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Experimental and Predictive Study on Salt Expansion Behaviors of Frozen Saline-alkali Soil

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Saline-alkali soil is typically expansible due to salt expansion. Salt expansion always affected by water migration and salt crystallization. As for the soil in frozen ground, salt expansion behavior is also influenced by the temperature and the salt-water reaction. Thus the expansion behavior of frozen saline-alkali soil is a complex and nonlinear problem, which brings damages to structures and engineering, such as subgrade and infrastructure deformations. In this paper, experiment of salt expansion behaviors is carried on, in which the soil samples are mixed with different content of water, salt. And the influence of the water and salt on the salt expansion is analyzed. To study the salt expansion characteristics, two different kinds of mathematical methods are applied, including the back propagation neural network (BPNN) and support vector machine for regression (SVR). 300 data are used for training, and 35 data are used for testing. The calculated results of BPNN and SVR are compared with the experimental data. The results indicate that SVR is superior to BPNN in prediction. And both methods indicated that water and salt influenced salt expansion strongly, which provides reference in environment engineering and chemical engineering.

1. Introduction

Saline soil is affected by salt and alkali. Such soil contains saline, alkali, and other soil at different degrees of salinization (Wang et al., 2017). In engineering, saline soil is defined as the soil with more than 0.3 % soluble salt (Zhang et al., 2015a). In saline soil regions, dissolution, settlement, salt expansion and corrosion always occur. Frozen soil refers to soil and rock containing ice below 0 ℃. Frozen soil can be divided into permafrost and seasonal frozen soil (Xu et al., 2010). Frost heave is caused by volume expansion when the water in soil freezes solid. Unlike ordinary frozen soil, frozen saline soil often experiences salt expansion caused by salt crystallization. Frost heaving of soil causes a number of serious engineering problems such as subgrade deformation, pavement crack, pile foundation uplift and so on. Thus, it is necessary to study the expansion of frozen saline soil.

The causes of the expansion of frozen saline soil can be well analysed through mathematical modelling and numerical simulation (Zhang et al., 2017a; Zhang et al., 2017b). However, factors affecting soil expansion are fuzzy and complex, and it is very difficult to distinguish frost heaving and salt expansion. To solve the problem involving complex influencing factors, machine learning is used as it shows a stronger ability in prediction. Almost all prediction approaches can be summarized in three categories: traditional statistical forecasting method, empirical nonlinear prediction method and statistical learning theory (Cherkassky and Mulier, 1999). The traditional statistical prediction method is based on the structure types of known parameters. Among the different mathematical methods, artificial neural network (ANN) is widely applied in pattern recognition, automation and other areas. It is often used to predict the deformations in civil engineering (Adeli, 2001), and SVM is widely used in different fields such as wind speed prediction, failure prediction and so on and has proved its excellent predicting effect (Zhou, 2016). Thus these two methods are applied in this paper.

This paper aims at revealing methodologies for predicting the expansion behaviours of frozen saline soil. According to the test results, it establishes the expansion behaviour prediction models. The ANN and SVM models are implemented using MATLAB. In these two models, 335 data are used to form four input variables, including water content, dry density, temperature, and salt content, and one output variable. Out of the

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experimental data, 300 are randomly selected as training data and the other 35 data as test training data, used to construct the models. The calculated results of ANN and SVM are compared with the experimental data.

2. Experimental study

2.1 Experimental materials

In this study, the soil studied was collected from Nong'an, Western Jilin, China. The soil at a depth of 40 cm is typical in terms of salt content and other aspects and is affected little by artificial disturbance. Thus, soil samples were collected at the depth of 40 cm for the experiments (Zhang et al., 2015b). The basic properties of the soil samples are shown in Table 1 and 2.

Table 1: Grain-size distribution and naming of original sample

Particle distribution proportion (%)			Naming
Sand	Slit	Clay	
2.53	42.66	40.13	Silty clay

Table 2: Basic physicochemical properties of original sample

Water content (%)	Density (g/cm^3)	Total soluble salt (%)	pH	Organic matter
26.55	1.92	1.398	7.04	1.12

2.2 Experiment and soil sample design

The influencing factors to soil frost heaving can be divided into two categories (Li, 2015): one is the internal factors of soil, such as grain size, physicochemical properties, water content, compactness, content of soluble salts and so on; and the other is the external factors, mainly including temperature and exterior load, etc.. This paper mainly focuses on engineering characteristics of frozen saline soil. The influencing factors to frost heaving can be summarized as follows - water content (W), compactness (C), content of soluble salts (S) and temperature (T). Water contents were selected according to the optimum water content in the experiment. Through the compaction test, the optimum water content was found to be 22 %, so water contents were set as 18 %, 20 %, 22 %, 24 % and 26 %, respectively. Based on the previous research (Wang et al., 2017), as the compactness increases, frost-heaving would usually get more obvious, but when compactness increases to a certain degree, the frost heave ratio would decrease. The compactness is required to be greater than 85 % in general engineering (Wang et al., 2016). So in this experiment, soil compactness was set at 85 %, 90 % and 95 %. Content of soluble salts is an important influencing factor to frost heaving - frost-heaving increases as the content of soluble salts increases (Huo, 2016). In previous sample research (Li, 2015), the content of soluble salts was as much as 2.6 %. Therefore, the content of soluble salts was set at 0 %, 0.75 %, 1.5 % and 3 % through desalinizing and salting. Considering the salt in saline soil can reduce the freezing temperature and actual soil horizon temperature, the experimental temperature was set as 15 °C, 10 °C, 5 °C, 0 °C, -5 °C, -10 °C and -15 °C.
Unloaded frost heave ratio was used in this experiment. The frost heave ratio can be calculated by the following equation:

$$\eta = {}^{\Delta h}/_{h_0} \times 100\% \tag{1}$$

where η is the frost heave ratio; Δh is the frost-heaving height of soil sample; and h_0 is the original height of soil sample.

2.3 Experimental method

Because the actual soil is semi-infinite space, the frost heave measuring instrument used in this experiment adopted the laterally restricted steel tube, which was closely connected with pedestal at the bottom. There was no external load on the top of the steel tube to ensure the soil sample can only extend to one direction. The steel tube was 55 mm in diameter and 100 mm in height, and frost heave was measured by a dial indicator with an accuracy of 0.001 mm. The experimental temperature ranged from -15 °C to 15 °C. The temperature controlling instrument could automatically enable the thermostat function and the temperature controlling accuracy was 0.1 °C.
First, the author compacted the remolded soil in five layers into the steel tubes and kept them in the frost heave measuring instruments indoors for 24 hours. The author placed all the frost heave measuring

instruments in the temperature controller and adjusted the dial indicator to record the initial value. Finally, the author used the temperature controller to adjust the temperature to 15 °C and maintained it for 6 hours. Then the author recorded the reading at 15 °C, lowered the temperature at 1 °C/h and recorded the frost heave at 10 °C, 5 °C, 0 °C, -5 °C, -10 °C and -15 °C, respectively. A total of 60 samples were tested and 420 data were recorded. After data sorting, some representative experimental results were obtained, as shown in Figure 1.

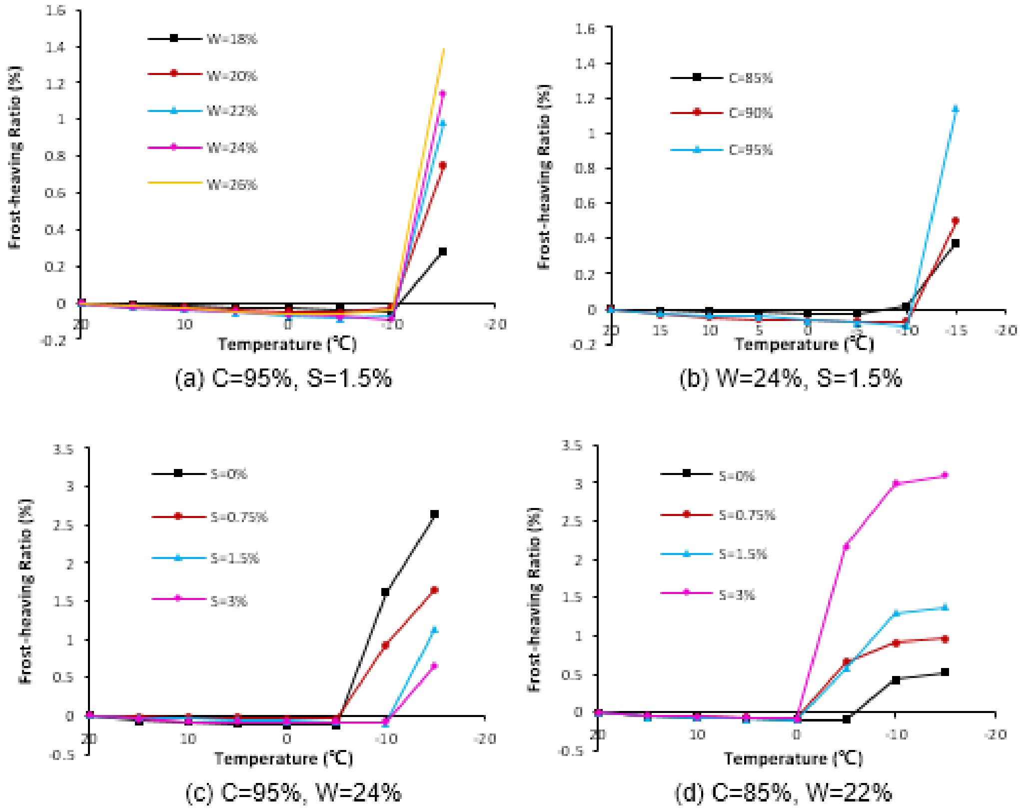

Figure 1: Relationship curves between frost heave ratio and temperature

From the experimental results, it can be seen that the soil samples collapsed slightly before temperature lowered to -5 °C, and expanded with the temperature continuing to cool down. Figure 1 (a) and (b) show that there was a positive correlation between frost heave ratio and water content or compactness as the water content or compactness increased at a certain minus temperature. The water in the sample expanded as it freezed, so water was the root cause of frost heave. And the more water there was in soil, the greater it would expand. As the compactness decreased, the large pores in soil became smaller gradually. Ice crystals could easily fill the pores and get soil to expand. So the frost heave ratio increased as water content or compactness increased within certain limits. From Figure 1 (c) and (d), it can be seen that the changes in frost heave showed no obvious pattern. This was because the initial freezing temperature and the unfrozen water content were affected by the variation of salt content. The coupling of temperature, water and salts make the relationship between salt content and frost heave more complicated. So this paper selects the artificial neural networks and support vector machine to solve this complex problem.

2.4 Development of ANN model

The artificial neural network is an information processing system which simulates the structure and functions of the biological nerve system. Nerve cell is the basic unit of the artificial neural network. In general, it is a multi-input and mono-output nonlinear unit. A nerve cell has three basic elements. The connection weights are corresponding to the synapses of biological nerve cells. And strength of connection between the nerve cells is represented by the weight of the connection weight. The summation unit is applied to the weighted sum of all the input signals. The activation function plays the nonlinear mapping role, and limits the output amplitude of nerve cells in scope. The *Sigmoid* function is the common activation function:

$$\varphi(x) = \frac{1}{1+exp(-ax)} \tag{2}$$

where a is the slope control parameter. The functional relations can be expressed as follows:

$$u_k = \sum_{j=1}^{p} w_{kj}x_j \, , y_k = \varphi(u_k - \theta_k) \tag{3}$$

where $x_1, x_2, \cdots, x_p$ are input signals, which act as dendrites of biological nerve cells. They are the input information of artificial neurons. $w_{k1}, w_{k2}, \cdots, w_{kp}$ are weights of artificial neuron k. u_k is the result of linear combination. θ_k is the threshold; $\varphi(\cdot)$ is activation function; and y_k is output signal, which acts as the axon of the biological nerve cell. It is output information of artificial neuron.

This paper uses the three-layer BPNN model to predict the frost heave of frozen saline soil. Water content, compactness, content of soluble salts and temperature are four input variables, respectively, and frost heave ratio is the only output variable. Among the experimental data, 300 are randomly selected as training data and the other 35 are test training data. Because the data have significant differences between variables in orders of magnitude, data should be normalized by the following formula:

$$X_n = (X - X_{\min}) / (X_{\max} - X_{\min}) \tag{4}$$

where X_n is the normalized data; X is the raw data; $X_{\min}$ is the minimum raw data; and $X_{\max}$ is the maximum raw data. The above-mentioned data were selected to train for the same times with different neuron numbers. Through comparison of the mean squared errors (MSEs) and R-square coefficients (R^2) of the two statistical parameters, the number of neurons in the hidden layer can be obtained:

$$\mathrm{MSE} = \frac{1}{N}\sum_{i=1}^{N}(experimented_t - predicted_t)^2 \tag{5}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(experimengted_t - predicted_t)^2}{\sum_{i=1}^{N}(predicted_t)^2} \tag{6}$$

where N is the number of samples, $experimented_t$ is the value of experimental data, and $predicted_t$ is the value of predicted data. A MSE and a large R^2 mean a better simulation effect.

2.5 Development of SVM model

Support vector machine is a new method of machine learning based on the statistical learning theory. The statistical learning theory adopts the structural risk minimization principle, which minimises the errors of samples and at the same time minimises the structural risks, with no limitations to the data dimension, so it is widely applied (Cortes and Vapnik, 1993). When the linear classification is used, the hyperplane is selected at the relatively distant location between two classes of samples. And by altering the high dimension space, we can transform the problem of nonlinear classification into linear classification.

In order to solve the regression and fitting problem of SVM, the insensitive loss function ε is introduced into the SVM-based classification method (Tay and Cao, 2002). Then the support vector machine for regression (SVR) is obtained and works very well (Flake and Lawrence, 2002). The basic idea of SVR is to search an optimal hyperplane to minimize the errors between all the training samples and this optimal hyperplane. Suppose the training set including l training samples is $\{(x_i, y_i, i = 1,2,\cdots,l)\}$, where $x_i(x_i \in R^d)$ is the input column vector of the *i*-th training sample, $x_i = [x_i^1, x_i^2, \cdots, x_i^d]^T$,and $y_i \in R$ is the corresponding output value. Suppose the linear regression function is established in the high dimensional feature space:

$$f(x) = w\Phi(x) + b \tag{7}$$

where $\Phi(x)$ is the nonlinear mapping function, $w \in R^{\mathrm{d}}$ and $b \in R$. ε is defined as the insensitive loss function:

$$L(f(x), y, \varepsilon) = \begin{cases} 0, & |y - f(x)| \le \varepsilon \\ |y - f(x)| - \varepsilon, & |y - f(x)| > \varepsilon \end{cases} \tag{8}$$

where $f(x)$ is the predicted value of the regression function, and *y* is the corresponding actual value.

3. Results and discussion

The programmes for both BPNN and SVR model are developed and implemented under MATLAB. Figure 2 shows the simulation results of the test set for BPNN model and SVR model. The results of MSE and R^2 for the two models are shown in Table 3.

Table 3: MSE and R^2 values under the BPNN and SVR models

Statistics parameters	BPNN		SVR	
	Training set	Test set	Training set	Test set
MSE	0.0011	0.0037	0.0006	0.0028
R^2	0.9637	0.8642	0.9941	0.9443

Figure 2 show the simulation results of the normalized frost heave ratio are very good for the test sets in both models. The simulation results of the test sets show that there are some differences between the experimental values and the simulated values when the η is very high or low. The reasons for such differences are as follows. When η is small, the frost heave ratio is below zero, which means that the soil sample is in a contractive condition (see Figure 1). This phenomenon is called frozen contraction. When the temperature does not reach the freezing point, or the water content is relatively low, water does not freeze or the pores are not filled with water. But with the temperature dropping, the volume of the air in the pores decreases, which reduces the volume of pores and causes the soil samples to contract. This frozen contraction phenomenon is very complex, leading to deviations in the simulation. As there are few data with large η, when η is large, there will also be some deviations in the simulation values.
MSE and R^2 values in Table 3 show the simulation effects of frost heave ratio by the BPNN and SVR models are very good. And the predictions of frost heave by the SVR model are more accurate than those by the BPNN model. The reason is that the BPNN model cannot ensure the global optimization result, because it adopts the most fast grads descent methodology to optimize weights. And it only guarantees converging to a one point in all optimal results. On the other hand, the simulation by the SVR model corresponds to the quadratic programming problem under linear constraint, and the solution is unique and optimal. Considering the multiphase and anisotropism of soil, and the many factors affecting the experimental design including water content, compactness, content of soluble salts and temperature, the simulation results of the SVR model are good enough for the complex situations.

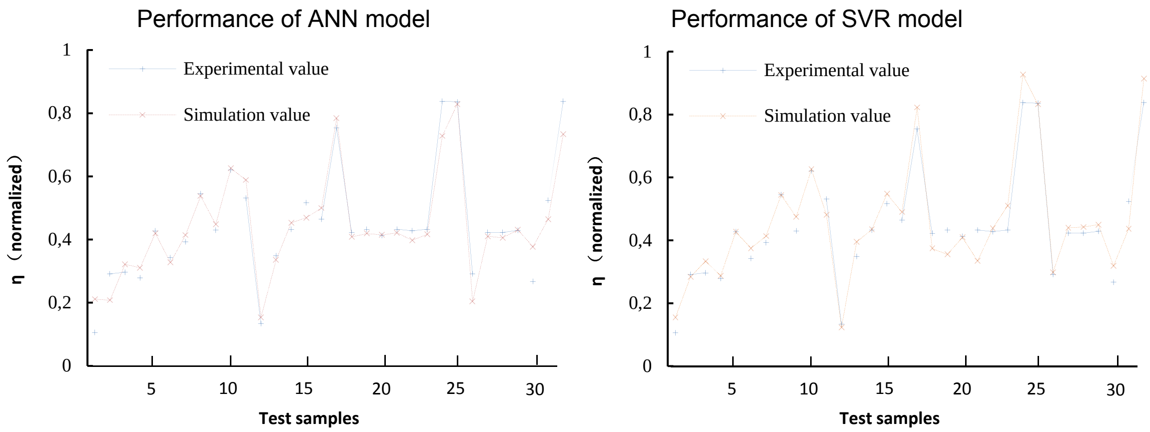

Figure 2: Simulation results of the test sets for ANN and SVR models

4. Conclusions

This paper designs four influencing factors to frost heave for the experiment, including water content, compactness, content of soluble salts and temperature, and discusses the effect of each factor on the frost heave. Besides, this paper also simulates the frost heave ratio with four influencing factors using the BPNN and SVR model. Both models use the same sample data for simulation and the MSE and R^2 values are compared. From this research, the following conclusions are obtained:

1. In this experiment, four influencing factors are selected and their value ranges are determined. The initial frost-heaving temperature is about -5 °C, and the frost heave ratio increases as the water content or compactness increases. The effect of the content of soluble salts on frost heave ratio is relatively complex without any obvious pattern.
2. In the prediction process, the empirical nonlinear prediction methods and statistical learning theory are used to predict the frost heave ratio of frozen saline soil in this paper. The empirical formula determines the neuron number of the hidden layer in the BPNN model and optimum parameters are selected by calculation in the SVR model. The simulation results show that both models are practicable and effective for predicting the frost heave ratio of frozen saline soil.

3. In order to compare the simulation effects of the BPNN and SVR models, two statistics parameters - mean squared error (MSE) and R-square coefficient (R^2) - are selected to calculate the errors between experimental values and simulation values. The smaller MSE value and the larger R^2 value in the SVR simulation show that the simulation effect of the SVR model is better than that of the BPNN model.

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