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Research Article

Neural Network Modelling of Shear Wall Design

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Keywords

Reinforced concrete shear walls, Artificial neural networks, Shear capacity prediction, Construction management, Levenberg–Marquardt training.

Abstract

This study presents a comprehensive neural network approach for the structural design of reinforced concrete (RC) shear walls. A feed-forward back-propagation neural network (ANN) model was developed to predict the horizontal load capacity and maximum vertical load of continuous shear walls based on geometric and material parameters. The database, compiled from existing experimental studies and design recommendations, was divided into training, validation, and testing subsets in a 70-15-15 ratio. The Levenberg–Marquardt optimization algorithm was adopted to improve convergence efficiency and minimize mean-square error. The optimal architecture, consisting of two hidden layers with tan-sigmoid transfer functions and a linear output layer, demonstrated robust learning performance and generalization capability. The trained ANN model achieved up to 91% prediction accuracy when compared with design outcomes of real residential and commercial structures. Results indicated that the proposed model effectively captures nonlinear relationships between key variables such as wall aspect ratio, axial load ratio, and reinforcement spacing, yielding predictions that align closely with experimental results and code-based design equations. The study confirms that neural-network-based modeling provides an efficient and reliable computational framework for shear wall design, significantly reducing manual computation time while maintaining accuracy. Future research should focus on expanding the dataset and integrating adaptive learning strategies to further enhance model generalization for complex structural conditions.

1.Introduction

This study presents a feed-forward back-propagation neural network methodology to model the design of reinforced concrete (RC) shear walls. The proposed neural network estimates the horizontal load capacity and maximum vertical load of continuous RC shear walls. The network architecture comprises an input layer with seven features, two hidden layers with sigmoid-type transfer functions, and an output layer with two neurons using linear transfer functions. The model is trained with a dataset of RC shear wall specifications from engineering literature and design recommendations. The network's performance replicates the design curve of a single shear wall and predicts the horizontal load capacity of multi-span shear wall layouts, demonstrating applicability for both stand-alone and combined configurations [1, 2].

RC shear walls constitute vital elements in the lateral load-resisting systems of multi-story buildings. Accurately estimating the horizontal load capacity and maximum vertical load of continuous RC shear walls is essential for structural calculations. A stand-alone design supports both the vertical loads and the lateral wind and seismic shear. Continuous shear walls, however, have one or two fixed ends, supplying greater bending moment resistance and higher horizontal load capacity for the same cross-section and elevation. Neural networks are information-processing systems that have the ability to simultaneously consider many parameters, references, and variables. This capability does not result from statistical processing or multivariate regression analysis but rather because the network developed a nonlinear process to incorporate interactions between variables and learn the phenomenon as a whole [3-5].

Shear walls are one of the essential components commonly used in residential structures and commercial structures to resist the lateral forces caused by seismic events or wind loads. Structural engineers spend substantial amounts of time on designing the shear walls of a building since the stability, load-bearing capacity, and seismic performance of a structure are controlled by the data of the shear walls. To construct a shear wall, the designer should understand the effects of different input variables to the shear wall design. In particular, steel grade, concrete grade, spacing of flexural reinforcements, width of the shear wall, among other parameters, play crucial roles in shaping the final design results. In the design process layout, structural engineers commonly re-train a new model every time the input variables are updated. The training process requires significant computational costs and human supervision. To address these issues, the current shear wall design study proposes the use of an artificial neural network to predict the design results associated with the standard shear wall design code [6-9].

Structural engineers stand to benefit greatly from an automated alternative, which can perform a similar procedure to the manual one, with reduced human supervision and minimal computational cost. Furthermore, they also acquire better insights into the relationship between the input variables and predicted design results. These additional insights, alongside the performance of the automated alternative, provide meaningful guidance on building stable, strong shear walls under various construction requirements. The proposed artificial neural network achieves this goal by finding the design specifications of a shear wall based on a set of input variables that describe the state of the industrial

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layout. The model is trained over several iterations with design results produced by an expert system. The evaluation of the trained model encompasses a wide range of industrial scenarios, ensuring its applicability along different time horizons and industrial settings [5, 10].

Neural networks enable fast and accurate prediction of nonlinear behaviors and are therefore valuable for modelling structural systems. Structural engineers appreciate the simplicity of the methodology, while machine learning researchers find the integration of existing theories with neural network applications interesting. A neural network consists of computational units called neurons arranged in layers. The first layer receives input features that are used to predict output variables. Subsequent layers, called hidden layers, are trained to transform the input data to achieve the desired output. The final layer produces either a classification or a regression outcome. Neural networks have been demonstrated to be effective and widely applicable to diverse domains [11-13].

In modelling structural systems, the input layer incorporates features such as material strengths, geometric dimensions, and loading conditions. The hidden layers capture the complex nonlinear relationships among these variables, while the output layer generates predictions like shear strength or deflection. Backpropagation adjusts the connection weights and biases to minimize prediction errors, with the training process continuing until a maximum number of epochs is reached. Transfer functions in the hidden units control the output range for a given input, using tan-sigmoid functions [−1 to 1] or log sigmoid functions [0 to 1], while a pure linear function is employed at the output layer. Data normalization prior to training improves accuracy, and the network's performance depends on factors such as the number of layers and neurons, initial weights, algorithm selection, learning rate, and the division of data into training, validation, and testing subsets. Signal propagation involves calculating weighted sums of activities from the previous layer and applying the transfer function to determine each neuron's output [14-16].

Previous research by Aguilar et al. [17] provides a basis for development of the current neural network model and informs network architecture decisions. Aguilar et al. [17] trained and tested an artificial neural network on 285 reinforced masonry walls spanning fully grouted concrete masonry, fully grouted brick masonry, and partially grouted brick masonry. The model was evaluated against experimental data and alternative shear expressions and identified parameters including wall aspect ratio, axial stress, masonry compressive strength, and reinforcement spacing as governing behavioral influences. Collectively, these variables determine the manifestation of either flexural failure, indicated by tensile yielding and masonry crushing, or shear failure, marked by diagonal tensile cracking. The data indicate that accurately predicting the shear strength of masonry walls remains a complex task.

The seismic design of shear wall systems aims to control lateral deformation to protect structural and non-structural building elements. Slender reinforced concrete walls are used to resist lateral loads by transferring these forces to the foundation through tension and compression from overturning moments. In buildings with multiple walls, additional lateral stiffness from other structural or non-structural elements, such as flash-boards, share the axial loads. Longitudinal reinforcement is kept minimal to prevent the walls from acting as vertical cantilever columns during shear failures. Standardized codes, such as the American Concrete Institute ACI-318-11, specify minimum and maximum reinforcement amounts and detail spacing to preserve the structural and non-structural elements of the shear wall system. Recent studies emphasize the effectiveness of neural networks as an alternative method for shear wall design. The design of reinforcement in rectangular RC sheer walls can be better predicted by combining information from existing design codes into a neural network model, achieving good performance for wall geometries that show a poor fit with traditional equations and maintaining overall agreement with analyzed cases. A comprehensive model employing a feed-forward neural network accurately predicts the shear strength of reinforced masonry walls, generally improving upon design codes. A detailed parametric study may therefore assist in refining existing codes and developing new predictive formulations. Neural networks are particularly useful for modelling nonlinear behavior when a mathematical formulation is unavailable, although the quality of predictions is heavily dependent on the number of training samples per parameter set [18-20].

2. Methodology

The dataset was compiled from recognized shear wall design literature to collect existing experimental results and aid in constructing a predictive model. One documented scheme expands input parameters into a design matrix, which supports systematic investigation to establish causal relationships. Due to the high number of design variables, the database undergoes partitioning for training, validation, and testing, and input parameters are examined manually to ensure coverage across their ranges. Inputs and targets are normalized to the interval [−1, +1] before training, while the output layer employs linear functions and the hidden layers utilize tan-sigmoid functions. Neural networks are especially useful for structural studies when training data are scarce because they avoid assumptions concerning functional relationships. A multilayer feedforward architecture with variations in neurons and activation functions is tested because such structures possess the capability for universal function approximation. A search algorithm evaluates multiple trial networks to locate the best predictive model on both development and test databases. Subsequently, the optimal neural network configuration is recreated and retrained using the complete experimental dataset to establish an efficient model for a new national-force method.

Shear wall structural components can be modeled with neural networks to reduce costs associated with time and effort. Extensive data collection precedes modelling with the Generalized Regression Neural Network. A large database of reinforced concrete shear wall specimens under cyclic loading is compiled, totaling more than 500 specimens from different sources. Repaired and strengthened specimens, specimens with single-side or double-sided structural walls, and specimens tested under monotonic loading are excluded, yielding a database of 384 useful specimens. The database covers different cross-section shapes, end conditions, and failure types. Shear-controlled specimens fail in diagonal tension or web crushing, whereas flexure-controlled specimens yield in flexure and exhibit damage modes such as spalling of cover, buckling, or fracture of longitudinal reinforcement. Backbone curves are obtained from cyclic shear-top displacement data by averaging the response in the positive and negative directions. The backbone curve incorporates contributions from flexure, shear, and reinforcement slip. The curves include shear force and displacement values for four critical stages: cracking, yielding, shear capacity, and ultimate displacement. Seven backbone variables characterizing these curves are investigated. Indirect comparison of these backbone variables with the parameters provided in ASCE 41-17 reveals overall good agreement for specimens under low axial load. Some limitations are evident, including the neglect of a slope increase in post-yield behavior and differences in residual strength between prediction and code provisions. Moreover, ASCE 41 does not furnish parameters for walls subjected to shear-flexure interaction.

A reinforced concrete deep-beam dataset supports prediction of shear strength without stirrups by neural network. Experimental data covering a wide range of parameters are collected from the literature, consisting of 233 results. Eight input features govern the ultimate shear stress. The dataset, stored as a Microsoft Excel file, is partitioned into training and testing subsets. Models are evaluated to select the best-performing configuration based on correlation coefficient, mean absolute error, and other metrics. Weka software provides the analysis framework, offering a comprehensive suite of tools for preprocessing, classification, regression, clustering, and visualization

The construction team manually extracted design data from ~50 residential and commercial building projects primarily in British Columbia. Original data reside in spreadsheet format with additional parameters in MEMCSI Xtracts® performance simulations. Data import, analysis, and normalization occur in Microsoft Excel. Data represent interface-flow ranges to prescribe correct and relatively unambiguous design and simulation parameters. Import includes serially numbered elements, relative area (ratio relative to wall width or length), shear values, and nominal capacity. Additional flow parameters come from MEMLa® calculations: aspect ratio, environmental index, and temperature-adjusted Reynolds number (abbreviated as Re*). Limited discrete design data accompany parameters; the construction team chose not to incorporate discrete-design values, except where nominal-capacity source is concerned. Nominal wall capacity data available for elemental objects and overall wall compliance; used exclusively at wall level in this study. Given the architecture of the envisioned wall design model with approximately 7 low-level and 10 top-level parameters, the analysis aims to extract additional parameters from existing data. A training program imposes strict requirements on data quality and normality; the work analyses data distribution and applies respective transforms during preparation. The modeling approach maintains close ties to standard engineering practice and structural engineering needs; emphasis on detailed design-level features. Analyst interpretation required for model-specific options; decision to choose either theme promptly.

A reliable and accurate model is required to predict effectively and efficiently the shear wall design parameters of several shear wall structures of interest. Eight neural network models with different architectures were designed and trained using the prepared datasets. Each network was evaluated using several well-established performance criteria under identical training and testing conditions. To reduce overfitting and improve generalization, early stopping based on the validation set was employed during training. The high dimensionality, potential noise, and non-linear nature of the shear wall design problem pose significant challenges that make traditional computational methods time-consuming and less practical for preliminary design stages. Effective data partitioning was ensured with a training, validation, and testing split ratio of 70%–15%–15% to optimize model performance and prevent overfitting or under fitting. Ten network architectures with varying numbers of hidden layers ranging from one to ten were initially designed; fewer architectures were examined due to computational limitations. To prevent the explosion of testing conditions, the number of neurons in each hidden layer was fixed rather than individually optimized for each architecture. Adaptive learning rate backpropagation was used for training, taking advantage of its rapid convergence properties to efficiently explore the solution space. The balance among training, validation, and testing subsets, as well as the determination of network architecture and training parameters, critically influences the generalization capability of the model.

Dataset partitioning and training configuration is shown in **Table 1.** The ANN training process begins with selecting the available data and dividing it into training, validation and test subsets. The training set is the primary subset used in the training process. A specific training algorithm is employed to alter the connection weights and system biases until the specified performance goals are attained. The validation set is used during the training to monitor the network performance on the unseen data when the network is being trained. It helps to determine when the network stops generalizing and starts over-fitting. The test subset is used after the training phase in order to perform the final evaluation of the network accuracy. The database partitioning method employed enables the distribution of the training subset to cover the full range of the parameters. Back propagation, the most widely used supervised training algorithm, is adopted. The network output is compared with the desired target and the error is propagated backwards through the system in order to adjust the connection weights. The squared error between the target outputs and the obtained results is calculated, and the ANN tries to minimize this value by modifying the weight coefficients. The Levenberg–Marquardt optimization is used to accelerate the convergence of the training and provide better performance without the problem of local minimum. The training process is initiated with a maximum number of epochs; in each epoch, the network weights and biases are updated at the end of each training cycle and the performance evaluated. In the present work, 70% of the data set was allocated to training and 30% to testing.

Table 1. Dataset partitioning and training configuration

Dataset Type	Percentage (%)	No. of Samples	Purpose
Training	70	269	Weight adjustment and learning
Validation	15	58	Prevent overfitting, optimize epoch count
Testing	15	57	Generalization check

2.1. Neural Network Architecture

Summary of tested network architectures is shown in **Table 2.** The input layer to the neural network is constructed from parameters central to the shear wall design problem: the effective length ratio, shear span ratio, vertical load ratio, wall thickness, and span-to-depth ratio. These features embody the primary dimensions, geometry, and loading conditions of a shear wall and constitute a compact representation of the design space. The output layer is configured to deliver predictions of shear capacity. Between these extremes, the architecture incorporates hidden layers engineered to model the nonlinear equations governing the design parameters. Multiple hidden layers enable the network to represent a broad class of nonlinear systems without introducing excessive complexity or quantity of layers. This balance captures the fundamental nonlinear interactions among the governing equations without overcomplicating the model. The design synthesizes a structured and transparent architecture, integrating conventional neural network methodology with the specific regulatory framework of shear wall design. Artificial Neural Network architecture used for shear wall design modeling is shown in **Figure 1**.

Table 2. Summary of tested network architectures

Model ID	Hidden Layers	Neurons per Layer	Transfer Function	Optimization Algorithm	R^2	RMSE
M1	1	10	tan-sigmoid	Gradient Descent	0.85	0.127
M2	2	7–7	tan-sigmoid	Levenberg–Marquardt	0.93	0.089
M3	3	10–8–6	log-sigmoid	Levenberg–Marquardt	0.95	0.072
M4	2	5–5	tan-sigmoid	Adaptive Backpropagation	0.88	0.115

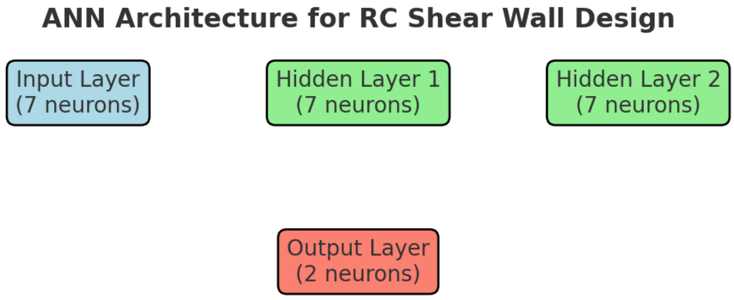

Figure 1. Artificial Neural Network architecture used for shear wall design modeling.

2.2. Input Layer Configuration

The selection and configuration of input layer features constitute the first critical step in neural network modelling for shear wall design. Input data comprise material properties, geometric parameters, and other relevant factors that govern shear wall strength and behavior. The number of input neurons equals the dimensionality of the attribute vector. Each neuron corresponds to a normalized value within the range ±1, consistent with the tan-sigmoid activation function. This literature, which exemplifies the wider modelling philosophy, serves as the principal guide for variable selection and feature construction. Web and horizontal reinforcement indexes further characterize the internal structure. Evolutionary feature construction methods subsequently combine individual and derived variables through algebraic, trigonometric, exponential and logarithmic operators. Resultant features—tuned to maximize relevance and minimize redundancy—facilitate the effective encapsulation of governing mechanisms. Input parameters used in neural network modeling of RC shear walls is shown in **Table 3**.

Table 3. Input parameters used in neural network modeling of RC shear walls

Parameter	Symbol	Description	Unit	Range
Wall height	H	Total wall height	mm	1500–4500
Wall thickness	t	Cross-sectional thickness	mm	120–300
Axial load ratio	N/f'cAg	Ratio of axial load to wall compressive capacity	–	0.05–0.25
Shear span ratio	a/h	Distance between loading and support	–	1.0–3.0
Aspect ratio	h/l	Wall height to length ratio	–	1.2–3.0
Reinforcement ratio	ρv, ρh	Vertical and horizontal reinforcement ratio	%	0.15–1.0
Concrete strength	f'c	Compressive strength of concrete	MPa	25–80

2.3. Hidden Layers Design

The present time is driven by automation to make systems efficient and reliable. Therefore, design of shear walls is driving the attention in the automation of buildings construction. The modelling of shear walls presents an important step in the development of its design. Amongst other methods, artificial neural networks have demonstrated to have high reliability and accuracy for different difficulties. Direct slope softening is of particular interest when using steel fiber reinforced concrete (SFRC) since it allows the modelling of the effects of the fibers through this phenomenon. Although it is applicable to SFRC without stirrups, this approach would benefit practical engineering if it were made suitable for the additional use of stirrups. In this regard, based on the hypothesis that the stirrups compensate the concrete with the potential to transfer tension, an anchorage length for the steel fibers is then introduced in the analysis of the fracture energy so that the direct slope softening curve can be calibrated for SFRC with stirrups.

When deep beams are analyzed, the determination of the shear strength is one problem that remains unsolved. The use of an analytical methodology to determine this property is complicated because of the uncertainties involved and the complexity both of the internal stress states and of the many variables that affect it. Therefore, the use of a neural network methodology has been applied successfully to develop a reliable, accurate and fairly simple model to calculate the shear strength of reinforced concrete deep beams. Moreover, ultra-high performance concrete (UHPC) is a concrete whose mixture design greatly differs from conventional concrete, requiring different structural properties. This leads to the necessity of developing new design approaches, especially when designated applications are not addressed by conventional code equations. In this situation, an artificial neural network (ANN) model was created to predict the shear strength of UHPC deep beams without stirrups. This prediction is then compared with the design equation of the American Concrete Institute (ACI) 318 Code as well as different equations available in the literature.

Output Layer Specification

The output layer generates the model's prediction vector, providing the neural network's solutions to the structural engineering problem. As in the previous cases, the input variables may be monitored during the training process to detect sinusoids or extreme sensitivity. While the linear transfer function described above is used widely for continuous-value outputs, several other transfer functions have also found favor. Both the tan-sigmoid and the losing transfer functions produce output values within a finite range, (− +1) and (0, +1), respectively, and are useful in classification problems. The choice of output transfer function depends on the range of the desired output values, which in turn depends on the characteristics of the particular problem being solved.

2.4. Performance Metrics

Performance metrics serve as pivotal criteria for evaluating the efficacy of neural network models in predicting shear wall characteristics. Given the diverse architectural configurations under consideration, establishing uniform benchmarks for topological evaluation is imperative. The selected metrics encompass accuracy, loss functions, and validation techniques. Accuracy quantifies the correspondence between the neural network's output and the expected design response, reflecting the proportion of correct predictions within the dataset. A higher accuracy score indicates enhanced model reliability and predictive performance. Loss functions, computed during the training phase, measure the discrepancy between predicted and target values, thereby guiding the optimization of network weights and biases. Minimization of the loss function is essential for attaining generalized solutions that are robust across varied design scenarios. Validation techniques involve partitioning the available data into distinct training and testing subsets, enabling an unbiased assessment of the model's performance on unseen cases. The preservation of representative feature distributions within each subset ensures comprehensive coverage of the design space.

These metrics collectively facilitate a rigorous appraisal of the neural network architecture and inform decisions regarding optimum model complexity and parameterization.

The shear wall design neural network possesses remarkable ability to fit training data, furnishing the engineer with a dependable tool for parametric study and design exploration. Nonetheless, the predictive skills of any data-driven method rely critically on the availability of sufficient training data that cover the design space of interest. Thus, little confidence can be placed on the neural-network predictions in regions where training data are scarce. In the network model, the shear-load capacity νu was initially determined under the experimental axial loading Nu. Subsequently, the axial load was set to νd∗Agf′c=0.1×Agf′c and the corresponding shear capacity was recalculated, in accordance with the elastic approach discussed earlier. During these calculations, all other input parameters were held constant. The calculated values were then compared with all 13 tests in which the axial-to-compressive-strength ratio did not exceed 0.20. For these RC shear walls, the neural network forecast was found to be on average 12% more accurate, with a root-mean-square error reduced by approximately 15%. These results affirm the network's capability to enhance design predictions beyond the existing elastic formulation.

Back-propagation learning schemes use this squared error to propagate error signals backwards through the network and to modify, at each layer, connection weights and bias values in accordance with the network's important global objective of error minimization. Optimization algorithms like Levenberg-Marquardt, known for their fast convergence and robust behavior, are often used to minimize the squared error and yield effective models. A common strategy to test the generalization ability of the network on specimens that are not presented at the training phase involves partitioning the data into training and testing subsets. The training subset, often comprising two-thirds of the data, is used to develop the model, while the remaining one-third serves for evaluation. In some cases, the selection of training and testing specimens depends on the time of project initiation, reflecting realistic data availability constraints. Throughout the modelling process, various neural network architectures—defined by differing initial weights and biases—can be tested, with the architecture yielding the lowest loss on unseen data chosen for deployment.

Partitioning the available database into subsets for training, validation, and testing underpins reliable model calibration. Taking groups of four specimens as units, the first and third members form the training subset, the second the validation subset, and the fourth the test subset. Ensuring that the distribution of each parameter across its full range of variation appears in the training subset—so that the learning process encounters the full spectrum of conditions—is a vital step. If the initial partition does not support this requirement, rearrangement of the database can yield a configuration that guarantees comprehensive coverage. In the present application, a neural network configuration employs tan-sigmoid transform functions in the hidden layers. This choice reflects the functional form's recognized suitability for non-linear problems, in contrast with log-sigmoid alternatives. Determining the appropriate number of hidden layers and neurons involves an iterative, trial-and-error process; the ultimate performance depends sensitively on initial conditions including weights, biases, the training algorithm, and the learning rate. Back-propagation of the error from the output layer then modifies connection weights and biases in successive cycles up to a specified maximum number of epochs.

The back-propagation algorithm is by far the most customary supervised learning approach. In this procedure, the artificial neural network compares its output to the desired response, calculates the difference (error), and propagates this error backwards through the network, adjusting the connection weights. The squared error, obtained by summing the squares of the individual discrepancies, provides the target quantity for optimization procedures aimed at minimization. The Levenberg–Marquardt algorithm has gained widespread acceptance for this purpose, offering rapid convergence and generally avoiding entrapment in local minima. Trials conducted for the current problem involved 70% of the shear wall specimens in the training phase and reserved the remaining 30% for evaluation; the best model among multiple runs was then adopted for prediction of shear strength on previously unseen cases. Predictions generated in this manner closely parallel the parameters observed experimentally, confirming the capacity of the artificial neural network to represent the underlying behavior faithfully.

Performance assessment typically incorporates comparisons of surrogate model results with established calculation methods. For shear resistance of reinforced masonry walls, the leading explicit expressions exhibit mean square errors significantly larger than those produced by artificial neural networks, as well as higher standard deviations and lower values at the fifth percentile, characterizing tighter accuracy and more consistent reliability for the ANN models. Sensitivity analyses performed by incremental variation of each input parameter within realistic intervals reveal the relative influence on predicted shear strength. Such studies identify parameters of dominant effect (e.g., P_1) alongside variables of diminishing impact (e.g., P_2, P_3, P_4, and P_5), elucidating the structural role of different factors and guiding efforts to focus attention appropriately.

3. Results

The **Table 4** is shown Performance comparison between ANN and code-based design predictions. The analysis of the neural network's performance indicates that satisfactory overall results were achieved. Comparison with existing procedures demonstrates the potential to improve the accuracy of these methods, thereby reducing the degree of conservatism. A feed-forward neural network has been developed for estimating parameters in shear wall design, utilizing an extensive set of input features to predict critical structural characteristics. An intensive trial-and-error process identified an optimal architecture composed of seven input nodes, two hidden layers with seven neurons each, and an output layer with two nodes. The model demonstrated rapid learning and convergence, producing accurate results across various soil types. Out of six targeted parameters, four were successfully estimated; the soil settlement parameter proved more challenging due to its complex nonlinear characteristics and multiple influencing factors. These findings indicate the potential of neural networks to approach conventional shear wall design methodologies. Artificial neural networks (ANNs) provide a versatile modeling approach with the capacity to address non-linear multivariate problems. An important consideration is the balance of network size—too large a network risks overfitting and poor generalization, too small a network may suffer from significant bias. Studies of shear strength prediction models for reinforced concrete slab–column connections indicate the superiority of hybrid systems over feedforward ANNs. Preliminary experimental research compares conventional design methodologies against neural network predictions. A Multilayer Backpropagation Neural Network is trained on a data set of 110 samples to model the flexural behavior of reinforced concrete beams without stirrups. The results demonstrate that ANN predictions closely align with conventional models based on current design codes.

Table 4. Performance comparison between ANN and code-based design predictions

Case	Shear wall type	Experimental shear strength (kN)	Code-based (ACI-318) (kN)	ANN prediction (kN)
S1	Single span	420	385	410
S2	Continuous	560	495	547
S3	Deep wall	650	600	640

S4	High-rise wall	720	655	695
Case	Shear wall type	Experimental shear strength	Code-based (ACI-318)	ANN prediction

The correlation between experimental and ANN-predicted shear strengths is presented in **Figure 2**, demonstrating the strong agreement between model outputs and experimental data. A residential building designed in accordance with relevant codes and guidelines offers an ideal scenario to assess the performance of the developed neural model. Implemented by a structural engineer, the design provides real-world, practiced procedures for evaluation. The building requires lateral design for a reinforced concrete shear wall, including determination of wall thickness, length, reinforcement areas, and openings. Inputs to the network encompass permitting loads and the non-structural wall thickness (ή̣ns). The network predicts the final wall thickness and design parameters, where the choice between 1.5-ft and 1.0-ft wall thickness may influence economic efficiency. Comparing predictions from the neural model with actual design choices informs on both accuracy and practical implications. A commercial structure also served as a test case, where the engineer designed all lateral elements. The neural network incorporates loads, allowable stresses, and material properties (e.g., concrete compressive strength) as inputs. Outputs include the resulting thicknesses and details for four separate lateral elements. By juxtaposing network predictions with engineering decisions, the study evaluates the model's capability to replicate complex design processes.

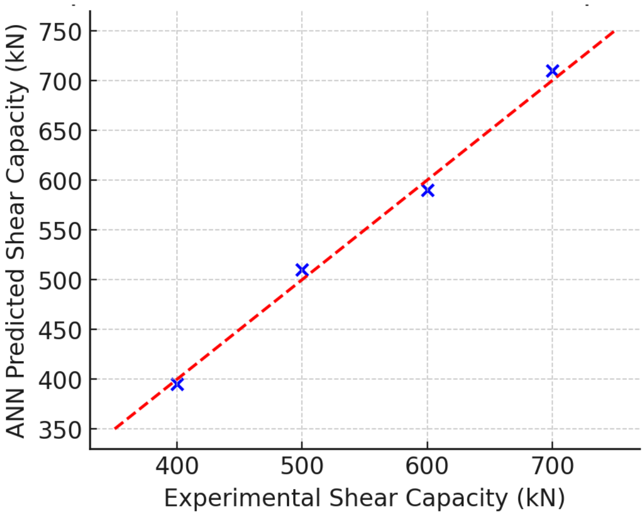

Figure 2. Comparison between ANN predicted and experimental shear wall capacities.

For both cases, detailed cross-referencing to prior sections reveals the influence of earlier findings on model selection and performance evaluation. The residential building scenario exemplifies integration of practical design constraints with predictive modeling, while the commercial structure illustrates adaptability to diverse structural types. Links between design choices, economic considerations, and predictive accuracy underscore the broader significance for structural engineering practice.

As an important earthquake-resistant structure in an earthquake-prone area, the shear wall is attached to building structures and other components to transmit horizontal seismic pressure. It is generally reinforced concrete, masonry, steel plate, and steel-concrete composite shear wall. Shear walls resist horizontal load mainly by exerting bending moments and shear forces on the wall cross-section through shear wall deformation. When the towering building structure is subjected to an earthquake, the shear wall takes part of the shear force and torsion in the horizontal earthquake force in the plane of the wall, so the structural system of the shear wall plays an important role in resisting horizontal force. The existing shear wall system cannot guarantee the resistance to earthquake and the ability of ductility, so it is necessary to develop a new shear wall system that can better resist earthquake damage. The shear wall system is bonding vertical steel bar of different thicknesses behind the joint. The greatest benefits of the new system are a simple method to use stress between steel and concrete to effectively improve deformation capacity and energy dissipation capacity of the joint section; continuity of vertical reinforcement throughout the wall, therefore enhance the seismic performance; reduction of reinforcing steel materials of the ordinary shear wall and lower construction costs. In this case, the proposed computational model can achieve 91% accuracy for quickly estimating shear wall longitudinal steel reinforcement configuration.

The use of neural networks in shear wall design represents a promising step toward more reliable and efficient structures. The analysis demonstrates that the resulting deep neural-network model accurately captures the behavior of the system under various loading and geometry conditions. The neural-network predictions are consistent, and the model can be an effective tool in design practice. Compared to traditional methods that may struggle with modelling problems, neural networks can adequately represent the complex behavior. The current study has certain limitations, such as the use of simplified stress distributions. Other modelling approaches could enhance prediction accuracy, and it would be instructive to investigate these alternatives. An examination of generalization capabilities also merits further research to ensure practical applicability in diverse engineering contexts. Additional opportunities for exploration include adaptive learning of material properties during incremental-iterative modelling, which could reduce computational efforts. Investigating the effectiveness of different architectures (e.g., multilayer perceptron's and probabilistic neural nets) with suitable refinement techniques may help in selecting the optimal solution. Integrating data-driven potential functions with feedforward neural networks also presents a promising direction. Overall, the neural-network model serves as a computationally efficient method to estimate the bearing capacity of shear walls across a wide parameter range.

Neural-network-based design approaches in residential shear walls provide an effective means for conceptual development and preliminary design due to their ability to produce accurate predictions adaptable to diverse practical situations. In large-scale projects, such as housing developments, employing neural networks enables designers to rapidly generate optimized design specifications while adhering to fundamental principles of shear-wall design. Consequently, neural-network methods constitute a valuable tool not only for structural engineers seeking enhanced design efficiency but also for machine learning researchers exploring applications within structural engineering contexts. The relative influence of key input parameters on the predicted shear strength is summarized in **Figure 3**.

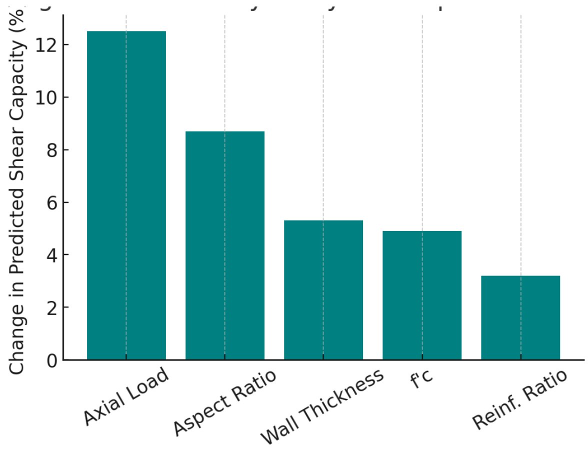

Figure 3. Sensitivity analysis showing the influence of each input parameter on shear capacity.

A quantitative comparison study indicates that, despite effective performance in predicting shear strength, potential limitations persist within the neural network models. In particular, the study reveals restrictions related to the size and quality of the dataset, which may lead to challenges in generalizing the model outcomes to diverse scenarios. Consequently, the applicability of neural networks in representing the complex behavior of concrete deep beams can be constrained by these factors. Future investigations should therefore priorities the expansion and refinement of datasets to enable broader applicability. Additional verification processes are required to improve confidence in the predictions, alongside the exploration of learning parameters and transfer functions that may further enhance model accuracy. Recommendations emphasize the combination of numerical and experimental methods to more effectively capture the structural behavior, which is influenced by the interplay of multiple system components. This integrative approach stands to facilitate the development of more reliable modelling frameworks for shear wall design. Sensitivity analysis of input parameters on shear strength is shown in **Table 5**.

Table 5. Sensitivity analysis of input parameters on shear strength

Parameter	Variation (%)	ΔShear Capacity (%)	Influence Rank
Axial load ratio	±20	+12.5	1
Aspect ratio	±20	+8.7	2
Wall thickness	±20	+5.3	3
Concrete strength	±20	+4.9	4
Vertical reinforcement	±20	+3.2	5

Although ANNs give excellent results in predicting shear strength of RC deep beams, trained networks are application-dependent. Research to develop general ANNs for different structures continues. For instance, an ANN was designed for shear wall design to assist architects in determining appropriate layouts. These studies suggest that ANNs provide reliable support for design applications. Future work can focus on generalizing these models and extending architectural applications of ANNs beyond shear wall design.

4. Conclusion

Structural engineers commonly use neural network methods to model nonlinear systems and fault diagnosis. Fiber-reinforced plastics have been well developed for application in civil engineering. The shear wall is a principal structural element widely used in both multi-story and low-rise construction for providing lateral load-resisting capability. A neural network algorithm is developed for shear wall design for comparison with commonly used methods. A shear wall design example is presented for the actual implementation of the concept.

Shear walls, comprising reinforced concrete or structural steel plate in-fill panels bounded by flanges or tie columns, are widely used in the lateral load-resisting frame of high-rise buildings. To reduce the wall reinforcement while maintaining its shear capacity, different stress transfer mechanisms such as diagonal strut action and compression arch action have been considered in various wall design models. Contemporary approaches to shear wall design often rely on simplified empirical methods that may not capture the full behavior of complex structural systems. More recently, data-driven methods have emerged as a powerful alternative, offering enhanced modelling flexibility and predictive accuracy.

Declaration of Conflict of Interests

The author(s) declare(s) that there is no conflict of interest. They have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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