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Original scientific paper

Collapsibility Prediction of Stabilized Soil with Styrene-Butadiene Rubber Polymer Using ANFIS

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Abstract: Collapsible soils are among the problematic soils in nature that, due to moisture content increasing and under the same stress, show a high rate of decrease in volume. This volume reduction leads to loss of soil structure and ultimately to significant subsidence. Such soils in many parts of the world, including the Kerman province of Iran, necessitate researches regarding the collapsible soils' behavior and characteristics. This study aims to investigate the effect of butadiene rubber on the stabilization of collapsible soils. The tested fine-grained soils that have been sampled from two different sites were stabilized through injecting different percentages of butadiene (the number of experiments was 84). The ASTM D5333 Double-Consolidation Method was applied to examine the stabilized soils on intact soil samples. The results show that the penetrations of butadiene rubber and the formation of butadiene rubber columns have led to a reduction in soil collapse. Considering the development of intelligent systems using the prediction behavior of stabilized collapsible soils, the adaptive neural-fuzzy inference system (ANFIS) model was used to predict the degree of collapsibility of soil samples stabilized by injection of Styrene Butadiene Rubber.

Keywords: ANFIS; collapsible soil stabilization; styrene-butadiene rubber

1 INTRODUCTION

Soil is one of essential materials in nature that has long been used by humans in building and engineering. All the constructions are practiced inside the ground/soil, on the surface or using it. Meanwhile, all soil types are not suitable for construction. Among these are the moisture-sensitive soils. An important issue in the case of these soils is the change in their properties because after wetting, the structure of these soils tends to unstable conditions. Collapsible soils fall into this group of soils. These soils are naturally loose and open-structure deposits that are mostly found in arid and semi-desert areas. Collapsing may occur only due to wetting or wetting with loading. The origin of collapsible soils can be transition soils, especially loamy soils, standing soils, or embankments that are not well compacted. The problems caused by collapsing soils became known entirely after World War II. For the first time, it was Jennings [1] that attributed the collapse of buildings in South Africa in 1955 to a change in the arrangement of subsoil particles relative to each other. In 1965, the collapsing phenomenon in Northern American clay-type soils had been reported by Klonjer. Traditional stabilizers such as cement, lime, and fly ash are mostly used to improve the mechanical properties of collapsible soils. Traditionally, injection and mixing have been used as two distinctive methods for the stabilization of collapsible soils. For the mixing fixation method, we can refer to the works by Feda [2], Bell [3] in which the polymer additive is added to the fine-grained soil. In 2013, SeyediGelsefidi [4] obtained acceptable results during the study of soil stability of nanomaterials located in northern Iran by nanomaterials. Fauzia Binti Ahmed et al. [5] reduced the soil plastic index using a new chemical stabilizer, Styrene-Butadiene rubber.

In 2016, Zheng et al. [6] added a biopolymer to the soil to improve its collapsing properties and achieved acceptable results. In 2016, Baghini [7] simultaneously examined the cement and Styrene-butadiene rubber and studied the effect of this additive material on road construction. Yahya Atomi et al. [8], have effectively improved soil properties by examining the improvement of soil properties of sterol butadiene rubber polymer. In 2020, Zimbardo et al. [9] used a special polymer in collapsible sand and observed a decrease in the compressibility of sand soil. In 2020, Isabel Augusta et al. compacted the collapsible soil, and after performing the double consolidation test, observed a decrease in collapsible soil index. Through the injection as the second fixation method, through an investigation in 1967, Gibbs and Bara injected the clay slurry to the loess mass; also in 2010 Abbeche [10] injected salt into the collapsible soil and after examining the geotechnical properties of the soil, observed that the collapsible index had decreased significantly. In 2010, Sharif Suleiman et al. stabilized the collapsible soil by silica injection and observed some pieces of evidence related to the decrease in collapsibility. In 2012, Mohammad Fattah et al. [11] investigated the behavior of soil compaction via the injection of grout; the results showed an improvement in collapsible soil properties. In 2012, Rasoul Aalovian [12] examined the effect of polyvinyl grout on soil geotechnical properties. Through his study, specific percentages of polymeric materials were mixed with water and injected into the soil. As a result, the soil strength and its modulus elasticity were increased. In 2017, Mohammad Ayeldeen et al. [13] investigated collapsible soil's mechanical behavior using two different types of injected biopolymers. In 2020, Silveria [14] investigated collapsible soil behavior and improved this type soil by compacting. In 2021, Johari et al. [15] used nano material for improving collapsible soil properties.

Intelligent systems are powerful tools in geotechnical engineering that can apply uncertainties with fuzzy methods. Momeni et al. [16] investigated the potential of different central regions of Iran using qualitative evaluation and fuzzy set analysis and argued that there was a good match between the experiments and the fuzzy inference system.

Due to the vast world-wide expanse of collapsible soils and the need for new environment-friendly chemicals that improve the compaction properties of compacted soil, the stabilization of this type of soil is increasingly being considered. A significant amount of Styrene-Butadiene rubber is being produced in a manner that has a good adaptation to the environment. Therefore, using this polymeric material to improve soil properties is receiving more and more attention. In the previous studies, various methods were used to improve the collapsible soil, but in this research, in addition to using a new additive, tests have been performed on virgin and intact soil to obtain acceptable results. Research conducted in the past showed that a huge amount of collapsible soils was located in central Iran and the city of Kerman [16]. Therefore, experiments have been performed in this region.

In this paper, the amount of abduction reduction by adding different percentages of butadiene rubber (2, 3, 4, 5, 6, 6) at different times (4, 7, 7, 14, 28 days) has been evaluated. The collapsible index has been then evaluated using ANFIS. After that, a calibrated model has been obtained using the results of 84 experiments collected from Kerman, the central region of Iran.

In the first step, the materials and also the sampling method are explained. Then, the results obtained from the experiments in the ANFIS system are modeled and the graphs are announced. At the end, the results are evaluated.

2 MATERIALS AND METHODS

The soil used in this study was prepared from two different sites in Kerman (Tab. 1). Selected sites for soil sampling were selected based on past studies on the sedimentation of those areas, and the sampling method is also shown in Fig. 1, [16].

Table 1 Sampling Site's Details

Site number	Geographical coordinate	Deep sample / m	Number of samples
1	30° 17' 45.7" 57° 01' 05.4" E	4	72
2	30° 17' 49.5" N 57° 05' 41.8" E	5.5	12

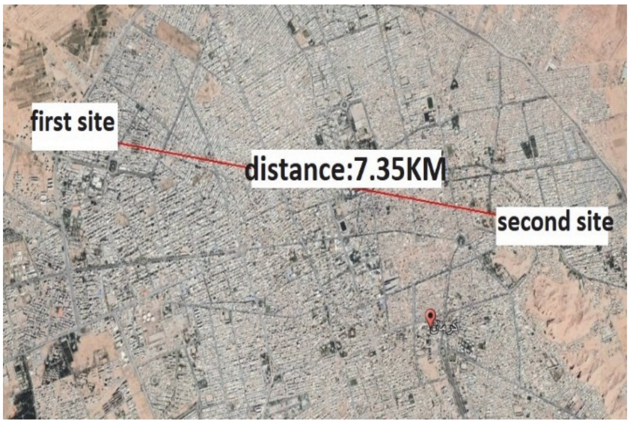


Figure 1 Map of the sampling place in Kerman city (a: first place and b: second place)

Soil samples were gathered from a depth of 4 to 6 meters beneath the natural ground level and according to the ASTM D1587 and ASTM D4-7015 instructions, the samples were prepared untouched and lumpy. The tests were performed according to the ASTM Standards. Fig. 2 shows the sampling place of the research. Also, Tab. 1 presents the details related to the sampling site. Tab. 2 provides the results obtained from the fundamental experiments that have been conducted to identify the geotechnical properties of the soil samples of sites 1 and 2.

Figure 2 Soil sample process

3 PREPARATION AND STABILIZATION BY SAMPLE INJECTION

3.1 Sample Preparation

The soil samples were prepared in the laboratory with acceptable accuracy according to the standard. First, the soil samples were placed inside the ring of the consolidation device (Fig. 2), [16]. Then, with the help of a drill machine, some holes of a one-millimeter diameter (D = 1 mm) and a distance to diameter ratio of 1/57 (S/D = 1,57) were drilled in the soil.

3.2 Preparation and Injection of the Slurry

The additive was poured into a container at different weight percentages and added to the soil with some dishwashing liquid to reduce friction and increase the permeability of the additive. Then through three stages with an interval of 30 to 40 minutes and using a syringe that has holes on the needle for all-round injection and maximum penetration into the soil (during the injection, we tried to exert a constant compressive force on the syringe), the material additive was injected to the soil in Fig. 3. The sample was isolated from one side to prevent material waste. Finally, after specified times (4, 7, 14, and 28 days), 84 experiments were performed on the samples according to the standard, then the results were written down and analyzed.

The reduction collapse soil index (Rcp) can be obtained using the following formula to determine this additive effect on fine-grained soil.

$$Rcp = \frac{cp\left(inatial\right) - cp\left(secondary\right)}{cp\left(inatial\right)} \tag{1}$$

$$Rcp = Rcp \times 100,\ \% \tag{2}$$

The number of the tests and the results of collapsibility tests performed at the different sites are provided in Tabs. 3 to 4.

Table 2 Characteristics of base soils used in this study

Number of site	Liquid limit, LL	Plastic Index, PI	Classification USCS	Special Weight, γ / kn/m^3	Moisture content, ω / %	CP / %	Degree of collapsible based ASTM
1	31,2	15	ML	1,46	21,2	11,1	sever
2	89	69	CH	1,4	23,86	13,1	sever

Table 3 Soil compaction test type 1

initial character γ =1,46 kn/m^3 ω = 21,2 e = 0,99 PI = 15 LL = 38				
Percent of additive material / %	Time / day	*CP* / %	average of *CP* / %	*RCP* / %
2	4	1,01	1,26	88,75
2	4	1,1		
2	7	1,8	1,08	90,35
2	7	1,9		
2	14	1,63	1,265	88,7
2	14	0,9		
2	28	1,25	1,242	88,91
2	28	1,23		
3	4	1,48	1,055	90,58
3	4	0,63		
3	7	0,39	0,31	97,23
3	7	0,26		
3	14	1,1	1,127	89,93
3	14	1,155		
3	28	0,98	1,065	90,49
3	28	1,15		
4	4	0,82	0,592	94,71
4	4	0,36		
4	7	0,77	0,69	93,83
4	7	0,61		
4	14	0,81	0,817	92,7
4	14	0,82		
4	28	0,96	0,932	91,6
4	28	0,9		
5	4	0,15	0,155	98,66
5	4	0,16		
5	7	0,71	0,685	93,88
5	7	0,66		
5	14	0,713	0,715	93,61
5	14	0,7		
5	28	0,94	0,766	93,16
5	28	0,585		
6	4	0,53	0,515	95,4
6	4	0,5		
6	7	0,75	0,755	93,25
6	7	0,76		
6	14	0,94	0,72	93,57
6	14	0,5		
6	28	0,46	0,392	96,5
6	28	0,325		
7	4	0,71	0,86	92,32
7	4	1,01		
7	7	0,61	0,585	94,77
7	7	0,56		
7	14	0,43	0,425	96,2
7	14	0,42		
7	28	0,94	0,92	91,71
7	28	0,92		

Table 4 Type 2 collapsible soil test

initial character γ = 1,4 kn/m^3 ω = 23,86 e = 0,642 PI = 69 LL = 89			
Percent of additive material / %	Time / day	*CP* / %	*RCP* / %
2	4	1,14	91,29
2	7	0,6	95,41
3	4	1,09	91,6
3	7	0,6	95,4
4	4	0,86	93,4
4	7	0,4	96,9
5	4	0,985	92,4
5	7	0,44	96,6
6	4	0,73	94,4
6	7	0,89	93,2
7	4	0,75	94,27
7	7	0,86	93,43

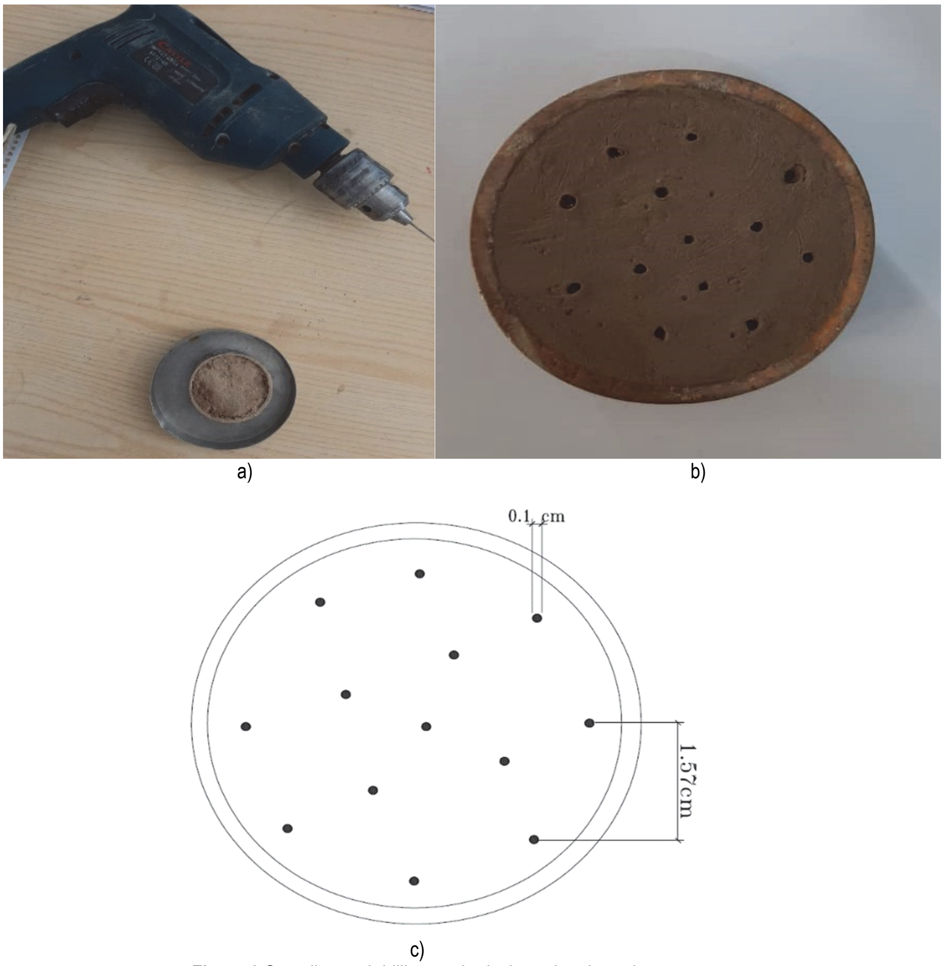


Figure 3 Sampling and drilling methods through a, b, and c stages

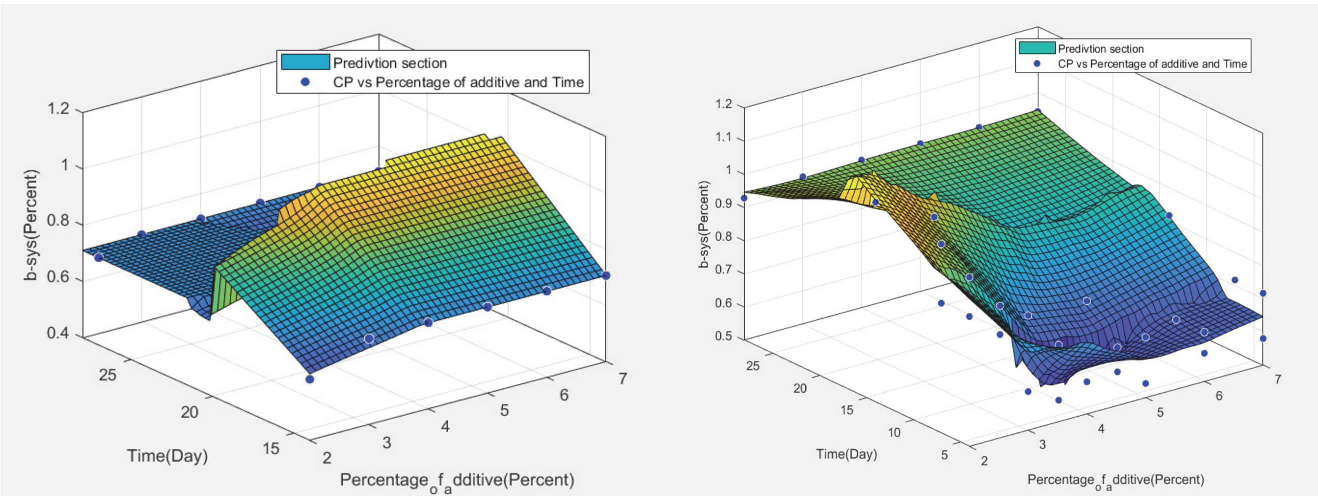


Figure 4 3D model of variable *CP %*, time and percentage of additives

Given that doing the experiments may not be possible in all circumstances, using a model can help. Finally, the results of the collapsibility are imported as input for MATLAB software and the use of fuzzy logic to design a model for calculating the collapsible index.

3.3 Microstructural Studies

To identify structural changes in soil samples, SEM photos were taken from soil samples. In this regard, a soil sample was made without additive and another sample with additive.

As is apparent in Fig. 4, the Styrene-Butadiene rubber influences new bonds between the particles.

4 ANFIS FUZZY NEURAL LOGIC SYSTEM

There are several investigations that have some similarities with our study; for example Shahin in 2010 [17] utilized artificial neural networks (ANNs), Alkroosh and Nikrazin 2011 [18] and Alkroosh and Nikraz 2012 [19] demonstrated the capability of gene expression programming (GEP) and Kordjazi et al. 2014 [20] used support vector machines (SVM) for prediction of improvement soil through experimental data. It is well-evidenced that the models resulting from the artificial intelligence have better performance in comparison with the traditional analytical formulas. In order to construct a prediction model and dealing with real world problems, it is better to replace such soft computing techniques with traditional methods. The significant features of the modern techniques like their capability of information processing such as non-linearity, high parallelism, robustness, fault and failure tolerance and their ability to generalize models, make them so attractive for applying to many civil engineering prediction problems (Alavi and Sadrossadat [21]; Fattahi and Babanouri [22]; Khandelwal and Armaghani [23]; Sadrossadat et al. [24], Tajeri et al. [25]; Xue et al. [26]; Ziaee et al. [27]; Žlender et al. [28]).

One of the main strengths of the ANFIS is that it combines the advantages of fuzzy inference systems (FIS) with the learning ability of ANN and presents all their benefits in a single framework. The selection of the FIS is the main concern in designating the ANFIS model (Jang et al. [29]). There is an enriched literature related to the FIS systems based on fuzzy reasoning and the employed fuzzy if then rules e.g. (Mamdani [30]; Takagi and Sugeno [31]; Tsukamoto [32]). There are two typical fuzzy inference systems: Mamdani and Takagi-Sugeno (TS) or Sugeno. Mamdani model includes fuzzy input and output variables [30], whereas, in TS or the sugeno inference system the output is expressed as a linear function of the input variables which takes a numerical value [31]. There is an important difference between them that is the fact that in order to design the membership functions and if-then rules, the Mamdani model uses human expertise and linguistic knowledge, but TS model uses optimization and adaptive techniques to establish the system modeling and also uses less number of rules. Moreover, in case a numerical or crisp output is required, the data-driven rule generation with TS model is selected. Also the output membership function in TS is simpler designed as either linear or constant [31, 33]. The using of this inference system is more pervasive in ANFIS for modeling problems [34]. Considering two input variables (x, y) and one output (f), the two if-then rules in first-order TS type can be represented as follows:

Rule 1: if $x = A_1$ and $y = B_1$, then $f_1 = p_1x + q_1y + r_1$

Rule 2: if $x = A_2$ and $y = B_2$, then $f_2 = p_2x + q_2y + r_2$

where p_i, q_i, and r_i are the consequent parameters obtained from the training, A and B labels of fuzzy set define suitable membership function.

Using the ANN architecture, ANFIS optimizes the model parameters. In ANFIS, the input variables are proliferated forward in a network similar to the MLP architecture layer by layer. Best consequent parameters are determined by the least-squares method (LSM), while the premise parameters are affected to be fixed for the current cycle through the training set. Next, the error values propagate backward to adapt the premise parameters, using back propagation gradient descent method (Sadrossadat et al. [33]; Žlender et al. [28]). Also it can be said that using ANFIS for rehabilitation of collapsible soil is a new method.

Generally, the adaptive neural-fuzzy inference model is a multilayer network consisting of nodes and arcs linked by the nodes. For the first-order fuzzy model, Sugeno with two inputs, one output, and two membership functions for each of the inputs of a fuzzy neural network model is presented in Fig. 5.

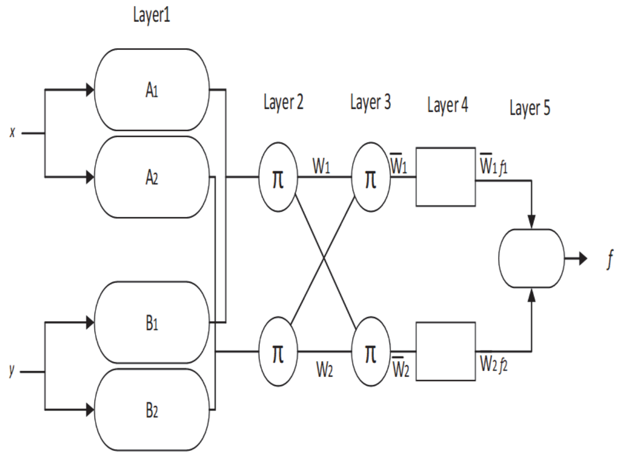
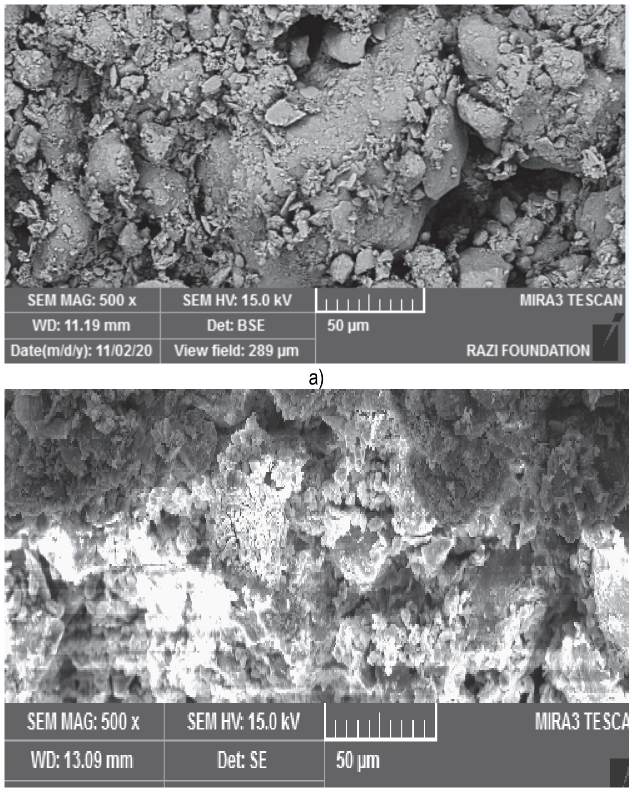


Figure 5 Schematic of a fuzzy neural network

To identify structural changes in soil samples, SEM photos were taken from soil samples. In this regard, a soil sample was made without additive and another sample with additivein Fig. 6.



a)

b)

Figure 6 SEM images of soil samples: a) without additive; b) with additive

4.1 Data Used for Modelling

For designing a model, input and forecast data must first be specified. This model has 36 inputs for training and 12 inputs for forecasting from two different sites. Then, the data presented in Tabs. 3 to 4, moisture percentage (W / %), soil liquid limit (*LL*), soil plastic index (*PI*), porosity ratio (*e*), soil specific gravity (*γ*), duration (*t*), and finally the percentage of the additive are considered as input and the abduction index (*CP* / %) as output during modeling. The parameters used for ANFIS training in the production model are presented in Tab. 5.

Table 5 Parameters Used in ANFIS for Abduction Index

ANFIS parameter type for *CP*	ANFIS
MF type	Gaussian
Number of linear parameters	7
Number of nonlinear parameters	3
Number of training data pairs	36
Number of checking data pairs	12
Number of fuzzy rules	8

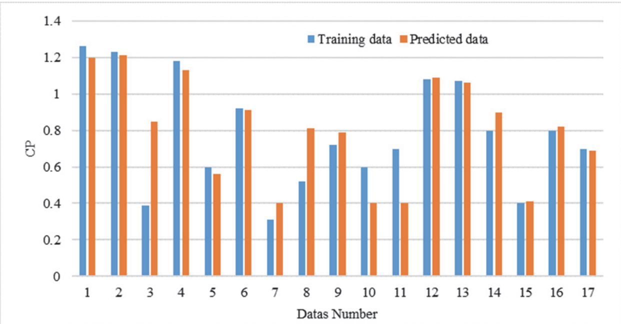


Figure 7 Results of artificial neural network versus laboratory values related to forecast data

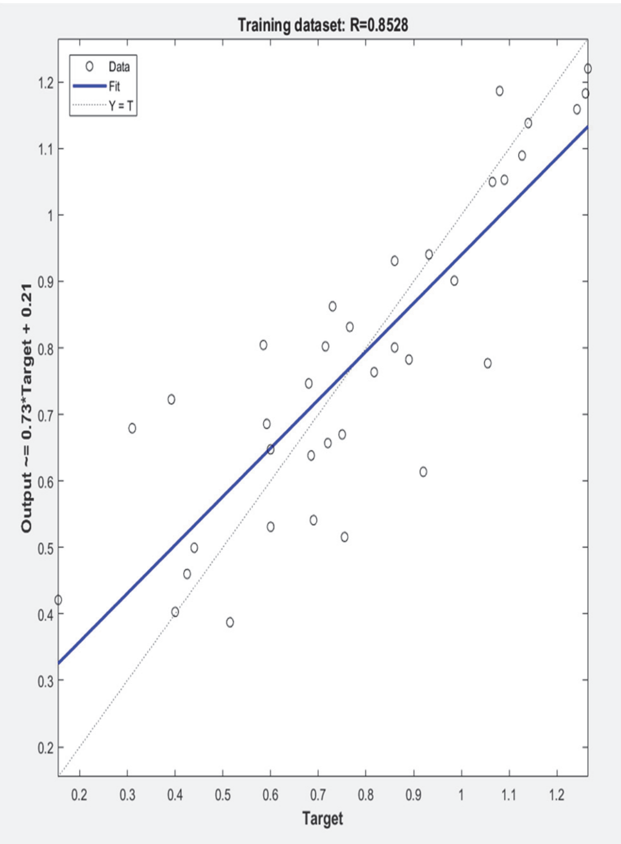


Figure 8 Results of neural network versus laboratory values related to experimental data

Figs. 7 and 8 show a comparison between the trained and predicted models of the collapsible index. The ANFIS function has, as it can be concluded from the graph, the most overlap in the real and predicted state.

5 DISCUSSION

From the outset until recent years, various additives, including butadiene, have been added to the soil to improve its compaction properties and examine their effect on the soil. In previous research, this material was used to improve soil strength properties (parameters such as compressive strength, etc.) in coarse-grained soils (road construction). This study investigated the effect of a new type of polymeric material of Styrene-butadiene rubber on improving the properties in Iran's central region, Kerman of the collapsible fine-grained soil. The base soil's main properties, including granulation, moisture percent, specific gravity, and collapse index, were examined and analyzed in different percentages of a specific additive in both types of fine-grained soil. To measure the properties of fine-grained soil, the additive was combined with 2, 3, 4, 5, 6, and 7% by weight of soil, and after different periods (4, 7, 14, and 28 days), a compaction test was performed on them. The results obtained from 84 experiments were compared to each other.

Fuzzy set theory has been used for the proposed modeling. The designed model in this study can predict compaction potential when the percentage of additive and initial soil potential is available, and the necessary conditions for injection of the desired tests are not available. From eighty percent of data for input 20 percent were used for training.

6 CONCLUSION

The main conclusions drawn from the reported study are given below. According to the experiments performed on two different soil samples, these soils were classified as ML and CH and had a moisture content of 21,2 and 23,86, respectively, as well as the specific gravity of 14,6 and 14 grams per cubic centimeter. According to the experiment results, it can be argued that butadiene rubber reduces the abduction of all the cases by more than 90 percent. It can be estimated that adding Styrene-butadiene rubber to the fine-grained soil at different times and percentages results in almost the lowest amount of soil compaction after seven days. Meanwhile, the best percentage of additives is about more than 4%. The generated ANFIS model was modeled using 36 input data for training and 12 prediction data, and the output is the so-called abduction index. The values of R^2 are equal to 0,99 and RMSE to 20,5%. Both of them have been obtained for the training data in ANFIS, and the results show the reasonable accuracy of each model. Finally, it can be said that this material has caused collapsible soil properties improved. In future research, the effect of this additive material (Styrene-Butadiene Rubber) on liquefaction can be investigated.

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