Magazine of Civil Engineering

ISSN 2712-8172

journal homepage: http://engstroy.spbstu.ru/

DOI: 10.34910/MCE.110.11

Estimation of soil properties by an artificial neural network

I.V. Ofrikhter[a]*, A.B. Ponomaryov[b], A.V. Zakharov[a], R.I. Shenkman[a]

[a] Perm National Research Polytechnic University, Perm, Russia

[b] Peter the Great St. Petersburg Polytechnic University, St. Petersburg, Russia

**E-mail: ian.ofrikhter@gmail.com*

Keywords: soils, soil mechanics, shear strength, geotechnical engineering, neural networks

Abstract. Empirical dependencies are often used in various fields of geotechnics and civil engineering. The existing empirical formulas are mainly developed with the use of regression and multiple regression. Recently, another predictor is gaining more and more popularity - artificial neural networks. Artificial neural networks (ANNs) are one of the artificial intelligence methods relatively new to geotechnical science. This paper discusses the use of artificial neural networks to estimate the mechanical parameters of soils based on known physical characteristics. This problem has been of interest to geotechnical scientists for a long time, and some new correlations between mechanical and physical characteristics still appear. To develop this correlation a fully connected artificial neural network of direct propagation was used in the research. The neural network was trained on the data of laboratory tests of soil samples in the city of Novosibirsk, Russia. The article contains a description of the main features of correlations developing with artificial neural networks. As a result of this study, an artificial neural network was obtained that allows predicting the angle of friction and specific cohesion of clay soil with reasonable accuracy. The topology of the neural network is proposed, and the comparison of the estimation accuracy with the existing equations is carried out. According to the comparison of the results, it turned out that the ANN allows increasing the estimation accuracy of both parameters.

1. Introduction

Friction angle and cohesion are among the essential geotechnical parameters of soils. Determining these parameters requires sampling and rigorous laboratory testing. It is both time-consuming and needs careful supervision. They are used in the design of structures, both by analytical methods and by the finite element method. The accuracy of determining the soil base's mechanical characteristics most strongly affects the proposed structural solutions for foundations.

However, it is onerous to conduct many laboratory soil tests to determine the soil base's cohesion and friction angle in some cases. The very primary soil data to be determined in any geological survey is the soil's physical characteristics. Simultaneously, it is well known that having the data about the soil's physical properties can approximate some of the mechanical properties. Previously, many researchers develop their correlations, trying to improve the accuracy of such predictions.

Several studies have reported the correlation between the effective angle of shearing resistance and plasticity index [1, 2]. Jain [3], in his research, states that the angle of internal friction depends on dry density, particle size distribution, the shape of particles, surface texture, and water content. Cohesion depends on particle size, clay minerals type, water content, and some other parameters. Roy et al. [4] conducted another similar study in 2014. In this work, the authors suggest correlating cohesion and angle of shearing resistance with specific gravity angle and soil bulk density, respectively. Using multiple regression and neural network approach, Goktepe et al. [5] analyzed relations between index properties

Ofrikhter, I.V., Ponomaryov, A.B., Zakharov, A.V., Shenkman, R.I. Estimation of soil properties by an artificial neural network. Magazine of Civil Engineering. 2022. 110(2). Article No. 11011. DOI: 10.34910/MCE.110.11

and shear strength parameters of plastic clays. Mousavi et al. [6] used genetic programming to develop a correlation between the internal friction angle and the physical properties of soils, such as the fine and coarse content, density, and liquid limit.

To develop correlations between soil variables, most geotechnical researchers use well-known mathematical approaches such as regression and multiple regression. Recently, however, neural networks for developing empirical correlations have become more and more promising. The very concept of artificial neural networks was proposed in the 1950s [7]. In 1994, there were proposals to use ANN in civil engineering [8]. Researchers believe that neural networks are the most promising method for the mathematical description of geotechnical characteristics [9]. Several researchers are currently developing databases that will facilitate artificial intelligence to analyze geotechnical data [10].

Although artificial neural networks (ANN) have not yet become a daily practice, they have already been used many times in different geotechnical problems. In some cases, it is possible to successfully replace the finite difference method with deep neural networks [11]. Resilient modulus of fine-grained materials was modeled with the use of ANN [12]. In addition, ANNs were used to prediction of the swelling potential of clay soils [13]. Many studies are devoted to the use of ANN for calculating the bearing capacity of the pile [14–16], piled raft [17], and shallow foundations [18]. ANNs were also used to analyze slope stability [19], reinforced sand strength [20], and many other geotechnical engineering issues. Some scientists previously carried out the development of correlation dependences of soil's mechanical properties on physical parameters [21–24].

It is important to note that the use of ANN changes the methodological order of conducting research. It is necessary to hypothetically assume a specific model of the system's operation in the usual order. Then you have to develop a mathematical description and, at last, carry out approbation in experiments. When researching using an ANN, the development of a mathematical description is actually automated by learning algorithms for a neural network. In the current state, it is a method of backpropagation of an error [25]. Simultaneously, the role of experimental data, their completeness, and the quality of their storage in digital form increase significantly.

2. Methods

In this study, an artificial neural network (ANN) was used to predict soils' mechanical characteristics. The artificial neural network is a mathematical model that in a simplified form emulates the work of the human brain. In particular, neural networks allow, to some extent, to imitate a person's ability to cognize and learn.

The most common ANN form that performs complex regression tasks and predicts various characteristics is a fully connected feedforward neural network. In general, such a model consists of an input layer, a hidden layer, and an output layer (Fig. 1). Because each neuron of the previous layer is connected with each neuron of the next one, the neural network is called fully connected.

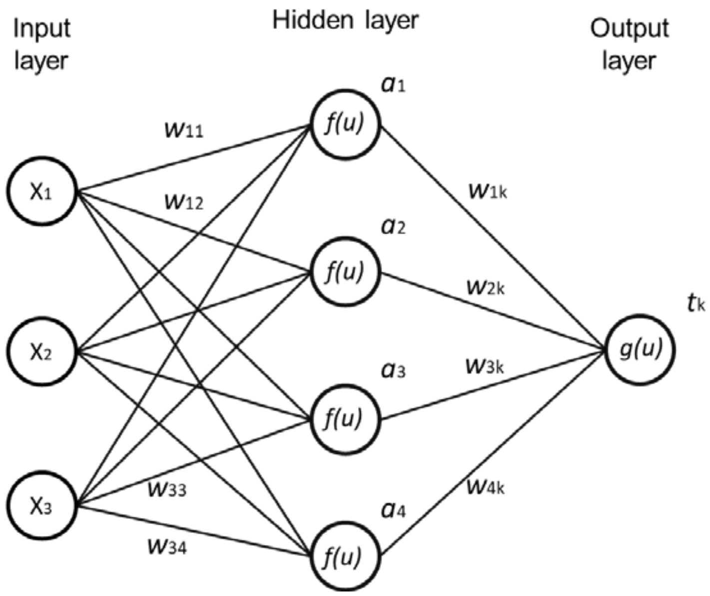

Figure 1. Fully connected direct propagation artificial neural network (ANN).

Fig. 1 X_i values in the input layer are the initial data of the predicted process. w_{ij} is link weights. The link weight w_{ij} is the number by which the output of the previous layer is multiplied. The neurons of the hidden and output layers are $f(u)$ and $g(u)$, where u is the sum of the input values multiplied by the corresponding connection weights w_{ij}. The functions $f(u)$ and $g(u)$ are called activation functions. In some papers, this functions are called perceptron, and the neural network is called multilayer perceptron. This historical name is not entirely correct. A perceptron can only give output values of 1 or 0, while a neuron's output can be anything between 1 and 0. This is a simplified explanation of the difference, but it should give a general idea. The parameters a_i and t_k are the outputs of the activation functions $f(u)$ and $g(u)$. Because of the above, a_i and t_k can be written as follows:

$$a_j = f\left(\sum_{i=1}^{N} w_{ij} x_i + b\right), \tag{1}$$

$$t_k = g\left(\sum_{j=1}^{N} w_{jk} a_j + b_k\right). \tag{2}$$

As can be seen from formulas (1) and (2), in this example, the activation functions $f(u)$ and $g(u)$ are linear. However, in real cases, the form of the function is selected individually. The artificial neural network in Fig. 1 has three neurons in the input layer, four neurons in the hidden layer, and one neuron in the output layer. In general, the output layer can include any number of neurons. Depending on the task, the hidden layer could consist of several neuron layers. The number of neurons and layers in the hidden layer is limited only by computational capabilities and expediency. In general, the more complex the process being modeled, the more neurons and layers are needed.

Before the ANN can make predictions, it is necessary to assign the correct bond weights and activation function coefficients. For this, the neural network needs to be trained. Neural network training is the process of finding weights of connections and coefficients of activation functions by means of successive iterations. The most common method for training neural networks is the backpropagation algorithm [25].

A training dataset is needed to train a neural network. A training dataset is a set of input and output data, by the example of which the network will be trained to make predictions of the output parameter based on the initial data. The key meaning of the ongoing process remains in the form of a set of numbers – weights of connections and activation function coefficients. As a rule, it is not available for interpretation. Simultaneously, a neural network can find and reproduce connections between phenomena, even if engineers do not know this connection. This is a massive advantage over traditional statistical methods.

The soil properties dataset for this research was collected from laboratory test data. A total of 420 shear test data of 102 cohesive soil layers were used. Sampling was carried out in the area of the city of Novosibirsk, Russia. All data were entered into a table, a small fragment of which is presented in Table 1.

Table 1. Fragment of the laboratory shear test data.

Sampling depth, m	Natural moisture content	Liquid limit	Plastic limit	Plasticity index	Bulk density, g/cm^3	Dry density, g/cm^3	Void ratio	Friction angle at natural humidity, degrees	Cohesion at natural Moisture Content, kPa
1.5	0.20	0.30	0.18	0.12	2.05	1.71	0.591	21	34
3.0	0.21	0.29	0.18	0.11	2.03	1.68	0.619	22	28
3.0	0.23	0.27	0.17	0.10	1.96	1.59	0.711	19	21
2.0	0.15	0.27	0.18	0.09	1.67	1.45	0.876	25	39
3.0	0.11	0.30	0.19	0.11	1.49	1.34	1.030	25	71
4.5	0.12	0.29	0.20	0.09	1.42	1.27	1.142	24	63

The soil's initial characteristics were sampling depth, natural moisture content, liquid limit, plastic limit, plasticity index, bulk density, dry density, and void ratio. Particle density was not used as an initial parameter, as all clay samples in the dataset had a particle density of 2.71 g/cm^3 to 2.72 g/cm^3. Accordingly, the neural network has seven neurons on the input layer. In this study, two ANNs were trained to predict the friction angle at natural humidity and specific cohesion at natural humidity. As a result, we got two ANNs with eight input parameters and one output parameter in each.

ANNs are believed to provide more accurate results when they do not extrapolate the range of data used for training [8, 26]. Although this is not the significant difference between ANN and other models, this feature is still a limitation. Therefore, it should be noted that the model, which is proposed in this article, is applicable and tested only in a limited range of data. The content of input and output characteristics used for training and testing is presented in Table 2.

Table 2. Fragment of the laboratory shear test data.

Input parameter	Range of values presented in the database
Sampling depth, m	1–27
Liquid limit	0.13–0.48
Plastic limit	0.11–0.30
Bulk density, g/cm^3	1.42–2.12
Dry density, g/cm^3	1.27–1.91
Output parameters	
Friction angle at natural humidity	14–31
Cohesion at natural humidity, kPa	10–69

When a neural network is trained, the simultaneous development of the generalization and memorization effects is observed. Generalization is the ability of a neural network to capture and reproduce some parameters' dependence on others. Memorization is the ability of a neural network to memorize a specific combination of inputs and outputs. In general, when developing an NN, generalization is a positive effect, and memorization is negative. When the neural network does not look for dependencies but remembers the data offered to it, it is overfitting. Memorizing data requires a more significant model size than generalization. Therefore, with the same number of training examples, a more extensive neural network is more likely to start memorizing data rather than looking for dependencies. The ANN's size should be sufficient to generalize the available sample but should not be too large to develop the overfitting effect.

The training dataset is used to fit the link weights using the backpropagation algorithm directly. A neural network has several hyperparameters that a person selects. These are such parameters as network topology, type of activation functions, loss function, number of learning epochs, learning step, etc. The validation dataset is not involved in finding the weights but is used to select these parameters. Therefore, it cannot be said that the validation dataset has no effect on the learning process. Finally, the test dataset is used to validate the finished model.

The entire dataset must be split into several parts to detect overfitting. This separation is called the cross-validation technique. According to the generally accepted rule [27], the dataset can be divided into training, validation, and test datasets. Several researchers have conducted a series of tests to determine the optimal ratios for different datasets [28]. For geotechnical issues, there are recommendations [28] based on which 20 % of the dataset should be used for validation. The rest data should be distributed by 70 % and 30 % for the training and test samples, respectively. Since the studies of the correlation of physical and mechanical properties of soils were carried out earlier [22, 29], there were no particular difficulties with the choice of hyperparameters in this study. Therefore, the entire dataset was divided into 80 % for training and 20 % for testing.

3. Results and Discussion

The artificial neural network has been trained with different types of architecture. Linear and ReLU activation functions gave the best results. Each training was tested at least ten times. ANN for friction angle prediction contained three layers of 150 neurons in the hidden layer. The hidden layer for cohesion prediction consisted of 4 layers of 200 neurons each. The input layers are the same for both ANNs.

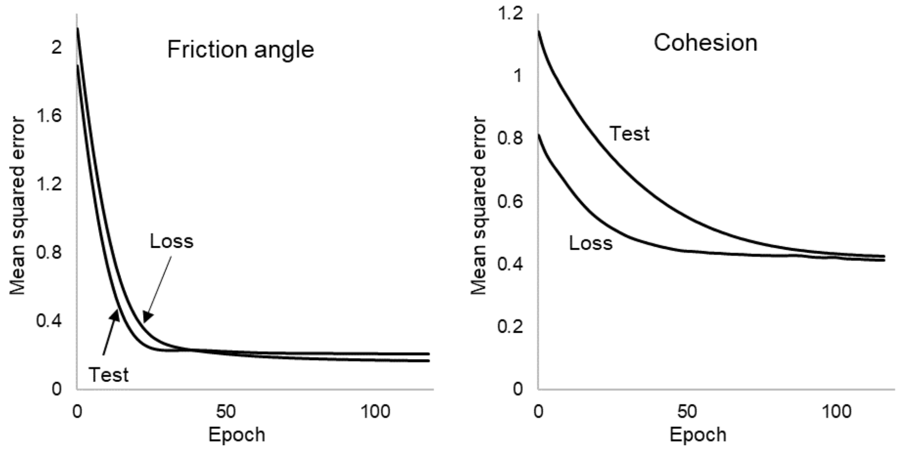

Figure 2. MSE plot of test and training (loss) datasets.

The error fall during training was plotted for both ANNs (Fig. 2) to track the effect of overfitting. Mean squared error (MSE) was used as a loss function for ANN training. Fig. 1 shows that the error decreased evenly throughout the ANNs fitting. In recent epochs, the loss function and the test dataset error have approximately the same values. This means that the network is not overfitted.

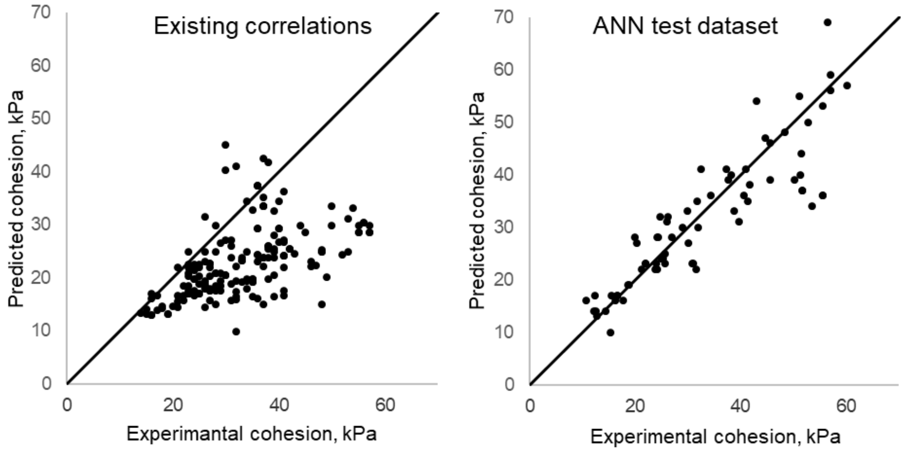

Figure 3. Comparison of experimental and predicted values of cohesion according to existing correlation and proposed ANN.

A comparison was made with the empirical dependencies presented in table A.2 of the national standard SP 22.13330.2016. Comparing the obtained data with the existing correlations included in national standards are presented in Fig. 3 and 4. As shown in Fig. 3, the proposed ANN-based method makes it possible to estimate the cohesion much more accurately than the existing correlations. The mean absolute percentage error (MAPE) of the ANN is 15.33 %. MAPE of existing correlations – 50.43 %.

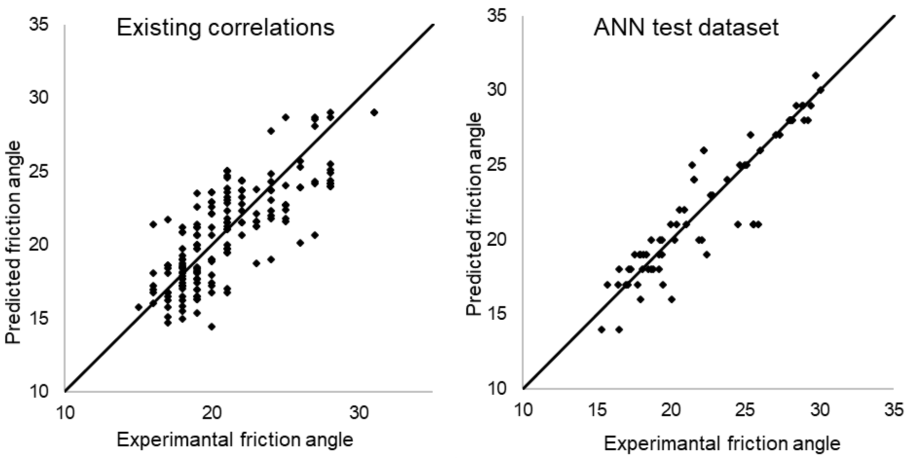

Figure 4. Comparison of experimental and predicted values of friction angle according to existing correlation and proposed ANN.

Comparison of experimental and predicted values of friction angle according to existing correlation and proposed ANN is shown in Fig. 4. In this case, the existing correlation dependences predict well the angle of internal friction. The estimation error using existing methods was 9.1 %. The ANN predicts the angle of internal friction with an accuracy of 6.5 %. An artificial neural network made it possible to build a more accurate correlation, but in general, both methods give good results.

Another identified advantage of an artificial neural network is the range of predicted values. Existing correlations are often applicable for clayey soils with $0 \le IL \le 1$. However, in the available dataset, about 47 % of the data had IL values, which were outside these limits. The artificial neural network was trained on a dataset that included negative IL, and this allowed the ANN to predict the angle of internal friction angle and cohesion over a broader range.

4. Conclusion

1. This article discusses the problems of using artificial neural networks to build correlation dependences for many variables. Based on the comparison results, it can be concluded that ANN is a promising method of analysis in geotechnics.

2. The article proposes a neural network topology that allows predicting soils' mechanical characteristics by their physical parameters. The accuracy of the determination is higher than that of the well-known statistical methods.

3. Since both the training dataset and the test dataset were collected in the same region, the proposed dependency may give an increased error in other regions. This may be due to regional soil conditions that are not considered in the original soil parameters. This problem can be avoided by using data from different regions.

5. Acknowledgements

This research was carried out with the financial support of the Ministry of Science and Higher Education of the Russian Federation in the framework of the program of activities of the Perm Scientific and Educational Center "Rational Subsoil Use"

References

1. Brooker, E.W., Ireland, H.O. Earth Pressures at Rest Related to Stress History. Canadian Geotechnical Journal. 1965. 2(1). Pp. 1–15. DOI: 10.1139/t65-001
2. Stark, T.D., Eid, H.T. Slope Stability Analyses in Stiff Fissured Clays. Journal of Geotechnical and Geoenvironmental Engineering. 1997. 123(4). Pp. 335–343. DOI: 10.1061/(asce)1090-0241(1997)123:4(335)
3. Rajeev Jain, Pradeep Kumar Jain, S.S.B. Computational Approach to predict Soil Shear Strength, International Journal of Engineering Science and Technology. International Journal of Engineering Science and Technology. 2010. 2(8). Pp. 3874–3885.
4. Roy, S., Dass, G. Statistical models for the prediction of shear strength parameters at Sirsa, India. International Journal of Civil and Structural Engineering. 2014. 4(4). Pp. 483–498.
5. Goktepe, A.B., Altun, S., Altintas, G., Tan, O. Shear strength estimation of plastic clays with statistical and neural approaches. Building and Environment. 2008. 43(5). Pp. 849–860. DOI: 10.1016/j.buildenv.2007.01.022
6. Mousavi, S.M., Alavi, A.H., Gandomi, A.H., Mollahasani, A. Nonlinear genetic-based simulation of soil shear strength parameters. Journal of Earth System Science. 2011. 120(6). Pp. 1001–1022. DOI: 10.1007/s12040-011-0119-9
7. Bishop, J.M. History and philosophy of neural networks. Computational Intelligence – Vol. 1. 2015. 1(February). Pp. 400.
8. Flood, I., Kartam, N. Neural networks in civil engineering. I: Principles and understanding. Journal of Computing in Civil Engineering. 1994. 8(2). Pp. 131–148. DOI: 10.1061/(ASCE)0887-3801(1994)8:2(131)
9. Moayedi, H., Mosallanezhad, M., Rashid, A.S.A., Jusoh, W.A.W., Muazu, M.A. A systematic review and meta-analysis of artificial neural network application in geotechnical engineering: theory and applications. 32(2) 2020.
10. Hui Wang, Xiangrong Wang, Robert Liang. Study AI based methods characterization geotechnical site2020. 51 p.
11. Gao, W., Lu, X., Peng, Y., Wu, L. A Deep Learning Approach Replacing the Finite Difference Method for in Situ Stress Prediction. IEEE Access. 2020. 8. Pp. 44063–44074. DOI: 10.1109/ACCESS.2020.2977880
12. Khasawneh, M.A., Al-jamal, N.F. Modeling resilient modulus of fine-grained materials using different statistical techniques. Transportation Geotechnics. 2019. 21. DOI: 10.1016/j.trgeo.2019.100263
13. Ermias, B., Vishal, V. Application of Artificial Intelligence for Prediction of Swelling Potential of Clay-Rich Soils. Geotechnical and Geological Engineering. 2020. 38(6). Pp. 6189–6205. DOI: 10.1007/s10706-020-01427-x
14. Suman, S., Das, S.K., Mohanty, R. Prediction of friction capacity of driven piles in clay using artificial intelligence techniques. International Journal of Geotechnical Engineering. 2016. 10(5). Pp. 469–475. DOI: 10.1080/19386362.2016.1169009
15. Harandizadeh, H. Developing a new hybrid soft computing technique in predicting ultimate pile bearing capacity using cone penetration test data. Artificial Intelligence for Engineering Design, Analysis and Manufacturing: AIEDAM. 2020. 34(1). Pp. 114–126. DOI: 10.1017/S0890060420000025
16. Alzo'ubi, A.K., Ibrahim, F. Predicting Loading–Unloading Pile Static Load Test Curves by Using Artificial Neural Networks. Geotechnical and Geological Engineering. 2019. 37(3). Pp. 1311–1330. DOI: 10.1007/s10706-018-0687-4
17. Rabiei, M., Choobbasti, A.J. Innovative piled raft foundations design using artificial neural network. Frontiers of Structural and Civil Engineering. 2020. 14(1). Pp. 138–146. DOI: 10.1007/s11709-019-0585-8

18. Ray, R., Kumar, D., Samui, P., Roy, L.B., Goh, A.T.C., Zhang, W. Application of soft computing techniques for shallow foundation reliability in geotechnical engineering. Geoscience Frontiers. 2020. DOI: 10.1016/j.gsf.2020.05.003
19. Das, S.K., Biswal, R.K., Sivakugan, N., Das, B. Classification of slopes and prediction of factor of safety using differential evolution neural networks. Environmental Earth Sciences. 2011. 64(1). Pp. 201–210. DOI: 10.1007/s12665-010-0839-1
20. Harikumar, M., Sankar, N., Chandrakaran, S. Prediction of strength parameters of sand combined with three dimensional components using Artificial Neural Networks. Australian Geomechanics Journal. 2016. 51(1). Pp. 97–108.
21. Kim, E., Stine, M.A., de Oliveira, D.B.M., Changani, H. Correlations between the physical and mechanical properties of sandstones with changes of water content and loading rates. International Journal of Rock Mechanics and Mining Sciences. 2017. 100. Pp. 255–262. DOI: 10.1016/j.ijrmms.2017.11.005
22. Pham, B.T., Son, L.H., Hoang, T.A., Nguyen, D.M., Tien Bui, D. Prediction of shear strength of soft soil using machine learning methods. 1662018.
23. Minns, A.W., Hall, M.J. Modélisation pluie-débit par des réseaux neuroneaux artificiels. Hydrological Sciences Journal. 1996. 41(3). Pp. 399–417. DOI: 10.1080/02626669609491511
24. Wrzesiński, G., Lechowicz, Z., Sulewska, M.J. Application of Artificial Neural Networks for the prediction of undrained shear modulus in cohesive soils. Ce/Papers. 2018. 2(2–3). Pp. 833–838. DOI: 10.1002/cepa.774
25. Goh, A.T.C. Back-propagation neural networks for modeling complex systems. Artificial Intelligence in Engineering. 1995. DOI: 10.1016/0954-1810(94)00011-S
26. Tokar, A.S., Johnson, P.A. Rainfall-runoff modeling using Artificial Neural Networks. Journal of Hydrologic Engineering. 1999. 4(3). Pp. 232–239. DOI: 10.1061/(ASCE)1084-0699(1999)4:3(232)
27. Stone, M. Cross-Validatory Choice and Assessment of Statistical Predictions (With Discussion). Journal of the Royal Statistical Society: Series B (Methodological). 1976. 38(1). Pp. 102–102. DOI: 10.1111/j.2517-6161.1976.tb01573.x
28. Shahin, M.A., Maier, H.R., Jaksa, M.B. Data division for developing neural networks applied to geotechnical engineering. Journal of Computing in Civil Engineering. 2004. 18(2). Pp. 105–114. DOI: 10.1061/(ASCE)0887-3801(2004)18:2(105)
29. Jasim, M.M., Al-Khaddar, R.M., Al-Rumaithi, A. Prediction of bearing capacity, angle of internal friction, cohesion, and plasticity index using ANN (case study of Baghdad, Iraq). International Journal of Civil Engineering and Technology. 2019. 10(1). Pp. 2670–2679.

Contacts:

Ian Ofrikhter, ian.ofrikhter@gmail.com
Andrey Ponomaryov, andreypab@mail.ru
Alexander Zakharov, zaharav@mail.ru
Roman Shenkman, Rshen@list.ru

Received 10.11.2020. Approved after reviewing 27.04.2021. Accepted 11.05.2021.