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Hybrid ANN-based techniques in predicting cohesion of sandy-soil combined with fiber

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Abstract. Soil shear strength parameters play a remarkable role in designing geotechnical structures such as retaining wall and dam. This study puts an effort to propose two accurate and practical predictive models of soil shear strength parameters via hybrid artificial neural network (ANN)-based models namely genetic algorithm (GA)-ANN and particle swarm optimization (PSO)-ANN. To reach the aim of this study, a series of consolidated undrained Triaxial tests were conducted to survey inherent strength increase due to addition of polypropylene fibers to sandy soil. Fiber material with different lengths and percentages were considered to be mixed with sandy soil to evaluate cohesion (as one of shear strength parameter) values. The obtained results from laboratory tests showed that fiber percentage, fiber length, deviator stress and pore water pressure have a significant impact on cohesion values and due to that, these parameters were selected as model inputs. Many GA-ANN and PSO-ANN models were constructed based on the most effective parameters of these models. Based on the simulation results and the computed indices' values, it is observed that the developed GA-ANN model with training and testing coefficient of determination values of 0.957 and 0.950, respectively, performs better than the proposed PSO-ANN model giving coefficient of determination values of 0.938 and 0.943 for training and testing sets, respectively. Therefore, GA-ANN can provide a new applicable model to effectively predict cohesion of fiber-reinforced sandy soil.

Keywords: shear strength parameters; fiber-reinforced sandy soil; hybrid predictive model; optimization techniques

1. Introduction

Despite the idea of improving soil strength by adding shreds and pieces has an ancient history, it proposed again in past decades. Nowadays, reinforced soil is completely known as a new construction material and because of promising results that is presented in vast studies and engineering applications, it is considered as a creative method for dealing with problematic construction field like slops on landfills. Reinforced element is used in this technique covers a vast variety of materials from natural to artificial fibers which affected by scientific growth and new technologies and include major parts of waste materials for example metals and polymers produced by industrial factories (Gan 1988, Fredlund 1996, Safa *et al.* 2020a, Safa *et al.* 2020b, Shariat *et al.* 2019). After (Vidal *et al.* 1969, Zornberg 2002, Trung *et al.* 2019b, Xu *et al.* 2019) as pioneers, proposed topic in the 1960s and provided a preliminary study on this approach theoretically and practically, the method of soil Reinforcement with randomly distributed fibers (RDFR) introduced in the 1970s. In this method, the involvement of tensile components (the reinforcement element) with soil grains improves the strength and soil shape ability. The behavior mechanism of reinforced soil is based on the interaction of soil and reinforcement elements so that friction between soil particles and fiber plays a fundamental role in enhancing soil properties. The study's results generally showed that reinforcement causes an obvious increase in soil shear strength and moreover a reduction effect in post-peak strength which is proportional to the amount of fibers (Michalowski 2004, Consoli *et al.* 2005, Shariati 2019). These promising outcomes encouraged researchers to suggest reinforced soils for various geotechnical applications.

Soil shear strength is the most determinant attribute which must be determined to design engineering projects on soil. Among other important parameters, cohesion (C) and internal friction angle (φ) are of most significant shear strength parameters which should be found inevitably (Gan 1988, Fredlund 1996, Das *et al.* 2008, Suhatril *et al.* 2019). Determining parameters relating to soil's shear strength using a direct approach has developed during the last

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century includes a variety of shear strength tests based on experimental techniques performed in either laboratory or in situ on undisturbed or disturbed (remolded) specimens. The best instances of this category are triaxial compression test, directional shear cell test, true triaxial test, plane strain compression test and CPT (Donaghe *et al.* 1988, Hornik *et al.* 1989, Guo 2008), utilizing adaptive Neuro-Fuzzy to predict friction angle of soils by Kayadelen d on the Atterberg limit and Cam–Clay model to represent the mechanical properties of the soils developed according to the interaction curve of water and soil and shear strength parameters of soil.

Considering reinforced soil as a material that shows an ever-increasing flourish in the engineering field, identifying its property just like normal soil, is one of the significant requirement in geotechnical science. In this regard, a very first investigation focused on the evaluation of the engineering characteristic by direct experimental studies and determining principles of behavior for reinforced soil. Reinforced sand with synthetic fiber under direct shear tests (Gray *et al.* 1983) numerous triaxial compression tests on sand (Al-Refeai 1986, Gray 1990, Zornberg 2002), determining soil strength by experimental and analytical methods regarding measure the effect of fiber inclusion , stiffness studies to investigate the fiber inclusions in granular (Consoli *et al.* 2005), Modified Proctor Compaction test (Tiwari *et al.* 2012), evaluation of compressive strength and ductility of fiber-reinforced cemented sand (Gray and Ohashi 1983, Gray 1990, Radoslaw *et al.* 2002, Michalowski 2004, Park 2011). In following works along with prediction of failure mood it is tried to predict the shear strength of soil reinforced with fibers (Zornberg 2002) or provide relation between friction angle and clay content (Kaya *et al.* 2007), Atterberg limits (Penumadu *et al.* 1999) or ΔPI (Waldron 1977, ranjan 1997, Radoslaw and Michalowski 2002, Wesley 2004, Babu *et al.* 2008). More recently, modeling approaches are used to understand behaviors of fiber-reinforced soils subjected to various tests. For instance effects of soil parameters (c and φ) on bearing capacity evaluated by using a model constructed on elastoplastic finite element analysis (Fenton 2003). Another model was built on the combination of the superposition method with the energy-based homogenization technique to fully capture before-failure and failure behaviors of fiber-reinforced clay subjected to triaxial compression (Wang *et al.* 2004, Arabnejad Khanouki *et al.* 2010, Shao *et al.* 2015, Khandelwal *et al.* 2016, Shariati *et al.* 2012, Toghroli *et al.* 2018b, Shao *et al.* 2019b). An investigation by (Basma *et al.* 2003, Khorramian *et al.* 2017, Khanouki *et al.* 2016, Nosrati *et al.* 2018, Katebi *et al.* 2019, Shariati *et al.* 2019d, Shariati *et al.* 2019e) is one of the first studies in geotechnical science that implemented ANNs for modeling time-dependent swell of expansive soils. Wide ranges of soil's properties have been studied by utilizing this promising approach and large part of these investigations aim to estimating soil shear strength (Zorlu *et al.* 2008, Kayadelen *et al.* 2009, Khalilmoghadam *et al.* 2009, Göktepe *et al.* 2010, Daie *et al.* 2011, Toghroli *et al.* 2014, Nosrati *et al.* 2018, Toghroli *et al.* 2018a, Mahdi Shariati 2019, Xu *et al.* 2019). In this regard, ANN particularly shows high potential as an alternative method for predicting internal friction angle. In one study conducted by (Penumadu and Zhao 1999, Das and Basudhar 2008), using four various properties of soil including CF (clay fraction), LL (liquid limit), PI (plasticity index), ΔPI (i.e., the deviation from the A-line in classification chart; $\Delta PI=PI-0.73(LL-20)$), an ANN model with acceptable degree of accuracy was proposed to predict residual friction angle regarding fraction of clay soil and its Atterberg's limits. In another work, three ANNs were introduced by (Khalilmoghadam *et al.* 2009), based on specific organic elements, topographic properties, distribution of particle size, and vegetation attributes to predict shear strength of surface soil. A research by (Armaghani *et al.* 2019) using shear strength parameters of 230 shale samples obtained from triaxial compression test, proposed an integrated PSO-ANN model to predict shear strength parameters. Prediction of soil strength developing four machine learning methods i.e., PANFIS (PSO-ANFIS), GANFIS (genetic algorithm-ANFIS), SVR (support vector regression) and ANN is another remarkable study conducted by (Pham *et al.* 2018). Another instance is (Tiryaki 2008) that predicted intact rock strength using ANN, multivariate statistics, and regression trees for mechanical excavations. Generally, a high correlation of the proposed ANN models infers their satisfying accuracy and applicability that encourage using these effective methods for studying reinforced soils as well.

ANN techniques as a new approach grab ever-increasing attention by many researchers to manage geotechnical problems (Das and Basudhar 2008, Ahmadi *et al.* 2012, Mohammadhassani *et al.* 2013, Mohammadhassani *et al.* 2014b, Safa *et al.* 2016, Mansouri *et al.* 2017, Toghroli *et al.* 2018b, Armaghani *et al.* 2019, Milovancevic *et al.* 2019, Shariati *et al.* 2019b, Shariati *et al.* 2019c, Shi *et al.* 2019a, Shi *et al.* 2019b, Trung *et al.* 2019a, Shariati *et al.* 2020). However, ANN has some inherent restrictions like slow learning rate and getting trapped in local minima that admitted in several studies (Shao *et al.* 2018, Shariat *et al.* 2018, Wang *et al.* 2018, Shao *et al.* 2019a). Recently, some optimization algorithms (OAs) introduced by researchers can improve the prediction of the model by modulating the distribution of ANN's weight and bias. So far, some OAs such as PSO, and genetic algorithm (GA), with a good competency work out for extensive geotechnical problems and suggest a promising technique in this regard.

In this study, a series of laboratory tests are conducted to investigate the shear behavior of sandy-soil combined with fiber and their results are evaluated and based on the obtained results, the most important parameters on cohesion are selected as model inputs. Then, two hybrid models i.e., GA-ANN and PSO-ANN are developed to predict the cohesion of sandy-soil combined with fiber and the best hybrid model among them is selected and introduced for prediction of soil shear strength parameters. In the following, backgrounds of methods applied in this study are described and then a description of data and tests used in the modelling will be given. Finally, modeling of intelligent systems in perdition of cohesion will be discussed and the best model among them will be selected.

2. Methods

2.1 Artificial neural network (ANN)

ANN is a computational model that mimics the nervous system's principles to construct an artificial system. It utilizes input training patterns to develop a careful prediction of the relationship between input and output data automatically, which distinguishes this system from any other known ones (Armaghani *et al.* 2019) Resemble a biological brain, an ANN use artificial neurons as its fundamental units to run data processing in a parallel manner. In a very first attempt to modeling neural net, (McCulloch *et al.* 1943, Shariati *et al.* 2012) formed a binary decision unit (threshold logic unit) and successfully modeled the behavior of artificial neurons. They allocated a total weight of input signals to any artificial node and achieve a more precise output by applying the activation function to these signals. A research by (Ch *et al.* 2012, Hosseinpour *et al.* 2018) describe ANNs as networks of interlocked nodes in remarkably parallel layers of computational systems. They showed that behavior and class of these network impressed by pattern of neurons connection.

Instruct the network for determined training samples allow to modify and upgrade network performance impressively. In other words, during the training phase, error minimization for output of any node in every layer, enabled by modifying connection weights, repetitively. Produced error for output is a function of error square as:

$$E = \frac{1}{2}\sum_{i=1}^{p}(t^{(i)} - y^{(i)})^2 \tag{1}$$

where t is target value, y is produced actual value, and P is the number of training patterns.

Structurally, ANN functions are divided into two major categories of feed-forward and feedback. Multilayer perceptron (MLP) is one of the most popular feed-forward multilayer networks which process data by activation functions in sequential layers (Haykin 1999, Priddy *et al.* 2005, Armaghani *et al.* 2019, Shariati *et al.* 2019e).

In another study, (Simpson 1990) presented a learning algorithm known as back-propagation (BP) that benefit a learning procedure based gradient to learning network. He showed that this algorithm which contain twofold training cycle (forward and a backward stage), deliver satisfying result particularly for nets which have feed-forward multilayer. In more complementary studies, other researchers explained the operation of each stage (Ahmadi and Shadizadeh 2012, Mohandes 2012, Ziaei-Nia *et al.* 2018, Shariati *et al.* 2019a). They showed that in one stage input signals travel forward and transmitted error signal for every node of the output layer, then resulting error rates moved backward and consequently weights and biases of network modify accordingly. Generally, by some activation functions applying on inputs, the output of any neuron is produced. In the next step, these outputs transmitted as inputs to the neurons of next layer. The complexity of a considered problem is the key point for determining the type of activation function. Therefore, for nonlinear problems, sigmoid transfer functions like tangent sigmoid or log sigmoid are of advantage.

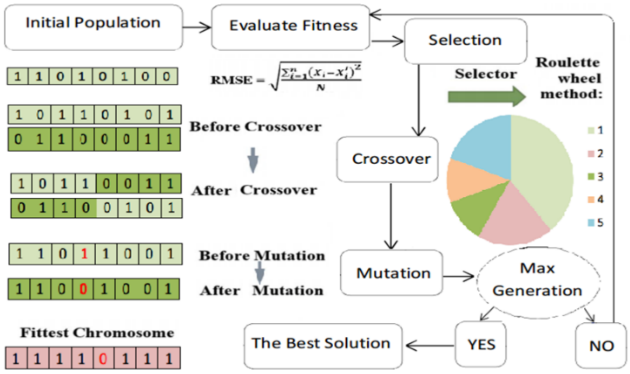


Fig. 1 GA algorithm process

For every layer, incoming signal (x_i) that multiply by corresponding weight coefficient (w_{ij}) delivers total weighted net input. In the next step summation function apply to result and then, a small amount of bias adds to it and the final result feed hidden neurons. By performing this process iteratively, the overall output of the system will be produced. Mathematical equation for every output neuron based total net input is:

$$net_{h_j} = \sum_{i=1}^{n} w_{ij} \cdot x_i + b_j \tag{2}$$

Therefore, total net input passed through an activation function, for example, sigmoid function, so that each hidden or output neuron can be calculated as:

$$y_j = 1 \Big/ \left(1 + \exp\left\{-net_{h_j}\right\}\right) \tag{3}$$

2.2 Genetic algorithm (GA)

Researcher (1992) introduced one of the important OA, known as the Genetic algorithm (GA). This algorithm uses an objective function to find an optimal solution for a problem, similar to the procedure used for select natural mechanism of evolution in biological species. In other word, it doesn't need searching through specific data and essentially run in a casual base (Saemi *et al.* 2007). The algorithm contains numerous optional solutions that each individually proposes their optimum solution. Chromosomes with linear string (as 0s and 1s) represent every proposed solution. A series of successive generations is produced and replaced one another and advance optimization process. Population size which denote by (s) equals to number of solutions. There are three genetic operators for fulfillment the generation task contained reproduction, crossover, and mutation. Reproduction includes searching chromosomes for the accordance with their scales with desirable criteria which lead to picking up the best ones for the next operation. Then, in crossover operation, special parts are combined as parents and produce new chromosomes as offspring. This process can be done in the form of single-point or two-point combination. First, offspring produces of combination of left side genes of one parent with the right side genes of other parent. Second, offspring is the production of the contrary process (Khandelwal and Armaghani 2016, Sedghi *et al.* 2018). After that, mutation performs in the form of applying random change to the chromosome's components. Fig. 1 depicts a GA process for optimization purposes. More detailed information about GA can be found in the literature (Ahmadi and Shadizadeh 2012, Mohamad *et al.* 2017).

2.3 Particle swarm optimization (PSO)

To optimize continuous problems, (Kennedy *et al.* 1995) introduced a new calculation approach known as particle swarm optimization (PSO). The nonlinear procedure of PSO inspired by social systems like fish shoals. Basically, the PSO contains several particles that are sorted randomly. In this method, the PSO algorithm utilizes a repetitive process to find an optimum value for a problem so that each particle arranges according to its experience comparing to others. This means particles should find their personal best position (P_{BEST}) and global best position (G_{BEST}) which is its best position through all other particles. During the training process, each particle tends to move toward its P_{BEST} and G_{BEST} based its velocity and its distance from the best positions during the learning stage. As a result, the amount of velocity in the next iteration determines the new position of each particle (Hajihassani *et al.* 2017).

According to Eq. (4), the particle's new velocity ($\overrightarrow{v_{new}}$) is calculated based on personal and global positions of particles ($\overrightarrow{pbest}$ and $\overrightarrow{gbest}$, respectively).

$$\overrightarrow{\mathrm{v_{new}}} = \vec{\mathrm{v}} + \mathrm{C_1} \times \left(\overrightarrow{\mathrm{pbest}} - \vec{\mathrm{p}}\right) + \mathrm{C_2} \times \left(\overrightarrow{\mathrm{gbest}} - \vec{\mathrm{p}}\right) \quad (4)$$

Also, in another equation the new particle position, $\overrightarrow{p_{new}}$, in the PSO determined by adjusts the vector to the P_{BEST} and G_{BEST}:

$$\overrightarrow{\mathrm{p_{new}}} = \vec{\mathrm{p}} + \overrightarrow{\mathrm{v_{new}}} \quad (5)$$

where, in these two equations, $\vec{v}$ is current particle velocity, $\vec{p}$ is current particle position, and C_1 and C_2 are coefficients of velocity. Fig. 2 presents the process of PSO in optimizing problems. In other literature, the structure of PSO and supplemental details can be found (Armaghani *et al.* 2019).

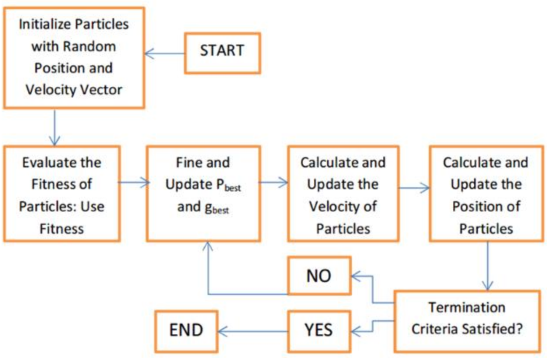


Fig. 2 Process of PSO in optimizing problems

2.4 Hybrid algorithm

Researchers tried to improve ANN's efficiency in solving engineering problems by mean of various optimization algorithms such as PSO and GA. Nevertheless, some algorithms like BP that act as a learning algorithm for local search cannot provide an acceptable solution for finding ANN optimum solution (Liou *et al.* 2009, Gordan *et al.* 2016). However, the OAs shows satisfactory results in terms of regulate bias and weight in ANNs to advancement ANN's prediction. While ANNs show more convergence at local minimums, OAs performs better at the global minimum. Therefore, by utilize ANNs compose to hybrid algorithms like PSO-ANN or GA-ANN, one can get advantages of both systems capabilities that means in first step GA and PSO find global minimum and then ANN use their result for optimize solution in local minimum. The successful use of these hybrid models has been reported by several researchers in the field of civil engineering (Hajihassani *et al.* 2017).

3. Experimental framework and established database

3.1 Materials and preparing specimens

The goal of this research is to achieve a new material mixed of soil reinforced with fiber and finding the optimal amount of fiber which can enhance the shear resistance of soil more operatively. The effect of fiber content and fiber length as variables has examined by triaxial tests. Hence, three various weight contents of 0.5%, 1.0% and 1.5% relative to weight of dry soil and fibers with three different lengths of 1, 2 and 3 cm were used in preparing samples. Before starting the tests, engineering characteristics of soil and fiber was determined. The soil used in this work is known as relatively uniformly graded sand with low content of silt that classified as SP according to the Unified Soil Classification System (USCS- ASTM D 2487). To accomplish the classification process of the soil, Aterberg limits determined according to ASTM D 4318-87, it is and revealed that this soil has no plasticity because of the inconsiderable amount of clay content. From standard Proctor compaction tests (ASTM D 698-78), the maximum dry density of the soil determined as 18.4 N/m^3 with 15.4 % optimum moisture content. In Fig. 3, the particle size distribution of soil can be seen.

Reinforcing elements are polypropylene fibers named DTY (Dipped Tire Yarn) that are considered as waste material of tire factory. These elements produced by Zanjan Tire Cord Co. The properties of fiber provided by tire factory are shown in Fig. 4 and Table 1. To produce this kind of fiber, in a two-stage condensation polymerization process, nylon salt converts to dry polyamide 66 chips, with high viscosity and high molecular weight. This product is passed through the spinning molds and the resulting product is thin filaments, which is woven together and produce fiber. The main feature of this fiber is high tensile strength, thermal resistance, fatigue strength, impact resistance, and quality stability (Liu *et al.* 2008, Nguyen-Thoi *et al.* 2010,

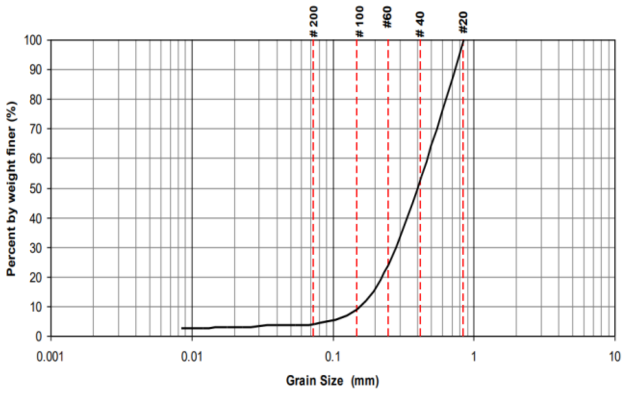


Fig. 3 Grain size distribution curve for sand

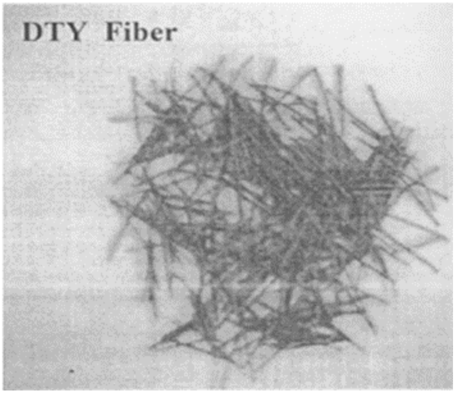


Fig. 4 Used DTY fiber

Table 1 Fiber properties

Property	Value
Density (kN/m3)	**9.1**
Water absorption (%)	13.97
Elasticity Module (N/mm^2)	104.99
Tensile Strength (N)	309
Ultimate strain (%)	27.99

Shariati *et al.* 2018, Toghroli *et al.* 2018b, Shariati *et al.* 2014, Davoodnabi *et al.* 2019, Trung *et al.* 2019b).

To prepare reinforced soil needed for Triaxial specimens, soil and fiber must be mixed homogeneously. Therefore, the specific weight of soil and fiber required for a specimen was divided into four equal portions and then each part of the soil was mixed well with one part of fibers. In next step cylindrical specimens for Triaxial CU tests with 150-mm high and 70-mm diameter were prepared with this mixed soil. It is important to mention that all specimens were built up uniformly so that isotropy of specimens can be assumed, therefore six layers of mixed soil were condensed in specimen mold according to under-compaction method proposed by (Ladd 1978). This method that is applicable for wet grain-sized soils suggested that each layer of sample that compressed in several layers must be compressed to a certain density that is less than the final density of the sample. So, compacting each of the subsequent layers increases the soil density of the lower layers. By using this method, all specimens were prepared with a density of 15.4 kN/m^3 and constant moisture of 12%.

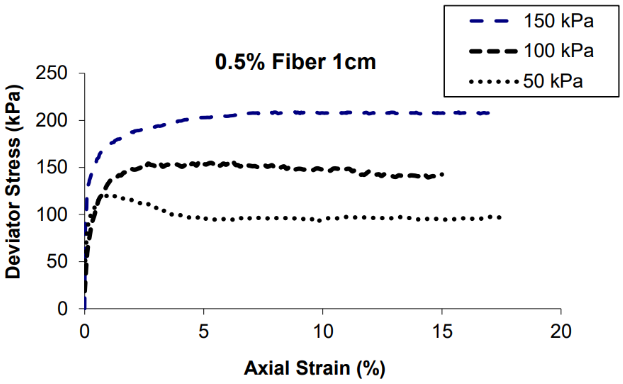
Fig. 5 GCTS triaxial apparatus used in the study

3.2 Test procedure

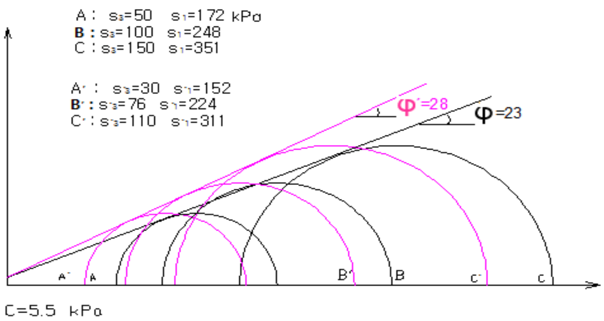
For the aim of studying the effects of reinforcing soil with fibers on shear strength and deformation of coarse grain soils, a series of consolidated undrained (CU) triaxial tests (ASTM D 4767-88) have been carried out. Using this test, the stress-strain behavior and shear strength of fiber-reinforced specimens can be evaluated. First, three CU Triaxial tests using three confining stresses were performed to determine the shear strength parameters of unreinforced soil. In the following, a series of triaxial test were performed on reinforced soils which are varied in the course of three different fiber weight contents and three different fiber's length means that a total of thirty consolidated undrained triaxial compression tests were conducted. Moreover, by performing verification tests, repeatability of experiments was studied too. The device used in this study is a three-dimensional fully automated machine in the Soil Mechanics Laboratory of Bu-Ali Sina University. The apparatus made by the Canadian company GCTS (Geotechnical Consulting and Testing Systems) is a hydroelectric type device with five digital sensors that its overview is shown in Fig. 5.

To perform consolidated undrained triaxial test, all specimens were saturated, then thoroughly consolidated under desirable confining stress of tests and then undergo loading at the right speed. During the saturation, B coefficient of Skempton's pore pressure was gauged constantly. After B-parameters exceeded 0.98%, the consolidation process was conducted at three different confining pressures of 50, 100 and 150 kPa. By completing the phase of saturation and consolidation, while backpressure is blocked to prevent drainage of th specimen,

Fig. 6 Preparing sample and running triaxial test



(a)



(b)

Fig. 7 0.5% fiber contents 1 cm; (a) stress–strain response for three different confining pressures and (b) Mohr-Coulomb failure envelopes

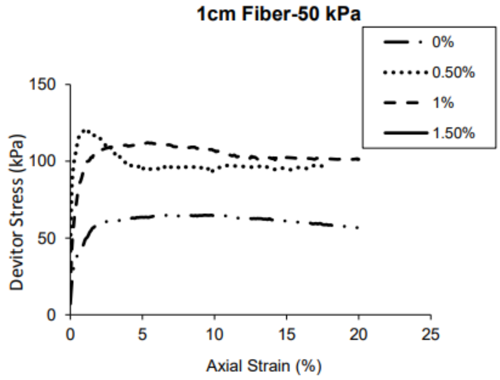
compression load was applied with a controlled strain rate of 0.15% per minute. Applying deviator stress was continued until the strain of 20%, except for samples that experience failure before this specific strain (Fig. 6).

3.3 Test results

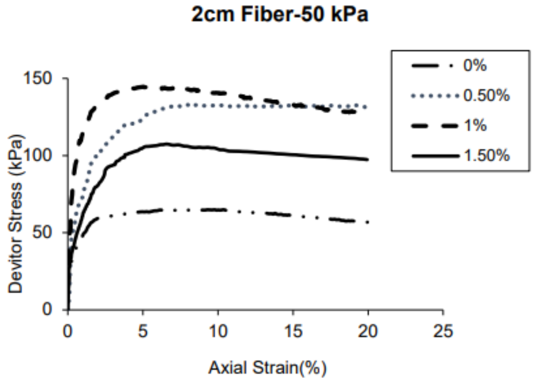
Samples with different length and weight percentage of fibers were investigated under three different confining pressures by Triaxial tests. Fig. 7(a) shows stress-strain diagram for samples reinforced with 0.5% fiber with 1cm length for three different confining pressures. Based on these three diagrams obtained from CU tests, deviator stresses (*Δσ*) are determined and for calculation the internal frictional angle (*φ*) and cohesion (*C*) of reinforced soil, Mohr-Coulomb failure envelopes was depicted as shown in Fig. 7b. Table 2 summaries triaxial CU test results for reinforced and unreinforced sand. According to this table, it can be seen that adding fiber can cause a considerable increase in the shear strength of soil, more particularly; in terms of *φ*. Effective parameters are discussed with more details in the following sections.

Table 2 Summary of all triaxial CU test results for reinforced and unreinforced sand (Δσ: deviator stress (kPa)- u: pore pressure (kPa)

Fiber (%)	0%		0.5%						1%						1.5%					
Fiber Length	-	-	1cm		2cm		3cm		1cm		2cm		3cm		1cm		2cm		3cm	
Confining Stress	Δσ	u	Δσ	u	Δσ	u	Δσ	u	Δσ	u	Δσ	u	Δσ	u	Δσ	u	Δσ	u	Δσ	u
50	60	15	122	20	128	23	147	24	110	15	144	22	151	23	85	16	105	19	142	21
100	114	38	148	24	198	32	220	40	184	22	240	41	245	44	133	33	170	28	240	35
150	170	45	201	40	270	50	300	61	254	33	317	63	335	65	202	41	240	55	320	58
φ (˚)	21		23		25		26		25		28		29		22		23		29	
C(kPa)	0		5.5		15.65		22.8		12.5		18.1		17.6		7.4		14.4		14.6	



(a)



(b)

Fig. 8 Effects of different length and percentage of fiber; (a) 1 cm and (b) 2 cm

3.3.1 Amount of fiber

According to Table 2, compared to fiber percentage,

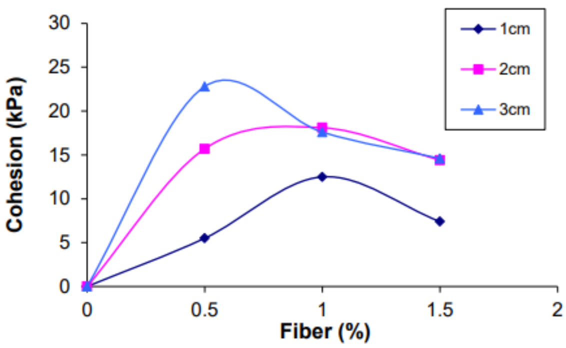


Fig. 9 Soil cohesion in terms of length and percentage of fiber

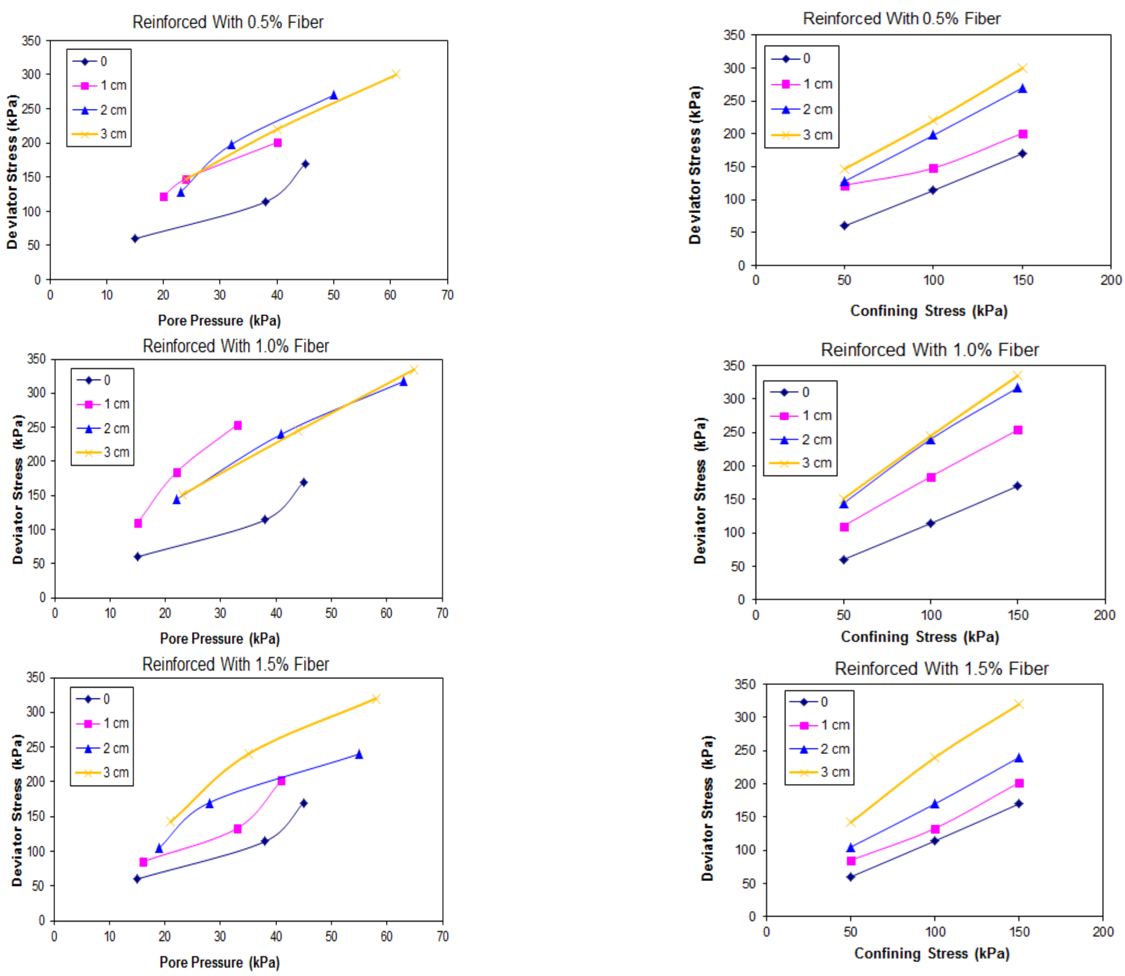


Fig. 10 Effects of fiber presence and confining stress on $\Delta\sigma$ and u

fiber length shows a more significant role in increasing the strength of the reinforced soil, as it is obvious that longer fiber leads to higher C and φ for all cases. On the other hand, in constant confining pressures and fiber length, the ultimate strength of samples directly improved with fiber percentage (see Fig. 8). However, as for the shear strength of reinforced sandy soil, there is an optimum amount for fiber percentages and fiber length which causes the highest results. Referring to Table 2, it is obvious that strength obtained for reinforced specimens with 1.5% fiber always were less than specimens with 1.0% fiber reinforcement. It seems that in a higher percentage of fiber despite the ameliorating effect of the tensile strength of the fiber in enhancing shear strength of soil, excess fiber plays a separator role between soil particles, which oppositely decreases the shear strength and determine the behavior of reinforced soil. Considering the interactions of fiber percentages and fiber lengths, it is not possible to attribute improvement in resistance properties of the reinforced soil to only one of these two parameters.

3.3.2 Shear strength parameters (C, φ)

Having said that enhancing the shear strength of soils is the most important goal of reinforcing soil and according to results, mixing soil with fiber in this study is successfully increased the shear strength parameters of the soil. The φ

values increase from 21° for unreinforced sample, to 29° in its maximum value for sample reinforced with 3cm fiber. Additionally, the sandy soil without any cohesion shows cohesion for all reinforced samples and get increase to 22.8 kPa for soil reinforced with 0.5% 3 cm fiber in its highest level. This considerable increase reveals the potential of soil reinforcement on improving soil shear strength. In Fig. 9, the variations in the cohesion factor based on the percentage and length of the fibers are compared.

It could be seen that increasing fiber percentage up to 0.5% can improve effects on cohesion, but after this specific percentage, it decreases for higher fiber percentage. However, 3cm fiber presents the highest value for ***C*.** It seems that the length of fiber plays an important role in enhancing the strength properties of soil. As to say, fiber's mobilized tensile force is controlling parameter in increasing strength of specimens. It must be said that tension failure of fibers here is not the case because it has higher tensile strength (309N) comparing to tensile forces arising during the test. The failure mood of the samples in a triaxial tests confirmed that the performance of reinforcement elements on the failure plane is slipping not rupturing. Once again, this is predictable due to the high resistance of DTY fibers to tensile strength. This mechanism has been reported in other similar studies (Babu *et al.* 2008).

3.3.3 Confining pressure, pore pressure (u), deviator stress (Δσ)

Regarding triaxial test, confining stress with specific values of 50, 100 and 150 kPa in each set of three CU tests, it does not play a direct role as a variable in soil reinforcement investigation. However, it does not mean that its effects can be underestimated. It can be asserted that various confining pressures have a determinant impact on the performance of fiber in soil specimens. This is due to the creation of different pull-out resistance in fibers. Additionally, confining stress represents itself by pore pressure fluctuation during the test as well. Since CU triaxial tests were performed in undrained condition, during the increase of deviator stress, the pore water pressure owing to deviator stress (u) increases in the specimen. Pore pressure records simultaneously during the test. Based on results presented in Table 2, at each normal stress, an increase in fiber content leads to an increase in deviator stress. It seems that parts of applied stresses are transferred to fibers and interaction between fiber and soil that has a frictional nature creates additional confinement effect. Therefore, it can be said that in higher confining stress samples need higher deviator stress to failure and this can be interpreted as enhancing the strength. Generally speaking, increasing in fiber length and percentage, causes an increase in deviator stress and pore pressure and this effect intensifies in higher confining stress that can be seen obviously in Fig. 10.

3.3.4 Soil deformation

Comparing to unreinforced soil, soil mixed with fiber shows more elastic behavior under shear stresses. More detailed, despite brittle behavior of plain soil, by adding fiber, reinforced soil act softer and more shapeable. This change in behavior can be deduced from the reduction of the initial slope of the curves and the increase of the strain at the maximum stress point (strain of fracture). Therefore, changing the behavior of the soil from fragile to more elastic along with increasing soil strength is a significant advantage in changing the behavior of reinforced soil.

Table 3 Descriptive statistics of the experimental database in this research

Parameter/Category	Unit	Range
Percentage of fiber/Input	%	0-2
Length of fiber/Input	cm	0-3
Deviator stress/Input	kPa	60-335
Pore water pressure/Input	kPa	15-65
Cohesion/Output	kPa	0-22.8

3.4 Selection of input parameters

This study investigates the shear strength of reinforced soil as a relatively new composed material. Cohesion parameter is a major character that determines the most important engineering properties of soil. Modeling techniques to predict *C* value for soils could improve geotechnical science considerably. Along with other similar studies (Najjar and Basheer 1996, Das and Basudhar 2008, Kayadelen *et al.* 2009), in this paper, 2 hybrid intelligent approaches (PSO-ANN and GA-ANN) are developed for the prediction of cohesion of reinforced soil. To introduce hybrid models to predict *C* values in reinforcement soil, first and foremost, the variables that is determinant enough to be considered as inputs of the model should be identified. Based on results of experiment, fiber percentage and length that effect directly on improvement of *C* values, and in the following deviator stress (Δσ) and pore water pressure (u), were considered as determinant input variables that affect by presence of fiber in soil.

The review of all results can be summarized as:

1- Addition fiber to sandy soil results in improving its shear strength.

2- Tensile strength of the fibers and friction interaction between fiber and soil environment are two key elements that cause enhancement of soil shear strength.

3- Confining pressure has an indirect effect on the amount of shear strength improvement so that it mobilizes the tensile strength of the reinforcement elements.

4- In presence of fiber, the internal friction angle and cohesion parameters of soil were improved considerably. The reinforcement fiber compensates the absence of plasticity in sandy soil.

5- Soil reinforcement increases soil shape ability and reduces its fragile behavior.

According to review of the previous investigations and available results of laboratory tests, the authors have decided to use fiber percentage, fiber length, deviator stress and pore water pressure as model inputs for prediction of cohesion of the sandy soil combined with fiber. Therefore, in the modeling of this study, these parameters were utilized for applying hybrid ANN-based models. Table 3 shows

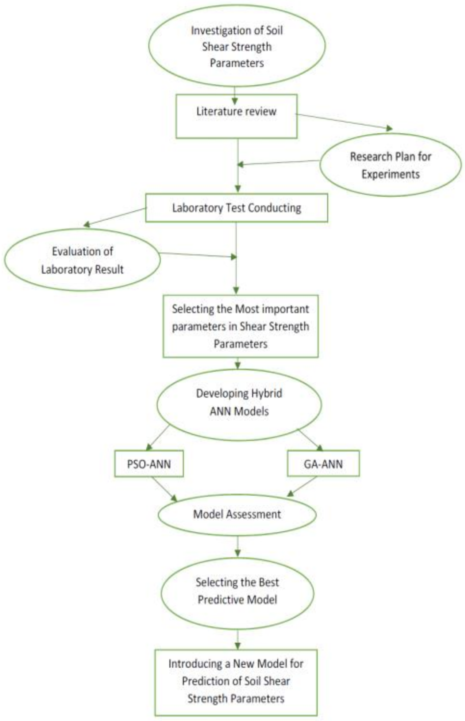


Fig. 11 Flowchart of this study to predict soil shear strength parameters

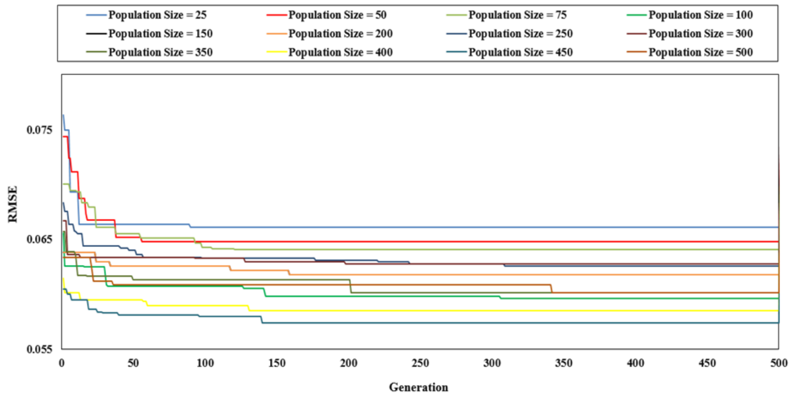


Fig. 12 Twelve GA-ANN constructed models in predicting cohesion of the soil

ranges of the input and output parameters used in this study. Besides, flowchart of this study from start to end of process is shown in Fig. 11 According to this flowchart, after conducting laboratory tests, their results will be evaluated and based on the obtained results; the most important parameters on cohesion will be selected as model inputs. Then, two hybrid models i.e., GA-ANN and PSO-ANN will be developed to predict cohesion of the soil and the best hybrid model among them will be selected and introduced for soil shear strength parameters

4. Development of hybrid predictive models

4.1 GA-ANN

To develop hybrid ANN-based predictive models, first, an ANN model should be designed. A research by (Liou *et al.* 2009) proposed an equation to normalize datasets of ANN in the first stage of modelling to simplify following process:

$$X_{norm} = (X - X_{min}) / (X_{max}-X_{min}) \quad (6)$$

where maximum and minimum values of the X are presented by X_{max} and X_{min} respectively, and X is measured value and X_{norm} is normalized value.

In next step, datasets should be distinguished based on their training or testing nature, before model evaluation started. A research by (Nelson *et al.* 1991) suggested that about 20%-30% of datasets should allocate to testing datasets. Accordingly, we dedicated 20% of whole datasets (30 datasets) to testing datasets (6 datasets). Moreover, many researchers showed that one hidden layer in ANN makes this system eligible to predict continuous functions (Koopialipoor *et al.* 2018, Mahdiyar *et al.* 2018, Armaghani *et al.* 2019). According to (Hornik *et al.* 1989) if

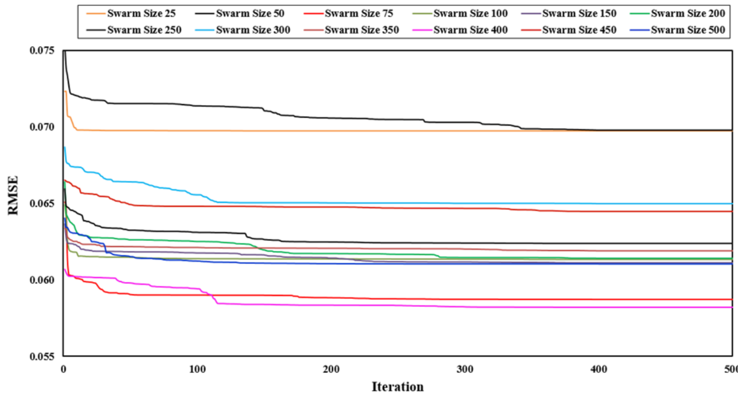


Fig. 13 Twelve PSO-ANN constructed models in predicting cohesion of the soil

N_i stand for input number, hidden nodes cannot exceed ($2\times N_i + 1$). Therefore, by considering $N_i = 4$, it seems that N_i range between 1 and 9 is suitable for predicting cohesion in sandy soil.

Many ANN models with this range of hidden nodes were constructed to predict cohesion of the soil. Root mean square error (RMSE) which is one of the best performance indices for evaluation of predictive models was used to evaluate ANN models. From the results of analysis, it was observed that an ANN model with 5 hidden nodes receives better prediction performance. Therefore, to predict cohesion in reinforced sandy soil, we used $4 \times 5 \times 1$ architecture for optimum model of ANN. Hence, in hybrid ANN-based models of this study, the same architecture is utilized.

Constructing GA-ANN model requires determination of GA most effective factors in first step. Regarding Momeni suggestion for rate of mutation probability, it assumed 25% of the population size.

Moreover, according to (Momeni *et al.* 2014, Armaghani *et al.* 2019), we utilized 9% of the population size for recombination percentage. Analysis of crossover operation performed by using single-point crossover with 70% probability, and tournament method selected among all to use two parents to generate two offspring. In the next step of designing GA-ANN, the population size (Spop) should be determined. Once again using trial and error approach and considering Spop amounts of 25, 50, 75, 100, 150, 200, 250, 300, 350, 400, 450, and 500, 12 GA-ANN models were constructed to predict cohesion of soil as presented in Fig. 12. By calculating RMSE values, the modeling results can be assessed. All 12 GA-ANN models were built using 500 numbers of generations. The minimum results of RMSE are related to Spop equal 450. Therefore, 450 were selected as the best Spop. Also, the results showed that generation equal to 350 is the point that RMSE results become constant; hence this value was selected as maximum number of generation in this study. The results associated to the best GA-ANN model will be described in more details later.

4.2 PSO-ANN

Multiple effective parameters including swarm size, inertia weight, number of iteration, and coefficients of velocity equation have pervasive effects on performance of PSO-ANN model. For purpose of this study, it is supposed that considering one (among suggestions like 0.25, 0.5, 0.75) for inertia weight for PSO-ANN models follows the principles of similar (Arabnejad Khanouki *et al.* 2011, Mohammadhassani *et al.* 2014a, Armaghani *et al.* 2017, Toghroli *et al.* 2017, Wei *et al.* 2018). Accordingly, PSO-ANN models are constructed by combinations of different values for C_1 and C_2 in a parametric study procedure. The results show that $C_1 = C_2 = 2$ are the optimal values which delivered lowest system error. Determination of swarm size (SS) and the maximum number of iteration (I_{Max}), contain examination of different values of 25, 50, 75, 100, 150, 200, 250, 300, 350, 400, 450, and 500 for SS with iteration number of 500. Using these assumptions and to predict cohesion for reinforced sandy soil, 12 different PSO-ANN models were built. The effect of SS and I_{Max} on accuracy of prediction in PSO-ANN models is depicted in Fig. 13. As it is displayed, SS=400 yields lowest system error which means its PSO-ANN model has the best potential for predicting cohesion of the reinforced sandy soil. Moreover, from iteration number of 1 to 300, for all SS values, RMSE were gradually decreased and stay constant in iteration number equal to 300 that selected for I_{Max} to predict cohesion. The best model of PSO-ANN in predicting cohesion will explain in the following section.

5. Model evaluation

In this section, results of predictive models for prediction of cohesion of reinforced sandy soil are evaluated. Three prediction performance indices including variance account for (VAF), RMSE and coefficient of determination (R^2) were considered to evaluate the predictive models as follows:

$$\mathrm{VAF} = \left[1- \frac{\mathrm{var}\ (y-y')}{\mathrm{var}\ (y)}\right] \times 100 \tag{7}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} (y-y')^2} \tag{8}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N} (y-y')^2}{\sum_{i=1}^{N} (y-\tilde{y})^2} \tag{9}$$

Table 4 Performance comparison for the proposed models

Model	Performance Index					
	R^2		RMSE		VAF (%)	
	Train	Test	Train	Test	Train	Test
GA-ANN	0.950	0.957	0.060	0.081	94.777	94.496
PSO-ANN	0.938	0.943	0.066	0.065	93.685	93.199

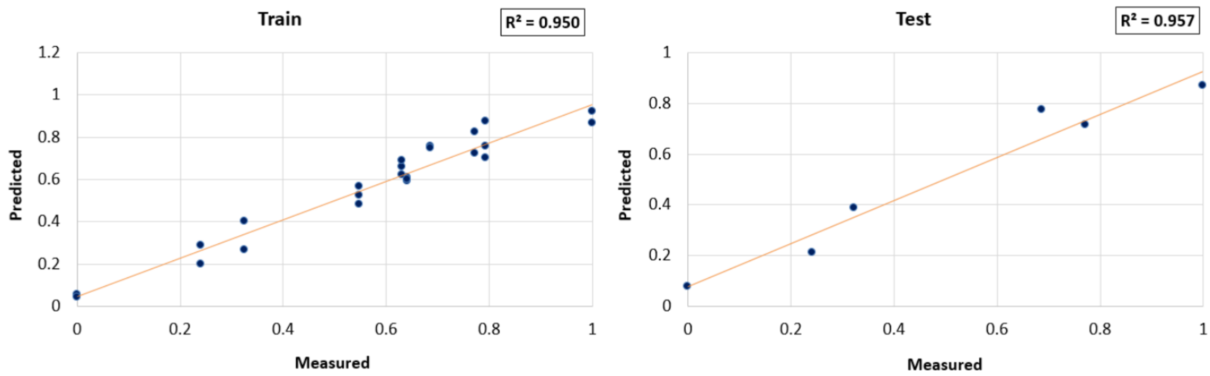


Fig. 14 GA-ANN results in estimating cohesion of the reinforced soil

In these equations, y and y' are the predicted and measured values, respectively, $\tilde{y}$ is the average of the y values and the total number of data showed by N. VAF = 100, RMSE = 0 and R^2 = 1 will be the ideal condition for predictive model.

For evaluation purposes, the computed values of performance indices relating to the proposed GA-ANN and PSO-ANN models are listed in Table 4. According to this table, it is found that both proposed models have excellent prediction results, but the accuracy level of GA-ANN hybrid model is more than PSO-ANN model. It can be seen that by developing a hybrid GA-ANN model, results of training and testing datasets will be increased. As a result, improvements of 0.012 and 0.013 in R^2, were obtained when a GA-ANN model is developed. Moreover, GA-ANN received lower error and higher VAF compared with PSO-ANN predictive model. Hence, the GA-ANN model is selected as the best predictive model of cohesion of fiber-reinforced sandy soil. In Fig. 14, relations between the reinforced soil's cohesion and the obtained values from the best model of GA-ANN for training and testing are displayed. It can be seen that in GA-ANN model, training and testing datasets deliver values of 0.950 and 0.957 for R^2, respectively. The introduced hybrid GA-ANN model shows more precise outcome for cohesion of reinforced soil. Thus, the developed GA-ANN model can be considered as a new model with more precise results in assessment of shear strength parameters of the reinforced sandy soil.

6. Conclusions

A series of consolidated undrained triaxial tests were conducted to survey inherent strength increase due to addition of polypropylene fibers to sandy soil. The results confirmed that fiber percentage, fiber length, deviator stress and pore water pressure have a deep impact on cohesion values and due to that these parameters were selected as model inputs in another contribution of this study developing intelligent systems i.e., GA-ANN and PSO-ANN. Considering all effective factors of the mentioned intelligent techniques, several GA-ANN and PSO-ANN models were built to predict cohesion of the sandy soil. Finally, the prediction capacity for each developed model was determined by calculating the three most common statistical indices, i.e. R^2, RMSE and VAF. The results showed that both hybrid ANN models can predict cohesion with high level of accuracy. According to the obtained statistical results, the proposed GA-ANN model with the R^2, RMSE and VAF values equal to 0.957, 0.081 and 94.496%, respectively, has a higher level of performance on the testing data set when comparing to the developed PSO-ANN model, which gives 0.943, 0.065 and 93.199 % for the same performance indices on testing data set. Hence, the proposed GA-ANN model was selected as the best hybrid predictive model and it can be utilized as an initial predictive model for estimating shear strength of the reinforced soil with fiber in site investigation phase. In this condition, inputs in the mentioned ranges of this study can be applied using the developed GA-ANN model.

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