

Adaptive neuro-fuzzy modeling for the swelling potential of compacted soils

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Received: 30 January 2008 / Accepted: 10 December 2008 / Published online: 6 February 2009
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Abstract This paper aims to present the usability of an adaptive neuro fuzzy inference system (ANFIS) for the prediction swelling potential of the compacted soils that are important materials for geotechnical purposes such as engineered barriers for municipal solid waste, earth dams, embankment and roads. In this study the swelling potential that is also one of significant parameters for compacted soils was modeled by ANFIS. For the training and testing of ANFIS model, data sets were collected from the tests performed on compacted soils for different geotechnical application in Nigde. Four parameters such as coarse-grained fraction ratio (CG), fine-grained fraction ratio (FG), plasticity index (PI) and maximum dry density (MDD) were presented to ANFIS model as inputs. The results obtained from the ANFIS models were validated with the data sets which are not used for the training stage. The analyses revealed that the predictions from ANFIS model are in sufficient agreement with test results.

Keywords Swelling potential · ANFIS · Compacted soils

Introduction

Swelling potential of soils is a parameter required for the design of many geotechnical projects such as foundations, embankments, compacted earth dams and compacted soil liners for containing contaminated solid and liquid wastes. For such structures, swelling properties is desired not to exceed a certain level that is appropriate for the design objectives.

Expansive soils can produce significant heave pressure to the engineering structures such as foundations, roads and sealing system for solid waste, when they are subjected to seasonal moisture changes. These types of soils can lead unexpected damage and large economic loss. In the United States, the economic cost of damage due to expansive soils is approximately 2.3 billion dollars per year (Dhowian et al., 1988). Therefore, the knowledge of swelling characteristics of soils is absolutely needed for the safe and economic construction of engineering structures. The main factor affecting swelling potential is the type of clay minerals in a soil. The soils which have high activity exhibit higher swelling potential. On the other hand, initial water content, dry density and grain size distribution are the other parameters affecting the swelling potential (El-Sohby and El-Sayed, 1981). Many correlation equations have been suggested for estimation of the swelling characteristics in literature (Mowafy and Bauer 1985, Mallikarjuna Rao, 1988, Erzin and Erol 2004). However these correlation equations has been mostly developed using limited number of data which consequently does not provide general identification for a wide range of soils. Therefore, it seems that the alternative methods are needed to obtain better predictions for the swelling potential. The spatial approaches such as artificial neural network (ANN) and fuzzy logic (FL) using black-box type computational

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process appear to be reasonable for the quick prediction of soil behavior since they enable to establish complex relationship between soil behavior and soil properties with nonlinear functions.

Recently, fuzzy methods has been successfully employed for modeling the complex systems in many engineering applications such as modeling the mechanical behavior of engineering materials, design of structures, automatic control, pattern recognition (Adam 2003). Fuzzy theory was first introduced by Lotfi Zadeh in 1965 developing the classical set theory. According to the classical set theory, a variable belongs to a set or not. In other words it crisply answers to a question. Whereas, fuzzy theory does not give a sharp answer to questions and enables partial belongings of a variable to different sets. The continuous membership functions that vary between 0 and 1 are employed for partial belonging. Mamdani and Takagi-Sugeno models are two types of fuzzy approaches used widely. In Mamdani model, the relationship between input variables and output variables is defined using the linguistic knowledge's by means of if-then rules. This provides flexible and intuitive feature. There are many similarities between Tagagi-Sugeno model and Mamdani model. The main difference is that the output membership functions are either linear or constant in TS model (Mamdani and Assilian 1975, Tagagi and Sugeno 1985). TS model which is preferred for mathematical analysis and computational efficient seems to be more advantageous. It uses optimization and adaptive techniques to establish the system modeling and also uses less number of rules than

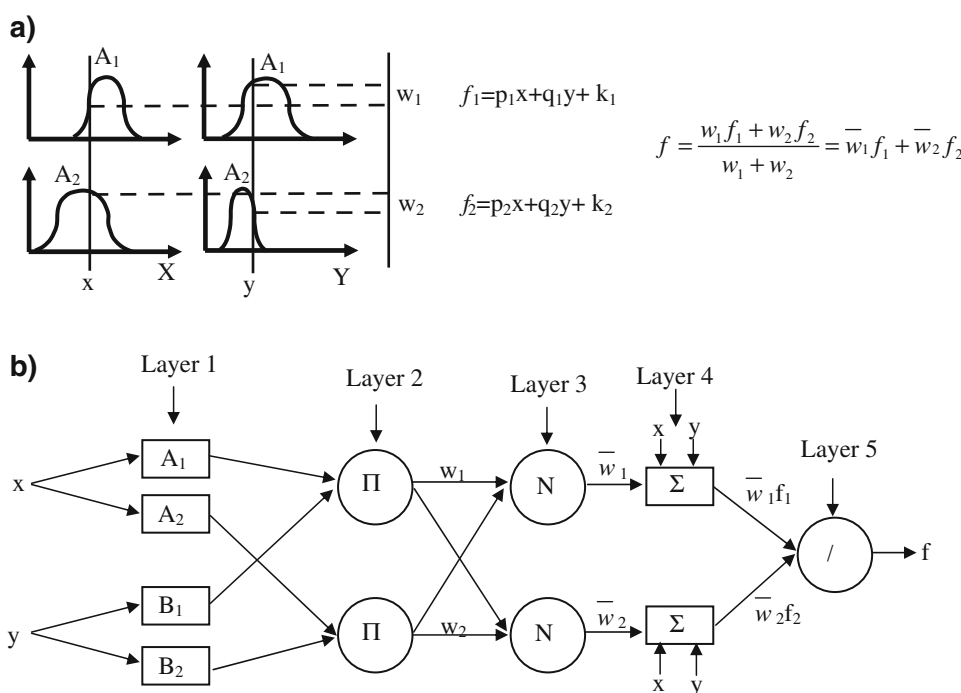
Mamdani. (Tütmez and Tercan 2007). ANFIS, a type of the TS model, is a new method in the field of practical engineering. In order to establish a relation between input variables and output variables, it allows using the learning techniques of ANN and adaptively determining the model parameters.

In the content of this work, ANFIS model was considered to predict the swelling potential of compacted soils. The data used for training and validating ANFIS models were obtained from the laboratory tests performed on compacted soils for different geotechnical applications around Nigde in Turkey. Four basic soil parameters, coarse-grained fraction ratio (CG), fine-grained fraction ratio (FG), plasticity index (PI) and maximum dry density (MDD) which are considered as major factors affecting the swelling potential were presented to ANFIS model as inputs.

Overview of adaptive neuro-fuzzy inference system (ANFIS)

Jang (1993) proposed a new fuzzy logic model called ANFIS which employs some properties of artificial neural network (ANN) such as learning and parallelism. ANFIS also makes use of adaptive properties of ANN to determine the fuzzy system parameters, fuzzy rules, and type of the membership function. For that purpose it uses two methods, grid partitioning and clustering (Şen 2001). The structure of the ANFIS model is depicted in Fig 1. In ANFIS model, either linear or constant output membership

Fig. 1 a) First order TS model reasoning b) ANFIS architecture (Padmini et al. 2008)



functions are used to find the consequence parameter. Linear function is named as first-order sugeno type fuzzy inference system and constant function is named as zero-order Sugeno type fuzzy inference system. A typical two if-then rules in first-order Sugeno type is given at following form:

$$\text{If } x = A_1 \text{ and } y = B_1 \text{ then } f_{1(x,y)} = p_1x + q_1y + k_1 \quad (1)$$

$$\text{If } x = A_2 \text{ and } y = B_2 \text{ then } f_{2(x,y)} = p_2x + q_2y + k_2 \quad (2)$$

where x (or y) is the input node i , p, q and k are the consequence parameters obtained from the training, A and B are labels of fuzzy set defined suitable membership function.

The membership function is updated by backpropagation learning algorithm or a hybrid learning algorithm which are described in detail in Demuth and Beale (2001). The computations in ANFIS model is performed in five layers. The membership values of an input parameter for the premise parameter are determined in first layer. The output of the i th node of the layer 1 is defined as;

$$U_{1,i} = \eta A_i(x) \text{ for } i = 1, 2 \text{ or} \quad (3)$$

$$U_{1,i} = \eta B_{i-2}(x) \text{ for } i = 3, 4 \quad (4)$$

Where, η shows the membership function. Typical membership function is as follow;

$$\eta_A(X) = \frac{1}{1 + \left| \frac{x-c_i}{a_i} \right|^{2b}} \quad (5)$$

where a_i, b_i and c_i is the parameter set known as premise parameters

In layer 2 in which each node represents the fire strength of the rule, the output $U_{2,i}$ which is the product of the incoming signals is calculated as shown below;

$$U_{2,i} = w_i = \eta A_i(x) \eta B_i(y) \text{ } i = 1, 2 \quad (6)$$

The ratio of the i th rule's firing strength versus all rules' firing strength, called normalized firing strengths is computed in Layer 3, as

$$U_{3,i} = U_{3,i} = \bar{w}_i = \frac{w_i}{w_1 + w_2}, \text{ } i = 1, 2 \quad (7)$$

In layer 4 the contribution of the i th rule to output is calculated with an adaptive node function:

$$U_{4,i} = \bar{w}_i f_i = \bar{w}_i(p_i x + q_i y + k_i) \quad (8)$$

where, \bar{w} is the normalized firing strength found from layer 3, p_i, q_i and k_i are the consequent parameters.

The single node in layer 5 calculates the overall output of the ANFIS using the equation shown below.

$$U_{5,i} = \sum_i \bar{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \quad (9)$$

Database

Data used for training and validating the neuro fuzzy models compiled for this study were taken from various projects from Nigde region in Turkey. The data base comprises a total of 98 cases. As seen in Table 1 the soils utilized in analyses are classified as CH, CI, CL, GC, GM, MH, MI, ML, according to The Unified Soil Classification System (or USCS). Many study given in previous section revealed that CG, FG, PI and MDD have considerably influence on the swelling potential of soils. Therefore, they were presented to ANFIS model developed in this study as input parameters. Dataset in Table 1 were divided into two groups. While first group data was used for training, the second group which was not included to the training group was used for testing.

Development of ANFIS model

In this section the ANFIS model developed for estimation of the swell potential is described. Two types of methods, grid partitioning and scatter partitioning, are generally utilized to generate the membership functions for developing the ANFIS model (Dubois and Prade 1980, Shahin et al. 2003, Abdulsamet et al. 2004, Yılmaz and Mahmut 2006, Topçu and Saridemir 2007). In grid partitioning method, the numbers of fuzzy rules are generated exponentially as depending on number of inputs and number of membership functions. This is marked as the inconvenience feature and leads that the ANFIS architecture has more complex structure. It is not mostly preferred in case the number of input parameters is more than 6 (Nayak et al. 2004, Padmini et al. 2008). On the other hand, in scatter partitioning, satisfactory results may not be obtained when any data does not belong to fuzzy cluster and it is away from the centre of cluster. This issue is not in question for the grid partitioning methods. It evaluates the entire range of the data in determination of the ANFIS structure (Padmini et al. 2008).

In this work, the ANFIS model was constructed using grid partitioning method for the estimation of the swell potential. On the other hand, the Gaussian membership function was selected and updated by hybrid learning algorithm in training stage. Fig. 2 shows the shape of the MFs. Surface graphs obtained from ANFIS model is given in Fig. 3. This figure shows the relationships between the inputs parameters and the output parameter. In other words, trend of the ANFIS model is viewed from this figure in terms of variation of the input parameters. The Fuzzy toolbox of MATLAB computer aided Software (Demuth and Beale 2001) was utilized for the necessary computation and for developing the ANFIS models in this work.

Table 1 Data used for training and testing

	Coarse-grained CG (%)	Fine-grained FG (%)	Plasticity Index (PI) (%)	Max Dry Density (MDD) (kg/cm ²)	Swell Potential (%)
1	36.5	63.5	30.06	1.532	17.00
2	26	74	33.26	1.431	19.79
3	27.5	72.5	28.03	1.556	9.79
4	20.5	79.5	28.92	1.552	13.89
5	44	56	25.11	1.776	9.58
6	39	61	29.17	1.718	10.15
7	40	60	22.66	1.722	16.42
8	25	75	27.11	1.467	16.37
9	25	75	27.11	1.467	16.37
10	25	75	28.12	1.572	15.53
11	40	60	28.13	1.704	10.00
12	43	57	25.67	1.640	14.58
13	34	66	23.90	1.609	14.79
14	30	70	19.50	1.693	9.21
15	35	65	25.37	1.651	13.58
16	51	49	20.51	1.832	11.42
17	44	56	20.90	1.720	10.53
18	47	53	22.78	1.778	11.84
19	43	57	21.65	1.743	19.36
20	50	50	22.38	1.806	8.89
21	41	59	14.48	1.840	10.26
22	45	55	15.36	1.660	9.35
23	26	74	18.05	1.638	12.89
24	36	64	16.91	1.686	9.89
25	36	64	16.91	1.686	9.89
26	25	75	17.87	1.549	15.11
27	25	75	17.87	1.549	15.11
28	39	61	19.71	1.770	17.47
29	39	61	19.71	1.770	17.47
30	34	66	19.83	1.728	15.89
31	35	65	21.90	1.758	10.26
32	46	54	19.95	1.698	8.47
33	47.5	52.5	16.85	1.979	13.05
34	45	55	17.53	1.885	7.32
35	46	54	14.72	1.914	9.11
36	46	54	23.23	1.826	14.79
37	39	61	17.65	1.910	9.21
38	43	57	21.15	1.739	10.53
39	44	56	22.68	1.649	10.53
40	51	49	14.86	1.831	4.84
41	33	67	17.80	1.783	8.42
42	30	70	15.68	1.778	6.05
43	48	52	14.94	1.814	8.00
44	46	54	14.11	1.761	8.00
45	30	70	15.57	1.772	6.60
46	25	75	15.66	1.749	6.60

Table 1 continued

	Coarse-grained CG (%)	Fine-grained FG (%)	Plasticity Index (PI) (%)	Max Dry Density (MDD) (kg/cm ²)	Swell Potential (%)
47	42.5	57.5	7.88	1.799	9.74
48	42.5	57.5	7.88	1.799	9.74
49	49	51	14.66	1.845	5.16
50	49	51	15.66	1.845	5.16
51	53	47	13.17	1.832	6.05
52	63	37	11.46	1.913	2.84
53	48	52	11.90	1.904	8.26
54	39	61	17.14	1.806	9.26
55	40	60	16.44	1.838	6.68
56	49	51	14.67	1.966	6.34
57	35	65	17.86	1.660	11.53
58	62.5	37.5	20.14	1.810	4.70
59	58.5	41.5	14.05	1.700	4.40
60	63	37	17.15	1.675	2.90
61	79	21	15.30	1.870	2.55
62	66	34	17.40	1.894	7.21
63	67.5	32.5	17.44	1.766	13.42
64	76	24	15.59	1.902	9.58
65	64	36	20.21	1.748	12.84
66	87	13	13.20	2.091	7.36
67	62	38	10.10	1.922	6.95
68	67	33	26.70	1.737	13.89
69	60	40	14.20	1.790	9.53
70	60	40	14.20	1.790	9.53
71	50	50	22.49	1.689	10.95
72	55	45	24.77	1.668	16.16
73	40	60	23.16	1.641	19.78
74	41	59	19.05	1.668	14.21
75	26	74	20.94	1.671	12.37
76	47	53	12.40	1.962	5.68
77	53	47	19.64	1.759	3.74
78	63	37	16.40	1.882	10.16
79	58	42	17.63	1.812	9.15
80	65	35	15.17	1.958	7.31
81	58	42	15.35	1.841	5.66
82	52	48	26.58	1.66	8.11
83	55	45	20.66	1.809	11.41
84	59	41	21.85	1.826	14.42
85	69	31	15.71	2.032	10.80
86	56	44	20.8	1.886	11.36
87	68	32	13.83	1.813	4.77
88	62	38	17.51	1.822	8.49
89	77	23	15.01	1.828	7.34
90	66.5	33.5	13.85	1.71	3.59
91	54.5	45.5	16.49	1.716	5.26
92	61	39	12.28	1.846	6.01

Table 1 continued

	Coarse-grained CG (%)	Fine-grained FG (%)	Plasticity Index (PI) (%)	Max Dry Density (MDD) (kg/cm ²)	Swell Potential (%)
93	68	32	15	1.695	7.70
94	67	33	13.18	1.881	7.70
95	81	19	15.1	1.926	5.13
96	85	15	7.37	2.016	3.97
97	73	27	8.55	2.02	9.75
98	76	24	15.84	2.034	9.24

Results and Discussion

In this section, it is focused to examine and discuss the performance of ANFIS models. Of the 98 data sets, 78 were used for training the ANFIS models and 20 were presented to ANFIS models for testing. As can be seen from most of previous studies, it is a common agreement to use percentages varying between %15–25 and many artificial intelligence software uses similar percentages for the test stage (Shahin et al. 2003, Topçu and Sarıdemir 2007, Padmini et al. 2008). In order to find out how accurate the results of developed ANFIS models are, some statistical

verification tools were utilized such as coefficient of correlation (R), standard errors (SE) and standard deviation (σ). Furthermore, t-test and F-test to indicate the significance of models were implemented to the results.

Estimated swelling potential values were graphically compared with the experimental counterparts in Fig. 4. As can be seen, the ANFIS models were found to be able to learn the complex relationship between the basic soil properties and the swelling potential. The satisfactory agreement between the ANFIS predictions and experimental data was obtained in terms of the R values. R values of the ANFIS model is 0.93. In statistics, the overall error performances of the relationship between two groups can be interpreted from the R values. According to Smith (1986), if a proposed model gives $R > 0.8$, there is a strong correlation between measured and estimated values over all the data available in the database.

The reliability of ANFIS model was also evaluated by SE value that is a statistical criterion showing a measurement of deviation around the regression line. This is important for statistic as well as R value, because sometimes a relationship with high R value may exhibit high SE value. It is desired that a model gives high R value and low SE value. The ANFIS model developed herein for the swelling potential yields SE value of 1.06. This is

Fig. 2 Membership functions for the swelling potential

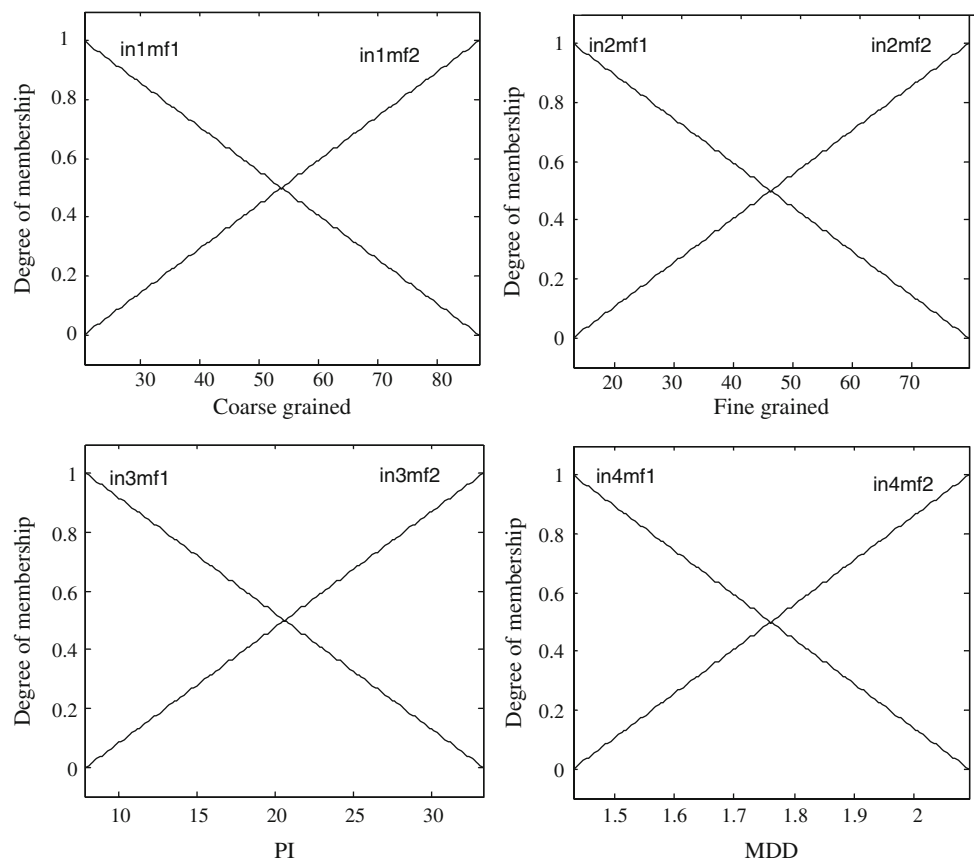
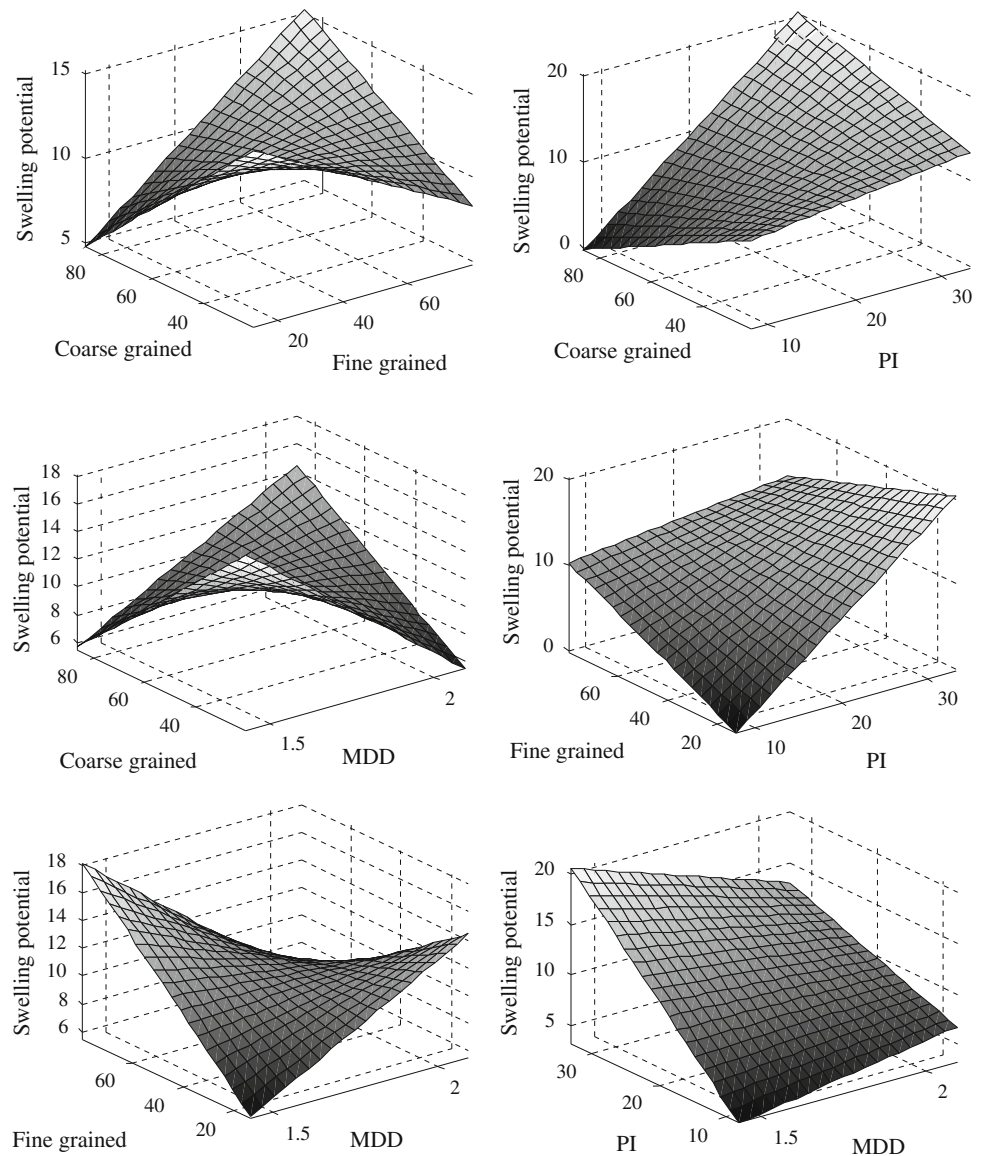


Fig. 3 Fuzzy surface showing the relationship between the input parameters and swelling potential



satisfactory value of the SE for reliable model of the swelling potential. On the other the σ value of the model was obtained as 2.82.

In order to evaluate the significance of R values, the t-test was performed. For that purpose both groups, namely experimental values and ANFIS predictions were adopted to be normally distributed. T-test includes the comparison of calculated t-value with the tabulated t-value using the null hypothesis which is set up to test differences in groups. The null hypothesis either is nullified or refuted as a viable possibility with respect to data. According to this, in case the calculated t-value is greater than the tabulated t-value, the null hypothesis is rejected. This indicates R value of a relation is significant. On the contrary, if the calculated t-value is less than the tabulated t-value, the null hypothesis

is not rejected and it is accepted that R is not significant (Drapper and Schmidt 1981, Tukey 1997, Rawlings 1998, Myers 1990). In this work, confidence level was taken as 95% and tabulated critical t-values corresponding to 95% confidence level were obtained as 2.093. T-value for the swelling potential was calculated as 4.42. According to this, it is understood that the results obtained from ANFIS model are significant. Analysis of variance was also performed to see the significance of relationship. For that that purpose ANNOVA analysis was applied. Assuming a 95% level of confidence F value for the swelling potential was obtained as 29.03. Since this value greater than tabulated F-value, the null hypothesis is rejected. ANOVA analysis and t-test show that there is acceptable relationship between ANFIS predictions and experimental data.

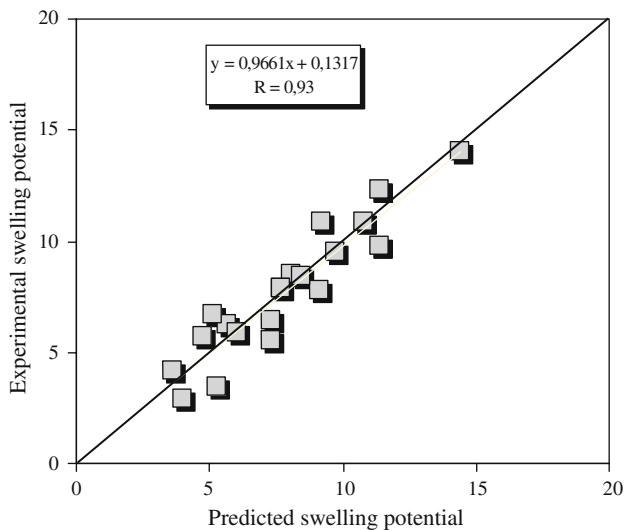


Fig. 4 Comparison between the predicted and experimental swelling potential

Summary and conclusion

In the content of this study, the applicability of adaptive neuro fuzzy inference system (ANFIS) for the prediction of the swelling potential of soils was investigated. The experimental data sets of compacted soils taken from different location of Nigde in Turkey were utilized to develop the ANFIS models. CG, FG, PI and MDD values of soils were presented as input parameters to ANFIS models. While the 78 data sets were employed for training, 20 data sets were used for testing. End of the analyses, it was observed that predicted values from ANFIS models are in the satisfactory agreement with the experimental counterparts. Some statistical tools were used to evaluate the performances of models. R value of the relationship between the predictions and experimental values was found to be at sufficient level in terms of the statistical. On the other hand, t-test and F-test was performed assuming a 95% level of confidence and it was observed that the ANFIS model is significant and valid. When the difficulties and limitations in soil testing procedures are considered, it can be concluded that the results obtained from ANFIS are very encouraging for the cases tested and the use of ANFIS is more reasonable method for the prediction of swelling potential of soils.

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