, they are designed to provide stiffness, strength, and stability to buildings [1, 2]. The main role of these walls is to transfer lateral loads perpendicular to their plane to the foundation, thereby preventing collapse or severe structural damage [3]. Masonry shear walls are widely used in residential, commercial, and industrial structures [4]. For instance, in residential buildings, they are often placed at the perimeter to resist wind loads, while in seismic regions, they are strategically located inside the structure to mitigate earthquake effects [5, 6]. In industrial buildings, they ensure lateral stability against loads from heavy machinery and equipment [7, 8].

Displacement of shear walls under lateral forces is a critical factor in structural performance. When subjected to such loads, shear walls undergo in-plane displacements that directly affect their stability and serviceability [9, 10]. The extent of displacement depends on multiple factors, including wall height and thickness, foundation stiffness, and the magnitude and duration of external forces. Traditionally, displacement has been estimated through analytical or numerical models [9, 11, and 12]. Accurate prediction of maximum displacement is especially vital in seismic-prone areas [13].

Extensive research has been conducted on the behavior of masonry walls under monotonic and cyclic in-plane loading. Internationally, numerous experimental and numerical studies have investigated unreinforced and reinforced masonry shear walls, their stiffness degradation, strength, and displacement capacity, as well as the influence of axial load and reinforcement detailing. Complementary to these, several works have focused on the seismic performance of masonry and masonry-like wall systems. Recent studies have extensively examined the mechanical and seismic behavior of masonry walls using both experimental and numerical methods [37]. Experimental investigations have evaluated shear behavior, failure mechanisms, and nonlinear response characteristics, underscoring the influence of cracking patterns and ductility on seismic performance

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[38]. Research on masonry walls reinforced with traditional wooden elements has further shown that timber inserts can enhance lateral strength and energy dissipation capacity [39]. On the numerical side, advanced modeling approaches—such as fixed-crack smeared-crack formulations and linear homogenization techniques—have been developed to capture the orthotropic behavior of masonry and improve global structural analyses [40, 41]. Additional work has also focused on strengthening strategies, including the use of FRP strips to improve the blast resistance of masonry walls [42]. These works underline the diversity of masonry wall configurations, loading conditions, and retrofitting schemes, and they highlight the persistent need for efficient predictive tools capable of estimating displacement capacity over a wide range of design and detailing parameters, which motivates the machine-learning framework proposed in the present study.

Numerous studies have explored machine learning techniques for structural prediction [34]. For example, Naderpour *et al*. [14] applied ANN, Group Method of Data Handling Neural Network (GMDH-NN), and Gene Expression Programming (GEP) to predict the shear strength of concrete shear walls, achieving high accuracy. Barkhordari and Tehranizadeh [15] combined ANN with Simulated Annealing (SA) to forecast the response of reinforced concrete shear walls using a dataset of 150 specimens, with highly effective results. Siam *et al*. [8] employed an unsupervised learning algorithm to categorize 97 reinforced masonry shear walls, then tested supervised models for classifying walls and predicting lateral displacement.

Although effective, traditional prediction methods remain time-intensive and expertise-dependent. By contrast, Artificial Neural Networks (ANN) can capture nonlinear input–output relationships and adjust predictions based on new data, making them particularly suitable for displacement modeling [16-19]. ANNs consist of interconnected nodes functioning like neurons in the human brain, processing geometric, material, and loading data to generate predictions [20, 21]. With an adequate database—such as the 93 experimentally tested walls used in this study [22]—ANNs can generalize displacement behavior under various loading conditions.

Recent findings [23] emphasize that the nonlinear displacement response of masonry walls is significantly influenced by boundary conditions, axial load ratio, and material anisotropy. Incorporating these parameters into ANN models enhances predictive performance, especially when datasets cover diverse failure modes and load scenarios. Such hybrid input features enable machine learning models to provide more reliable displacement thresholds compared to traditional approaches.

Despite the promising outcomes of previous studies, several research gaps remain unaddressed. Earlier works have concentrated on predicting shear strength or classifying failure modes, while the specific task of estimating the maximum displacement capacity of masonry shear walls has received limited attention. Furthermore, existing datasets were often small in size or mainly restricted to reinforced concrete specimens, which reduces their applicability to masonry walls under lateral loading. Another limitation is that many studies relied solely on predictive models, such as ANN, without incorporating ensemble approaches that can enhance interpretability [35]. As a result, little attention has been paid to identifying which geometric, material, or loading parameters exert the greatest influence on displacement behavior.

To fill these gaps, the present study develops a machine learning-based framework that combines accurate prediction with improved interpretability. A Multi-Layer Perceptron Artificial Neural Network (MLP-ANN) is employed to capture nonlinear relationships between input variables and maximum displacement, while its performance is systematically evaluated across training, validation, and testing datasets. Complementary analysis using the Random Forest (RF) algorithm quantifies the relative importance of key parameters, highlighting the role of wall geometry, reinforcement ratios, material strength, and axial load ratio. By integrating ANN and RF, this study not only achieves reliable displacement prediction but also provides valuable engineering insights, thereby offering a practical tool for seismic performance assessment and the resilient design of masonry structures.

2- Methodology

This section describes the dataset employed in the study, the preprocessing procedures, and the development of the prediction models. It also outlines the performance metrics adopted to evaluate predictive accuracy. The overall workflow of the proposed framework is shown in Fig. 1.

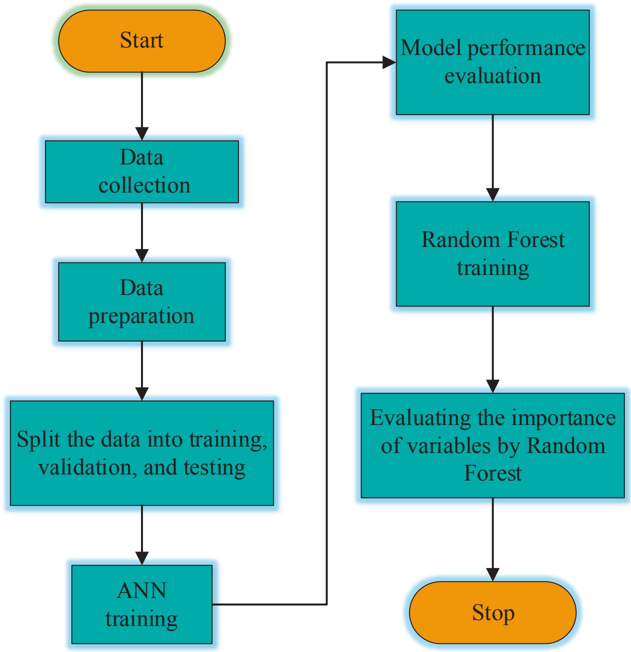

Fig. 1. Flowchart of the proposed methodology, including Artificial Neural Network (ANN) and Random Forest (RF) algorithm.

Table 1. Factors considered as variables affecting the formation of wall displacement.

Variable ID	Variable type	Unit	Description
$\Delta_{80\%}$	Out-Put (Target)	mm	Ultimate displacement capacity
Δ_y	Input	mm	Yield lateral displacement
H_w	Input	mm	Wall height
L_w	Input	mm	Wall length
d_b	Input	mm	Bar diameter of vertical reinforcement
d_{sh}	Input	mm	Diameter of shear (horizontal) reinforcement
t_w	Input	mm	Wall thickness
f'_m	Input	MPa	Masonry compressive strength
f_y	Input	MPa	Yield strength for reinforcement steel bars
ρ_{sh}	Input	%	Horizontal reinforcement ratio
ρ_v	Input	%	Vertical reinforcement ratio
P	Input	N	Axial compressive load

The experimental dataset was randomly partitioned into training (70%), validation (15%), and testing (15%) subsets to provide a sufficiently large sample for model learning while maintaining independent sets for performance monitoring and generalization assessment; this random split was repeated several times to minimize potential ordering bias. Input parameters were selected based on structural significance, consistency of available experimental measurements, and established evidence from previous masonry wall studies. Geometric characteristics, mechanical properties, and loading-related variables were initially considered, after which a preliminary correlation analysis and engineering judgment were used to remove redundant or weakly informative features before model training.

2- 1- Dataset and Variables

The dataset used in this study was obtained from the experimental program of Siam *et al*. [8], which investigated the in-plane behavior of reinforced masonry shear walls. A total of 93 fully grouted walls with rectangular cross-sections, constructed using concrete block units, were tested under displacement-controlled quasi-static cyclic loading with a cantilever-type curvature demand. The database provides detailed information on geometric dimensions (length, height, thickness, and aspect ratio), reinforcement details (vertical and horizontal reinforcement ratios, bar diameters, and yield strength of steel), material properties (masonry compressive strength), applied axial load levels, and the corresponding displacements. These parameters form the basis for developing the machine learning models in this study. Statistical techniques were applied to the dataset to ensure the accuracy and reliability of the collected measurements. Table 1 summarizes all the variables considered in the modeling process.

2- 2- Data Description

The statistical characteristics of the variables considered in this study were analyzed to ensure a clear understanding of the dataset. A summary of these characteristics is provided in Table 1, while Table 2 presents a more detailed breakdown. Along with measures of central tendency and dispersion (mean, variance, and standard deviation), the tables report minimum and maximum values to define the observed ranges. Skewness and kurtosis are also included to describe the asymmetry and overall shape of the data distribution relative to a normal curve. Collectively, these descriptors offer a comprehensive view of the dataset's variability and distributional properties, reinforcing the reliability of the subsequent machine learning analyses.

2- 3- Data Preparation

Rescaling variables is a fundamental step in data preprocessing when working with multiple features that vary in magnitude. In the dataset analyzed for this study, for example, the wall height parameter H_w ranges from 700 to 3660, whereas the horizontal reinforcement ratio ρ_{sh} lies within a much smaller range of 0.0001 to 0.0063. Such differences in scale can distort the learning process of machine learning algorithms, particularly those that rely on Euclidean distance as their objective function, because smaller-valued variables may be underestimated in their relative importance compared to larger-valued ones.

To address this imbalance, the variables in this study were rescaled as part of the data preparation process. Specifically, a normalization technique was applied to transform all input variables into a unified range between 0 and 1, as defined by Eq. (1). This ensures that each variable contributes proportionally during the model training phase, improving the stability and accuracy of the predictive analysis.

Table 2. Summary of descriptive statistics for quantitative variables that impact wall displacement.

Variable	Mean	Variance	Standard deviation	Minimum	Maximum	Skewness	Kurtosis
L_w	1631.677	227995.75	477.489	810	3000	0.219	-0.309
H_w	2116.215	664605.06	815.233	700	3660	0.461	-0.121
H_w/L_w	1.442	0.786	0.887	0.580	4.520	1.923	4.181
ρ_v	0.005	0	0.002	0.002	0.013	0.943	1.445
d_b	17.595	17.352	4.166	12.700	29.9	0.224	-0.742
ρ_{sh}	0.002	0.000	0.001	0	0.006	0.799	1.127
d_{sh}	11.886	6.026	2.455	6	16	-0.684	0.698
f_y	436.325	2301.102	47.970	318	624	-0.465	3.434
f'_m	19.936	24.009	4.9	13.1	31	0.573	-0.441
$P/(f'_m A)$	0.059	0.003	0.052	0	0.183	0.726	-0.107
$\Delta_{80\%}/H_w$	1.610	0.655	0.809	0.33	4.620	0.926	0.937

$$N_i = \frac{i - i_{min}}{i_{max} - i_{min}} \tag{1}$$

The properties of the desired variable are indicated by N_i, i, i_{min}, and i_{max}, which respectively represent the normalized value, actual value, minimum actual value, and maximum actual value [16].

2- 4- Artificial Neural Network (ANN)

Neural networks, modeled after the complex functions of the human brain, have emerged as groundbreaking instruments in data analysis and machine learning. These advanced architectures are composed of interconnected processing units that mimic the behavior of biological neurons, operating in parallel to manage information [30]. The distinctive feature of artificial neural networks lies in their outstanding capacity to solve complex, nonlinear problems without being restricted by the quantity or type of influencing factors. As a result, they are highly effective in detecting and representing intricate relationships between inputs and outputs, which conventional linear models are unable to capture [30].

The architecture of an ANN typically follows a three-tier structure:

- An entry point through the input layer, where initial data features are introduced
- One or more hidden layers that serve as the network's processing powerhouse, performing sophisticated non-linear computations
- A final output layer that produces the desired results

The fundamental building blocks of these networks are the processing units, or artificial neurons, which are interconnected across these layers. Each neuron's behavior is governed by an activation function, while its operation is fine-tuned through parameters known as weights and biases. These parameters are carefully adjusted using specialized optimization algorithms to ensure optimal performance. The mathematical foundation of a neuron's output in an ANN follows a specific computational formula that integrates all these elements. The general architecture of an ANN, consisting of input, hidden, and output layers, is illustrated in Fig. 2

ANNs are composed of three different layers: the input layer, which contains input variable(s); hidden layers, which contain neurons; and the output layer, which contains output variable(s) [21, 24]. MLP-ANNs are the most common and practical types of ANNs, where each neuron is connected to its neighboring neurons [25, 26]. X_1 to X_n represent the input variables, W_1 to W_n represent the weights for these variables, d is a fixed number, f is a transfer function, and z represents the neuron's output. The process of calculating the values of the weighted sum and y is shown in Eqs. (2) and (3):

$$weighted\ sum = b + \sum_{i=1}^{n} W_i X_i \tag{2}$$

$$y = f(weighted\ sum) \tag{3}$$

The optimization method in the ANN is used to determine the weights, W_i, and constant number, b, in neurons. ANNs generally use three transfer functions: the Hyperbolic tangent

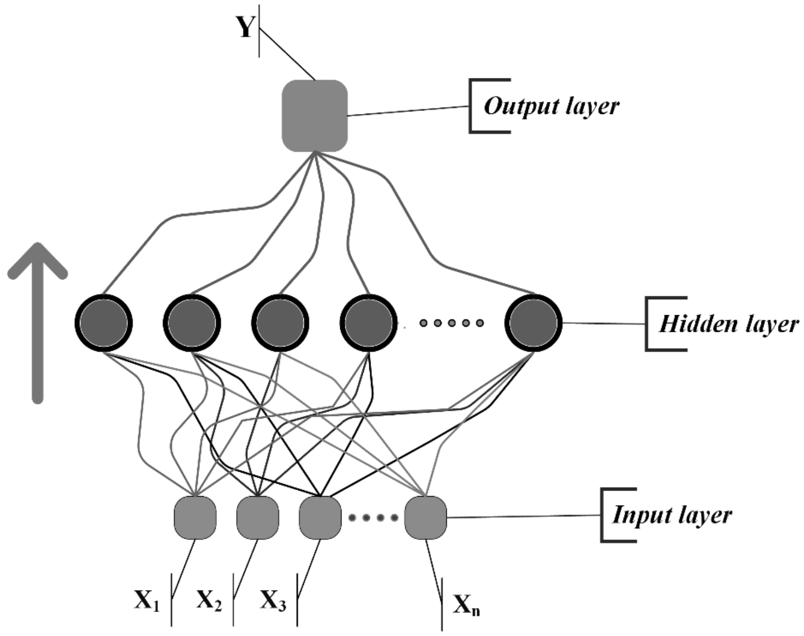

Fig. 2. Structure of an ANN showing input, hidden, and output layers.

Table 3. Analysis of various modes parameters for identifying the most suitable architecture of MLP-ANN.

Parameter	ID	Hidden layers	Setting
Number of hidden layers	NHL	-	1 and 2
Number of runs	NR	-	30
Number of neurons	NN	1 2	1-30 1-30 and 5, 10, 15, 20, 25, 30
Type of transfer function	TF	1 2	TANSIG and LOGSIG Best transfer function in one layer

sigmoidal (TANSIG), the logarithmic sigmoid (LOGSIG), and the pure linear transfer function (PURELIN). These transfer functions are shown in Eqs. (4) to (6) [27].

$$TANSIG(x) = \frac{2}{1 + e^{-2x}} - 1 \tag{4}$$

$$LOGSIG = \frac{1}{1 + e^{-x}} \tag{5}$$

$$PURELIN(x) = x \tag{6}$$

This study aimed to predict the displacement (Δ) as the primary output variable by utilizing ten selected input parameters that reflect the geometric, material, and loading characteristics of masonry shear walls. The dataset was randomly divided into three subsets: 70% for training, 15% for testing, and 15% for validation, ensuring robust model development and unbiased performance evaluation. Determining the optimal architecture of a Multi-Layer Perceptron Artificial Neural Network (MLP-ANN), including the number of hidden layers, the number of neurons per layer, the selection of transfer functions, and the choice of optimization algorithms, lacks a universally accepted formula. Instead, model configuration often relies on an iterative trial-and-error process aimed at minimizing prediction error while avoiding overfitting. In this study, a systematic experimental approach was adopted, where multiple configurations were evaluated based on performance metrics such as the Mean Squared Error (MSE) and the coefficient of determination (R^2). Through this process, the architecture delivering the most accurate and stable predictions was identified, as summarized in Table 3.

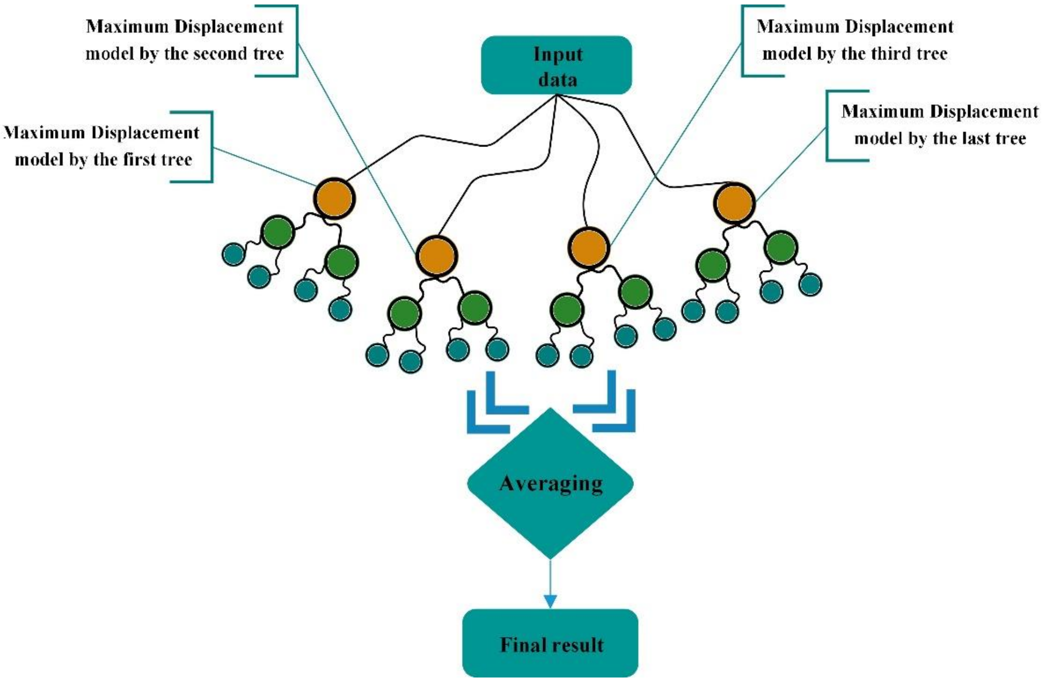

Fig. 3. Algorithmic process for identifying the optimal architecture of the MLP-ANN.

The step-by-step procedure adopted for identifying the optimal architecture of the MLP-ANN is illustrated in Fig. 3. This flowchart summarizes the iterative process of adjusting hidden layers, neurons, transfer functions, and optimization methods to achieve the best predictive performance. Through this process, the architecture delivering the most accurate and stable predictions was identified, as described in the next section.

2- 5- Random Forest algorithm

Random Forest (RF) algorithm is a well-known algorithm designed by Breiman [28] to solve regression and classification problems. This algorithm is composed of multiple decision trees, which are non-parametric supervised learning methods capable of making decisions on the dataset and solving classification and regression problems using the tree structure. The RF algorithm allows for measuring the relative importance of variables associated with target prediction. Breiman [28] proposed a method for determining variable importance [29]. To determine the importance of the H/L variable, for example, the displacement prediction accuracy model is first calculated without *H/L*, and then another prediction model is developed with *H/L*. The *H/L* importance is determined by the difference in accuracy of these two models. Random forest algorithm measures the importance of variables in relative terms between 0 and 1, with the sum of all variable importance equal to 1. The random forest method was used to assess variable importance for displacement prediction.

2- 6- Evaluating machine learning methods

In order to rigorously evaluate the predictive accuracy and error characteristics of the developed models, several widely recognized statistical performance metrics were applied. These included the Mean Squared Error (MSE), Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and the coefficient of determination (R^2). Together, these indices provide a comprehensive understanding of both the magnitude and the dispersion of the prediction errors. Incorporating these measures allowed for an objective benchmarking of alternative model architectures and facilitated the identification of configurations offering the highest reliability in displacement prediction.

The investigation extended to Multi-Layer Perceptron Artificial Neural Networks (MLP-ANNs) with two hidden layers, thereby substantially increasing the number of potential architectural scenarios. To manage this complexity, the optimal transfer function and optimization algorithm—initially determined from extensive trials on a single hidden layer network—were consistently applied to both layers in the two-layer configurations [16, 25]. The experimental design involved scaling the number of neurons in the first hidden layer to five times the baseline value, while systematically varying the number of neurons in the second hidden layer from 1 to 30. This parameter sweep enabled a structured exploration of the combinatorial design space.

Given the inherent stochasticity of MLP-ANN training, each candidate architecture was executed n independent times to capture variability in convergence behavior. In this study, n = 25 runs were conducted for every architectural configuration, with the model exhibiting the lowest aggregate error retained as the optimal solution. This rigorous multi-run evaluation mitigated the influence of random initialization effects and ensured reproducibility of results. The complete methodological sequence adopted for architecture determination is depicted in Fig. 4. By following this procedure, a general displacement prediction model encompassing all relevant input variables was constructed, and achieved both improved accuracy and enhanced generalization capability.

3- Results and Discussion

3- 1- ANN model Performance

The study begins by constructing a comprehensive displacement prediction model that incorporates all available input variables, capturing the geometric, material, and loading characteristics of the masonry shear walls under investigation. The predictive framework is primarily based on the Multi-Layer Perceptron Artificial Neural Network (MLP-ANN), which is trained and optimized to capture the complex nonlinear relationships between the input parameters and the target displacement (Δ). Once the general model is established, detailed results are presented, highlighting the predictive performance across the dataset. Following this, the MLP-ANN approach is employed iteratively to refine the architecture, minimize error metrics, and ensure generalization capability. In parallel, the Random Forest (RF) algorithm is implemented, not as a primary predictor but as a robust interpretative tool, leveraging its ensemble-based variable importance analysis to quantify the relative contribution of each input parameter to displacement prediction.

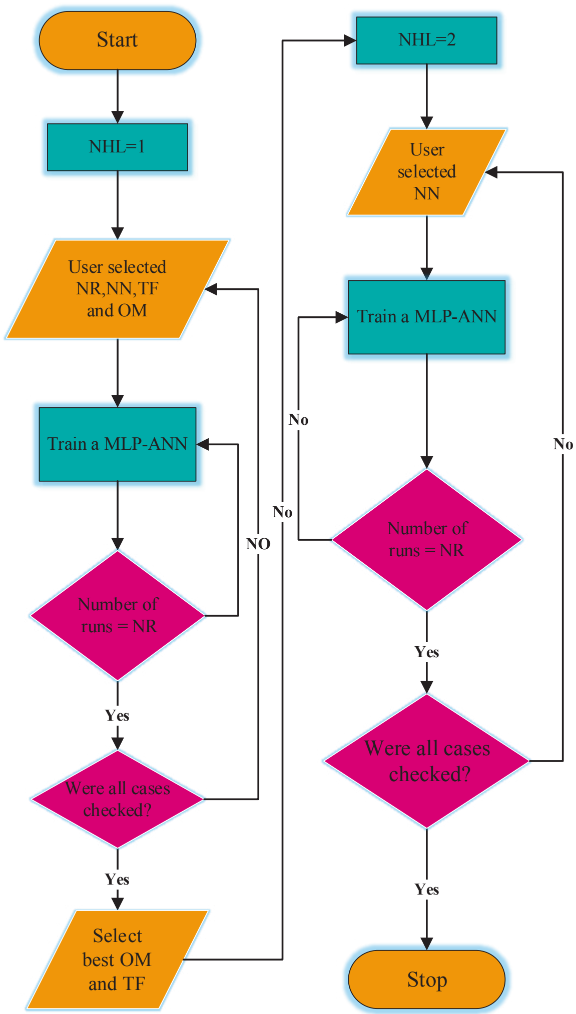

Fig. 4. The process of using an algorithm to identify the most efficient structure for a MLP-ANN.

The developed general prediction model, constructed using the MLP-ANN approach, integrated all ten input variables presented in Table 1, enabling a comprehensive representation of the geometric, material, and loading conditions. As described in the previous sections, a systematic trial-and-error strategy was employed to determine the optimal network architecture. Due to the inherently stochastic nature of heuristic learning algorithms, each configuration was executed 25 times, culminating in over 1000 independent runs. Through this exhaustive evaluation, the combination of the LOGSIG transfer function and TRAINLM optimization algorithm consistently yielded the lowest predictive error, with a mean squared error (MSE) of 0.17. Once the architecture was finalized, the model was constructed to meet the defined specifications, producing a robust and generalizable framework for displacement prediction. Fig. 5 illustrates the comparative performance across training, validation, and testing datasets, delivering R^2 values of 0.98, 0.97, and 0.90, respectively, demonstrating exceptional alignment between predicted and measured displacements.

The results presented in Fig. 5 further reinforce the model's predictive credibility, highlighting its ability to precisely capture complex input–output relationships. Across the full dataset, the predicted values closely follow the experimental displacement measurements, with only minor deviations attributable to localized overestimation or underestimation. These discrepancies are both infrequent and marginal, underscoring the ANN model's capacity to achieve high-fidelity forecasts even in scenarios characterized by nonlinearity and parameter interdependence. Collectively, the performance metrics, coupled with visual verification from the comparative plots, confirm that the proposed MLP-ANN model is not only a statistically accurate predictor of wall displacement but also an effective engineering tool capable of supporting decision-making in structural safety assessment and performance-based seismic design.

In this study, the predictive performance of the proposed models was evaluated through a comprehensive set of statistical indicators, namely the Nash–Sutcliffe Efficiency (NSE), Mean Squared Error (MSE), Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and the coefficient of determination (R^2). These metrics collectively provide both absolute and relative measures of model

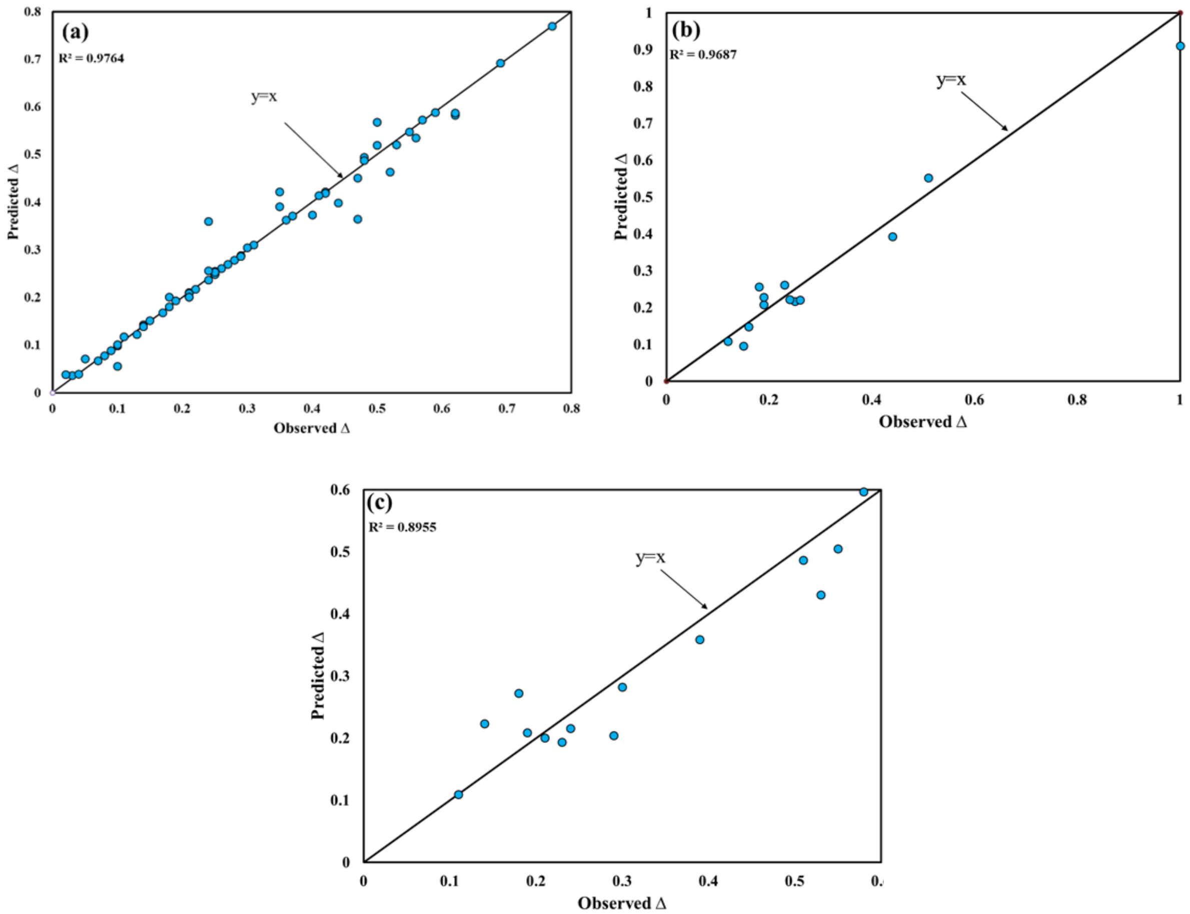

Fig. 5. Predicted versus actual displacement values of the general ANN model for (a) training, (b) validation, and (c) testing datasets.

accuracy and reliability. Among them, RMSE and R^2, each bounded between zero and one, are particularly indicative of predictive precision, while lower MAE, MSE, and RMSE values correspond directly to higher accuracy in replicating observed displacements.

As detailed in Table 4, the overall performance of the general Artificial Neural Network (ANN) model was robust across all three dataset partitions, training, validation, and testing, demonstrating its ability to generalize well beyond the training phase. For the training dataset, the model achieved exceptionally low error values (MAE = 0.144, MSE = 0.080, RMSE = 0.279) along with high NSE and R^2 values (0.9764), indicating a very strong correlation between predicted and observed outputs, and minimal deviation from actual displacement values.

When evaluated on the validation dataset, which represents unseen data, the ANN maintained high predictive accuracy with MAE = 0.256, MSE = 0.250, RMSE = 0.670, and an impressive R^2 of 0.9687. The NSE value of 0.9423 further confirms the model's capability to maintain stability and precision in real predictive scenarios.

The testing dataset results MAE = 0.361, MSE = 0.140, RMSE = 0.480, and R^2 = 0.8955 show that even under cross-checking conditions, the ANN exhibited good agreement between predictions and measurements. Although slightly lower than the training and validation results, these metrics still indicate strong performance, reflecting the expected minor variability inherent in testing phases.

Overall, the ANN model proposed in this research demonstrated not only high accuracy but also an excellent balance between fitting capability and generalization, as evidenced by its consistently high NSE and R^2 values across all datasets. Such stability across different data partitions underscores the model's potential as a reliable predictive tool for displacement estimation in masonry shear walls under varying lateral loading conditions.

3- 2- RF Variable Importance Analysis

By employing the RF algorithm, the relative significance of each input variable contributing to faulting and displacement prediction was quantitatively assessed. This ensemble-based method computes variable importance on a normalized scale, providing a transparent basis for identifying the parameters with the greatest influence on model output. As illustrated in Fig. 6, the percentage contribution of each predictor was calculated for the simplified models, revealing that certain

Table 4. Performance evaluation of the developed ANN model across training, validation, and testing datasets.

Model name	Type of data	MAE	MSE	NSE	RMSE	R^2
General	Training data	0.144	0.080	0.9764	0.279	0.9764
General	Validation data	0.256	0.250	0.9423	0.670	0.9687
General	Testing data	0.361	0.140	0.9174	0.480	0.8955

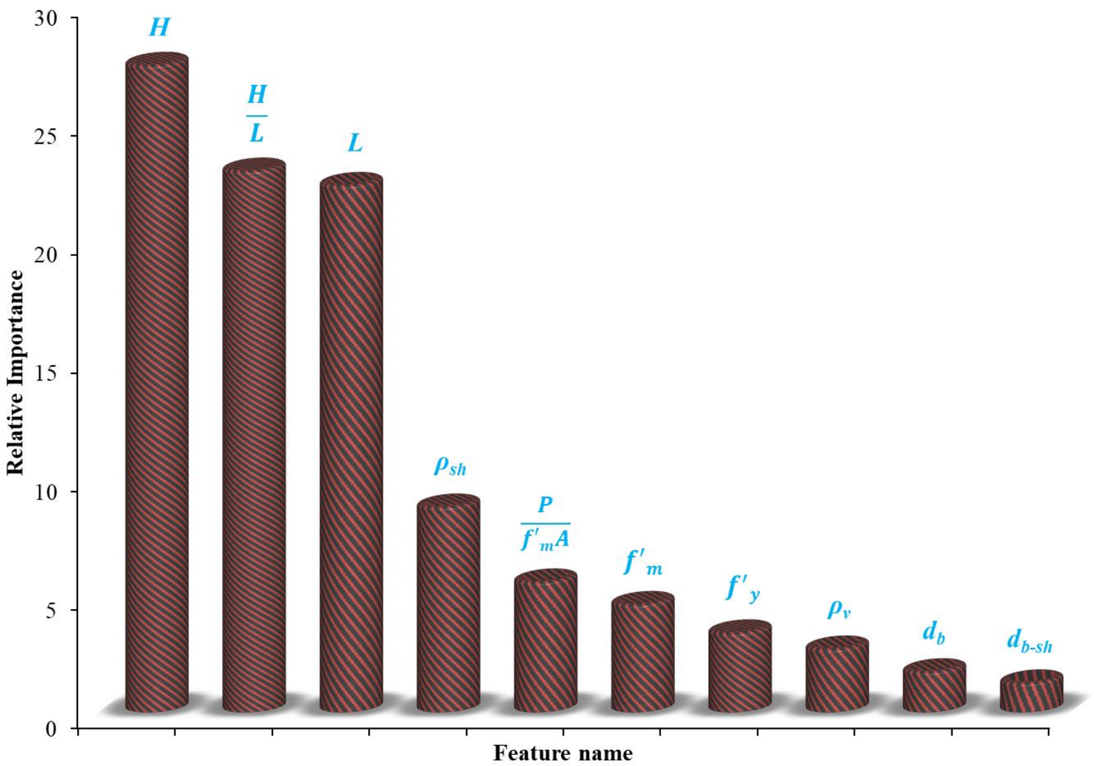

Fig. 6. Variable importance ranking in displacement prediction obtained from the RF algorithm.

variables dominate the prediction process. Among these, L_w, H_w and H_w/L_w stand out as the most critical geometric measures affecting displacement behavior.

In addition to geometric parameters, several reinforcement and material properties were also highlighted as highly influential. The variables ρ_v, d_b, ρ_{sh}, $d_{b\text{-}sh}$, $f_y^{'}$, $f_m^{'}$, and $\frac{P}{f_m^{'}A}$ demonstrated a substantial role in the RF ranking results, indicating their strong correlation with the displacement capacity of masonry shear walls. These influential parameters collectively govern aspects such as stiffness, load-bearing capacity, and resistance to crack development, thereby shaping the overall structural response. The variable importance ranking derived from RF thus serves a dual role: guiding the simplification of predictive models by focusing on the most impactful variables, and enhancing engineering interpretation through a data-driven understanding of parameter influence, ensuring that predictive accuracy is maintained while promoting model efficiency.

3- 3- Numerical Validation

To validate the accuracy of the proposed ML-based framework, a finite element model (FEM) was developed in Abaqus. Among the walls included in the dataset, wall Sh_2

Table 5. Key properties of the wall specimen Sh_2 [8].

ID	L_w (mm)	H_w (mm)	H_w/L_w	ρ_v (%)	d_b (mm)	ρ_{sh} (%)	d_{sh} (mm)	f_y (MPa)	f'_m (MPa)	$P/(f'_m A)$	$\Delta_{80\%}/H_w$ (%)
Sh_2	1800	3600	2	0.78	20	0.13	9.5	502	14.8	0.006	1.86

Table 6. Comparison of experimental vs. numerical results.

Parameter	Test	FEM	Difference (%)
Ultimate load (Q_U) (kN)	260	275	5.8
Drift at Q_U (%)	0.53	0.48	9.5
Drift at 80% Q_U (%)	1.54	1.40	9.7

[8]—corresponding to *wall 2* in Shedid *et al.* [31]—was selected for validation due to its intermediate reinforcement ratio (ρ_v = 0.78%) and its well-documented experimental results (Table 5).

The experimental dataset employed in this study is derived from full-scale laboratory tests on masonry shear walls subjected to monotonic in-plane lateral loading under controlled axial compression, from which load–displacement behavior, stiffness degradation, failure mechanisms, and the maximum displacement capacity ($\Delta_{80\%}$) were directly obtained. In parallel, a finite element model (Fig. 7) was developed solely for numerical verification. This model simulates the nonlinear response of masonry walls and is validated by comparing its load–displacement results with those of one experimentally tested wall.

The masonry wall was modeled using three-dimensional solid elements (C3D8R) for the masonry blocks and grout, while steel reinforcement was represented through embedded truss elements (T3D2) using an embedded-region constraint. Masonry behavior was captured with the Concrete Damage Plasticity (CDP) model, calibrated based on compressive strength (f'_m = 14.8 MPa), prism test results, and defined tensile and compressive damage evolution laws, with a small viscosity parameter included to aid numerical convergence. Reinforcement was modeled as bilinear elastoplastic with a yield strength of f_y = 502 MPa. A mesh size of 25–50 mm was adopted following refinement studies and sensitivity checks to ensure mesh-independent results [33, 36]. Boundary conditions reproduced the experimental setup, consisting of a fully fixed base and displacement-controlled lateral loading applied at the top in terms of drift ratios, with axial compression introduced prior to lateral loading [32]. The loading protocol, step definitions, increment strategy, and stabilization controls were explicitly defined. This comprehensive numerical modeling framework—including material calibration, element selection, mesh configuration, and boundary and loading conditions—provides full transparency and ensures reproducibility of the software simulation.

Fig. 7 compares the load–displacement backbone curves of the FEM against experimental data. Table 6 summarizes the key response parameters, showing close agreement with deviations below 10%. The FEM captured the flexural cracking, plastic hinge formation, and bar yielding observed experimentally, though a slightly stiffer initial response and marginally smaller ultimate drift were obtained.

Numerical validation confirmed the reliability of the proposed ML framework. The FEM reproduced the experimental backbone within an engineering tolerance, providing additional confidence in both the numerical modeling approach and the predictive capability of the ML-based framework.

4- Conclusions

This study investigated the application of machine learning techniques to predict the maximum displacement of masonry shear walls subjected to lateral loads, aiming to provide a more efficient and accurate alternative to traditional analytical methods. Based on the conducted analysis, the following conclusions can be drawn.

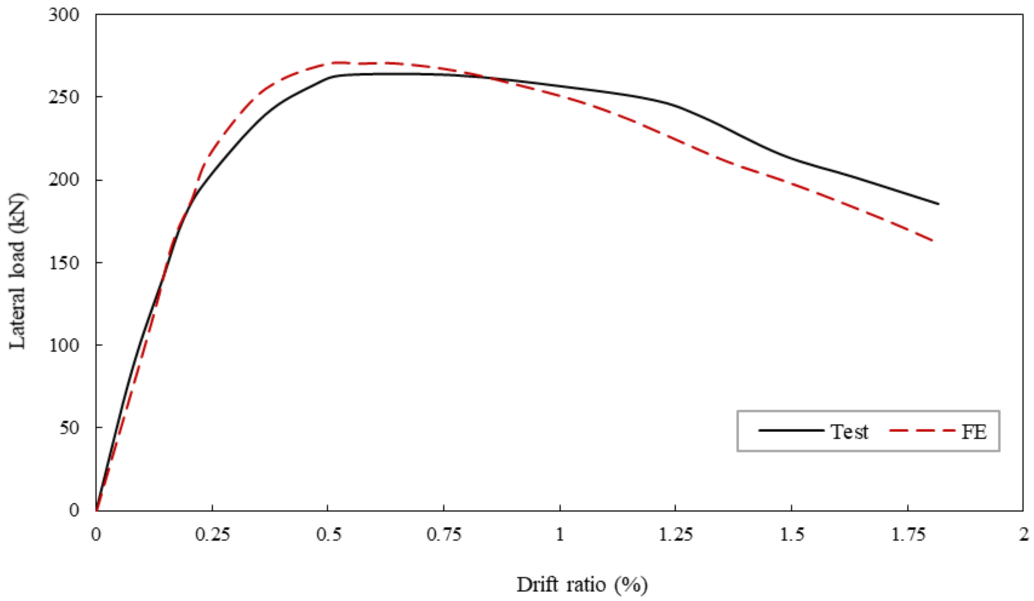

Fig. 7. Experimental vs. numerical backbone curves of wall Sh_2.

4- 1- Key Findings

- A Multi-Layer Perceptron Artificial Neural Network (MLP-ANN) was successfully developed and optimized for predicting the maximum displacement of masonry shear walls.
- The optimized ANN architecture achieved strong predictive performance with R^2 values of 0.98 (training), 0.97 (validation), and 0.90 (testing), confirming its generalization capability.
- Error indices confirmed the robustness of the ANN model, with MAE = 0.256, MSE = 0.250, and RMSE = 0.670 for the validation dataset.
- Complementary analysis using the Random Forest (RF) algorithm identified wall length, wall height, and reinforcement ratios as the most influential predictors of displacement behavior, followed by material strength and axial load ratio.
- Finite element validation of experimental specimen demonstrated < 10% deviation from experimental results in stiffness, peak load, and ultimate drift, thereby corroborating both the ML predictions and the mechanical plausibility of the framework.
- Combining ANN for prediction accuracy with RF for parameter interpretability and FEM for numerical validation offers a multi-layered advantage: reliable forecasting, engineering insight into key parameters, and independent corroboration.
- This three-way consistency among experiment, ML, and FEM further supports the reliability and practical utility of the framework.

4- 2- Limitations and Future Works

- The experimental database was limited to 93 masonry wall specimens, which may restrict the generalizability of the developed models to other wall types, geometries, or boundary conditions.
- Only two algorithms (ANN and RF) were employed; benchmarking against additional approaches such as Support Vector Machines, Gradient Boosting, or Deep Learning architectures could further enhance predictive accuracy.
- A key direction for further development is the formulation of a simplified predictive equation—using approaches such as Linear Regression or ElasticNet—to provide an engineer-friendly expression based on the same parameters employed in the machine-learning models.
- FEM validation was restricted to one representative wall; extending such analyses to other specimens would strengthen the framework.
- Future studies may expand to diverse wall materials and load conditions, as well as integrate ML–FEM hybrid approaches for more comprehensive seismic design support.

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