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Influence of Gravel Soil Gradation Characteristics on Permeability Coefficient Based on Neural Network

Hao Ma[1, 2], Dandan Jin[1,*], Tao Wang[3] and Mirza Iftikhar Ahmad[4]

[1]*Faculty of Civil Engineering and Mechanics, Jiangsu University, Zhenjiang 212000, China*
[2]*School of Intelligent Construction, Wuchang University of Technology, Wuhan 430223, China*
[3]*School of Mechanical Engineering, Hefei University of Technology, Hefei 230009, China*
[4]*School of Civil Engineering and Architecture, Wuhan University of Technology, Wuhan 430070, China*

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Abstract

The permeability coefficient of gravel soil is closely related to gradation characteristics and plays a key role in engineering safety and stability. Among the studies on the correlation between gravel soil gradation characteristics and permeability coefficient, traditional empirical formulas and theoretical models are subjected to specific limitations, failing to accurately capture the complex nonlinear relations. In this study, considerable test data on gravel soil were collected. The model establishment, training, and optimization were performed using a backpropagation (BP) neural network. The complex relations between gravel soil gradation characteristics and permeability coefficient were explored. Moreover, the influence of each particle size on permeability coefficient was demonstrated. The prediction results of full gradation and common gradation were comparatively analyzed. Results show that, the prediction results on permeability coefficient by neural network are more accurate. In this study, the sample size is enlarged to 138 groups, which significantly improves the prediction accuracy. d_{60} is the boundary particle size. The permeability coefficient increases with the increase in the fine particles with a size of d_{60} or below, whereas it decreases as the coarse particles with a size above d_{60} increase. The influence degree of different particle gradations on permeability coefficient is heterogeneous. d_{10} is a high-sensitivity particle size, which exerts the greatest influence on permeability coefficient, followed by d_{20} and d_{40}, which are medium-sensitivity particle sizes. The relative weights of other particle sizes are small, being low-sensitivity particle sizes. The influence of fine particles on permeability coefficient is greater than that of coarse particles, and full gradation achieves a better prediction result for permeability coefficient compared with common gradation. p_5 is also a key factor affecting permeability coefficient.

Keywords: Neural network, Gravel soil, Gradation characteristics, Permeability coefficient

1. Introduction

In recent years, water inrush accidents have occurred frequently in water conservancy, hydropower, and road engineering projects. For example, in 2015, a major water inrush accident occurred in Jiangjiawan Coal Mine in Datong City, Shanxi Province, causing 21 casualties and major economic losses. In 2021, a water inrush accident happened in Shijingshan construction tunnel in Zhuhai City, Guangdong Province, which led to the collapse of the vault and the death of 14 construction workers. In 2023, water seepage occurred in the third bid section of the second phase of Bomeng Expressway in Anhui Province during foundation excavation, which caused the collapse of the earthwork. Traffic, construction, and other projects have set increasingly strict requirements for the performance of foundation soil. The permeability characteristics of gravel soil, which is an important geotechnical material in engineering construction, directly affect the stability, durability, and safety of engineering structures, possibly triggering serious geological disasters. Permeability coefficient has been widely used to describe the ability of fluid to pass through porous media, which is one of the key parameters in seepage analysis and accurately quantifies the seepage rate under the unit hydraulic gradient. The larger its value, the stronger the ability of soil to allow water to pass through and the higher the water permeability. Permeability coefficient is easily influenced by other factors, such as particle gradation, medium type, particle morphology, surface-to-volume ratio, and compactness [1-3]. Among them, particle gradation is a comprehensive reflection of particle size and particle distribution at all levels, and it is the main influencing factor of permeability coefficient. The study on particle gradation and permeability coefficient is of great realistic significance and plays an important role in permeability analysis and antiseepage design in geotechnical and hydraulic engineering.

The relationship between particle gradation characteristics and permeability coefficient has been extensively studied and discussed, but such studies have been mostly based on field tests. Corresponding empirical formulas have been put forward, and d_{10} , d_{20} , d_{30} , and d_{60} are taken as key parameters [4-7]. Such formulas have been modified and improved by some scholars, e.g., introducing the nonuniformity coefficient and curvature coefficient in the Terzaghi formula to further improve the scope of application and accuracy of study results, which provides the means of estimation for exploring the complex relation between the two. Given the complex composition of gravel soil particles and their irregular shapes, however, the gradation characteristics present a highly nonlinear relation

*E-mail address: jindd@ujs.edu.cn
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with permeability coefficient. Considerable existing literature has shown that discreteness exists in the prediction of permeability [8]. The calculation as per the empirical formulas considering gradation characteristics is tedious. The traditional theoretical derivation hardly captures the complex relationship between gravel soil gradation characteristics and permeability coefficient accurately, accompanied with a large prediction error and specific limitations in the application of empirical formulas [9]. In addition, tailor-made large-scale instruments are usually needed in the related tests of the influence of gravel soil gradation characteristics on permeability coefficient, resulting in relatively high costs of tests, and the accuracy is affected by manual operation. Substantial samples are required in the statistical analysis of parameters such as gradation and permeability coefficient based on test data [10].

Along with the popularization and application of artificial intelligence (AI) algorithms, neural networks, presenting outstanding advantages such as nonlinear mapping ability and self-adaptation, provide reliable technical support for evaluating gravel soil permeability in engineering practice. They have been utilized by a few scholars to reveal the influence of gradation characteristics on permeability coefficient [11-12]. However, the test data size is relatively small, and the structure is relatively simple, along with the proneness to local optima in the training process, resulting in the failure to obtain an optimal model prediction result. Although Raza and Sharma [10] applied a neural network model to prediction, they focused on porous asphalt mixture instead of gravel soil. On the basis of existing research, in this study, thorough experimental data on the gradation characteristics and permeability coefficient of gravel soil were added, and a neural network model with three hidden layers was constructed for training and prediction to improve prediction accuracy. With the added hidden layers, the network could learn more complex feature combinations and abstract representations, then more accurately fit the highly nonlinear data distribution, and improve the accuracy and precision of permeability coefficient prediction results through refined data or feature extraction. The influence of gradation characteristics on permeability coefficient was analyzed and predicted using the neural network model based on 138 groups of test data. Furthermore, the potential relation laws between gravel soil gradation characteristics and permeability coefficient were accurately revealed, expecting to provide a valuable decision-making basis for engineering practice.

2. State of the art

Permeability coefficient reflects the permeability of soil and directly affects engineering safety. To facilitate engineering application, scholars have introduced empirical formulas for permeability coefficient in combination with different soil characteristics. The existing empirical formulas for permeability coefficient, which are specifically representative and have been widely used in theoretical research and practical work, were obtained by different scholars through experiments. These formulas have been improved and optimized by some scholars. For instance, taking clayey soil as the study object, Zhou et al. [13] corrected the Kozeny–Carman formula and found that the prediction result based on new formulas is more accurate.

Empirical formulas and indoor tests play a dominant role in the studies on the relationship between gradation characteristics and permeability coefficient. Bao et al. [14] explored the permeability of coarse-grained soil and incorporated the gradation area into the model, which improved the traditional empirical formula. Based on a series of experimental tests, the results were reliable. In a study based on image techniques and falling head tests, Tang and Huang [15] determined that the smaller the particle gradation, the lower the permeability coefficient. Zhang et al. [16] used discrete and finite element methods to test the influence of particle size on permeability coefficient and indicated that porosity and pore connectivity also affect permeability coefficient, of which the latter exerts a more significant influence. Tang et al. [5] conducted laboratory tests and model predictions based on the gradation characteristics of different particles. They found that the gradation characteristics have a significant impact on permeability coefficient, and permeability coefficient will increase with the decrease in gradation range and particle size. Li et al. [17], taking debris-flow fans as the research object, emphasized that particle size distribution is an important parameter for determining permeability. Experimental research demonstrated that the permeability coefficient was greater than the initial value when the content of fine particles was 10% and 15%; when the content was increased to 20%, 25%, and 30%, the permeability decreased. Chen et al. [6] investigated the influence of particle properties on permeability coefficient and established a numerical simulation model based on particle discrete element software. They found that the Kozeny–Carman equation can well predict the permeability coefficient of porous media with different gradations, and d_{30} can best represent the particle size characteristics of the particle system.

Despite the many empirical formulas for permeability coefficient, the parameter types and function forms adopted by scholars differ considerably. Because different soil samples and measurement methods are used in different tests, the calculated results of the same sample under different formulas are inconsistent [18]. This inconsistency is accompanied with large errors in comparison with the measured result, which stresses the necessity for predicting permeability coefficient on the basis of AI algorithms [19-20]. The permeability prediction models established in the existing literature mainly rely on porosity or pore characteristics [21], while the influence of particle gradation characteristics has rarely been taken into account [22]. Although some indicators representing particle gradations have been considered by a few scholars, only one or several particle sizes have been included, failing to systematically and comprehensively explain the influence of different particle gradation characteristics on permeability coefficient. The current empirical formulas are prone to such problems as large errors, considerable time consumption, high costs of indoor experimental studies, and weak universality. To address these problems, this study scientifically predicted the complex nonlinear relation between particle gradation characteristics and permeability coefficient using neural networks, expecting to realize simulation training through test samples within a large scope and improve the accuracy of prediction results.

The remainder of this study is organized as follows: In Section 3, the prediction process for permeability coefficient based on neural network modeling, test sample data, and gradation characteristics is briefly introduced. In Section 4, the results are analyzed and discussed, the permeability coefficient is predicted on the basis of the characteristic parameters of full gradation and common gradation, the sensitivity of each particle size is analyzed, and the results are compared. In Section 5, the summary and expectations are given, conclusions are drawn, the research limitations are explained, and future research directions are indicated.

3. Methodology

3.1 Neural network modeling

Neural network is a multilayer feedforward neural network trained by error backpropagation, which is characterized by high flexibility, self-learning ability, and nonlinear mapping ability. The schematic of the neural network constructed in this study to predict permeability coefficient is shown in Fig. 1.

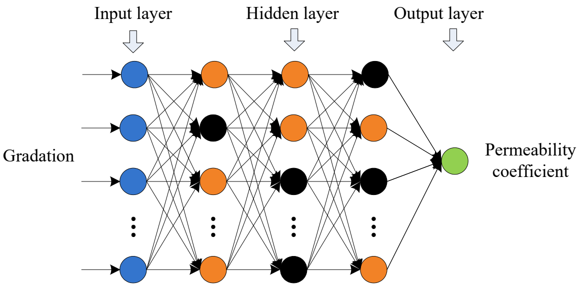

Fig. 1. Neural network schematic

The black color in Fig. 1 indicates nodes or neurons randomly deleted via the dropout method, which can prevent overfitting.

3.2 Test sample data

For establishing an accurate and reliable neural network prediction model, the relevant literature documents were consolidated and summarized through theoretical analysis. Gravel soil test data from different sources were widely collected, and a total of 138 groups of test samples were obtained. These data covered multiple gradation characteristic parameter combinations and the corresponding measured values of permeability coefficient, with extensive coverage and specific representativeness. The maximum particle size $d_{\max}$ varies in the test data of different literature, which may lead to great differences in the influence of particle size on permeability coefficient. As deemed by some scholars, void ratio is a key factor influencing permeability coefficient [21], and its coupling relationship with gradation determines permeability. Given training and predicted data as test data, the void ratio already reached a compact state under this gradation, and the deviation in the study result caused by the difference in void ratio could be neglected. The permeability coefficient was a saturated permeability coefficient obtained through tests based on Darcy's law under standard temperature (K_{20}), which could effectively avoid the influence of temperature difference. The samples were all common irregular gravel soil particles with approximate appearance, generating minor disturbance on the prediction result.

In consideration of the dimension differences of different indicators, 138 groups of sample data were preprocessed. The related data such as particle size and gradation characteristic parameters were normalized to make them fall into the range of 0–1, preventing the gradient problem in the training process induced by the difference in data magnitude, to accelerate the model training speed and improve the training effect. On this basis, the processed gravel soil gradation characteristic parameters were taken as the input layer of the neural network model and the corresponding permeability coefficient as the output layer. Tansig and Purelin were chosen as activation functions.

3.3 Prediction process and sensitivity evaluation

The preprocessed dataset was divided into training and validation sets in accordance with a certain proportion. In this study, 95% of the test data were selected for training, i.e., 131 groups were used to train the neural network model, and the combinations of full gradations d_{10} , d_{20} , d_{30} , d_{40} , d_{50} , d_{60} , d_{70} , d_{80} , d_{90} , and d_{100} with the measured permeability coefficients were taken as the training samples. The gradation characteristics were taken as the input variables, and the permeability coefficients were taken as the output variables. Then, training was performed to obtain the nonlinear mapping relation between the two. The connection weights between neurons were continuously adjusted to reach the minimum error between the predicted permeability coefficient in the model output layer and the actual value. The maximum training step size was set to 1000, and the error was smaller than 5%. The remaining seven groups were used to verify the accuracy and reliability of the model. Specifically, the seven groups of sample gradation characteristic parameters in the validation set were input into the trained model to obtain the predicted permeability coefficient and compare it with the actual permeability coefficient.

In this study, the sensitivity of gradation characteristics was analyzed through the mean impact value method with reference to the practice of existing studies. This method can be used to evaluate the sensitivity of input neurons to output neurons. Its symbols represent the related directions, and the absolute value stands for the importance of the influence, i.e., the degree of the influence of the change in a gradation characteristic parameter on permeability coefficient. First, the seven groups of sample particle sizes or gradation characteristics in the validation set were added or deducted by 10% on the basis of the original value to form a new incremental sample S_1 or decremental sample S_1' . Two groups of samples were imported into the neural network model for simulation to obtain two groups of predicted permeability coefficients K_1 and K_1' , and the difference between the two was marked as MIV_1, i.e., $MIV_1 = K_1 - K_1'$. Second, the above steps were repeated for the rest of the samples to finally obtain $MIV_1 \sim MIV_7$ corresponding to the seven groups of samples in the validation set, and the mean value MIV was calculated on this basis.

4. Result analysis and discussion

4.1 Full gradations and permeability coefficient

In this study, the prediction accuracy of the neural network was evaluated using the relative error, calculated by the following formula (1):

$$\delta = \frac{|Kt - K|}{K} * 100\% \tag{1}$$

In this formula, K is the test value of permeability coefficient, Kt denotes the predicted value of permeability coefficient, and δ is the error.

On the basis of the neural network model constructed in Chapter 3.1, the curve graph of training errors changing with the number of iterations was obtained, as shown in Fig. 2.

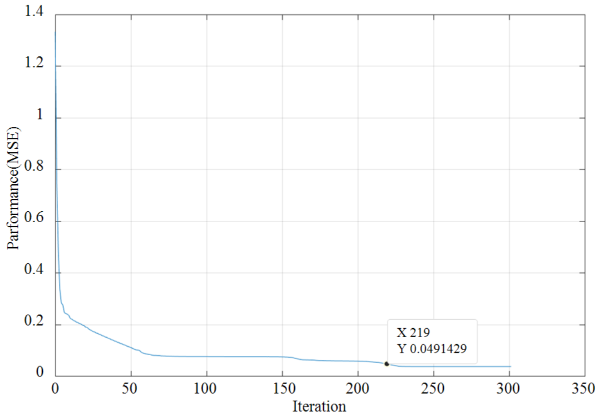

Fig. 2. Training Curve

The error histogram after neural network training is displayed in Fig. 3. The errors were mostly concentrated near −0.001, indicating a good fitting effect, and the overall model accuracy was acceptable.

The seven groups randomly selected were used for prediction to test the generalization ability of the neural network model. The prediction and test results for permeability coefficient by full gradations are shown in Table 1. The predicted value was close to the test value. The maximum relative error was 28.50% from the test number T5, and the minimum error was 0 from the test number T7. This finding indicated that particle gradation was the key factor affecting permeability coefficient, and permeability coefficient could be predicted well with full gradations. Over 85% of the samples in the validation set had errors between the predicted and test values below 10%. The average error was 7.62%, which was significantly lower than the average error of 19.60% obtained by Wang et al. [11]. Additional gravel soil permeability test sample data were collected, trained, and predicted using the neural network to improve the prediction accuracy for permeability coefficient and effectively solve such problems as high indoor test costs, considerable time consumption, and weak universality. The maximum error might be ascribed to the fact that permeability coefficient is affected by many factors, including void ratio, pore connectivity, bedding architecture, compactness, particle shape, and roughness, which would influence the study result to some extent. Nevertheless, the error was acceptable in engineering projects.

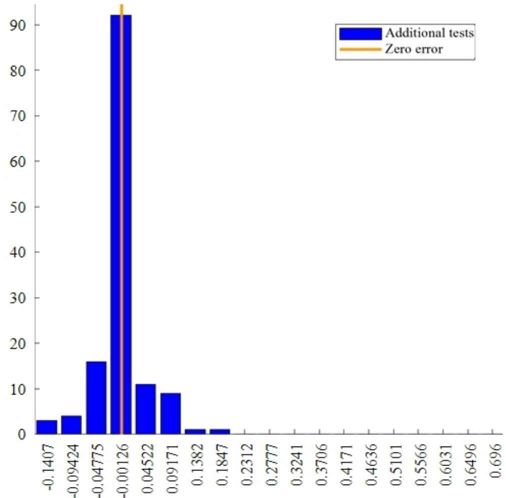

Fig. 3. Error histogram

Table 1. Full gradations and prediction results of permeability coefficient

No.	Cumulative mass percentage (%)										**K** /(cm/s)	**Kt** /(cm/s)	**δ** /(%)
	d_{10}	d_{20}	d_{30}	d_{40}	d_{50}	d_{60}	d_{70}	d_{80}	d_{90}	d_{100}			
T1	2.50	5.70	9.32	13.83	19.97	25.07	31.76	40.59	49.21	60.00	0.73	0.78	6.85
T2	10.00	16.70	23.30	30.00	40.00	50.00	60.00	70.00	80.00	90.00	5.63	5.64	0.18
T3	2.00	6.70	11.50	18.90	36.20	50.00	67.00	102.40	150.00	200.00	0.24	0.25	4.17
T4	5.00	7.36	9.50	12.99	17.84	26.00	35.84	45.05	52.46	60.00	0.35	0.32	8.57
T5	6.70	40.00	130.00	292.90	429.60	503.70	577.80	651.90	725.90	800.00	2.00	2.57	28.50
T6	0.60	2.26	5.32	9.81	12.85	16.26	19.74	23.41	27.43	31.50	0.79	0.75	5.06
T7	1.10	2.00	5.00	7.50	10.00	20.00	25.00	30.00	35.00	40.00	0.12	0.12	0.00

Notes: T1–T7 represent the test numbers in the validation set, K is the test value of permeability coefficient, Kt denotes the predicted value of permeability coefficient, and δ is the relative error value. The same below.

The sensitivity evaluation results of gradation characteristics, obtained through the mean impact value method, are listed in Table 2. The MIV values of $d_{10}-d_{60}$ were 0.11, 0.07, 0.04, 0.06, 0.02, and 0.01, respectively, which were positive, meaning that the permeability coefficient increased with the increase in particle size. The values of $d_{70}-d_{100}$ were –0.04, –0.05, –0.03, and –0.01, respectively, which were negative, indicating that the permeability coefficient decreased with the increase in particle size. The absolute value represents the relative importance of the influence of the corresponding particle size on permeability coefficient. Therefore, d_{60} could be considered the boundary particle size, which differed from existing studies, in which d_{50} was taken as the characteristic and boundary particle size [11,23]. In this study, when the number of fine particles with a size of d_{60} or below increased, the pore structure of soil could be optimized to some extent, effectively expanding seepage pore channels and further elevating the permeability coefficient. Meanwhile, large particles might expand the pore volume when piled up. The permeability coefficient would increase somehow according to the relationship between permeability coefficient and void ratio. When the coarse particles with a size above d_{60} increased, small particles that entered the pores combined into large particles, the effective channel area for water flow was reduced, the seepage path was considerably zigzag, and the permeability coefficient declined.

According to the sensitivity evaluation results of particle sizes, the permeability coefficient was directly influenced by each particle size, but the degree of influence was greatly different. d_{10} had the greatest influence on permeability coefficient, being a high-sensitivity particle size. In the study of Hatanaka et al. [24], d_{10} and d_{20} were taken as key parameters affecting permeability coefficient. The relative weights of d_{20} and d_{40} were within 0.5–0.7, being medium-sensitivity particle sizes. The relative weights of other particle sizes were lower than 0.5, being low-sensitivity particle sizes. The filling effect of fine particles played a critical role in permeability coefficient, and its degree of influence was much higher than that of coarse particles. However, the relative weights of d_{80} and d_{60} were 0.45 and 0.36, respectively, indicating that the skeleton effect of coarse particles also exerted an important effect on permeability coefficient control.

Table 2. *MIV* and sensitivity of each particle size

Variable	Cumulative mass percentage (%)									
	d_{10}	d_{20}	d_{30}	d_{40}	d_{50}	d_{60}	d_{70}	d_{80}	d_{90}	d_{100}
MIV	0.11	0.07	0.04	0.06	0.02	0.01	−0.04	−0.05	−0.03	−0.01
Weight	1.00	0.64	0.36	0.55	0.18	0.36	0.27	0.45	0.27	0.09
Sensitivity	High	Medium	Low	Medium	Low	Low	Low	Low	Low	Low

According to the previous discussion on *MIV*, it reflects the difference in permeability coefficient between the new incremental sample and the decremental sample formed by adding or subtracting 10% from different gradation characteristics. Thus, the influence degree of a particle size increase of 20% on permeability coefficient was further determined, as shown in Fig. 4. The figure demonstrates the degree of influence of specific particle sizes on permeability coefficient, which provides an intuitive basis for studying the seepage characteristics of porous media such as rock and soil. In engineering design, the corresponding particle size of materials can be selected on the basis of this figure to meet the requirements for the permeability of soil and other materials.

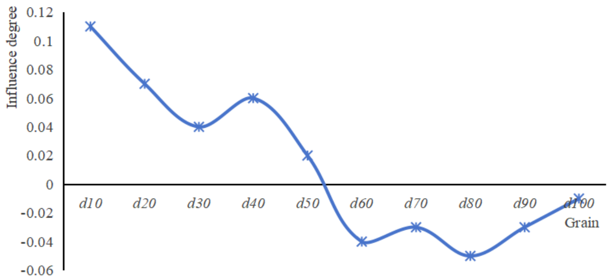

Fig. 4. Influence degree of a particle size increase of 20% on permeability coefficient

4.2 One or multiple gradation characteristics and permeability coefficient

In the study on permeability coefficient, commonly used gradation characteristics include d_{10}, d_{20}, d_{30}, and d_{60} [3,6]. These values were taken as representative particle sizes to investigate the influence of common gradation characteristics on permeability coefficient. On the basis of the previously trained neural network model, the test samples in the validation set were selected for prediction, with the results listed in Table 3. The test values of permeability coefficient of most samples were close to the predicted values, indicating that the permeability coefficient could be predicted through the common gradation characteristics in some cases, and the results were accurate. However, the relative error of TM5 was high, reaching 86.00%, and the prediction deviation was large. On the one hand, the particle size of coarse-grained soil was relatively uniform, the particle size span was small, and the skeleton gaps formed between large particles could be filled with fine particles, so the permeability coefficient decreased steadily. When the content of fine particles completely filled the gaps in the skeleton, a structure similar to fine-grained soil would be formed if fine particles were continuously added. The permeability coefficient would be further reduced. By contrast, when the content of fine particles was small, or they were unevenly distributed, a large seepage channel was formed locally, which led to an increase in permeability coefficient. On the other hand, the particle size span in gravel soil was very large, and the skeleton formed by large particles easily formed a multilevel pore structure, such as the skeleton pores formed by medium-sized particles filling large particles and the secondary pores between medium-sized particles filling fine particles. Although the pores of large particles were reduced to some extent, some connectivity remained, and the filling effect of medium-sized particles and the filling and plugging effect of fine particles acted together on the permeability coefficient. If the fine particles had a certain viscosity, an adsorption layer would be formed on the pore surface, which would further reduce the permeability coefficient.

The *MIV* value of d_{10} was 0.05, which was lower than that (0.07) of d_{20}, whereas the prediction results of full gradations showed that the *MIV* value of d_{10} was much greater than that of d_{20}. The contradiction was possibly due to the poor accuracy of single or multiple gradation characteristics in predicting permeability coefficient. Meanwhile, the model training and prediction results relied on the support from the permeability test data of a large sample size. The *MIV* value of p_5 was −0.08, indicating that with the increase in p_5, the permeability coefficient would gradually decline. That is, they showed a negative correlation, which accorded with the current research conclusions drawn by scholars. This finding, to some extent, manifested that the prediction of permeability coefficient through the neural network is reliable and that the prediction result is of specific universality.

Table 3. Common gradations and prediction results of permeability coefficient

Variable	Cumulative mass percentage (%)					*K* /(cm/s)	*Kt* /(cm/s)	*δ* /(%)
	d_{10}	d_{20}	d_{30}	d_{60}	p_5			
TM1	2.50	5.70	9.32	25.07	17.80	0.73	0.81	10.96
TM2	10.00	16.70	23.30	50.00	8.30	5.63	5.28	6.22
TM3	2.00	6.70	11.50	50.00	16.00	0.24	0.27	12.50

TM4	5.00	7.36	9.50	26.00	10.00	0.35	0.41	17.14
TM5	6.70	40.00	130.00	503.70	9.00	2.00	3.72	86.00
TM6	0.60	2.26	5.32	16.26	28.90	0.79	0.83	5.06
TM7	1.10	2.00	5.00	20.00	30.00	0.12	0.13	8.33
MIV	0.05	0.07	0.05	0.06	−0.08	—	—	—

Notes: TM1–TM7 represent the test numbers in the validation set; p_5 is the cumulative mass content percentage, corresponding to a particle size of 5 mm.

4.3 Comparison of prediction results between full and common gradations

Comparison of the prediction results between full and common gradations showed that the former achieved a better prediction effect. The maximum, minimum, and mean errors of permeability coefficient predicted using full gradations were 28.50%, 0%, and 7.62%, respectively, but the error obtained by single or multiple gradation characteristics was relatively large. Although the error of most test samples was acceptable, the error of individual test samples reached 86.00%, indicating that predicting permeability coefficient using full gradations is more reliable and accurate. According to the *MIV* values of different particle sizes in Table 3, the *MIV* value of d_{20} was the maximum, revealing its great influence on permeability coefficient, followed by d_{60} whose *MIV* value was 0.06. d_{10} influenced the permeability coefficient in the same way as d_{30} did, failing to embody the different influences of key particle sizes, and the prediction result was not accurate.

The reasons are as follows: First, the integrity of gradation information affects permeability coefficient. Single or several gradation parameters can only reflect the characteristics of specific particle sizes or some particle sizes in soil particles and fail to fully reflect the distribution and filling effect of other particle sizes. Limited gradation information may lead to distorted prediction results. Second, the pore structure of soil is also a key factor affecting permeability coefficient [25]. It has a certain complexity, which is determined by particle gradation. Single or multiple commonly used gradation parameters cannot accurately describe the size, shape, connectivity, and distribution of pores. Hence, the influence of different particle sizes on permeability coefficient, such as the skeleton function of gravel and the filling and plugging function of sand, should be fully considered in prediction. Third, full gradation takes the information of all particles into the model and considers the interaction between particles, which can gain more accurate prediction results. However, single or several gradation parameters cannot fully consider the arrangement and contact mode of particles with different sizes, as well as the effects on water flow. Consequently, the results obtained cannot accurately reflect the permeability characteristics.

5. Conclusions

Given 138 groups of gravel soil permeability test sample data, the relationship between gravel soil gradation characteristics and permeability coefficient was studied using a neural network. Then, training and simulation were performed on the basis of full and common gradations, and the prediction results of permeability coefficient were comparatively analyzed. The following conclusions were drawn:

(1) The traditional empirical formulas for predicting permeability coefficient exhibit limitations. By contrast, the neural network-based prediction result is favorably accurate and reliable, conforming to the needs of roughly estimating permeability coefficient in general engineering projects.

(2) Particle gradation is the key factor affecting permeability coefficient, and d_{60} is the boundary particle size. When the number of fine particles with a size of d_{60} or below increases, the permeability coefficient increases. When the number of coarse particles with a size above d_{60} increases, the permeability coefficient declines. Different particle sizes exert diverse influences on permeability coefficient, where d_{10} has the greatest impact on permeability coefficient, being a high-sensitivity particle size, followed by d_{20} and d_{40}, being medium-sensitivity particle sizes. The impact of other particle sizes on permeability coefficient is weak, being low-sensitivity particle sizes.

(3) Compared with single or multiple gradation characteristics, full gradation can better predict the permeability coefficient. The influence of fine particles on permeability coefficient is greater than that of coarse particles, and the filling and plugging effects of fine particles and the skeleton effect of coarse particles act together on the permeability coefficient. p_5 is also a key factor affecting permeability coefficient.

In this study, the influences of full and multiple gradation characteristics on permeability coefficient are investigated on the basis of a neural network, while the effects of porosity, pore size and distribution, and roughness are not considered. In the follow-up study, these factors will be included into a unified analytical framework to obtain more universal and comprehensive research conclusions. Test sample data within a larger scope will be trained for prediction to further improve the prediction accuracy for permeability coefficient. Furthermore, an indoor experimental study will be performed to verify the effectiveness of model prediction from multiple angles.

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