


ORIGINAL RESEARCH

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Neural network application in forecasting maximum wall deflection in homogenous clay



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Abstract

An attempt was carried out by using a neural network to predict the maximum deflection and its position caused by braced excavation in homogeneous clay. Six input variables, including excavation depth, Ratio of EI wall/EI of brace, the vertical distance between bracing, Length to width ratio of an excavation, shear strength, and the coefficient of lateral earth pressure, were adopted. Two models were developed, one is to estimate the maximum deflection and the other one to estimate the position of maximum deflection. The ANN models were developed and verified using a database of (169) cases of actual measured and presumptive cases using the analysis with the Finite element of maximum deflection. A sensitivity analysis was accomplished, to examine the relative significance of the parameters that influence the maximum deflection of the wall and its position; it indicates that the Ratio of EI wall/EI of brace has the most significant effect on the maximum wall deflection, while the properties of the soil have the most considerable effects on the position. The results show that the ANN can reasonably forecast the magnitude of the maximum deflection of the wall, as well as its position. Design charts are developed based on the ANN model.

Highlights

- Neural Networks was used to forecast maximum deflection of braced excavation in homogeneous clay and its position.
- A sensitivity analysis was accomplished to examine the relative significance of the parameters that influence the models.
- The results confirm that the developed ANN model is able to predict maximum deflection and its position reliably.
- Design charts were developed based on the ANN model.

Keywords: Maximum wall deflection, Braced excavation, Homogeneous clay, Neural network, Forecasting

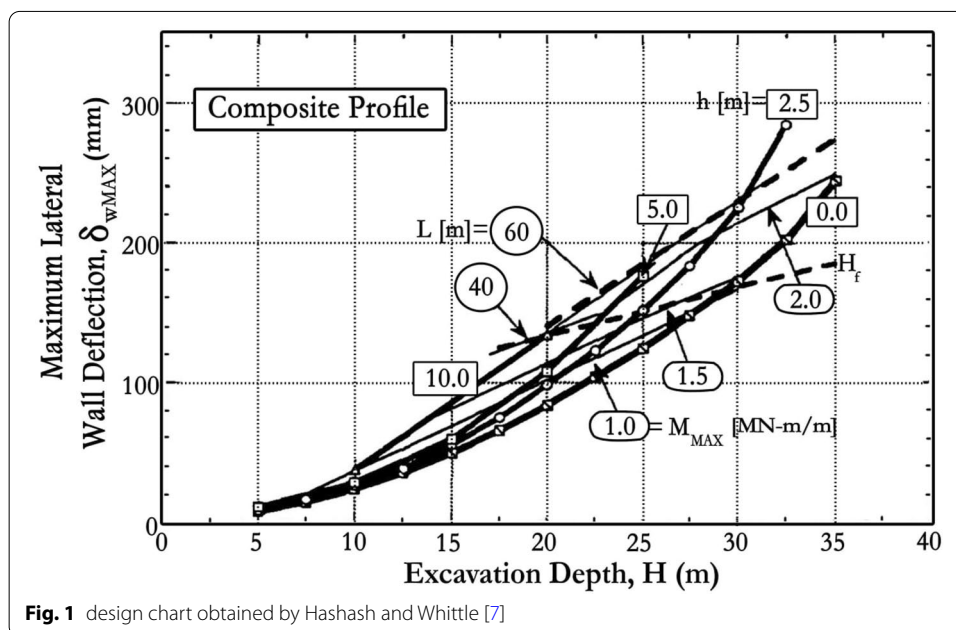
Introduction

Geotechnical engineers facing complicated multivariate problems, which include several interacting factors. Generally, the relationship among these factors is not exactly known. The extraction of information to develop a relationship between these factors required advanced techniques for modeling beside a human experience. Braced excavation is popular in construction such as high multistoried buildings with basements, underground structures for transportation stations, and parking.

A safe excavation can be achieved using a satisfactorily braced wall; the braced wall also reduces deformations in the surrounding ground due to excessive wall deflections, which are most important to avoid costly damages to neighboring structures and buildings. In deep excavation projects, observational methods are involved to ensure safe construction, as well as used a finite element to forecast deflections of the wall in deep excavations [1, 15, 16].

Some design charts were established for predicting the maximum lateral deflection of the wall based on depth of excavation, support system, and wall length [7, 9] see Fig. 1.

Artificial neural networks (ANNs) form a category of frameworks, which are mimicked neural networks in living creatures. An important merit of ANNs is learning, learning models, (ANNs) can deal with incomplete, qualitative, and uncertain data effectively. Therefore, for modeling sophisticated problems in which the equations that govern the problems are difficult to set, ANN is a highly promising tool. ANNs can be performed in mapping, transitory and optimization problems, besides modeling dynamic processes [3]. Generally, the number of input parameters used should be small in artificial neural networks to predict the maximum lateral deflection of the wall in clays with soft to medium consistency. The database used to develop the ANN is generated from presumptive cases employing the method of finite element (FEM) [11] and case histories of deep excavations for training, testing, and verification [8]. The objective of this work is



to employ (ANNs) to build a model to forecast maximum lateral wall deflection and its position in homogenous clays.

Methodology

Artificial neural networks

Artificial neural networks (ANNs) are simulated the nerve cells in the brain, they are considered as computational devices. Despite the complexity of the brain that cannot be approached by ANNs, there are two kinds of similarities. First, the computational units of networks are simple and interconnected to a high degree. The second one is that the connections among neurons set the function and feature of the network [5].

By adjusting weights among neurons, ANNs may be trained to perform a selected function. Neural networks are trained to perform complicated functions in extraordinary fields of application such as identification, pattern recognition, speech, vision, classification, and control systems.

Various tools have been used by engineers to perform informal modeling (mapping from cause to effect for estimation and prediction) and inverse mapping (mapping from effects to causes) which include knowledge-based systems, optimization, regression, statistics, probability, and others. Thus, ANN can be considered as another tool for engineers to perform either the modeling or inverse mapping [10]. Neural networks are applied in different fields of geotechnical engineering including parameter assessment, underground openings, foundations, site investigation, liquefaction, retaining structures, slopes, and ground movement [17].

Back-propagations

One of the neural networks is back-propagation which is vastly used in solving problems that need modeling nonlinear relationships. By modifying the weights so the error among the actual target and the desired target is minimized, as a result, the simulation of the networks will produce the output units, and the forecasting of the neural networks to the outputs is highly more correct.

When the internal parameters of the network have been corrected, the mechanism of correction begins with the output layers then the error back-propagates backward through each internal (hidden) layer. Hence, for this kind of network, the backpropagation is used [2].

Levenberg Marquardt algorithm.

The algorithm is based on the newton method variation in which the functions which are the sum of squares of other nonlinear functions are minimized, it is appropriate when MSE (Mean Square Error) is the index of performance.

The basic step of the Levenberg–Marquardt algorithm is:

$$X_{K+1} = X_K - [J^T J + \mu I]^{-1} J^T e \quad (1)$$

where (e) is a vector of network errors, (J) is the Jacobian matrix, (I) is a unit matrix, and (μ) is a positive scalar. The algorithm becomes gradient descent with a small step size when μ is large. For some input/output patterns, the Levenberg–Marquardt algorithm is very fast and effective compared to the standard gradient algorithms. Thus, in this

study, the training algorithm used is the Levenberg–Marquardt algorithm with the mean square of errors as a performance function.

Prediction of maximum wall deflection and it's position by ANN

Development of ANN Models

The database includes a total of (169) cases recorded from site observations and finite element analysis for homogeneous clayey soil types. The six parameters used as the ANN model inputs have the most considerable effect on the deep excavations in homogeneous clayey soil. Parameters include: Excavation depth (H) m, Ratio of Length of wall/width of excavation (L/B), ratio of EI of the wall / EI of the brace, the vertical distance of bracing (h_g) m, undrained shear strength of soil (S_u , kN/m²), and the earth pressure coefficient of at rest (K_0). Table 1 shows the dataset used and its sources.

In this work, a computer program MATLAB (2015) Neural Network Toolbox is used for modeling the neural network. A summary of the basic characteristics of the ANN model utilized in this study is as follows: Type of network: Feed-forward backpropagation, Algorithm of training: (TRAINLM) Levenberg–Marquardt algorithm, the function of Learning: (LEARNGDM) Gradient descent with momentum, the function of performance: (MSE) Mean square error and the coefficient of correlation (R), the first layer transfer function: Sigmoid, the second transfer function: tangent-sigmoid.

The functions of the Sigmoid (logsig) and the hyperbolic tangent-sigmoid (tansig) can be expressed as in Eqs. 2 and 3 respectively:

$$\text{logsig}(n) = 1/(1 + \exp(-n)) \quad (2)$$

$$\text{Tansig}(n) = [2/(1 + \exp(-2n))] - 1 \quad (3)$$

where: n is any value between $(-\infty)$ and $(+\infty)$. Figure 2 shows the details of (ANN).

Data division and pre-processing

The data set was randomly divided into three sets through the nntools box using the default percentages. The percentage of the training, testing, and validation are, 70%, 15% and 15% respectively. Before building the neural network, the data Pre-processing is essential to put them into proportional form, which is carried out by scaling (normalizing) them so that they fall into a standard range – 1 to 1. In the output layer, the variables have to be normalized to be proportional to the transfer function limits that used in the output layer [5].

Scaling the data is important to assure that during the training, all the variables will receive equal attention. The scaled value X_n is calculated as follows:

$$X_n = \frac{2 \times (X - X_{min})}{(X_{max} - X_{min})} - 1 \quad (4)$$

Results and discussion

Two models were built one for maximum wall deflection and the other to the position of the maximum deflection, each model has six nodes that represent the inputs used and one node for the output required.

Table 1 Data used in building the neural networks

References	Input variables						Output	
	Excavation Depth, H (m)	Length to width ratio of excavation L/B	Ratio of EI of wall/ brace	Vertical Spacing between bracing, S (m)	Undrained Shear strength of clay, S_u (kN/m ²)	Coefficient of earth pressure at rest, K_0	Maximum deflection, δ_H (mm)	Position of maximum deflection, (m)
Lam et al. [12]	2.16	0.204	0.108	1	25.5	0.53	92	3
	4.32	0.204	0.108	2	25.5	0.53	78	5.6
	5.15	0.204	0.108	3	25.5	0.53	38	6
	2.16	0.204	2.808	1	25.5	0.53	34	9
	4.32	0.204	2.808	2	25.5	0.53	12	9
	5.15	0.204	2.808	3	25.5	0.53	7	9
	2.16	0.204	8.509	1	25.5	0.53	90	8
	4.32	0.204	8.509	2	25.5	0.53	23	8
	5.15	0.204	8.509	3	25.5	0.53	3	8
Hashash et al. [6]	2.5	1	3.117	1	15	0.53	10	0
	5	1	3.117	2	15	0.53	15	12
	7.5	1	3.117	3	15	0.53	28	15
	10	1	3.117	4	15	0.53	45	17.5
	12.5	1	3.117	5	15	0.53	62	20
	15	1	3.117	6	15	0.53	84	22.5
	2.5	1	3.229	1	15	0.59	47	20
	5	1	3.229	2	15	0.59	37	20
	7.5	1	3.229	3	15	0.59	27	17.5
	10	1	3.229	4	15	0.59	16	15
	12.5	1	3.229	5	15	0.59	11	10
Nicholson [14]	15	1	3.229	6	15	0.59	8	0
	2.6	0.15	0.796	2.5	16	0.6	1	70
	7.6	0.15	0.796	2.5	16	0.6	8	80
	14.7	0.15	0.796	2.5	16	0.6	10.5	95
Lam [13]	17.5	1.333	3.229	2.5	80	0.53	100	25
	17.5	1	3.229	2.5	80	0.53	110	25
	17.5	0.8	3.229	2.5	80	0.53	120	25
	17.5	0.667	3.229	2.5	80	0.53	130	25
Jen [9]	5	0.625	3.229	2.5	80	0.53	17	10
	5	0.625	12.915	2.5	80	0.53	17	10
	5	0.625	19.355	2.5	80	0.53	17	10
	5	0.625	25.806	2.5	80	0.53	17	10
	5	0.625	32.287	2.5	80	0.53	17	10
	5	0.625	38.71	2.5	80	0.53	17	10
	7.5	0.625	6.455	2.5	80	0.53	35	14
	7.5	0.625	12.915	2.5	80	0.53	38	14
	7.5	0.625	19.355	2.5	80	0.53	38	14
	7.5	0.625	25.806	2.5	80	0.53	38	14
	7.5	0.625	32.287	2.5	80	0.53	38	14
	7.5	0.625	38.71	2.5	80	0.53	40	14
	10	0.625	6.455	2.5	80	0.53	50	16
	10	0.625	12.915	2.5	80	0.53	55	16
	10	0.625	19.355	2.5	80	0.53	56	16
	10	0.625	25.806	2.5	80	0.53	57	16
	10	0.625	32.287	2.5	80	0.53	58	16
10	0.625	38.71	2.5	80	0.53	60	16	

Table 1 (continued)

References	Input variables						Output	
	Excavation Depth, H (m)	Length to width ratio of excavation L/B	Ratio of EI of wall/ EI of brace	Vertical Spacing between bracing, S (m)	Undrained Shear strength of clay, S_u (kN/m ²)	Coefficient of earth pressure at rest, K_0	Maximum deflection, δ_H (mm)	Position of maximum deflection, (m)
	12.5	0.625	6.455	2.5	80	0.53	79	20
	12.5	0.625	12.915	2.5	80	0.53	84	20
	12.5	0.625	19.355	2.5	80	0.53	86	20
	12.5	0.625	25.806	2.5	80	0.53	89	20
	12.5	0.625	32.287	2.5	80	0.53	92	20
	12.5	0.625	38.71	2.5	80	0.53	97	20
	15	0.625	6.455	2.5	80	0.53	150	25
	15	0.625	12.915	2.5	80	0.53	200	25
	17.5	0.625	6.455	2.5	80	0.53	300	25
	2.5	0.625	3.229	0	80	0.53	17	0
	2.5	0.75	3.229	0	80	0.53	17	0
	2.5	0.875	3.229	0	80	0.53	17	0
	2.5	1	3.229	0	80	0.53	17	0
	5	0.625	3.229	2.5	80	0.53	20	15
	5	0.75	3.229	2.5	80	0.53	20	15
	5	0.875	3.229	2.5	80	0.53	20	15
	5	1	3.229	2.5	80	0.53	20	15
	7.5	0.625	3.229	2.5	80	0.53	39	18
	7.5	0.75	3.229	2.5	80	0.53	39	18
	7.5	0.875	3.229	2.5	80	0.53	39	18
	7.5	1	3.229	2.5	80	0.53	39	18
	10	0.625	3.229	2.5	80	0.53	60	22.5
	10	0.75	3.229	2.5	80	0.53	55	22.5
	10	0.875	3.229	2.5	80	0.53	55	22.5
	10	1	3.229	2.5	80	0.53	55	22.5
	12.5	0.625	3.229	2.5	80	0.53	95	25
	12.5	0.75	3.229	2.5	80	0.53	80	23
	12.5	0.875	3.229	2.5	80	0.53	80	23
	12.5	1	3.229	2.5	80	0.53	80	23
	15	0.625	3.229	2.5	80	0.53	150	25
	15	0.75	3.229	2.5	80	0.53	120	25
	15	0.875	3.229	2.5	80	0.53	110	25
	15	1	3.229	2.5	80	0.53	110	25
	17.5	0.625	3.229	2.5	80	0.53	210	25
	17.5	0.75	3.229	2.5	80	0.53	185	30
	17.5	0.875	3.229	2.5	80	0.53	150	27
	17.5	1	3.229	2.5	80	0.53	14.5	27
	17.5	2.667	3.229	2.5	80	0.53	70	25
	17.5	2	3.229	2.5	80	0.53	80	25
	17.5	1.333	3.229	2.5	80	0.53	95	27
	17.5	1	3.229	2.5	80	0.53	105	27
	17.5	0.8	3.229	2.5	80	0.53	115	27
	17.5	0.667	3.229	2.5	80	0.53	125	27
	17.5	0.571	3.229	2.5	80	0.53	135	27
	17.5	0.5	3.229	2.5	80	0.53	145	27
	2.5	0.313	3.229	0	100	0.56	10	0
	2.5	0.375	3.229	0	100	0.56	10	0
	2.5	0.438	3.229	0	100	0.56	10	0

Table 1 (continued)

References	Input variables					Output		
	Excavation Depth, H (m)	Length to width ratio of excavation L/B	Ratio of EI of wall/ EI of brace	Vertical Spacing between bracing, S (m)	Undrained Shear strength of clay, S_u (kN/m ²)	Coefficient of earth pressure at rest, K_0	Maximum deflection, δ_H (mm)	Position of maximum deflection, (m)
	2.5	0.5	3.229	0	100	0.56	10	0
	5	0.313	3.229	2.5	100	0.56	15	12
	5	0.375	3.229	2.5	100	0.56	15	12
	5	0.438	3.229	2.5	100	0.56	15	12
	5	0.5	3.229	2.5	100	0.56	15	12
	7.5	0.313	3.229	2.5	100	0.56	30	17
	7.5	0.375	3.229	2.5	100	0.56	30	17
	7.5	0.438	3.229	2.5	100	0.56	30	17
	7.5	0.5	3.229	2.5	100	0.56	30	17
	10	0.313	3.229	2.5	100	0.56	45	20
	10	0.375	3.229	2.5	100	0.56	45	20
	10	0.438	3.229	2.5	100	0.56	45	20
	10	0.5	3.229	2.5	100	0.56	45	20
	12.5	0.313	3.229	2.5	100	0.56	65	25
	12.5	0.375	3.229	2.5	100	0.56	60	20
	12.5	0.438	3.229	2.5	100	0.56	60	20
	12.5	0.5	3.229	2.5	100	0.56	60	20
	15	0.313	3.229	2.5	100	0.56	95	25
	15	0.375	3.229	2.5	100	0.56	80	24
	15	0.438	3.229	2.5	100	0.56	80	24
	15	0.5	3.229	2.5	100	0.56	80	24
	17.5	0.313	3.229	2.5	100	0.56	127	25
	17.5	0.375	3.229	2.5	100	0.56	108	30
	17.5	0.438	3.229	2.5	100	0.56	102	27
	17.5	0.5	3.229	2.5	100	0.56	102	27
	20	0.313	3.229	2.5	100	0.56	152	25
	20	0.375	3.229	2.5	100	0.56	14.6	30
	20	0.438	3.229	2.5	100	0.56	126	30
	20	0.5	3.229	2.5	100	0.56	124	30
	17.5	0.313	3.229	2.5	110	0.58	105	25
	17.5	0.375	3.229	2.5	110	0.58	87	30
	17.5	0.438	3.229	2.5	110	0.58	83	27
	17.5	0.5	3.229	2.5	110	0.58	83	27
	20	0.313	3.229	2.5	110	0.58	125	25
	20	0.375	3.229	2.5	110	0.58	115	30
	20	0.438	3.229	2.5	110	0.58	102	28
	20	0.5	3.229	2.5	110	0.58	102	28
	17.5	0.313	3.229	2.5	130	0.64	70	25
	17.5	0.375	3.229	2.5	130	0.64	63	30
	17.5	0.438	3.229	2.5	130	0.64	63	28
	17.5	0.5	3.229	2.5	130	0.64	63	28
	20	0.313	3.229	2.5	130	0.64	80	25
	20	0.375	3.229	2.5	130	0.64	75	30
	20	0.438	3.229	2.5	130	0.64	73	28
	20	0.5	3.229	2.5	130	0.64	73	28
	17.5	0.313	3.229	2.5	140	0.7	62	25
	17.5	0.375	3.229	2.5	140	0.7	57	30
	17.5	0.438	3.229	2.5	140	0.7	57	28

Table 1 (continued)

References	Input variables						Output	
	Excavation Depth, H (m)	Length to width ratio of excavation L/B	Ratio of EI wall/ EI of brace	Vertical Spacing between bracing, S (m)	Undrained Shear strength of clay, S_u (kN/m ²)	Coefficient of earth pressure at rest, K_0	Maximum deflection, δ_H (mm)	Position of maximum deflection, (m)
	17.5	0.5	3.229	2.5	140	0.7	57	28
	20	0.313	3.229	2.5	140	0.7	73	25
	20	0.375	3.229	2.5	140	0.7	66	28
	20	0.438	3.229	2.5	140	0.7	66	28
	20	0.5	3.229	2.5	140	0.7	66	28
	5	0.625	3.229	2.5	80	0.53	16	12
	5	0.625	0.172	2.5	80	0.53	27	8
	5	0.625	0.113	2.5	80	0.53	30	8
	5	0.625	0.043	2.5	80	0.53	34	7
	5	0.625	0.024	2.5	80	0.53	37	6.5
	5	0.625	0.01	2.5	80	0.53	40	6
	7.5	0.625	3.229	2.5	80	0.53	25	15
	7.5	0.625	0.172	2.5	80	0.53	50	12
	7.5	0.625	0.113	2.5	80	0.53	55	11
	7.5	0.625	0.043	2.5	80	0.53	67	10.5
	7.5	0.625	0.024	2.5	80	0.53	72	10
	7.5	0.625	0.01	2.5	80	0.53	78	9.5
	10	0.625	3.229	2.5	80	0.53	45	20
	10	0.625	0.172	2.5	80	0.53	81	14
	10	0.625	0.113	2.5	80	0.53	88	13
	10	0.625	0.043	2.5	80	0.53	105	12.5
	10	0.625	0.024	2.5	80	0.53	120	12
	10	0.625	0.01	2.5	80	0.53	162	12
	12.5	0.625	3.229	2.5	80	0.53	72	25
	12.5	0.625	0.172	2.5	80	0.53	122	17
	12.5	0.625	0.113	2.5	80	0.53	138	16.5
	12.5	0.625	0.043	2.5	80	0.53	21.4	16

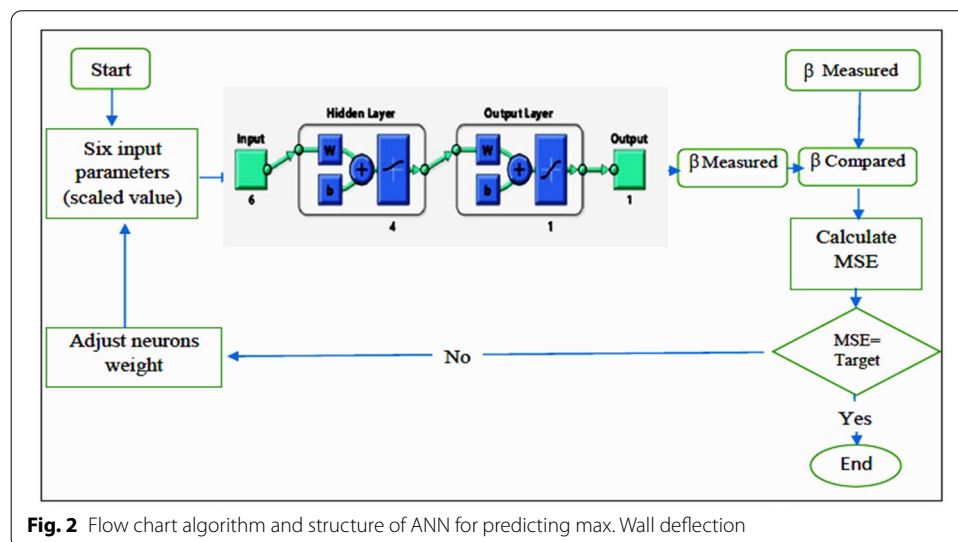


Fig. 2 Flow chart algorithm and structure of ANN for predicting max. Wall deflection

Table 2 Statistics parameters of Input and Output data used in (ANN)

Data set	Statistical parameters	Input variables						Output	
		Excavation depth, H (m)	Length to width ratio of excavation L/B	Ratio of EI wall/ EI of brace	Vertical Spacing between bracing, S (m)	Undrained Shear strength of clay, Su (kN/m ²)	Coefficient of earth pressure at rest, Ko	Maximum deflection, δH (mm)	Position of maximum deflection, (m)
All Data n= 169	Maximum	20.0	2.7	38.7	6	140.0	0.70	300.0	95.0
	Minimum	2.2	0.2	0.010	0	15.0	0.53	1.0	0.0
	Mean	11.3	0.6	5.7	2.4	81.8	0.6	65.4	19.5
	Std.dv	5.6	0.3	8.2	0.8	30.7	0.0	46.5	11.8
	Range	17.8	2.5	38.7	6.0	125.0	0.2	299.0	95.0

ANNs with 1 to 12 hidden layer nodes are trained, to determine the optimum network geometry.

Training of data

Table 2 summarizes statistical parameters of variables used to construct and validate the network and their histograms are shown in Fig. 3. The retaining structures are formed of either stiff or flexible walls with Excavation depth up to 20 m and maximum width up to 80 m was considered.

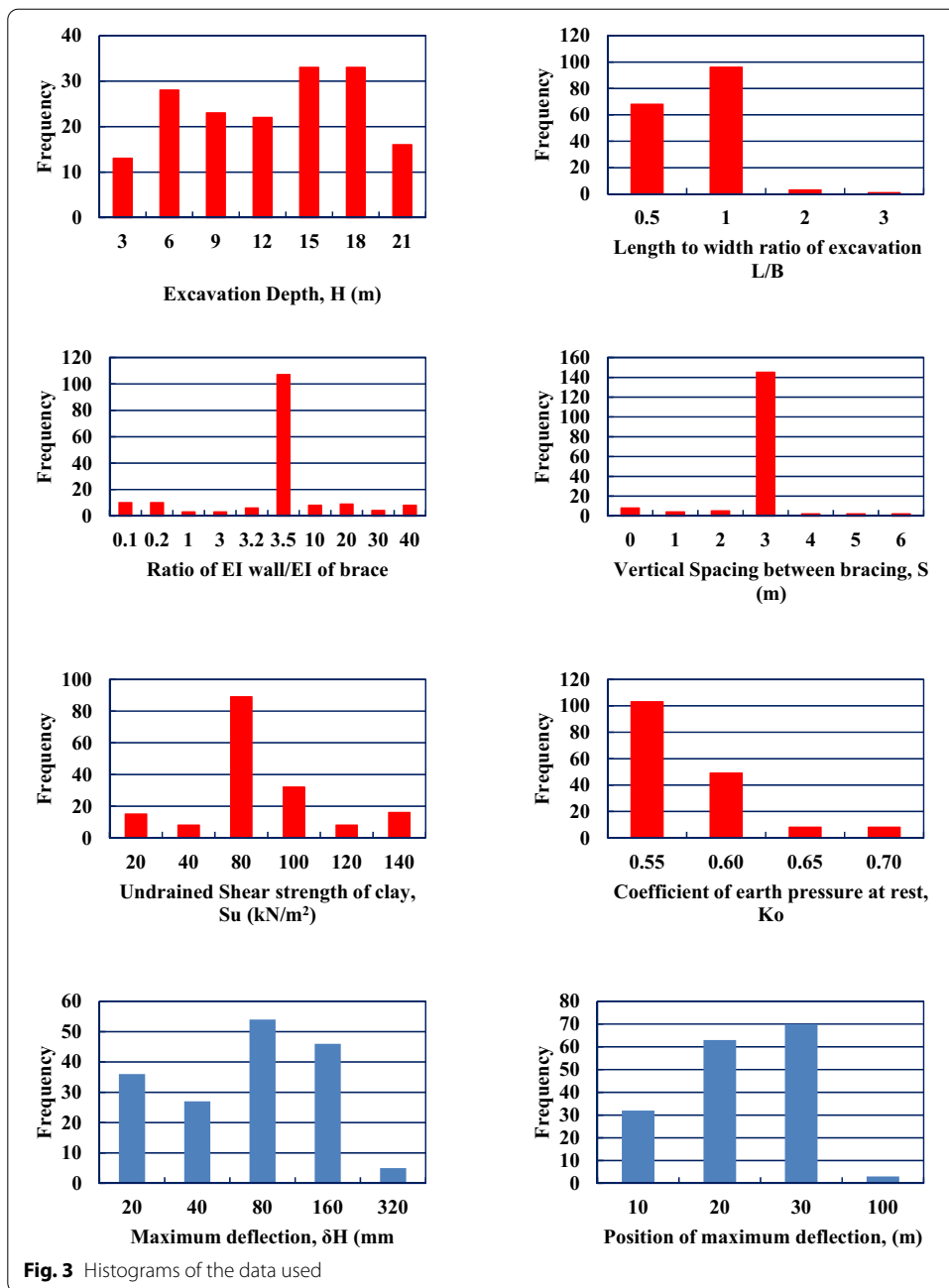
Figures 4 and 5 indicate the variation of the average of Mean Squared Error (MSE) with the number of hidden neurons of the networks for the maximum deflection and its position respectively. The difference in (MSE) is relatively small after hidden neuron no. 4 and hidden neuron no. 3 for the maximum deflection and its position respectively. Figure 4 shows that the networks for max. deflection and its position with 4 and 3 hidden layer node respectively. It is considered optimal, as its prediction error (MSE) is not far from the network with 12 hidden layer nodes coupled with smaller number of connection weights and with high coefficient of correlation as shown in Fig. 5

Figures 6 and 7 show a comparison between the measured and predicted value of the maximum deflection and its position respectively. It shows a good agreement between the measured and predicted values.

Sensitivity analysis of the ANN model inputs

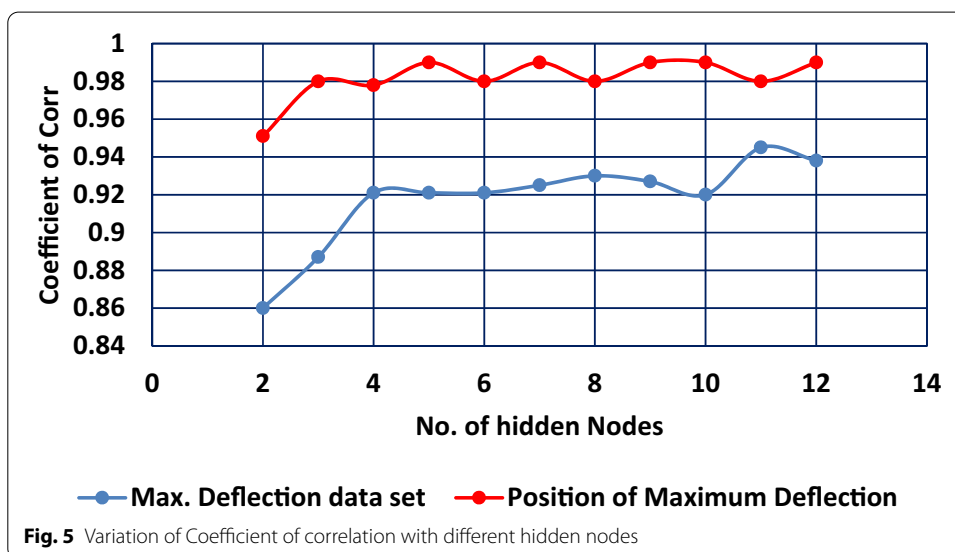
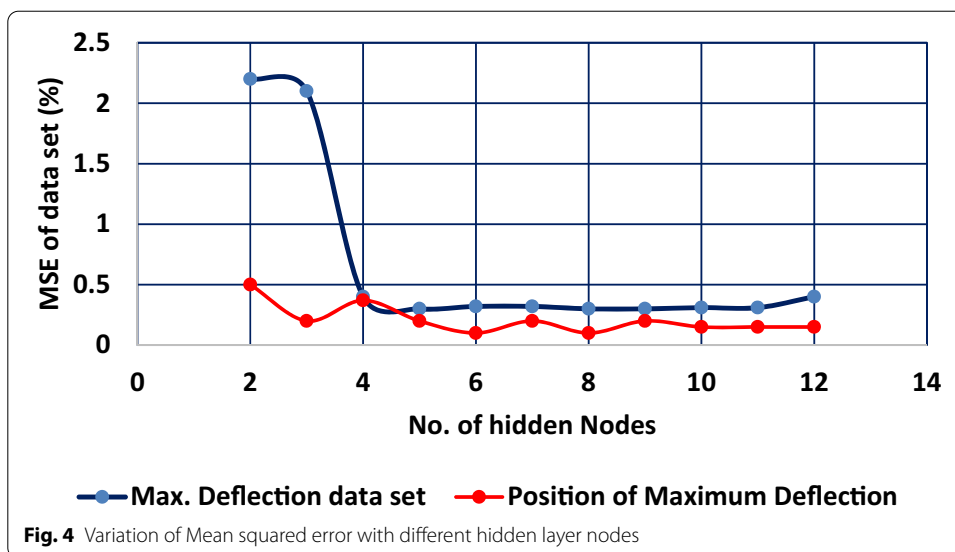
Garson [4] proposed an innovative and simple technique that is used to explain the relative significance of the input variables by examining the connection weights of the trained network. For a network with 4 hidden nodes, the technique involves a process of partitioning the hidden output connection weights into components associated with each input node.

The results indicate that the ratio of the EI wall/EI of brace has the most considerable effect on the predicted maximum deflection followed by Ko, L/B, H, Su, and hs respectively. The results are presented in Fig. 8a. Similarly, the results indicate that Su and Ko have the most significant effect on the predicted position of maximum deflection followed by L/B, H, hs, and EI/Ks, the results are presented in Fig. 8b.



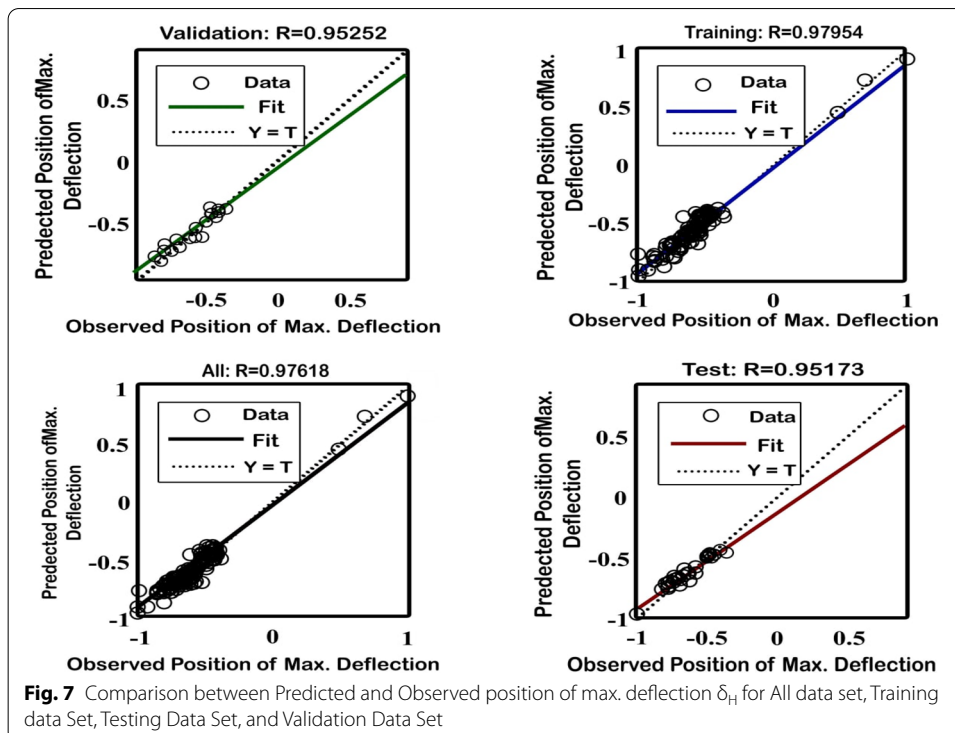
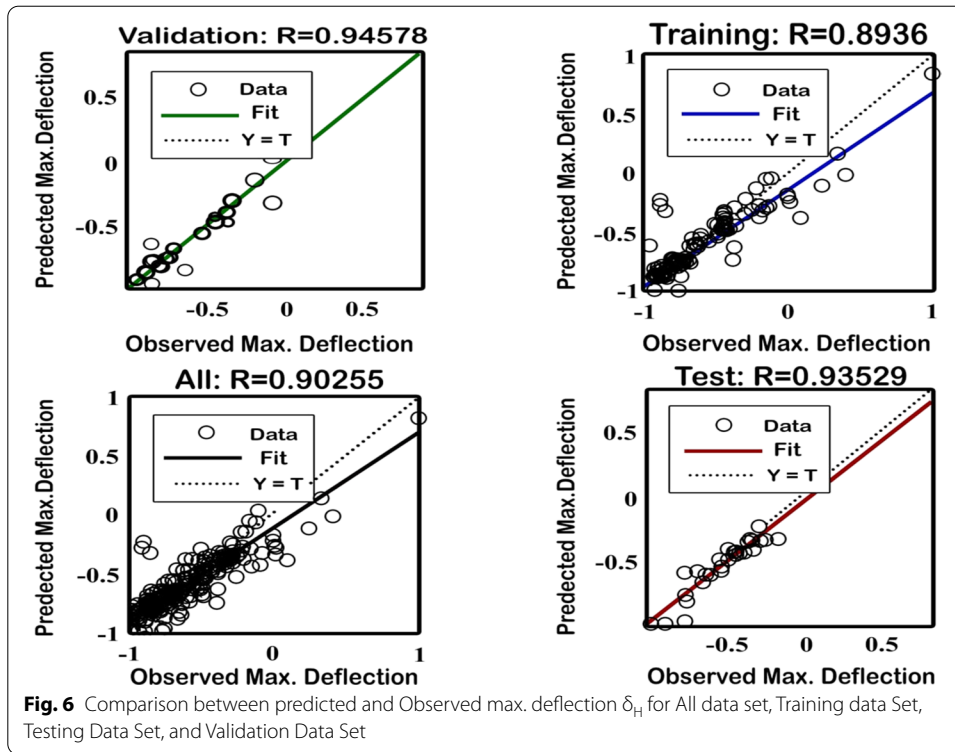
Parametric study

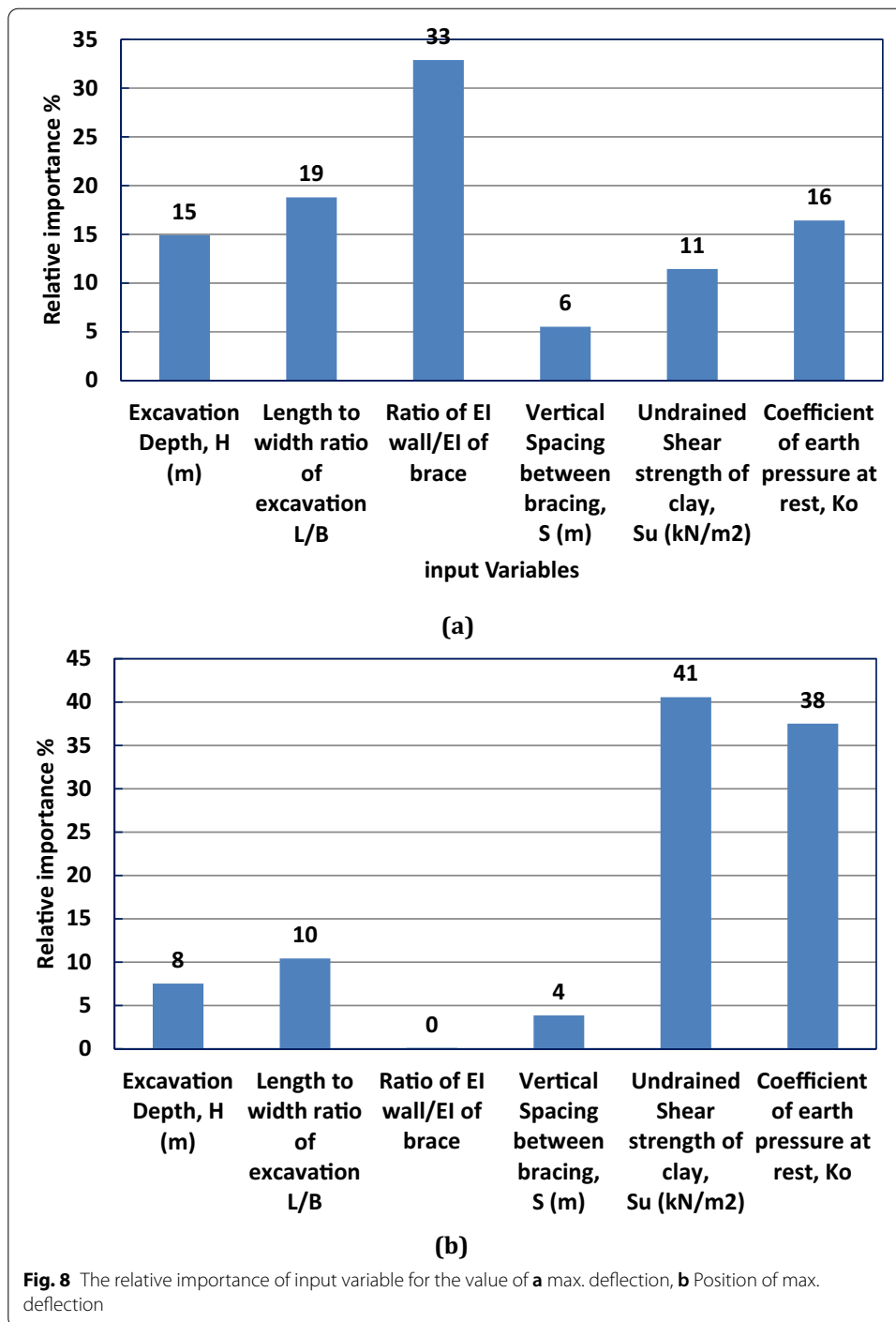
Parametric studies were carried out to estimate whether the model has convenient trends, to confirm the validation of the trained network and the generalization ability of the model. the first five input variables (i.e. (L/B), EI of wall/stiffness of braced, Vertical distance of bracing, Undrained shear strength of soil (S_u), coefficient of Earth pressure at rest (K_o)), except one, are fixed to their mean values used for training. The increasing values of artificial ranging (10–20%) of the total range between the minimum and maximum values. Figure 9a–d reveal that the general trend of the maximum wall deflection is to increase with an increase in excavation depth, increasing (L/B), (EI wall/EI of bracing)



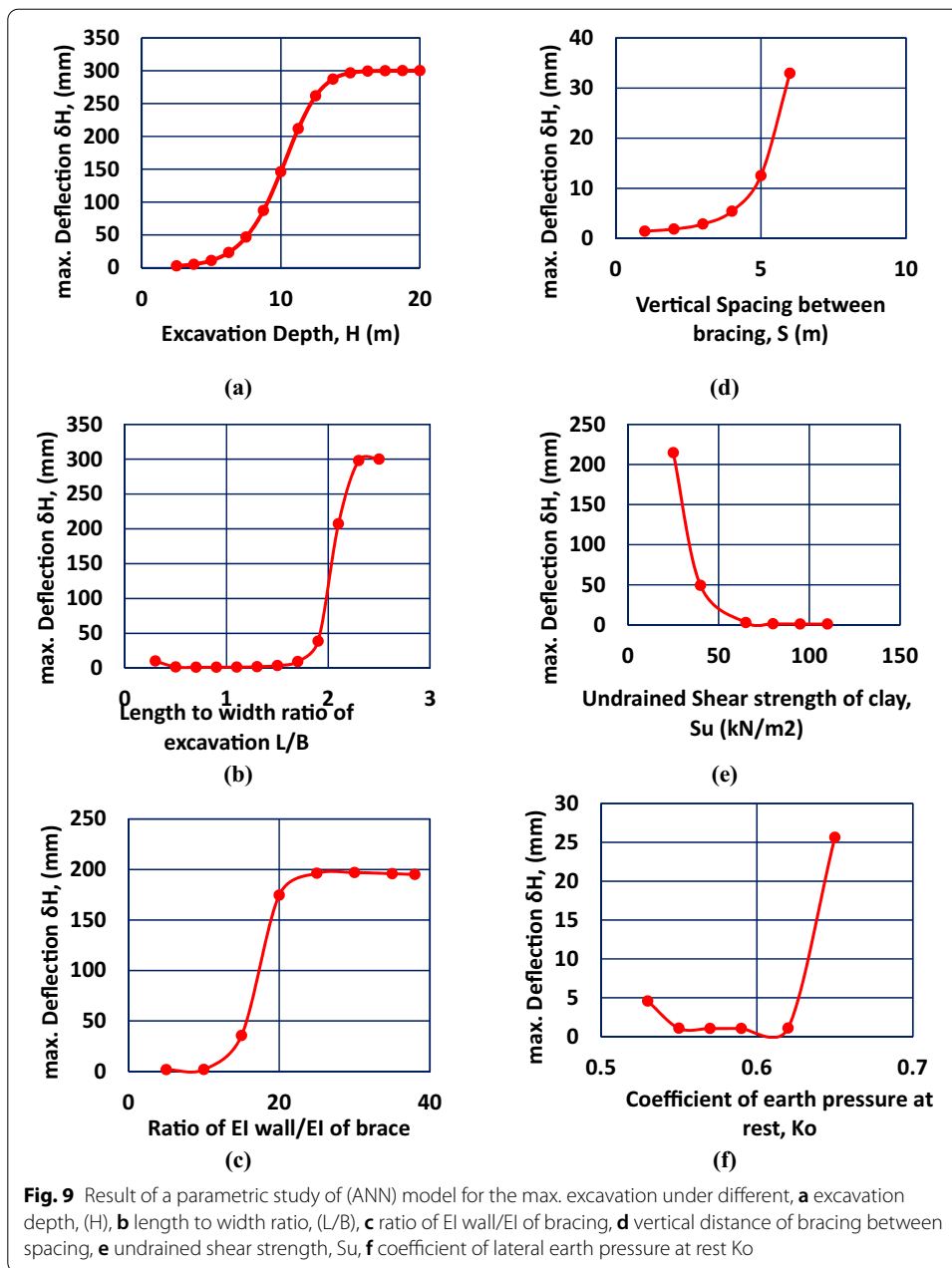
ratios and vertical distance of bracing respectively as expected. Figure 9e shows that the changes in max. wall deflections were less significant for S_u greater than 75 MPA, and increase with the increasing coefficient of lateral earth pressure as shown in Fig. 9f.

The general trend for the position of max. Wall deflection was revealed in Fig. 10a–f, it increases with the increase in excavation depth, while decreases with (L/B) ratios, (EI/stiffness of bracing) ratios, and the vertical distance of bracing (h_s), on the other hand the position of max. deflection increases with the increase in shear strength of the soil (S_u) up to 60 kN/m² then decreases, and the same trend observed with the coefficient of lateral earth pressure (K_0). Consequently, the trained neural network model was approved to give reasonable and appropriate relationships between the diverse input variables. The developed ANN has shown satisfactory performance.





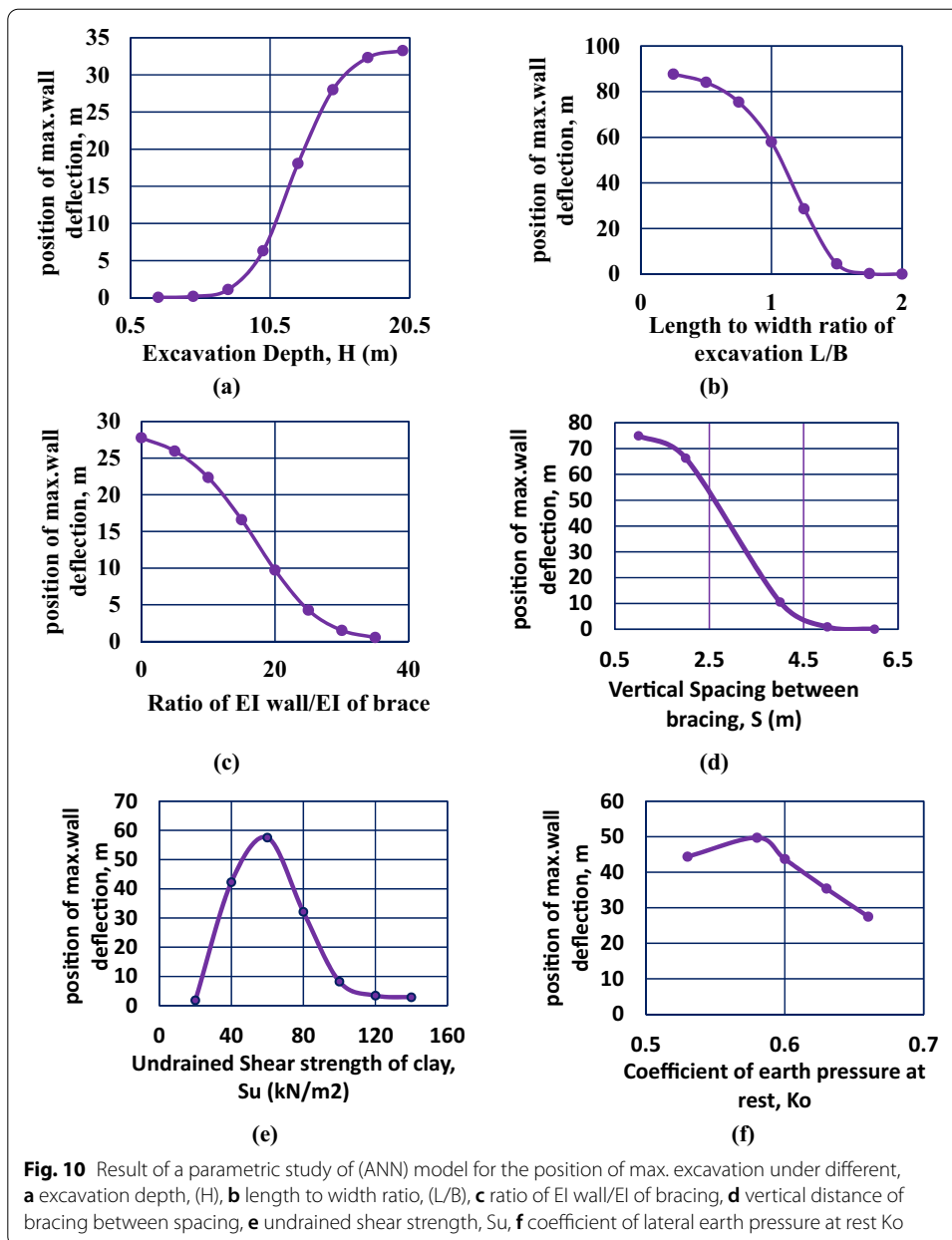
A set of design charts are developed. It's carried out by using synthetic input values within the ranges of data shown in Table 2. Figure 11 is an illustrative sample of the design charts obtained for $L/B = 1$, $K_0 = 0.53$, $h_s = 2.5$ m, the increasing trend of varying with excavation depth (H) for all cases, maximum deflection increases as the excavation depth increases and as expected.



On the other hand, the robustness of the (ANN) for the position of max. deflection can be determined by examining with input values within the ranges of data shown in Table 2, the sample of design chart obtained for $L/B = 1$, $K_0 = 0.53$, $h_s = 2.5$ m, EI wall/EI brace = 7, It was found that the trends of the design charts are in good agreement with what one would expect as shown in Fig. 12

Summary and conclusions

In this study, a neural network-based procedure to predict maximum wall excavation during excavation has been proposed. Based on a large number of case studies generated by observation techniques and FEM, the ANN model is developed to predict the



max. wall deflection induced by excavation. Six input variables are adopted to build the ANN model; they are excavation depth, system stiffness, the vertical distance between bracing, excavation width/wall length ratio, shear strength, and the lateral earth pressure coefficient. The effect of using a various number of a hidden layer on the ANN model results was investigated. The relative importance of the factors that affect maximum lateral deflection and its position was achieved by sensitivity analysis. The typical behavior of braced excavation in soft to medium clay is confirmed by the results of the extensive assessment of the ANN model developed.

The results showed that the sensitivity analysis indicates that the system stiffness has the most significant effect on the maximum wall deflection. The soil properties

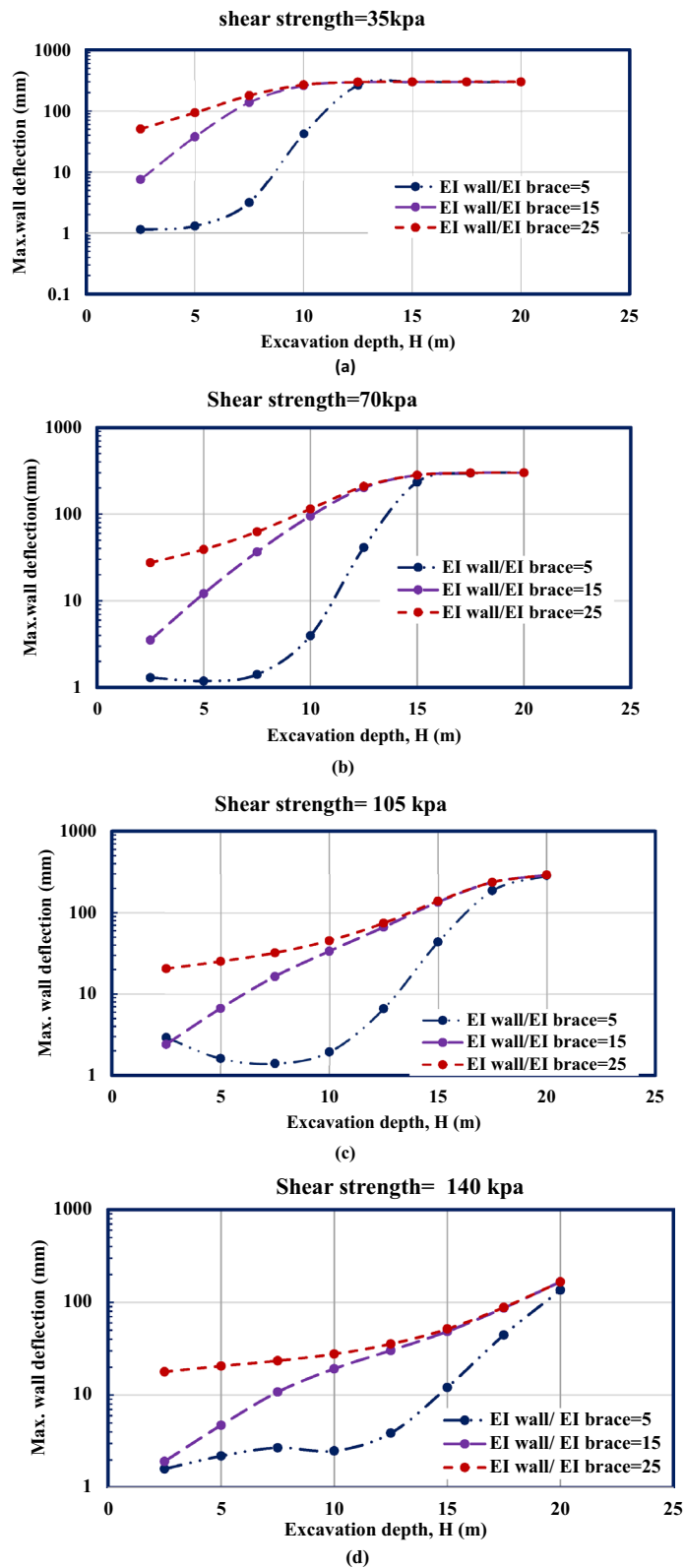
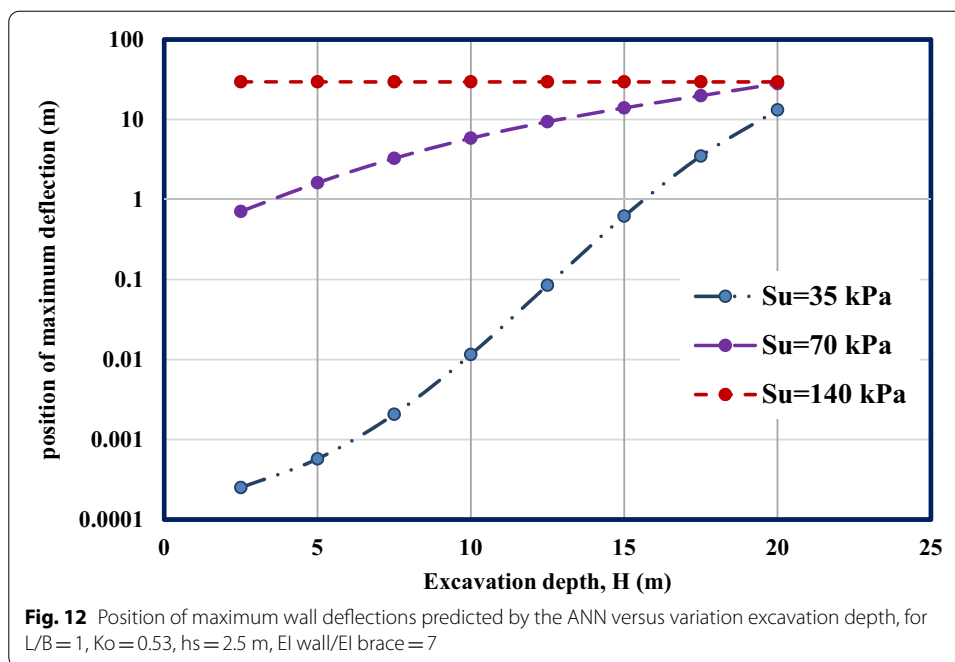


Fig. 11 Maximum wall deflections predicted by the ANN versus variation excavation depth, for $L/B = 1$, $K_0 = 0.53$, $h_s = 2.5$ m



have the most significant effects on the position, alternately the system stiffness and the vertical distance between bracing were found to have minor effects compared to the soil properties depending on the position of max. wall deflection.

The ANN developed has shown to be able to predict the wall deflections satisfactorily as showed by the results of the validation. Degree of accuracy was acceptable ($R=0.922$, $MSE=0.4\%$, and the number of optimum hidden layer nodes was found to be four) for predicted maximum wall deflection, and ($R=0.978$, $MSE=0.22\%$, and the number hidden layer nodes was found to be three hidden layer nodes) for predicted position of maximum wall deflection. The developed ANN trend to improved results based on the mean of case histories.

Acknowledgements

The authors would like to thank the University of Anbar, college of engineering for their support to carry the study

Authors' contributions

All authors read and approved the final manuscript.

Declarations

Competing interests

The authors declare that they have no competing interests.

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Received: 8 July 2020 Accepted: 24 May 2021

Published online: 07 October 2021

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