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MIX RATIO DESIGN AND PERFORMANCE OF PERMEABLE CONCRETE BASED ON A BP NEURAL NETWORK

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As an important part of a sponge city and China's rapid urbanisation process, pervious concrete can be widely used in urban light traffic roads and sewage systems. However, at present, there are many factors affecting the performance of pervious concrete, and the flexural strength of ordinary pervious concrete is poor, so its application is limited. A BP neural network model serves as the foundation for the study, which is optimised using the Tianniu Xu search algorithm and the Levenberg Marquardt algorithm in order to address the aforementioned problems. At the same time, the factors influencing the performance of permeable concrete are analysed using a multi-factor and multi-level experimental result visualisation analysis approach. According to the study's findings, the enhanced BP neural network prediction model may reach an optimal convergence state with an error of just 1.663×10^{-6} after just 25 iterations. After the BP-M2VA analysis, the optimal pervious concrete mix ratio of ST1 is 13.95 kg, of ST2 is 7.3 kg, the cement content is 4.30 kg, and the water consumption is 1690 mL. In summary, the analysis method proposed in this study can effectively predict and optimise the mix ratio of perishable concrete, prepare perishable concrete materials with both low cost and high efficiency, and then improve the ecology and environment of the urbanisation process, enhance the safety and comfort of motorists, and promote the sustainable development of urban traffic.

INTRODUCTION

Nowadays, the situation surrounding global environmental problems, such as land desertification and climate warming, is becoming more and more serious. Therefore, creating a green and sustainable urban environment has become a top priority in the world [1]. With the rapid development of China's urbanisation and the vigorous promotion of construction, automobile and other industries, China is also faced with serious levels of environmental pollution and energy shortages. In order to achieve the requirements of an ecological balance and sustainable development, the new concept of a sponge city came into being [2]. Pervious concrete is a very important material in the composition of sponge cities, which can be used to build the ecological balance of the city and create a green and environmentally friendly urban living environment, and has huge market and research prospects [3]. In recent years, China has experienced an increasing frequency of heavy rainfall in various cities. During periods of clear weather, groundwater is excessively exploited, and the transpiration of plants is intensified, leading to a decline in the urban groundwater levels. This situation not only causes roads to become prone to cracking and collapse, but also poses a significant threat to social security and development. Concurrently, the rapid growth of China's national economy has expedited the urbanisation process, which, in turn, has spurred the development and construction of the transportation infrastructure. To meet the demands for strength and durability, urban traffic pavements are designed to be impervious yet breathable. These airtight pavements, together with modern dense reinforced concrete high-rise buildings, cover the entire city, impenetrable to wind. Therefore, in this severe form, the preparation of breathable pervious concrete pavement materials that are more stable and can meet the needs of urban pavement has an important role in the further development of urbanisation in China. At present, the artificial neural network of deep learning has developed rapidly. Among them, the backpropagation (BP) neural network is widely used by domestic and jointly with foreign researchers to predict various types of concrete performance analysis, system simulation and classification [4]. This achieves the goal of managing storm water. In order to ensure the performance of permeable pavement in most areas affected by heavy rain and floods in China, Mehta and Sharma [5] analysed three types of permeable blocks and tested their blocking performance. For solving the problems of building energy consumption and cost reduction, Lu et al. [6] designed a green permeable concrete by using the dry-mix compaction technology. The strength is significantly enhanced, and it has very satisfactory water permeability.

Through the above research, it can be found that there are many experimental results on pervious concrete, but most of these research directions are relatively simple, only a single-factor analysis of materials under fixed conditions, and it is difficult to build accurate mathematical models for a multi-factor analysis. The contribution of the research is to predict and optimise the mix ratio of pervious concrete physical and mechanical properties through a BP neural network with excellent prediction accuracy, and to design different mix ratio optimisation schemes to maintain a comfortable urban thermal environment, which has a positive effect on the protection of urban groundwater resources. An enhanced BP neural network prediction model was produced by optimising the BP neural network model using the Beetle Antennae Search (BAS) algorithm in order to mitigate the urban "heat island effect" issue and investigate the best mix design of permeable concrete. The influence of permeable concrete was examined using the M^2 VA method, a multi-factor and multi-level experimental result visualisation analysis technique. This provides a scientific and reasonable material configuration scheme for building a green sponge city. The innovation of the research mainly includes the following three points: First, because there are many factors affecting the preparation and performance of pervious concrete, the research uses a uniform test method to reasonably design a small number of tests, so that the number of test levels can be increased from 3 levels in common orthogonal tests to more levels, so as to improve the credibility of establishing quantitative relationships. The second point is to construct a complex non-linear mapping relationship between the influencing factors and the performance indicators through the multi-layer BP neural network. The third point is to build a BP neural network model, conduct a numerical analysis and an analysis through the interpretation method, and describe the change law in the performance index of pervious concrete under a variety of different influencing factors. The research structure is mainly divided into four additional parts, the second part is related to the domestic and foreign research results, the third part is designed based on the BP neural network of the pervious concrete mix ratio optimisation method, the fourth part is the effectiveness and feasibility of the research method verification, and the last part is the summary of the research results.

REVIEW

Pervious concretes are porous concretes that are permeable to water, usually by mixing aggregates, cement, special additives and tap water in a certain proportion [7]. They can be used in various fields such as in pavements, transportation facilities and parks, allowing rainwater to penetrate into the ground quickly, ensuring the safety and comfort of the pavement, and reducing the occurrence of the urban heat island effect. Therefore, many scholars have conducted in-depth analyses on pervious concrete and provided valuable discussion points. In response to the problem of excessive water accumulation on the impervious surface existing in today's infrastructure, Lee et al. [58] explored the water permeability of different pervious concrete interlocking brick design schemes. The test results proved that these permeable blocks can be used in concrete design, and develop a complete cleaning and care system [8]. To verify the feasibility and applicability of permeable concrete, Kandalekar et al. [9] collected the precipitation and pavement conditions in the period of 5 years, and designed a pervious concrete pavement for peak hours and low traffic volume. In order to solve the problem of heavy metal pollution, Liu et al. [10] studied the effect of cement materials to remove heavy metal pollution. The experimental results demonstrate that the effect of functionalised permeable concrete is very good in removing heavy metals. Lawal and Agboola [11] evaluated the compressive strength of concrete using different curing methods and studied the curing of 72 cubes with a mixing ratio of 1:2:4 under various curing conditions, followed by curing at an average temperature of 28 °C in the laboratory. The results showed that the average compressive strength values at 7, 14, 21, and 28 days varied with the different curing methods. Among them, the compressive strength and density of the accumulated water were the highest, followed by covering and sprinkling. Then, the compressive strength and density of the cubes that were not cured or completely cured for two days were the lowest, and the shrinkage limit was the highest. Therefore, standing water is the most effective curing method, and compared to the other curing methods, the completely uncured concrete shrinks faster. The research findings can provide certain guidance for this study, which is beneficial in preparing concrete design schemes with better performance and environmental friendliness, consistent with the goals of sustainable urban development and infrastructure resilience.

Artificial Neural Network (ANN) technologies have developed rapidly in recent years. Among them, a back-propagation neural network (BPNN) has a strong self-learning ability, and is capable of analysing the hidden associations and laws between input and output data through learning. In addition, its operation is very simple, and the prediction results are accurate and reliable. It has been widely used in classification, image recognition and processing, and optimal prediction. Tang [12] investigated the resale behaviour of consumers in the context of big data, and studied the use of BPNNs and questionnaires for training and prediction functions. The experimental results demonstrated that the model based on BPNN achieved certain results, providing a powerful theory for the follow-up. To improve the applicability of human resource management systems, Wei and Jin [13] constructed an improved grey model (GM). The research results demonstrate that the three-layer BPNN model has excellent prediction performance and excellent practical effect. For the problem of accurate temperature prediction, Dou [14] constructed an adaptive genetic operator to optimise the BPNN, which verified the excellent prediction effect of the optimised BPNN model. In order to improve the quality of human resources performance management, Zhang [15] studied the use of import and export trade quotas in a city to verify the prediction effect and accuracy of the improved BPNN model. The experimental results demonstrated that the convergence speed and prediction accuracy of the model were capable of being very good, which was capable of meeting the current forecasting needs and provided a solid theoretical basis for any subsequent follow-up research.

From the above research, we are capable of knowing that, in the past, many domestic and foreign research projects are related to pervious concrete and BPNNs, and that they have achieved relatively mature results in various fields. However, the current research on the mix ratio of pervious concrete in China cannot take both the pervious and mechanical properties into account, and there are many influencing factors on the basic properties of pervious concrete, so one by one testing takes a long period and consumes a lot of materials, time and manpower, and the relationship between the influencing factors and the performance indicators of pervious concrete is very complicated. In order to improve the BP neural network's ability to anticipate the mix fraction of permeable concrete, the study optimises the BP neural network model using the BAS algorithm. Then, in order to create the ideal permeable concrete mix proportion and support the green and environmentally friendly urbanisation process, the M2VA approach is utilised to thoroughly study the impact of various factors on the mix percentage.

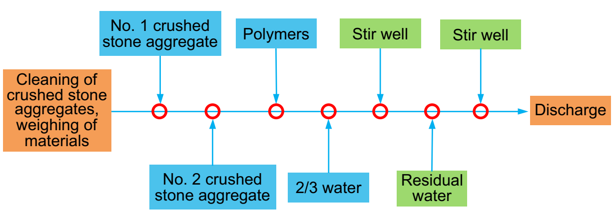


Figure 1. Flow chart of the pervious concrete mixing.

RESULTS AND DISCUSSION

Optimal design of the permeable concrete mix ratio based on a BP neural network

Design of the initial permeable concrete mix ratio

When designing the mix proportion of permeable concrete, the first step is to select the raw materials, and according to the quality requirements of Ordinary Portland Cement (GB175-2007), the following were selected China Resources Runfeng brand PO 42.5R ordinary Portland cement, crushed stone aggregates with particle sizes of 4.75-9.5 mm and 9.5-46 mm, powdered polyacrylate high water absorbent resin from Anju Environmental Protection Technology Company, VAE latex powder from Haosheng New Materials Company, and tap water was used as the mixing water. Due to the lack of a general data set on pervious concrete materials at present, the study prepared a certain sample through the preparation standard of pervious concrete, and then changed the amount of material through influencing factors, and then obtained the required data through measurement and calculation. The mixing method of pervious concrete is very special. A manual mixing method was used. The specific process is shown in Figure 1.

Figure 1 shows the sample preparation procedure. In order to prevent the accuracy of the water absorption test from being affected during the subsequent mixing process, the ash on the crushed stone aggregate's surface must first be cleaned. Next, the crushed stone aggregate, cement, and powdered polyacrylate super absorbent resin (also known as SAP) are combined with the VAE latex powder and thoroughly stirred. Next, two-thirds of the stirring water is added, and the mixture is stirred for one minute. Finally, after the mixture's surface has been soaked, the remaining water is added until the mixture's surface displays a metallic sheen and can be formed into a group by hand. At this point, the material can be released. Due to the dry and hard characteristics of permeable concrete, the water on the surface of the aggregate is very volatile. In addition, in order to ensure uniform layering and high water permeability on the surface of the mixture, it is most suitable to use a plate vibrator to vibrate the moulding surface. The hammer forming method is the easiest to operate and the easiest to control the hammer strength among the methods of vibration of the forming surface. The process is as follows: First, the mould of the concrete specimen is divided into three parts, and the modulus of each entry should be controlled to be 1/3 of the total weight of the test block; after each mould is installed, use a wooden hammer to evenly hammer it 50 times; Finally, after the concrete form is installed, use a wooden hammer to hammer the test block until the concrete height drops by 2-3 cm, add a small amount of concrete again, and continue hammering after the form is flat until it shows that it no longer sinks. After waiting for the test piece to be formed, cover it with plastic wrap, put it into a standard curing box for curing, remove the mould after one day, and then put it into a standard curing box for curing for 28 days to test the various indicators. The data collection includes four types: permeability coefficient, porosity, compressive strength, and flexural strength. The determination of the water permeability coefficient mainly uses the constant water head method jointly with the falling water head method. The water permeability coefficient calculation of the constant water head method is shown in Equation (1).

$$K_T = \frac{V_1 W}{S \Delta H t} \tag{1}$$

where K_T represents the water permeability coefficient V_1 when the water temperature is °C, T represents t the amount of water seeping out in the time period, W is the thickness of the specimen, S represents the area of the permeable interface, ΔH represents the water level difference, jointly with t, which is the measurement time period. The water permeability coefficient of the falling head method is K_F calculated as Equation (2).

$$K_F = \frac{\Delta V}{\Delta t} \tag{2}$$

where ΔV represents the change of water volume, jointly with Δt, which represents the time interval between the height difference of the water volume change. The water permeability of pervious concrete is affected by the connected pores, jointly measuring its porosity, which is important for water permeability. The porosity of pervious concrete was determined as P using the volume method, whose calculation is shown in Equation (3).

$$P = 1 - \frac{\Delta m \rho_w}{V_2} \times 100\% \tag{3}$$

where Δm represents the difference between the mass of the specimen after drying jointly with mass in water, in which ρ_w represents the density of water and is the V_1 volume of the specimen. For the determination of the compressive strength of permeable concrete, a cube specimen f_{cc} with a side length of 10 cm is used to place it into a pressure testing machine for testing, whose calculation is shown in Equation (4).

$$f_{cc} = \frac{F}{S_1} \tag{4}$$

where F represents the failure load of the S_1 specimen, and represents the area of the specimen under compression. Since permeable concrete often has a low flexural strength, an evaporation test is conducted to examine the concrete's water retention and release. A 4 × × 4 × 16 cm specimen is utilised and placed in a cement electric anti-folding machine. The permeable water per cubic metre is determined using the aggregate bulk density and the distribution area of different indicators derived from the historical research results. This allows for a more thorough analysis of the performance of permeable concrete by designing the mix ratio by combining the empirical method and the uniform test method. The specific design steps are as follows: First, the total amount of crushed stone aggregate needs to be calculated m_g, as shown in Equation (5).

$$m_g = \zeta \rho_g V_3 \tag{5}$$

where ζ represents the correction factor, generally in the range of 0.95-0.98; ρ_g represents the close packing density; V_3 it is the total volume of all the test blocks. According to the previous research results, it is determined that the bone-cement ratio ψ is distributed in the interval of 4-6, and the cement dosage m_c interval is determined in combination with Equation (5), which is calculated as Equation (6) [16].

$$m_c = \frac{m_g}{\psi} \tag{6}$$

According to the research results that have been verified, the water-cement ratio ξ is distributed in an interval of 0.25-0.45, and the water-cement ratio m_c is capable to be determined by combining with m_w in Equation (7) [17].

$$m_w = \frac{m_c}{\xi} \tag{7}$$

The past experimental results show that the ratio of the VAE polymer infiltration to cement content is τ in the distribution range of 0 to 0.15, so as to calculate the distribution range of the VAE polymer infiltration mass m_f, as shown in Equation (8) [18].

$$m_f = \tau\, m_c \tag{8}$$

The previous research results have proved that the ratio of the SAP infiltration amount to cement dosage is ϑ in the distribution range of 0-0.05, and the distribution range of the SAP infiltration quality is calculated m_f', as shown in Equation (9) [19].

$$m_f' = \vartheta\, m_c \tag{9}$$

By calculating the value ranges of the above five basic variables, combined with the four evaluation indicators of the permeability coefficient, porosity, compressive strength and flexural strength of the PC, the material range of various materials per cubic metre of permeable concrete can be obtained as follows: 4.75-9.5 mm crushed stone aggregate is 0-1277 kg, 9.5-16 mm crushed stone aggregate is 1250-0 kg, cement is 200-319 kg, SAP is 0-47.6 kg, VAE is 0-3.21 kg, tap water is 50-128 L. Based on the above range of materials used, the range of materials used for one feeding can be further calculated. Then, a uniform test plan with five factors and multiple levels was designed using the uniform test design method. Ten samples were configured for each of the five sets of quantities, as shown in Table 1.

Table 1. Five sets of mix ratio design of the once-mixed pervious concrete.

Material range	V	W	X	Y	Z
4.75-9.5 mm crushed stone aggregate (kg)	10.13	18.37	8.35	14.46	20.67
9.5-16 mm crushed stone aggregate (kg)	10.36	2.05	12.63	6.18	0.00
Cement (kg)	3.474	4.410	4.773	4.951	5.148
Water (mL)	1500	1722	1890	1890	2208
SAP (g)	15	22	35	16	51
VAE (g)	692	78	0	387	775
Water-cement ratio (%)	39.18	35.05	35.60	34.17	36.75
Glue collection ratio	4.91	4.58	4.33	3.87	3.39
Water permeability (mL·s^{-1})	103.5	107.2	70.8	101.9	107.8
Porosity (%)	36.0	40.7	30.0	35.2	39.5
Compressive strength (MPa)	12.4	11.3	14.5	13.3	11.4
Flexural strength (MPa)	2.47	2.98	2.60	2.29	2.52

Optimal design of the mix ratio based on the BP neural network

Due to its straightforward design, reliable operation, and ease of hardware implementation, BP neural networks now have a broad variety of applications in the optimum prediction. The fundamental idea of BP neural networks is to use gradient search technology to minimise the mean square error between the network's actual and predicted output values. In order to improve experimental efficiency and provide a solid theoretical foundation for the design of permeable concrete pavement mix proportions for sponge city construction, BP neural networks can be used to analyse and predict the mechanical and physical properties of permeable concrete. The non-linear data map relationship between the five basic influencing factors of pervious concrete and the four performance indicators, the most common used non-linear system analysis method in today's technology is the BP-M^2 VA analysis method, which can simulate the learning process of the human brain and has a very powerful non-linear processing capability. The specific flow of the BP-M^2 VA analysis method is shown in Figure 2.

In Figure 2, the implementation process of the BP-M2VA analysis method is as follows: Firstly, the 5 factors and 4 properties of the permeable concrete in this experiment are inputted into the initial mix proportion of the permeable concrete. At the same time, the threshold range of each material of the permeable concrete and the percentage of the admixture are determined through the relevant data. Next, construct a BP neural network model, train the model based on the above data, and then determine whether the error requirements meet the requirements. If they meet the requirements, the optimal mix ratio can be determined. Otherwise, adjust the weights and thresholds to return to the step of building the model. At the same time, predict and simulate the experimental results. It is necessary to normalise the sample data before being input into the model training. The research adopts zero-mean (z-score) normalisation processing, and the sample data are scaled proportionally to make the data within a specified range that can be compared. In addition, the normalised training sample data have a mean of 0-1. The normalised calculation of the z-score Z is shown in Equation (10).

$$Z = \frac{u-\mu}{\sigma} \tag{10}$$

where u represents the data of the training samples, μ represents the mean σ of the sample data, which is the standard deviation of the sample data. The calculation of the standard deviation is shown in Equation (11).

$$\sigma = \sqrt{\frac{1}{N}\sum_{a=1}^{N}\left(u_a-\mu\right)^2} \tag{11}$$

where N represents the total number of sample data points.

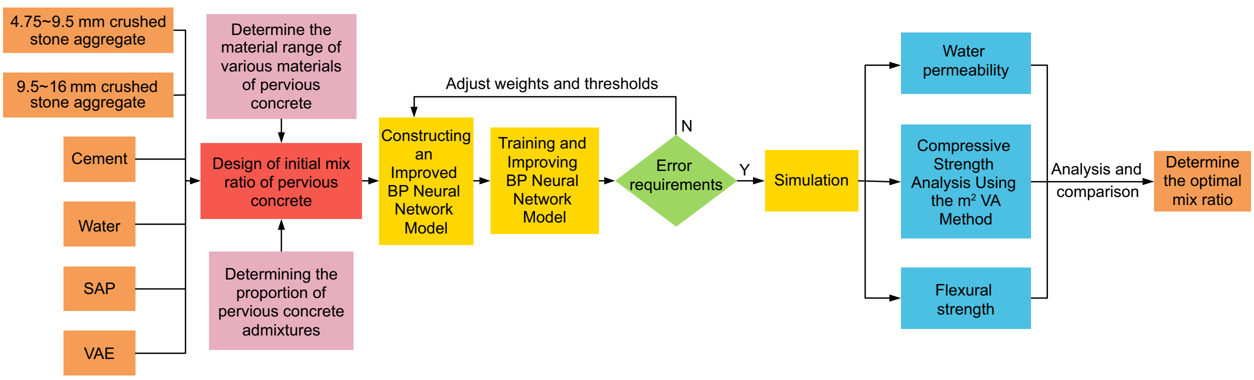


Figure 2. The specific process of the BP-M2 VA analysis method.

After the sample data are normalised, the parameters of the model need to be set. The most crucial nodes that have a direct impact on the BPNN model's performance are those in the input and output layers. As a result, the study's input vector consists of five permeable tangible components. As output layer nodes, four performance assessment indicators are employed. A higher number of hidden layers will boost the BPNN's accuracy, but too many layers will produce a great deal of redundant information, which will significantly slow down the network's rate of learning and computation. As a result, a two-layer hidden layer structure is used in the study. By modifying the weights, the hidden layer's nodes may increase the accuracy of the network learning and training while also extracting and storing the correlation and regularity of the sample data. There are three main reference calculation Equations for the number of hidden layer nodes, the first one is shown in Equation (12).

$$L_1 = N - 1 \tag{12}$$

where N corresponds to node count in the input layer. The reference calculation of the number of nodes in the second hidden layer is shown in Equation (13).

$$L_2 = \sqrt{M + N_I} + C \tag{13}$$

where the N_I node count representing the input layer and the M representing the output are C constants ranging from 1 to 10. The reference calculation of the node count in the third hidden layer is shown in Equation (14).

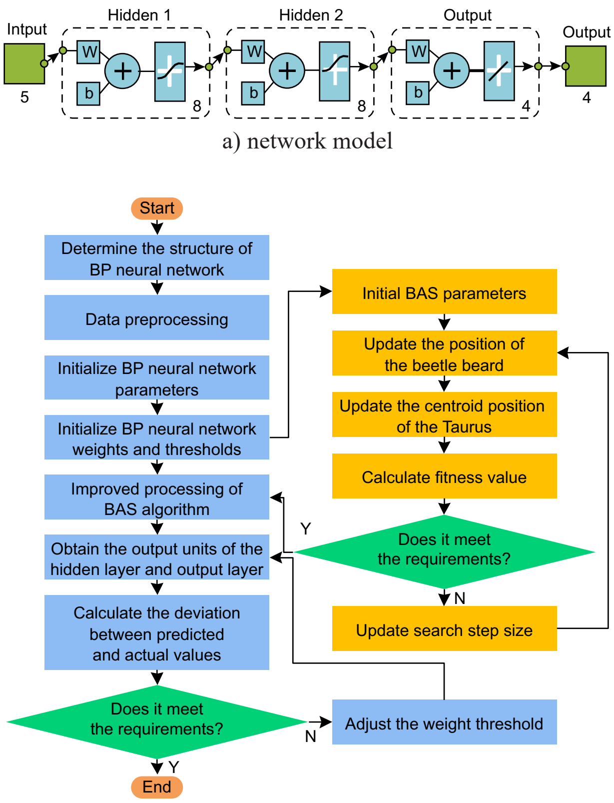
$$L_3 = \log_2 N_I \tag{14}$$

According to the above reference Equation for the hidden layer node counts, the interval of the number of nodes can be obtained as [3, 13], and the optimal hidden layer node counts can be determined by using the trial-and-error method to be 8. In the process of selecting network training functions, based on previous research results, it can be found that the Levenberg Marquardt (LM) algorithm has better network generalisation ability compared to other algorithms, while effectively reducing the difficulty in determining the optimal network structure. Therefore, the study uses the LM algorithm as a network training function, which can effectively improve the stability of iterations by adding a regularisation term to the function, thereby reducing the iteration step size. The calculation is shown in Equation (15).

$$\Delta u = -(H + \eta I)^{-1} G \tag{15}$$

where the H hessian matrix ηI representing the multi-dimensional vector represents the adjustment factor, where η is the step size, I is the identity matrix, and G is the first-order gradient of the multi-dimensional vector. In the selection of the transfer function of the network, to ensure that the neurons of the BPNN have abilities to process differential information, the transfer function of tansig + logsig + purelin combination is adopted.

In order to achieve higher design accuracy, a four-layer BP neural network model structure with dual hidden layers was constructed, see Figure 3a. The structure of the BP neural network model is constructed as follows. First, a vector group is input to the input layer 5 × n, and then the first and second hidden layers are constructed according to the determined number of neurons in the hidden layer, which is 8. Finally, four performances of permeable concrete are used. The evaluation metric determines the output layer as a 4 × n vector group. Although the BP neural network constructed above has good self-learning ability, adaptive ability, and response ability in dealing with complex linear problems, it also has certain problems, such as a slow convergence speed. If the learning rate is too low, it will cause a slow convergence speed. If the learning rate is too high, it will cause the neural network to oscillate, resulting in incomplete convergence. Moreover, the initial value and threshold randomness of the model are very strong. If the selection is not appropriate, it will have a significant impact on the update speed of the network weights. In addition, the above model is prone to minimum value problems and getting stuck in local optimal solutions. The BAS algorithm has good convergence speed and global search ability, which is beneficial for the BP neural network model to avoid falling into local minima,



b) schematic diagram

Figure 3. BP network model structure of pervious concrete (a) and schematic diagram of improving the BP neural network process (b).

thereby improving the model's generalisation ability. It can also be used to optimise the initial values and thresholds of the BP neural network, which can further improve the prediction accuracy of the BP neural network. Therefore, the study used the BAS algorithm to optimise the above model and obtained an improved BP neural network model. The specific flowchart is shown in Figure 3b.

As shown in Figure 3b, the structure and normalisation pre-processing of the BP neural network remain unchanged, while the search direction of the beetle is initialised through Equation (16) because its orientation is random.

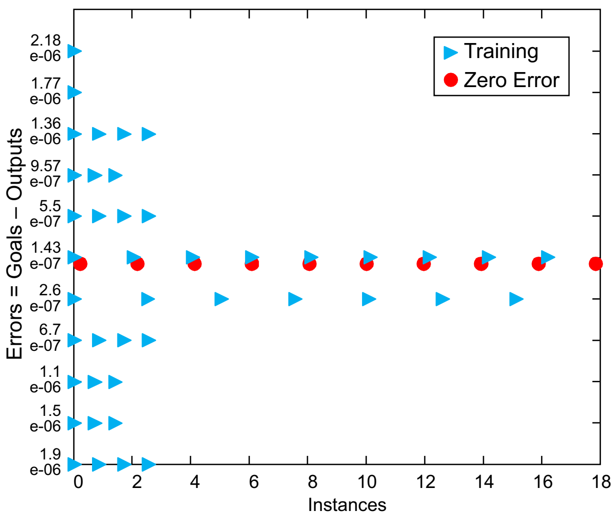
$$N = A \times B + B \times 1 + B + 1 \quad (16)$$

where N, A, and B correspond to spatial dimensions, random spatial unit vectors, and hidden layer neural networks, respectively. Then, the step size was set using a linear decreasing method, and the root mean square error (RMSE) was used as the fitness function to improve the spatial region search. Finally, the optimal weights and thresholds optimised by the BAS algorithm are inputted into the BP neural network for repeated iterative training until the requirements are met or the maximum number of iterations is reached, at which point it can be stopped. Based on the output results of the improved BP neural network prediction model, simulation experiments can be established to analyse the four performance indicators of perspective concrete and optimise the combination of the design mix proportions.

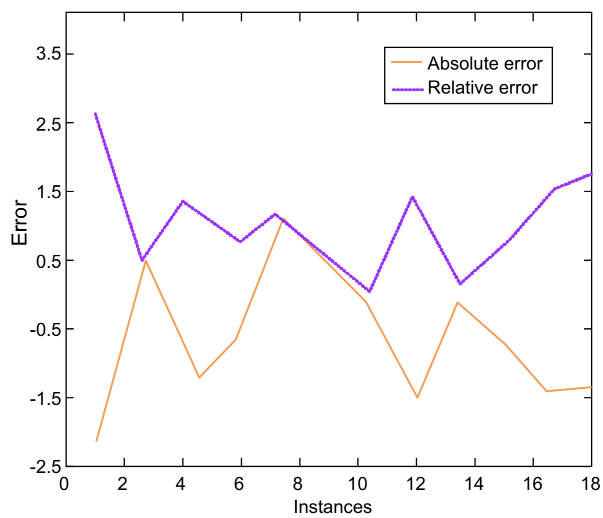
Performance and application analysis of the mix ratio optimisation design based on the BP neural network

To verify the performance of the BPNN prediction model, the research used MATLAB software to train the BPNN model. The specific process is as follows: Firstly, the neural network tool provided by the MALTAB software is used to train the constructed BP neural network model using the L-M algorithm. Secondly, the data and results from the uniform experiment method in Table 1 are used as training samples for the BP neural network model. 90 % of the training sample data are randomly selected, 5 % of the data are validated for effectiveness, and the remaining 5 % of the data are trained in the actual testing. Then, by using the proportional variation method of experimental factors, the five factors of the uniform experiment were adjusted to obtain each single factor experiment. Then, a BP neural network model was constructed to predict the experimental results and establish a simulation experiment. To verify the performance of research methods more scientifically, the current mainstream algorithms were selected for comparison, namely Random Forest Based on Improved Feature Filtering (RF-IFF); Extreme Learning Machine Optimised Based on the Tuna Swarm Algorithm (ELM-TSA); The joint exhaustive search strategy and logistic regression algorithm prediction method (ESS-LRA). In addition, the study used the RMSE, relative error, and correlation coefficient for the performance evaluation. Firstly, after inputting the 20 trained sample data points into the BP neural network prediction model, the error situation between the model's output results and the actual target, as well as the relative error and test error results, can be obtained, as shown in Figure 4.

Figure 4a shows the error between the output of the improved BP neural network prediction model and the actual target, while Figure 4b shows the relative error and the test error of the improved BP neural network prediction model. Figure 4a shows that the output results of the model have achieved the expected target, with a target error of 10^{-6}, indicating that the simulation



a)

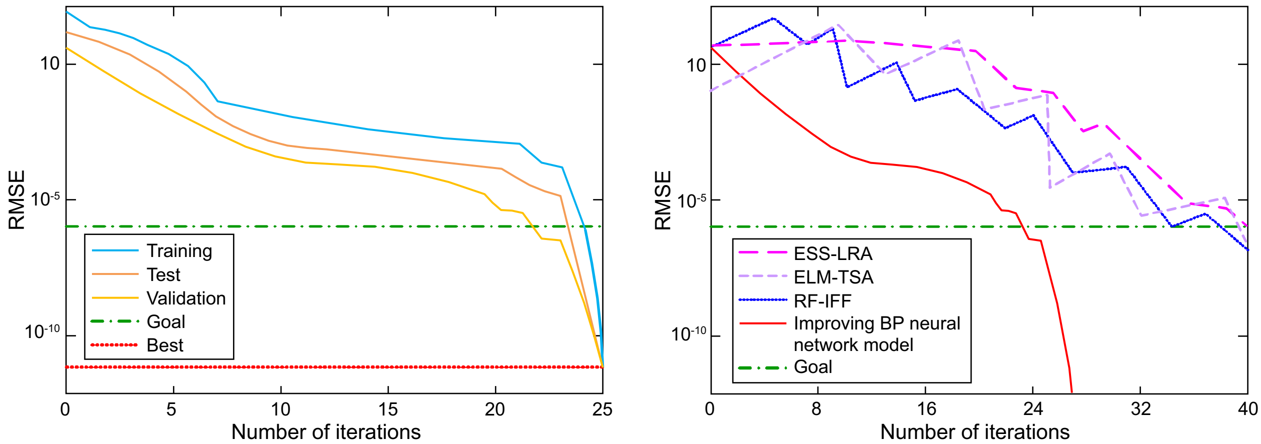


b)

Figure 4. The error situation between the output results of the improved BP neural network prediction model and the actual target, as well as the results of the relative error and testing error.

results obtained by the BP neural network prediction model are true and reliable. Figure 4b shows that the relative and absolute error ranges of the improved BP neural network prediction model are [-2.2, 1.1] and [0.3, 2.6], respectively. This indicates that the improved BP neural network prediction model has a higher prediction accuracy and can provide prediction results closer to the actual values. In the training process of the BPNN prediction model, the target error is set to 1.663×10^{-6} and the variation curve of the number of iterations of the root mean square error of the model is obtained as shown in Figure 5.

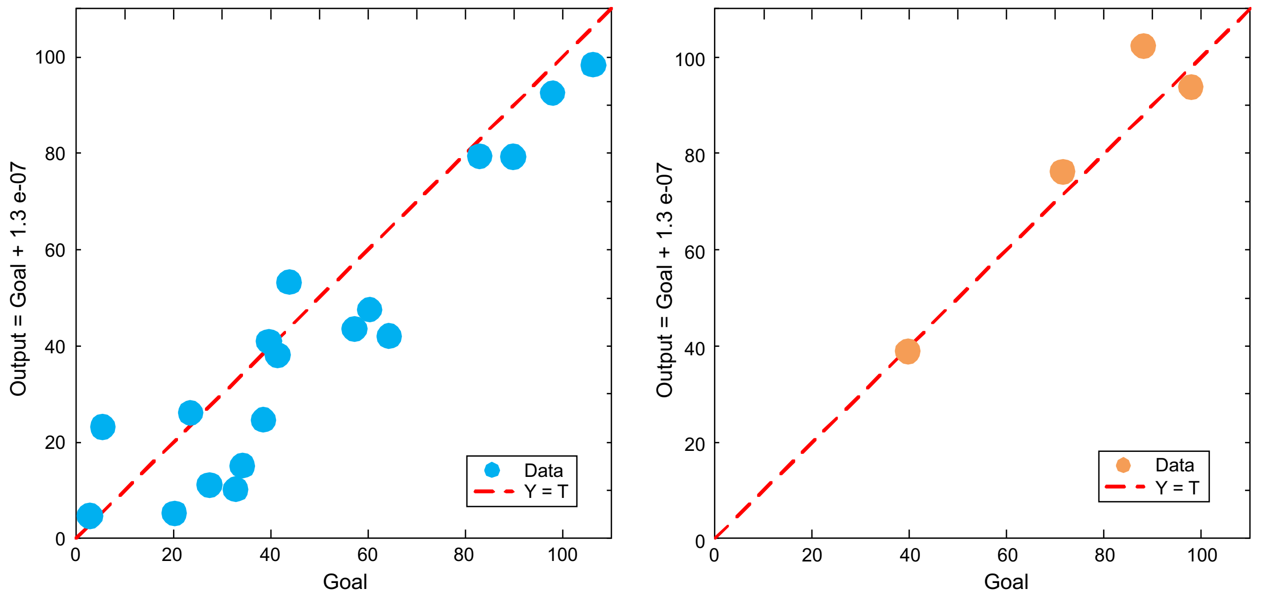
Figure 5a shows the variation curve of the RMSE iteration times of the model in the different datasets, and Figure 5b compares the RMSE results of the different prediction methods in all the samples. Figure 5a shows that, during the training, testing, and validation phases, the root mean square error of the BP neural network prediction model decreases with the increase in the iteration times. When there are 25 iterations, a target root mean square error of 1.66×10^{-12} can be achieved, and the model has the best convergence state. In the iteration curve of the verification phase, only 22 iterations can achieve the optimal target root mean square error. Figure 5b shows that the number of iterations for the improved BP neural network prediction model, RF-IFF, ELM-TSA, and ESS-LRA to reach the target mean square error is 25, 37, 39, and 40, respectively. This indicates that the research method has a good generalisation ability and prediction accuracy in handling complex data in a timely



a) improving the RMSE results of BP neural network prediction model on different datasets

b) RMSE results of different prediction methods

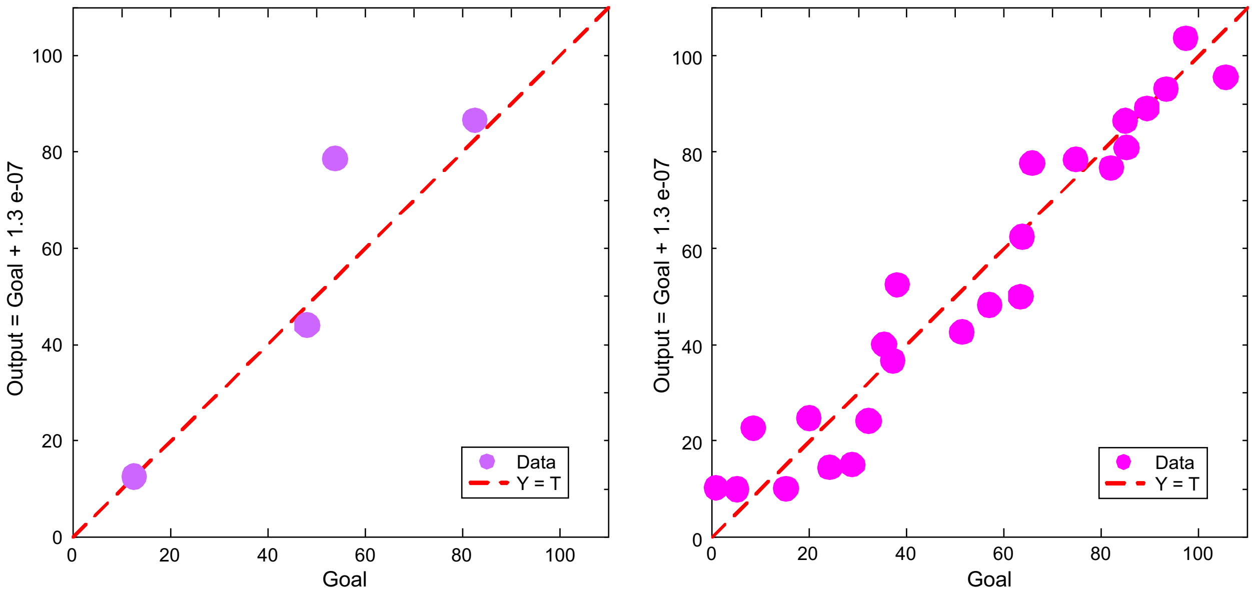
Figure 5. RMSE results of the different data and prediction methods.



a) training set

b) verification set

Figure 6. Improving the fitting effect of the BP neural network prediction model on the different datasets. *(Continue on next page)*



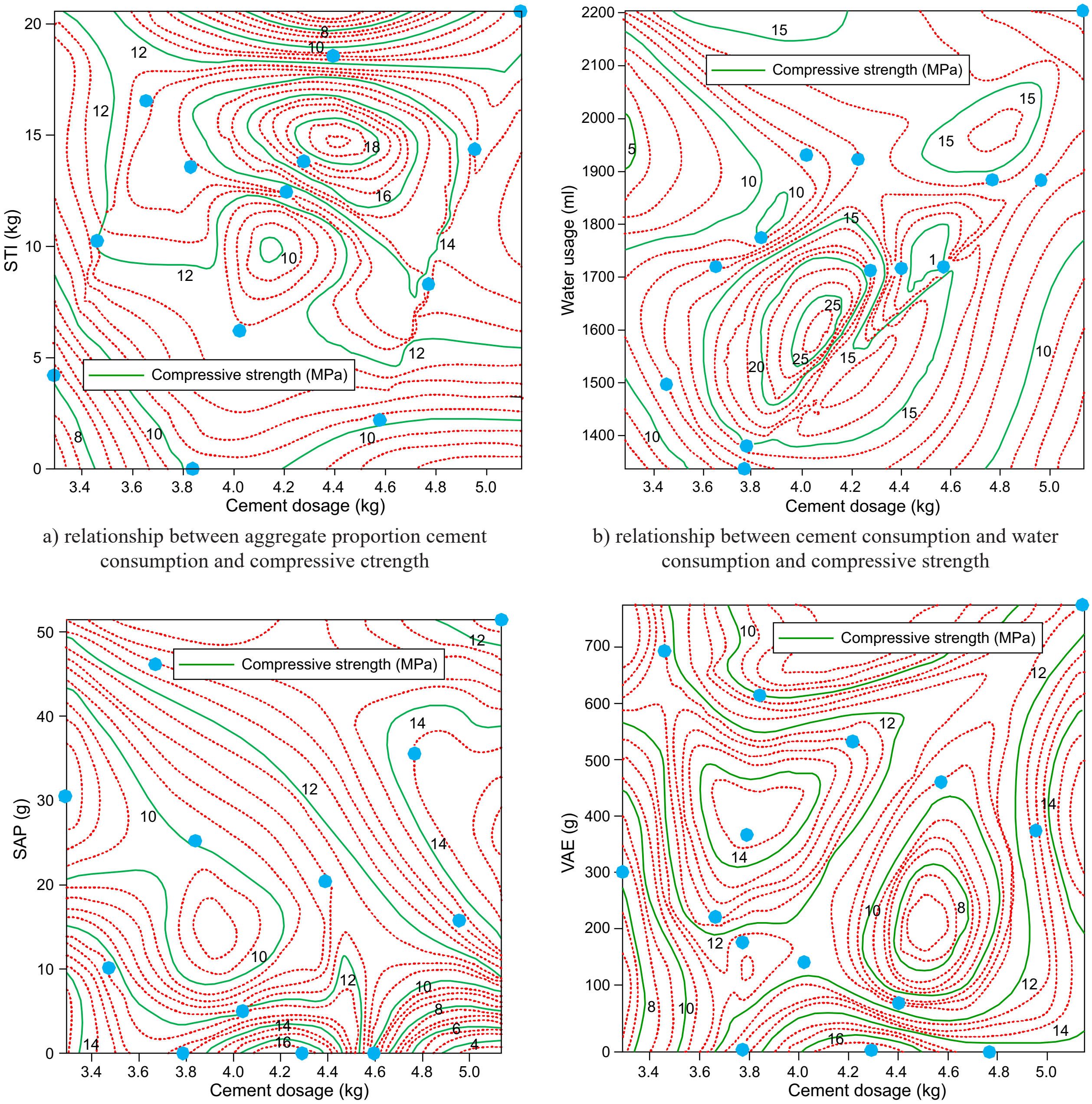
c) test set   d) all samples

Figure 6. Improving the fitting effect of the BP neural network prediction model on the different datasets.

manner. In order to explore the relationship between the actual and predicted value of the training sample, a regression analysis was performed on the results of the BPNN prediction model, and results are shown in Figure 6.

Figure 6a-d correspond to the fitting performance of the improved BP neural network prediction model in the training set, validation set, test set, and all the samples, respectively. From Figure 6, it can be observed that the correlation coefficient of the model in the training set is 0.9543, and the correlation coefficient in all the samples is 0.9674. The above results indicate that the research method has an excellent data fitting effect and high accuracy. To verify the application and improvement of the BP-M^2 VA analysis method based on the BPNN in the optimal design of the mix ratio of the permeable concrete, the M^2 VA method was used to explore the relationship between five influencing factors and the four performance indicators, in order to find compliance with the best mix design of the permeable concrete. According to the standard requirements of the permeability coefficient of permeable concrete for pavement permeability, the cost-effectiveness during construction, and the flexural strength that needs to meet the requirements of urban sidewalks or bicycle lanes at 2.5 MPa or above, the permeability, porosity, and flexural strength of groups 1-5 can meet the basic functions of construction, and the cost benefit difference is small, but the compressive strength is very poor. Therefore, it is important to explore an improvement in the compressive strength. By analysing the relationship between the amount of each influencing factor and the compressive strength by the M^2 VA method, the relationship between the materials and the compressive strength of the different permeable concrete mix ratios can be obtained, as shown in Figure 7.

According to Figure 7a, it can be seen that the crushed stone aggregate with a size of 4.75-9.5 mm is ST1, and the crushed stone aggregate with a size of 9.5-16 mm is ST2. With the increase in the ST1 material, the compressive strength shows a first increasing and then decreasing change. When its dosage is about 15 kg, the cement dosage is 4.2-4.5 kg, and the bone cement ratio is in the range of 4.6-4.9, the compressive strength of permeable concrete can reach the pavement application standard of over 25 MPa. Figure 7b that the water consumption has a great influence on the compressive strength. When the water consumption is 1500-1700 mL and the cement consumption is 3.85-4.2 kg, the compressive strength with the pervious concrete can meet the basic functional requirements. As can be seen from Figure 7c, when the cement dosage is less than 4.4 kg, without adding or adding less than 0.2 % SAP, the compressive strength is capable of meeting the requirements, but adding the amount will reduce the compressive strength; however, when the cement dosage exceeds 4.6 kg, with the growth of the SAP infiltration, the compressive strength shows a first increasing with a slight decreasing trend; but when the cement dosage is 4.6-5.14, the most suitable SAP infiltration amount is 25-40 g, accounting for 25-40 g of cement and 0.54-0.83 % of the dosage. It is possible to be observed from Figure 7d that when no VAE is added, as the cement compressive strength increases, the compressive strength increases and then decreases; when the cement dosage is 4.29 kg and the bone-to-cement ratio is 4.8, the compressive strength is the largest, is 17.5 MPa, which cannot meet the basic functional requirements; when the cement dosage is 3.8-4.0, adding 10 % of VAE helps to increase the compressive strength by about 15 %, and the compressive performance is able to meet the requirements. The research results show that the relationship between the five influencing factors of the pervious concrete and the compressive strength from strong to weak are the water consumption, ST1, cement, VAE, SAP, and when the consumption of ST1 is about 75 % of the total aggregate consumption, the water consumption at about 1600 mL, when the cement dosage is 3.75-4.3 kg, the optimised mix ratio is able to be designed. In addition, when the cement dosage is less than 4.3 kg, the pervious concrete is capable of obtaining better performance when the SAP is less infiltrated; when the VAE infiltration amount is 9 % to 10 %, it is possible to actively promote the mechanical properties of the PC. In addition, the density of permeable concrete increases monotonically with the change in the porosity, and the thermal resistance performance is closely related to the porosity. Permeable concrete with higher porosity has better thermal resistance performance. High porosity can also reduce the heat island effect by lowering the surface temperature, thereby increasing its internal resistance. According to the optimise mix proportion design range of the PC, four groups of improved test mix proportion designs can be obtained as shown in Table 2.



a) relationship between aggregate proportion cement consumption and compressive ctrength

b) relationship between cement consumption and water consumption and compressive strength

c) relationship between SAP infiltration amount cement dosage and compressive strength

d) relationship between VAE infiltration amount cement dosage and compressive strength

Figure 7. Analysis of the influence of the five basic influencing factors on the compressive strength of the pervious concrete by the M^2 VA method.

Table 2. Five sets of mix ratio design of the once-mixed pervious concrete.

Mix ratio indicator	A	B	C	D
ST1 (kg)	13.95	12.96	12.96	12.96
ST2 (kg)	7.3	6.98	6.98	6.98
Cement (kg)	4.30	3.79	3.79	3.79
Water (mL)	1690	1340	1340	1385
SAP (g)	0	0	0	0
VAE (g)	0	190	0	377
Water-cement ratio (%)	39.97	35.12	36.03	33.91
Glue collection ratio	4.94	5.03	5.28	4.80

From Table 2, it can be seen that the mix design of the Group A permeable concrete requires more raw materials compared to the other three groups, with an increase of 1.44-1.63 kg per cubic metre. Therefore, the cost of the material consumption is relatively higher. The optimised permeable concrete mix design was uniformly tested, and the performance of the optimised mix design was evaluated using four evaluation indicators. The results are shown Table 3.

Table 3. Result analysis of the optimised PC mix design.

Performance evaluation index	A	B	C	D
Water permeability ($mL \cdot s^{-1}$)	65.6	74.0	91.0	83.5
Porosity (%)	32.2	36.4	38.4	37.6
Compressive strength (MPa)	3.66	2.36	2.36	3.24
Flexural strength (MPa)	17.6	13.2	11.6	14.8

It can be observed from Table 3 that the applicable range of the materials in group A is more suitable for the improved mix ratio of BPNN, and the mechanical properties are significantly improved compared with the other three groups. Among them, group C has the highest water difference and worse mechanical properties also. When the water-cement ratio is 0.38-0.43, the pervious concrete can have better mechanical effect, which verifies the prediction of the BPNN model. The permeability coefficient of Group A mix design is determined to be 65.6 $mL \cdot s^{-1}$, which is much higher than the general permeability of 200 $L \cdot (m^2 \cdot min)^{-1}$. This is equivalent to a 100 mm high pavement structure capable of achieving a permeability of 393 L per square metre per minute. The standard for permeable concrete is that the permeability coefficient is not less than 4.5-6.5 cm per second. This indicates that even if the permeability coefficient and porosity of Group A decrease, it can still meet the basic permeability function of the road surface. In addition, when the VAE penetration is about 10 %, the mechanical effect is improved, which proves the correctness of the prediction of the BPNN model. According to the above content, the following conclusions can be drawn: When ST1 is 13.95 kg, ST2 is 7.3 kg, the cement amount is 4.30 kg, and the water consumption is 1690 mL, the compressive strength can meet the functional requirements, and can ensure good mechanical properties and water permeability at the same time. Based on the above content, it can be concluded that the research method has excellent performance and application effects, and has wide applicability, which can be applied to other materials. However, there are still certain limitations to the research methods. The study only analyses the optimisation of the material dosage and mix proportion of permeable concrete, and comparative experiments on the factors, such as the mixing method and curing technology in sample preparation, have not yet been tested.

CONCLUSION

Permeable concrete is a crucial functional material in the building of sponge cities, and the novel management concept of sponge cities may effectively mitigate the urban heat island effect under emerging circumstances. Thus, research into high-performance permeable concrete is necessary. In order to analyse the factors influencing the performance of permeable concrete and achieve an optimised mix design for permeable concrete, research is being performed on optimising the BP neural network prediction model using the BAS algorithm, obtaining an improved BP neural network prediction model, and combining it with the M^2VA method. According to the experimental findings, the BP neural network prediction model may reach the optimal convergence state with an error of about 1.663×10^{-6} after just 25 iterations. The final ideal permeable concrete mix design calls for a cement content of 4.30 kg, water usage of 1690 mL, ST1 of 13.95 kg, and ST2 of 7.3 kg. In conclusion, the study method's performance and predicted accuracy are both quite good. In order to successfully reduce urban waterlogging and safeguard urban groundwater resources, the BP-M2VA analysis technique may optimise the mix proportion of prospective concrete. However, there are still limitations to the research. In future research, the superior performance of solid waste can be utilised by incorporating it in the form of admixtures to obtain higher performance, low-cost, and green ecological permeable materials.

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