

## Research Article

# Assessment of Soil Thermal Conductivity Based on BPNN Optimized by Genetic Algorithm

Chenyang Liu <sup>1</sup>, Xinmin Hu,<sup>1</sup> Ren Yao,<sup>2</sup> Yalu Han,<sup>1</sup> Yong Wang,<sup>1</sup> Wentong He,<sup>1</sup> Huabin Fan,<sup>3</sup> and Lizhi Du <sup>1</sup>

<sup>1</sup>College of Construction and Engineering, Jilin University, Changchun 130000, China

<sup>2</sup>Shanghai Zhongpu Exploration Technology Research Institute Co., Ltd., Shanghai 200000, China

<sup>3</sup>Jiaoke Transport Consultants Ltd., Beijing 100000, China

Correspondence should be addressed to Lizhi Du; [dulizhi98@jlu.edu.cn](mailto:dulizhi98@jlu.edu.cn)

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Thermal conductivity is a critical parameter playing an important role in the heat transfer process in thermal engineering and enormous other engineering fields. Thus, the accurate acquisition of thermal conductivity has significant meaning for thermal engineering. However, compared to density test, moisture content test, and other physical property tests, the thermal conductivity is hard and expensive to acquire. Apparently, it has great meaning to accurately predict conductivity around a site through easily accessible parameters. In this paper, 40 samples are taken from 37 experimental points in Changchun, China, and the BPNN optimized by genetic algorithm (GA-BPNN) is used to evaluate the thermal conductivity by moisture content, porosity, and natural density of undisturbed soil. The result is compared by two widely used empirical methods and BPNN method and shows that the GA-BPNN has better prediction ability for soil thermal conductivity. The impact weight is obtained through mean impact value (MIV), where the natural density, moisture content, and porosity are 30.98%, 55.57%, and 13.45%, respectively. Due to high complexity of different parameter on thermal conductivity, some remolded soil specimens are taken to study the influence of individual factors on thermal conductivity. The correlations between moisture content and porosity with thermal conductivity are studied through control variable method. The result demonstrates that the impact weight of moisture content and porosity can be explained by remolded soil experiment to some extent.

## 1. Introduction

With the development of human activity, a great consumption of traditional fuels has produced huge amounts of greenhouse gases that are bad to the climate and a corresponding further increased shortage of the traditional fuels, such as oil, natural gas, and coal [1–9]. Due to this situation, thermally active engineering projects, such as heat exchanges systems, geothermal energy foundations, and energy piles, have attracted a great attention to government planners and engineering designers [7, 10–16]. Commonly, soil thermal properties are important in thermal engineering fields, which consists of thermal diffusivity, thermal capacity, and thermal conductivity [3, 17, 18]. Meanwhile, thermal conductivity, representing the ability to transfer heat, is one of

the most important parameters in thermally active engineering projects [19–21]. However, it is not easy to directly measure the soil thermal conductivity, because of high cost, complicated work, and used shortage for larger-scale applications [20]. Therefore, it is meaningful to obtain accurate soil thermal conductivity from easily measured physical parameters, such as moisture content, density, and porosity.

Soil thermal conductivity is thought to be affected by moisture content, porosity, density, mineralogy composition, particle size, gradation, temperature, pore shape, pore orientation, pore size and spatial arrangement of pores, and so forth [22–28]. In the past few years, many studies investigated the relationship between these parameters and thermal conductivity and predicted the thermal conductivity through different models [10, 22, 29–35]. For example,

Johansen proposed a model to evaluate the thermal conductivities of unsaturated soils in both unfrozen and frozen states by the relationship between degree of saturation ( $S_r$ ) and the normalized thermal conductivity [36]. Based on Johansen's work, Ewen and Thomas proposed a new model to solve the shortage, which underestimated the thermal conductivity at low moisture content [37]. But ECôté and Konard conducted that the influence of the fabric and the grain mineralogy should be considered in evaluating soil thermal conductivity [38]. Wang et al. studied the relationship between thermal conductivity and electrical resistivity [19]. Mikey indicated that moisture content and density can basically reflect the soil thermal conductivity through in situ measured results [39]. Zhang et al. observed the effects of moisture content, particle size, and density on thermal conductivity of four types of soils and put forwarded a new model [40]. Particularly, all the above-mentioned researches were studied at the room temperature ( $20^\circ \pm 2^\circ\text{C}$ ).

Artificial neural network (ANN) has already been used in predicting soil thermal conductivity. For example, Zhang Tao et al. proposed some ANN models to evaluate different types of soil thermal conductivity based on dry densities and moisture, including coarse, clay, fine sand, silty sand, and silt [41]. Moreover, the generalized model (PM-G) was proposed to evaluate the five type soils, and the results can be basically predicted. As the above passage mentioned, the soil thermal conductivity is under the multiple factors effect, such as moisture content, porosity, density, pore shape, and pore size. Thus, the prediction of thermal conductivity, based on moisture content and dry density, is not comprehensive. Not only does the dry density reflects less information for actual engineering comparing to natural density, but also, as for the PM-G (a generalized model), where  $c$  (clay content) and  $q_c$  (quartz content) are added, there is a lack of persuasion. The mineral composition of soil is hard to acquire, compared to the basically physical parameters, such as moisture content, porosity, and density. Nowadays, ANN has been used in various fields of engineering and plays an important role in predicting and distinguishing. But, for the prediction of thermal conductivity, the application of ANN is still less and limited to the BPNN. While the BPNN is one of the most widely used ANN in engineering fields, it still has limitation in optimize weights and thresholds, for falling into local optimum. However, the genetic algorithm can well resolve these problems, and this paper uses the genetic algorithm to optimize the BPNN [42, 43].

In order to accurately evaluate soil thermal conductivity, moisture content and porosity, which are easily obtained and have huge influence on thermal conductivity, are selected [1, 30, 36, 39]. Comparing the natural density and dry density, natural density can better reflect the actual situation than density, such as the distribution of soil particles, pore size, pore shape, and pore orientation. Furthermore, the natural density, which is multifield coupled, can reflect more information, benefiting for evaluating thermal conductivity. Particularly, the measurement of dry density is complicated compared to natural density and easily disturbed, leading to underestimating the accuracy. As for the saturation,  $S_r$  has

an obvious influence on soil thermal conductivity. But it can be reflected directly or indirectly by natural density, moisture content, and porosity. Therefore, this paper will study the relationship between natural density, moisture content, porosity, and thermal conductivity.

## 2. Materials and Methods

**2.1. Preparation of Soil Samples.** The silty clay is selected as the research object, which is obtained from Changchun, Jilin Province, China. In order to make the result more reliable, 40 samples are drilled at 37 different locations in Changchun. All the soil samples are obtained in the depth varying from 4 m to 6 m. A total number of 40 soil samples are tests. Sampling position of the silty clay is shown in Figure 1.

**2.2. Measurement of Soil Physical Parameters.** The natural density ( $\rho$ ), moisture content ( $w$ ), and porosity ( $n$ ) of soil samples are precisely measured; among them, the natural density is obtained through Wax seal experiment. The moisture content of soil samples is statistically calculated by drying experiment. Schematic of physical parameters test systems is shown in Figure 2.

As for the porosity ( $n$ ), the results are calculated through the natural density and moisture content, caused to the high cost and low accuracy of direct measurement. The porosity is obtained by the following equation:

$$\begin{cases} \rho_d = \frac{\rho}{1+w}, \\ n = 1 - \frac{\rho_d}{\rho_s}, \end{cases} \quad (1)$$

where  $\rho$  is the natural density ( $\text{g}\cdot\text{cm}^{-3}$ ),  $\rho_d$  is the dry density ( $\text{g}\cdot\text{cm}^{-3}$ ), and  $\rho_s$  is soil particle density. Normally, the soil particle density of silty clay is in the range of  $2.71$  to  $2.73 \text{ g}\cdot\text{cm}^{-3}$ . In order to simplify calculations, this paper set the soil particle density ( $\rho_s$ ) of silty clay as  $2.7 \text{ g}\cdot\text{cm}^{-3}$ .

The transient plane source (TPS) method is used to obtain the thermal conductivity of all the soil samples. The experimental apparatus is the Hot Disk Thermal Conductivity Analyzer (as shown in Figure 3), which has  $\pm 3\%$  measurement accuracy.

The principle of TPS method is based on the transient temperature response of a step-heated disc-shaped heat source. The relationship between temperature of probe and dimensionless time constant is shown in the following equation:

$$\overline{\Delta T}(\tau) = \frac{Q}{\lambda r \sqrt{\pi^3}} D(\tau), \quad (2)$$

where  $\overline{\Delta T}(\tau)$  is the temperature variation value,  $Q$  is the total output of power,  $D(\tau)$  is the dimensionless time constant, and  $r$  is the radius of Kapton film sensor. The detailed experimental procedures can be acquired in other previous works [44]. All the data is precisely measured, and the result of the natural soil density, moisture content, porosity, and thermal conductivity is shown in Table 1.

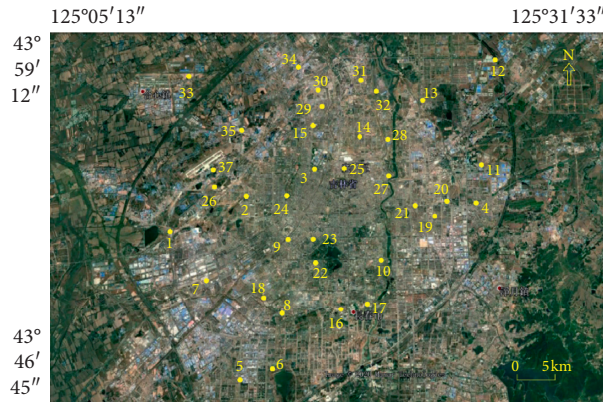


FIGURE 1: Sampling positions of the silty clay.

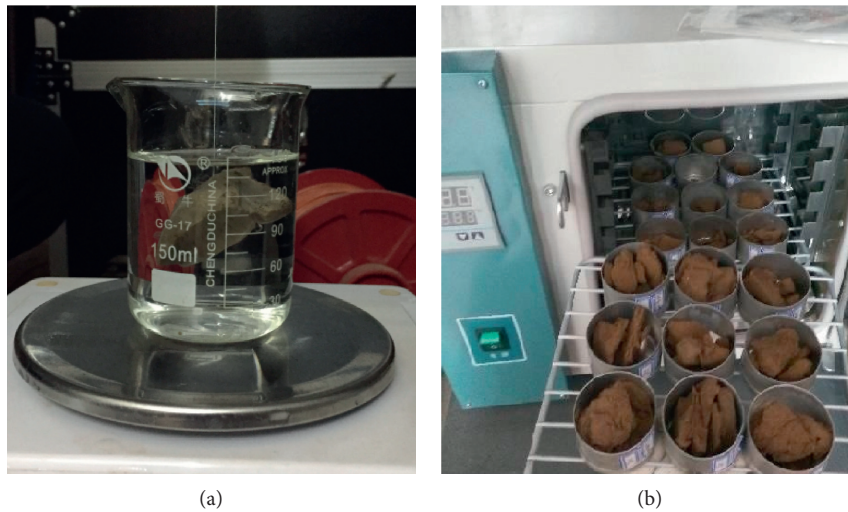


FIGURE 2: Schematic of physical parameters test system. (a) Wax sealing experiment. (b) Drying experiment.

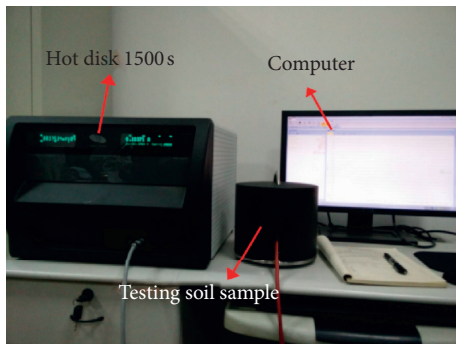


FIGURE 3: The thermal conductivity test system.

**2.3. Building Model.** In this study, 40 data sets (each set contains the values of 4 factors: natural soil density, moisture, porosity, and thermal conductivity) are used to compare the BP Neural Network optimized by genetic algorithm (GA) and some commonly used models. The subsequent passage gives a useful overview of BPNN and genetic algorithm (GA).

BP Neural Network (BPNN) is a commonly used ANN model, which can be divided into three layers: an input layer, a hidden layer, and an output layer. Each layer is connected through processing elements [45]. Each neuron is connected to all the neurons of next layer, and the connection medium is called weight [41]. Although the BPNN is so popular in ANN, it also has the limitation in optimizing weights and thresholds, for falling into local optimum. While the GA is useful searching technique proposed by Holland and applied in many different fields [46, 47], through the adaptation biological and survival processes, the GA is used to obtain the near-optimal solutions in every search space. Generally, the GA starts with the initial population using binary bits, such as 1 and 0, strings generated through random ways. All the integers, real numbers, and the potential solutions are encoded by these binary strings and are taken from the problem search space, which is included with all the potential solutions. These strings are decoding into a search space and the performance of these strings is evaluated through computing the fitness value for objective function. The fitness is key factor of the quality of each string in

TABLE 1: Physical parameters of silt clay and thermal conductivity.

Sample no.	Soil natural density ( $\rho$ ) ( $\text{g}\cdot\text{cm}^{-3}$ )	Moisture content ( $\omega$ ) (%)	Porosity ( $n$ ) (%)	Thermal conductivity ( $\lambda$ ) ( $\text{Wm}^{-1}\text{K}^{-1}$ )
1	1.854	48.83	45.49	1.149
2	1.809	27.21	38.56	1.418
3	2.160	36.65	33.15	1.348
4	2.304	7.37	11.12	1.209
5	1.944	10.30	25.39	1.501
6	1.998	13.76	25.81	1.390
7	2.043	13.91	24.46	1.392
8	2.052	7.43	19.79	1.378
9	1.908	12.50	27.95	1.476
10	2.088	6.07	17.99	1.321
11	2.169	13.74	20.31	1.388
12	1.971	20.40	30.49	1.465
13	2.097	13.92	22.74	1.393
14	2.079	14.86	23.91	1.359
15	2.214	6.98	13.90	1.295
16	2.291	15.23	26.34	1.666
17	2.227	18.21	30.21	1.634
18	2.380	26.34	30.52	1.688
19	2.125	22.31	35.64	1.390
20	2.192	17.63	30.98	1.594
21	2.213	19.63	31.46	1.585
22	2.162	23.64	35.21	1.406
23	2.045	35.79	44.22	1.296
24	1.910	42.31	50.31	1.158
25	1.900	37.49	48.82	1.210
26	2.273	19.64	29.64	1.665
27	2.212	24.61	34.26	1.451
28	2.091	36.22	43.15	1.314
29	1.978	45.61	49.69	1.149
30	2.381	10.98	20.55	1.584
31	2.241	12.65	26.31	1.638
32	2.025	33.87	43.95	1.309
33	1.976	31.96	44.55	1.314
34	2.024	26.58	40.78	1.361
35	2.100	27.63	39.11	1.360
36	2.110	34.22	41.77	1.337
37	2.215	13.85	27.93	1.644
38	2.231	19.85	31.05	1.611
39	2.386	11.66	20.87	1.599
40	2.418	28.93	30.54	1.692

problem's domain. After the evaluation of the strings, a better population will be created through genetic operators. The GA is used to optimize the BPNN. The flowchart of the BPNN optimized by the genetic algorithm is shown in Figure 4.

As shown in Figure 4, the weights and thresholds of BPNN are encoded, when the topology of BPNN is determined. Training is determined by the thresholds and specified weights. In the genetic algorithm part, the fitness value, selection, crossover, and mutation are calculated. Decide if the new group is satisfied; if not, the weights and thresholds of BPNN are changed till the requirement is met. In the end, the optimized weights and thresholds are obtained. As the analysis of above passage, the natural density ( $\rho$ ), moisture content ( $\omega$ ), and porosity ( $n$ ) of soil samples are set for the input parameters. The thermal conductivity is set as the only output parameter, named as predicted conductivity,  $\lambda_p$ . These values of all the parameters are listed in Table 1.

The cross-validation technique is adopted, and the training data and testing data account for 75% (30 sets) and 25% (10 sets) of the database in total, respectively. One hidden layer is adopted in this paper, which caused one hidden layer to have the ability to approximate any continuous functions in geotechnical engineering. The training and testing processes are used in the artificial neural network toolbox in MATLAB 2018b, due to their application and accuracy. The momentum factor ( $\mu = 0.01$ ) is set for the GA-BPNN model for the most efficient structure, while the maximum training cycle,  $c_{\max}$ , is selected as 1000 times in this paper. The minimum error is set as 0.00001, while the highest failure time is selected as 6. The gradient descent method is used in this study. The pure line (pure liner function) and tan-sigmoid function, which are selected as the transfer functions, are employed for hidden layer and output layer. The best hidden neurons are 6, which is obtained after the training and testing processes.

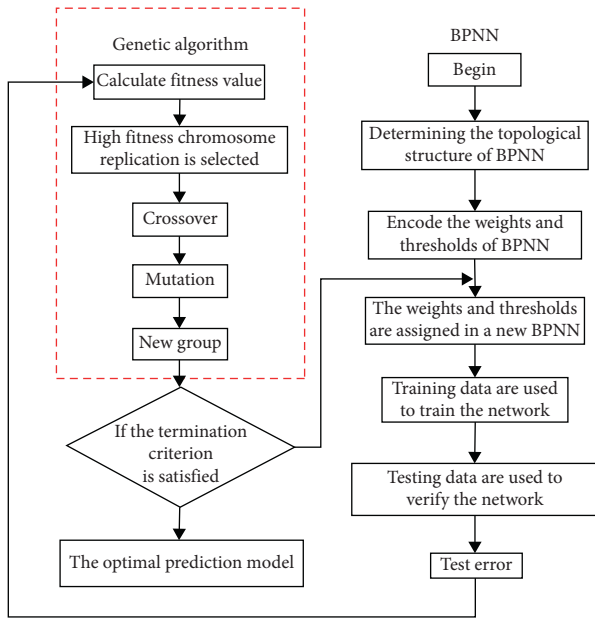


FIGURE 4: Flowchart of the GA-BPNN structure.

2.4. *Verification of BPNN and GA-BPNN.* In order to verify the accuracy and application of GA-BPNN and BPNN, the result of GA-BPNN is compared with BPNN. Figure 5 reflects the relationship between the measured thermal conductivity and predicted thermal conductivity.

The red points stand for the training data, and the black points and the blue points are stand for BPNN and GA-BPNN, respectively. As shown in Figure 5, it can be easily found that, for both BPNN method and GA-BPNN method, predicted thermal conductivity values are all quite close to the measured thermal conductivity, which means high quality of this model. Comparing the GA-BPNN method with the BPNN method, it can be approximately observed that the prediction results of GA-BPNN have higher degree of fit with measured thermal conductivity than BPNN. In order to further compare the BPNN and GA-BPNN, the prediction results and measured results of testing data are shown in Figure 6.

For Figure 6, it can be easily found that the GA-BPNN method has better prediction and higher accuracy than BPNN method, especially at point 9. As for the BPNN method, it cannot reflect the law of change well for the measured thermal conductivity. Usually, the coefficient of correlation ( $R^2$ ), mean absolute percentage error (MAPE) for variability accounted for (VAF), mean absolute error (MAE), and root mean square error (RMSE) are used to quantitatively check the reliability of results. Meanwhile, the model is considered as excellent, when the errors in terms of RMSE and MAE are close to 0, and the VAF and  $R^2$  are close to 1. In this paper, these parameters are used to further compare the BPNN and GA-BPNN. The results of BPNN and GA-BPNN are shown in Table 2.

As is listed in Table 2, it is evident that both BPNN and GA-BPNN are accurate in predicting thermal conductivity since  $R^2$  is close to 1 and the maps are both lower than 5%. In

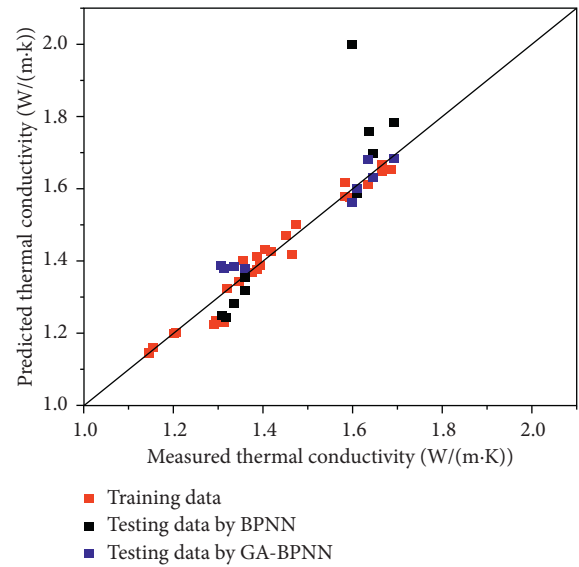


FIGURE 5: Comparison of predicted thermal conductivity values by measured thermal conductivity.

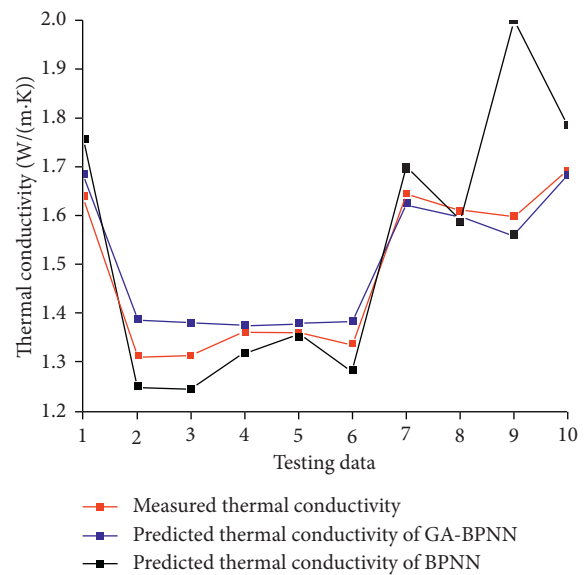


FIGURE 6: The prediction results and measured results of testing data.

TABLE 2: Calculation results of performance indexes for GA-BPNN and BPNN.

Model	RMSE/W (m·K)	MAE/W (m·K)	MAPE (%)	$R^2$
BPNN	0.0896	0.0602	3.955	0.9496
GA-BPNN	0.0301	0.0246	1.7496	0.9912

addition, all the parameters of GA-BPNN are superior to those of the BPNN; in particular, the RMSE, MAE, and MAPE of GA-BPNN are largely lower than those of BPNN,

which means the GA-BPNN is greater than BPNN in thermal conductivity prediction.

**2.5. Comparison of GA-BPNN with Empirical Models.** Actually, many calculation models were proposed for own purpose [48–50]. Dong et al. thought the existing thermal conductivity predicting models can be basically divided into three parts: mathematical models, empirical models, and mix models [51]. Among them, mathematical models do not fit engineering application, due to their much input parameters and complicated calculation. Nevertheless, this paper aims to solve actual engineering issues. Therefore, two typically empirical models (Kersten models and Gangadhara model) are used for comparison with the GA-BPNN.

Kersten studied the relationship between moisture content, dry unit weight ( $\gamma_d$ ), and thermal conductivity [52]. The proposed empirical model is shown in the two following equations.

$$\lambda = 0.1442 \times [0.7 \log \omega + 0.4] \times 10^{0.6243\gamma_d} \quad (\text{for sandy soil, } \omega \geq 1\%), \quad (3)$$

$$\lambda = 0.1442 \times [0.9 \log \omega - 0.2] \times 10^{0.6243\gamma_d} \quad (\text{for silt and clay soils, } \omega \geq 1\%), \quad (4)$$

where  $\lambda$  is soil thermal conductivity;  $\gamma_d$  is the dry unit weight in 1 b/ft<sup>3</sup>; and  $\omega$  is moisture content.

$$\frac{1}{\lambda} = [1.07 \times \log \omega + b]^{-1} \times 10^{(-0.01 \times \gamma_d + 3)}, \quad (\text{for clayey soils, } \omega \geq 10\%), \quad (5)$$

where  $b$  is the dimensionless parameter. For coarse sand, fine sand, silt sand, silt, and clay, the  $b$  values are 0.73, 0.7, 0.12, -0.54, and -0.73, respectively.

The comparisons of prediction performance between GA-BPNN and two empirical models are calculated, and the results are shown in Figure 7.

It can be observed in Figure 7 that Gangadhara model leads to underestimation in thermal conductivity of clay soil. The comparison of GA-BPNN and Kersten models demonstrates that GA-BPNN possesses a superior prediction performance.

In fact, the thermal conductivity of soil is influenced by many parameters, which is coupled. Thus, the effect of input parameters on the thermal conductivity is important to evaluate the thermal conductivity. In ANN analysis, the impact of input neurons on the output neurons can be obtained by the examination of the internal weight matrix value [54]. Based on this concept, mean impact value (MIV) method is used to evaluate variable correlation in ANN [55, 56]. The minus MIV means the inverse correlation and the plus MIV indicates the positive, while the absolute value indicates the relative importance or contribution of the impact factor. In this paper, we use MIV method to quantify the impact of natural density, moisture

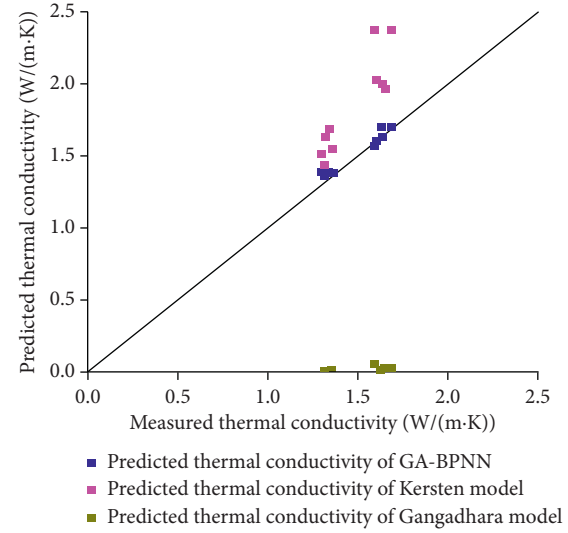


FIGURE 7: Comparison of predicted thermal conductivity between GA-BPNN and empirical models.

Gangadhara model tested the thermal conductivity of five different soils and proposed an empirical relationship as expressed in the following equation [53]:

content, and porosity on the thermal conductivity. Table 3 shows the MIV and impact weight of all the input parameters.

It can be found that the correlation of thermal conductivity and porosity is negative, while the correlation of natural density and moisture content is positive. The weight of moisture content is more than the sum of the natural density and porosity. As for the natural density, it has 30.98% of impact weight on thermal conductivity, which means it contributes 30.98% on the influence on the thermal conductivity. Particularly, the natural density is a result of many parameters coupling, the 30.98% of impact weight means the natural density is a well input parameter to evaluate the thermal conductivity of soil. For the porosity, it only contributed 13.45% of weight impact.

### 3. The Impact Weight through Remolded Soil Experiments

The abovementioned factors have a significant effect on the method; thus, it is hard to study the relationship between single factor and thermal conductivity. Thus, control variable method is adopted to conduct the correlation between moisture content, porosity, and thermal conductivity

TABLE 3: MIV and impact weight of the input parameters.

Parameters	Natural density	Moisture content	Porosity
MIV	0.0027	0.0049	-0.0012
Impact weight (%)	30.98	55.57	13.45



FIGURE 8: Remodeled soil experiment. (a) Dried soil particles. (b) Some remodeled soil samples.

through remodeled soil experiment. The preparation of remodeled soil with different moisture content can be divided into two steps: (1) Crush the undisturbed soil and dry it (Figure 8(a)). The soil particles are divided into 15 parts and 2 kg each, followed by spreading the soil on the plant. (2) The remodeled soil samples are made with different moisture content, which is 10%, 12%, 13%, 14%, 15%, 16%, 17%, 18%, 19%, 20%, 22%, 24%, 26%, 28%, 30%, and 32% (liquid limit), respectively. Some remodeled soil samples are shown in Figure 8(b).

All these parameters and thermal conductivity are accurately measured. The results are plotted in Figure 9.

As shown in Figure 9, with the increase of moisture content, the increase rate of thermal conductivity decreases. The increase trend can approximately be divided into two parts by 27% of moisture content. When the moisture content is lower than 27%, the thermal conductivity increases rapidly with the increase of moisture content. This phenomenon is mainly caused by the liquid bridge [22, 57]. When the moisture content is more than 27%, the thermal conductivity tended to stabilization. Especially for the initial stage, the thermal conductivity has increased over 49% range from 10% to 20% of moisture content. We study the proportion of moisture content of undistributed content (Figure 10).

There are 27 distributed soil specimens with moisture content lower than 27%, while there are 13 undistributed soil samples with moisture content greater than 27%. It means that most distributed soil in the stage is sensitive to moisture content. In the prediction of thermal conductivity, moisture content should be considered as a key factor, when the moisture content is in the range of 0% to 27%, regarded as sensitive stage. In order to study the correlation between porosity and thermal conductivity, remodeled soil samples are made with the same moisture content and different

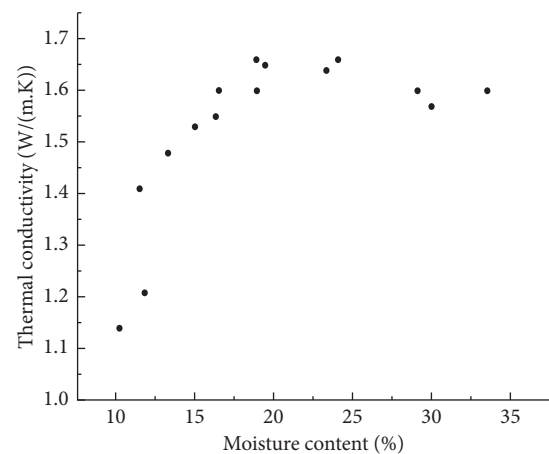


FIGURE 9: Thermal conductivity change with moisture content.

porosities. The procedure can be divided into three parts: (1) Crush the undisturbed soil and divide it into 9 parts evenly. (2) Use the compactor to compact these remodeled soil specimens, and the porosity is obtained by controlling the height of soil specimens. (3) The thermal conductivity of remodeled soil is precisely measured. The result is shown in Figure 11.

It can be observed that the thermal conductivity decreases with the increase of porosity, which is the same as the result of MIV in the above passage. When the porosity is over 25%, the thermal conductivity tends to stabilize. It is mainly because the heat conduction is mainly through soil particles, rather than the moisture content. From the range of 25%–45%, the thermal conductivity has decreased 8.1%, which is far less than the increase rate of thermal conductivity of moisture content. The distribution of undistributed

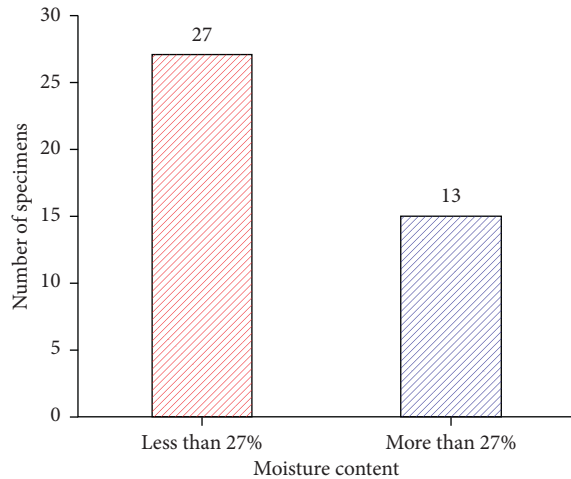


FIGURE 10: Distribution of undistributed soil specimens under different moisture content.

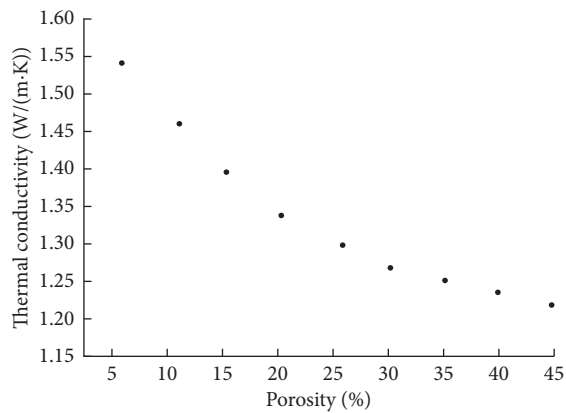


FIGURE 11: Thermal conductivity change with porosity.

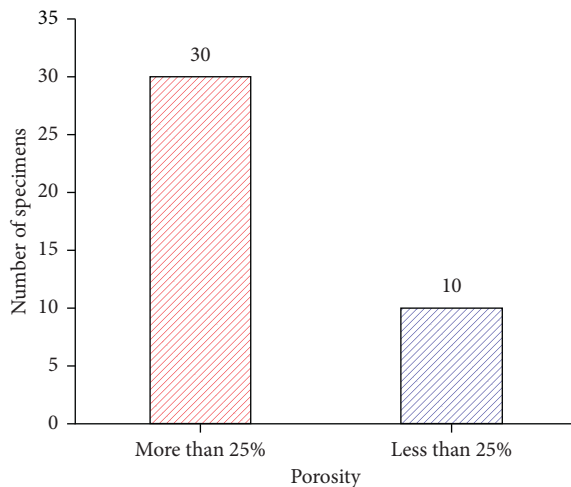


FIGURE 12: Distribution of undistributed soil specimens under different porosity.

soil specimens under different porosity is shown in Figure 12.

It can be seen that the number of undistributed soil specimens, whose porosity is more than 25%, is 3 times that in the other undistributed soils. To some extent, the rates of

8.1% and 48.6% can demonstrate the MIV weights of 13.45% and 55.57%, respectively. This chapter studies the influence of moisture content and porosity on thermal conductivity and gives a reason for the impact weights of MIV.

#### 4. Summary and Conclusions

Thermal conductivity is a critical parameter in thermal conductivity, which is hard and expensive to obtain. Many researchers have done many works to predict thermal conductivity. Causing the soil thermal conductivity to be affected by many parameters, existing prediction models are underestimated in accuracy and application. This paper proposed a GA-BPNN model, whose input parameters are natural density, moisture content, and porosity, to evaluate soil thermal conductivity. The proposed GA-BPNN models have been verified and compared with BPNN and two empirical models to reinforce their applicability and superiority. Moreover, the impact weight of the natural density, moisture content, and porosity is conducted through MIV method. The correlation between moisture content and porosity with thermal conductivity is studied through remolded soil experiment, which also explained the impact weight to some extent. The following conclusions can be advanced from this paper:

- (1) Owing to difficulty and high cost for obtaining precise value of thermal conductivity, accuracy prediction of thermal conductivity has significant meaning through easily obtained parameters, such as moisture content, natural density, and porosity. Causing the natural density to be the result of multifield coupling, it can reflect more information of actual condition. This paper set natural density, moisture content, and porosity as input parameters to predict thermal conductivity, which achieved good results.
- (2) Due to the limitation of BPNN in optimizing weights and thresholds, for falling into local optimum, this paper uses genetic algorithm (GA) to optimize the BPNN, and the predictions of empirical models are compared. The result shows the application and accuracy of GA-BPNN, which can be used in similar thermal conductivity prediction.
- (3) The impact weights of natural density, moisture content, and porosity are conducted through MIV method, which are 30.98%, 55.57%, and 13.45%, respectively.
- (4) The experiment of remolded soil is used to further study the correlation between moisture content and porosity with thermal conductivity. The result can explain the impact weight of moisture content and porosity to some extent.

#### Data Availability

The experimental data used to support the findings of this study are included within the article.



## Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

## Acknowledgments

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