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# Shear Strength Prediction of Reinforced Concrete Shear Wall Using ANN, GMDH-NN and GEP

**Hosein Naderpour[1], Mohammadreza Sharei[2], Pouyan Fakharian[2*], Mohammad Ali Heravi[2]**

1. Professor, Faculty of Civil Engineering, Semnan University, Semnan, Iran
2. Faculty of Civil Engineering, Semnan University, Semnan, Iran

Corresponding author: *pouyanfakharian@semnan.ac.ir*

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## ABSTRACT

To provide lateral resistance in structures as well as buildings, there are some types of structural systems such as shear walls. The utilization of lateral loads occurs on a plate on the wall's vertical dimension. Conventionally, these sorts of loads are transferred to the wall collectors. There is a significant resistance between concrete shear walls and lateral seismic loading. To guarantee the building's seismic security, the shear strength of the walls has to be prognosticated by using models. This paper aims to predict shear strength by using Artificial Neural Network (ANN), Neural Network-Based Group Method of Data Handling (GMDH-NN), and Gene Expression Programming (GEP). The concrete's compressive strength, the yield strength of transverse reinforcement, the yield strength of vertical reinforcement, the axial load, the aspect ratio of the dimensions, the wall length, the thickness of the reinforced concrete shear wall, the transverse reinforcement ratio, and the vertical reinforcement ratio are the input parameters for the neural network model. And the shear strength of the reinforced concrete shear wall is considered as the target parameter of the ANN model. The results validate the capability of the models predicted by ANN, GMDH-NN, and GEP, which are suitable for use as a tool for predicting the shear strength of concrete shear walls with high accuracy.

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## 1. Introduction

Physical, experimental, numerical, and statistical models have been used in different researches to find the shear strength capacity of reinforced concrete shear walls. The results of the mentioned researches have been integrated into different manuals for engineers, guidelines, and standards for constructors as well as building codes [1–7].

In addition to strut-and-tie models, a variety of other models have been proposed for estimating shear wall strength [8]. An investigation of the strength and behavior of low-rise shear walls made of high-strength concrete subjected to reversed cyclic loading [9]. Additionally, high-strength concrete is likely to be brittle, making ductile responses in shear walls difficult [10].

Based on prior studies the shear strength of shear wall mainly depends on the compressive strength of the concrete, the yield strength of transverse reinforcement, the vertical reinforcement ratio, the wall length, the transverse reinforcement ratio, the thickness of the reinforced concrete shear wall, the yield strength of vertical reinforcement, the axial load, and the aspect ratio of the dimensions of the wall., studies have indicated that the peak shear strength results were subject to substantial variation based on these analytical/empirical/design equations [11,12].

Artificial neural networks (ANNs) are widely used in fields such as meteorology, hydrology, and engineering due to their simplicity of implementation and high accuracy in solving complex problems [13–16]. An artificial neural network, or ANN, uses a large set of neural units in a mathematical model to represent brain functions and structures to solve complex problems modeled as inputs and outputs. The ANN has a better prediction performance than traditional methods such as regression, as demonstrated by Chithra et al. [13] and Khademi et al. [17]. Several drawbacks exist in an ANN's implementation, such as the slow learning rate and the solution trap in finding the local minimum [18].

To overcome the disadvantages of ANN algorithms, different optimization algorithms have been developed such as self-optimization and hybrid optimization. Although self-optimization algorithms reduce computing efficiency, they cannot completely prevent premature convergence of the network [19].

Recently, developing an artificial intelligence-based formula for predicting mechanical characteristic based on collected experimental data have attracted researchers' interest. In this regard, Naderpour et al. proposed an ANN model for predicting the compressive strength of environmentally friendly concrete which reused recycled aggregate concrete (RAC) [20]. Moreover, Naderpour and Mirrashid used ANN for predicting the compressive strength of mortars having calcium inosilicate minerals [21]. In another study, Naderpour et al. proposed a GMDH-based approach for estimating the moment capacity of ferrocement members [22]. Further, Ilkhani et al. [23] proposed a novel approach for the torsional strength prediction of reinforced concrete beams.

Chen et al. proposed a hybrid ANN-PSO model for predicting the shear strength of squat reinforced concrete shear walls. Moradi and Hariri-Ardebili [24] developed a library for the shear wall database and used ANN for models for stiffness and strength of steel and reinforced concrete shear walls. Emamian and Eskandari [25] propose a compressive and flexural strength prediction model based on ANN and GEP for cementitious partial replacements cement mortar with micro and nano-silica and GEP formulation for freeze and thaw cycle [26]. Shahmansouri et al. proposed numerical models for eco-efficient GGBS-based geopolymer concrete compressive strength prediction using the GEP method [27]. Murad [28] developed uniaxial and biaxial joint shear strength of reinforced concrete beam and column connection models by GEP. Additionally, Jueyendah et al. [29] present the same procedure for cement mortar with partial replacement by a support vector machine. Additionally, some other researches in the realm of civil engineering have been performed using soft computing methods [30–38].

Due to the behavioral properties of concrete materials and the nature of construction and utilization of this type of material in the construction industry, these unique features of the neural network can be used to predict the shear strength of reinforced concrete more accurate.

In soft computing, information processing is done by the possibility of extracting hidden patterns and relationships in scientific data, which has become possible in recent decades with the growth of computer science and software technology which gives researchers a new aspect of engineering analysis. Soft computing methods have been widely accepted by researchers due to the prediction and analysis of multidimensional and complex problems in recent decades, and therefore the advantage of using these methods in this research seems reasonable and justified.

Within this context, this article proposes a framework based on 115 experimental datasets which are collected from the various articles which aim to formulate the shear strength of reinforced concrete shear walls by artificial intelligence-based algorithms such as Artificial Neural Networks (ANN), Neural Network-Based Group Method of Data Handling (GMDH-NN) and Genetic Algorithms (GEP).

The article is structured as follows. Section 2 gives a brief discussion on the experimental dataset and corresponding features that affect the shear strength of the shear wall. In Section 3, the strategy of using Artificial Neural Networks is described. The Neural Network-Based Group Method of Data Handling is described in Section 4. In section 5, the performance and properties of Gene Expression Programming are described. In Section 6, the application and comparison of these formulations with ACI 318 and the experimental dataset are presented. Finally, the conclusions of this study are **elucidated** in Section 7**.**

## 2. Experimental dataset and processing

In this research, the experiment dataset of the shear walls was collected from the existing literature [8–10,19,39–46].

The effective parameters on the shear strength of shear walls are included thickness of the shear wall ($t$), length of shear wall ($L_w$), aspect ratio ($a_w = {}^{H}/_{L}$), axial load ($N_u$), compressive strength of concrete ($A_{sw}$), the cross-sectional area ($A_{sw}$), area of the wall-bounded by the web thickness and wall length ($A_{cw}$), and ratio and yield strength of horizontal and vertical reinforcements ($\rho_t f_{yt}$, $\rho_v f_{yv}$). In this research, the mentioned parameters would be contemplated in order to evolve the prediction model of shear strength capacity.

The dataset for predicting the shear strength of the walls is thoroughly selected from 115 datasets.

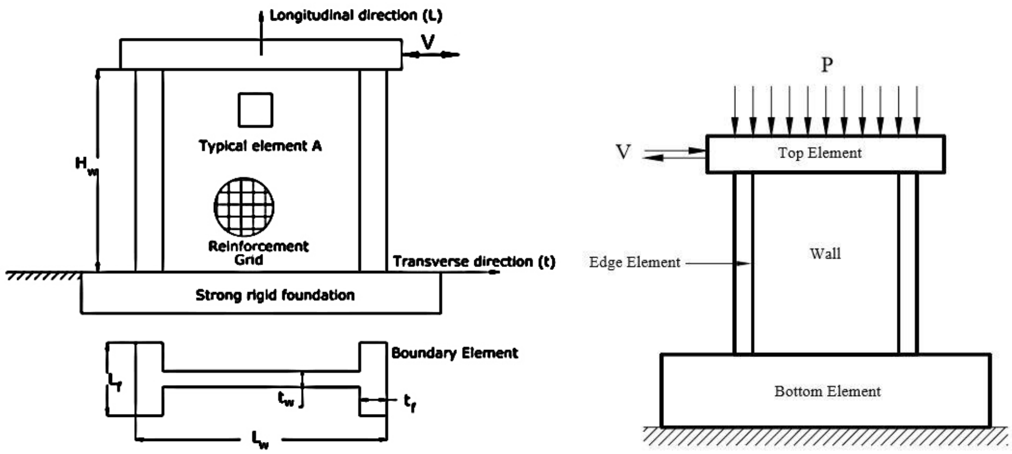


**Fig. 1.** Schematic view of a shear wall.

By performing a lot of modeling and impacting the various parameters and their composition and relationship, the parameters were selected as inputs, which had the closest response to the experimental results. The statistical properties of these parameters, which have been collected from various laboratory papers, are presented in Table 1 (see Appendix. A for more detail).

**Table 1**
Statistical properties of the parameters in shear strength of reinforced concrete shear walls.

| Parameter | Symbol | Unit | Min | Max | Mean | COV |
|---|---|---|---|---|---|---|
| The thickness of the shear wall | $t$ | $cm$ | 2 | 75 | 14.68 | 19.8 |
| Compressive strength of the cylinder concrete | $f_c'$ | $MPa$ | 16.4 | 137.5 | 42.32 | 23.76 |
| Vertical reinforcement ratio | $\rho_v$ | -- | 0 | 3.22 | 0.98 | 0.66 |
| Length of the wall | $L_w$ | $cm$ | 60 | 396 | 148.42 | 19.8 |
| Horizontal reinforcement ratio | $\rho_t$ | -- | 0 | 1.38 | 0.65 | 0.293 |
| Yield strength of transverse reinforcement | $f_{yt}$ | $MPa$ | 0 | 1079 | 496.36 | 198.1 |
| Yield strength of vertical reinforcement | $f_{yv}$ | $MPa$ | 0 | 2147 | 544.8 | 297.06 |
| Axial load | $N_u$ | $kN$ | 0 | 0.305 | 0.03 | 0.65 |
| Aspect ratio | $a_w = \frac{H}{L}$ | -- | 0.24 | 2.39 | 0.98 | 0.46 |

The equations for calculating the shear capacity of a concrete shear wall from ACI-318 are presented in Table 2. For all equations, the shear strength depends on the compressive strength of the concrete, the ratio of dimensions, the axial force, the vertical and horizontal reinforcement ratio, and the cross-section of the wall.

**Table 2**
The shear capacity equations of a concrete shear wall.

| Models | Concrete shear resistance $V_c$, Reinforcement shear resistance $V_s$ |
|---|---|
| ACI 318-14-11 [6] | $\mathrm{Vc} = \min \left\{ \begin{array}{l} \left(0.274\lambda' \sqrt{f'_c} + \frac{N_u}{4L_w d}\right) hd \\ \left[ 0.05\lambda' \sqrt{f'_c} + \frac{\left(0.104\lambda' \sqrt{f'_c} + 0.2\frac{N_u}{L_w h}\right)}{\frac{M_u}{V_u L_w} - \frac{1}{2}} \right] hd \end{array} \right\}, \mathrm{V}_s = \frac{A_v f_{yd} d}{S}$ |
| ACI 318-14-18 [6] | $\mathrm{V_u} = \mathrm{V_c} + \mathrm{V_S} \quad \mathrm{V}_c = A_{cw} \times \alpha_c \lambda' \sqrt{f'_c} \quad \mathrm{V_S} = A_{cw} \times \rho_t f_{yt}$ |

Due to the significant range of the experimental data values and improving the stability and accuracy of the prediction model, all input parameters normalized using the following min-max normalization equation:

$$X_{i,nor} = \left[ (0.9 - 0.1) \times \frac{(X_i - X_{\min})}{(X_{\max} - X_{\min})} \right] + 0.1 \tag{1}$$

where $X_i$ is the input parameters, and $X_{min}$ and $X_{max}$ are the minimum and maximum of each input parameter respectively.

## 3. Artificial neural networks (ANN)

ANNs are composed of artificial neurons that are conceptually derived from biological neurons structures and functions of the human brain. The neural network structure consists of three main layers which are the input layer, hidden layer, and output or target layer [47]. The input values of data are given to the input layer which in this research are parameters of shear strength of shear walls. The hidden layers are the layers between input layers and output layers, where artificial neurons take in a set of weighted inputs and produce an output through an activation function which maps the relationships between the input parameters and shear strength by neurons. Finally, the target or the output layer is the prediction result of the shear strength of the shear wall with a set of weighted inputs and biases. During each process of modeling, as shown in Fig. 2, the input parameter values are processed by each neuron by taking a place two-step. First, the input parameters are combined linearly through weight and bias. Second, an activation function is applied to predict or acquire the final result of the combination. At end of the process, the shear capacity result of shear walls, $V_u$, obtained by linear combination output of each neuron.

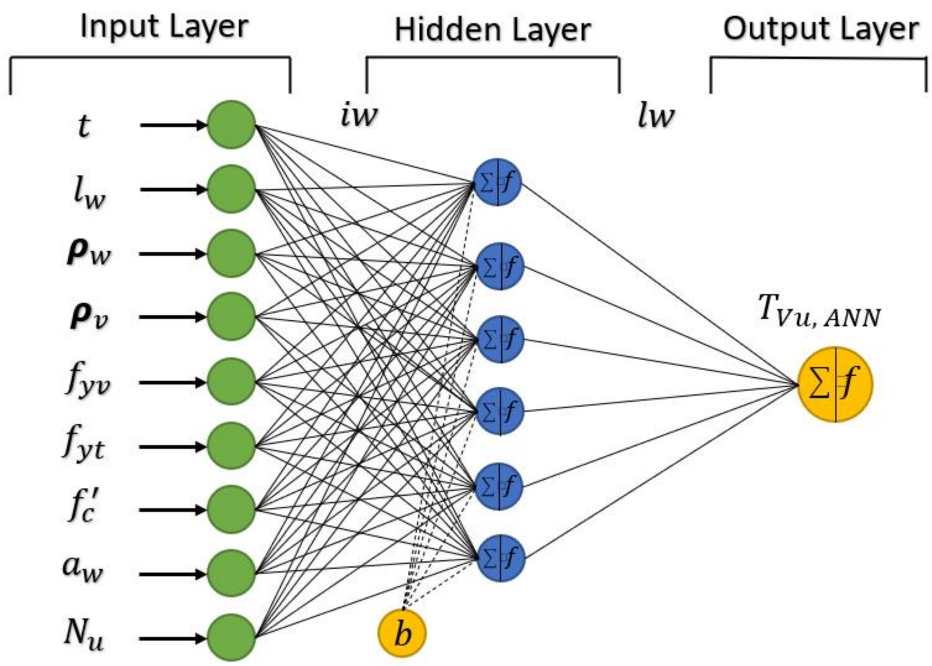


**Fig. 2.** ANN Process.

$$n = w.x + b \tag{2}$$

$$a_{out} = f\left(n\right) \tag{3}$$

In this paper, the weights $w$, bias $b$, coefficient $c$ is termed as the mapping coefficient in the shear strength prediction model. The error estimation functions are:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(V_{u(ANN)} - V_{u(Exp)}\right)^{2}} \tag{4}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{V_{u(ANN)} - V_{u(Exp)}}{V_{u(Exp)}}\right)\times 100 \tag{5}$$

$$R^{2} = 1 - \frac{\sum_{i=1}^{n}\left(V_{u(ANN)} - V_{u(Exp)}\right)^{2}}{\sum_{i=1}^{n}\left(V_{u(ANN)}\right)^{2}} \tag{6}$$

For analyzing and choosing the robust neuron layers of ANN, 9 different ANN models with neuron layers ranging from 8 to 16 have been considered. On this basis, the robust neuron layer is the one that has the least mean absolute error (MSE). Table 3 demonstrates the result of the Train, Validation, and Test data correlation coefficient and MSE which was gained by averaging 20 runs of each network.

**Table 3**
Correlation coefficient and MSE values for trained networks with the number of different neurons in the hidden layer.

| Neurons | Train | Validation | Test | All | MSE |
|---|---|---|---|---|---|
| 8 | 0.988 | 0.984 | 0.961 | 0.984 | 0.000922 |
| 9 | 0.99 | 0.983 | 0.983 | 0.988 | 0.00108 |
| 10 | 0.991 | 0.983 | 0.903 | 0.979 | 0.00936 |
| 11 | 0.995 | 0.94 | 0.788 | 0.978 | 0.00157 |
| **12** | **0.996** | **0.985** | **0.897** | **0.979** | **0.00679** |
| 13 | 0.996 | 0.981 | 0.971 | 0.984 | 0.00158 |
| 14 | 0.998 | 0.912 | 0.904 | 0.948 | 0.00353 |
| 15 | 0.958 | 0.944 | 0.859 | 0.948 | 0.00255 |
| 16 | 0.979 | 0.984 | 0.974 | 0.978 | 0.000536 |

As shown in Table 3, the model created with 12 neurons with MSE 0.00679 and regression 0.979, is shown in Fig. 3, for the main sample. For better understanding, these results are displayed graphically (Figs. 4-6).

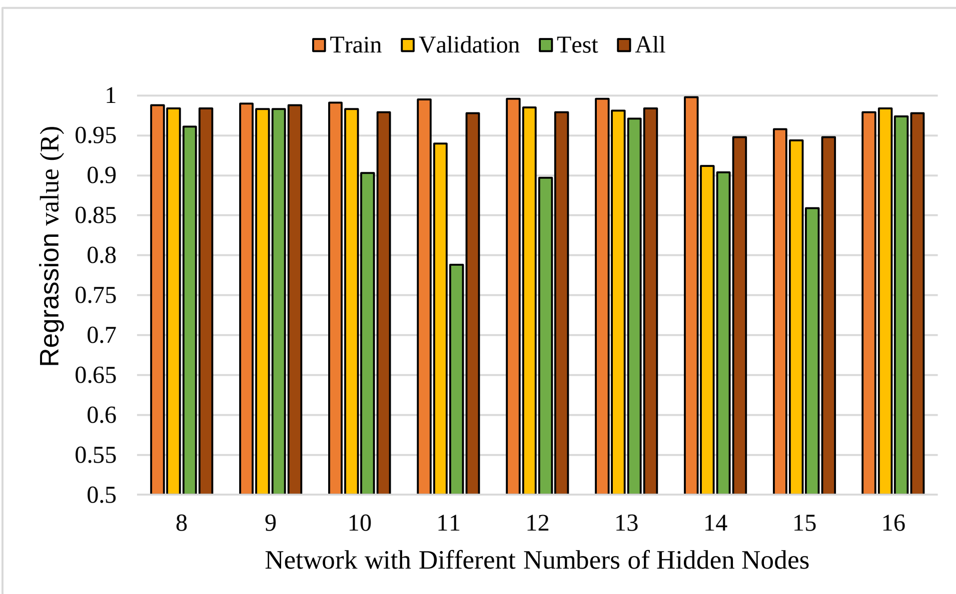


**Fig. 3.** Correlation coefficient.

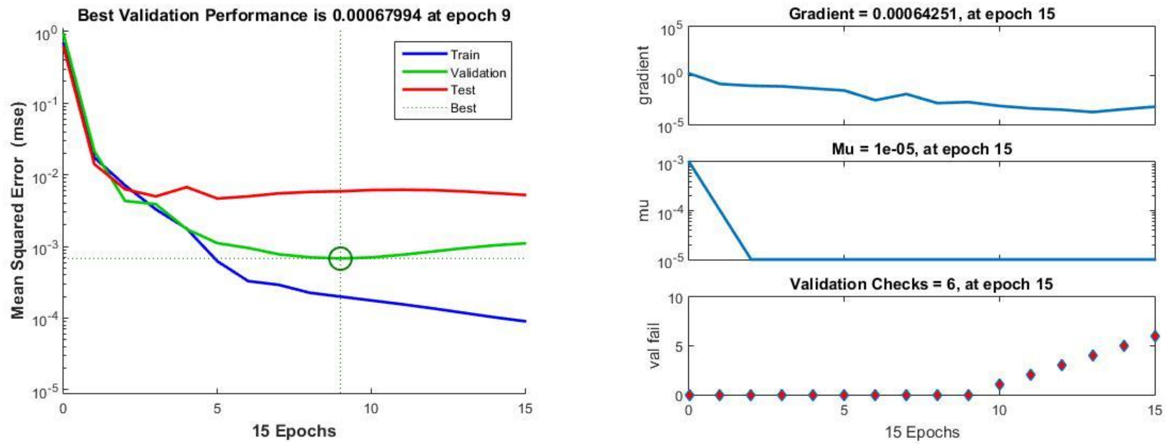


**Fig. 4.** The performance and evaluation of Training state.

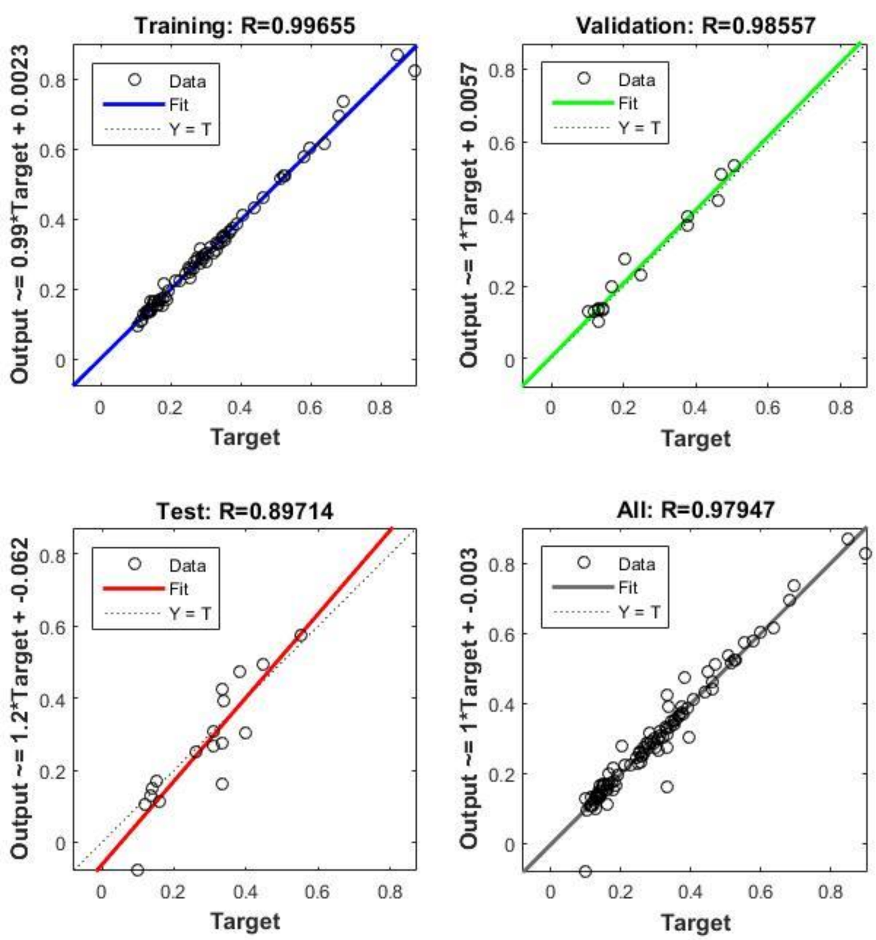


**Fig. 5.** Regression of training, validation, and test simulated.

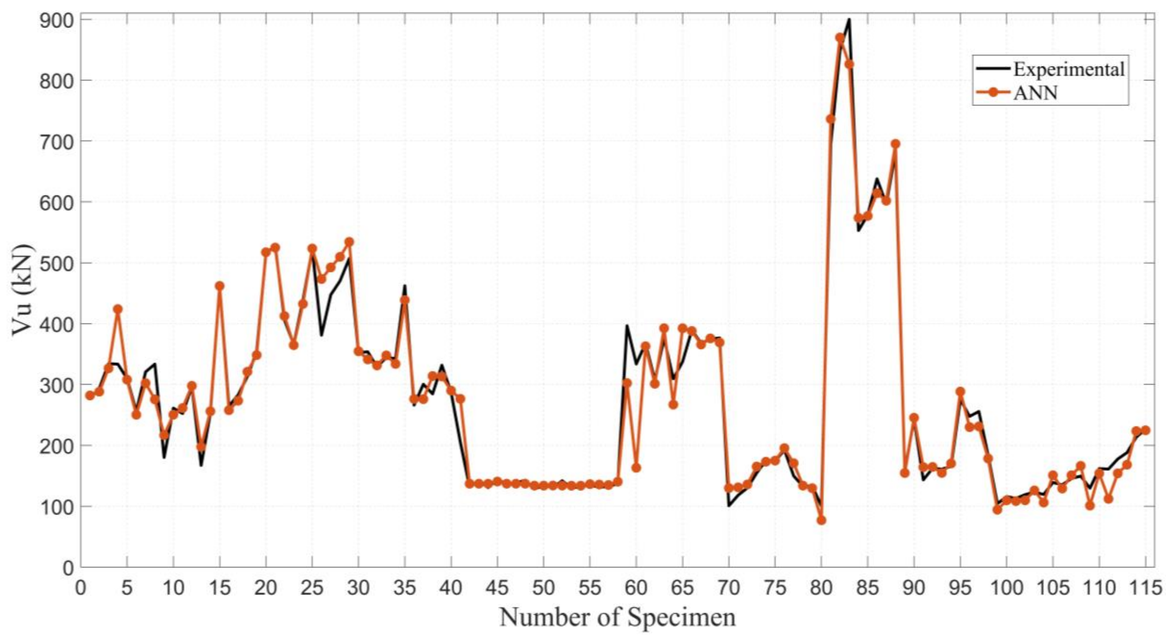


**Fig. 6.** Verification of simulated results against experimental data.

## 3.1. Analyze the sensitivity of the input parameters

Analysis based on weight values is based exclusively on the values stored in the static weight matrix to determine the relative effect of each input data on the network output data. Different equations based on weights are presented. One of the most practical equations is the Milne equation [48]. This relationship is calculated by multiplying the weights (the binding weight between the input neurons i and the hidden neuron j) and (the binding weight between the hidden neurons j and the output neuron o) for each of the hidden neurons in the network as a sum of the product of the multiplication Calculated is obtained.

$$Q_{ik} = \frac{\sum_{j=1}^{nhidden} \frac{w_{ji}}{\sum_{l=1}^{ninputs} \left| w_{jl} \right|} . w_{oj}}{\sum_{k=1}^{ninputs} \left( \sum_{j=1}^{nhidden} \left| \frac{w_{jk}}{\sum_{l=1}^{ninputs} \left| w_{jl} \right|} . w_{oj} \right| \right)} \tag{7}$$

In this equation, the sum of the binding weights between the input N neurons and the secret neurons J is the percentage effect of the input variable $xi$ on the output variable $y_k$. Using this method, the correct ratios are obtained for both positive and negative weights. $iw\{1,1\}$ is the weight of input parameters and $iw\{2,1\}$ is output weight.

$$iw\{1,1\} = \begin{bmatrix} 0.79885 & 0.12435 & -0.88989 & 0.43893 & 0.65011 & -0.27492 & -0.22946 & -0.17556 & 0.40568 \\ 0.99454 & -0.37775 & -0.39734 & -0.14325 & 0.87554 & 0.55015 & 0.54764 & 0.82895 & 0.32065 \\ 0.7547 & -10.498 & 0.032505 & -0.8866 & -0.58447 & 0.88062 & -0.14563 & -0.37414 & 0.24926 \\ 0.87775 & -0.87573 & -0.40707 & -0.53337 & -0.2338 & -0.78567 & -0.769 & -0.74279 & 0.6787 \\ 0.32597 & 0.2068 & -0.39117 & -12.131 & -0.59391 & 0.43096 & -0.90942 & -0.95974 & -0.82035 \\ -0.90588 & -0.35627 & 10.366 & -0.2838 & 0.59622 & -0.73981 & -0.06647 & -0.90269 & 0.26674 \\ 11.228 & 0.35428 & 0.56932 & -0.30063 & 0.4648 & 0.5889 & -0.42228 & -21.101 & -0.58737 \\ 1.157 & -0.01103 & 11.543 & 0.24323 & -0.90976 & -0.88903 & -0.56117 & 0.26536 & -12.421 \\ 17.773 & 0.17198 & 0.40958 & -0.36446 & -0.12192 & 0.96387 & -0.08667 & -0.68155 & -0.20183 \\ -0.49044 & 11.257 & -0.54069 & 10.109 & -0.50685 & 0.30483 & 0.64841 & 0.56148 & -0.17078 \\ 0.74626 & 0.16075 & -1.213 & -0.15769 & 10.108 & 0.59293 & -0.48722 & -0.37096 & 0.41962 \\ -0.95536 & -0.93659 & 0.21149 & 0.54539 & 0.37845 & 0.98596 & -0.06521 & 0.49552 & -0.02378 \end{bmatrix}$$

$$iw\{2,1\} = \begin{bmatrix} 0.064911 & 0.14974 & 0.035279 & -0.62772 & -0.29496 & 0.58922 & -0.73306 & 0.418 & 0.86226 & 0.29803 & 0.91698 & -0.56587 \end{bmatrix}$$

As shown in Fig. 7, the results of the sensitivity analysis show that $t$ has the highest impact percentage and $(F_c')$ has the least impact percentage on the target function.

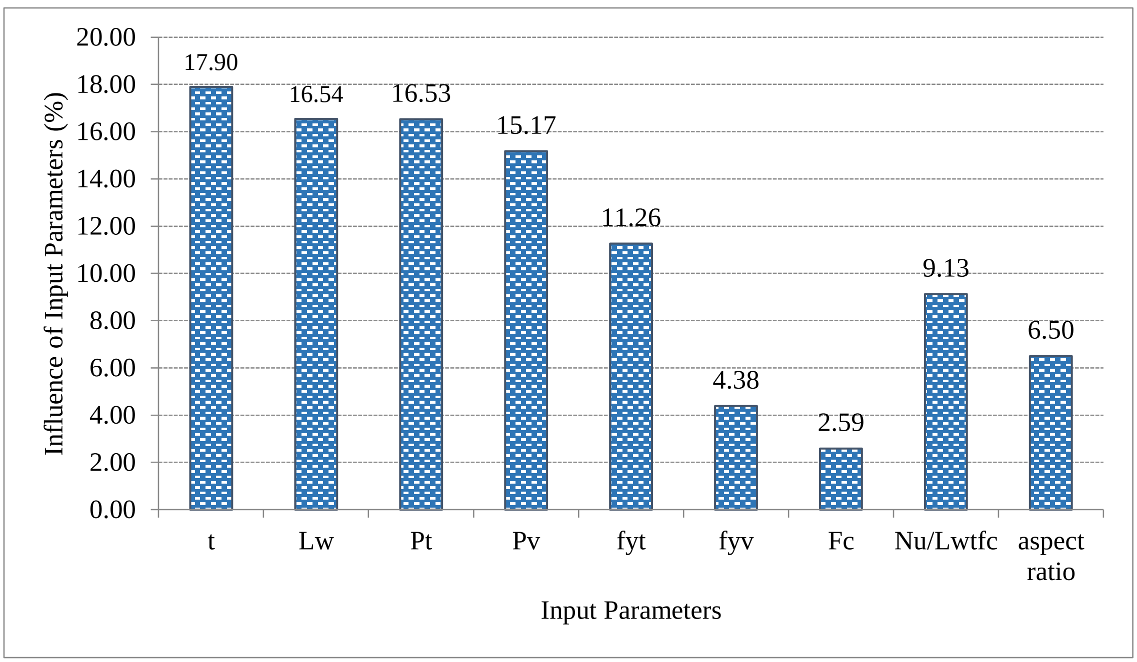


**Fig. 7.** The results of the sensitivity analysis.

# 4. Neural network-based group method of data handling (GMDH-NN)

The Group Method of Data Handling (GMDH) based on the principle of heuristic self-organizing and automatic optimization of mules was proposed by Ivakhnenko in 1971 [49].

The GMDH-NN method contains a set of neurons generated by a quadratic polynomial. By combining quadratic polynomials from all neurons, the network describes the approximate function $(\hat{f})$ with output $(\hat{y})$ and for a set of inputs $x = \{x_1, x_2, x_3, \ldots\}$ with the least error compared to the actual output, so the dataset which contains $M$ data and includes $n$ inputs (i.e. in this paper 9 parameters) and one output (i.e. the shear strength of reinforced concrete wall) the actual results are displayed as follows:

$$y_i = f(x_{i,1}, x_{i,2}, x_{i,3}, ..., x_{i,n})_{(i\ =\ 1,\ 2,\ ...,\ M)} \tag{8}$$

Which the prediction with GMDH-NN is $\hat{y}$ for each set of input $x$, so:

$$\hat{y}_i = \hat{f}(x_{i,1}, x_{i,2}, x_{i,3}, ..., x_{i,n})_{(i\ =\ 1,\ 2,\ ...,\ M)} \tag{9}$$

The GMDH-NN method objective function would be to minimize the error square between the actual outputs and the prediction:

$$\sum_{i=1}^{M} (\hat{y}_i - y_i)^2 \to \min \tag{10}$$

The relationship between input and output variables can be expressed using the polynomial function as follows:

$$\hat{y}_i = a_0 + \sum_{i=1}^{n} a_1 x_i + \sum_{i=1}^{n}\sum_{j=1}^{n} a_{ij} x_i x_j + \sum_{i=1}^{n}\sum_{j=1}^{n}\sum_{k=1}^{n} a_{ijk} x_i x_j x_k + ... \tag{11}$$

Which is commonly known as Kolmogorov-Gober polynomial. The quadratic form and the two variables of this polynomial are used as follows

$$\hat{y}_i = G(x_i, x_j) = a_0 + a_1 x_i + a_2 x_j + a_3 x_i x_j + a_4 x_i^{\ 2} + a_5 x_j^{\ 2} \tag{12}$$

The unknown coefficients $(a_i)$ Eq. (9) is determined by regression techniques such that the difference between the actual output, $(y)$, and the calculated values $(\hat{y})$ are minimized for each pair of input variables $(x_i, x_j)$. A set of polynomials is constructed using Eq. (9), the unknown coefficients of all of which are obtained using the square squares method. For each function $(G_i)$ (constructed neurons) the coefficients are obtained to quantify the total error of the neurons to optimally match the inputs of all pairs of output-input sets.

$$E = \frac{\sum_{i=1}^{M} (\hat{y}_i - y_i)^2}{M} \to \min \tag{13}$$

In the basic methods of the GMDH algorithm, all binary compounds (neurons) are made of $n$ input variable, and the unknown coefficients of all neurons are obtained using the least-squares method. Thus:

$$\binom{n}{2} = \frac{n(n-1)}{2} \tag{14}$$

The neurons in the second layer are made up of the following sets:

$$\{(y_i, x_{ip}, x_{iq}) | (i = 1, 2, ..., M) \ \& \ p, q \in (1, 2, ..., M)\} \tag{15}$$

By using the quadratic form of the function expressed in Eq. (9) for each $M$ of the triple row. These equations can be expressed in the form of the following matrix:

$$A\mathbf{a} = Y \tag{16}$$

In this equation, $A$ is the vector of the unknown coefficients of the quadratic equation shown in Eq. (9), i.e.:

$$\begin{aligned} &\mathbf{a} = \{a_1, a_2, a_3, ..., a_n\} \\ &Y = \{y_1, y_2, y_3, ..., y_M\}^T \end{aligned} \tag{17}$$

And:

$$A = \begin{bmatrix} 1 & x_{1p} & x_{1q} & x_{1p}x_{1q} & x_{1p}^2 & x_{1q}^2 \\ 1 & x_{2p} & x_{2q} & x_{2p}x_{2q} & x_{2p}^2 & x_{2q}^2 \\ \dots & \dots & \dots & \dots & \dots & \dots \\ 1 & x_{Mp} & x_{Mq} & x_{Mp}x_{Mq} & x_{Mp}^2 & x_{Mq}^2 \end{bmatrix} \tag{18}$$

The least-squares method of multiple regression analysis solves the equations as follows:

$$\mathbf{a} = (A^T A)^{-1} A^T Y \tag{19}$$

This vector equation gives the coefficients of Eq. (9) for all $M$ sets of three. In this method, (the direct solution is SNE) probability of error due to rounding errors and the possibility of singularity in equations may be occurred [50,51].

### 4.1. Predict shear strength of shear walls using GMDH-NN algorithm: *proposed method*

For trying to analyze the dimension of network input parameters using the results of the neural network using the 9-variable mathematical model simplification approach as the GMDH-NN. Variables are selective; these 9-variables are the combination of the previous neural network inputs with arbitrary dies and do not necessarily represent the contribution of each section to the shear wall shear capacity. The 9-variables and model presentation for them are as follows and the results of the prediction using these equations are presented in Fig. 8:

$$Y_1 = -0.0549316 + 0.302178 f_{yv} - 0.28247 f_{yv}{}^2 + 0.97383 N_2 \tag{20}$$

$$\begin{aligned} &N_2 = 0.012 + 1.28N_4 + 3.06N_3N_4 - 2.99N_4{}^2 - 0.34N_3 \\ &N_3 = 0.062 + 1.01\rho_t N_4 - 0.16\rho_t{}^2 + 0.37N_4 + 0.24N_4{}^2 \\ &N_4 = -0.085 + 0.47 f_{yt} + 0.701 f_{yt} N_5 - 0.57 f_{yt}{}^2 + 0.64N_5 \\ &N_5 = -0.160 + 1.24t - 1.15t^2 + 0.93N_6 \\ &N_6 = -0.027 + 0.408L_w - 0.176L_w F_c + 0.367L_w{}^2 + 0.527F_c \end{aligned} \tag{21}$$

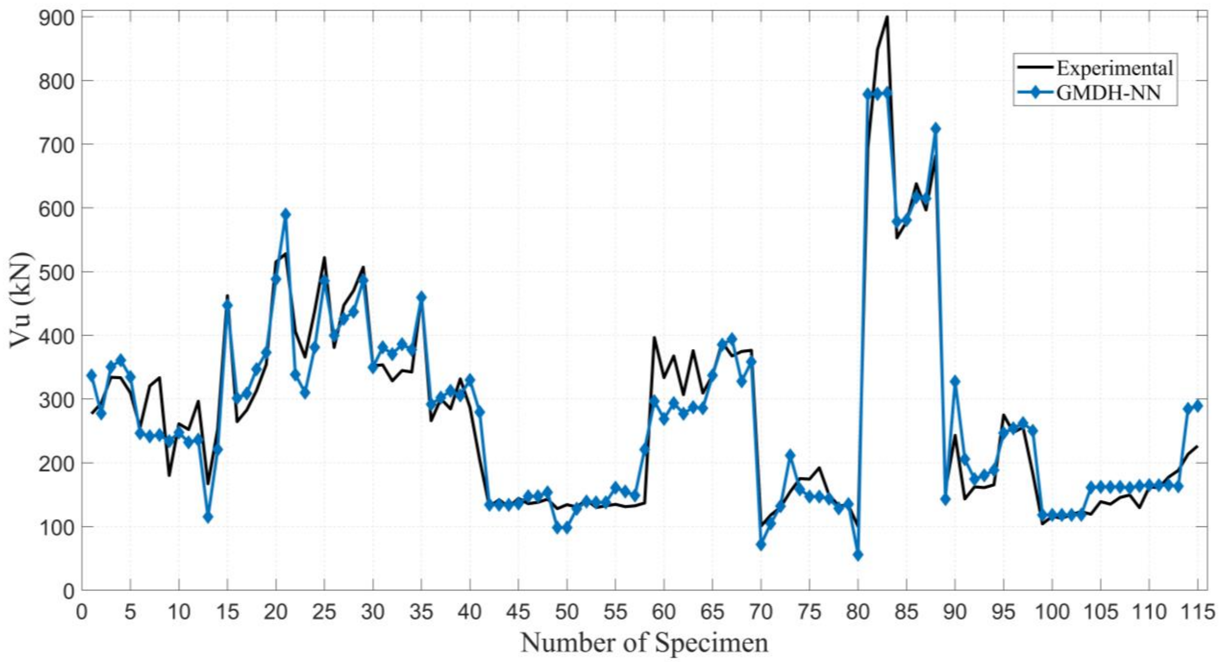


**Fig. 8.** Verification of simulated results against experimental data.

As shown in Fig. 8, the shear strength of reinforced concrete shear wall prediction with the GMDH algorithm has acceptable with an absolute error of 12.54%.

## 5. Gene expression programming (GEP)

Gene Expression Programming (GEP) is a developed genetic algorithm and genetic programming that was proposed by Ferreira in 2001 [52]. This algorithm, like genetic algorithm and genetic programming, first, randomly or algorithmically, several solutions for the problem generate. This set of answers is called the primitive population. Each answer is called a chromosome. Then, using the genetic algorithm operators, after choosing the best chromosomes, the chromosomes combined and make a jump in them. Finally, the current population with the new population that results from the combination and mutation in the chromosomes, combined. Steps for designing and implementing the GEP algorithm for resilience:

- Definition of the fitness function
- Definition of terminals and functions
- Determine the structure of chromosomes (number in genus, length of genes, and their number)
- Determining the Linking Function
- Determine the characteristics of the operators and finally implement the algorithm

The flowchart of the GEP's algorithm is based on Ferreira's opinion as follows:

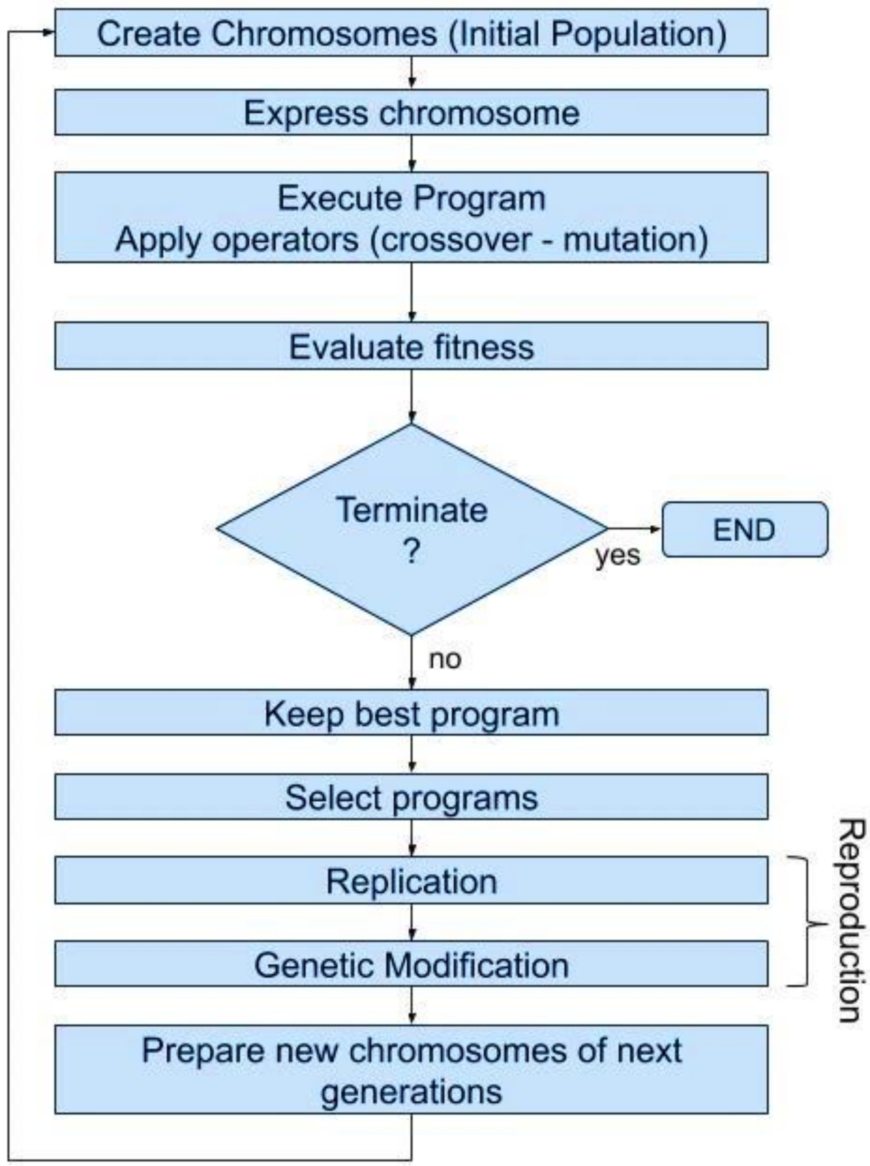


**Fig. 9.** The flowchart of the GEP's algorithm.

## 5.1. Predict shear strength of shear walls using GEP algorithm: *proposed method*

Table 4 is the GEP parameters that were used for estimating the shear strength of reinforced concrete Shear Walls. Fig. 10 shows the output of the GEP software, which shows the comparison between the experimental model and the model obtained from the software. The data taken in the software is considered to be 70 to 30.


**Fig. 10.** The output of the GEP.

**Table 4**
GEP parameters were used for estimating the shear strength of concrete Shear Walls.

| Parameter | Value |
|---|---|
| Head Size | 8 |
| Chromosomes | 25-35 |
| Number of genes | 3 |
| Mutation Rate | 0.045 |
| Inversion Rate | 0.1 |
| Rate One-Point Recombination | 0.3 |
| Rate Tow-Point Recombination | 0.3 |
| Gene Recombination Rate | 0.1 |
| IS Transposition Rate | 0.1 |
| RIS Transposition Rate | 0.1 |
| Gene Transposition Rate | 0.1 |
| Fitness Function Error Type | RMSE |
| Linking Function | Addition (+) |

Finally, the governing equation and its parameters for predicting the shear strength of reinforced concrete shear walls are as follows:

$$V_u = \sin\left(L_w\sqrt{\sin t}\right) + f_{yt}\left(\rho_t + \left(\rho_t \times f_c'^2 \times \rho_v\right)\right) + L_w\left(\sqrt{\rho_t} \times \left(f_{yt} + N_u / L_w f_c' t\right)\right) \tag{22}$$

## 6. Comparison and results

In this section, in order to evaluate the accuracy and efficiency of the model made by the Neural Network, GMDH-NN, and GEP to predict the shear strength, comparison of the results obtained from the models with the results obtained from the relationships of the valid ACI318 design code are presented. As can be obtained, an average absolute error of prediction for ANN, GMDH-NN, GEP, and ACI is 6.39%, 12.54%, 12.27%, and 22.19% respectively. It should be mentioned that the far difference between experimental and ACI318 design code results are generated due to code design reliability factor for safety and uncertainty.

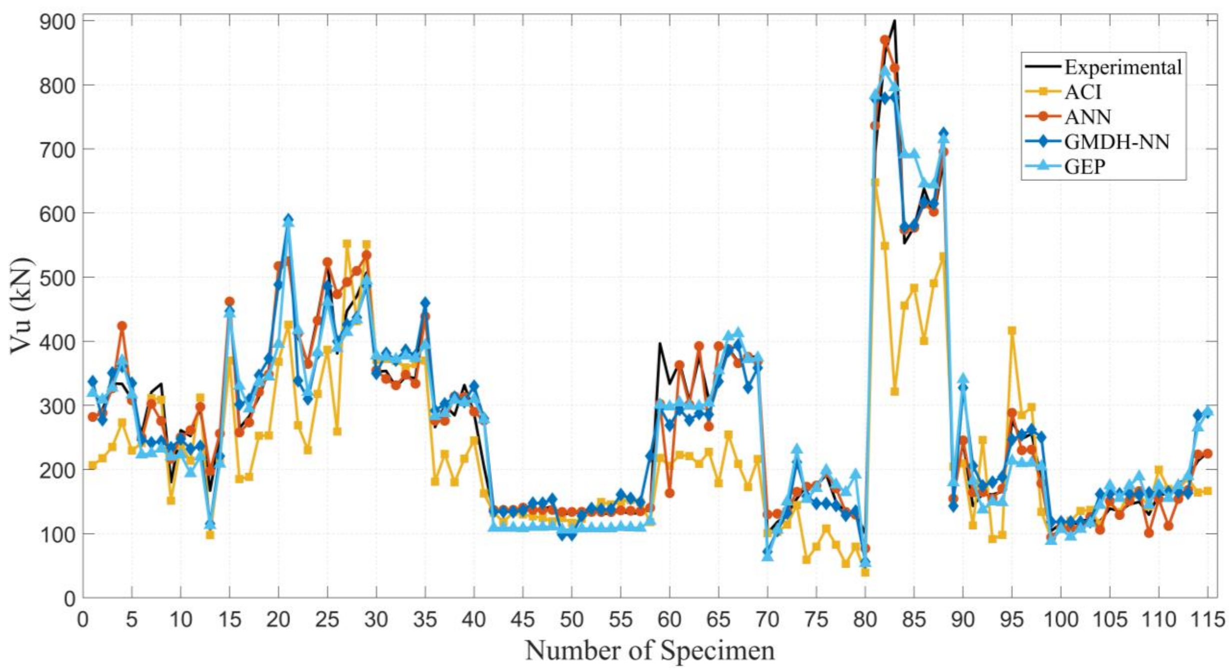


**Fig. 11.** Comparison of Experimental and ACI results with ANN, GEP, and GMDH-NN.

## 7. Conclusion

In this paper, the shear strength of the reinforced concrete shear wall is determined using artificial intelligence-based algorithms, including artificial neural network (ANN), group method of data handling (GMDH) neural network, and evolutionary algorithm gene expression programming (GEP). Determining the shear strength of the reinforced concrete shear wall is a very vital issue from both economic and technical aspects because the behavior of the reinforced concrete wall can be better predicted by accurately predicting its shear capacity. Parameters affecting the shear capacity of reinforced concrete shear wall based on information collected from 115 laboratory samples available in scientific articles including aspect ratio, concrete shear wall thickness, concrete shear wall length, the ratio of transverse and vertical reinforcement, yield strength of transverse and vertical reinforcement, axial load and compressive strength of concrete. Comparison of the results predicted by ANN, GMDH-NN, and GEP with laboratory results shows high accuracy and very low data error.

A comparison was made between the methods used in this study and according to the relevant graphs, the result indicates that the model is the closest to the laboratory results of the artificial neural network and has an error rate of 6.3 percent.

- The Artificial Neural Network predicts the shear capacity of the concrete shear wall by method with an average absolute error of 6.39% and a correlation coefficient of 0.97.
- The equation presented by the GMDH-NN algorithm showed a good mapping of the shear capacity of concrete shear wall and with an average absolute error of 12.54% showed an acceptable prediction of the shear capacity of concrete shear wall.
- The equation presented by the GEP algorithm with the mean absolute error of 12.27% has shown an acceptable prediction of the shear capacity of the concrete shear wall.
- The equation provided by the ACI regulation with an average absolute error of 22.19% has shown a large error concerning the relationships proposed by computational intelligence algorithms the shear capacity of the concrete shear wall.

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## Conflicts of interest

The authors declare no conflict of interest.

# Appendix A. Details of shear wall dataset

**Table A1**
Experimental data that affect the shear strength of shear walls.

| Reference | Year | $t$ | $L_w$ | $\rho_v$ | $\rho_t$ | $f_{yv}$ | $f_{yt}$ | $f_c'$ | $N_u/l_w t_f$ | $a_w$ | $V_u$ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Oesterle et al. [41] | 1984 | 10.2 | 190.5 | 1.37 | 0.63 | 444.4 | 444.4 | 45.3 | 0.000 | 2.40 | 761.3 |
| | | 10.2 | 190.5 | 1.37 | 0.63 | 440.9 | 440.9 | 21.8 | 0.022 | 2.40 | 824.4 |
| | | 10.2 | 190.5 | 1.37 | 0.63 | 458.2 | 458.2 | 49.4 | 0.012 | 2.40 | 979.6 |
| | | 10.2 | 190.5 | 1.37 | 1.38 | 447.8 | 447.8 | 42 | 0.015 | 2.40 | 976.9 |
| | | 10.2 | 190.5 | 1.25 | 0.63 | 430.6 | 430.6 | 45.6 | 0.013 | 2.40 | 886.7 |
| Maier and Thurliama [42] | 1985 | 10 | 118 | 1.16 | 1.03 | 574 | 574 | 36.9 | 0.010 | 1.02 | 680 |
| | | 10 | 118 | 1.16 | 1.03 | 574 | 574 | 35.4 | 0.040 | 1.02 | 928 |
| | | 10 | 118 | 2.46 | 1.03 | 530 | 574 | 36.7 | 0.010 | 1.02 | 977 |
| | | 10 | 118 | 1.05 | 1.03 | 574 | 574 | 32.9 | 0.007 | 1.02 | 392 |
| | | 10 | 118 | 1.16 | 1.03 | 574 | 574 | 37.3 | 0.009 | 1.02 | 701 |
| | | 10 | 118 | 1.13 | 0.57 | 479 | 537 | 35.6 | 0.010 | 1.02 | 667 |
| | | 10 | 118 | 1.13 | 1.01 | 555 | 555 | 34.1 | 0.041 | 1.02 | 836 |
| Kabeasawa et al. [43] | 1993 | 10 | 118 | 0.98 | 0 | 560 | 0 | 29.2 | 0.008 | 1.02 | 342 |
| | | 10 | 118 | 2 | 0.98 | 496 | 496 | 31 | 0.007 | 1.02 | 670 |
| | | 8 | 170 | 0.84 | 0.53 | 1187 | 1001 | 93.6 | 0.014 | 1.76 | 1468 |
| | | 8 | 170 | 0.65 | 0.25 | 848 | 1001 | 55.5 | 0.023 | 1.18 | 714 |
| | | 8 | 170 | 0.88 | 0.25 | 593 | 753 | 54.6 | 0.018 | 1.76 | 784 |
| | | 8 | 170 | 1.07 | 0.49 | 593 | 753 | 60.3 | 0.019 | 1.76 | 900 |
| | | 8 | 170 | 1.15 | 0.49 | 1187 | 753 | 65.2 | 0.015 | 1.76 | 1056 |
| | | 8 | 170 | 0.84 | 0.53 | 1187 | 753 | 103.3 | 0.011 | 1.76 | 1670 |
| | | 8 | 170 | 0.84 | 0.53 | 848 | 1079 | 137.5 | 0.009 | 1.18 | 1719 |
| | | 8 | 170 | 1.42 | 0.35 | 848 | 1079 | 70.8 | 0.024 | 1.18 | 1254 |
| | | 8 | 170 | 1.34 | 0.21 | 339 | 792 | 65.1 | 0.018 | 1.18 | 1100 |
| | | 8 | 170 | 1.54 | 0.53 | 565 | 792 | 71.8 | 0.016 | 1.18 | 1378 |
| | | 8 | 170 | 1.54 | 0.53 | 848 | 792 | 103.4 | 0.011 | 1.18 | 1696 |
| | | 8 | 170 | 1.54 | 0.49 | 848 | 792 | 76.7 | 0.025 | 1.18 | 1158 |
| | | 8 | 170 | 1.69 | 0.72 | 1187 | 792 | 74.1 | 0.016 | 1.18 | 1411 |
| | | 8 | 170 | 1.84 | 0.92 | 1158 | 792 | 71.5 | 0.016 | 1.18 | 1498 |
| | | 8 | 170 | 2.17 | 1.34 | 1469 | 792 | 76.1 | 0.015 | 1.18 | 1639 |
| | | 8 | 170 | 1 | 0.74 | 2147 | 810 | 62.6 | 0.018 | 1.18 | 1049 |
| | | 8 | 170 | 1 | 0.74 | 1187 | 810 | 60.8 | 0.021 | 1.18 | 1054 |
| | | 8 | 170 | 1 | 0.74 | 1187 | 810 | 57.7 | 0.024 | 1.18 | 958 |
| | | 8 | 170 | 1 | 0.74 | 1187 | 810 | 62.2 | 0.022 | 1.18 | 1020 |
| | | 8 | 170 | 1 | 0.74 | 1187 | 810 | 59.7 | 0.018 | 1.18 | 1011 |
| | | 8 | 170 | 0.84 | 0.53 | 1187 | 810 | 93.6 | 0.013 | 1.18 | 1468 |
| Gupta [9] | 1996 | 75 | 100 | 1.06 | 0.52 | 545 | 578 | 65.1 | 0.001 | 1 | 719.6 |
| | | 75 | 100 | 1.06 | 0.52 | 545 | 578 | 69 | 0.002 | 1 | 850.7 |
| | | 75 | 100 | 1.61 | 0.52 | 533.2 | 578 | 73.1 | 0.001 | 1 | 790.2 |
| | | 75 | 100 | 1.61 | 0.52 | 533.2 | 578 | 70.5 | 0.002 | 1 | 970 |
| | | 75 | 100 | 1.06 | 1.06 | 545 | 545 | 71.2 | 0.001 | 1 | 800 |
| | | 75 | 100 | 1.06 | 0.52 | 545 | 578 | 60.5 | 0.001 | 1 | 486.6 |
| Dabbagh [10] | 2005 | 10.2 | 190.5 | 0.96 | 0.48 | 527.9 | 496.1 | 23.5 | 0.000 | 1 | 884.8 |
| | | 75 | 100 | 2.52 | 0.45 | 536 | 536 | 86 | 0.002 | 1 | 992 |
| | | 75 | 100 | 3.22 | 1.34 | 498 | 498 | 86 | 0.002 | 1 | 1190 |
| | | 75 | 100 | 2.82 | 0.75 | 498 | 536 | 96 | 0.002 | 1 | 1107 |
| | | 75 | 100 | 3.22 | 0.45 | 498 | 536 | 83 | 0.002 | 1 | 1134 |
| | | 75 | 100 | 2.95 | 0.94 | 498 | 498 | 83 | 0.002 | 1 | 1141 |
| Barda et al. [44] | 1993 | 10.2 | 190.5 | 0.73 | 0.44 | 543 | 496.1 | 29 | 0.000 | 0.50 | 1217.3 |
| | | 10.2 | 190.5 | 0.26 | 0.44 | 552 | 499.6 | 16.4 | 0.000 | 0.50 | 977.6 |
| | | 10.2 | 190.5 | 0.97 | 0.44 | 545.1 | 513.4 | 27 | 0.000 | 0.50 | 1107.2 |
| | | 10.2 | 190.5 | 0.75 | 0.44 | 496.8 | 496.8 | 21.3 | 0.000 | 0.50 | 875.6 |
| | | 10.2 | 190.5 | 0.96 | 0.41 | 531.3 | 501.6 | 25.7 | 0.000 | 0.25 | 1138.6 |
| Benjamin and Williams [45] | 1957 | 5 | 61 | 0.5 | 0.5 | 359 | 359 | 20.1 | 0.000 | 0.92 | 89 |
| | | 5 | 91 | 0.5 | 0.5 | 359 | 359 | 21.5 | 0.000 | 0.62 | 155 |
| | | 5 | 122 | 0.5 | 0.5 | 359 | 359 | 19.5 | 0.000 | 0.46 | 201 |
| | | 5 | 178 | 0.5 | 0.5 | 359 | 359 | 26.4 | 0.000 | 0.31 | 294 |

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Yamada et al. [46] | 1974 | 4 | 133 | 0.31 | 0.31 | 286 | 286 | 35.6 | 0.186 | 0.45 | 373 |
| | | 4 | 133 | 0.63 | 0.63 | 286 | 286 | 30.4 | 0.201 | 0.45 | 370 |
| | | 4 | 133 | 1.26 | 1.26 | 286 | 286 | 31.5 | 0.218 | 0.45 | 438 |
| | | 3 | 133 | 0.84 | 0.84 | 286 | 286 | 32.8 | 0.221 | 0.45 | 276 |
| | | 2 | 133 | 0.63 | 0.63 | 286 | 286 | 30.1 | 0.305 | 0.45 | 211 |
| | | 2 | 133 | 1.26 | 1.26 | 286 | 286 | 33.7 | 0.293 | 0.45 | 213 |
| | | 3 | 60 | 0.23 | 0.21 | 293 | 293 | 25.7 | 0.271 | 1.17 | 86 |
| Hwang et al. [8] | 2001 | 12 | 396 | 0.66 | 0.66 | 572 | 572 | 20.6 | 0.120 | 0.45 | 2354 |
| | | 12 | 396 | 0.66 | 0.66 | 572 | 572 | 20.8 | 0.228 | 0.45 | 2942 |
| | | 12 | 396 | 0.66 | 0.66 | 572 | 572 | 21.3 | 0.155 | 0.45 | 3138 |
| | | 12 | 396 | 0.33 | 0.33 | 572 | 572 | 19.6 | 0.097 | 0.45 | 1814 |
| | | 12 | 396 | 0.33 | 0.33 | 572 | 572 | 20.8 | 0.097 | 0.45 | 1912 |
| | | 12 | 396 | 0.69 | 0.66 | 284 | 284 | 20.5 | 0.110 | 0.45 | 2138 |
| | | 12 | 396 | 0.69 | 0.66 | 284 | 284 | 19.6 | 0.106 | 0.45 | 1981 |
| | | 12 | 396 | 0.77 | 0.74 | 397 | 397 | 20.9 | 0.116 | 0.45 | 2305 |
| Chen et al. [19] | 2018 | 7.62 | 190.5 | 0 | 0 | 0 | 0 | 40.3 | 0.000 | 1 | 305.6 |
| | | 7.62 | 190.5 | 2.87 | 0.93 | 448 | 455 | 43.6 | 0.000 | 1 | 632.1 |
| | | 10 | 120 | 0.28 | 0.28 | 610 | 610 | 23.9 | 0.070 | 1 | 251.3 |
| | | 12 | 100 | 0.25 | 0.38 | 407 | 415 | 20.3 | 0.000 | 2 | 323.8 |
| | | 16 | 85.1 | 0.4 | 1.08 | 407 | 415 | 17.8 | 0.110 | 1.88 | 318.9 |
| | | 16 | 85.1 | 0.4 | 1.08 | 407 | 415 | 20.8 | 0.094 | 1.88 | 335.8 |
| | | 15.2 | 137.1 | 0.25 | 0.27 | 424 | 424 | 28.3 | 0.100 | 0.89 | 754 |
| | | 15.2 | 137.1 | 0.25 | 0.27 | 424 | 424 | 31.9 | 0.050 | 0.89 | 649.5 |
| | | 15.2 | 137.1 | 0.25 | 0.27 | 424 | 424 | 36 | 0.050 | 0.89 | 680 |
| | | 8 | 191 | 0.94 | 0.27 | 448 | 414 | 43 | 0.000 | 1.08 | 519 |
| | | 8 | 191 | 2.93 | 0.27 | 448 | 465 | 42.5 | 0.000 | 1.08 | 569 |
| Hirosawa [39] | 1975 | 15.2 | 137.1 | 0.25 | 0.27 | 424 | 424 | 30 | 0.000 | 0.89 | 404.8 |
| | | 6 | 80 | 0.22 | 0.23 | 433 | 433 | 23.5 | 0.000 | 1.075 | 102 |
| | | 6 | 80 | 0.73 | 0.82 | 433 | 433 | 23.5 | 0.000 | 1.075 | 147 |
| | | 6 | 80 | 0.44 | 0.41 | 433 | 433 | 23.5 | 0.000 | 1.075 | 135 |
| | | 6 | 80 | 0.73 | 0.82 | 433 | 433 | 23.5 | 0.000 | 1.075 | 159 |
| | | 6 | 80 | 1.17 | 1.17 | 433 | 433 | 23.5 | 0.000 | 1.075 | 175 |
| | | 6 | 120 | 0.24 | 0.23 | 433 | 433 | 24.5 | 0.000 | 0.72 | 160 |
| | | 6 | 120 | 0.78 | 0.82 | 433 | 433 | 24.5 | 0.000 | 0.72 | 235 |
| | | 6 | 120 | 0.44 | 0.41 | 433 | 433 | 24.5 | 0.000 | 0.72 | 220 |
| | | 6 | 120 | 0.78 | 0.82 | 433 | 433 | 24.5 | 0.000 | 0.72 | 260 |
| | | 6 | 120 | 1.17 | 1.17 | 433 | 433 | 24.5 | 0.000 | 0.72 | 275 |
| | | 6 | 120 | 0.22 | 0.23 | 433 | 433 | 25.5 | 0.000 | 0.72 | 199 |
| | | 6 | 120 | 0.8 | 0.82 | 433 | 433 | 25.5 | 0.000 | 0.72 | 322 |
| | | 6 | 120 | 0.36 | 0.41 | 433 | 433 | 25.5 | 0.000 | 0.72 | 319 |
| | | 6 | 120 | 0.8 | 0.82 | 433 | 433 | 25.5 | 0.000 | 0.72 | 382 |
| | | 6 | 120 | 1.17 | 1.17 | 433 | 433 | 25.5 | 0.000 | 0.72 | 422 |
| Mo and Shiau [40] | 1995 | 7 | 86 | 0.72 | 0.81 | 302 | 302 | 32.2 | 0.001 | 0.76 | 205 |
| | | 7 | 86 | 0.72 | 0.81 | 302 | 302 | 32.2 | 0.001 | 0.76 | 247 |
| | | 7 | 86 | 0.72 | 0.81 | 302 | 302 | 32.1 | 0.001 | 0.76 | 202 |
| | | 7 | 86 | 0.72 | 0.81 | 443 | 302 | 29.5 | 0.001 | 0.76 | 255 |
| | | 7 | 86 | 0.72 | 0.81 | 302 | 302 | 37.5 | 0.001 | 0.76 | 223 |
| | | 7 | 86 | 0.72 | 0.81 | 302 | 302 | 37.5 | 0.001 | 0.76 | 231 |
| | | 7 | 86 | 0.72 | 0.81 | 302 | 302 | 39.9 | 0.000 | 0.76 | 250 |
| | | 7 | 86 | 0.58 | 0.81 | 302 | 302 | 18 | 0.001 | 0.76 | 193 |
| | | 7 | 86 | 0.58 | 0.81 | 302 | 302 | 18 | 0.001 | 0.76 | 217 |
| | | 7 | 86 | 0.58 | 0.81 | 302 | 302 | 29.7 | 0.001 | 0.76 | 203 |
| | | 7 | 86 | 0.58 | 0.81 | 443 | 302 | 30.7 | 0.001 | 0.76 | 246 |
| | | 7 | 86 | 0.58 | 0.81 | 443 | 302 | 30.2 | 0.001 | 0.76 | 200 |
| | | 7 | 86 | 0.58 | 0.81 | 443 | 302 | 30.2 | 0.001 | 0.76 | 210 |
| | | 7 | 86 | 0.58 | 0.81 | 443 | 302 | 39.3 | 0.000 | 0.76 | 219 |
| | | 7 | 86 | 0.58 | 0.81 | 443 | 302 | 37 | 0.001 | 0.76 | 205 |
| | | 7 | 86 | 0.58 | 0.81 | 443 | 302 | 34.5 | 0.001 | 0.76 | 210 |
| | | 7 | 86 | 0.58 | 0.81 | 302 | 302 | 66 | 0.000 | 0.76 | 227 |

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