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Research on prediction of soil suction in expansive soil

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Abstract: Soil-water characteristic curves of expansive clay are usually measured in the laboratory, but soil suction in the field is extremely difficult and time consuming. In this paper, the method of artificial neural network (ANN) is adopted to predict soil suction in the field by using measured water contents. This is done by training the network using laboratory measured soil-water characteristics. Prediction soil suctions using the ANN with some limited in-situ measured water contents are compared with actual suction measurements in the field. Prediction results are discussed.

Key words: expansive soil; soil-water characteristic curve (SWCC); artificial neural network (ANN); suction

Expansive soil is a problematic plastic unsaturated clay with distinct characteristics of swelling and shrinking when there is a change of water content. The behavior of unsaturated soils is strongly related to the pore size and pore geometrical distribution. As a result, soil-water characteristic curve (SWCC) defines the degree of saturation corresponding to a particular suction in the soil and becomes a dominant relationship for understanding unsaturated soil behavior. A number of equations have been proposed to fit SWCC empirically[1-5], but the parameters of the equation of SWCC are difficult to determine.

SWCC can usually be measured by using a pressure plate apparatus in the laboratory[6,7]. Very often unsaturated soils in the field are subjected to repeated cycles of drying and wetting throughout the year. So SWCC cannot describe the effect of those factors (for example, cycles of drying and wetting, climatic condition, evaporation, transpiration, temperature, etc.). Suction is one of the essential characteristic parameters of unsaturated soils that is relative to the strength and strain of the unsaturated soils and the slope stability of unsaturated soils.

Moreover, measuring suction is very difficult and complicated. We try to apply the artificial neural network (ANN) to perform the prediction suction because ANN is a function with: ① Robustness which can contain errors; ② Study capacity which may obtain the study rule by way of training; ③ Adaptive nonlinear. The method that depends on partial water content-suction data sets training and gets the connection weight values of neurons is to perform the purpose of prediction suction. The prediction results and precision show that the method is very effective.

1 Training an Artificial Neural Network

The objective of training for an ANN is to produce a desired output when presented with an input. There are two types of ANN training: unsupervised and supervised. Unsupervised training involves the presentation of input to the ANN without a target output for comparison. The goal of this type of training is to produce consistent outputs without knowing what the outputs should be. Supervised training uses two data sets, one is the input and the other is the target output. Used in conjunction, these data sets are from a training pair. Supervised training of a three-layer network is a two-step process involving a forward pass through the network followed by a backward propagation of errors, which is used to modify the network weights. This process is repeated until the network produces the desired results. At this point, training is said to have converged and is completed.

A forward pass for a three-layer ANN begins by presenting input data to the network. These input data (signals) are broadcast from each node in the input layer to each node in the hidden layer. The process of broadcasting requires that each signal passes through a weighting function which either inhibits or enhances the signal.

Upon the arrival and summation of all weighted signals, each uses a threshold, or activation, function to calculate an output value. The threshold function

$$f(x) = \frac{1}{1 + e^{-x}} \tag{1}$$

must be continuous and differentiable, because its

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derivative is used for training the network. Eq. (1), a sigmoid function, is especially useful because its first derivative is simple.

$$f'(x) = \frac{1}{1+e^{-x}}\left(1-\frac{1}{1+e^{-x}}\right) = f(x)(1-f(x)) \qquad (2)$$

A sigmoid function works well because it provides noise suppression while limiting the dynamic range of the output signal. The values for each hidden-layer node are broadcast to all of the nodes in the output layer. As is the situation for the previous layer, these values are modified by weighting functions, then summed and passed through the threshold function at the appropriate node. In the output layer, each node calculates an error value based on the difference between the output value and the training target value. If the error value is larger than a desired value, the process of training is invoked.

The most widely used technique for modifying the weights in multilayer ANNs, termed backpropagation, was independently discovered by several researchers[8,9]. Backpropagation is a method of modifying the weight values between nodes, including the weights for the hidden layers. The backpropagation algorithm is based on the delta rule, which propagates the error between the actual output and the desired output backward through the ANN. The delta rule attempts to minimize the error by using the method of steepest descent. This technique is known as hill-climbing. Rich[10] and Winston[11] presented detailed descriptions of hill-climbing as a search technique. Stone[12] presented a rigorous description of the delta rule. The backpropagation algorithm is similar to the reverse of a forward pass through an ANN. The connection weights are modified by propagating the error backward through the network.

2 Measurement of SWCC

2.1 Test method of SWCC

The test soil samples of unsaturated expansive soil are collected from Ningxia. SWCC is measured by means of a pressure plate in the laboratory. The following steps are included in measuring SWCC:

① Soil sample saturated Soil sample with ring is saturated in the DIK-3520 (an instrument of SWCC) for 24 h and the saturated weight of soil specimen is measured.

② Soil sample dried When air pressure is smaller than 3.5 kPa, the soil sample is dried in the DIK-3520 soil box with 0.3 MPa ceramic plate. When air pressure is greater than 3.5 kPa, the soil sample is dried in the DIK-3400 (an instrument of SWCC) pressure plate with a 1.5 MPa ceramic plate. When moisture is balanced in a pressure in 48 to 72 h, the soil sample weight will be measured after the moisture balance and soil-water data are got.

2.2 Test results of SWCC

There are 10 groups of experimental data of SWCC measured by using the pressure plate apparatus in the laboratory (see Tab.1) in depth 0 to 2 m. Those experimental data of SWCC are the drying procedures of SWCC.

Tab.1 Experimental data of water content —suction %

Depth/m	Suction/kPa															
	1.0	2.0	3.2	5.0	7.9	10.0	15.8	20.0	25.1	39.8	50.1	79.4	126	200	500	1 000
0.2	41.5	41.2	40.6	40.4	40.2	39.4	35.2	31.1	28.4	22.7	21.4	18.8	17.7	15.9	13.6	13.1
0.4	42.1	41.9	41.2	40.8	40.4	39.0	35.2	27.4	24.9	20.1	17.0	14.9	14.3	12.5	11.0	10.2
0.6	42.3	41.0	40.0	39.1	39.0	37.0	33.7	25.9	23.4	17.6	16.3	14.1	13.7	11.6	10.4	9.4
0.8	48.3	47.6	46.6	45.2	43.8	41.0	31.7	29.9	26.1	20.5	16.1	17.6	16.9	14.3	12.5	11.6
1.0	46.0	45.4	44.5	43.0	42.6	40.2	34.8	28.3	24.8	23.0	17.3	13.7	13.3	11.4	9.5	8.6
1.2	43.2	42.6	42.1	41.0	41.0	39.3	34.3	32.4	28.2	20.8	15.8	15.0	13.8	11.7	9.9	8.9
1.4	**47.1**	**46.3**	**45.4**	**44.5**	**44.3**	**42.1**	**35.9**	**32.7**	**29.9**	**22.4**	**18.2**	**16.9**	**15.7**	**12.7**	**10.9**	**9.6**

3 Using an ANN to Predict Suction of Expansive Soils

3.1 Suction prediction

Suction is one of the principal characteristic parameters. Measuring suction is very difficult in the field and laboratory. We try to use ANN to perform prediction suction. The ANN is a three-layer neural network with one hidden layer. There are 16 input neurons, 30 hidden neurons and 16 output neurons.

Training analysis of ANN consists of two stages. The first stage is called supervised study; the second stage is called unsupervised study. In the implementation of the neural network technique, data are categorized as input patterns and target patterns. The input patterns are fed to the network, which then performs feed-forward computation to calculate output patterns. The output patterns are compared with corresponding target patterns, and the summation of the square of the error is calculated. The error is then back-propagated through the network using the gradient-decent route to modify the weights and minimize the summed squared error. Thus a good mapping between input patterns and target patterns can be achieved, resulting in a network capable of predicting the target patterns for given input pattern. Least square error criterion is expressed as

$$E(w) = \sum_{\alpha}\sum_{i}(O^{\alpha i} - O^{\alpha i}_{\mathrm{des}})^2 \tag{3}$$

where α is the pattern number, i is the neuron number of output layer, $O^{\alpha i}$ is the output pattern, and $O^{\alpha i}_{\mathrm{des}}$ is the desired output pattern.

At the unsupervised study stage, the weight gotten at the supervised study stage is used to calculate output values for unknown input patterns. Those output values are the prediction results of our requirement.

In order to demonstrate the practice and effect of the neural network technique, the experimental data in Tab.1 are utilized for calculating and predicting. The data of three groups are used as input-target patterns for supervised study in the depth 0.4, 1.6 and 2.0 m from Tab.1. In the data, water content is used as input patterns, suction as target patterns. The results of the supervised study are shown in Tab.2, simultaneously, connecting weight values of neurons are obtained in the stage. Using those weight values to calculate another 7 groups of data in other different depths in Tab.1, the computation results are shown in Tab.3.

Tab.2 Calculating data of suction—prediction suction kPa

Depth/m	Suction/kPa															
	1	2	3.2	5.0	7.9	10.0	15.8	20.0	25.1	39.8	50.1	79.4	126	200	500	1 000
0.4	1.1	2.2	3.4	5.2	8.3	10.2	16.2	20.8	25.1	40.5	51.4	80.8	128.3	202.7	501.2	989.7
0.8	0.8	2.0	3.1	4.8	7.3	9.6	15.1	18.6	24.9	38.0	48.7	76.9	121.1	198.1	503.2	997.1
1.4	0.9	2.2	3.3	5.0	8.0	10.2	15.8	20.1	25.1	39.8	50.2	79.4	126.1	200.6	500.5	987.9

Tab.3 Predicting data of suction kPa

Depth/m	Suction/kPa															
	1	2	3.2	5.0	7.9	10.0	15.8	20.0	25.1	39.8	50.1	79.4	126	200	500	1 000
0.2	1.1	2.5	3.7	5.5	9.1	10.8	17.2	22.7	25.3	42.5	53.5	84.5	134.5	205.5	498.4	972.8
0.6	0.9	2.0	3.1	4.8	7.5	9.7	15.4	19.2	25.0	38.8	49.1	77.5	122.8	198.7	502.3	994.4
1.0	0.9	2.0	3.1	4.8	7.5	9.7	15.4	19.1	25.1	38.9	49.2	77.8	123.6	198.2	501.0	995.0
1.2	0.9	2.2	3.3	5.1	8.2	10.2	16.0	20.6	25.2	40.3	50.8	80.4	127.8	202.0	500.0	984.1

3.2 Comparison of prediction suction with measuring data in the laboratory

Generally, the work on prediction suction is performed by SWCC. Eq. (4) proposed by Fredlund and Xing[1] is applied to predict suction.

$$\theta_{\mathrm{w}}(u_{\mathrm{s}}, a_{\mathrm{s}}, n_{\mathrm{s}}, m_{\mathrm{s}}) = C(u_{\mathrm{s}})\frac{\theta_{\mathrm{s}}}{[\ln(e + (u_{\mathrm{s}}/a_{\mathrm{s}})^{n_{\mathrm{s}}})]^{m_{\mathrm{s}}}} \tag{4}$$

where θ_{w} is the volumetric water content, θ_{s} is the volumetric water content at saturated, u_{s} is the soil suction, a_{s} is the soil parameter approximating the air entry of the soil, n_{s} is the soil parameter related to the rate of desaturation, m_{s} is the soil parameter related to residual water conditions, and $C(u_{\mathrm{s}})$ is the correction factor to ensure that the function goes through 100 MPa of suction at zero water content. For the data of SWCC in Tab. 1, $a_{\mathrm{s}} = 13.13$, $n_{\mathrm{s}} = 0.892$, $m_{\mathrm{s}} = 1.87$. The suction values predicted by Eq. (4) are compared with the values predicted by ANN in the depth 0.6 m (see Tab. 4). The prediction results show that the prediction precision of ANN is better than SWCC's for the laboratory data. If there are cycles of drying and wetting data for ANN training, the effect of the hysteresis of cycles of drying and wetting on SWCC will be considered to predict the soil suction.

Tab.4 Prediction analysis kPa

Suction values	1	2	3.2	5.0	7.9	10.0	15.8	20.0	25.1	39.8	50.1	79.4	126	200	500	1 000
Suction predicted by ANN	0.9	2.0	3.1	4.8	7.5	9.7	15.4	19.2	25.0	38.8	49.1	77.5	122.8	198.7	502.3	994.4
Suction predicted by Eq. (4)	0.9	1.9	3.9	6.3	9.4	11.8	15.7	27.5	33.3	58.0	68.2	94.9	101.8	168.6	442.1	894.2

3.3 Comparison of prediction suction with measuring data in the field

It is recognized that there are many factors affecting the effects of soil suction distributions of unsaturated soil mass in the ground. The affecting factors include initial density and water content, permeability, cracks, rainfall infiltration, evaporation, etc. To study matrix suction distribution, we monitor soil suction and volumetric water content with thermal conductivity sensors at different depths in the ground at Gongerzhuang expansive canal slope of Yan-Huan-Ding Hydraulic Engineering of the Ningxia Autonomous Region. The monitoring data are shown in Tab.5. ANN is used to predict the soil suction of different depths according to water monitoring content data in the field, and the prediction suction data are also shown in Tab. 5. However, the monitoring data collected in the field were few because the tensiometers had been destroyed.

Tab.5 Monitoring and ANN predicting data in the field

Depth/m	Monitor position 1			Monitor position 2		
	Monitoring suction/kPa	Water content/%	ANN predicting suction/kPa	Monitoring suction/kPa	Water content/%	ANN predicting suction/kPa
0.5	33.8	24.8	34.7	20.6	31.8	19.3
1.0	27.6	26.3	25.9	26.1	29.7	26.8
1.5	39.2	20.7	36.2	37.5	21.5	40.5
2.0	40.4	19.5	39.6	38.3	21.1	37.4

From the above prediction and analysis results, the results predicted by ANN are in agreement with experimental values, which show that ANN is very effective and practical. In practical engineering, we can predict suction of the expansive soil slope based on partial data of water-suction with ANN.

4 Conclusions

1) Artificial neural network technology can be applied to predict the soil suction of unsaturated expansive soils using partial water content-suction data. The results of prediction suction using ANN show that the method is effective and practical, and the prediction suction of ANN is of high precision.

2) The prediction precision of SWCC is not good because SWCC are got in the laboratory. Unsaturated soils in the field are subjected to repeated cycles of drying and wetting throughout the year, so SWCC can not describe the effect of those factors. If there are cycles of drying and wetting data for ANN training, the effect of the hysteresis of cycles of drying and wetting on SWCC will be considered to predict the soil suction.

3) The prediction technology of ANN can be used to analyze the stability of the expansive soil slope because the soil suction predicted of unsaturated expansive soils can be used to study the strength of unsaturated expansive soils.

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膨胀土中的吸力预测研究

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摘要: 膨胀土的水分特征曲线通常是在实验室测得的, 在现场测量膨胀土的吸力不仅费时而且也非常困难. 本文采用人工神经网络技术用现场测得的含水量来预测土的吸力. 网络训练首先采用水分特征曲线相应的试验数据进行监督训练, 然后利用监督训练得到的网络单元的连接权值对现场测得含水量数据进行吸力预测, 预测结果与实测结果相近, 同时并对预测结果进行了分析讨论.

关键词: 膨胀土; 水分特征曲线; 人工神经网络; 吸力

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