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ORIGINAL PAPER

Prediction of geotechnical properties of treated fibrous peat by artificial neural networks

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Abstract
This paper concentrates on measuring the geotechnical properties of cement peat mixed with different dosages of well-graded sand as filler. Several geotechnical tests, namely unconfined compression strength (UCS), California bearing ratio (CBR) and compaction, were performed on the treated fibrous peat samples. The filler was used in a wide range of 50 to 400 kg/m^3 of wet peat. In addition, time-dependent changes of geotechnical properties of treated peat were also studied after 14, 28 and 90 days of air curing. Besides, different artificial neural networks trained by a back-propagation algorithm (ANN-BP) and particle swarm optimization method (ANN-PSO) were used to estimate the UCS of stabilized fibrous peat. Results indicate that after a 90-day curing period, the UCS and CBR of treated samples with 300-kg/m^3 cement only, increased by a factor as high as 8.54 and 13.66, respectively, compared to untreated peat. Besides, in the compaction tests, adding filler content to the cement peat increased the maximum dry density (MDD) significantly. In addition, the results of soft computing techniques indicated that the performance indices of the ANN-PSO model was better compared to the ANN-BP model. Finally, sensitivity results showed that the filler content and curing time were the most influential factors on estimating UCS.

Keywords Fibrous peat · Stabilization tests · Cement · Natural filler · CBR · Artificial neural network

Introduction

Fibrous peats are an unconsolidated organic material since they are loosely arranged and their particles are not cemented together. Mostly, they have accumulated under water in acidic conditions (Huat et al. 2014). These problematic soils can be found throughout the world. Almost 8% of the Earth's land is coved with peat (Mesri and Ajlouni 2007). These soils are classified as fibrous when the fiber and organic content is more than 66% and 75%, respectively (ASTM 2000). In subgrade construction, they are generally considered as problematic soils because of their high compressibility and low shear strength properties in their natural state (Huat 2004). These kind of soils cannot be useful for foundation floors (Edil 2003). In particular, these extremely acidic soils are made of organisms, animals and fresh fibers (Kalantari and Prasad 2014). As a result, high permeability, high rates of creep and low pH are the other geotechnical properties of the peats. Additionally, due to high in situ void ratios of the peats (7.5 to 30), the in situ water content of these soils ranges from 500 to 2000%, respectively (Moayedi et al. 2014).

A great volume of research works has been performed to evaluate the effect of cement on the strength properties of peats (Table 1). However, the research to date has tended to focus on peat soil stabilization using different binders rather than filler effect. Regarding the filler effect, Celik and Canakci

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Table 1 Studies conducted on the peat soil stabilization using cement

Soil specification (average)	Location	Test details	Results
Fibrous peat (H_3 to H_7), untreated UCS = 14.23 kPa, pH = 5, (Kolay et al. 2011)	Malaysia	Cement was added at OWC 28-day water curing	No optimum in UCS results was observed, UCS increased by OPC increment 20% OPC, increased the UCS to 115 kPa
Fibrous peat, untreated UCS = 28 kPa Cc = 3.64 (Kalantari et al. 2010)	Malaysia	Cement was added at field water content (198%-417%) after 90-day air curing 5% to 50% OPC was used	25% OPC, increased the UCS to 330 kPa 25% OPC, increased the CBR to 25%
Fibrous peat, untreated UCS = 54 kPa (Boobathiraja et al. 2014)	India	Cement was added at OWC 10% to 50% OPC was used	50% OPC, increased the UCS to 125 kPa
Fibrous peat, water content = 1400% (Axelsson et al. 2002)	Sweden	The stabilized samples were subjected to the dispersed pressure of 18 kPa after 28- days air curing 50 kg/m^3 to 250 kg/m^3 OPC was used	250 kg/m^3 OPC, increased the UCS to 300 kPa Addition of 100 kg/m^3 sand gave an increment of 30 kPa in shear strength
Sphagnum (H_6), water content = 210% (Francisco and Al Tabbaa 2004)	Ireland	100 to 500 kg/m^3 OPC was used (relative to the wet mass of peat) 28 days and 90-days air curing	Range of 300 – 400 kg/m^3 cement was proposed for peats (W/C = 1)
Fibrous peat (H_4), untreated UCS = 2 kPa, organic content = 96% (Hashim and Islam 2008)	Malaysia	300-kg/m^3 OPC + sodium bentonite (85:15) + 25% sand Air curing	After 7 days curing, UCS reached to 37 kPa
Irish fibrous peats, untreated UCS = 20 kPa (Hebib and Farrell 2003)	Ireland	150,200 and 250 kg/m^3 OPC (relative to the wet mass of peat) 28 and 90-day water curing	150,200 and 250 kg/m^3 OPC raised UCS of untreated peat to around 200,220 and 500 kPa, respectively
Fibrous peat, untreated UCS = 28 kPa (Kalantari and Prasad 2014)	Malaysia	UP to 50% OPC with three different curing method: (i) air (ii) water (iii) water + surcharge load (10 kPa) (28,90 and 180-days)	Water curing method with surcharge load gave the highest UCS values with 50% OPC
Fibrous peat, water content = 697% (EuroSoilStab 2002)	Netherland	7 and 28-days water curing 200 and 400 kg/m^3 OPC (relative to the wet mass of peat) mixed with slag	200 and 400 kg/m^3 OPC mixed with slag increased UCS of untreated peat to around 400 and 600 kPa, after 7-day water curing, respectively
Banting peat (H_1 to H_6) (Alwi 2008)	Malaysia	Cement and Bentonite (85:15) selected dosages: 250 Water curing 56-days	300-kg/m^3 cement with 41% sand, increased the UCS up to 425 kPa
Fibrous peat (H_4) (Deboucha et al. 2008)	Malaysia	15% cement, 15% sand and 70% peat - Water curing for 56-days	Increased the CBR from 10% to 25%

Note: OWC = optimum water content, OPC = ordinary Portland Cement, UCS = unconfined compression strength, CBR = California bearing ratio

(2014) evaluated the geotechnical characterizations of fibrous peat mixed with natural filler. In their study, the effects of filler dosages on compaction, shear strength and compressibility of fibrous peat were investigated. In the sample preparation, the untreated soil was mixed with filler at its maximum dry density (MDD) and optimum water content (OWC). Their results indicate that when the sand content increases in the peat, internal friction angle increases while the cohesion of the peat is reduced. Moreover, the compression ratio of the fibrous peat is marginally reduced when the filler content is increased.

The objective of this study is to discuss the effects of natural filler dosages on the geotechnical characterization of the treated peat samples. In addition, this study focuses on finding the optimum or proper filler range to improve the engineering properties of fibrous peat stabilized with cement using different geotechnical tests. Finally, an expert artificial neural network (ANN) trained with particle swarm optimization method is employed to estimate the UCS of treated peat samples from the other geotechnical properties such as California bearing ration, cement content, filler content, MDD and optimum water content.

Experimental study

In this study, Undisturbed and disturbed peat samples were obtained from the Pontian area of the state of Johor in Malaysia. To get the undisturbed peat samples a special cylindrical tube with an internal diameter of 150 mm and with a height of 230 mm was used. Based on Von Post (Von 1992) classification system the peat was H_3. In the present study, a total of 11 tests on unimproved peat samples and 90 tests on the stabilized peat samples were prepared at various binder compositions and dosages. It should be noticed that, in order to evaluate the filler effect, all the stabilization tests were carried out with fixed cement content of 300 kg/m^3 relative to wet mass of peat with different dosages of fillers. This amount was derived based on previous studies on the UCS of treated samples (Dehghanbanadaki et al. 2017). In case, we performed unconfined compressions (hereafter UCS) tests based on BS 1377:1990: Part 7: section 7 (British Standard Institution 1990) under strain control condition with the rate of 0.0125 mm/s. California bearing ratio (CBR) tests and compaction tests were carried out on treated samples based on ASTM D 1883-07E02 and ASTM D-698 (1992), respectively. In this research, for each experimental test two samples were prepared cured and tests and the average result of the tests was considered as final result. Table 2 summarizes the geotechnical properties of materials used in this study. Table 3 shows the detail of mix designs of each test. Grain size distributions of fibrous peat and filler used in this study are shown in Fig. 1 while, Fig. 2 demonstrates the sample preparation in this research. It should be mentioned that the details of sample preparation for the tests can be found in previous publication (Dehghanbanadaki et al. 2017).

Table 2 Properties of the peat, filler and cement used in this study (Dehghanbanadaki et al. 2013 & Dehghanbanadaki et al. 2017)

Peat	
Item	Results
WC %	495
OC (%)	91
pH	4.1
Classification	Fibrous (H_3)
Unit weight (kN/m^3)	10
Permeability (m/day)	0.89
Specific gravity	1.38
C_c	3
C_α (average)	0.065
LL	260
C_u – VST (kPa)	11
C_u – UCS (kPa)	10
FC (%)	80
Void ratio	11
Filler (SW)	
Item	Results
MDD	17.51
Friction angle	36.8
Minimum void ratio	0.32
Specific gravity	2.64
Fineness modulus	2.81
Cement	
Item	Content (%)
CaO	68.6
SiO_2	21.6
Al_2O_3	5.3
Fe_2O_3	3.3
MgO	1.1
SO_3	<0.01
Na_2O	<0.01
K_2O	<0.01

Note: WC: in situ water content of the peat; OC: organic content; VST: vane shear test, C_c: compression index; C_α: secondary compression index; LL: liquid limit; C_u: undrained shear strength; FC: fiber content; MDD: maximum dry density (kN/m^3)

Simulation by ANN models

Details of ANN

ANNs are considered very powerful tools to estimate any indistinct functional data (Rojas 2013; Maren et al. 2014; Baughman and Liu 2014). Therefore, for the estimation purposes, we used MATLAB R2016a software (nftool) to train

Table 3 Mix designs of the stabilized peat specimens

Number of tests	Test details	Curing time (days)
5	UCS: UP	–
21	UCS: UP + C (150, 200, 250, 300,325, 350 and 400 kg/m^3)	14, 28 and 90
3	UCS: UP + C (300 kg/m^3)	14, 28 and 90
3	UCS: [UP + C (300 kg/m^3)] + F (50 kg/m^3)	14, 28 and 90
3	UCS: [UP + C (300 kg/m^3)] + F (75 kg/m^3)	14, 28 and 90
3	UCS: [UP + C (300 kg/m^3)] + F (100 kg/m^3)	14, 28 and 90
3	UCS: [UP + C (300 kg/m^3)] + F (125 kg/m^3)	14, 28 and 90
3	UCS: [UP + C (300 kg/m^3)] + F (175 kg/m^3)	14, 28 and 90
3	UCS: [UP + C (300 kg/m^3)] + F (200 kg/m^3)	14, 28 and 90
12	Compaction: UP + C (150, 200, 250, 300 kg/m^3)	14, 28 and 90
3	Compaction: UP	–
3	Compaction: UP + C (300 kg/m^3) + F (50 kg/m^3)	14, 28 and 90
3	Compaction: UP + C (300 kg/m^3) + F (100 kg/m^3)	14, 28 and 90
3	Compaction: UP + C (300 kg/m^3) + F (150 kg/m^3)	14, 28 and 90
3	Compaction: UP + C (300 kg/m^3) + F (200 kg/m^3)	14, 28 and 90
3	CBR: UP	–
3	CBR: UP + C (300 kg/m^3)	14, 28 and 90
3	CBR: UP + C (300 kg/m^3) + F (50 kg/m^3)	14, 28 and 90
3	CBR: UP + C (300 kg/m^3) + F (75 kg/m^3)	14, 28 and 90
3	CBR: UP + C (300 kg/m^3) + F (100 kg/m^3)	14, 28 and 90
3	CBR: UP + C (300 kg/m^3) + F (125 kg/m^3)	14, 28 and 90
3	CBR: UP + C (300 kg/m^3) + F (150 kg/m^3)	14, 28 and 90
3	CBR: UP + C (300 kg/m^3) + F (175 kg/m^3)	14, 28 and 90
3	CBR: UP + C (300 kg/m^3) + F (200 kg/m^3)	14, 28 and 90

• UP: untreated peat, C: cement, F: filler, UCS: unconfined compression strength, CBR: California bearing ratio.

• UP + C (300 kg/m^3) = untreated peat mixed with 300-kg/m^3 cement only.

• UP + C (300 kg/m^3) + F (50 kg/m^3) = at first: untreated peat mixed with 300-kg/m^3 cement then 50 kg/m^3 well-graded sand as filler was added to the mixture.

and develop different ANN models. Briefly, different multi-layer feed-forward perceptron (MLP-FF) networks trained by Levenberg–Marquardt (LM) backpropagation (BP) were adopted, while for the transfer function, we selected a logistic sigmoid function. In the MLP models, CBR, curing time, filler content, OWC and MDD were considered as inputs, whereas UCS was selected as the target of the ANN. In data classification, we followed the method proposed by Shahin et al. (2004) with 70% of data for training, 15% for validating and 15% for testing was considered. Finally, for error analysis, we used mean square error (*MSE*) and a coefficient of correlation (R). The MLP details of this study are shown in Fig. 3.

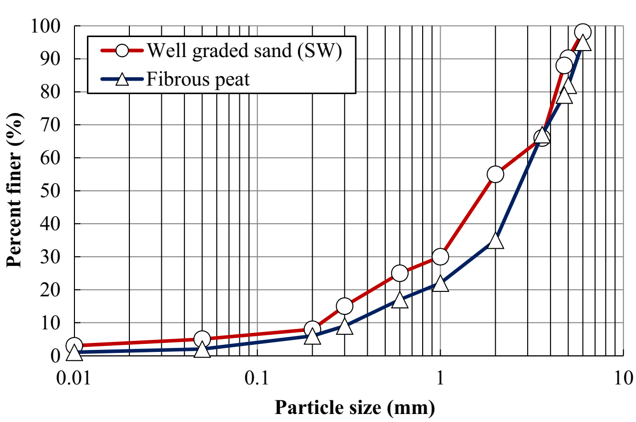

Fig. 1 Grain size distributions of soil and filler (Dehghanbanadaki et al. 2017)

Implementation of particle swarm optimization in MLP training

One of the drawbacks of the BP algorithm is a slow training rate and trapping in local minima (Jadav and Panchal 2012; Momeni et al. 2014). Several smart and evolutionary algorithms such as particle swarm optimization (PSO) algorithm, imperialist competitive algorithm (ICA), genetic algorithm (GA), bacterial foraging optimization technique (BFOT) and bee colony (BC) algorithm can be applied as a training methods in ANNs (Nanda and Panda 2014; Sun and Xu 2016). These population-based algorithms with

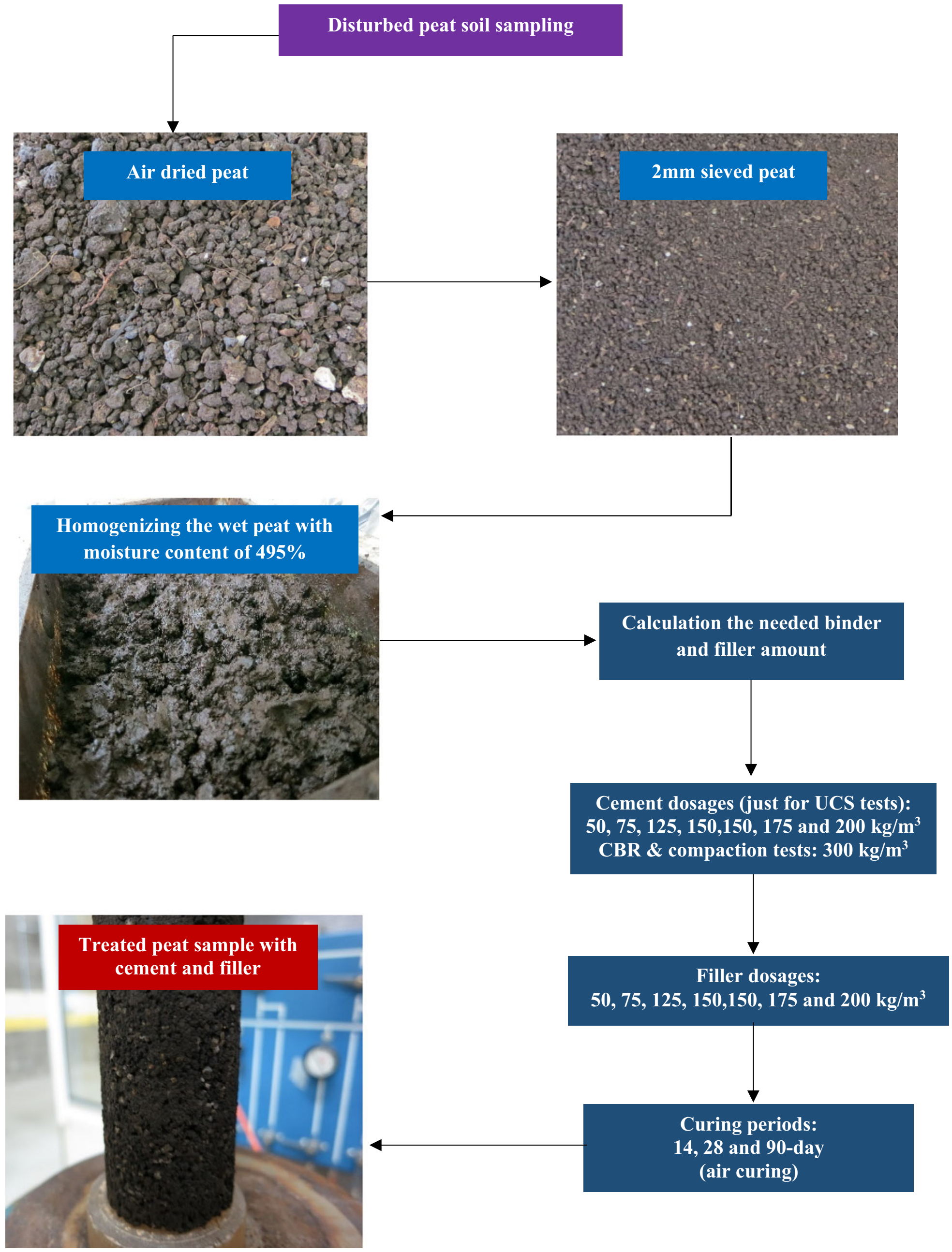

Fig. 2 Sample preparation in this research (Dehghanbanadaki et al. 2017)

approximately similar concepts can improve the performance of the ANN models. Each agent in the population competes and shares the information to achieve certain tasks and better performance (Rahmanian et al. 2012). Consequently, in this paper, we selected PSO which is a population-based stochastic algorithm to increase the accuracy rate of the best ANN-MLP (BP) model. This smart algorithm was first proposed by Kennedy and Eberhart (1995). The training improvement performance of ANN-MLP models using PSO technique have been proven by several researchers (Zhang et al. 2007; Zamani and Sadeghian 2010; Hajihassani 2013; Sun and Xu 2016). the following items briefly show the implementation of the PSO algorithm in training of MLPs.

- Determination of PSO parameters (pre-defined coefficients, acceleration constants & coefficient of inertia weight)
- Random population of ANN weights & biases using vector-encoding technique
- Evaluation of cost function – *MSE* (mean square error) of ANN trained by BP
- Finding the local & global best of each particle

  If:
- Improvement in fitness for a certain number of iterations is not observed = termination
- Using ANN-PSO

  Else:
- Updating the particles

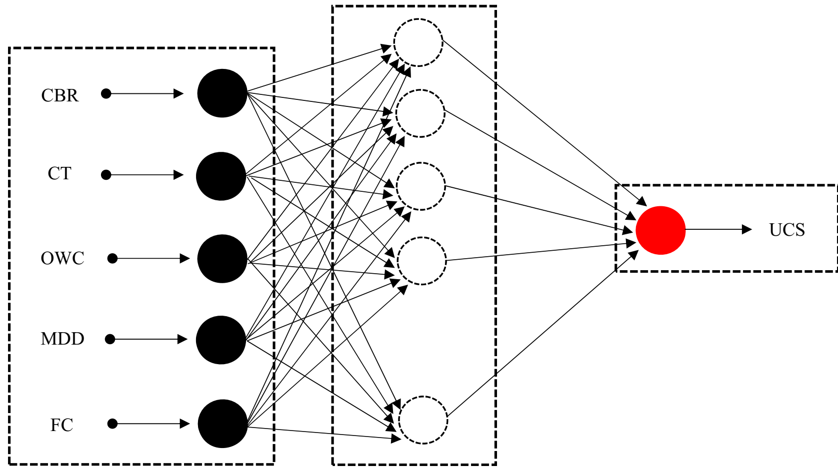

Fig. 3 MLP model of this study. Note: CBR = California bearing ration, CT = curing time, OWC = optimum water content, MDD = maximum dry density and FC = filler content

Results and discussions

UCS tests results

Figure 4 shows the UCS of treated peat samples at different cement dosages after 14-, 28- and 90-day curing periods. As can be seen, since the initial water content of the peat is fixed during the stabilization process, when the cement content was in the range of 150 to 200 and 300 to 400, no improvement in UCS was observed. Besides, it is evident from past studies that the UCS of treated peat samples with 300-kg/m^3 cement dosages should give higher shear strength compared to this research (Axelsson et al. 2002; EuroSoilStab 2002; Hebib and Farrell 2003; Alwi 2008, Kalantari et al. 2010; Motamedi et al. 2015). A possible explanation for this difference might be that the fibrous peat soil in this research has a high organic content of 91% which can impede the cement stabilization process significantly. In contrast, the achieved UCS values of treated peat samples were consistent with the results of Hashim and Islam (2008). They stabilized the Malaysian fibrous peat with low shear strength (UCS = 2 kPa) and high organic content (96%) with 300-kg/m^3 cement + sodium bentonite (85:15) + 25% sand an using air-curing technique. They gained 37 kPa for the UCS of treated peat after 7-day air curing. To evaluate the degree of improvement of the stabilized soil, the UCS results were compared to Table 4 as proposed by Terzaghi et al. (1996). The optimum amount of filler content to increase the strength of cement peat was determined to be 125 kg/m^3 based on previous research of the first author (Dehghanbanadaki et al. 2013). Therefore, using this optimum amount (125 kg/m^3) mixed with 300-kg/m^3 cement increased the UCS of untreated peat up to 944% after a 90-day curing time. This finding corroborates the results of Wong et al. (2013).

CBR and compaction tests results

The trend of CBR changes of cement peat mixed with various percentages of filler content is presented in this section.

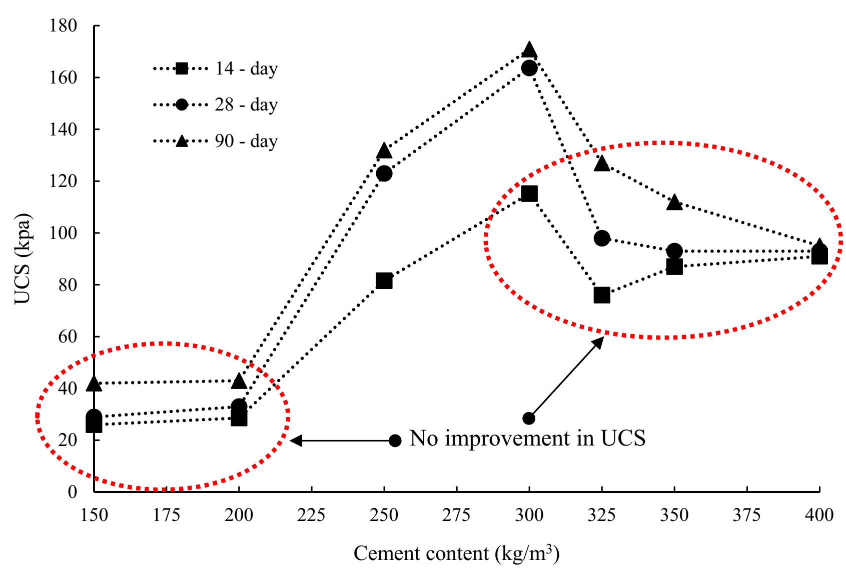

Fig. 4 UCS of treated peat samples at different cement dosages

Table 4 Consistency classification

Consistency	UCS (kPa)	This study
Very soft	< 24	20 (untreated)
Soft	24-50	
Medium	50-100	
Stiff	100-200	170 (improved)
Hard	200-400	
Very hard	> 400	

Figure 5 illustrates the variations of CBR values of cement peat with 300-kg/m^3 cement mixed with different dosages of filler cured for 14, 28 and 90-day. The horizontal lines represent the CBR of peat and cement only. For standard CBR, the CBR of natural fibrous was found at 3%. This value reached to 21% using optimum cement content in 14-day curing, which is seven times higher than the original value. Over more curing time the CBR values increased to 36% and 41% in 28 and 90-day, respectively. The CBR of untreated peat showed that the soil has poor Geotechnical properties (0 to 3%). This low CBR of compared to the stabilized samples is mainly attributed to inherent low shear strength of peats which is due to high void ratio and less solid particles of these problematic soils. According to Fig.5, inclusion of the filler content

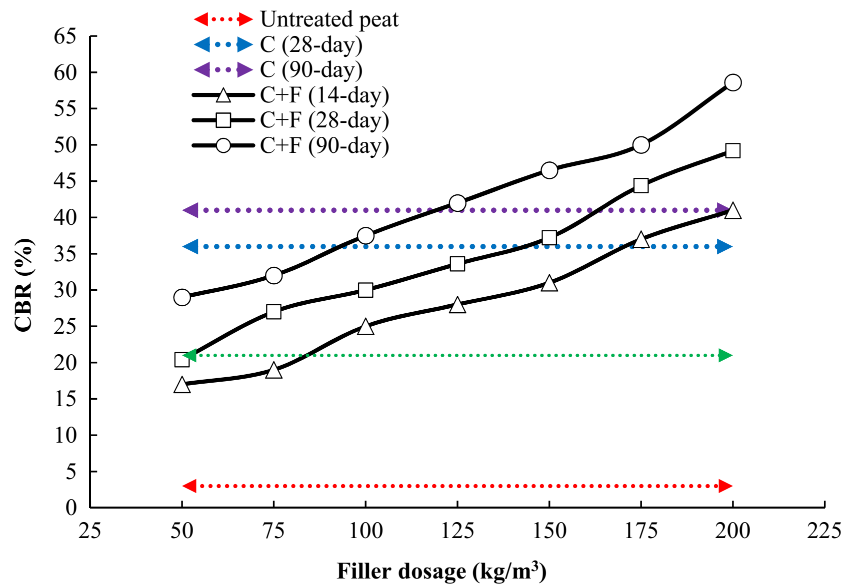

Fig. 5 CBR values of cement peat with 300-kg/m^3 cement mixed with different dosages of filler cured for 14, 28 and 90 days

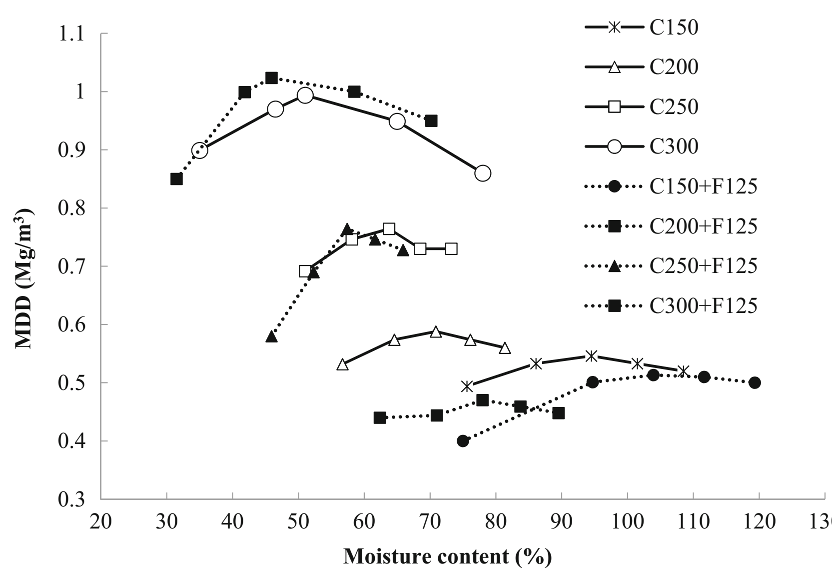

Fig. 6 Maximum dry density of treated peat mixed with 125-kg/m^3 dosages of filler cured for 28 days

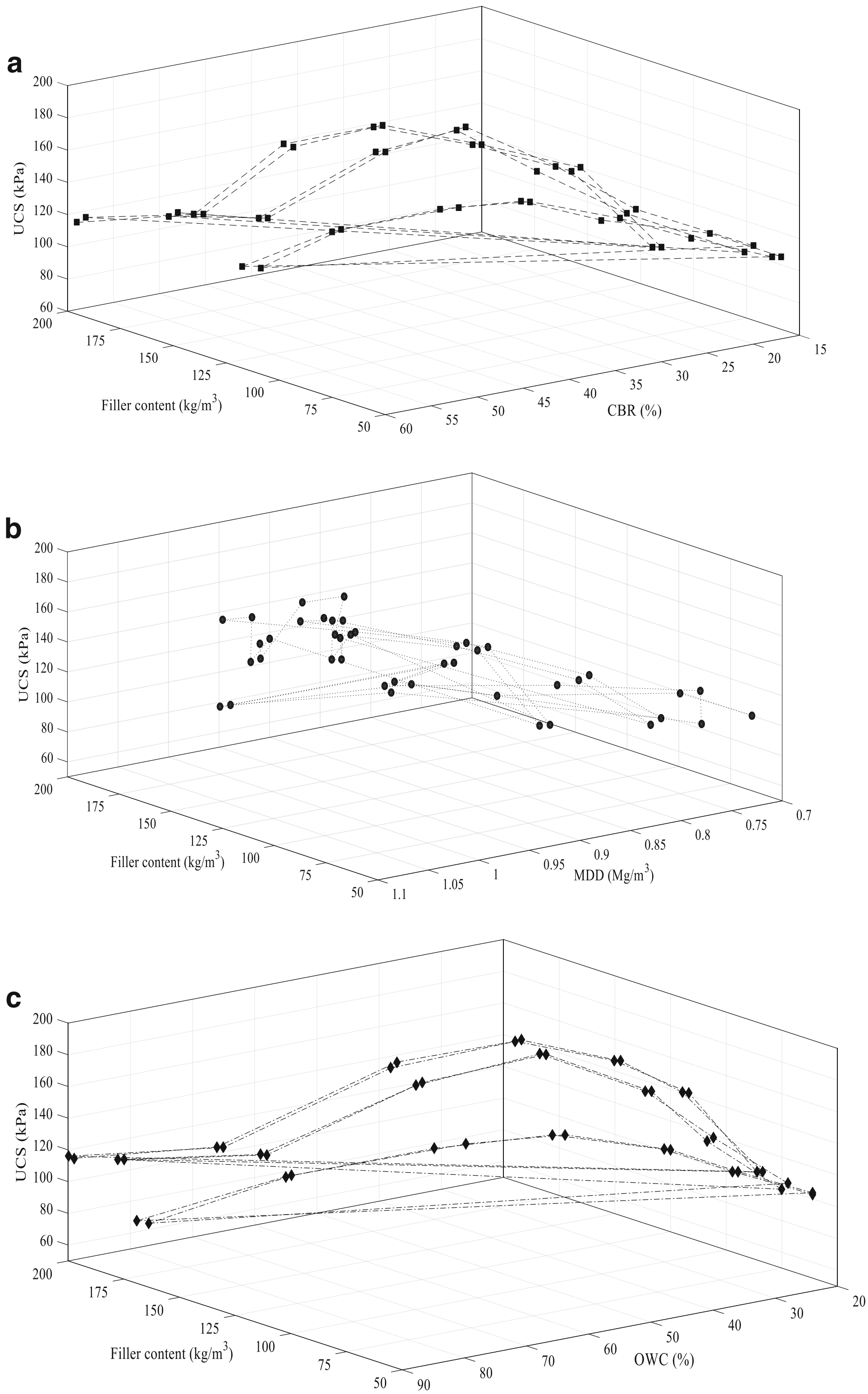

Fig. 7 Variation of filler effect on the UCS of treated samples with (**a**): CBR, (**b**): MDD and (**c**): OWC

in the cement peat mixture did not show any optimum amount. By adding the filler amount from 50 kg/m^3 to 200 kg/m^3 the CBR values of treated peat increased sharply. For an example, using 200 kg/m^3 filler in comparison of cement peat, the CBR increased from 41% to 58.6% in 90 days curing period. In comparison with untreated soil, the CBR of cement peat mixed with 200 kg/m^3 filler content was increased by a factor as high as 19.4 times. The results of this analysis imply that for stabilized peat samples with more than 200 kg/m^3 filler dosages, higher CBR value can be expected.

Figure 6 shows the MDD/moisture content relationship of cement peat samples and cement peat samples mixed with different filler dosages. For example, in the case of 125-kg/m^3 filler content, OWC and MDD for untreated peat was found to be 135% and 0.42 Mg/m^3, respectively. It should be noticed that the trend of untreated peat in compaction tests differs from some published studies (Kolay et al. 2011). These differences can be explained by the texture of the peats which they are significantly site-dependent. As shown in Fig. 6, for peat samples treated with cement, an increase in cement content resulted in an increase of MDD and decrease in OWC. In addition, it was observed that when filler content increased, in comparison with cement peat only, the MDD increased while OWC reduced. In this case, the increase in MDD could be mainly due to increasing the solid particles of treated peat. For example, in comparison between C300 and C300 + F200, the MDD of stabilized peat increased from 0.97 Mg/m^3 to 1.03 Mg/m^3, while the OWC decreased

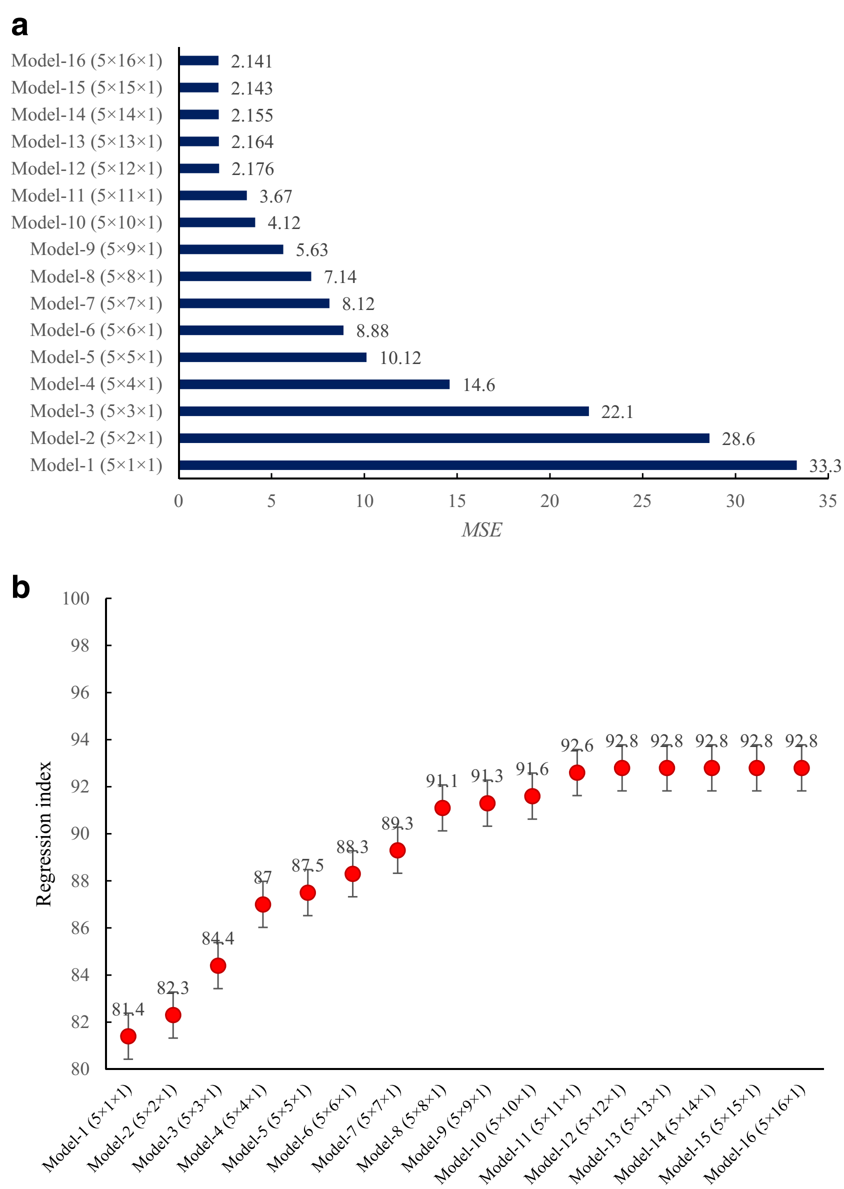

Fig. 8 Performance indices of ANN modes. (a) *MSE*. (b) Regression index

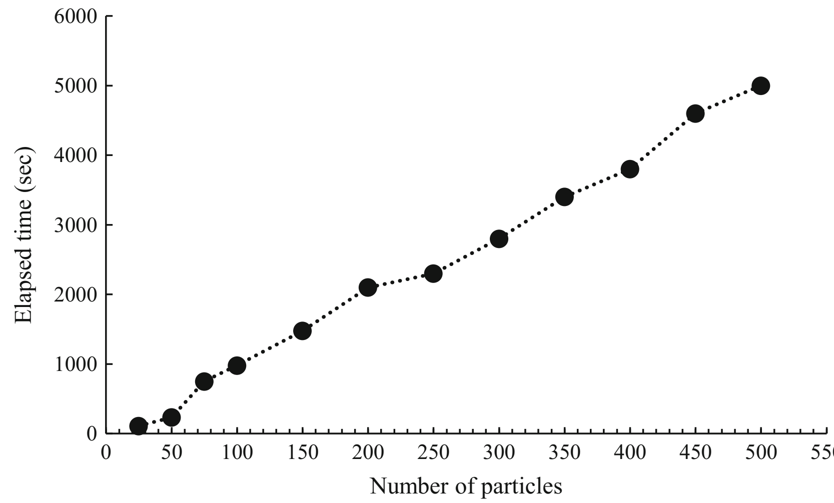

Fig. 9 Effect of number of particles on training time of ANN-PSO model

from 51% to 45%. This decrease in OWC may be explained by the fact that, due to an increase in the solid particles in the stabilized peat samples, the number of peat particles became less. Therefore, the rate of water absorption by peat particles decreased significantly. Finally, for the comparison purpose, Fig. 7 shows the combination effects of FC with (a): CBR, (b): MDD and (c): OWC on the UCS of treated samples.

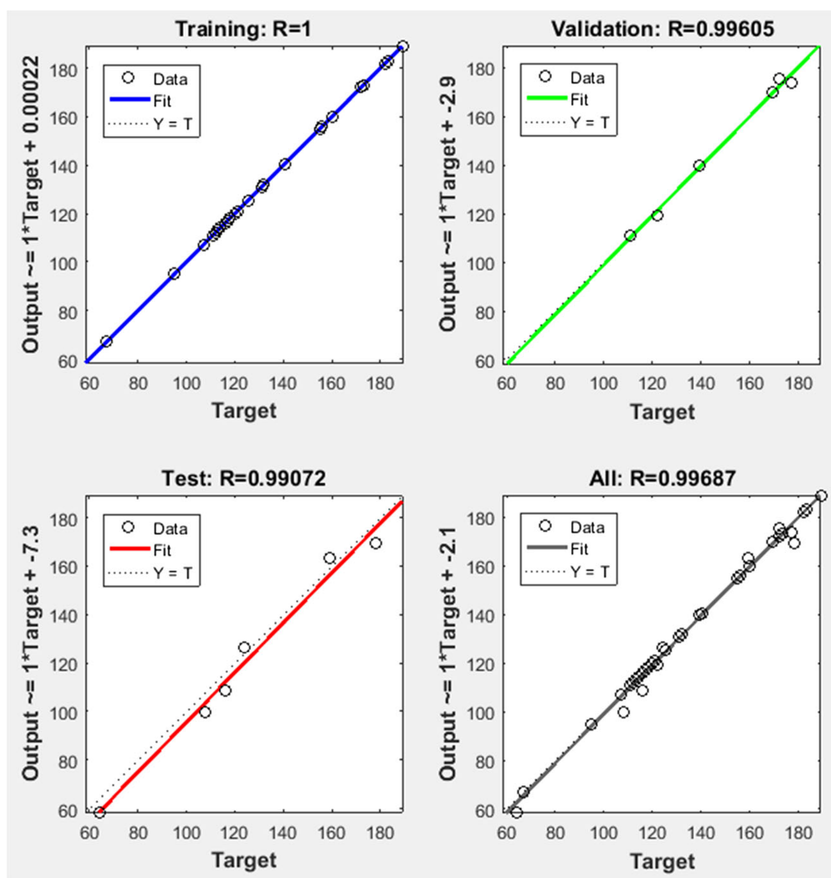

Fig. 10 Regression indices of the best ANN-PSO model (5 × 12 × 1)

Table 5 Weights of the best ANN-PSO (input to hidden layer)

Items	Input – 1 (CT)	Input – 2 (CBR)	Input – 3 (FC)	Input – 4 (MDD)	Input – 5 (OWC)
N-1	−0.6799	0.3861	2.2683	−0.2556	−0.426
N-2	−2.4176	−0.5843	0.3873	−2	−0.4817
N-3	1.2871	1.305	−1.2879	−1.0671	0.7759
N-4	1.3237	1.3227	1.9525	−0.5788	−1.9293
N-5	1.6131	0.8813	0.9755	−0.6561	−0.0051
N-6	−0.1277	−1.5509	−0.2891	1.4241	0.1116
N-7	−3.0236	0.1245	−1.4531	−2.1145	0.8234
N-8	1.5703	−0.2498	1.1623	−0.7946	0.3969
N-9	0.0648	−1.1734	−1.4146	−0.5297	−1.3481
N-10	1.2922	−1.2642	−0.3751	0.9055	−0.1274
N-11	0.7684	−0.5837	−1.9875	−0.6265	−1.128
N-12	−2.0329	0.4457	1.4819	0.4029	−1.3905

ANN results

As mentioned before, in the simulation process of the ANNs, just one hidden layer including different hidden neurons was used. Figure 8 a, b shows the performances of different ANN models from model-1 ($5 \times 1 \times 1$) to model-16 ($5 \times 16 \times 1$) trained by the BP algorithm. It should be indicated that in Fig. 9a, b the results of *MSE* and regression indices are the average of train, validation and test data. As can be seen in Fig. 8a, by increasing the number of hidden neurons from 1 to 11 the *MSE* decreased sharply, while from model-12 to model-16 approximately, the *MSE* remained constant. Moreover, increasing the number of hidden neurons more than 12 did not improved the performance of the ANN significantly. Accordingly, based on Fig. 8b, the regression indices of the models raised by the increase of the hidden neurons. Consequently, from Fig. 8a, b, the best ANN-BP model was selected as model-12 with an $MSE = 2.143$ and $R = 92.8$. After determination th of best ANN-BP model, the PSO algorithm was applied for improving the performance of the selected model. Regarding this, different swarm sizes of 25 to 500 were selected and evaluated for the training process. Meanwhile, when the swarm size (number of agents) increased, the needed time to find the best cost function and best particle position increased, as shown in Fig. 9. Therefore, we selected 300 for the optimum number of particles. Of note, in the training process, the number of iterations was determined by trial and error tests. For example, in all models after 350 iterations, the decrease rate of cost function (*MSE*) remained constant. Besides, for the particles updating, based on suggestions of Shi and Eberhart (1999), acceleration constants were chosen as ($C_1 = C_2 = 2$). Figure 10 shows the regression indices of the best ANN-PSO model. As can be seen, the average of regression indices was 1, 0.996 and 0.99 for training, validation and test data, respectively. In addition, by using the PSO learning algorithm, the average *MSE* of ANN-BP decreased from 2.143 to 0.73. It should be mentioned that the results training ANN-BP model with a PSO technique of this study was compatible with the results of previous researchers (Zhang et al. 2007; Hajihassani 2013; Sun and Xu 2016).

Sensitivity results

After determination of the best ANN-PSO model, the sensitivity analysis was performed using two different methods, namely Garson's algorithm (Garson 1991) and

Table 6 Weights of the best ANN-PSO (hidden to target layer)

N-1	N-2	N-3	N-4	N-5	N-6	N-7	N-8	N-9	N-10	N-11	N-12
1.014	−0.539	0.496	−0.698	1.012	0.459	0.602	0.436	0.467	−0.134	0.368	−0.515

Note: N – 1 = neuron number one

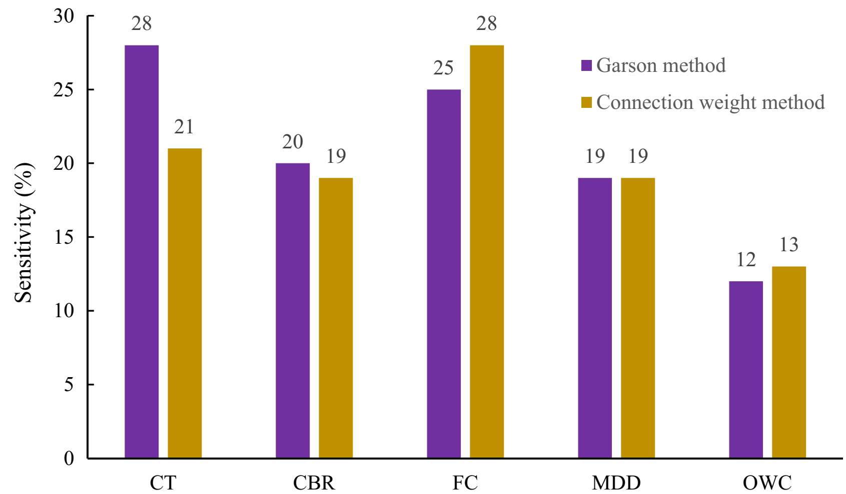

Fig. 11 Sensitivity analysis of the best ANN-PSO model

the connection weight approach (Olden and Jackson 2002). These algorithms use the weights of input the to hidden layer and hidden to the output layer of the best ANN model. The outputs of weights and biases can be extracted by pre-defined commands in MATLAB software (2016). Tables 5 and 6 illustrate the details of the weights of the best ANN-PSO model of this study. Figure 11 establishes the results of aforesaid algorithms on the hidden weights of the best ANN-PSO model which is called sensitivity analysis. As can be seen, in both methods, CT and FC were introduced as the most important parameters in the estimating of UCS of treated fibrous peat. To be noticed, in reality, the texture of CBR and UCS are closer to each other in comparison with FC and CT. On the other hand, as mentioned in basic test results (Table 2), the untreated fibrous peat soil used in this study had an average void ratio of 11. Therefore, it could be expected that FC increases the UCS as high as CBR. As can be seen in Fig. 11 based on these two mentioned methods, no significant difference between parameters was seen. For example, in Garson's algorithm, just a 5% difference was observed between FC and CBR. On the other hand, it was interesting that in both methods, OWC had the minimum effect on the UCS. It can be concluded that in sensitivity analysis, both methods showed approximately similar trends.

Conclusions

In this study, the geotechnical characteristics of cement-stabilized peat mixed with filler were investigated using UCS, CBR and compaction tests. Also, different ANN modes trained by back-propagation and particle swarm optimization methods were utilized to estimate UCS of treated peat samples. Finally, sensitivity analysis was performed to evaluate the most important parameters on the UCS of treated samples. The results indicated that to achieve the highest undrained shear strength in the UCS tests, 300-kg/m^3 cement was determined as the optimum cement content at the natural water content of the peat. By using filler, the undrained shear strength of cement-treated peat increased slightly. In the cases of CBR tests, the role of filler was more comparable to the other tests. In these tests, by adding the filler content to the mixture of cement peat, the CBR values increased significantly. Additionally, in compaction tests, the MDD of cement-stabilized peat decreased with the increase in cement content while the OCW reduced. This trend repeated in the tests using filler too. Moreover, results of soft computing methods showed that ANN-PSO models had better performance than ANN-BP. The best ANN-PSO model had an $MSE = 0.73$ and the average regression index of around one (1, 0.996 and 0.99 for training, validation and test data, respectively), showing the high performance of the model. Finally, sensitivity analysis introduced filler content and curing time as the most influential factors in the estimation of UCS of treated peat samples.

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Compliance with ethical standards

Conflict of interests The authors declare that there are no conflicts of interest regarding the publication of this paper.

Appendix

Table 7 Database used for ANN

Test no.	CBR (%)	CT (day)	OWC (%)	MDD (Mg/m^3)	FC (kg/m^3)	UCS (kPa)
1	17	14	24	0.73	24	111
2	19	14	28	0.75	28	117
3	25	14	30	0.88	30	121
4	28	14	39	0.93	39	125.4
5	31	14	49	0.83	49	113
6	37	14	64	1	64	95
7	41	14	79	0.76	79	67
8	18	14	24	0.78	24	112
9	21	14	27	0.73	27	116
10	23	14	29	0.82	29	120
11	27	14	37	0.94	37	124
12	29	14	44	0.82	44	112
13	36	14	63	0.99	63	95
14	39	14	77	0.78	77	64
15	20	28	28	0.82	28	121
16	27	28	31	0.84	31	140.6
17	30	28	33	0.91	33	160
18	34	28	41	1.023	41	178
19	37	28	52	0.93	52	155
20	44	28	67	0.88	67	111
21	49	28	81	0.83	81	107
22	21	28	29	0.83	29	118
23	28	28	32	0.85	32	139
24	32	28	32	0.92	32	159
25	35	28	40	1	40	177
26	38	28	51	0.94	51	156
27	45	28	68	0.89	68	112
28	48	28	82	0.82	82	108
29	30	90	32	0.93	32	131
30	33	90	36	0.94	36	173
31	38	90	37	1.02	37	182
32	43	90	44	1.1	44	189
33	47	90	56	1.02	56	169
34	51	90	74	0.97	74	121
35	58	90	90	0.9	90	116
36	31	90	33	0.94	33	132
37	34	90	35	0.95	35	172
38	39	90	38	1.04	38	183
39	44	90	45	0.98	45	189
40	48	90	55	0.97	55	172
41	52	90	75	0.96	75	122
42	59	90	89	0.91	89	114

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