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Utilizing an Artificial Neural Network Model to Predict Bearing Capacity of Stone Columns

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ABSTRACT: Ultimate bearing capacity of soft ground reinforced with stone column was recently predicted using various artificial intelligence technologies such as artificial neural network because of all the advantages that they can offer in minimizing time, effort and cost. As well as, most of applied theories or predicted formulas deduced analytically from previous studies were feasible only for a particular testing environment and do not match other field or laboratory datasets. However, the performance of such techniques depends largely on input parameters that really affect the target output and missing of any parameter can lead to inaccurate results and give a false indicator. In the current study, data were collected from previous related literature including parameters handling the behavior of stone column and governing its bearing capacity. They included some parameters that were not considered previously; the undrained cohesion of soil, angle of internal friction and modulus of elasticity of fill material, area replacement ratio, and length to diameter ratio. The new model was generated using Neural Network Toolbox in MATLAB, all the five key parameters were treated as input data while the bearing capacity as the output data wanted to be predicted. A single hidden layer of twenty artificial neurons has been adopted in the generation of the model. The results and the regression analysis showed a high potential of using neural artificial network method in predicting the ultimate bearing capacity of soil strengthened with stone column. Thus, the study contributes in producing a reliable outcome as an alternative to using findings of costly and time consuming field or experimental tests.

Keywords: Stone columns, artificial neural network, ultimate bearing capacity, ground improvement, Matlab neural network toolbox, neural technology model.

Abbreviations: SC, stone column; c_u, undrained shear strength of the ground; ϕ_c, internal angle of shear resistance of the column substance; E_c, modulus of elasticity of the column; L/D, length to diameter ratio of stone column; a_r, area replacement ratio; q_u, ultimate bearing capacity of the improved ground with stone column; ANN, artificial neural network.

I. INTRODUCTION

Stone columns SCs are a common remedy method employed in many loading situations to support soft ground and increase its bearing capacity [1]. However, they probably cannot offer a required load capacity because of the reduction in the lateral confinement provided by the ground [2]. The performance of a single stone column is chiefly controlled by the characteristics and nature of soil, the characteristics of the stone column material and geometry; and the loading configuration [3]. The undrained shear strength of surrounding ground c_u can play a considerable role in confirming the feasibility of using this technique, much research stated a value of c_u more than 15 kPa is essential to deliver an acceptable lateral confinement [3].

Conversely, SCs are unfeasible when c_u of the ground beyond 50 kPa due to the excessive resistance of the penetrating which developed during the formation of the column [4]. Also, the mass of soil substituted by the fill which called area replacement ratio a_r and indicated the ratio between the area of the granular column and the area composited from the column and nearby ground, has an important weight on the degree of enhancement accomplished [5].

In addition, the characteristics of SC' s fill like internal angle of friction ϕ_c and modulus of elasticity E_c can govern the conduct of SC. For attaining a maximum bearing capacity, much research within this area was incorporated with using SCs of high internal angle of friction. Stone column SC will take a bigger share of the applied load if the modulus of elasticity of the stone material was greater than that of the surrounding ground [6]. Furthermore, the influence of the geometry of SC represented by the length to diameter ratio (L/D) is has a key significance in recognizing the failure type of SCs. Also, while increasing the length of the stone column L can manipulate the settlement of the foundation, the diameter of the stone column D contributes in increasing the bearing capacity [7].

Many researchers predicted the bearing capacity of soil post reinforcement with SCs in situ using conventional field load tests [8, 9].

Although such studies presented a reliable verification of design of SCs, they still costly, uncontrolled and produce few data. Others estimated the bearing capacity experimentally [10, 11]. The results under such circumstances gained under control conditions and can effectively give more data in comparison to the field test but they usually associated with errors due to scale effect, weather variation, and human mistakes [3]. So an applicable analytical or theoretical research is similarly essential [12]. Some examiners deduced analytical studies where others employed accessible software to estimate the act of SCs [13, 14]. Many theories and analysis are adopted for computing bearing capacity of the ground after inserting SCs.

On the contrary, majority of the applied theories were restricted to circumstances of the site and did not give a high harmony with the actual data. So, several artificial intelligence approaches like artificial neural network (ANN), and support vector regression (SVR), have been employed for anticipating an output parameter after entering several input parameters [12]. The input data for ANN model presented by Das and Dey, 2018 [12] included undrained shear strengths of surrounding clay, spacing to diameter ratio, angle of internal friction of the granular fill, columns length. Results of both SVR and ANN produced empirical equation which was not restricted to site condition and could be employed at any site with identified values of c_u, φ_c, spacing to diameter ratio, and L. However, E_c of the column has not taken into consideration.

Al-Kubaisi (2018) developed finite element models of soil strengthened with SCs [15]. The behavior of reinforced stone column was determined after adopting an input data that reflect the effect of the soil and stone material properties. Author integrated his finite element model with an ANN model. He generated the ANN model to study the effect of the input parameters represented by length and diameter of SC and the spacing among columns on the output parameter represented by the bending moment, settlement, or vertical stresses. Author used (IBM SPSS) software with employing one hidden layer of three neurons. In the hidden layer, the hyperbolic tangent function had been adopted. Whereas in the output layer, the identity function had been used. As stated by the researcher, the ANN model indicated a virtuous prediction of the output data (bending moment, shear force, and settlement of the footing) in comparison to the finite element and the ruled factor was L but the spacing among the columns had the smallest effect. It was clear that the ANN input parameters were represented by the geometry and spacing of SC only while the c_u of soil and ϕ_c and E_c of SC were not considered.

Bagińska and Srokosz (2018) investigated the feasibility of building deep neural networks DNNs to anticipate the q_u of shallow footing under circumstances of employing a limited laboratory data in networks training [16] . The input data included foundation dimensions (depth and width), stone column geometry (length and diameter), properties of column fill (ϕ_c and unit weight). The findings indicated that estimating the q_u by means of ANN models gaining lesser but high quality laboratory training data with a lower error. It was noticed more layers adopted in the model cause in worse accuracy. Again it can be seen that c_u, E_c, and a_r did not deliberated.

To sum up, the key parameters that could affect the q_u represented by c_u, a_r, ϕ_c, E_c and L/D, were revised. Also, the methods followed previously including developing ANN models to predict the bearing capacity were briefly reviewed. Although the previous few ANN examples showed a good performance in anticipating the bearing capacity of SCs. However, some significant parameter were missing and not considered as input data. Thus, that could cause in misleading and effect the outcomes accuracy. In this study the potential of adopting a new ANN model in which the five key parameters are entered as inputs, has been studied.

II. THE CONCEPT OF THE ANN METHOD

The ANN is a computational system structured to simulate input-output dependencies through a chosen number of hidden layers. A hidden layer consist of interconnected processing units or nodes which can loosely duplicate the biological neurons and called the artificial neurons.

Routinely, a neurons calculate the weighted average of its associated input, and then the weighted sum will be delivered to a nonlinear function, frequently called activation function [17]. Increasing the accuracy of prediction usually achieved by evaluating several datasets and amending connection weights such that each neuron effect other neutrons according to its weight.

Thus, after construction of a network for a chosen application, the network will be trained. First, the primary weights are selected arbitrarily. Afterward, the training, or learning starts [18]. The typical representation of the ANN system for the input-output dependencies and for the neuron configuration are demonstrated in Fig. 1.

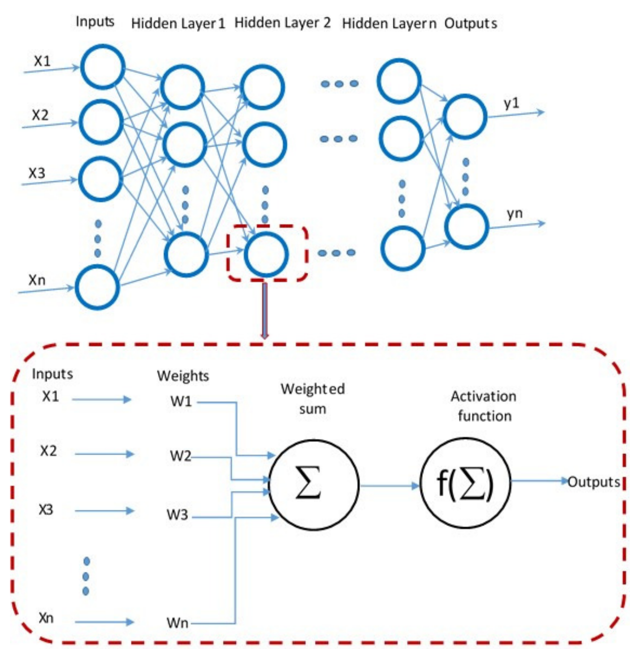

Fig. 1. The ANN system (a) The input-output dependencies diagram in typical representation, (b) the neuron representation diagram.

III. NORMALIZATION OF THE COLLECTED DATA

To evaluate the bearing capacity of SCs, 64 sets of data were congregated from the published previous related studies as shown in Table 1. The collected data in this study were gathered from nine references for different laboratory environment and different soil, column properties and geometries.

Table 1: Comparative study between passive and active systems.

S.N.	References	C_u in kPa	a_r	ϕ^0_c	EcinkPa	L/D	Q_u in kPa
1.	Ambily & Gandhi, 2007 [6]	31.00	0.227	43.00	55000	4.500	740.900
2.	Ambily & Gandhi, 2007 [6]	15.00	0.227	43.00	55000	4.500	349.950
3.	Ambily & Gandhi, 2007 [6]	7.00	0.227	43.00	55000	4.500	174.020
4.	Ambily & Gandhi, 2007 [6]	30.00	0.101	43.00	55000	4.500	647.100
5.	Ambily & Gandhi, 2007 [6]	13.00	0.101	43.00	55000	4.500	304.980
6.	Ambily & Gandhi, 2007 [6]	7.00	0.101	43.00	55000	4.500	151.970
7.	Ambily & Gandhi, 2007 [6]	29.00	0.057	43.00	55000	4.500	609.000
8.	Ambily & Gandhi, 2007 [6]	13.00	0.057	43.00	55000	4.500	283.010
9.	Ambily & Gandhi, 2007 [6]	7.00	0.057	43.00	55000	4.500	140.980
10.	Bredenberg & Borms, 1983 [19]	10.00	0.110	35.00	15000	8.000	20.000
11.	Bredenberg & Borms, 1983 [19]	10.00	0.100	35.00	15000	10.000	10.000
12.	Belal *et al*., 2019 [20]	20.00	0.111	39.06	16875	5.250	51.900
13.	Belal *et al*., 2019 [20]	20.00	0.111	39.06	16875	4.200	59.980
14.	Das and Dey, 2018 [12]	20.00	0.444	37.27	45000	6.000	382.000
15.	Das and Dey, 2018 [12]	20.00	0.250	37.27	45000	6.000	365.000
16.	Das and Dey, 2018 [12]	20.00	0.160	37.27	45000	6.000	352.000
17.	Das and Dey, 2018 [12]	20.00	0.111	37.27	45000	6.000	307.000
18.	Das and Dey, 2018 [12]	20.00	0.082	37.27	45000	6.000	265.000
19.	Das and Dey, 2018 [12]	20.00	0.444	37.27	45000	8.000	394.000
20.	Das and Dey, 2018 [12]	20.00	0.250	37.27	45000	8.000	382.000
21.	Das and Dey, 2018 [12]	20.00	0.160	37.27	45000	8.000	367.000
22.	Das and Dey, 2018 [12]	20.00	0.111	37.27	45000	8.000	304.000
23.	Das and Dey, 2018 [12]	20.00	0.082	37.27	45000	8.000	282.000
24.	Das and Dey, 2018 [12]	20.00	0.444	37.27	45000	10.000	403.000
25.	Das and Dey, 2018 [12]	20.00	0.250	37.27	45000	10.000	394.000
26.	Das and Dey, 2018 [12]	20.00	0.160	37.27	45000	10.000	379.000
27.	Das and Dey, 2018 [12]	20.00	0.111	37.27	45000	10.000	316.000
28.	Madun *et al*., 2018 [21]	15.00	0.900	35.00	40000	20.000	36.942
29.	Madun *et al*., 2018 [21]	15.00	0.900	35.00	40000	7.813	49.000
30.	Madun *et al*., 2018 [21]	15.00	0.900	35.00	40000	7.813	45.260
31.	Madun *et al*., 2018 [21]	15.00	0.900	35.00	40000	5.123	70.461
32.	Madun *et al*., 2018 [21]	15.00	0.900	35.00	40000	2.273	58.920
33.	Madun *et al*., 2018 [21]	15.00	0.900	35.00	40000	7.813	48.132
34.	Madun *et al*., 2018 [21]	15.00	0.900	35.00	40000	9.091	53.732
35.	Madun *et al*., 2018 [21]	15.00	0.900	35.00	40000	7.813	49.097
36.	Madun *et al*., 2018 [21]	15.00	0.900	35.00	40000	16.447	37.473
37.	Madun *et al*., 2018 [21]	15.00	0.900	35.00	40000	12.500	43.165
38.	Madun *et al*., 2018 [21]	15.00	0.900	35.00	40000	7.813	44.486
39.	Madun *et al*., 2018 [21]	15.00	0.900	35.00	40000	5.000	41.087
40.	Madun et al., 2018 [21]	15.00	0.900	35.00	40000	1.188	53.390
41.	Malarvizhi & Ilamparuthi, 2007 [22]	15.00	0.174	48.00	13300	5.000	19.050
42.	Malarvizhi & Ilamparuthi, 2007 [22]	15.00	0.174	48.00	13300	7.500	21.450
43.	Malarvizhi & Ilamparuthi, 2007 [22]	15.00	0.174	48.00	13300	9.330	30.150
44.	Malarvizhi & Ilamparuthi, 2007 [22]	18.00	0.174	48.00	13300	5.000	21.960
45.	Malarvizhi & Ilamparuthi, 2007 [22]	18.00	0.174	48.00	13300	7.500	27.000
46.	Malarvizhi & Ilamparuthi, 2007 [22]	18.00	0.174	48.00	13300	9.330	39.960
47.	Mohanty & Samanta, 2015 [23]	15.00	0.220	42.00	50000	6.667	23.000
48.	Mohanty & Samanta, 2015 [23]	15.00	0.220	42.00	50000	6.667	45.000
49.	Mohanty & Samanta, 2015 [23]	15.00	0.220	42.00	50000	6.667	66.030
50.	Mohanty & Samanta, 2015 [23]	15.00	0.220	42.00	50000	6.667	97.300
51.	Mohanty & Samanta, 2015 [23]	30.60	0.220	42.00	50000	6.667	29.560
52.	Mohanty & Samanta, 2015 [23]	30.60	0.220	42.00	50000	6.667	61.230
53.	Mohanty & Samanta, 2015 [23]	30.60	0.220	42.00	50000	6.667	93.310
54.	Mohanty & Samanta, 2015 [23]	30.60	0.220	42.00	50000	6.667	115.900
55.	Mohanty & Samanta, 2015 [23]	36.45	0.220	42.00	50000	6.667	35.320
56.	Mohanty & Samanta, 2015 [23]	42.30	0.220	42.00	50000	6.667	44.000
57.	Mohanty & Samanta, 2015 [23]	48.25	0.220	42.00	50000	6.667	55.000
58.	Naseer *et al*., 2019 [24]	54.00	1.000	30.00	25000	4.000	73.980
59.	Naseer *et al*., 2019 [24]	32.00	1.000	30.00	25000	4.000	34.560
60.	Naseer *et al*., 2019[24]	14.00	1.000	30.00	25000	4.000	14.840
61.	Watt *et al,* 1967 [25]	25.00	0.220	40.00	36000	10.500	220.000
62.	Watt *et al,* 1967 [25]	15.00	0.200	40.00	36000	6.500	150.000
63.	Watt *et al,* 1969 [25]	20.00	0.200	40.00	36000	6.000	150.000
64.	Watt *et al,* 1969 [25]	20.00	0.330	40.00	36000	6.000	150.000

Since, the bearing capacity of SCs depends on c_u, a_r, ϕ_c, E_c, and L/D, as was explained in the introduction section of this paper. Therefore, the presented ANN model treats these five key parameters as input datasets and whereas it treats the bearing capacity wanted to be predicted q_u as an output parameter.

A single hidden layer with twenty artificial neurons, has been employed as will be discussed in the following section (Section IV). By adopting the typical representation, the new ANN model can be represented as shown in Fig. 2.

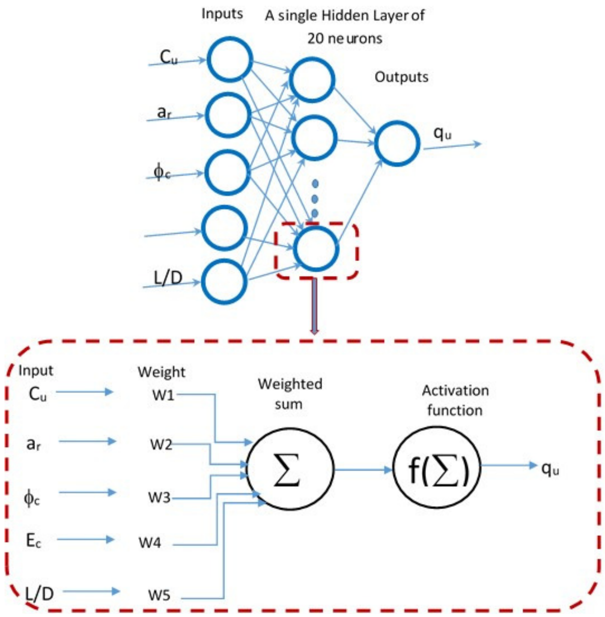

Fig. 2. The presented ANN model.

IV. GENERATION OF THE PRESENTED ANN MODEL

The presented ANN model was programmed in MATLAB R2010b environment using Neural Network Toolbox called as Neural Network Fitting Tool. Since, adoption more hidden layers in an ANN model can result in worse accuracy according to Bagińska and Srokosz (2018) [16], a single hidden layer only was selected for generating the model.

Twenty artificial neurons have been adopted in the hidden layer. The number of hidden neurons was chosen based on the optimization method such that the best performance was achieved. The hyperbolic tangent function and linear function have been used within the hidden and the output respectively, Fig. 3.

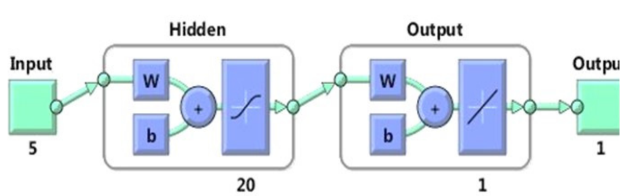

Fig. 3. The ANN model diagram in the Matlab software.

The collected data from the previous literature on the bearing capacity of SCs were divided into training, testing, and validation sets. First, the input datasets were trained through the network model and then they were tested and validated, so that the trained model is been verified and consequently choosing the best network configuration with a high quality outcome.

For the same reason, Levenberg–Marquardt back propagation algorithm was employed because it shows perfect performance in comparison to other applied algorithms. Ninety percent 90% (58 sample) of the data has been selected randomly in the training of the model while 5% (3 of the remaining data) has been selected randomly for testing the generated model.

The remaining 5% (3 of the data) has been held out for verification of the final ANN model.

V. RESULTS AND DISCUSSION

After building the new ANN model, a corresponding MATLAB code has been generated. Thus, running the code after typing five values (represented the inputs of the five important parameters related to the column fill and the surrounding ground) on the command window, will result in appearing the output value reflects the predicted bearing capacity on the Matlab screen.

A good correlation between the network target and the output was observed to predict the bearing capacity of a ground reinforced with SCs. The prediction was evaluated using regression R analysis of the training, testing, validation, and all. The recorded outcomes showed that the R values were 0.99891, 0.9995, 0.999964 and 0.99886 respectively.

Also, the output-target relationships are established for all regression types and the associated equations of target were developed from the outputs as shown in Fig. 4. In comparison to the results through training of the previous study presented by Das and Dey (2018) [12], the regression value of the current study is higher as they indicated R = 0.95472 and R = 0.94846 for tenfold cross-validation and non-cross-validation respectively.

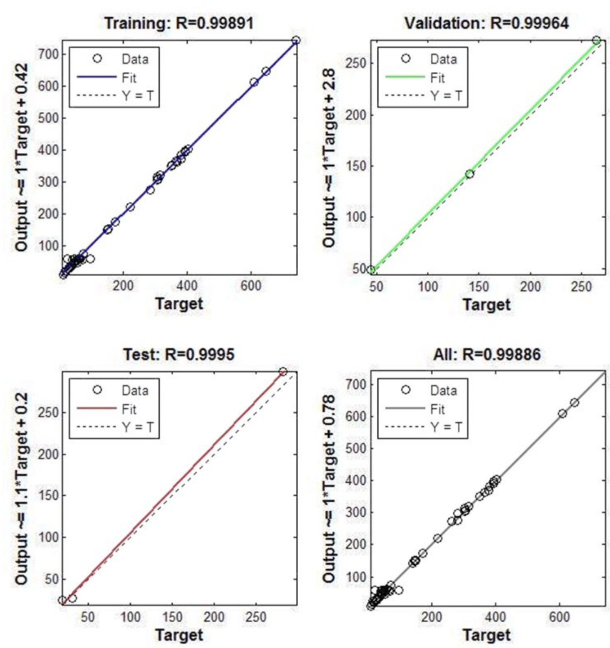

Fig. 4. The regression analysis of the data for training, testing, validation and all.

The error which is represented by the difference between target and output values for all stages of the analysis were analyzed.

For training process 72.4% of the data (42 of samples out of 58 samples showed a minimum error, did not exceed average value of 0.43. For testing process 66.7% of the tested data (two sample of the three selected tested samples) showed an average error bounded between 4.14 and -7.00.

For the validation process a 100% percentages of the data (all the three selected samples for the validation) showed an average error bounded between 0.43 and -7.00. For more details about the errors corresponding to the model, see the error histogram corresponding shown in Fig. 5.

In addition to this, the best validation performance was achieved at epoch 13 out of 19 epochs when the mean square error reached the value 30.17 as illustrated in Fig. 6. However, the best validation of the previous study by [12] was achieved at epoch 1000 out of 1000 for tenfold cross-validation model and at 2 out of 2 for non-cross validation model.

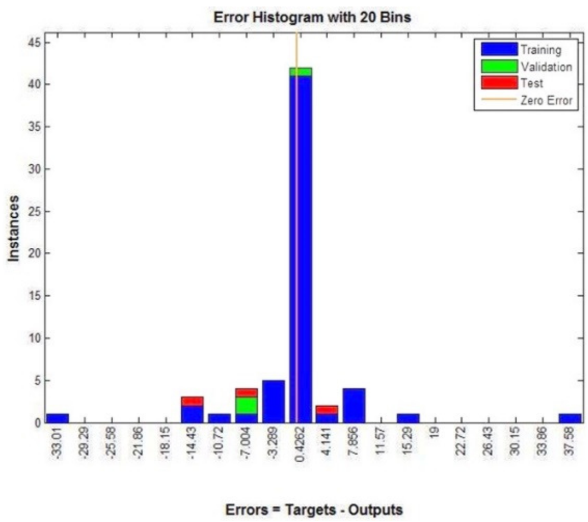

Fig. 5. The error histogram for the ANN model.

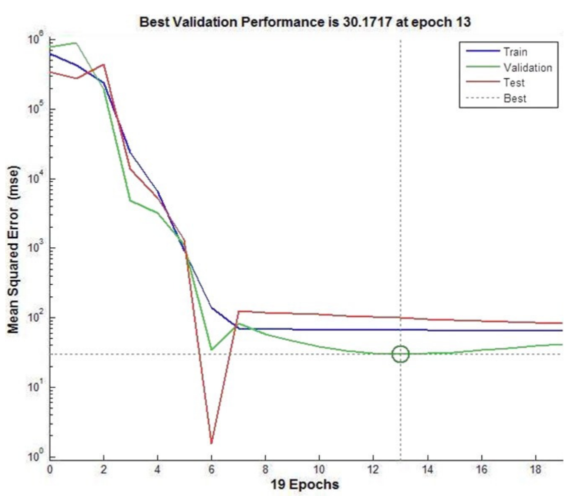

Fig. 6. The best validation performance of the adopted ANN model.

VI. CONCLUSION

A new ANN model was generated using MATLAB software. A single hidden layer of twenty neurons was adopted. The parameters; c_u. a_r, ϕ_c, E_s and L/D were considered as input data whereas the bearing capacity q_u as the output data required to be anticipated. The findings and the regression analysis showed a high potential of using neural artificial network method in anticipating the q_u.

VII. FUTURE SCOPE

Although this research has presented a reliable ANN model to predict the bearing capacity of treated ground based on a variety of input key factors, there are still essential parameters and situations that need further investigation. Thus, other parameters such as tensile strength and thickness of geo-material are required to be included in case of using geo-material as encasement to the SC. Furthermore, the effect of number of SCs and their configuration needs to be studied if grouped SCs are considered.

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Conflict of Interest. No conflict of interest.

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