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Prediction of SWCC using artificial intelligent systems: A comparative study

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Abstract The significance of the Soil Water Characteristic Curve (SWCC) or soil retention curve in understanding the unsaturated soils behavior such as shear strength, volume change and permeability has resulted in many attempts for its prediction. In this regard, the authors had previously developed two models, namely. Genetic-Based Neural Network (GBNN) and Genetic Programming (GP). These two models have identical set of input parameters. These parameters include void ratio, initial water content, clay fraction, silt content and logarithm of suction normalized with respect to air pressure. In this paper, performance of these two models is further investigated using additional test data. For this purpose, soil samples from 14 different locations in Shiraz city in the Fars province of Iran are tested and their SWCCs are established, using a pressure plate apparatus. Next, the results are used to demonstrate the suitability of the previously proposed models and to evaluate relative importance of the input parameters. Assessment of the results indicates that predictions from GBNN model have relatively higher accuracy as compared to GP model.

1. Introduction

Compacted fine soils are often used in landfills and foundations of many structures. As compacted soil barriers are frequently unsaturated, modeling of flow and transport in these soils requires knowledge of their unsaturated hydraulic properties. SWCC, which relates suction (matric or total) to water content or degree of saturation, is an important part of any constitutive relationship for unsaturated soils. SWCC can be expressed as a continuous sigmoidal function, describing the water storage capacity of a soil as it is subjected to various soil suctions. SWCC includes important information about the amount of water contained in the pores at any soil suction and the pore size distribution, corresponding to the stress state in the soil. Unsaturated soil behavior such as shear strength, volume change, diffusivity and absorption, as well as most of soil properties such as specific heat, permeability and thermal conductivity can also be related to the soil water characteristic curve [1].

The methods for predicting the SWCC of a particular soil can be classified into five groups as follows:

1. Fitting type equations for the SWCC. In this group of equations a simple mathematical equation is fitted to the experimental data, and the unknown parameters are determined [2–4].
2. Water contents at different suctions are correlated to specific soil properties such as D_{10} (sieve size for 10% passing) and porosity. This process generally requires a regression analysis followed by a curve fitting procedure [5,6].
3. Correlating parameters of an analytical equation with basic soil properties such as grain size distribution and dry density, using a regression analysis [7,8].
4. Physico-empirical modelling of SWCC. This approach converts the grain size distribution into a pore size distribution, which is in turn related to a distribution of water content and associated pore pressure [9–12].
5. Artificial Intelligence (AI) methods such as neural network, genetic programming and other machine learning methods have been used in various disciplines of civil engineering [13–15]. Prediction of SWCC, using artificial intelligence falls into the fifth group [16–18].

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Table 1: Properties of tested soils.

Sample	USCS classification	Gs[b]	LL[b]	PI[b]	Clay (%)	Silt (%)	Sand (%)	Optimum[c] water content	Maximum dry density (kg/m^3)
1	ML[a]	2.70	20	5	35.2	52.0	12.6	14.0	1808
2	CL[a]	2.76	28	7	3.8	69.3	26.9	20.0	1685
3	CL	2.75	28	11	4.4	60.9	34.6	18.0	1714
4	ML	2.73	19	2	23.0	54.0	19.3	15.0	1834
5	CL–ML[a]	2.77	27	7	1.7	64.4	33.9	21.5	1662
6	ML	2.67	21	3	11.6	65.2	23.3	15.2	1798
7	ML	2.73	24	4	5.4	77.8	16.8	15.5	1710
8	ML	2.69	21	5	33.4	57.5	8.6	12.5	1913
9	ML	2.74	22	3	22.0	54.8	21.9	15.0	1845
10	CL	2.70	32	12	5.7	62.8	31.5	18.5	1728
11	CL–ML	2.74	24	6	7.3	66.4	26.3	17.0	1780
12	CL	2.69	28	9	7.2	60.0	27.4	18.0	1764
13	CL	2.72	26	7	8.1	53.5	38.2	17.0	1796
14	CL	2.71	23	6	15.0	71.2	13.9	15.5	1813

[a] ML: Low plasticity silt, CL: Low plasticity clay, CL–ML: Low plasticity silty clay.
[b] Gs: Specific gravity, LL: Liquid limit, PI: Plastic limit.
[c] Standard Procter test.

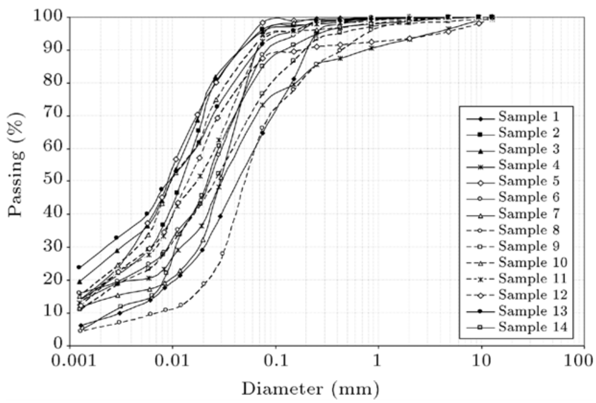

Figure 1: Grain size distribution curves of the soils.

Among the above mentioned five groups, artificial intelligence methods are known to have a better accuracy and a relatively straight forward approach [16,17]. The purpose of this paper is to investigate the performance of two AI systems, namely, Genetic-Based Neural Network (GBNN), and Genetic Programming (GP). To this end, an experimental program was planned to test 14 soil samples in laboratory pressure plate apparatus and examine the accuracy of the models predictions against these data. Details of the experimental program are presented in the next section.

2. Experimentation

Experimental methods include pressure plate, osmotic method, tensiometers, pressure membranes and electrical measurements [19]. These methods measure the pore water pressure in the soil directly or indirectly by imposing a known air pressure to the soil and allow the water content to come to equilibrium with the imposed air pressure. The method used to measure the SWCC depends on the texture of soil (coarse versus fine) and the magnitude of the suctions that must be established.

The presence of fine grained soils in a vast area of Shiraz plain on one hand and the frequent change in the behavior of this type of soil by absorbing and desorbing of water on the other hand clearly necessitates careful examination of the soil behavior for any project. Since the most important tool for assessing the behavior of unsaturated soils subjected to a change in their water content is SWCC, it was decided to obtain soil samples from several locations of Shiraz plain in order to determine their SWCCs, using pressure plate apparatus. This task was important both for developing a database for the soils in this region and to study their possible differences. Details of the soil properties, preparation and test method are presented in the following sections.

3. Soil properties

Bulk samples of soil were taken from boreholes and excavation walls from fourteen locations in Shiraz city in the Fars province of Iran. Sampling sites were selected so that they represent different soil types (CL, ML and CL–ML, classified according to unified classification system) with maximum overall coverage over the city. The grain size distribution curves of these soils are depicted in Figure 1. Atterberg limits, specific gravity and other index properties are presented in Table 1.

4. Compaction test

Compacted soil specimens were prepared for pressure plate test using optimum water content and maximum dry unit weight. This procedure was adopted, considering the fact that maximum specific weight is frequently used in embankments and other earth structures. For this purpose, the compaction curves of the soil samples were developed based on ASTM D698-70 [20]. The initial conditions of the compacted samples are depicted in Table 1.

5. Sample preparation

The following steps were adopted for preparing the testing soil samples:

1. Compacted samples were obtained in standard Procter mold, using the optimum water content.
2. The compacted samples were then taken out of the mold, using a jack, and cut horizontally into slices of about 2 cm thick. Then, each soil slice was pushed into a standard sharp-edged thin metal ring (soil retainer) and carefully trimmed to provide a smooth surface on both sides.
3. The samples were placed on the high air entry ceramic disk in a symmetrical arrangement. Although the 15 bar ceramic

stone in the pressure plate apparatus was sufficient for the purposes of the experiments, in order to expedite the test and also to reach a higher precision in determining the initial points of the curves, two pressure plate apparatus with 15 and 5 bar ceramic stones were used simultaneously. The 5 bar ceramic stone was used for samples tested at 0.0, 10, 50 and 100 kPa of suction, whereas the 15 bar ceramic stone was used for samples tested at 200, 400, 800 and 1100 kPa of suction.

4. A porous stone with a diameter equal to that of the samples and a surcharge of 200 g was laid on each sample. In order to saturate the samples, water was poured over the ceramic disk. This operation was continued until the water reached about 2 mm below the top edge of the rings. This technique helps in saturating the sample from bottom to top and thus minimizing the trapped air in the samples. To ensure an acceptable saturation and equalization inside the sample, which could satisfy the recommended standard, the samples were kept under this condition for 24 h.

6. Testing method

After 24 h, the weights and the porous stones were removed from the samples and the water around the rings was collected, using a syringe in order to prevent error in determining the water content of the samples. Next, the drainage pipe was connected to the ceramic disk and the pressure plate cap was fastened, using available screws. The desired air pressure was applied for two days (for air pressures below 1000 kPa) and four days (for air pressures above 1000 kPa), based on the recommendation of ASTM D6836 [21].

After each increment of pressure application, one sample was taken for water content determination and the procedure was repeated for the next increment of air pressure. Extraction of the samples from the pressure chamber was quick enough to minimize the possibility of change in water content of the samples.

7. Test results

Following the steps explained in Section 5 for the soil samples taken from different areas of Shiraz city, their SWCCs were established as shown in Figure 2. All the samples indicated almost a similar trend, but had different initial saturated water content.

8. GBNN modeling of SWCC

In ordinary NNs, the "back propagation law" is used as a device for determining the minimum of function with weight variables connecting the layers. In Genetic-Based Neural Network (GBNN) model, based on the optimization features of the Genetic Algorithm (GA), it is used for determining the optimal weights of a NN, for predicting SWCC. The optimum number of hidden neurons, is determined by trial and error. The network characteristics adopted here are those explained in [15]. A brief description of the network is given below.

Five parameters, namely, void ratio, initial water content, clay fraction, silt content and logarithm of suction normalized, with respect to air pressure $[\log(u_a - u_w)/p_a]$, (u_a = air pressure, u_w = pore water pressure, p_a = atmospheric pressure taken as 100 kPa) were selected as the input neurons. The hidden layer consisted of five neurons with one output neuron yielding the gravimetric water content corresponding to the assigned input suction.

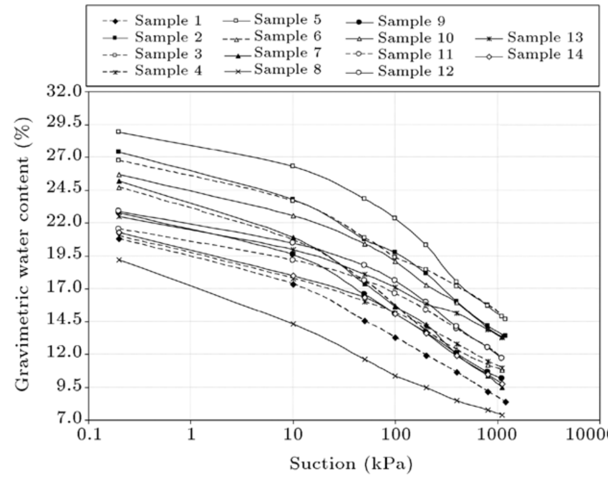

Figure 2: The SWCCs of the soil samples.

Table 2: Relative importance of input parameters.

Input parameters	Relative importance (%)
Initial void ratio	23.2
Initial water content (%)	21.7
$\log(u_a - u_w)/p_a$	33.6
Clay (%)	14.1
Silt (%)	7.4

Table 3: Range of basic soil properties of specimens adopted for developing model.

Property	Range
Initial void ratio	0.46–2.85
Suction (kPa)	0.2–104857.6
Specific gravity	2.28–2.92
Water content (%)	0.18–98.27
Dry density (kg/m^3)	702–1811
Initial water content (%)	17.34–105.41
Clay content (<0.005 mm) (%)	4.4–76.7
Silt content (0.005–0.075 mm) (%)	10.3–87.5
Sand content (>0.075 mm) (%)	0.1–55.3

The input parameters were selected after a thorough study of various combinations of soil parameters and their impact on the output error. The relative importance of various input parameters was evaluated using the procedure suggested by Garson [22] and the results summarized in Table 2.

Based on Table 2, suction has the highest influence on the predicted value for water content followed by void ratio and initial water content.

Results of the pressure plate tests performed on clay, silty clay, sandy loam and loam soil reported by various researchers and compiled in [23] were adopted for the analysis. Table 3 indicates the range of the basic soil properties employed for this study. This database consists of the results from 186 pressure plate tests, together with their grain size distributions. Figure 3 shows the proposed network configuration, and Table 4 indicates the optimal connection weights of the model.

In order to match the starting point of the model with the laboratory results, all the outputs of the model were corrected as follows:

$$\omega = X(Y/Y_0), \tag{1}$$

Table 4: Optimal connection weights of GBNN [16].

Hidden neuron	Initialvoid ratio	Initial water content	$[\log(u_a - u_w)/p_a]$	Clay (%)	Silt (%)	Input bias	Output neuron
1	−12.92	17.83	19.87	7.58	17.05	−34.60	−10.75
2	−10.20	25.41	−28.80	26.54	0.15	6.80	1.07
3	8.67	10.06	−20.52	−3.74	−10.24	−8.29	7.78
4	−18.14	−0.13	−12.80	4.09	2.56	1.19	−2.72
5	4.71	−10.83	8.30	−2.54	−0.89	0.05	−4.79
Bias	–	–	–	–	–	–	−0.04

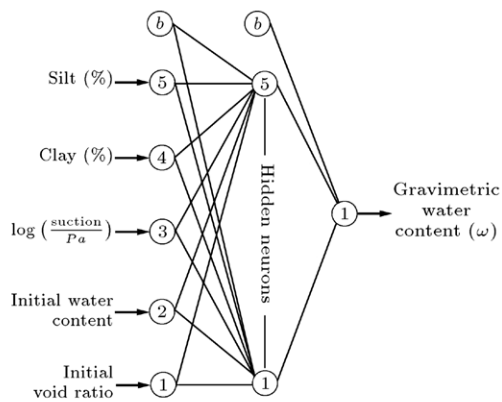

Figure 3: The proposed neural network for the prediction of SWCC.

Table 5: Comparing error of GBNN and GP models.

Samples	GP		GBNN	
	MSSE	Av. relative error (%)	MSSE	Av. relative error (%)
1	3.78	16.11	1.06	7.83
2	0.28	2.78	2.52	8.01
3	0.95	4.30	1.33	5.47
4	2.66	10.83	1.08	6.46
5	0.93	4.26	0.61	3.59
6	0.32	3.30	0.74	4.16
7	1.60	8.90	0.84	6.28
8	4.77	21.29	1.99	12.93
9	0.03	0.99	0.19	2.65
10	0.31	2.94	0.64	4.16
11	0.88	5.66	1.89	8.53
12	0.14	1.55	0.15	2.32
13	2.63	9.49	0.76	4.45
14	11.33	24.24	3.40	10.59
Average	2.19	8.33	1.23	6.25

where:

Y predicted gravimetric water content;

Y_0 predicted initial water content (at suction 0.2 kPa);

X initial gravimetric water content.

9. GP modeling of SWCC

Genetic Programming (GP), a branch of the genetic algorithm, is a method for learning the most fit computer programs (formula) by means of artificial evolution. In GP model, a large number of generations are done to search a formula with minimum error to predict SWCC with an as short as possible length. More details of this model are described in [16]. In their model, five parameters, namely, void ratio, initial water content, logarithm of suction normalized with respect to atmospheric air pressure, clay content and silt content were selected as the input terminals. The output terminal was the gravimetric water content corresponding to the assigned input suction. The ranges of these data are shown in Table 3. The optimum GP (optimum formulation) obtained had the following form:

Table 6: Comparing performance of GBNN and GP approaches.

Method	Av. relative error (%)	MSSE	R^2
GBNN	6.25	1.23	0.96
GP	8.33	2.19	0.95

$$Y = 0.794(X_2 + 0.215)(((0.116^{X_3} \times X_4^{X_5})^{(X_1+0.234)} + (X_4^{0.368(X_5/X_4)})(X_3^{X_1} - X_3))X_4)^{X_3^2}. \quad (2)$$

Outputs of the model then were adjusted based on the initial water content, to yield:

$$\omega = X_2(Y/Y_0), \quad (3)$$

where:

Y predicted water content;
Y_0 predicted initial water content (at suction 0.2 kPa);
X_1 initial void ratio;
X_2 initial water content;
X_3 log[suction (kPa)/p_a] where p_a: atmospheric pressure (taken as 100 kPa);
X_4 clay content (%);
X_5 silt content (%);
ω adjusted water content.

10. Prediction of SWCC using AIS

Two artificial Intelligent Systems (AIS), namely, GBNN and GP were employed to evaluate their capability for prediction of the SWCC. Two examples are presented in Appendix to illustrate the procedure for prediction of SWCCs, using GBNN and GP models.

In order to compare the predictions of the models, the prediction errors of different samples using both models were calculated. The results of these calculations are shown in Table 5. To illustrate the correlation quality of each model, the experimental results and their corresponding predictions were plotted against each other. Figures 4 and 5 show the results of these calculations.

Tables 5 and 6 presents the error estimate from GBNN and GP predictions, compared with the experiment data. It is to be noted that the models were calibrated using SoilVision [23] database, and their accuracy was evaluated using the experimental data from Shiraz silty clay. In these tables, the relative error is defined as:

$$\mathrm{RE} = \left|\frac{A_i - P_i}{A_i}\right| \times 100, \quad (4)$$

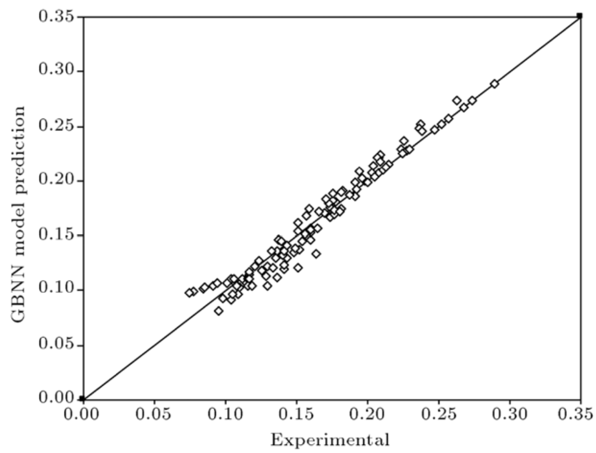

Figure 4: Actual versus predicted gravimetric water content using GBNN model ($R^2 = 0.96$).

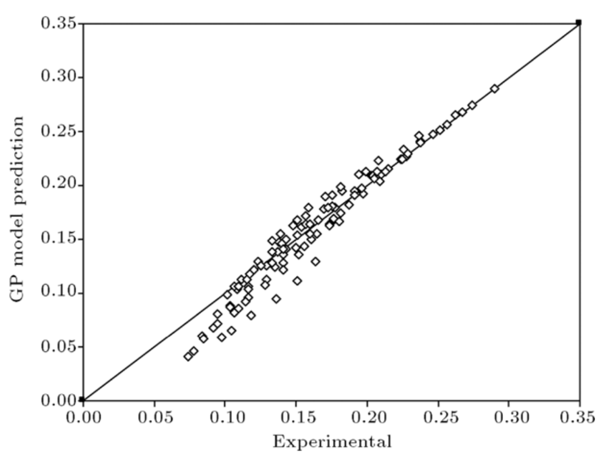

Figure 5: Actual versus predicted gravimetric water content using GP model ($R^2 = 0.95$).

and the sum of squared errors is defined by:

$$\mathrm{SSE} = \sum_{i=1}^{n} (A_i - P_i)^2, \tag{5}$$

$$R^2 = \text{Correlation coefficient} \times \left[\frac{\sum_{i=1}^{n} (A_i - \bar{A})(P_i - \bar{P})}{\sqrt{\sum_{i=1}^{n} (A_i - \bar{A})^2 \sum_{i=1}^{n} (P_i - \bar{P})^2}} \right]^2, \tag{6}$$

where:

A_i actual value for data i;
$\bar{A}$ mean of actual values;
P_i predicted value for data i;
$\bar{P}$ mean of predicted values;
n number of data point for each experiment.

Based on Table 5 and Figures 4 and 5, Table 6 was prepared to compare the overall errors of the models. Errors shown in Table 6 clearly indicate that the neural network model has been more successful than the GP model in predicting the SWCCs of fine grained soils of Shiraz plain.

Table A.1: Basic soil properties of specimen used for model validation (sample number 5).

Property	Value	Property	Value
Initial void ratio	0.79	Sand (%)	1.72
Initial water content (%)	28.94	Silt (%)	64.38
Dry density (kg/m^3)	1660	Clay (%)	33.90
LL (%)	27.33	Gs	2.77
PI (%)	6.98	–	–

11. Conclusion

In this paper, the pressure plate test results from 14 samples taken from various areas of Shiraz city in the Fars province of Iran were obtained. Then the results were used for testing GBNN and GP models. Comparing the results from these models with the experimental data indicates the robust performance of these models for prediction of SWCC of Shiraz fine grained soil. However, predictions from GBNN model shows relatively higher accuracy compared to the other model. Investigating the relative importance of the input parameters indicates that suction has the highest influence on the predicted value for water content followed by soil void ratio and its initial water content. These models have certain limitations in that they do not take into account the hysteresis phenomena, soil fabric effects and influence of the stress state.

The authors suggest the following future works for further improvements and extension on the topic:

- To validate the conclusions drawn in this paper as further data becomes available.
- To study other types of AI systems such as RBF (Radial Basis Function) and GRNN (Generalized Regression) neural networks.
- Extending the AI systems to include hysteresis phenomena, soil fabric and stress state effects.
- To extend the AI model to bimodal SWCCs.
- To employ other AI models such as neuro-fuzzy networks for SWCC prediction.

Appendix

In this Appendix, two examples were presented to illustrate the procedure for prediction of SWCCs, using GBNN and GP models. For this purpose, the laboratory results of the sample No. 5 were employed. Basic soil properties of this specimen are shown in Table A.1.

Prediction of SWCC by GBNN model

The steps of prediction, by this model, for this certain sample are as follows:

1. The input parameters of the model were normalized to lie in an interval of [0, 1], using a max–min approach. The results are shown in Table A.2.

   For each arbitrary suction point, for instance 10 kPa, the normalization is done as follow:

   $$X_3 = \frac{(\log(10/100) - \log(0.2/100))}{(\log(104857.6/100) - \log(0.2/100))} = 0.30.$$

2. By multiplying the input-hidden network weights $[W]$ (presented in Table 4) and by the normalized input vector $[I]$ (presented in Table A.2), the input hidden neuron matrix $[Z]$ is obtained ($[W] * [I] = [Z]$).

Table A.2: Normalization of input parameters.

Variable	Input neuron	Value	Upper limit	Lower limit	Normalized value ([I])
Initial void ratio	1	0.79	2.85	0.46	0.14
Initial water content (%)	2	28.94	105.41	17.34	0.13
Arbitrary suction (kPa)	3	10.00	104857.6	0.2	0.30
Clay (%)	4	0.34	0.77	0.04	0.41
Silt (%)	5	0.64	0.88	0.10	0.70

Table A.3: Comparing the performance of GBNN with experimental approach.

Suction (kPa)	Experiment water content	GBNN water content prediction	Relative error (%)	SSE
0.2	28.94	28.94	0.0	0.0
10	26.27	27.36	4.15	1.19
50	23.80	24.60	3.38	0.65
100	22.33	22.88	2.45	0.30
200	20.29	20.76	2.35	0.23
400	17.51	18.17	3.76	0.43
800	15.66	15.06	3.80	0.35
1100	14.84	13.52	8.90	1.74
			ARE[a](%) = 3.59	MSSE = 0.61

[a] Average relative error.

$$\begin{pmatrix} -12.84 & 17.83 & 20.03 & 7.58 & 17.05 & -34.56 \\ -10.20 & 25.41 & -28.80 & 26.54 & 0.15 & 6.80 \\ 8.67 & 10.06 & -20.84 & -3.74 & -10.28 & -8.29 \\ -18.14 & -0.13 & -12.81 & 4.09 & 2.56 & 1.19 \\ 4.69 & -10.83 & 8.30 & -2.54 & -0.89 & 0.05 \end{pmatrix} \times \begin{pmatrix} 0.14 \\ 0.13 \\ 0.30 \\ 0.41 \\ 0.70 \\ 1.0 \end{pmatrix} = \begin{pmatrix} -13.03 \\ 11.10 \\ -20.67 \\ -1.70 \\ 0.08 \end{pmatrix},$$

where 1.0 in $[I]$ matrix is the bias neuron value.

3. By applying sigmoid activation function to each element of vector $[Z]$, output vector from hidden neuron $[R]$ is obtained.

$$\begin{pmatrix} -13.03 \\ 11.10 \\ -20.67 \\ -1.70 \\ 0.08 \end{pmatrix} \xrightarrow{\text{Sigmoid}} \begin{pmatrix} 0.002 \\ 0.996 \\ 3\text{e}-5 \\ 0.299 \\ 0.510 \end{pmatrix}.$$

4. By multiplying the hidden-output network weights $[U]$ (presented in Table 4), by the output vector from hidden neuron $[R]$, the input of output neuron matrix $[S]$ is obtained ($[U] \times [R] = [S]$).

$$(-10.73 \quad 1.07 \quad 7.78 \quad -2.72 \quad -4.79 \quad -0.04) \times \begin{pmatrix} 0.002 \\ 0.996 \\ 3\text{e}-5 \\ 0.299 \\ 0.510 \\ 1.0 \end{pmatrix} = (-2.25).$$

Table A.4: Normalization of input parameters.

Variable	Name	Value	Normalized value
Initial void ratio	X1	0.79	0.14
Initial water content (%)	X2	28.94	0.13
Arbitrary suction (kPa)	X3	10.00	0.30
Clay (%)	X4	0.34	0.41
Silt (%)	X5	0.64	0.70

5. By applying sigmoid activation function to element of vector $[S]$, output vector from output neuron $[Y]$ is obtained.

$$(-2.25) \xrightarrow{\text{Sigmoid}} (0.24).$$

6. By de-normalizing the output of the network,

$$Y_{(\text{Normalizes})} = 0.245$$
$$\Rightarrow Y_{(\text{De-normalizes})} = 0.245^{*}(0.9827 - 0.0018) + 0.0018 = 0.242.$$

7. By scaling the $Y_{(\text{De-normalizes})}$,

$$\omega = X(Y_{(\text{De-normalizes})}/Y_{0(\text{De-normalizes})})$$
$$\Rightarrow \omega = 28.94(0.242/0.256) = 27.36,$$

where $Y_{0(\text{De-normalizes})}$ is the water content corresponding to the zero suction.

For determining the water content corresponding to the other desired suction, the above steps are followed. Table A.3 shows the result for 8 points in sample 5.

Prediction of SWCC by GP model

The steps of prediction, by this model, for an arbitrary sample (sample 5) are as follows:

1. Same as in GBNN model, the input parameters of the model were normalized to lie in an interval of [0, 1], using a max-min approach. The results are shown in Table A.4.
2. By placing the above normalized value into the Eq. (2), the result will be:

$$Y_{(\text{Normalizes})} = 0.253$$
$$\Rightarrow Y_{(\text{De-normalizes})} = 0.253 * (0.982777 - 0.00188) + 0.00188 = 0.25.$$

For calculating Y_0, Eq. (2) is used. For this purpose, the magnitudes of X_1, X_2, X_4 and X_5 are the same as in step 1, while X_3 is calculated as:

$$X_3 = \frac{(\log(0.2/100) - \log(0.2/100))}{(\log(104857.6/100) - \log(0.2/100))} = 0.0$$
$$\Rightarrow Y_{0(\text{Normalizes})} = 0.275$$
$$\Rightarrow Y_{0(\text{De-normalizes})} = 0.2370 * (0.982777 - 0.00188) + 0.00188 = 0.272.$$

Table A.5: Comparing performance of GP with experimental approach.

Suction (kPa)	Experiment water content	GP water content prediction	Relative error (%)	SSE
0.2	28.94	28.94	0.0	0.0
10	26.27	26.59	1.22	0.10
50	23.80	23.96	0.65	0.02
100	22.33	22.50	0.74	0.03
200	20.29	20.87	2.85	0.33
400	17.51	19.09	9.01	2.49
800	15.66	17.19	9.79	2.35
1100	14.84	16.29	9.77	2.10
			ARE (%) = 4.26	MSSE = 0.93

3. Based on the results of steps 2 and 3, the de-normalized water content for suction of 10 kPa is calculated as:

$$\omega = X_2(Y_{(\text{De-normalizes})}/Y_{0(\text{De-normalizes})})$$

$$\Rightarrow \omega = 28.94(0.250/0.272) = 26.59.$$

For determining the water content corresponding to the other desired suction points, the above steps are taken. As a result, Table A.5 will be developed.

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