Characteristics and Prediction of Frost Heave of Saline Soil in Western Jilin Province

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ABSTRACT

Frost heave of saline soil in seasonal frozen areas causes a serious loss to construction and agriculture production. Predicting the frost heave in any condition accurately can provide a basis for engineering and elimination of the frost heave disasters as much as possible. According to the results of the laboratory experiments, the deformation of the saline soil initially increases until it stablizes as the temperature decreases It increases as the moisture content and the degree of compaction increases, and it initially increases and then decreases as salt content increases. So there is always a complex nonlinear relationship between the frost heave and temperature, moisture content, salt content, and degree of compaction. RBF can easily achieve the local minimum and approximate any arbitrary accuracy of the global nonlinear relationship. Therefore, it has strong ability of processing and forecasting nonlinear data. Based on the results of the laboratory experiments of saline soil in Nong'an, located in western Jilin Province, RBF neural network model is established with the influencing factors of temperature, moisture content, salt content and degree of compaction. 30 groups of data are used as training samples and 5 groups are used as prediction samples to inspect the accuracy. The results show that the RBF model presents good ability in handling and predicting. It has high accuracy and the errors are small. So frost heave can be studied by the results of laboratory tests and be predicted by RBF model.

Keywords: Frost heave, RBF neural network, Saline soil, Prediction, Temperature.

1. INTRODUCTION

Saline soil is defined as a kind of special soil in which soluble salt content is higher than 0.3%. It is widely distributed in the world. In China, the area of saline soil is about 19.08×10^4 km², which accounts for 2% of the national territory [1-2]. Saline soils are a widely distributed important land resource. Salt-affected soils are mainly distributed in the northeast China plain, central-north area, northwest inland, north China and coastal areas [3]. However, saline soil is a specific geological environment which brings a serious loss to construction and agriculture production [4]. The western area of Jilin Province is a typical saline soil distribution area in northeastern China [5]. Additionally, it is a typical seasonal frozen region [3]. The winters are severely cold. In winter, this area is has poor properties of ice crystals and soluble salt. Salt and water migrate from underground to the freezing front with frozen soil[11]. In spring, the ice melts and salt migrates to the surface, and with the evaporating of moisture, salt crystals remain [3]. Thus, the ecosystem in this area is very fragile, and the changing of moisture, salt, temperature increases the degree of soil salinization and frost heave [6].

Saline soil in western Jilin Province is mainly soda saline soil [3, 5-6]. Though the frost heave of soda saline soil is smaller than sulphate saline soil, it has still causes a serious loss to construction, such as frost boiling, frost heave, differential settlement [6]. Therefore, it is necessary to analyze the frost heave properties of saline soil to eliminate disasters. Accurate prediction of the frost heave in any condition can provide a basis for the design of engineering and eliminate the frost heave disasters as much as possible.

Mathematical model and numerical simulation are becoming more and more popular [7-8]. There are many influencing factors with frost heave, and they have the properties of complexity, fuzziness and nonlinearity. So, use of a quadratic polynomial to establish the mathematical model of frost heave is not appropriate. Recently, many researchers have used a nonlinear method to predict the frost heave. There are many nonlinear methods [9-10]. Artificial neural network is a kind of nonlinear method, and BP neural network is the most widely used artificial neural network [11-12]. However, the latter has the disadvantages of strike conditions, slow convergence speed, stuck in local minimum and is difficult to achieve the global optimum. To solve the disadvantages of BP neural network, Moody proposed the radial basis function (RBF) neural network [13]. RBF neural network was used to predict frost heave of saline soil in this paper, and the results were proved by laboratory experiments.

2. RBF NEURAL NETWORK
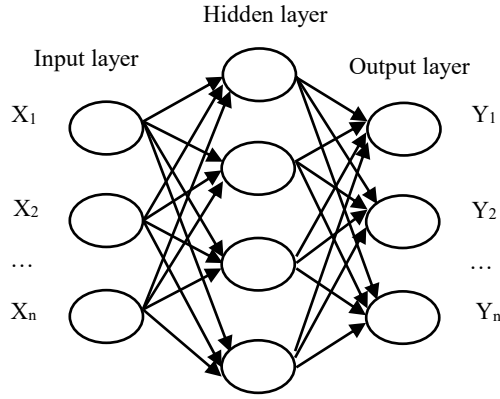
Figure 1. Neural network structure of RBF

RBF, a kind of efficient feed-forward network, is based on function approximation theory [14]. As shown in **Figure 1**, RBF is formed of three layers, namely the input layer, hidden layer and output layer. The main function of the input layer is to map the input vector directly to the hidden layer. They are signal source nodes. The hidden layer is composed of some hidden nodes. The mapping function of the hidden layer is a radical basis function, which has a radial symmetry to its center and decay nonnegative nonlinear function. The output layer can accomplish linear mapping. The RBF neural network, a unity of linear function and nonlinear function, has the advantages of simple structure, self-adapting architecture determination and quick convergence speed [15]. Gaussian function is used as the transfer function in the hidden layer, and the formula is:

$$R_i(x) = \exp\left[-\|x - C_i\|^2 / (2\alpha_i^2) \right], \text{i=1, 2, ..., r}$$

where $R_i(x)$ is the ith neurons node, x is n dimensional input vector, C_i is the center of the ith hidden node function, α_i is the normalized parameter of the ith hidden node, and r is the number of the hidden layer nodes.

The RBF neural network is composed of unsupervised learning and supervised learning. K-means clustering method is used in supervised learning stage to determine the clustering center C_i and α, after which, RBF becomes linear output. Thus, in the supervised learning stage the least square method is adopted to output the weight W_j. The steps are as follows:

(1) The data is normalized to a certain scope with the method of minimum or maximum normalization.

(2) Calculate the output value Y_h in the hidden layer with the radial basis function.

(3) Calculate the output value Y_j of the jth neural node in the output layer. The formula is:

$$Y_j = f\left(\sum_{i=1}^{r} W_{ji} Y_{hi} \right)$$

where Y_{hi} is the output value of the ith neural node in the hidden layer, and W_{ji} is the weight of the ith neural node in the hidden layer to the jth neural node in the output layer. The form of function f is Sigmoid:

$$f(x) = 1 / (1 + \exp(-x / x_0))$$

(4) Calculate the output error.

$$\Delta Y_j = Y_j (-Y_j)(y_j - Y_j)$$

where y_j is the real value of the jth neural node.

(5) Adjust the weight coefficient until the error meets the requirement.

$$\Delta W = \varepsilon \times \Delta Y_j (1 - Y_j)(y_j - Y_j), W_j' = W_j + \Delta W$$

where W_j' is the adjusted weight, and ε is the speed of learning.

After the clustering center C_i and the weight W_j are determined, prediction can be conducted through the trained model.

3. STUDY AREA

Jilin Province, in the west of China, is a typical seasonal frozen region, where salinization is very severe. The summers are quite hot and the winters here are severe cold. The difference in temperature between winter and summer is quite large. Winters last from November to March with temperatures below zero [5]. The highest recorded temperature in this province was 38℃ and the lowest temperature was -36.5℃. The average temperature is 4.6℃. The precipitation is concentrated from June to August, and the annual precipitation is low [3]. The spring and autumn periods have strong evaporation, which results in the soil lacking effective leaching, so salt accumulation is far greater than the leaching effect. Thus, a large amount of salt accumulates in the surface of the soil, making Jilin Province a typical saline soil area. The study area in this paper is located in Nong'an which belongs to the western area of Jilin Province. The coordinate of the sampling site is N44°20′46″, E124°58′07″. The soil samples were collected on November 19th, 2014. On-site investigation showed that salinization phenomena often occurred in this area. The surface of the land was dry, and the color was grayish white because of the accumulation of soluble salt crystals. Through laboratory experiments, the soil in this province is defined as carbonate saline soil. The granulometric composition of samples were tested by a combination of the settling and sieving methods. According to the results, silt (0.075-0.005 mm) was the main constituent. The natural moisture content varies from 8% to 34%, and the soluble salt content varies from 0.3% to 2.69%. The PH values varies from 6.48 to 7.32, and the organic matter content is 0.25%-1.61%.

4. EXPERIMENTS OF FROST HEAVE

Many scholars have determined that temperature, salt content, moisture content and degree of compaction are important factors influencing the frost heave of saline soil through many studies. So in this paper, these four factors are considered in the experiments of frost heave. It is necessary to compact saline soil in engineering for its poor properties. But the moisture content should be near the optimum

moisture content when the soil is compacted. Through the standard compaction test, the optimum moisture content of the saline soil in Nong'an is 22%. The soil was dried in air, crushed and sieved to ensure the particles were less than 2mm. Distilled water was added to replicate the moisture content of 18%, 20%, 22%, 24% and 26%. Long-term monitoring reveals that the soluble salt content varies from 0.3% to 2.69%. So in this paper, Na_2CO_3 was added to replicate the salt content of 0.5%, 1.42%, 2% and 3%. Soil samples were compacted into steel tubes (large rigidity to avoid lateral deformation) of 10cm in height and 5.4cm in diameter with a compaction degree of 85%, 90% and 95%. All the samples were put into a home-made freezing and thawing apparatus. Frost heave happens in temperatures below zero, so in this study, the frost heave experiment was conducted under the temperatures of 0℃, -2℃, -5℃, -8℃, -12℃, -20℃ and -25℃.

4.1 Influence of temperature

As **Figure 2** shows, with the decrease in temperature, frost heave initially increases and then levels off at a stable value. Using a quadratic polynomial as the fitted curve is best. A temperature below zero is the precondition of the frost heave, but the freezing temperatures of different forms of water in soils vary. Water under gravity and capillary water begin to freeze at 0℃, and loosely bound water on the surface of the soil particles begins to freeze at -1℃ due to adsorption. The water layer is completely frozen under -20℃-30℃, and strongly bound water begins to freeze at -78℃. Hence, water in soil will gradually freeze to generate a significant frost heave effect as the temperature decreases. When the temperature reaches -20℃, loosely bound water will be completely frozen and the frost heave will be basically stable. So, the frost heave initially increases and then levels off at a stable value.
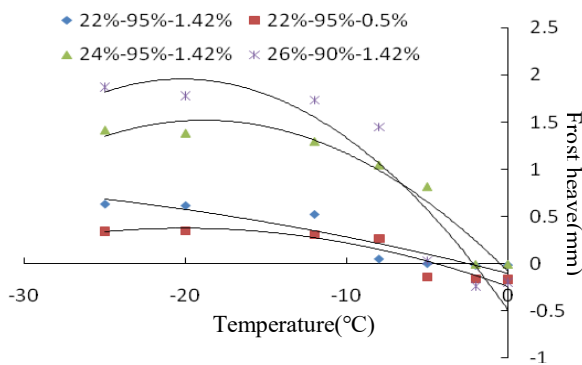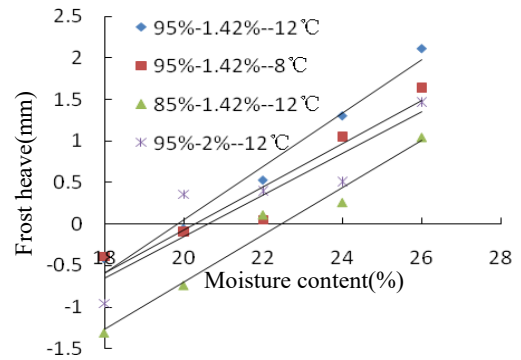

Figure 2. Relationship between frost heave and temperature

4.2 Influence of moisture content

As **Figure 3** shows, frost heave increases with the moisture content. When the moisture content is low, water cannot fully saturate the intergranular pores. Even if volume swells when water changes into ice, the formed ice cannot fully immerse the pores as well. Additionally, soil particles and air will shrink in low temperature, so the soil shrinks. Water gradually fills the intergranular pores fully with the increase

of moisture content. In low temperatures, the formed ice not only can fill pores, but also increase the space of soil grains, so the soil expands. Frost heave increases with the moisture content overall.

Figure 3. Relationship between frost heave and moisture content

4.3 Influence of salt content

As **Figure 4** shows, frost heave initially increases with the salt content and then decreases. Use of a quadratic polynomial as the fitted curve is best. Salt itself has the property of salt heave in low temperature. Although the freezing temperature of the solution reduces when salt is dissolved, the lasting time of the freezing increases, allowing the salt crystals and ice crystals to develop fully. Additionally, Na^+ increases the unfrozen moisture content, so the frost heave effect increases. At the same time, Na^+ can absorb some bound water when salt content is high. The absorbed bound water has extremely strong binding with ions. It will contribute to the frost heave only when the temperature is very low. Moreover, Na_2CO_3 will take out part of the crystal water which has an inhibitory effect to frost heave. Therefore, frost heave initially increases with the salt content and then decreases.
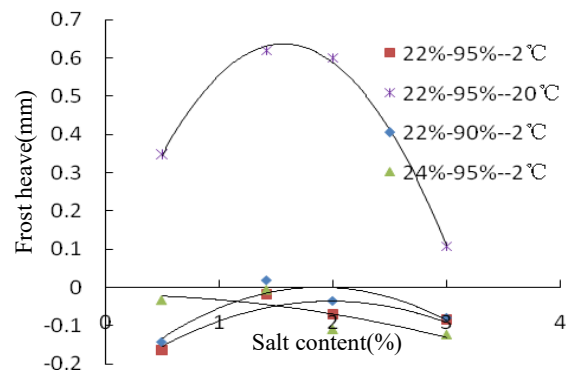
Figure 4. Relationship between frost heave and salt content

4.4 Influence of compaction

Figure 5 shows the relationship between frost heave and degree of compaction. Frost heave increases with the degree of compaction. When the degree of compaction is low, the soil is relatively loose and the porosity is high. The formed ice in low temperatures cannot fully saturate the pores. When the degree of compaction increases, soil gradually becomes denser and porosity becomes lower. Then film water gradually changes into capillary water leading to the increase of potential soil water. Unfrozen moisture content becomes

larger and helps to increase the space of soil grain, so frost heave increases with the degree of compaction.
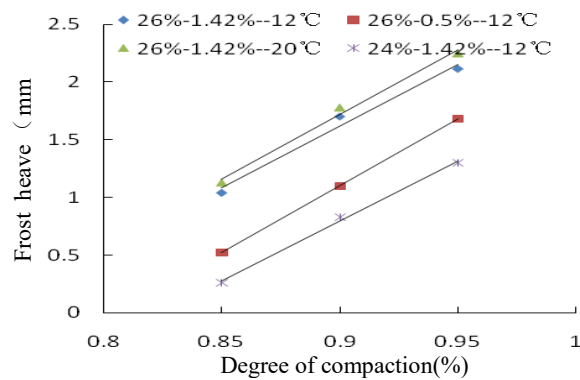

Figure 5. Relationship between frost heave and degree of compaction

4.5 Influence degree of each factor

From the experiments above, it can be seen that temperature, moisture content, salt content and degree of compaction have a certain relationship with frost heave, but the degrees of influence are different. The path analysis method was first proposed by Sewall Wright in 1921 to analyze the relativity of more than one independent variable and dependent variable. Path analysis is a multivariate statistical technique that is based on regression analysis It aims to determine the influence of dependent variable affected by independent variables in complex conditions. Regarding frost heave as a dependent variable and four factors (temperature, moisture content, salt content and degree of compaction) as independent variables, the relativity of frost heave and four factors is determined through path analysis as shown in **Table1**.

Table 1. Pearson correlation between frost heave and the four factors

	Frost heave	Temperature	Moisture content	Salt content	Degree of compaction
Frost heave	1	0.304	0.667	0.260	0.229
Temperature	0.304	1	-0.251	0.050	-0.382
Moisture content	0.667	-0.251	1	-0.077	0.390
Salt content	0.260	0.050	-0.077	1	0.101
Degree of compaction	0.229	-0.382	0.390	0.101	1

Table 1 shows that the order of factors according to relativity is as follows: moisture content > temperature> salt content>degree of compaction. The correlation coefficient is 0.667, 0.304, 0.260, 0.229 respectively.

5. PREDICTION OF FROST HEAVE

Laboratory experiments reveal that frost heave has complex nonlinear relationship with temperature, moisture content, salt content and degree of compaction. So, the RBF model can be established through part of stochastic experiment data. Temperature, moisture content, salt content and degree of compaction are used as the input layer and frost heave is used as the output layer. Then, frost heave in any condition can be predicted when the factors are input. Due to the complex environment, predicting the frost heave in any condition accurately can provide a basis for the design of engineering and eliminate the frost heave disasters as much as possible.

The RBF neural network model of saline soil in Nong'an was established based on MATLAB. Temperature, moisture content, salt content and degree of compaction were used as input layers and frost heave was used as the output layer. 35 groups of experimental data were selected randomly to participate in the training and predicting of the model. Among them, 30 groups were used for training and 5 groups were used for predicting. To avoid large errors caused by the dimensional and numerical differences of different influencing factors, each influencing factor was standardized to [0, 1] first with the method of minimum or maximum normalization. Then, the standardized data were input into the RBF model to predict the frost heave and examine the accuracy of the RBF model. The training result is shown in **Figure 6**, and the predicting result is shown in **Figure 7**. **Figure 8** shows the error and **Figure 9** shows the error percentage.
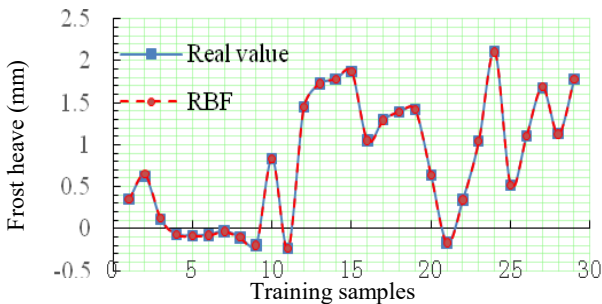

Figure 6. Training frost heave with RBF

As Figure 6 shows, the RBF model has strong generalization ability in the progress of training data. The sum of the training errors is only 0.044mm, and the training effect is quite good. In the progress of predicting, shown in Figure 7, the result has a good fit with the real values. They fluctuate little with the real values. The sum of the predicting errors is only 0.024mm. In both the training stage and predicting stage, as shown in Figure 8, errors are small and relatively balanced. Some are positive and some are negative, which means that the results are not always larger or smaller than the real values. As Figure 9 shows, the error percentages are very small, with almost every error percentage fluctuating little with 0 except for a few individual points. The largest error percentage is 12.1% and the average percentage is 0.298%. The average absolute error percentage is 1.127%.
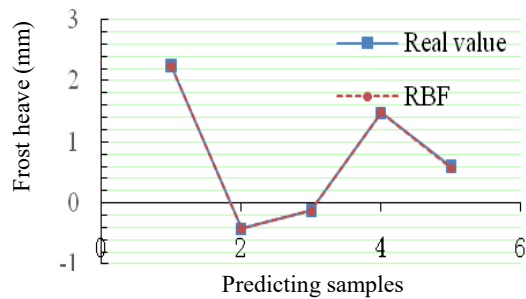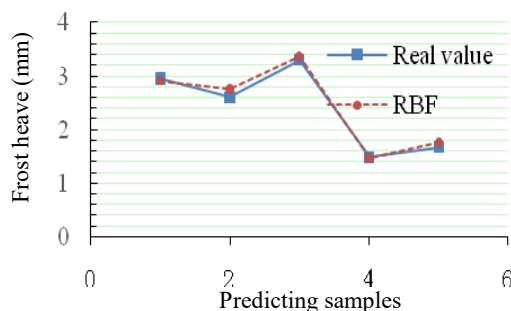
Figure 7. Prediction frost heave with RBF
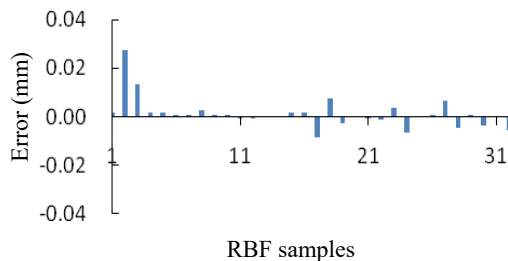
Figure 8. Error of the frost heave with RBF
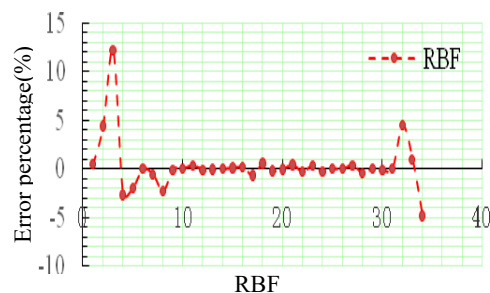
Figure 9. Error percentage of the frost heave with RBF

Figure 10. Prediction frost heave in reference [12]

In order to enhance the reliability of this method, five groups of other data in Nong'an were selected from the reference [12] to validate the effect of the RBF model. The sampling site in the reference [12] is near the sampling site of this study, and the saline soil has similar properties with this study. So it's feasible to use the established RBF model in this paper to predict frost heave in the reference [12]. As Figure 10 shows, the predicting effect is excellent. So the RBF neural network model has good prediction results within the calibrated condition.

The RBF neural network model uses temperature, salt content, moisture content and degree of compaction as input layers, and has a good effect in predicting frost heave of saline soil. It can not only predict the expansion phenomenon and shrink phenomenon, but the errors are also relatively balanced with some negative values and some positive values.

The results are not always larger or smaller than the real values. According to the safety coefficient (1.2-1.3) in the civil engineering standard, the predicting errors of the RBF model are in the range of security. The RBF neural network has the advantages of high universality and high accuracy. Although it requires a certain amount of measured data for the early training stage, it can predict frost heave in any condition as long as the data are obtained through laboratory experiments or field monitoring.

6. CONCLUSIONS

(1)   Frost heave is influenced by many factors with complex interacting relationships. It can be seen that temperature, salt content, moisture content and degree of compaction have significant relationships with frost heave through the laboratory experiments. Frost heave has a positive correlation with moisture content and degree of compaction. Frost heave initially increases with temperature and then levels off at a stable value. Frost heave initially increases with the salt content and then decreases.

(2)   Temperature, moisture content, salt content and degree of compaction have a certain relationship with frost heave, but the degrees of influence vary. Through the method of path analysis, the order of factors according to relativity with frost heave is moisture content, temperature, salt content, degree of compaction.

(3)   The RBF neural network model uses temperature, salt content, moisture content and degree of compaction as input layers, and has a good effect in predicting frost heave of saline soil. It can predict the expansion and shrinkage phenomena while maintaining the level of errors relatively balanced.

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