Artificial Neural Networks Analysis of Treatment Process of Gypseous Soils

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Abstract

Artificial Neural Networks (ANNs) are used to relate the properties of gypseous soils and evaluate the values of compression of soils under different conditions. Therefore, one-layer perception training using back propagation algorithm is used to assess the validity of application of ANNs for modelling the settlement ratio for wetting process, $(S/B)_w$, and the settlement ratio for soaking process, $(S/B)_s$.

It was found that ANNs have the ability to predict the compression of gypseous soil due to soaking, washing process with high degree of accuracy. Also, performance of ANNs showed that one hidden layer with one hidden nodes is practically enough for the neural network analysis.

The sensitivity analysis indicates that the viscosity and specific gravity have the most significant effect on the predicated settlement ratio and the density of injection material and void ratio have moderate impact on the settlement ratio. The results also show that the initial gypsum content, stress and time have the smallest impact on settlement ratio.

It was concluded that the artificial neural networks (ANNs) have the ability to predict the settlement ratio for wetting process $(S/B)_w$, and settlement ratio for soaking process $(S/B)_s$ of gypseous soil with high degree of accuracy. The equations obtained using (ANNs) for $(S/B)_w$, and $(S/B)_s$ showed excellent correlation with experimental results where the coefficients of correlation are (0.9541) and (0.991), respectively.

Keywords: Gypseous soil, treatment, artificial neural network.

التحليل بالشبكات العصبية الاصطناعية لعملية معالجة الترب الجبسية

الخلاصة

تستخدم الشبكات العصبية الاصطناعية لربط خواص الترب الجبسية و تقييم قيم الانضغاط للتربة تحت ظروف مختلفة. و عليه أستخدم تدريب المدرك الحسي ذي الطبقة الواحدة بإتباع تقنية الانتشار الرجعي لتقييم صلاحية تطبيق الشبكات العصبية الاصطناعية في تمثيل نسبة الهبوط للعملية الرطبة (S/B)w و نسبة الهبوط للعملية عند الغمر (S/B)s) ، (حيث أن S يمثل هبوط الأساس الذي عرضه B).
لقد وجد بان الشبكات العصبية الاصطناعية قادرة على دراسة المتغيرات مع بعضها البعض كمجموعة واحدة وإيجاد علاقة بينها بدقة عالية. استخدم في هذه الدراسة طبقة مخفية واحدة احتوت على عقدة واحدة مخفية .
اظهر تحليل الحساسية لنماذج الفحوصات باستخدام الشبكات العصبية الاصطناعية بأن لزوجة المادة المحقونة والكثافة النوعية للتربة لهما التأثير الأكبر على نسبة الهبوط وأظهرت النتائج أن كثافة المادة

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المحقونة مع نسبة الفجوات للتربة ذات تأثير متوسط على نسبة الهطول كما أظهرت النتائج أن نسبة الجبس الابتدائية والإجهاد والزمن لها تأثير ضئيل في تحديد نسبة الهبوط.

لقد تم التوصل إلى استنتاج أن الشبكات العصبية الاصطناعية لها القابلية على تخمين نسبة الهبوط للعملية الرطبة $(S/B)_w$ و نسبة الهبوط للعملية عند الغمر $(S/B)_s$ للترب الجبسية مع درجة عالية من الدقة، فقد أبدت المعادلات التي تم الحصول عليها لتقدير $(S/B)_w$ و $(S/B)_s$ علاقات ممتازة مع النتائج العملية حيث كانت قيم معامل الارتباط (0.9541) و (0.991) على التوالي.

Introduction:

In recent years, artificial neural networks have been advocated as an alternative to traditional forecasting models. Neural networks have become significant data analytic tools that allow data to be analyzed in order to find the functional relationships among the variables under consideration. These variables are usually experimental data and classified into dependent and independent variables, the neural network allows the use of more than one dependent in a functional relationship, (Toll, 1996).

Neural networks, or simply neural nets, are computing systems which can be trained to learn a complex relationship between two or many variables or data sets. Basically, they are parallel computing systems composed of interconnecting simple processing nodes, (Toll, 1996).

In this paper, the neural network analysis was carried out using the program software Matlab and Simulink R2007a to estimate the settlement ratio in case of washing $(S/B)_w$, and the settlement ratio in case of soaking $(S/B)_s$ of model test. A data base of actual laboratory measurements of these four parameters with time during the soaking and washing processes is used to develop and verify the ANN models.

The objectives of this study are to provide:

1. Practical equations for prediction of settlement ratio in washing and soaking, strain percentage, and collapse potential percentage in gypseous soils.
2. Information on the relative importance of the factors affecting the soaking and washing processes.

ANNs Application in Geotechnical and Foundation Engineering

During the last few years, the use of ANNs has increased in many areas of engineering. In particular, ANNs have been applied to many geotechnical engineering problems and have demonstrated some degree of success. ANNs have been used successfully in modelling soil behaviour, liquefaction and earthquakes, site characterization, earth retaining structures, slope stability, tunnels and underground openings, soil swelling and classification of soils, prediction of pile capacity and foundation settlement.

Wharry and Ashely, (1986), and Siller, (1987) present one of the earliest knowledge based system (KBSs) to address the problem of determining the required level of geotechnical investigation. This is based on the requirements of a proposed structure and the level of information known about the site. The aim is to reduce the risk involved with the subsurface to an acceptable level.

Grives and Reagan, (1988) described a neural network approach for evaluating slope stability and recommending appropriate types of treatment or soil slope. It is linked to analytical methods for calculating slope stability.

Smith and Oliphant, (1991) described a KBS to assist with the planning stages of a site investigation. The system provides suggestions as to the next stage of the site investigations. The information obtained from the subsoil exploration stage was also used to create a 2-D visual representation of soil layers.

Hadipriono et al., (1991) described a KBS which was under development for determining the causes of foundation failures. The system contains knowledge on possible causes for failure, slope instability and foundation corrosion.

A KBS for retaining wall selection and design is presented by Arockiasamy et al., (1991). The system has knowledge about ten wall types including concrete gravity, cantilever, counterfort, gabions, reinforced earthen cribs, slurry, sheet pile, tieback and soil nailed walls.

The stress-strain behaviour of soils has been modelled using neural networks. Penumadu et. al., (1994) have attempted to model the stress-strain behaviour of clays, incorporating rate dependant behaviour.

Lee and Lee, (1996) utilized error back propagation neural networks to tests performed by them besides the in situ pile load tests obtained from other research works were used for the verification of the neural networks. The results showed that the maximum error of prediction did not exceed 25%, except for some bias data. These limited results indicated the feasibility of utilizing neural networks for pile prediction problems.

Nawari et al., (1999) developed an optimal neural network model for the design of piles subjected to axial and lateral loads using only simple input data. These data included SPT–N values and the geometrical properties. They developed models for steel H–piles, steel pipe piles, and prestressed and reinforced concrete piles. The models involved were back propagation and generalized regression neural networks. Prediction results and a comparison with the commonly used design methods show that the neural network approach is feasible and more accurate than the commonly used techniques for the design of pile foundations.

Najjar et al., (2000) performed a two phase research study to develop a combined artificial neural network (ANN) reliability based soil swell prediction models. In phase one, a responsible sized database representing 514 swell soil tests retrieved from over 51 different projects in Kansas was used to develop both neural networks based (NNB) and statistical based (SB) swell potential prediction models. Direct comparison of results obtained showed that NNB models provide significant improvements in prediction accuracy over their SB counterparts. In the second phase, predictions obtained using the developed NN models along with the available experimental database were used to produce reliability (probability) factor matrices. These matrices were used to assign a specific confidence level to predictions obtained via NNB models in order to classify the soil under considerations as a swelling or non swelling type.

Jose et al., (2000) developed an ANN model to predict the diaphragm wall deflection of deep excavation. Training data were collected from the construction projects in the Taipi Basin eighteen case histories with 4–7 excavation stages each, resulting in a total of 93 sets of wall deflection, with eight input variables and one output were analyzed. They concluded that the ANN prediction model does not require a rigorous understanding of cause and effect. Moreover, the soil models are nor significant to the predictions of wall deflections in deep excavation as compared with other factors. The developed ANN model can reasonably predict the magnitude as well as the location of maximum deflection of diaphragm wall.

Shahin, (2003) used a back-propagation neural network to predict the settlement of shallow foundations on cohesionless soils. A large database of actual measured settlements was used to develop and verify the ANN model. The results between the measured and predicted settlement utilized by ANNs are compared with three traditional methods. The results indicated that back propagation neural networks have the ability to predict the settlement of shallow foundations on cohesionless soils with an acceptable degree of accuracy (R=0.819). Also, the results obtained demonstrate that the ANN method outperforms the traditional methods.

Al-Janabi, (2006) utilized multilayer perception training using the back propagation algorithm to build two ANN models, one for dissolved gypsum (DG) and the other for leaching strain (L.S). It was found that ANNs have the ability to predict the dissolved gypsum and leaching strain through process in gypseous soils with a good degree of accuracy.

Al-Neami, (2006) uses ANNs to relate the properties of gypseous soils and evaluate the values of delayed compression for such types of soils under different conditions. Therefore, multi-layer perception training using back propagation algorithm is used to assess the validity of application of ANNs for modelling the delayed compression (creep) of gypseous soils. It was found that ANNs have the ability to predict the secondary compression of gypseous soil due to soaking, leaching process and repeated loading with a good degree of accuracy.

Prediction of the Settlement Ratio in Washing and Soaking Process by ANN Analysis

Development of ANN models:

The data used to calibrate and validate the neural network models are obtained from the literature and the experimental results of Al-Lamy (2008) who conducted laboratory tests on model of a gypseous soil. The grouting process was applied using acrylate liquid to decrease the collapse and settlement of the soil. The data include laboratory measurements of the "settlement ratio" as well as corresponding information regarding the soil properties, apparatus used and testing conditions. Full details of the database are given in Table (1) (in Appendix).

The steps for developing ANN models include the determination of model inputs and outputs, division of the available data, the determination of appropriate network architecture, and optimization of the connection weights. A PC-based commercial software system called Matlab R2007a is used, in which optimal network architecture is determined by trial and error.

Model input and output:

It is generally accepted that seven parameters have the most significant impact on the washing and soaking process in treated gypseous soils, and are thus used as the ANN model inputs, (Al-Lamy, 2008).

These include the following:-

1- Initial void ratio, e_o.
2- Initial gypsum content, G_c (%).
3- Applied stress during washing, σ_s, (kPa).
4- Specific gravity of soil, G_s.
5- Viscosity of injection material, υ, (c.Poise).
6- Density of injection material, ρ, (gm/cm^3), and
7- Time, t, (hrs).

The output of the model are settlement ratio $(S/B)_w$ and settlement ratio $(S/B)_s$. The available data extracted from the database in Table (1) (in Appendix) are given in Table (2) (in Appendix for the $(S/B)_w$ model only).

Data division:

The next step in the development of ANN models is dividing the available data into their subsets. Cross-validation is used as the stopping criteria in this research. Consequently, the data are randomly divided into three sets: training, testing and validation.

In total, 80% of the data are used for training and 20% are used for validation. The training data are further divided into 70% for the training set and 30% for the testing set.

Scaling of data:

Once the available data have been divided into their subsets, the input and output variables are pre-processed by scaling them to eliminate their dimensions and to ensure that all variables receive equal attention during training. Scaling has to be commensurate with limits of the transfer functions used in the hidden and output layers (i.e. -1.0 to 1.0 for tanh transfer function and 0.0 to 1.0 for sigmoid transfer function). The simple linear mapping of the variables extremes to the neural networks practical extremes is adopted for scaling, as it is the most commonly used method, (Shahin, 2003). As part of this method, for each variable x with minimum and maximum value of x_{min} and x_{max}, respectively, the scaled value x_n is calculated as follows:

$$x_n=\frac{x-x_{min}}{x_{max}-x_{min}} \qquad \ldots\ldots\ldots\ldots\ (1)$$

Model architecture, optimization and stopping criteria:

One of the most important and difficult tasks in the development of ANN models is determining the model architecture (i.e. the number and connectivity of the hidden layer nodes). A network with one hidden layer can approximate any continuous function, provided that sufficient connection weights are used, (Shahin, 2003). Consequently, one hidden layer with learning rate equal to 0.2 and momentum term equal to 0.8 is used in this research.

The general strategy adopted for finding the optimal network architecture and internal parameters that control the training process is as follows: a number of trials are carried out using the default parameters of the software used with one hidden layer and 1, 2, 3, ………, 13 hidden layer nodes, (Caudill, 1988).

Sensitivity analysis of the ANN model input:

In an attempt to identify which of the input variables have the most significant impact on the settlement ratio predictions, a sensitivity analysis is carried out on the ANN model. A simple and innovative technique proposed by (Garson, 1991) is used to interpret the relative importance of the input variables by examining the connection weights of the trained network. For a network with one hidden layer, the technique involves a process of partitioning the hidden output connection weights into components associated with each input node. For model $(S/B)_w$, the method is illustrated as follows. The data base for correlation was taken from the experimental results of Al–Lamy (2008) who conducted laboratory tests on model of a gypseous soil. The grouting process was applied using acrylate liquid to decrease the collapse and settlement of the soil. The model has seven input nodes, one hidden node, and one output node with connection weights as shown in table (1).

The computations proposed by (Garson, 1991) are as follows:-

1- For each hidden node i, the product p_{ij} is obtained (where j represents the column number of the weights mentioned above) by multiplying the absolute value of the hidden-output layer connection weight by the absolute value of the hidden-input layer connection weight of each input variable j. As an example:
   p_{11} = 1.5264 x 0.22 = 0.3358

This is shown in table (2).

2- For each hidden node, p_{ij} is divided by the sum of all input variables to obtain Q_{ij}. As an example:

Q_{11}=(0.3358)/
(0.3358+0.0010+0.0010+0.3350+0.4734+ 0.2529+0.0010)
Q_{11} = 0.2398

This is shown in table (3).

3- For each input node, Q_{ij} is divided by the sum of all input variables to obtain S_j. As an example:
   S_j=(0.2398)/
   (0.2398+0.0070+0.0070+0.2393+ 0.3381+0.1806+0.0070)
   S_j = 0.2354

This is shown in table (4).

4- Divide S_j by the sum for all input variables to get the relative importance of all output weights attributed to the given input variable. As an example, the relative importance for input node 1 is equal to:-
   (0.2354x100)/
   (0.2354+0.0007+0.0007+0.2349+0.3319+0.1773+0.0007) = 23.98%

This is shown in table (5).

In the same method, the relative importance for $(S/B)_s$ is shown in table (6).

The results indicate that the viscosity has the most significant effect on the predicted settlement ratio (washing) followed by initial void ratio with a relative importance of 33.81% and 23.98%, respectively. The results also indicate that the specific gravity has a moderate impact on settlement ratio with a relative importance equal to 23.93%, while density of injection material, initial gypsum content, time and washing stress have the smallest impact on the settlement ratio with relative importance of 18.06, 0.071, 0.071, and 0.071, respectively. The results are also presented in Figure (1). On the other hand, results indicate that the specific gravity has the most significant effect on the predicted settlement ratio (soaking) followed by the viscosity with a relative importance of 36.94 and 31.45%, respectively. The results also indicate that the density of the injection material has moderate impact on the settlement ratio with a relative importance equal to 22.72%, while, initial void ratio, soaking stress, time and initial gypsum content have the smallest impact with relative importance of 8.74, 0.1, 0.03 and 0.02%, respectively. The results are also presented in Figure (2).

ANN model equation:

The small number of connection weights obtained for the optimal ANN model enables the network to be translated into relatively simple formula. To demonstrate this, the structure of the ANN model is shown in Figure (3), while the connection weights and threshold levels are summarized in tables (7) and (8).

Using the connection weights and the threshold levels shown in tables (7) and (8), the predicted settlement ratio can be expressed as follows:-

$$(S/B)_w = \frac{1}{1+e^{(0.1673+0.22\tanh x)}} \quad \ldots\ldots\ldots\ldots (2)$$

$$(S/B)_s = \frac{1}{1+e^{(0.1826+0.1998\tanh x)}} \quad \ldots\ldots\ldots\ldots (3)$$

where,

$$x = \theta_8 + w_{81}\, e_o + w_{82}\, G_c + w_{83}\, \sigma_s + w_{84}\, G_s + w_{85}\, \upsilon + w_{86}\, \rho + w_{87}\, t \quad \ldots\ldots\ldots\ldots (4)$$

It should be noted that, before using Equations (2) and (3), all input variables (i.e. e_o, G_c, σ_s, G_s, υ, ρ, and t) need to be scaled between 0.0 and 1.0 using Equation (1) and the data ranges in the ANN model training. It should also be noted that the predicted value of $(S/B)_w$% and $(S/B)_s$% obtained from Equations (2) and (3) is scaled between 0.0 and 1.0 and in order to obtain the actual value, this settlement ratio has to be re-scaled using Equation (1). Equations (2), (3) and (4) can be rewritten as follows:

$$(S/B)_w = \frac{36}{1+e^{(0.1673+0.22\tanh x)}} \quad \ldots\ldots\ldots\ldots (5)$$

$$(S/B)_s = \frac{22}{1+e^{(0.1826+0.1998\tanh x)}} \quad \ldots\ldots\ldots\ldots (6)$$

and

$$x_w = 0.231+10^{-3}[0.21e_o+1.7\rho-(0.3\times G_c+2.1\times G_s)]+3.1\times\upsilon+1.2\times\sigma_s-0.011\times t \quad \ldots\ldots\ldots\ldots (7)$$

$$x_s = 0.112+10^{-3}[0.31e_o+1.01\rho-(0.4\times G_c+3.4\times G_s)]+2.9\times\upsilon+1.6\times\sigma_s-0.009\times t \quad \ldots\ldots\ldots\ldots (8)$$

where:

$(S/B)_w$ = predicted settlement ratio in washing, (%),

$(S/B)_s$ = predicted settlement ratio in soaking, (%),

e_o = initial void ratio,

Gc = initial gypsum content, (%),

σ_s = soaking stress, (kPa),

G_s = specific gravity of soil,

υ = viscosity of injection material, (c.Poise),

ρ = density of injection material, (gm/cm^3), and

t = time, (hrs).

Validity of the ANN Model Equations:

To assess the validity of the derived equations for the settlement ratio, (S/B)w and the settlement ratio, $(S/B)_s$, the equations are used to predict these values on the basis of all training sets used, (Al-Lamy, 2008).

The predicted values of the settlement ratio, $[(S/B)_w]_p$ and the settlement ratio, $[(S/B)_s]_p$, are plotted against the measured (observed) values, $[(S/B)_w]_m$ and $[(S/B)_s]_m$, in Figures (4), (5), respectively.

It is clear from these figures, the generalization capability of ANN techniques for any data set used within the range of data used in training the ANN. The models show very good agreement with the actual measurements as noticed from the coefficient of correlation (R^2) which was found (0.9541) and (0.991).

Conclusions

Based on the equations, the following conclusions can be made:

1. In this study, one hidden layer with one node is practically enough for the neural network analysis to define the settlement ratio $(S/B)_w$, and settlement ratio $(S/B)_s$.
2. Artificial neural networks (ANNs) have the ability to predict the settlement ratio for wetting process $(S/B)_w$, and settlement ratio for soaking process $(S/B)_s$ of gypseous soil with high degree of accuracy. The equations obtained using (ANNs) for $(S/B)_w$, and $(S/B)_s$ showed excellent correlation with experimental results where the coefficients of correlation are (0.9541) and (0.991), respectively.
3. The results indicate that the viscosity of grout has the most significant effect on the predicted settlement ratio (washing) followed by initial void ratio with a relative importance of 33.81% and 23.98%, respectively while the specific gravity has the most significant effect on the predicted settlement ratio (soaking) followed by the viscosity of grout with a relative importance of 36.94 and 31.45%, respectively.

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Table (1) Connection weights.

Hidden Nodes	Weights							
	e_o	G_c	σ_s	G_s	υ	ρ	t	$(S/B)_w$
Hidden 1	1.5264	-0.0033	0.0033	-1.5226	2.1518	1.1497	0.0030	-0.22

Table (2) Computation of the product p_{ij}.

	e_o	Gc	σ_s	Gs	υ	ρ	t
Hidden 1	0.3358	0.0010	0.0010	0.3350	0.4734	0.2529	0.0010

Table (3) Computation of Q_{ij}.

	e_o	Gc	σ_s	Gs	υ	ρ	t
Hidden 1	0.2398	0.0070	0.0070	0.2393	0.3381	0.1806	0.0070

Table (4) Computation of S_j.

	e_o	Gc	σ_s	Gs	υ	ρ	t
Hidden 1	0.2354	0.0007	0.0007	0.2349	0.3319	0.1773	0.0007

Table (5) The relative importance of all output weights $(S/B)_w$ case.

	e_o	G_c	σ_s	G_s	υ	ρ	t
Relative Importance, (%)	23.98	0.071	0.071	23.93	33.81	18.06	0.071

Table (6) The relative importance of all output weights $(S/B)_s$ case.

	e_o	G_c	σ_s	G_s	υ	ρ	t
Relative Importance, (%)	8.74	0.02	0.1	36.94	31.45	22.72	0.03

Table (7) Weights and threshold levels for the ANN optimal model $(S/B)_w$.

Hidden layer nodes	W_{ji} (weight from node i in the input layer to node j in the hidden layer)							Hidden layer threshold θj
	i=1	i=2	i=3	i=4	i=5	i=6	i=7	
j=8	1.5264	-0.0033	0.0033	-1.5226	2.1518	1.1497	0.0030	-4.0430
Output layer nodes	W_{ji} (weight from node i in the input layer to node j in the output layer)							Output layer threshold θj
	i=8							
j=9	-0.2200							0.1673

Table (8) Weights and threshold levels for the ANN optimal model $(S/B)_s$.

Hidden layer nodes	W_{ji} (weight from node i in the input layer to node j in the hidden layer)							Hidden layer threshold θj
	i=1	i=2	i=3	i=4	i=5	i=6	i=7	
j=8	0.5676	-0.0014	0.0043	-2.3988	2.0426	1.4757	0.0018	1.7989
Output layer nodes	W_{ji} (weight from node i in the input layer to node j in the output layer)							Output layer threshold θj
	i=8							
j=9	0.1998							0.1826

Appendix

Table (1) - Database used for ANN models.

Case No.	Reference	Location of Sampling	Initial Void Ratio (e_o)	Initial Gypsum Content (G_c), %	Stress, (σ_s), kPa	Specific of Gravity (G_s)	Viscosity of Injection Material (υ), (c.pois)	Density of Injection Material (ρ), (gm/cm^3)	Time t, (hrs)	$(S/B)_s$, %	$(S/B)_w$, %
1	Present Work	Ain Al-Tamor	0.833	72	12.5	2.36	2.02	1.082	24	1.09	1.10
2	Present Work	Ain Al-Tamor	0.833	72	25	2.36	2.02	1.082	48	1.67	1.72
3	Present Work	Ain Al-Tamor	0.833	72	50	2.36	2.02	1.082	72	2.24	2.15
4	Present Work	Ain Al-Tamor	0.833	72	100	2.36	2.02	1.082	96	4.46	4.57
5	Present Work	Ain Al-Tamor	0.833	72	200	2.36	2.02	1.082	120	6.23	6.76
6	Present Work	Ain Al-Tamor	0.833	72	200	2.36	2.02	1.082	144	11.98	14.31
7	Present Work	Ain Al-Tamor	0.833	72	200	2.36	2.02	1.082	168	13.42	17.92
8	Present Work	Ain Al-Tamor	0.833	72	200	2.36	2.02	1.082	192	15.62	19.42
9	Present Work	Ain Al-Tamor	0.833	72	200	2.36	2.02	1.082	216	16.71	22.31
10	Present Work	Ain Al-Tamor	0.833	72	200	2.36	2.02	1.082	240	18.31	23.42
11	Present Work	Ain Al-Tamor	0.833	72	200	2.36	2.02	1.082	264	19.67	24.29
12	Present Work	Ain Al-Tamor	0.833	72	200	2.36	2.02	1.082	288	20.31	25.67
13	Present Work	Ain Al-Tamor	0.833	72	200	2.36	2.02	1.082	312	20.98	26.77
14	Present Work	Ain Al-Tamor	0.833	72	200	2.36	2.02	1.082	336	21.31	27.49
15	Present Work	Ain Al-Tamor	0.833	72	200	2.36	2.02	1.082	360	21.97	28.92

Case No.	Reference	Location of Sampling	Initial Void Ratio (e_o)	Initial Gypsum Content (G_c), %	Stress, (σ_s), kPa	Specific of Gravity (G_s)	Viscosity of Injection Material (υ), (c.pois)	Density of Injection Material (ρ), (gm/cm^3)	Time t, (hrs)	$(S/B)_s$, %	$(S/B)_w$, %
16	Present Work	Ain Al-Tamor	0.833	72	200	2.36	2.02	1.082	384	22.03	29.39
17	Present Work	Ain Al-Tamor	0.833	72	200	2.36	2.02	1.082	408	23.43	30.79
18	Present Work	Ain Al-Tamor	0.833	72	200	2.36	2.02	1.082	432	23.67	31.91
19	Present Work	Ain Al-Tamor	0.833	72	200	2.36	2.02	1.082	456	24.02	32.67
20	Present Work	Al-Hussainya	0.746	55	12.5	2.4	2.02	1.082	24	0.92	0.89
21	Present Work	Al-Hussainya	0.746	55	25	2.4	2.02	1.082	48	1.43	1.46
22	Present Work	Al-Hussainya	0.746	55	50	2.4	2.02	1.082	72	1.98	2.01
23	Present Work	Al-Hussainya	0.746	55	100	2.4	2.02	1.082	96	2.42	2.39
24	Present Work	Al-Hussainya	0.746	55	200	2.4	2.02	1.082	120	3.09	3.12
25	Present Work	Al-Hussainya	0.746	55	200	2.4	2.02	1.082	144	8.22	11.32
26	Present Work	Al-Hussainya	0.746	55	200	2.4	2.02	1.082	168	10.44	14.21
27	Present Work	Al-Hussainya	0.746	55	200	2.4	2.02	1.082	192	12.02	17.39
28	Present Work	Al-Hussainya	0.746	55	200	2.4	2.02	1.082	216	13.98	19.42
29	Present Work	Al-Hussainya	0.746	55	200	2.4	2.02	1.082	240	14.77	20.92
30	Present Work	Al-Hussainya	0.746	55	200	2.4	2.02	1.082	264	15.82	21.32
31	Present Work	Al-Hussainya	0.746	55	200	2.4	2.02	1.082	288	16.78	22.89

Case No.	Reference	Location of Sampling	Initial Void Ratio (e_o)	Initial Gypsum Content (G_c), %	Stress, (σ_s), kPa	Specific of Gravity (G_s)	Viscosity of Injection Material (υ), (c.pois)	Density of Injection Material (ρ), (gm/cm^3)	Time t, (hrs)	$(S/B)_s$, %	$(S/B)_w$, %
32	Present Work	Al-Hussainya	0.746	55	200	2.4	2.02	1.082	312	17.59	23.72
33	Present Work	Al-Hussainya	0.746	55	200	2.4	2.02	1.082	336	18.47	24.83
34	Present Work	Al-Hussainya	0.746	55	200	2.4	2.02	1.082	360	19.32	25.72
35	Present Work	Al-Hussainya	0.746	55	200	2.4	2.02	1.082	384	20.03	26.31
36	Present Work	Al-Hussainya	0.746	55	200	2.4	2.02	1.082	408	20.98	27.02
37	Present Work	Al-Hussainya	0.746	55	200	2.4	2.02	1.082	432	21.29	27.98
38	Present Work	Al-Hussainya	0.746	55	200	2.4	2.02	1.082	456	21.96	28.10
39	Present Work	Al-Askary	0.775	29	12.5	2.44	2.02	1.082	24	0.78	0.72
40	Present Work	Al-Askary	0.775	29	25	2.44	2.02	1.082	48	1.09	1.12
41	Present Work	Al-Askary	0.775	29	50	2.44	2.02	1.082	72	1.42	1.53
42	Present Work	Al-Askary	0.775	29	100	2.44	2.02	1.082	96	1.84	1.79
43	Present Work	Al-Askary	0.775	29	200	2.44	2.02	1.082	120	2.03	2.23
44	Present Work	Al-Askary	0.775	29	200	2.44	2.02	1.082	144	7.79	12.45
45	Present Work	Al-Askary	0.775	29	200	2.44	2.02	1.082	168	9.89	15.31
46	Present Work	Al-Askary	0.775	29	200	2.44	2.02	1.082	192	12.04	18.62
47	Present Work	Al-Askary	0.775	29	200	2.44	2.02	1.082	216	13.77	20.46

Case No.	Reference	Location of Sampling	Initial Void Ratio (e_o)	Initial Gypsum Content (G_c), %	Stress, (σ_s), kPa	Specific of Gravity (G_s)	Viscosity of Injection Material (υ), (c.pois)	Density of Injection Material (ρ), (gm/cm^3)	Time t, (hrs)	$(S/B)_s$, %	$(S/B)_w$, %
48	Present Work	Al-Askary	0.775	29	200	2.44	2.02	1.082	240	14.67	21.57
49	Present Work	Al-Askary	0.775	29	200	2.44	2.02	1.082	264	15.98	22.74
50	Present Work	Al-Askary	0.775	29	200	2.44	2.02	1.082	288	16.89	23.39
51	Present Work	Al-Askary	0.775	29	200	2.44	2.02	1.082	312	17.42	24.56
52	Present Work	Al-Askary	0.775	29	200	2.44	2.02	1.082	336	17.99	25.79
53	Present Work	Al-Askary	0.775	29	200	2.44	2.02	1.082	360	18.17	26.92
54	Present Work	Al-Askary	0.775	29	200	2.44	2.02	1.082	384	18.42	27.57
55	Present Work	Al-Askary	0.775	29	200	2.44	2.02	1.082	408	18.89	28.39
56	Present Work	Al-Askary	0.775	29	200	2.44	2.02	1.082	432	19.02	29.96
57	Present Work	Al-Askary	0.775	29	200	2.44	2.02	1.082	456	19.34	30.21
58	Present Work	Al-Sa'ad	0.598	18	12.5	2.52	2.02	1.082	24	0.63	0.59
59	Present Work	Al- Sa'ad	0.598	18	25	2.52	2.02	1.082	48	0.82	0.79
60	Present Work	Al- Sa'ad	0.598	18	50	2.52	2.02	1.082	72	1.12	1.09
61	Present Work	Al- Sa'ad	0.598	18	100	2.52	2.02	1.082	96	1.43	1.39
62	Present Work	Al- Sa'ad	0.598	18	200	2.52	2.02	1.082	120	1.64	1.69
63	Present Work	Al- Sa'ad	0.598	18	200	2.52	2.02	1.082	144	4.21	8.47

Case No.	Reference	Location of Sampling	Initial Void Ratio (e_o)	Initial Gypsum Content (G_c), %	Stress, (σ_s), kPa	Specific of Gravity (G_s)	Viscosity of Injection Material (υ), (c.pois)	Density of Injection Material (ρ), (gm/cm^3)	Time t, (hrs)	$(S/B)_s$, %	$(S/B)_w$, %
64	Present Work	Al- Sa'ad	0.598	18	200	2.52	2.02	1.082	168	5.31	9.31
65	Present Work	Al- Sa'ad	0.598	18	200	2.52	2.02	1.082	192	6.41	11.43
66	Present Work	Al- Sa'ad	0.598	18	200	2.52	2.02	1.082	216	7.39	12.32
67	Present Work	Al- Sa'ad	0.598	18	200	2.52	2.02	1.082	240	8.68	13.63
68	Present Work	Al- Sa'ad	0.598	18	200	2.52	2.02	1.082	264	9.42	14.41
69	Present Work	Al- Sa'ad	0.598	18	200	2.52	2.02	1.082	288	10.02	15.21
70	Present Work	Al- Sa'ad	0.598	18	200	2.52	2.02	1.082	312	10.98	17.32
71	Present Work	Al- Sa'ad	0.598	18	200	2.52	2.02	1.082	336	11.24	19.41
72	Present Work	Al- Sa'ad	0.598	18	200	2.52	2.02	1.082	360	12.31	20.32
73	Present Work	Al- Sa'ad	0.598	18	200	2.52	2.02	1.082	384	12.97	21.39
74	Present Work	Al- Sa'ad	0.598	18	200	2.52	2.02	1.082	408	13.11	22.36
75	Present Work	Al- Sa'ad	0.598	18	200	2.52	2.02	1.082	432	13.98	23.92
76	Present Work	Al- Sa'ad	0.598	18	200	2.52	2.02	1.082	456	14.02	24.24

Table (2) Training, Testing and Validation Data for $(S/B)_w$ Model.

Case No.	Input Variable							Output
	Initial Void Ratio (e_o)	Initial Gypsum Content (G_c), %	Stress, (σ_s), kPa	Specific of Gravity (G_s)	Viscosity of Injection Material (υ), (c.pois)	Density of Injection Material (ρ), (gm/cm^3)	Time t, (hrs)	$(S/B)_w$, %
1	0.833	72	12.5	2.36	2.02	1.082	24	1.10
2	0.833	72	25	2.36	2.02	1.082	48	1.72
3	0.833	72	50	2.36	2.02	1.082	72	2.15
4	0.833	72	100	2.36	2.02	1.082	96	4.57
5	0.833	72	200	2.36	2.02	1.082	120	6.76
6	0.833	72	200	2.36	2.02	1.082	144	14.31
7	0.833	72	200	2.36	2.02	1.082	168	17.92
8	0.833	72	200	2.36	2.02	1.082	192	19.42
9	0.833	72	200	2.36	2.02	1.082	216	22.31
10	0.833	72	200	2.36	2.02	1.082	240	23.42
11	0.833	72	200	2.36	2.02	1.082	264	24.29
12	0.833	72	200	2.36	2.02	1.082	288	25.67
13	0.833	72	200	2.36	2.02	1.082	312	26.77
14	0.833	72	200	2.36	2.02	1.082	336	27.49
15	0.833	72	200	2.36	2.02	1.082	360	28.92
16	0.833	72	200	2.36	2.02	1.082	384	29.39
17	0.833	72	200	2.36	2.02	1.082	408	30.79
18	0.833	72	200	2.36	2.02	1.082	432	31.91
19	0.833	72	200	2.36	2.02	1.082	456	32.67
20	0.746	55	12.5	2.4	2.02	1.082	24	0.89
21	0.746	55	25	2.4	2.02	1.082	48	1.46
22	0.746	55	50	2.4	2.02	1.082	72	2.01
23	0.746	55	100	2.4	2.02	1.082	96	2.39
24	0.746	55	200	2.4	2.02	1.082	120	3.12
25	0.746	55	200	2.4	2.02	1.082	144	11.32
26	0.746	55	200	2.4	2.02	1.082	168	14.21
27	0.746	55	200	2.4	2.02	1.082	192	17.39
28	0.746	55	200	2.4	2.02	1.082	216	19.42
29	0.746	55	200	2.4	2.02	1.082	240	20.92

Case No.	Input Variable							Output
	Initial Void Ratio (e_o)	Initial Gypsum Content (G_c), %	Stress, (σ_s), kPa	Specific of Gravity (G_s)	Viscosity of Injection Material (υ), (c.pois)	Density of Injection Material (ρ), (gm/cm^3)	Time t, (hrs)	$(S/B)_w$, %
30	0.746	55	200	2.4	2.02	1.082	264	21.32
31	0.746	55	200	2.4	2.02	1.082	288	22.89
32	0.746	55	200	2.4	2.02	1.082	312	23.72
33	0.746	55	200	2.4	2.02	1.082	336	24.83
34	0.746	55	200	2.4	2.02	1.082	360	25.72
35	0.746	55	200	2.4	2.02	1.082	384	26.31
36	0.746	55	200	2.4	2.02	1.082	408	27.02
37	0.746	55	200	2.4	2.02	1.082	432	27.98
38	0.746	55	200	2.4	2.02	1.082	456	28.10
39	0.775	29	12.5	2.44	2.02	1.082	24	0.72
40	0.775	29	25	2.44	2.02	1.082	48	1.12
41	0.775	29	50	2.44	2.02	1.082	72	1.53
42	0.775	29	100	2.44	2.02	1.082	96	1.79
43	0.775	29	200	2.44	2.02	1.082	120	2.23
44	0.775	29	200	2.44	2.02	1.082	144	12.45
45	0.775	29	200	2.44	2.02	1.082	168	15.31
46	0.775	29	200	2.44	2.02	1.082	192	18.62
47	0.775	29	200	2.44	2.02	1.082	216	20.46
48	0.775	29	200	2.44	2.02	1.082	240	21.57
49	0.775	29	200	2.44	2.02	1.082	264	22.74
50	0.775	29	200	2.44	2.02	1.082	288	23.39
51	0.775	29	200	2.44	2.02	1.082	312	24.56
52	0.775	29	200	2.44	2.02	1.082	336	25.79
53	0.775	29	200	2.44	2.02	1.082	360	26.92
54	0.775	29	200	2.44	2.02	1.082	384	27.57
55	0.775	29	200	2.44	2.02	1.082	408	28.39
56	0.775	29	200	2.44	2.02	1.082	432	29.96
57	0.775	29	200	2.44	2.02	1.082	456	30.21
58	0.598	18	12.5	2.52	2.02	1.082	24	0.59

Case No.	Input Variable							Output
	Initial Void Ratio (e_o)	Initial Gypsum Content (G_c), %	Stress, (σ_s), kPa	Specific of Gravity (G_s)	Viscosity of Injection Material (υ), (c.pois)	Density of Injection Material (ρ), (gm/cm^3)	Time t, (hrs)	$(S/B)_w$, %
59	0.598	18	25	2.52	2.02	1.082	48	0.79
60	0.598	18	50	2.52	2.02	1.082	72	1.09
61	0.598	18	100	2.52	2.02	1.082	96	1.39
62	0.598	18	200	2.52	2.02	1.082	120	1.69
63	0.598	18	200	2.52	2.02	1.082	144	8.47
64	0.598	18	200	2.52	2.02	1.082	168	9.31
65	0.598	18	200	2.52	2.02	1.082	192	11.43
66	0.598	18	200	2.52	2.02	1.082	216	12.32
67	0.598	18	200	2.52	2.02	1.082	240	13.63
68	0.598	18	200	2.52	2.02	1.082	264	14.41
69	0.598	18	200	2.52	2.02	1.082	288	15.21
70	0.598	18	200	2.52	2.02	1.082	312	17.32
71	0.598	18	200	2.52	2.02	1.082	336	19.41
72	0.598	18	200	2.52	2.02	1.082	360	20.32
73	0.598	18	200	2.52	2.02	1.082	384	21.39
74	0.598	18	200	2.52	2.02	1.082	408	22.36
75	0.598	18	200	2.52	2.02	1.082	432	23.92
76	0.598	18	200	2.52	2.02	1.082	456	24.24

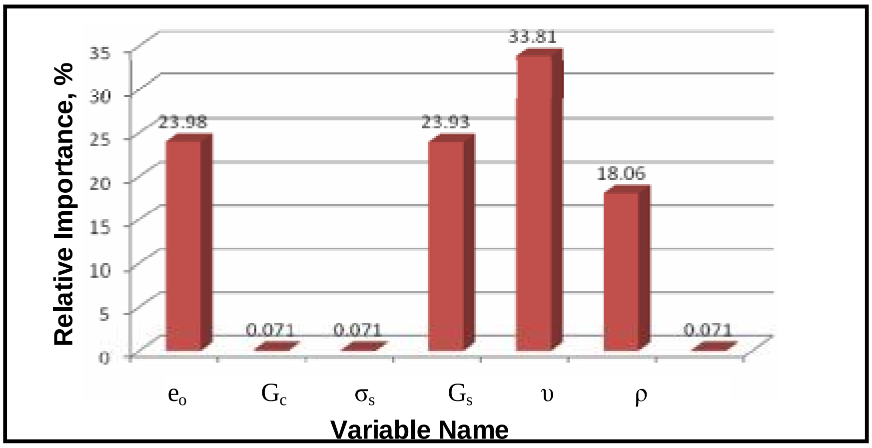

Fig. (1) Relative importance of the input variables for model $(S/B)_w$.

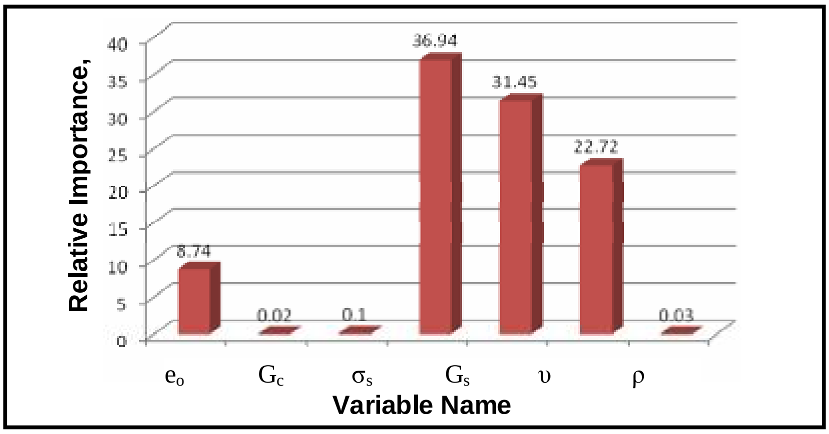

Fig. (2) Relative importance of the input variables for model $(S/B)_s$.

Fig. (3) Structure of the ANN optimal model $(S/B)_s$ or $(S/B)_w$.

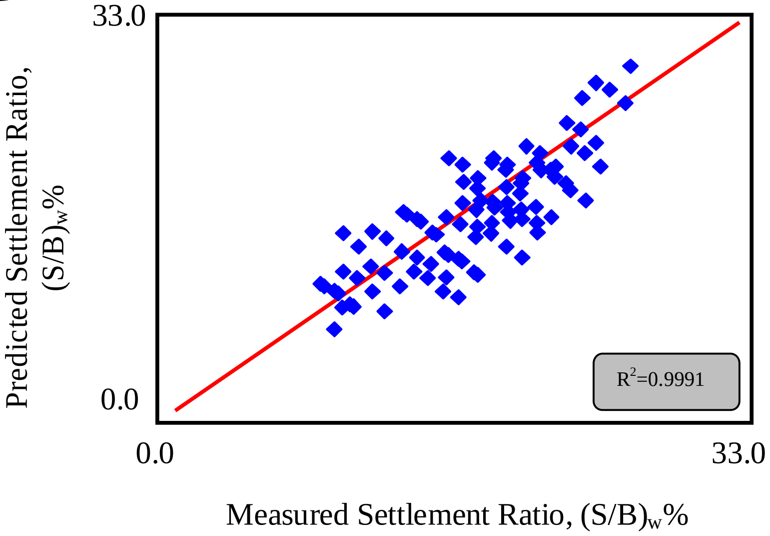

Fig. (4) Comparison of predicted and measured settlement ratio in washing process.

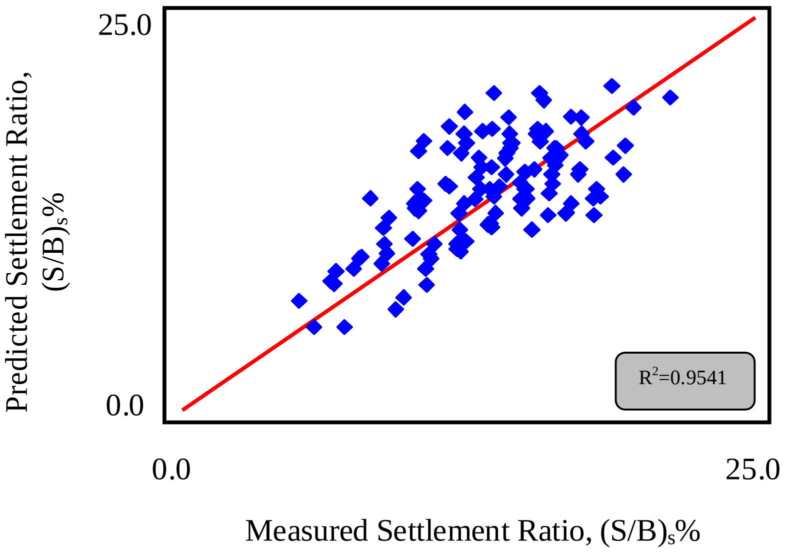

Fig. (5) Comparison of predicted and measured settlement ratio in soaking process.