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Predicting the Grouting Ability of Sandy Soils by Artificial Neural Networks Based On Experimental Tests

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ABSTRACT: In this paper, the grouting ability of sandy soils is investigated by artificial neural networks based on the results of chemical grout injection tests. In order to evaluate the soil grouting potential, experimental samples were prepared and then injected. The sand samples with three different particle sizes (medium, fine, and silty) and three relative densities (%30, %50, and %90) were injected with the sodium silicate grout with three different concentrations (water to sodium silicate ratio of 0.33, 1, and 2). A multi-layer Perceptron type of the artificial neural network was trained and tested using the results of 138 experimental tests. The multi-layer Perceptron included one input layer, two hidden layers and one output layer. The input parameters consisted of initial relative densities of grouted samples, the average size of particles (D50), the ratio of the grout water to sodium silicate and the grout pressure. The output parameter was the grout injection radius. The results of the experimental tests showed that the radius of grout injection is a complicated function of the mentioned parameters. In addition, the results of the trained artificial neural network showed to be reasonably consistent with the experimental results.

Keywords: Artificial Neural Network, Chemical Grout, Grout-Ability, Sandy Soil.

INTRODUCTION

In the past two centuries, the injection method has been used for improving soil properties. Various methods of grouting such as permeation grouting, filling grouting, fracture grouting, compaction grouting, and electro-osmosis chemical grouting have been developed for injection in soils (Liao et al., 2011). Among the different grouting methods, chemical grouting is commonly applied in order to increase the soil resistivity and improve its physical and mechanical characteristics.

There are a considerable number of studies on the improvement of soil characteristics such as permeability reduction or shear strength increase using the grouting methods; however, relatively a limited number of experimental works has been undertaken for determining the grout-ability of sands through chemical grouting.

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In this respect, Portland cement was first used in a single injection; however, in sample cases with tiny pores in sediments, adequate penetration of the injection would have been a problem due to the large cement grains compared to the size of soil pores (Karol, 1983).

Grouts are divided into two general categories namely the grouts with suspended beads (rough grout) and soluble grouts (soft grout). The mixture of water and cement, clay, Bentonite, and etc. are categorized as rough grouts. In contrast, Silicates, Lignosulfonate, Amyloplast, Akrylamide, Polyester, Urea, Ethan, and some other chemicals are known as soft chemical grouts (Army Corps of Engineers, 1995).

The grouting of granular soils has been studied for years. For example, Lenahan and Herndon (1976) suggested some limits for the grout-ability of soils considering the grain size of soil (Herndon and Lenahan, 1976). Bell (1993) and Cerenand Incecik (1995) examined the grout-ability of soil only based on the grain size of soil and cement (Bell, 1993; Incecik and Ceren, 1995). However, large-scale experiments showed that the injection of the granular soil is affected by various parameters of soil and grout (Akbulut, 1999; Kutzner, 1996). These parameters included the size of soil and grout grains, the fine content of the soil (FC), grout pressure (GP), soil relative density (Dr), and water to cement ratio (W/C) (or viscosity) of the grout injected (Saute and Saglamer, 2002). Also, Dano et al. (2004) evaluated the grout-ability of sandy soil with very fine-grained cement grout (Dano et al., 2004).

In this paper, the grouting ability of sandy soils with particles of medium to silt size using sodium silicate grout was experimentally investigated. The grout used was a chemically based grout. Ata and Vipulanandan (1998, 1999) studied the effective factors on the mechanical and creep properties of sands being injected with this grout (Ata and Vipulanandan, 1998 and 1999). Hassanlourad et al. (2010) examined the mechanical properties and the shear strength behavior of grouted sands using sodium silicate through unconfined and drained and un-drained triaxial tests (Hassanlourad et al., 2012).

The Artificial Neural Network (ANN) technique also was used for simulating the grouting process of the soil. The ANN is a simple simulation of the human brain and accepted as a reliable data-modeling tool to capture and register complex relationships between inputs and outputs (Caglar and Arman, 2007; Banimahd et al., 2005). ANNs have been also developed as a new tool for analyzing geotechnical problems. Once the network is trained with a proper number of sample data sets, a new output having a relatively similar pattern will be predicted on the basis of the previous learning (Grima et al., 2000).

From the early 1990s, ANNs have been applied to almost every problem in geotechnical engineering such as compaction and permeability (Agrawal, 1994; Goh, 1995b; Gribb and Gribb, 1994; Sinha and Wang, 2008), soil classification (Cal, 1995), soil density (Goh, 1995b), blasting (Lu, 2005),dams (Kim and Kim, 2006), environmental geotechnics (Shang, 2004), earth anchoring (Shahin and Jaksa, 2004, 2005, 2006), grout-ability prediction of soil with micro-fine cement grouts Liao et al, 2011), determination of the pile bearing capacity (Teh et al., 1997; Lee and Lee, 1996), thermal properties of soils (Erzin et al., 2006), and foundation settlement analysis (Shahin et al., 2002).

In summary, the effective parameters on the grout radius of injection (ROI) for the sandy-silty soil included soil relative density (Dr), soil average size (D_{50}), grout water to sodium silicate ratio (W/S), and grout pressure (GP), which were examined using the ANN technique in this research. It was observed that an artificial neural network is well capable of learning and predicting complex relations between these parameters in the grouting process.

EXPERIMENTAL DATA GENERATION

Based on the soil mechanics knowledge, parameters affecting the soil injection include particle size distribution, grain size, compaction of soil, and grout concentration and pressure. Therefore, a number of experimental tests were carried out as presented below.

Particle Size of the Used Sand

A broken silty sand as called Firoozkooh sand was used for the testing purpose. To examine the effect of the soil particle size on its grout-ability using chemical grout, three types of particle size distributions including medium (remained on the sieve #100 and passed from sieve #40), fine (remained on the sieve #200 and passed from sieve #100), and very fine (%50 remained on the sieve #200 and %50 passed from sieve #200) were prepared. Figure 1 shows the prepared three particle size distributions.

Combination of Grout

The selected grout for injection in the soil was a chemical based grout called sodium silicate. The advantages of this grout are it's relatively low cost and easy penetration to the soil voids. Another benefit of this grout is its low environmental hazards (Army Corps of Engineers, 1995).

The main compositions of the grout are sodium silicate ($Na_2O_2SiO_2$) as the main cause of the connectors and water as an element for hydration and viscosity reduction factor. Also, other additives such as formamide as the chemical reactor and aluminum sulfate as an accelerator of the chemical reactions were used. Sodium silicate grout is usually used to increase the bearing capacity of soft soils and/or groundwater seepage control. Experiments show that sodium silicate grout is resistant in acidic, alkaline, salt, and fungal environments (Army Corps of Engineers, 1995).

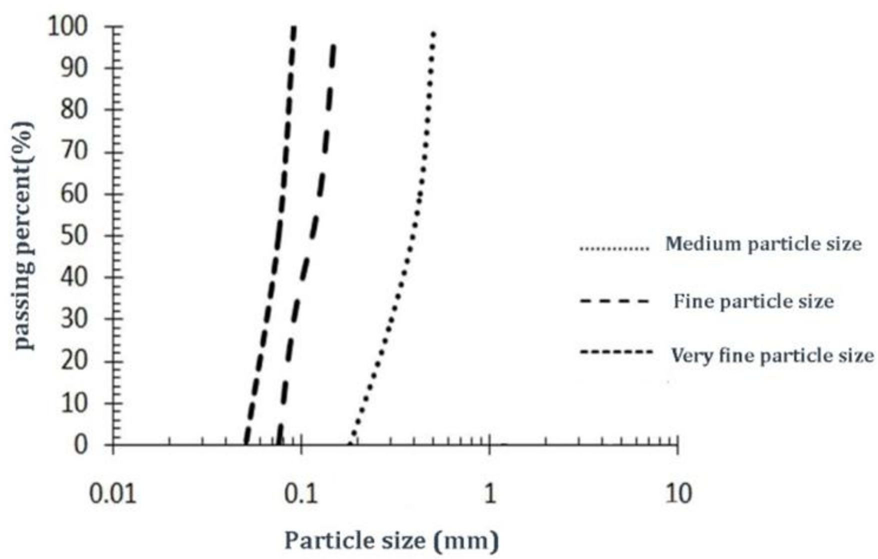

Fig. 1. Particle size distribution of the used sand samples.

Grouting

The injection system consists of a grout tank, a cylindrical mold of sampling which is 100cm in length and 4 cm in diameter, and a piping system to enter and exit the grout. The tank, pipes, and the mold are made of a transparent plastic (plaxi glass) so that the grout injection could be observed and traced. For a more precise control, the necessary pressure for the grout injection was gradually adjusted as the tank elevation controls different injection pressure. The minimum and maximum elevation of the tank was considered to be 100cm and 500cm, respectively, and each elevation increment of the tank was selected as 28 cm for increasing the grout pressure. The grouted samples were positioned horizontally and then injected. Figure 2 illustrates the grouting machine.

Sample Preparation

The grouted samples were made of three relative densities using the dry deposition method and then injected by three different grout combinations (Water/sodium silicate ratio). In total, 138 grouting steps were taken on the samples. Results of the experiments are summarized in Table 1.

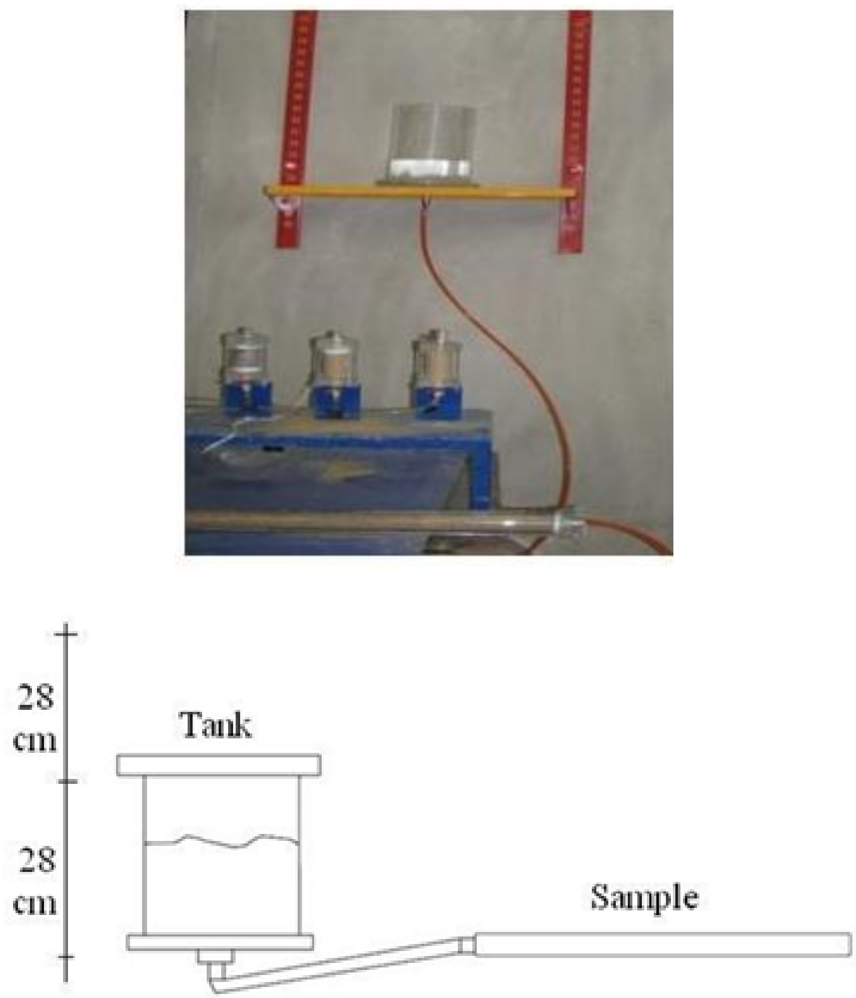

Fig. 2. Grouting machine.

Table 1. Experimental data.

D_{50} (mm)	Dr (%)	W/S	GP (cm)	ROI (cm)	D_{50} (mm)	Dr (%)	W/S	GP (cm)	ROI (cm)
0.375	50	2	120	60	0.11	50	2	176	100
			148	100			1	120	24
		1	120	35				148	38
			148	70				176	61
			176	100				204	83
		0.33	120	24				232	100
			148	40			0.33	120	16
			176	62				148	29
			204	80				176	38
			232	100				204	49
0.375	90	2	120	29				232	63
			148	53				260	75
			176	79				288	88
			204	100				316	100
		1	120	24		90	2	120	21
			148	40				148	46
			176	56				176	67
			204	72				204	88
			232	88				232	100
			260	100			1	120	19
		0.33	120	16				148	32
			148	29				176	48
			176	38				204	62
			204	47				232	76
			232	56				260	90
			260	65				288	100
			288	74			0.33	120	16
			316	83				148	22
			344	92				176	31
			372	100				204	40
0.375	30	2	120	80				232	49
			148	100				260	58
		1	120	42				288	67
			148	78				316	76
			176	100				344	85
		0.33	120	30				372	93
			148	57				400	100
			176	79		30	2	120	49
			204	100				148	85
0.11	50	2	120	37				176	100
			148	80			1	120	39

Table 1. Experimental data. (Continued)

D_{50} (mm)	Dr (%)	W/S	GP (cm)	ROI (cm)	D_{50} (mm)	Dr (%)	W/S	GP (cm)	ROI (cm)
0.11	30	1	148	60	0.075	50	0.33	344	38
			176	82				372	41
			204	100				400	44
		0.33	120	20				428	45
			148	38		90	1	120	6
			176	56				148	12
			204	74				176	18
			232	100				204	22
0.075	50	1	120	7				232	28
			148	13				260	33
			176	19				288	38
			204	24				316	42
			232	30				344	46
			260	35				372	49
			288	40				400	52
			316	44				428	53
			344	48			0.33	120	5
			372	51				148	9
			400	54				176	14
			428	56				204	18
		0.33	120	5				232	22
			148	10				260	26
			176	15				288	30
			204	20				316	33
			232	24				344	37
			260	28				372	39
			288	32				400	40
			316	35				428	41

ARTIFICIAL NEURAL NETWORK (ANN)

The ANN is a data processing system that is formed by simple processing elements which are closely related. They are some sort of computational models which are based on the information processing system of the human brain. Neural networks are the combination of the simple elements which operate in parallel with each other and are inspired by the biological nervous systems. As in nature, the network function is determined largely by the connections between the elements (Demuth and Beale, 2003). In fact, in an ANN hidden knowledge behind the data is transferred to the network structure. The artificial neural network, in which there is no explicit knowledge and clear relationship about the problem elements, was used in this study.

Multi - Layer Perceptron (MLP) Architecture

Each ANN is formed by a number of computational units called neurons which are connected together. ANNs are composed of three different layers of neurons: one input layer, one or more hidden layers, and one output layer (Griffiths and Andrews, 2011). In the MLP type of the network, each neuron in each layer is connected to the next layer neurons and there is no connection to the back layer of the network. Architecture of a simple neuron is shown in Figure3.

In each neuron, each input (p) is multiplied by a weight (w) (which is changed adaptively to improve the performance of the network based on the pairs of external and internal signals) and is summed with a bias (b). Then, (n) is used as an indicator in the transfer function (f) that finally gives an output (a).

The input layer consists of neurons which receive the data from external sources (Basheer and Hajmeer, 2000). The hidden layer processes the data received from the input neurons and passes it on to the output layer (Nelson and Illingworth, 1991). The output layer receives the data from the hidden layer and transforms them into a predicted value of the output (Griffiths and Andrews, 2011).

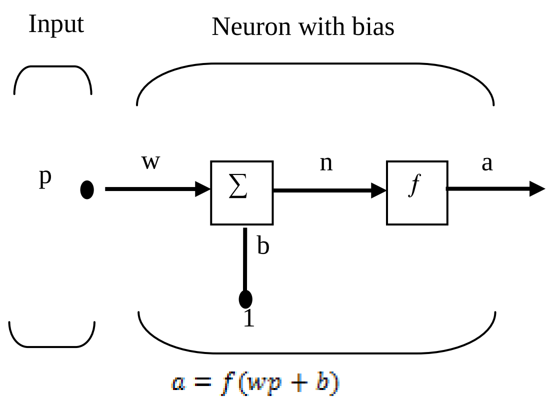

Fig. 3. Architecture of a simple neuron.

Training of the Network

Prior to the ANN training, a learning rule is selected which explains how weights will be modified in order to minimize the output prediction error. In the process of modeling, the back-propagation algorithm is the most common learning rule applied for training multi-layer ANNs (Balakrishnan and Weil, 1986; Maier and Dandy, 2000).

The Levenberg-Marquardt (LM) algorithm is an iterative technique that locates the minimum of a multivariate function that is expressed as the sum of squares of non-linear real-valued functions (Marquardt, 1963; Levenberg, 1944). It has become a standard technique for non-linear least-squares problems (Mittelmann, 2004), widely adopted in a broad spectrum of disciplines. However, the Train LM (Levenberg-Marquardt) method is usually considered as a faster error back-propagation algorithm.

Using the gradient descent method, the Mean Square Error (MSE) is minimized. The MSE value is obtained from the following equation (Eq. (1)):

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y - \bar{y})^2 \tag{1}$$

in which y and $\bar{y}$ are the network and experimental outputs respectively. N is the number of samples.

ARCHITECTURE OF THE NEURAL NETWORK

The MATLAB package's neural network toolbox was used for the network progress (Demuth and Beale, 2003). Multi-layer Perceptron with basic feed-forward back-propagation was chosen for the learning of the neural network which includes one input layer with four input parameters of Dr, D_{50}, W/S, and GP. Two hidden layers with 5 and 3 neurons in each layer and one output layer including the ROI considered for the network (Figure 4). It should be noted that if the relationships between the operation parameters and the quality responses are difficult to identify, two hidden layers may be used. In this state, the network performance is better than that of one hidden layer. A comparison between the results obtained using one and two hidden layers are made and its findings are shown in Table 2. When each neuron in a feed-forward network is connected to the adjacent neurons in the forward layer, the architecture is referred to as multi-layer Perceptron (Griffiths and Andrews, 2011). Also, the number of neurons is selected through trial and error.

In total, 138 available data sets were employed in order to develop the model. To avoid being over-trained, the data sets were divided into three categories. From all the data sets, 75 sets were used for training, 28 sets were left for the test, and 35 sets were used for validating the network.

The network training data were selected randomly (Griffiths and Andrews, 2011). The validation data sets were utilized to test the ANN during the training process, so that the training could be terminated once the validation error began to rise in order to avoid the memorization of the data (Basheer and Hajmeer, 2000). The test data set was used after training to evaluate the ANN performance. Figure 4 shows the architecture of the neural network model that was used.

The tangent sigmoid function was used as an activation function in the hidden layer and the linear (Purelin) function was used as an activation function in the output layer. The Levenberg-Marquardt method was used for the network training.

EVALUATION OF THE NETWORK PERFORMANCE

Performance of the developed network was evaluated by the correlation coefficient (R), mean absolute error (MAE), and root mean square error (RMSE).

R was calculated by the regression equation that determines the relationship between the network outputs and the experimental results (Eq. (2)). The R value of one indicates the network's good performance and that the network is well extended to all the data. The R value of about zero reflects that there is no relationship between the network outputs and experimental results, and the network does not perform properly.

$$R = \frac{\sum_{i=1}^{N}(y_i - \bar{y}_i)(t_i - \bar{t}_i)}{\sqrt{\sum_{i=1}^{N}(y_i - \bar{y}_i)^2 \sum_{i=1}^{N}(t_i - \bar{t}_i)^2}} \quad (2)$$

in which y_i and t_i are the network outputs and experimental results, $\bar{y}_i$ and $\bar{t}_i$ are the average of the network outputs and experimental results, respectively, and N is the number of samples.

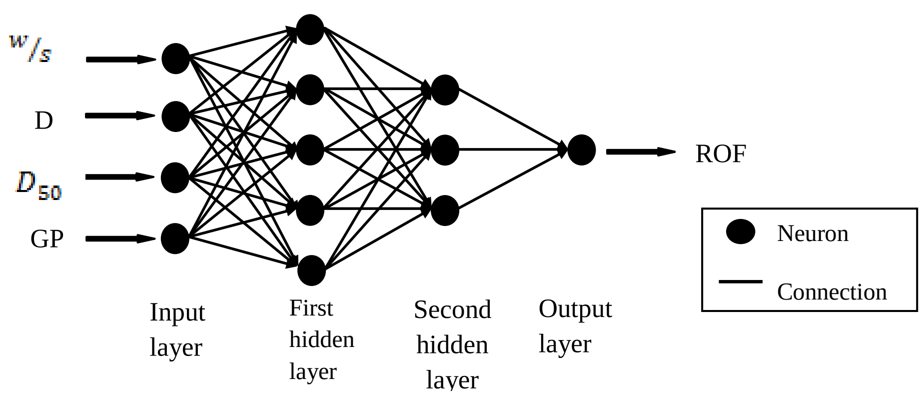

Fig. 4. Architecture of the used neural network model.

The RMSE is a suitable criterion to evaluate the network performance. The RMSE is of interest and it is widely reported in the literature (Willmott and Matsuura, 2005). The RMSE value is much closer to zero for the better performance of a network, and is obtained from the following equation (Eq. (3)):

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(y_i - t_i)^2}{N}} \quad (3)$$

The MAE is an absolute measure of how close the predicted values are to an actual outcome. Investigations indicate that the MAE is a more natural measure of average error and is unambiguous. Dimensioned evaluations and inter-comparisons of the average model-performance error should be therefore based on the MAE (Willmott and Matsuura, 2005). The MAE value is much closer to zero for the better performance of a network (Eq. (4)). The best model is represented by a R value close to 1.0 and RMSE and MAE close to 0.

$$MAE = \frac{\sum_{i=1}^{N}(y_i - t_i)}{N} \quad (4)$$

RESULTS AND DISCUSSION

As already anticipated, the radius of grout injection (ROI) is reduced by reducing the soil particle size, increasing the soil compaction or relative density, and decreasing the grout viscosity or W/S ratio and the injection pressure. Experimental tests showed that the particle size of soil to be grouted has the most effect on the radius of grout injection so that silt size particles resulted in a rapid reduction in the radius of grout injection. The effects of other mentioned parameters depended on the particle size of soil. The determination of the effects of these parameters on the radius of grout injection is hard. Figures 5-7 illustrate the effects of the soil particle size, soil relative density, and grout viscosity (W/S ratio) on the radius of grout injection, respectively, which include experimentally observed results and ANN predictions. It is obvious that the network has trained the experimentally tests results well and the effective parameters on the injection radius is well traced so that the network would be able to reasonably predict the effects of each parameter.

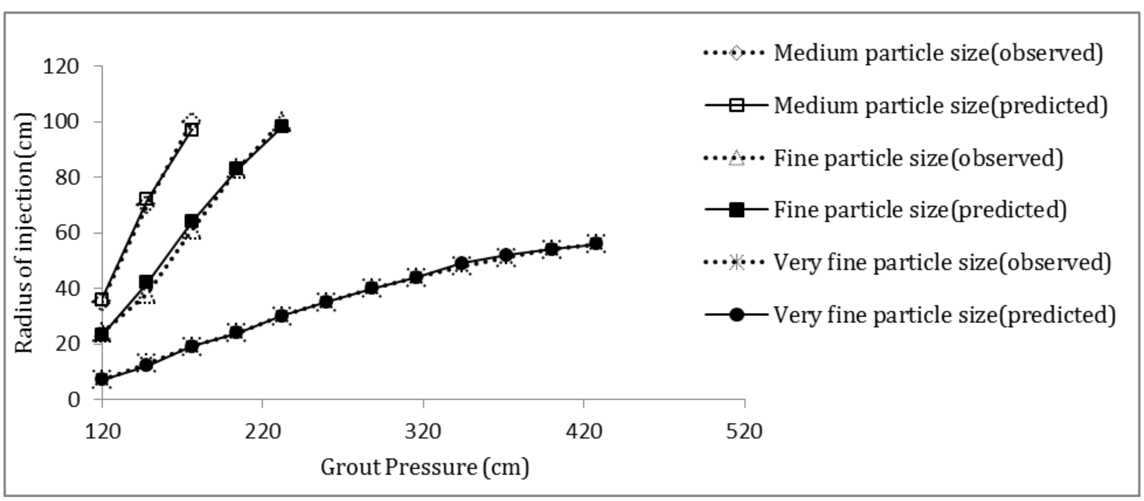

Fig. 5. Effect of soil particle size on the radius of slurry injection based on experimental tests and ANN predictions (W/S=1 and Dr=50%).

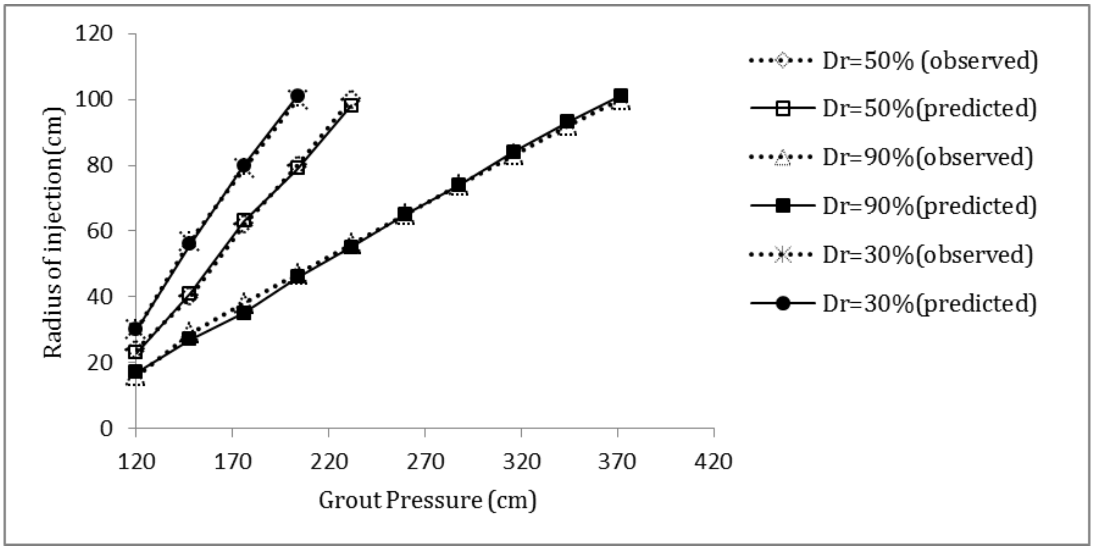

Fig. 6. Effect of soil relative density on the radius of slurry injection based on experimental tests and ANN predictions (medium soil and W/S=0.33).

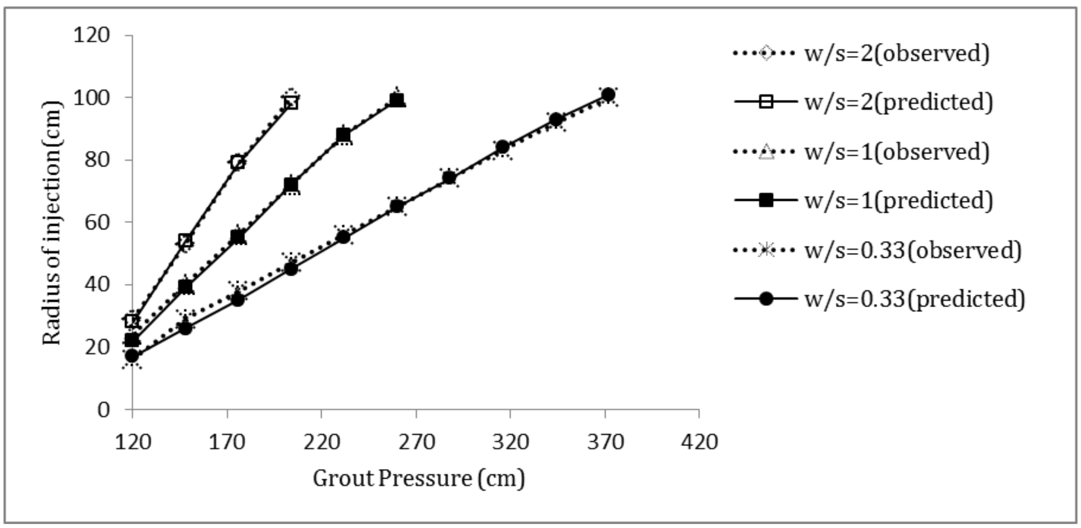

Fig. 7. Effect of grout viscosity (W/S ratio) on the radius of slurry injection based on experimental tests and ANN predictions (medium soil and Dr=90%).

Figure 8 show a comparison between the total experimentally observed and ANN predicted training dataset. Figure 9 also illustrate them for the testing dataset. It is observed that the ANN has well trained and tested.

The value of R between the experimentally observed and ANN predicted data was 0.99 for the trained datasets and 0.98 for the tested datasets. The MAE value was obtained 0.17 and 0.29 for the trained and tested datasets, respectively, which are acceptable values. Also, the RMSE value was calculated 2.03 and 4.12 for the trained and tested datasets, respectively. It indicates the close relationship between the experimentally observed and ANN predicted data. All the ANN model characteristics are summarized in Table 2.

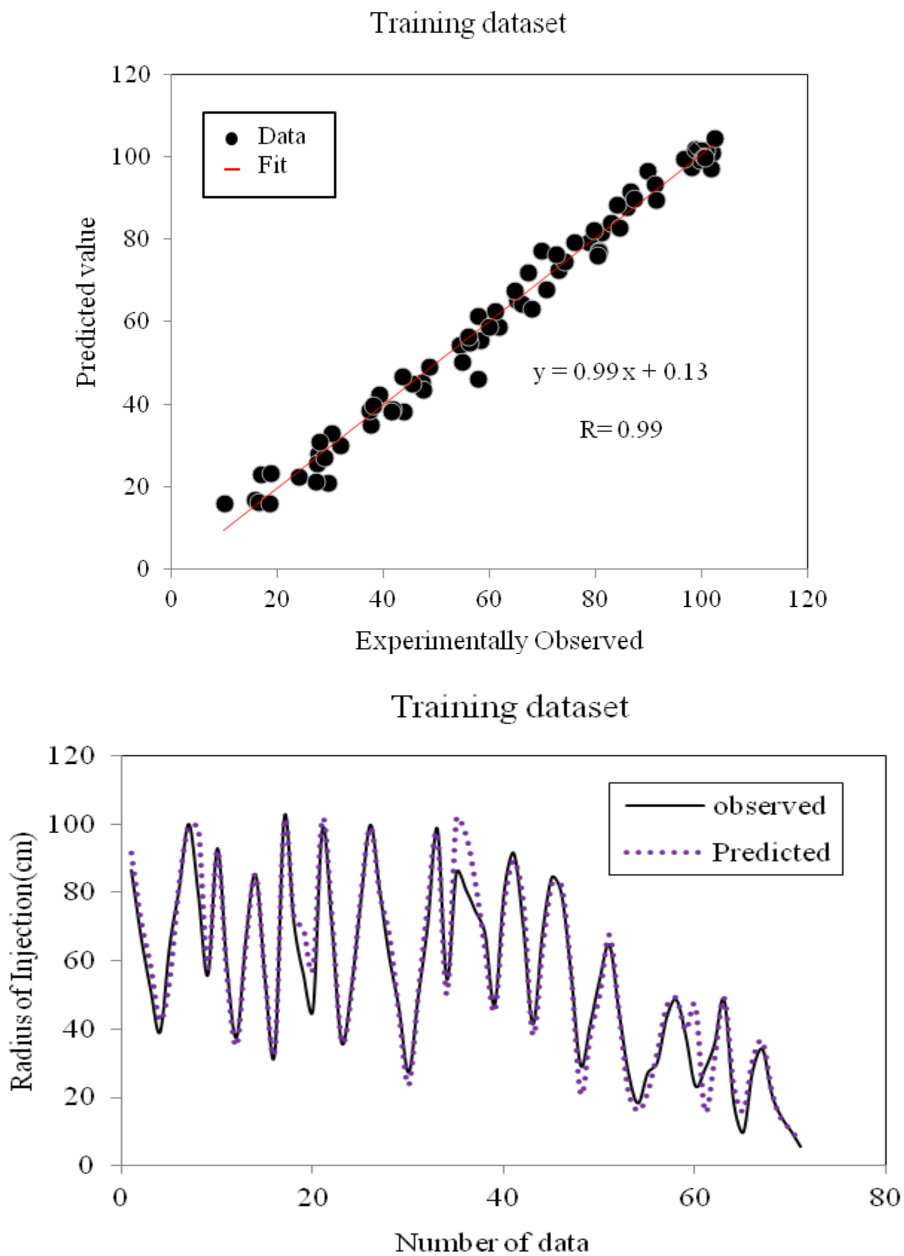

Fig. 8. Comparison of the experimentally observed and ANN predicted values for training dataset.

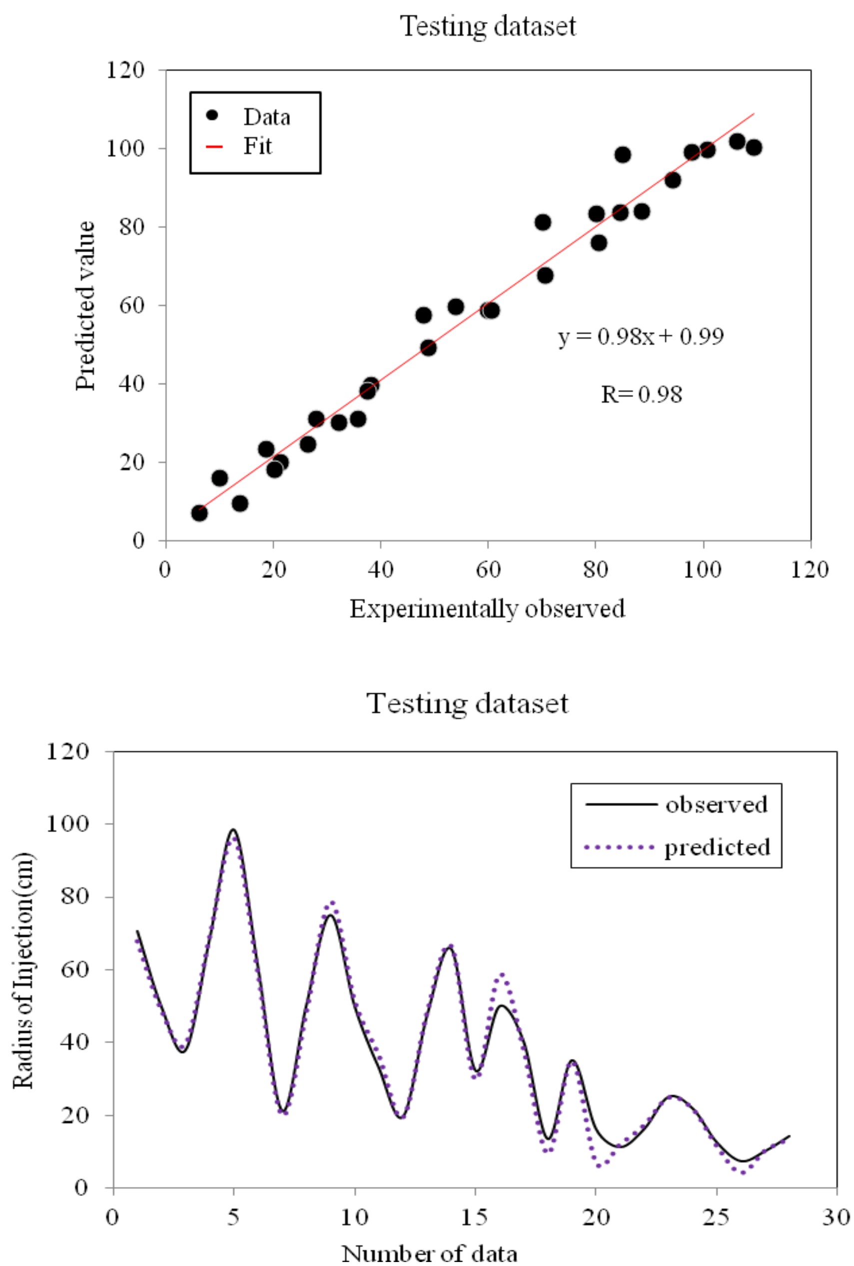

Fig. 9. Comparison of the experimentally observed and ANN predicted values for testing dataset.

Table 2. Characteristics of ANN's Model.

Type of character	Value/Description	Value/Description
Number of training data	75	75
Number of testing data	28	28
Number of validating data	35	35
Number of hidden layers	2	1
Number of optimum neuron in each hidden layers	5,3	5
Activation Function of hidden layers	Tan-Sig	Tan-Sig
Activation Function of output layer	Linear	Linear
Global Error Function	MSE	MSE
Number of optimum epochs stage	35	60
Training algorithm	Levenberg_Marquardt	Levenberg_Marquardt
MAE for training stage	0.17	0.23
MAE for testing stage	0.26	0.24
RMSE for training stage	2.03	2.50
RMSE for testing stage	4.12	6.07
R for training stage	0.99	0.99
R for testing stage	0.98	0.98

CONCLUSIONS

The grout-ability potential of sandy-silty soils was experimentally tested using a chemical grout called sodium silicate. The artificial neural network technique was used to simulate the relatively complex relationship between the effective parameters on the radius of grout injection, which include the soil particle size, soil relative density, grout concentration and grout pressure.

The experimental tests showed that the radius of grout injection is reduced by reducing the soil particle size, increasing the soil compaction or relative density, and decreasing the grout concentration and injection pressure. The particle size of soil to be grouted has the most effect on the radius of grout injection so that silt size particles result in a rapid reduction in the radius of grout injection. The other parameters have side effects and their effects depend on silt size particles.

The determination of the effects of these parameters on the radius of grout injection is a hard task. In this research, the artificial neural network trains the experimental test results well and the effective parameters on the injection radius are well traced so that the network developed in this study is able to predict the effect of each parameter.

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