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ESTIMATING THE CLAY COHESION BY MEANS OF ARTIFICIAL INTELLIGENCE TECHNIQUE

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ABSTRACT

Sampling from the soils that reveal similar features would be difficult; even if the sample layers are from the same side. It must be also noted that the cohesion feature of the clay is one of the most important parameters of soil mechanics. In order to determine the cohesion proportion of the soil, it is necessary to perform the strength tests. If the cohesion features can be determined by means of physical parameters of soil as well as by typical fieldwork, time and cost will be saved. This article attempts at firstly performing a series of fieldwork, getting some result, and then using the existing results in order to build data bank to conduct fuzzy logical analysis. And it secondly attempts at considering the physical parameters that are effective for cohesion strength by means of artificial intelligent. Finally it attempts at comparing the results obtained from the experiments.

Key Words: Fuzzy logic, Clay cohesion, SPT test.

INTRODUCTION

The parameters of soil concerned with the soil strength have been the main focus of engineers. They have been looking for ways to determine and to estimate such parameters. These parameters are essential for designing any structure such as dams, foundations and roofs that are attached to the soil. Hence it is necessary to predict this parameter with an accepted approximation for doing the calculations. As in the large and vast fields is limited number of digging, the estimation of soil strength parameters is generally done by means of experimental tests as well as engineering decisions. Getting untouched clay samples is too difficult and taking experimental tests are highly time and money-consuming. The present research aims at using the general laboratory experiments and SPT test results, known as the most typical field experiments, to estimate and to determine the cohesion strength in the clay soil. The approach of analysis is applying the neural network-fuzzy.

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Today, this approach is regarded as the most significant one for analyzing problems having the multi-parameters variations.

EXPERIMENTAL PROCEDURE

The soil samples considered for the system training, presented in table 1, are associated to the parameters. The cohesion proportion is obtained by means of unconfined test. 25 test results taken from the south of Tehran related to 2009-2010 are used for providing the data bank and also 5 samples are used as the experimental samples for comparing the results and system outputs (Ab Kavosh Sarzamin Co. 2010). The mentioned information is presented in the table below.

Table-1. The specifications of input data

NO:	The percentage of passing through a sieve200	Humidity Rate	Liquid limit	SPT number	Cohesion
1	86.5	35.6	54	17	0.43
2	90.6	34.0	44	15	0.45
3	89.3	32.0	44	11	0.40
4	90.1	34.1	47	18	0.47
5	84.9	30.9	42	24	0.58
6	88.3	31.7	41	17	0.45
7	90.3	36.2	52	24	0.55
8	89.7	35.4	48	18	0.48
9	84.9	25.7	40	19	0.54
10	91.4	31.6	42	27	0.49
11	89.4	24.6	42	27	0.47
12	89.0	26.8	43	36	0.68
13	85.5	33.8	47	29	0.56
14	91.8	34.5	49	28	0.54
15	91.6	28.6	46	26	0.65
16	84.6	38.4	53	36	1.20
17	86.2	35.5	54	28	0.84
18	90.5	36.0	43	26	0.88
19	85.5	35.0	45	20	0.79
20	89.1	32.6	42	25	0.49
21	84.0	29.8	45	29	0.79
22	88.1	33.1	43	35	0.56
23	86.9	35.0	47	31	0.83
24	87.3	35.6	49	29	1.05
25	93.5	35.7	52	21	0.48

Based on the theories of Dubios and Prade (1980) and also Pal and Kajumfler (1988), it is said that when X is defined in terms of a limited set of $\{x_1, x_2, \ldots\ldots\ldots x_n\}$, called as a sub-category of fuzzy, it is referred to as the fuzzy set. It is defined within X as follows:

$$A = \sum_{i=1}^{n} \mu_A(x_i)/x_i$$

In which xi is one member of fuzzy set A and A $(x_i)\mu$ is the membership degree xi in A. One multiple set of $\{A_1, A_2, \ldots A_n\}$ of fuzzy set:

$$\forall x \in X, \sum_{j=1}^{n} \mu_{Aj}(x) = 1$$

In order to do the analysis, the method of neural network-fuzzy is required. There are various models and approaches and this research attempts at utilizing the model of takagi-sugeno and the approach of sub-cluster. Each one of the parameters of C_u, SPT, W and pp200 are defined as a means for fuzzy set. In addition, for determining the phaziness of each one of these means, there must be membership functions. As the sub-cluster approach is used, the cluster membership functions as well as their rules will be determined (Ji & Pan 2000).

There are series of training data and experimental data required in the takagi-sugeno model (Takagi & Sugeno 1985). The fuzzy rules in system training data are classified appropriately and finally they are improved by one of the virtual training systems like neural network or the genetic algorithm (Jang 1993). The results have been obtained by employing the method of sub-clustering and fuzzy-neural network. The MATLAB software has been used for making the calculations (MATLAB help 2006).

The rules of fuzzy used for making the clusters and then for analyzing them are presented according to figure (1). Moreover the membership functions are presented in figure (2) based on the constructed clusters for the fourth data.

Figure-1. The window related to the fuzzy rules

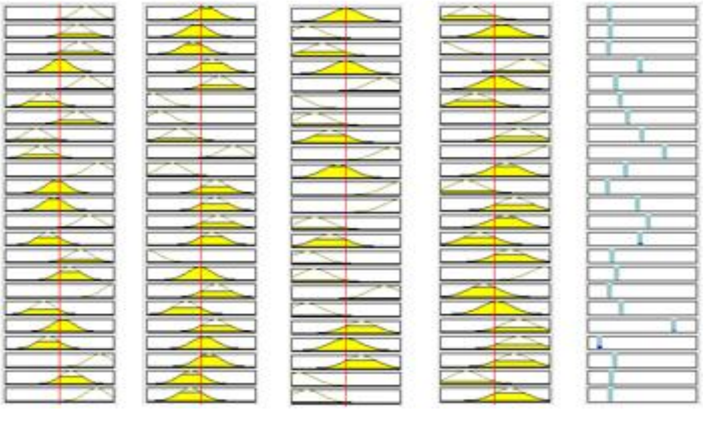
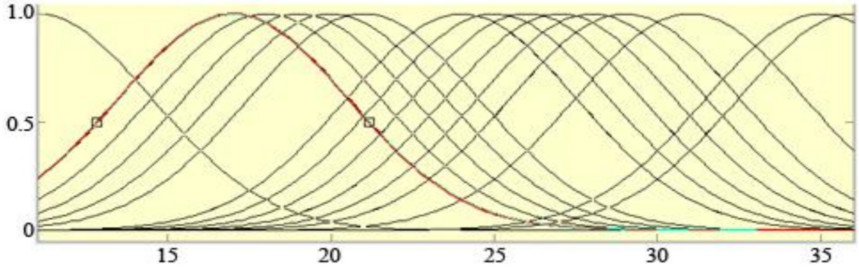


Figure-2. The membership functions of fourth data clusters



RESULT AND DISCUSSION

The effect of input data on the output data and the effect of two mutual parameters are shown by the figures

Figure-3. The diagram of the first and second dependency to the output

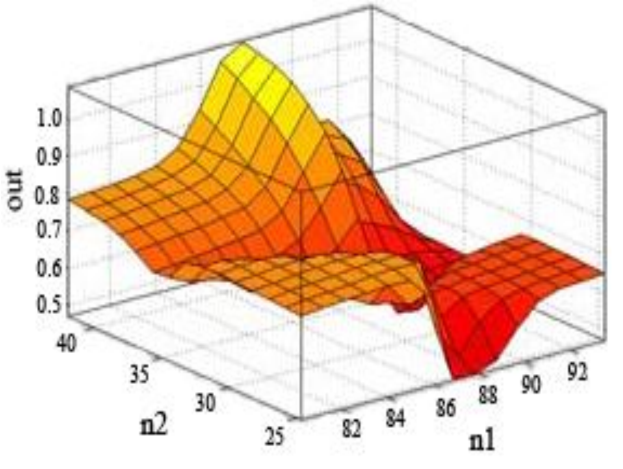


Figure-4. The diagram of the first and fourth dependency to the output

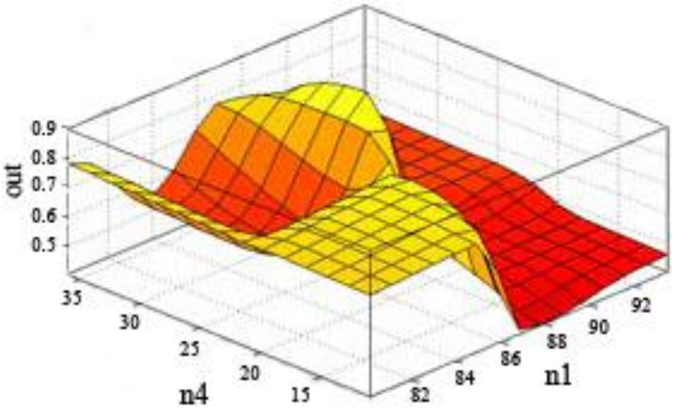


Figure-5. The diagram of the second and fourth dependency to output

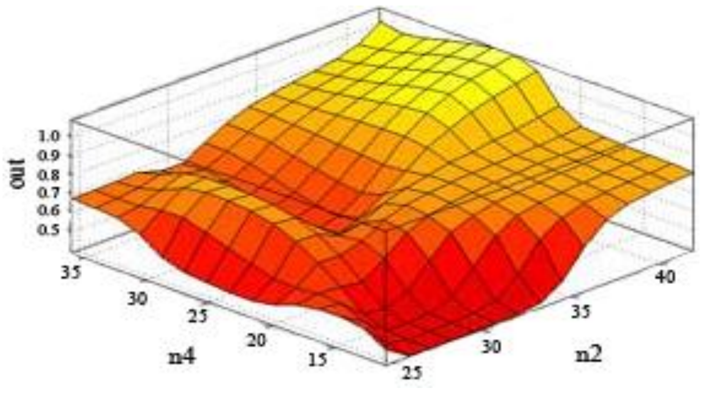
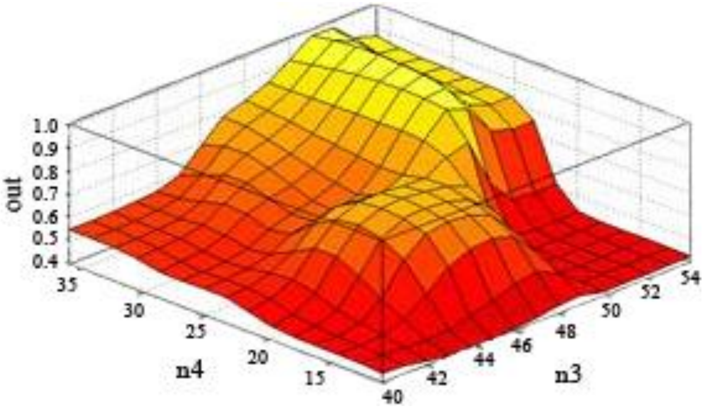


Figure-6. The diagram of the third and fourth dependency to the output



It is deduced from the diagrams as well as from the neuro-fuzzy system that the first and second input affected the output. The effects of the second and third are shown as being similar by SPT in addition to the different effects of these inputs by SPT. Both effects are clearly presented in figure 4-5-6.

The results are accepted due to the obtained parameters and the use of neuro-fuzzy system. These results are depicted in tables and diagrams below. In the figure (1) is the difference in results coming out of the experiment and estimation. In the table (2) are the numerical quantities. Figure (7) presents certain square dots showing the experimental results. There are also star-like dots showing the predicted results coming from neuro-fuzzy system. Table (2) presents the column C_u is reflecting the experimental proportions as well as the column PC_u reflecting the neuro-fuzzy system results.

Figure-7. Comparison of outputs resulted from experimental results and neuro-fuzzy system.

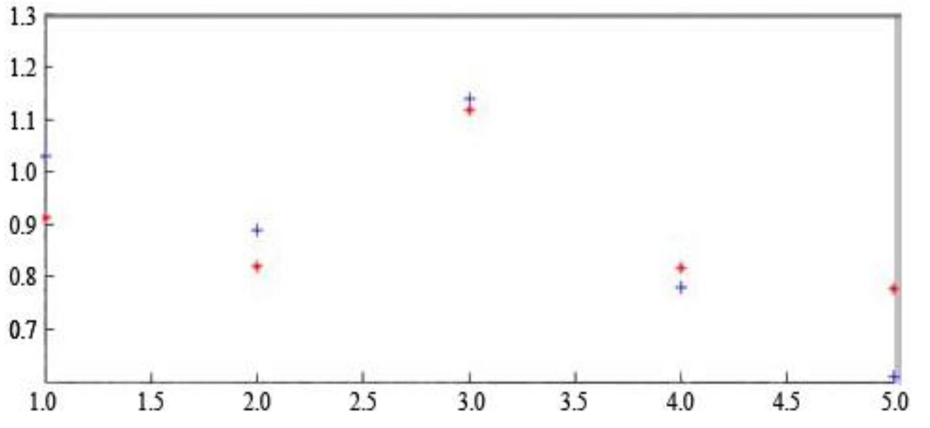


Table-2. The output proportions resulted from the experiment and system

NO:	The percentage of passing 200 through a sieve	Humidity Rate	Liquid limit	Number SPT	(cohesion) C_u	PC_u
26	90.3	36.8	45	28	1.03	0.93
27	86.7	38.4	44	29	0.89	0.82
28	80.2	32.7	54	34	1.14	1.12
29	88.0	41.9	44	17	0.78	0.81
30	84.2	32.8	46	14	0.61	0.77

CONCLUSION

The experimental results of several sites were used for making analysis by means of neuro-fuzzy network. The fuzzy relationship among clay cohesion, humidity and SPT were investigated. 5 samples were chosen to conduct the experiment for system estimation. After comparing the results of estimations and experimental data, it was proved that the system estimations and data are quite similar except about the data number 30. It must be said that the task has been done delicately and it has been accepted in the engineering tasks. Furthermore, it must be noted that, the system will provide more results connected to the experimental experiments if the data bank includes much data and more parameters.

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