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Hybrid ECBO–ANN Algorithm for Shear Strength of Partially Grouted Masonry Walls

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Abstract

In recent years, artificial neural network (ANN) has become one of the popular and effective machine learning models, having a unique ability to handle very complex problems and the potential to predict accurate results without a defined algorithmic solution. However, the ANN structure and parameters are usually chosen by experience.

The behavior of Partially Grouted (PG) masonry shear walls is complex due to the inherent anisotropic properties of the masonry materials and the nonlinear interactions between mortar, blocks, grouted cells, non-grouted cells, and reinforcing steel.

In this study, the aim is to develop an artificial neural network model by combining the ECBO meta-heuristic algorithm with the artificial neural network structure to optimize the feed forward propagation network parameters for analyzing the shear strength of PG walls. A total of 255 test data on PG collected from the available literature were used to generate training and test data sets. Various validation criteria such as mean square error, root mean square error and correlation coefficient (R) are used to validate the models. In this study, the optimal number of neurons used in the hidden layer and also the optimal number of CBs required in the ECBO algorithm were obtained. The mathematical formulation of the optimized neural network model with the combination of meta-heuristic algorithm is also presented.

Keywords

Artificial Neural Network, metaheuristic algorithm, Feed Forward Backpropagation, ECBO algorithm, predicting shear strength of the PG

1 Introduction

An artificial neural network is a massively parallel computing model that mimics brain function. Similar to a biological model consisting of a large number of interconnected neurons, an ANN is composed of a large number of similarly connected computational elements called artificial neurons. Artificial neural networks have been widely used in complex nonlinear function mapping, image processing, pattern recognition and classification, etc. [1].

The common point of meta-heuristic optimization algorithms with artificial neural network is that the artificial neural network ends up with an optimization problem after designing its structure for training. Here, instead of gradient methods, one can use meta-heuristic optimization algorithms to determine the neural network weights.

In recent years, the power of the artificial neural networks has been increased by using a combination of different networks and metaheuristcs [2] to [9]. However, the application of different types of neural networks is different in each case.

In our recent research [8], it was found that the combination of ECBO meta-heuristic algorithm with feed-forward neural network had the best results compared to other combinations. Therefore, in this research, this combination was used to obtain the shear strength of the masonry shear wall. Of course, there are many other recent advanced applications of metaheuristcs algorithms such as [10–13].

Masonry is the oldest structural material that is still used for a wide variety of contemporary buildings. Masonry structures are generally classified as reinforced (RM) or unreinforced (URM), and RM is further classified as fully grouted (FG) or partially grouted (PG) (i.e., where Grout is placed only in cells containing reinforcing steel). Reinforced masonry accounts for about 10% of all low-rise construction in the United States. Partially grouted (PG) walls are preferred over FG walls due to ease and speed of construction and economy. The vast majority of reinforced masonry structures in the Midwestern and Eastern United States are partially grouted (PG) [14].

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Partially grouted (PG) concrete block shear walls are a common system to resist lateral forces in masonry structures. Unlike fully grouted (FG) masonry, PG walls are grouted only in locations where reinforcement bars are placed (vertically aligned cells with vertical flexural reinforcement and/or horizontal bond beams with shear reinforcement) [15] and [16].

The behavior of PG walls under shear loading is not yet well understood. Despite fundamental differences in behavior between FG and PG walls, currently available design equations are empirically formulated based on FG wall data and applies a reduction factor to PG walls to achieve safety levels comparable to FG walls [17].

The shear strength and behavior of PG walls is dependent on variables such as the wall geometry, level of axial load (increasing interlocking between masonry units in diagonal cracks), ratio of net/gross area, and distribution of horizontal (increasing ductility and energy dissipation) and vertical reinforcement (resisting shear loading at crack openings) [18] and [19].

This paper is organized as follows: In Section 2 an overview of the artificial neural networks is provided. Section 3 presents the enhanced colliding body optimization algorithm (ECBO). In Section 4, experimental database gathering is described. Section 5 consists of the quality assessment criteria and Section 6 is a discussion on the training. Section 7 provides the formulation of the proposed ECBO-ANN approach, and finally conclusions are derived in Section 8.

2 Overview of artificial neural networks

Artificial neural networks, which are one of the machine learning tools, are used for prediction, learning and classification inspired by the biological nervous system. These networks, like the human biological neural network, which is made of neurons to process information, are composed of subsets such as neurons. As shown in Fig. 1, the biological neural network includes various parts, including the nerve cell, Axon, dendrite and synapse. Artificial neural networks are artificial neurons that are replaced by the main body of the biological nerve cell, and dendrites and axons are the data input and output, respectively. Weights in artificial neural networks replace synapses in biological neural networks.

Artificial neural networks can contain one or more hidden layers. In fact, the network is a massive parallel system consisting of several elements processed by weighted links. Feed Forward and Feed Forward Back Propagation (FFBP) networks are the most popular ANNs [20].

Typically, a feed-forward backpropagation network such as MLP uses processing units that are placed in three types of input, hidden, and output layers. Each unit in a layer is connected to units in adjacent layers with an associated weight (connection strength). It is the adjustment of these weights that is done during network training, because network training involves repeatedly changing the weights between neurons until the output signal matches the target output within the desired minimum error. When training open feedforward networks, the studied data set is usually divided into a training set and a validation set. While the training set is used to train the network, the validation set is applied to check the error performance of the network. Finally, it is common to reserve a third set of cases (the test set) for external prediction to ensure that the results in the training and validation set are real and not artifacts of the training process.

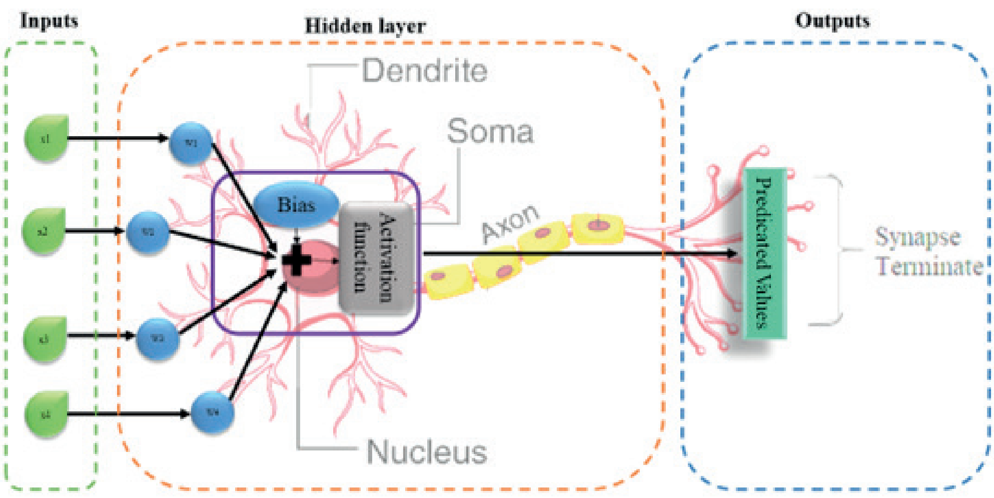

Fig. 1 The schematic imitation of the artificial and computational cell

In such feedforward backpropagation networks, connection weights are set to random values at the beginning of training. Descriptor values for all parameter sets under study are passed through the network (feed forward) and the output responses are compared with the target values of the input properties to obtain an error value. Then the weights are adjusted for the second pass of the data through the network to reduce the amount of error obtained. Since the adjustment of weights starts with the correction of the last layer and then continues backward to the first layer, this mode is called backpropagation [21]. This entire procedure is repeated iteratively to minimize the amount of error. Finally, a regression coefficient may be calculated between the observed product properties and the network predicted values. In general, feedforward backpropagation networks suffer from two potential problems: a) data overfitting in the presence of too many adjustable weights; and b) overtraining the network if there are too many training cycles. Considering these two problems, the number of adjustable weights plays an important role, which also affects the predictability of the final network. Finding the optimal network topology to achieve a balance between those two extreme situations is an important point in network learning [22].

3 Enhanced colliding body optimization algorithm (ECBO)

Colliding bodies optimization (CBO) is a new meta-heuristic search algorithm that in this technique, one object collides with other object and they move towards a minimum energy level. The meta-heuristic ECBO algorithm is actually an improvement of the CBO algorithm. It uses memory to store a number of historical best CBs and also uses a mechanism to escape from local optima [23]. One of the advantages of this algorithm is its simplicity, which does not depend on any internal parameters.

In our recent research [10], it was found that the combination of ECBO meta-heuristic algorithm with feed-forward neural network had the best results compared to other combinations. Therefore, in this research, this combination was used to obtain the shear strength of the masonry shear wall. Fig. 2 shows the schematic flowchart of the combination of neural network and ECBO algorithm.

In order to determine the structure of the artificial neural network, the feed-forward backpropagation model, which has a single input layer and one hidden layer with the tan-sigmoid activation function as it is shown in Eq. (1), and an output layer having linear activation function, is used.

$$Tangent\ Sigmoid = \frac{1}{1+e^{-x}} \quad (1)$$

4 Experimental database gathering

A comprehensive database is needed to use machine learning models. A database is actually a collection of input and output data in a system. In this research, the design parameters of the masonry shear wall are considered as input. In Table 1, the inputs are introduced along with their units. An experimental dataset totaling 255 PG masonry shear walls was compiled from 22 independent studies (Table 2) [24]. The collected samples are divided into 5

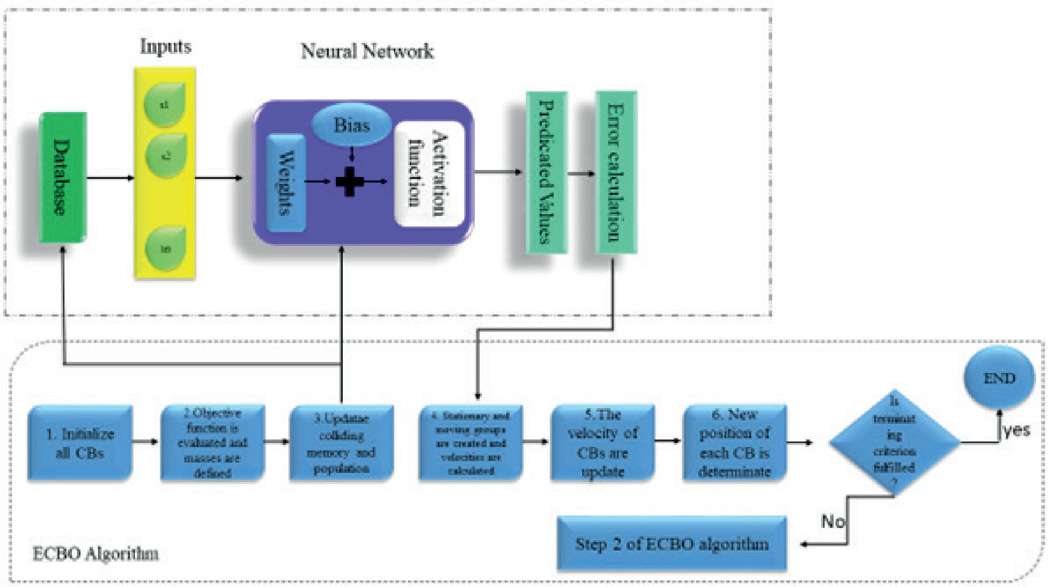

Fig. 2 The computation procedure of the ANN-ECBO

categories from A to E. This division is given in Table 3. The range of parameters used in ANN modeling is given in Table 4. All input and output variables in the database are normalized on a scale, following this formula:

$$Norm\ x_i = \left[\frac{x_i - \min(x)}{\max(x) - \min(x)} \times 2\right] - 1\,, \tag{2}$$

where x is the input or output variable to be normalized, x_i is its corresponding value, and $Norm\ x_i$ is the calculated value. The correlation matrix related to the data values is shown in Fig. 3.

Table 1 Input variables adopted in the study

Type	Num.	Symbol	Unit
wall geometry	1	A_{scaled}	mm^2
	2	M/VL	-
Partial grouting	3	A_{net}/A_{gross}	-
Masonry materials	4	$f'_{mcor,eff}$	MPa
Vertical reinforcement	5	$\rho_v f_{yv}$	MPa
Horizontal reinforcement	6	$\rho_h f_{yh}$	MPa
Axial stress	7	σ_{gross}	MPa
Experimental shear capacity	8	V_{avg}	kN

Table 2 Database collected in this study [24]

References	No. of samples	Proportion%
Scrivener, 1967	12	5
Mayes et al., 1976	2	1
Chen et al. (1978) / Hidalgo, 1978	4	1.5
Thurston and Hutchison, 1982	3	1
Matsumura, 1987	29	11
Tomaževic and Lutman, 1988	10	4
Johal and Anderson, 1988	16	6
Ghanem et al., (1992	4	1.5
Schultz, 1996	6	2.5
Schultz et al., 1998	6	2.5
Voon and Ingham, 2006	2	1
Haach et al., 2007	4	1.5
Maleki et al., 2009	5	2
Elmapruk, 2010	6	2.5
Minaie et al., 2010	4	1.5
Baenziger and Porter, 2011	8	3
Nolph et al., 2012	5	2
Oan, 2013	66	26
Hoque, 2013	18	7
Hamedzadeh, 2013	21	8
Rizaee, 2015	14	5.5
Ramirez et al., 2016	10	4
	255	**100**

Table 3 PG dataset variations for neural network analysis

Description	Dataset						
	complete	A	B	C	D	E	F
Number of specimens	255	255	150	150	120	120	120
Data synthetization	✦	✦	✦	✦	✦	✦	✦
Specimens without sufficient information to predict removed		✦	✦	✦	✦	✦	✦
Monotonic specimen removed			✦	✦	✦	✦	✦
ESECMaSE specimen removed					✦	✦	✦
Horizontal reinforcement modified				✦		✦	✦
Boundary vertical reinforcement neglected; only interior vertical bars considered							✦

The frequency distribution of the experimental data to express the parameters of the samples, including A_{scaled}, M/VL, A_{net}/A_{gross}, $f'_{m,eff,corrected}$, $\rho_v f_{yv}$, $\rho_h f_{yh}$, σ_{gross}, V_{avg} is shown in Fig. 4. As can be seen, the empirical data collected covers a wide range. Therefore, these parameters can be suitable inputs for model development.

5 Quality assessment criteria

In this study, several quality evaluation criteria such as Mean Square Error (MSE), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Normalized Mean Absolute Error (NMAE), Normalized Root Mean Square Error (NRMSE), correlation coefficient (R) were used to evaluate and compare the models. The following equations show the formulation of these criteria:

$$RMSE = \sqrt{\sum_{i=1}^{N} \left(z_0 - z_p\right)^2 / N}\,, \tag{3}$$

$$R = \sqrt{1 - \frac{\sum_{i=1}^{N} \left(z_0 - z_p\right)^2}{\sum_{i=1}^{N} (z_0 - \bar{z}_i^2}}\,, \tag{4}$$

$$MAE = \frac{1}{N} \sum_{i=1}^{N} \left|z_0 - z_p\right|, \tag{5}$$

$$MSE = \frac{1}{N} \sum_{i=1}^{N} \left|z_0 - z_p\right|^2, \tag{6}$$

Table 4 Range of parameters used in ANN modelling

Input	Variable	Minimum value	Maximum value	mean	StD	SKewness
Input 1	A_{scaled} [m^2]	0.66	19.42	3.686	2.883	1.992
Input 2	M/VL	0.25	2.30	0.739	0.320	1.881
Input 3	A_{net}/A_{gross}	0.36	0.81	0.611	0.095	-0.594
Input 4	$f'_{m,eff,corrected}$ [MPa]	4.30	22.30	12.448	3.830	0.221
Input 5	$\rho_v f_{yv}$ [MPa]	0.00	4.82	1.149	1.029	0.993
Input 6	$\rho_h f_{yh}$ [MPa]	0.00	1.29	0.315	0.260	0.584
Input 7	σ_{gross} [MPa]	0.00	2.78	1.087	0.854	0.334
Input 8	V_{avg} [kN]	23.10	772.2	219.1	131.483	1.020

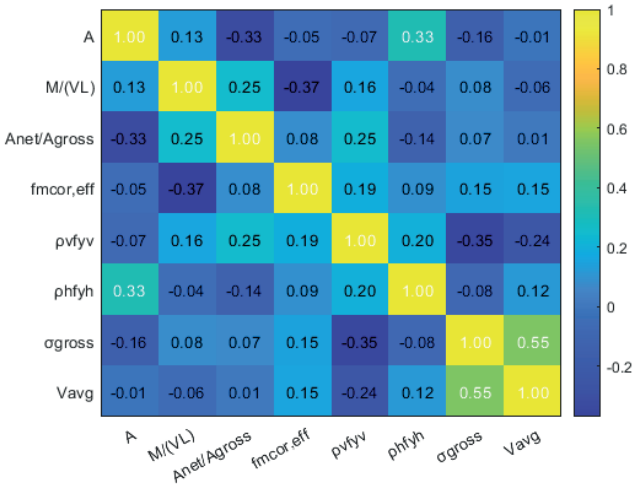

Fig. 3 Output correlation matrix

$$NMAE = \left[\frac{\frac{1}{N}\sum_{i=1}^{N} \left| z_0 - z_p \right|}{max\left(z_0\right) - min\left(z_0\right)} \right] \times 100 , \quad (7)$$

$$MAPE = \frac{1}{N} \left[\frac{\sum_{i=1}^{N} \left| z_0 - z_p \right|}{\sum_{i=1}^{N} \left| z_0 \right|} \right] \times 100 , \quad (8)$$

$$E = \left[\frac{\frac{1}{N}\sum_{i=1}^{N} \left| z_0 - z_p \right|^2}{max\left(z_0\right) - min\left(z_0\right)} \right] \times 100 , \quad (9)$$

where z_0 and z_p are actual measured values and corresponding model values, z_i are the average values of the evading index, and N is the total number of input data. The correlation coefficient (R) is valued from [-1, 1]. The absolute value of R close to 1 means a successful prediction.

6 Discussion

The training of the connection weights of the network neurons was done using backpropagation combined with the ECBO algorithm using MATLAB software.

The trial and error method was used to obtain the number of suitable hidden neurons and the optimal artificial neural network. The number of hidden layer neurons in this study is considered 3 to 12.

Conventional statistical error and performance measures, such as mean squared error (MSE), correlation coefficient (R) and mean absolute percentage error (MAPE), are used to select the best configuration. Based on this, the evaluation index (R, MSE, MAPE) is determined for each model and the results are ranked based on the merit of the responses. Finally, the sum of the ranks assigned to each of the proposed patterns is evaluated and the best network configuration is selected.

The ranking results of artificial neural network in band strength estimation are shown in Table 5.

The obtained results from the hybrid ECBO-ANN for training and testing phases are evaluated according to Eqs. (3) to (9), which are common criteria for evaluating the error and model performance, including the Mean Square Error (MSE), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Normalized Mean Absolute Error (NMAE), Normalized Root Mean Square Error (NRMSE), correlation coefficient (R). It must be noted that for providing a clear comparison between models' error values, these criteria are evaluated using the real target values that are converted from normalized data Detailed results are presented in Table 6 for the developed model with different neuron values for the hidden layer.

The comparison between the measured and predicted values obtained from the ECBO-ANN model with different numbers of neurons in the training stages is presented in Fig. 5. The ideal fit is a diagonal line that shows the maximum fit and fit of the models and occurs when the correlation coefficient (R) is equal to unity.

The accuracy of the proposed model in training, testing and validation is shown in Fig. 6.

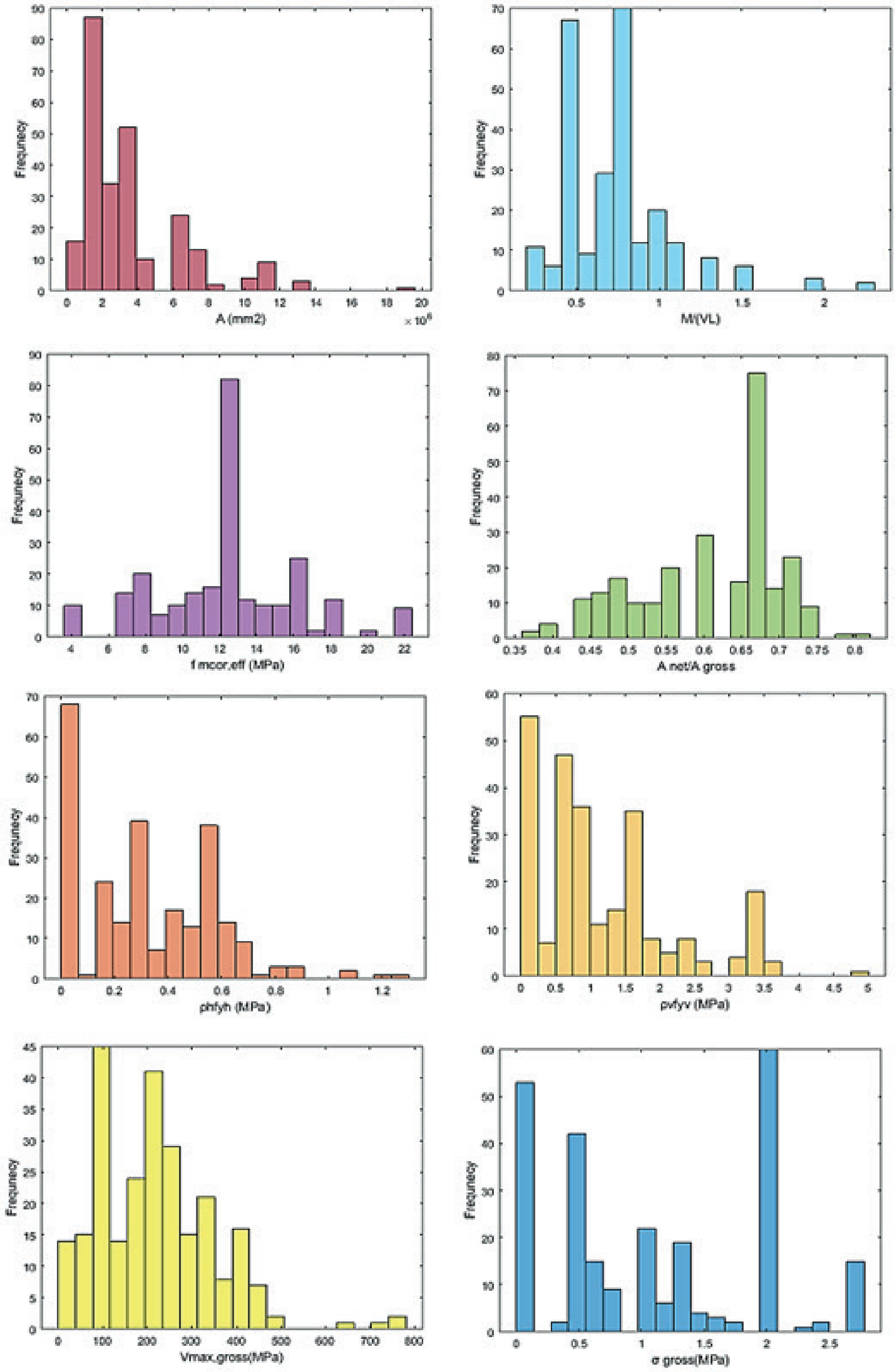

Fig. 4 The frequency of the design parameters

The purpose of ECBO algorithm is to find suitable weights and optimize them in the search environment. To achieve this goal, different types of ECBO-ANN patterns with different numbers of CBs were formed in relation to the proposed artificial neural network structure with 7 neurons in the hidden layer. Based on this, increasing the number of CBs is repeated until the minimum error is achieved, and other parameters related to the internal adjustment of the algorithm related to the search space were determined by trial and error. Fig. 7 shows the evolution of MSE in ECBO-ANN with different CBs from 10 to 1000 for 600 iterations.

Table 5 ANNs performances and ranking for optimized model

	Value						Rank						
	R		MSE		MAPE		R		MSE		MAPE		
Neurons	training	testing	training	testing	training	testing	training	testing	training	testing	training	testing	SUM
3	0.85112	0.84114	0.0206	0.0354	0.0139	0.2601	10	8	6	9	3	6	42
4	0.91482	0.96098	0.0146	0.0155	0.0052	0.0459	7	1	3	3	1	2	17
5	0.90559	0.91352	0.0142	0.0255	0.0206	0.1439	8	4	2	6	4	3	27
6	0.93213	0.85831	0.0179	0.0225	0.064	0.3643	4	7	4	5	7	8	35
7	0.94784	0.91167	0.0117	0.015	0.0071	0.0192	1	5	1	2	2	1	12
8	0.90117	0.81673	0.027	0.017	0.0869	0.3351	9	9	9	4	8	7	46
9	0.91923	0.91427	0.019	0.0108	0.0515	0.1924	6	3	5	1	6	4	25
10	0.92402	0.92987	0.024	0.0329	0.0984	0.7764	5	2	8	7	9	9	40
11	0.93844	0.76773	0.0146	0.0342	0.037	0.2534	3	10	3	8	5	5	34
12	0.94711	0.86298	0.0226	0.0562	0.121	0.836	2	6	7	10	10	10	45

Table 6 PG model error and performance

No. Neurons		MAE	NMAE%	MAPE	MSE	RMSE	NRMSE%	R
	Training	0.0136	0.7541	0.0139	0.0206	0.1436	7.9468	0.85112
3	Testing	0.0463	2.5775	0.2601	0.0354	0.188	10.4633	0.84114
	Training	0.0049	0.244	0.0052	0.0146	0.1207	6.0338	0.91482
4	Testing	0.0068	0.3794	0.0459	0.0155	0.1245	6.9668	0.96098
	Training	0.0197	1.068	0.0206	0.0142	0.119	6.4428	0.90559
5	Testing	0.0263	1.3516	0.1439	0.0255	0.1598	8.1968	0.91352
	Training	0.0581	2.9794	0.064	0.0179	0.1338	6.8648	0.93213
6	Testing	0.0762	5.6859	0.3643	0.0225	0.15	11.1958	0.85831
	Training	0.0066	0.3277	0.0071	0.0117	0.1084	5.4187	0.94784
7	Testing	0.0036	0.2581	0.0192	0.015	0.1227	8.7556	0.91167
	Training	0.0761	3.8047	0.0869	0.027	0.1644	8.2207	0.90117
8	Testing	0.0767	9.5602	0.3351	0.017	0.1304	16.2638	0.81673
	Training	0.0468	2.339	0.0515	0.019	0.1379	6.8972	0.91923
9	Testing	0.042	4.9209	0.1924	0.0108	0.1039	12.178	0.91427
	Training	0.0919	4.5958	0.0984	0.024	0.1548	7.7394	0.92402
10	Testing	0.1394	7.9394	0.7764	0.0329	0.1814	10.328	0.92987
	Training	0.034	1.701	0.037	0.0146	0.1209	6.0441	0.93844
11	Testing	0.0483	4.0303	0.2534	0.0342	0.1851	15.4473	0.76773
	Training	0.1109	5.6327	0.121	0.0226	0.1505	7.6397	0.94711
12	Testing	0.1686	11.5301	0.836	0.0562	0.2371	16.2202	0.86298

As shown in Fig. 8, the mean squared error value when we consider the number of neurons to be 7 is the lowest value that the hybrid neural network is in its optimal state.

7 Proposed ECBO-ANN approach formulation

The performance of artificial neural networks is possible when the weights of the network along with its bias values are known. Unlike many previous studies in which only the optimized network structure is presented, and in order to provide a simple way to achieve the presented results, the network weights along with the bias values in different layers for ECBO-ANN are presented in Table 7.

The mathematical equation between the normalized input parameters, $[IW]$, layer weight matrix, $[LW]$, and biases, $b1$, $b2$ for the neural network model, a normalized prediction is calculated:

$$v_{max,gross} = Tangent\ Sigmoid \times \left\{ b_0 + \sum_{k=1}^{n} \left[Tangent\ Sigmoid \times LW \left(b_{1K} + \sum_{i=1}^{m} (IW_{ik} Z_i \right) \right] \right\} \quad (10)$$

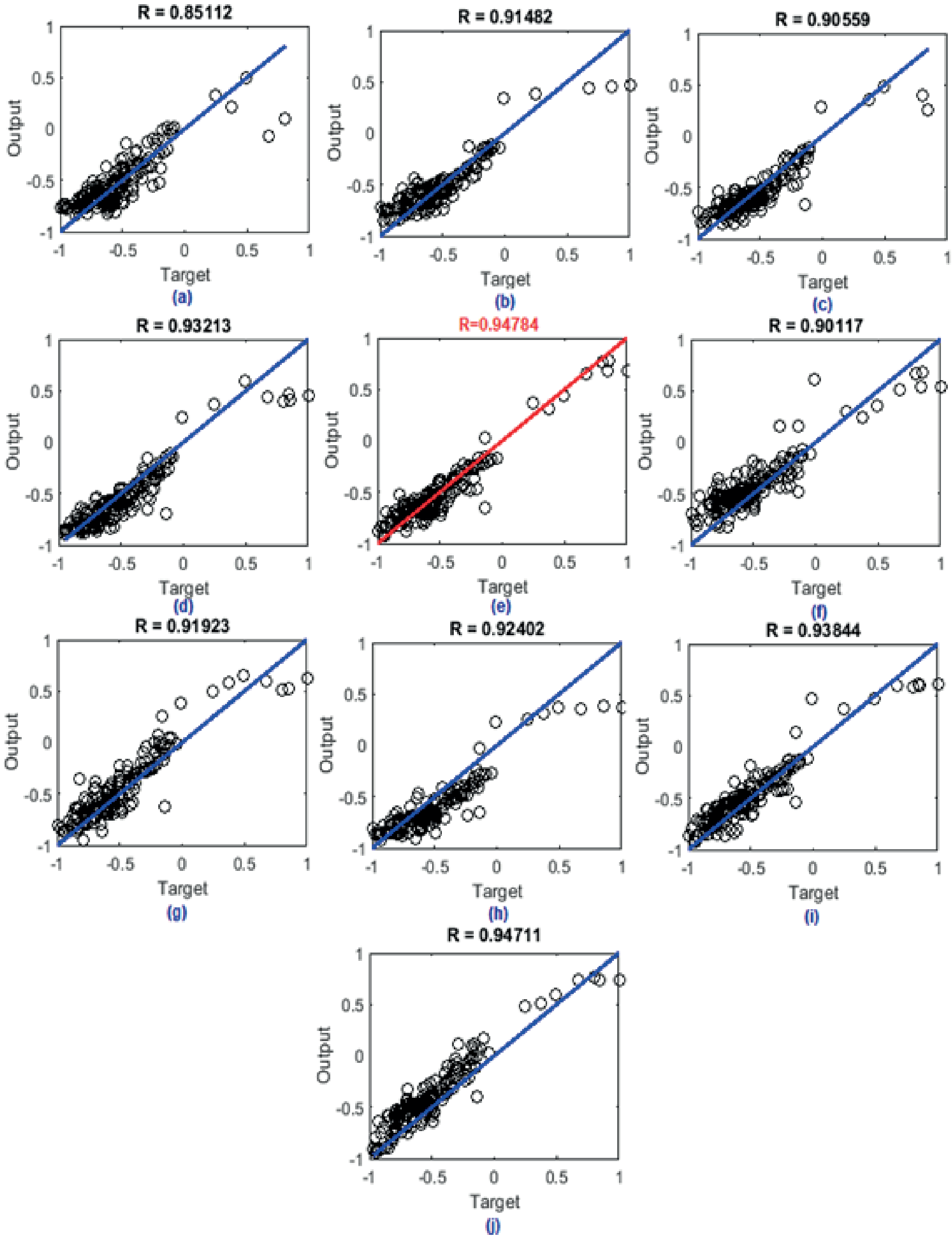

Fig. 5 Correlation comparison in ECBO-ANN

$v_{max,gross}$ represents the normalized shear strength of PG walls, "Tangent Sigmoid" is the activation function, n indicates hidden layer neuron numbers, Z_i indicates the normalized values of network input, m is the number of the input variables, IW_{ik} indicates the linking weights between the i^{th} input and k^{th} neuron in the hidden layer, LW is the link weight between the k^{th} neuron in the hidden layer and the independent output neuron, b_{1k} shows the bias in the k^{th} neuron of the hidden layer and b_0 is the bias value in the output layer. The shear strength of PG walls is obtained from the following equation:

$$v_{max,gross} = -0.395A_1 - 0.0935A_2 + 0.0191A_3 + 0.999A_4 + 0.2890A_5 + 0.4135A_6 - 0.2619A_7 + 0.0265 \quad (11)$$

where A_i, (i = 1 to 7) are hidden neuron responses that feed the network output value and can be calculated with the following equation:

$$\begin{bmatrix} A_1 \\ A_2 \\ A_3 \\ A_4 \\ A_5 \\ A_6 \\ A_7 \end{bmatrix} = Tansig\left(\left(\begin{bmatrix} 0.865 & -0.214 & -0.618 & -0.069 & 0.341 & -0.996 & 0.025 & -0.999 \\ 0.069 & -0.969 & -0.7581 & -0.2030 & 1.00 & 1.00 & -0.4274 & -0.3943 \\ -0.9065 & 0.8495 & -0.9397 & 0.3877 & 0.9719 & 0.7970 & -0.6440 & 0.2985 \\ 0.9795 & 0.9968 & 0.6284 & -0.9983 & -0.9007 & 0.9505 & -0.0086 & 0.2820 \\ -0.0891 & -0.9365 & -0.7910 & 0.9903 & 0.9173 & -0.7788 & 0.9998 & 0.9786 \\ -0.4293 & 0.8383 & 0.6796 & -0.5617 & 0.9909 & -0.9559 & 0.7206 & -0.2825 \\ -0.6964 & 0.8966 & 0.9618 & 0.9543 & 0.3028 & 0.9650 & 0.9991 & -0.9380 \end{bmatrix}\begin{bmatrix} A \\ M/VL \\ A_{net}/A_{gr} \\ f'_{m,eff} \\ \rho_v f_{yv} \\ \rho_h f_{yh} \\ \sigma_{gross} \\ V_{avg} \end{bmatrix}\right) + \begin{bmatrix} -0.6824 \\ -0.2916 \\ -0.5286 \\ -0.8682 \\ -0.2541 \\ 0.7344 \\ -0.5933 \end{bmatrix}\right) \quad (12)$$

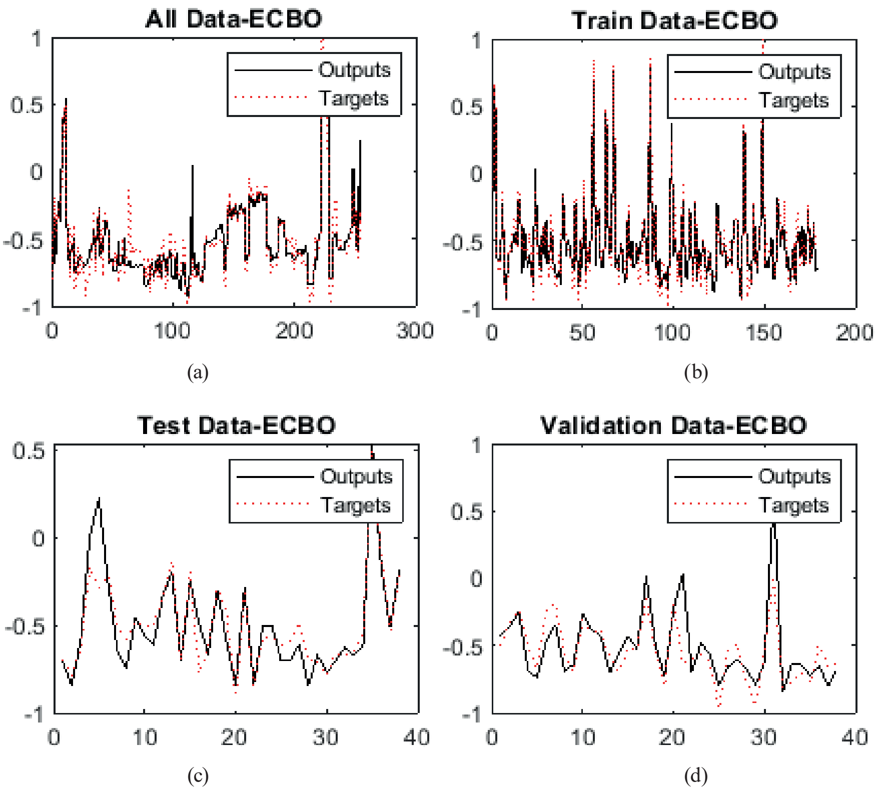

Fig. 6 ANN-ECBO with 100 CBs and 7 neurons (a) all data, (b) train data, (c) test data, (d) validation data

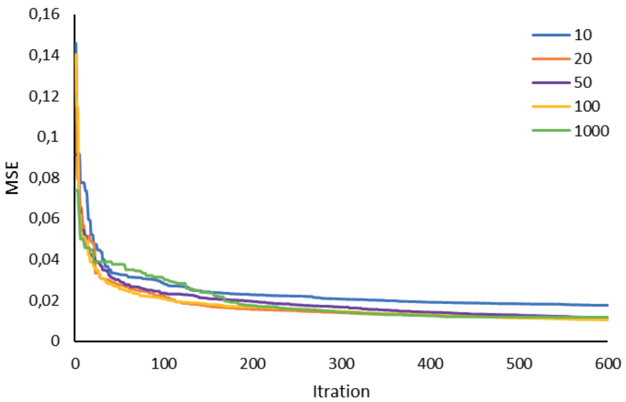

Fig. 7 Trained model performance with different artificial CBs population

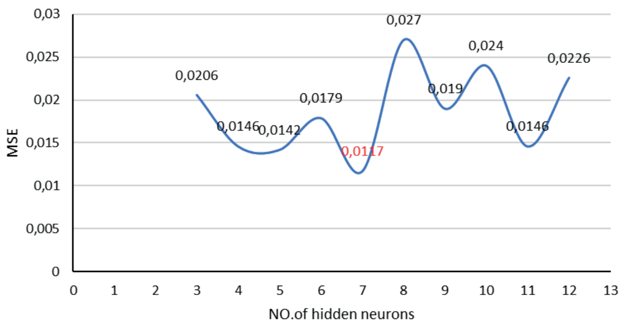

Fig. 8 The sensitivity analysis carried out for ANN, based on the number of hidden neurons

Table 7 The weights and bias values of the ECBO-ANN

	Weight										
Neuron Number	*IW*								*LW*	Bias	
	A_{scaled}	M/VL	A_{net}/A_{gross}	$f'_{m,eff}$	$\rho_v f_{yv}$	$\rho_h f_{yh}$	σ_{gross}	σ_{gross}	$v_{max,gross}$	b_{1k}	b_0
1	0.8659	-0.2146	-0.6181	-0.0696	0.3413	-0.9961	0.0253	-0.99	-0.395	-0.6824	
2	0.069	-0.9690	-0.758	-0.2030	1.0000	1.0000	-0.427	-0.394	-0.0935	-0.2916	
3	0.9065	0.8495	-0.9397	0.3877	0.9719	0.7970	-0.644	0.2985	0.0191	-0.5286	
4	0.9795	0.9968	0.6284	-0.9983	-0.900	0.9505	-0.008	0.2820	0.9999	-0.8682	0.0265
5	-0.089	-0.9365	-0.7910	0.9903	0.9173	-0.7788	0.9998	0.9786	0.2890	-0.2541	
6	-0.429	0.8383	0.6796	-0.5617	0.9909	-0.9559	0.7206	-0.282	0.4135	0.7344	
7	-0.696	0.8966	0.9618	0.9543	0.3028	0.9650	0.9991	-0.938	-0.2619	-0.5933	

8 Conclusions

In this article, the shear strength of partially grouted (PG) masonry shear walls is estimated by the optimized artificial neural network with the help of ECBO meta-heuristic algorithm. The neural network used is feed forward backpropagation. In this regard, an experimental dataset including 255 PG masonry shear walls from 22 independent studies was collected. In order to get proper answers, first all the data used were normalized between 1 and -1. The parameters include A_{scaled}, M/VL, A_{net}/A_{gross}, $f'_{m,eff,corrected}$, $\rho_v f_{yv}$, $\rho_h f_{yh}$, σ_{gross}, σ_{gross} as Input parameters were considered to obtain shear strength of partially grouted (PG) masonry shear walls. The model results were evaluated using a common error, and the performance evaluation criteria include MSE, RMSE, MAE, MAPE, NMAE, NRMSE, R. For the model training stage, 70% of available experimental data were used and the rest were kept as part of testing and validation.

In this research, the optimal number of neurons for the hidden layer and the optimal number of CBs to obtain the optimal neural network model were assessed. The number of hidden layer neurons in this study is considered 3 to 12. The results showed that the best number of neurons for the hidden layer is 7 and also the optimal number of CB is 100. The proposed empirical equation, which is constructed using the optimal weights and constants of the PG wall, can be easily implemented to evaluate the shear strength of the partially grouted masonry shear wall. Quantitative results obtained from the analysis are reported below.

- Feed forward basic neural network with a hidden layer and variable number of neurons between 3 and 12 neurons and sigmoid activation function was considered as neural network structure. It was combined with the meta-heuristic ECBO algorithm and the results showed that the correlation value in the number of neurons equal to 7 is 0.94784, which is the highest value compared to the rest of the cases.
- Refer to Fig. 8 to better understand the comparison of MSE values.

According to Table 5, the value of points obtained from the classification of evaluation parameters based on merit, it can be concluded that the results are better in the ECBO-ANN model with 7 neurons.

- Other error and performance evaluation criteria such as RMSE, MAE, MAPE, NMAE, NRMSE, which are reviewed in the article, their values are detailed in Table 6, for example, comparing the results of NRMSE shows that among the number of neurons different, for 7 neurons have lower values, which shows the superiority of this model over other models.
- Finally, it might be interesting to mention that the force method of structural analysis can be used in place of the displacement method with great benefit for structures with smaller degrees of static indeterminacy than the kinematic indeterminacy [25–28].

Conflict of interest

No potential conflict of interest was reported by the authors.

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