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# Modeling of compressive strength of recycled concrete under different loading conditions by steel fibers based on back propagation neural network

**Sumei Shi[1,*] and Zhenye Xing[2]**
[1] School of Intelligent Science and Engineering, Xi'an Peihua University, Xi'an, Shaanxi, 710100, China
[2] Design Department, Shanxi Huarui Investigation and Design Limited Company, Xi'an, Shaanxi, 710100, China
Corresponding authors: (e-mail: Ssm150698@163.com).

**Abstract** Steel fiber blending can effectively improve the performance of recycled concrete, but the change rule of compressive strength under different loading conditions is complicated. This paper investigates the compressive performance of steel fiber reinforced recycled concrete under different loading conditions and establishes a prediction model based on BP neural network. The study selected apparent density of recycled coarse aggregate, water absorption, steel fiber parameters, cement dosage, water-cement ratio, sand rate and recycled coarse aggregate substitution rate as input parameters, and slump, 28d compressive strength and elastic modulus as output parameters. The model was trained by 7-20-3 network structure with trainlm function. The results show that: the prediction accuracy of the constructed BP neural network model is high, and the overall root-mean-square error is only 0.8671%, which has a good generalization ability; when the water-cement ratio is 0.66, the overall compressive strength of concrete decreases with the increase of the substitution rate of the recycled coarse aggregate; the compressive strength of granular shaping recycled coarse aggregate concrete is higher than that of the simple crushed recycled coarse aggregate concrete; the simple crushed steel fiber recycled concrete has the optimum water-to-cement ratio (0.45) was higher than that of particle shaped steel fiber recycled concrete (0.4); the compressive strength of particle shaped steel fiber recycled concrete was the greatest within the range of water-to-cement ratios from 0.35 to 0.4. The model reliably reflects the influence of steel fiber admixture, recycled aggregate properties and water cement ratio on the compressive strength of concrete, which provides a scientific basis for the actual proportion design.

**Index Terms** Steel fiber recycled concrete, BP neural network, Compressive strength, Prediction model, Water cement ratio, Aggregate substitution rate

## I. Introduction

In recent years, with the rapid development of industry and construction, 160 million tons of waste concrete will be produced every year, and the excessive construction waste has triggered people's concern about environmental problems [1]. It is an effective method and way to solve the problem of waste concrete by crushing the waste concrete through the crushing process and obtaining recycled aggregate in accordance with a certain grading ratio, which is added to the concrete instead of natural sand and gravel aggregate [2]. At present, due to the shortcomings of recycled aggregate concrete itself, such as poor solidity and high water absorption, it is mainly used in the pavement base layer or non-load-bearing structure, but in fact, the application in recycled concrete is not very common, because recycled concrete is easy to crack [3]-[6]. Especially, its strength is lower than the ordinary concrete strength, and there is no sufficient observation and research on recycled concrete in engineering construction, still lack of experimental analysis and systematic research, and a variety of research information is not perfect [7]-[9]. If the compressive strength of recycled concrete can be improved, the application of recycled concrete will be more and more emphasized. In the actual project, if the recycled concrete can be effectively utilized, it not only saves the cost of waste disposal, but also reduces the pollution to the environment, especially also solves a series of negative environmental problems caused by the difficulty of dealing with concrete waste, which is of great significance to environmental protection [10]-[13].

With the development of the times, the steel fiber mixed into the recycled concrete to improve the tensile strength of recycled concrete and inhibit the expansion of cracks, so that it can be better applied to the actual engineering and construction, which will be more and more people's attention [14]-[16]. In previous studies, the compressive strength of concrete reflected by split tensile test is not very accurate [17]. And the existing models are difficult to predict the steel fiber reinforcement under different loading conditions with the risk of overfitting [18].

Backpropagation neural network is a nonlinear prediction model based on neural network. By simulating the connection of neurons in the human brain to build a complex network structure, so as to be able to deal with nonlinear relationships, it has a strong ability in data fitting and prediction, and is used by most scholars in the research of concrete compressive strength [19], [20].

Concrete is one of the most widely used building materials in today's construction projects, and in the face of the double demand for resource utilization of construction waste and the development of green and low-carbon buildings, recycled concrete technology has attracted much attention. However, the mechanical properties and durability of recycled concrete are usually inferior to those of ordinary concrete due to its raw material characteristics, which limits its application in high-performance engineering. Currently, incorporating steel fibers into recycled concrete has been proven to be an effective way to improve its performance. Steel fiber reinforced recycled concrete is a composite material formed by mixing steel fibers with traditional recycled concrete components, which can comprehensively play the dual advantages of fiber reinforcement and reuse of waste concrete. Existing studies have shown that the addition of steel fibers can significantly improve the mechanical properties of recycled concrete, especially in resisting crack expansion and increasing tensile strength. However, the performance of steel fiber recycled concrete is affected by a variety of factors, including fiber type, length, admixture, quality of recycled aggregate, and proportion parameters, etc., and the interaction of these factors forms a complex nonlinear relationship. Traditional mathematical regression methods and empirical formulas are difficult to accurately describe this multivariate, highly nonlinear mapping relationship, so it is particularly important to seek more efficient prediction methods. Artificial neural networks, as an advanced machine learning technology, can handle complex nonlinear problems by simulating the working principle of neurons in the human brain, and do not need to pre-determine the mathematical relationship between the variables, and have shown great potential in the field of material performance prediction.BP neural network, as a typical feed-forward neural network, utilizes the error back propagation algorithm for learning, and is able to reflect the complexity of the relationship between the mix ratio and the performance of fiber doped recycled concrete. BP neural network, as a typical feed-forward neural network, can accurately reflect the complex relationship between the proportion and performance of fiber-doped recycled concrete and provide a theoretical basis for the optimization of concrete performance.

In this study, BP neural network is applied to predict the compressive strength of steel fiber recycled concrete, and the compressive strength prediction model is established by constructing a 7-20-3 network structure with steel fiber parameters, recycled aggregate characteristics and mix ratio parameters as inputs. In the study, 10 sets of specimens including normal concrete and steel fiber recycled concrete were designed and prepared using steel fibers with different fiber lengths (6mm, 12mm, 18mm) and volume fractions (0.2%, 0.4%, 0.6%) for mechanical property testing and data collection. By normalizing and scientifically segmenting the collected data, 80% was used in the training set to establish the network model and 20% was used in the testing set to verify the model accuracy. On the basis of optimizing the network parameters, the influence laws of aggregate type, substitution rate, water-cement ratio and other factors on the compressive strength of steel fiber recycled concrete were explored to provide scientific reference for engineering applications.

## II. Preparation of the experiment

Mixed fiber recycled concrete is a man-made composite material formed by steel fibers, cement, water, fine aggregate, natural coarse aggregate, recycled coarse aggregate, and a certain amount of water reducing agent according to a certain mixing ratio and hardened by condensation [21], [22]. In the case of recycled aggregate substitution rate is determined, its performance mainly depends on the amount of fiber, the proportion of different fibers, as well as the test piece production process and maintenance means. This chapter introduces the various raw materials used in the specimen fabrication process, and the design of various mixing ratios as well as the description of the equipment used in the test process.

### *II. A. Test raw materials and their properties*

#### II. A. 1) Cement and fly ash

Commonly used cement mainly includes slag cement and silicate cement, this test is selected for the silicate cement produced by Tongchuan Shengwei Building Materials Limited Liability Company, and the fly ash is secondary fly ash. The measured performance indexes of cement and fly ash are shown in Table 1 and Table 2.

Table 1: Measured performance indicators of cement

| Category | Specific surface area (m ² /kg) | Setting time (min) | | Flexural strength (MPa) | | Compressive strength (MPa) | |
|---|---|---|---|---|---|---|---|
| | | Initial coagulation | Final solidification | 3d | 28d | 3d | 28d |
| National standard | ≥400 | ≥52 | ≤700 | ≥3.7 | ≥5.8 | ≥16.3 | ≥41.8 |
| Measured value | 319 | 166 | 224 | 5.2 | 7.6 | 32.9 | 50.6 |

Table 2: Measured performance indicators of fly ash

| Category | Fineness (45 $\mu m$ square hole(Sieve residue) % | Water demand ratio % | Burn loss ratio % | Water content % | Sulfur trioxide % |
|---|---|---|---|---|---|
| Quality Requirements (Grade II II) | ≤29.3 | ≤111 | ≤8.4 | ≤1.2 | ≤3.5 |
| Measured value | 18.8 | 101.5 | 2.62 | 0.0 | 2.53 |

**II. A. 2) Natural aggregates**

Aggregate is divided into coarse aggregate and fine aggregate, fine aggregate particle size is 0.15mm~4.75mm, coarse aggregate particle size is ≥4.75mm, fine aggregate is common river sand, natural coarse aggregate comes from a stone factory, natural aggregate grading and performance parameters are shown in Table 3~Table 6.

Table 3: Fine aggregate gradation

| Sieve hole (mm) | 4.68 | 2.28 | 1.09 | 0.62 | 0.32 | 0.19 | <0.21 |
|---|---|---|---|---|---|---|---|
| Residual % of the perforated sieve | 7.22 | 11.4 | 10 | 17.3 | 34.4 | 12.2 | 4.4 |
| Cumulative screening residue % | 8 | 20 | 30 | 44 | 82 | 88 | 100 |

Table 4: Measurement table of basic parameters of fine aggregate

| Apparent density (kg/m ³) | Bulk density (kg/m ³) | Compactness density (kg/m ³) | Mud content % | Water content % |
|---|---|---|---|---|
| 2626 | 1644 | 1815 | 2.05 | 3.04 |

Table 5: Coarse aggregate gradation

| Sieve hole (mm) | 16 | 12 | 8.8 | 4.69 | 2.28 | <2.28 |
|---|---|---|---|---|---|---|
| Residual % of the perforated sieve | 30.25 | 26.35 | 41.05 | 1.26 | 0 | 0 |
| Cumulative screening residue % | 21 | 48 | 69 | 100 | 100 | 100 |

Table 6: Actual parameter measurement table of recycled coarse aggregate

| Apparent density (kg/m ³) | Bulk density (kg/m ³) | Compactness density (kg/m ³) | Mud content % | Crushing index % |
|---|---|---|---|---|
| 2736 | 1535 | 1635 | 0.321 | 6.25 |

**II. A. 3) Recycled coarse aggregates**

The recycled coarse aggregate used in this test was obtained by crushing concrete beams with design strength of C30 and standard curing for 90 days by crusher (4.75-26.5mm continuous gradation), and its gradation and basic parameters are tabulated as shown in Tables 7 to 8.

Table 7: Recycled coarse aggregate gradation

| Sieve hole (mm) | 16 | 12 | 8.8 | 4.69 | 2.28 | <2.28 |
|---|---|---|---|---|---|---|
| Residual % of the perforated sieve | 30.25 | 26.35 | 41.05 | 1.26 | 0 | 0 |
| Cumulative screening residue % | 21 | 48 | 69 | 100 | 100 | 100 |

Table 8: Actual measurement of basic parameters of recycled coarse aggregates

| Apparent density (kg/m ³) | Bulk density (kg/m ³) | Compactness density (kg/m ³) | Mud content % | Crushing index % |
|---|---|---|---|---|
| 2532 | 1372 | 1512 | 0.53 | 11.5 |

#### II. A. 4) Water

According to “Concrete Water Code”, ordinary tap water was used for this test mix.

#### II. A. 5) Fibers

The fibers used in this test were produced from a company's, the basic performance parameters of steel fibers are shown in Table 9.

Table 9: Basic performance parameters of steel fibers

| Density (g/cm ³) | Diameter (μm) | Length (mm) | Tensile strength(MPa) | Elastic modulus(GPa) | Elongation % |
|---|---|---|---|---|---|
| 1.22 | 34 | 20 | 1925 | 34.72 | 7.82 |

#### II. A. 6) 2.1.6 Water reducing agents

The water reducing agent used in this test is the Nai system water reducing agent produced by Hongda Building Material Factory of Qindu District, Xianyang, which is a dark brown viscous liquid with obvious water reducing effect and good adaptability to concrete. The basic parameters of the water reducing agent are shown in Table 10.

Table 10: Basic parameters and recommended dosage of water reducing agent

| Color | Appearance | Water reduction rate% | PH | Gas content % | Bleeding rate ratio % | Suggested dosage % |
|---|---|---|---|---|---|---|
| Dark brown | Viscous | 18.27 | 6.62 | 4.14 | 29.82 | 1.47 |

### *II. B.Test profile and mixing ratio design*

#### II. B. 1) Overview of the experiment

This test selects the new high elongation steel fiber and short-cut impregnated steel fiber, and to separate and two kinds of fibers in accordance with a certain proportion of mixed admixture into the recycled aggregate substitution rate of 50% recycled concrete to form a total of 22 groups of different admixture ratio of the specimens and carry out the durability and basic mechanical properties of the test, the research content is as follows: will be the steel fibers each with a volume of the admixture rate of 0.2%, 0.4%, 0.6% by volume of steel fibers into the base recycled concrete, and ordinary recycled concrete to form a total of 7 groups of comparative tests, and to the total volume of the mixing rate is still 0.2%, 0.4%, 0.6% of the two kinds of fibers mixed into the base recycled concrete, concrete durability and basic mechanical properties of the test.

#### II. B. 2) Mixing ratio design for testing

The premise of concrete ratio design is to meet the construction quality and strength requirements, and also to achieve economic rationality. Up to now, domestic and foreign scholars on the design of recycled concrete ratio is generally based on the natural aggregate concrete ratio of recycled aggregate equal quality to replace the natural aggregate, and due to the recycled aggregate is generally larger porosity, so it is necessary to appropriately increase the unit water consumption.

Based on the normal concrete ratio in the “concrete ratio design specification” (JGJ55-2011), 50% of the natural coarse aggregate is replaced by recycled coarse aggregate, and the unit water consumption is set to 175kg/m3 when making specimens, taking into account the concrete's compatibility, and the amount of water reducing agent is 1.5% of the cementitious material, the recycled concrete ratio is shown in Table 11. Keeping the unit dosage of each of the above materials unchanged, polyvinyl alcohol fibers and steel fibers were added to the matrix recycled concrete by external mixing, and the steel fibers were mixed singly with volume mixing amounts of 0.2%, 0.4%, and 0.6%, respectively.

Table 11: Mix proportion of recycled concrete

| Cement $kg/m^3$ | Water-cement ratio $kg/m^3$ | Sand ratio $kg/m^3$ | Water $kg/m^3$ | Cement $kg/m^3$ | Sand $kg/m^3$ | Natural coarse aggregate $kg/m^3$ | Regenerated coarse aggregate $kg/m^3$ | Water reducing agent kg% |
|---|---|---|---|---|---|---|---|---|
| 41.81 | 0.42 | 0.43 | 169 | 344 | 829 | 505 | 505 | 1.25 |

### *II. C.Test equipment, specimen preparation and maintenance*

#### II. C. 1) Test equipment

(1) Molds: mold size 200mm×200mm×200mm and 200mm×200mm×800mm, the specimens made in the former are used for compression, split tensile, freeze-thaw cycle test and sulfate dry and wet cycle test, and the specimens made in the latter are used for flexural test.

(2) Mixer and shaker: the mixer used in the process of specimen production is an ordinary bedroom mixer.

(3) Basic Mechanical Property Test Apparatus: The apparatus used for the three basic mechanical property tests of the specimens are hydraulic servo universal pressure testing machine.

#### II. C. 2) Specimen preparation and maintenance

In the process of preparing fiber recycled concrete, the fibers are agglomerated, which makes them unfavorable for uniform dispersion in the recycled concrete, and the poor dispersion of fibers will have a large negative impact on the performance of the recycled concrete specimens, so the fibers should be dispersed uniformly as much as possible in the recycled concrete when preparing fiber recycled concrete. Finally, the specimens were moved to the curing room at 20±2°C with relative humidity greater than 95% for curing for 3d, 28d and 56d.

## III. Establishment of BP neural network model for recycled concrete performance

### *III. A. Selection of network structure*

#### III. A. 1) Training samples

There are many factors affecting the performance of recycled concrete, such as water-cement ratio, sand rate, type of recycled aggregate and steel fiber, cement variety and dosage, admixtures and so on. When establishing the network model, due to the test conditions, data acquisition limitations and network structure, it is impossible to take all the influencing factors into account, but to find out the main factors, this paper based on the engineering practice of comprehensive considerations to select the apparent density of recycled coarse aggregate, water absorption, steel fibers, cement dosage, water-cement ratio, sand rate, recycled coarse aggregate substitution rate of a total of seven factors as the input parameters of the BP neural network, to slump, 28d compressive strength, modulus of elasticity 3 factors as the output parameters of BP network.

#### III. A. 2) Normalization of sample data

Due to the large range of data under each parameter of the sample data, some values are not in an order of magnitude, if the original data are used directly for training, the time used for convergence will be very long, and an optimization algorithm solution is needed. In addition, the connection function between neurons in the BP neural network has a value range between (-1, 1), and the range of the sample data of the neural network should also be between (-1, 1), so it is necessary to transform the sample data first, and the general simple normalization is shown in Equation (1):

$$X' = \frac{X_{\max} - X}{X_{\max} - X_{\min}} \tag{1}$$

where $X'$ is the normalized value, $X$ is the actual value, and $X_{\max}$ and $X_{\min}$ are the maximum and minimum of the actual value, respectively.

In BP neural network, the sample set is normalized by formula (1) and then trained, which can speed up the convergence and shorten the time. However, since the maximum value range of the activation function of the BP algorithm is $(-1,1)$, the gradient of the network decreases gently near 0 and 1, and the training process can be completed in this interval, and the training time may take very much time, this formula is not optimized enough. In this paper, we will use formula (2) to further normalize the training sample set data to a smaller range $[0.2, 0.8]$ interval, to reduce the training difficulty of the network, and the results show that the BP network activation function has the maximum learning rate in this interval, which effectively improves the performance of the network. Namely:

$$X' = 0.2 + \frac{0.6(X - X_{\min})}{X_{\max} - X_{\min}} \tag{2}$$

where $X'$ is the normalized value, $X$ is the actual value, and $X_{\max}$ and $X_{\min}$ are the maximum and minimum of the actual value, respectively.

#### III. A. 3) Determination of the number of hidden layers and the number of nodes

Too few nodes in the hidden layer and the network training does not converge. Too many nodes, the network learning rate becomes slower, and may also fall into the local minima. The number of hidden layer nodes can only be selected using the trial-and-error method, combined with some empirical formulas to make a preliminary determination of the hidden layer nodes. The following are 3 empirical formulas:

(1) Hecht-Nielsen, after discussing the functionality of ANNs with a single hidden layer, proposed a formula for the number of nodes in the hidden layer as $2n+1$, where $n$ is the number of nodes in the input layer.

(2) $l=\sqrt{(m+n)}+a$ where $l$ is the number of hidden layer nodes, $n$ is the number of input nodes, $m$ is the number of output layer nodes, and $a$ is a constant between 0 and 10.

(3) $l=\log_2 n$ where $l$ is the number of implicit layer nodes, $n$ is the number of input layer nodes.

## *III. B. Setting of network parameters*

### III. B. 1) Choice of transfer function

Transfer function, also called activation function, is the link between neurons, neuron signal transmission from input to output layer by layer is realized through the connection of the transfer function.The transfer function in the BP network model has a linear function and S-type function, the common point of these functions must be continuous, and the existence of the derivative function. Commonly used transfer functions are purelin function, tansig function, logsig function, comprehensive consideration in this paper, the transfer function between the input layer and the implied layer uses logsig function, the transfer function between the implied layer and the output layer uses tansig function.

### III. B. 2) Selection of training algorithm and parameters

The training algorithm of the network is the most important part of the network establishment, and the selection of the training algorithm should also be made by the comparison method, which comprehensively considers all the performances of the network, including the network convergence speed, training time, etc. The training algorithm of the BP network is the most important part of the network establishment. In essence, it is an algorithm that adjusts the weights and thresholds inversely according to the error function, and MATLAB contains almost all the more mature BP algorithms [23], [24]. The training functions for BP networks are: traingbr, traincgb, traincgf, traincgp, traingd, traingdm, traingda, traingdx, trainoss, trainr, trainrp, trainscgd, etc. Each function expresses the correction method of weights and thresholds in the training process, and each has its own advantages and disadvantages, and it is often necessary to experiment in order to determine a more appropriate training function for specific problems. Through reviewing a large amount of related information and experimental examples, it is found that the Levengerg-Marquardt training method using the training function for trainlm has fast convergence, short training time and high accuracy. 1000 is the maximum value of the number of training times, training time is unlimited, the minimum performance gradient is 1×107, and the maximum number of confirmed failures.

### III. B. 3) Selection of network expectation error

The choice of network expected error should be analyzed depending on the specific problem, some problems need to get an approximate solution, then the error accuracy does not need to be so large. While some problems require higher accuracy, but also to take into account the disadvantages of the network will bring, the cost of setting a smaller value of the expected error is to increase the number of nodes in the hidden layer and training time. In general, it is necessary to set several desired errors to train the established neural network, and determine a desired error by comparing and considering the comprehensive factors. In this paper, we are going to utilize the BP neural network model to achieve the nonlinear prediction of recycled concrete performance indexes, and an expected error of 0.001 is sufficient.

## *III. C. Network weights and training process*

### III. C. 1) Network weights

The process of neural network training is essentially the process of correcting the weights. The choice of the initial value of the weights is related to the convergence of the network, the length of the training time, and so on. Artificial neural networks are nonlinear, the learning of the network is carried out along the gradient direction from a certain point, if the initial value is too large, the weighted summation of neurons falls in the saturation region of the activation function, the network can not continue to converge, and the training process is terminated. In this study, the initff function in the neural network toolbox is used to initialize the weights and thresholds of the three-layer neural network, because the initialization is random, the initff function is used to generate 10 sets of initial weights and thresholds before training the network, and the smallest of them is selected to enter the network training.

### III. C. 2) Training process

According to the analysis of the above network structure and parameter settings, it can be obtained that the input layer of the established BP neural network model is a 7×49 vector group, denoted by P. The output layer is a vector group of 3×49, denoted by T. The network structure is 7-20-3, the network training function adopts the trainlm function, the transfer function between the input layer and the implied layer adopts the logsig function, and the transfer function between the implied layer and the output layer adopts the tansig function, and the BP neural network model established for the performance of recycled concrete is trained after the network parameters are set.

# IV. Compressive Strength Study of Recycled Concrete with Steel Fiber Admixture

BP neural network can realize from the existing data automatically summarize the sample data and target data between the inherent nonlinear law, especially suitable for dealing with imprecise and fuzzy information processing problems that need to consider many factors and conditions at the same time, is a powerful information processing system that can realize a variety of complex nonlinear operations. Based on a large amount of experimental data on the strength properties of steel fiber-adulterated recycled concrete previously conducted by the group, this paper adopts BP artificial neural network technology to establish the relationship between the influence of various factors on the compressive strength of steel fiber-adulterated recycled concrete. In this paper, the nonlinear structural model reflecting the mapping relationship between the mixing ratio and strength of recycled concrete was established with steel fiber-adulterated recycled concrete as the research object, and the validity of the research scheme of this paper was verified from the two aspects of model validation analysis and model application analysis. The detailed analysis process is shown below:

## *IV. A. Model validation analysis*

### IV. A. 1) Training data

In this paper, a layer BP network model is developed, and both training and test samples are prepared from the specimens above, to design the composition ratio of each part of the materials for steel fiber-added recycled concrete, i.e., the ratio between water W, cement C, coarse aggregate G, fine aggregate S, and admixtures. According to the design strength of the base concrete required for the test (C50 concrete) and the fiber admixture method. Appropriate amount of steel fibers were added to the plain concrete and mixed to make it. The corresponding mix ratio per cubic meter of steel fiber concrete is water, cement: fine aggregate: coarse aggregate: fly ash: admixture = 200: 500: 1000: 700: 50: 10 = 20: 50: 100: 70: 100: 5: 1. Specimen numbering instructions: B indicates the recycled concrete with steel fiber admixture. 6, 12, 18 indicates the length of the fiber in mm. 0.2, 0.4, 0.6 denote the volume fraction of fiber admixture.C50 denotes plain concrete, B6-0.2 denotes the fiber content of admixture is 0.2% and the length is 6mm.Table 12 shows the BP neural network samples, where sample 1~sample 14 are the training samples, and after preparing the training data, they are randomly disrupted and divided into two groups: 80% is the training set (C50, B18-0.2, B6-0.2, B12-0.4, B18-0.6, B6-0.6, B12-0.2, B18-0.4), and 20% for the test set (B6-0.4, B12-0.6). And there is no overlap between the data and they are independent of each other. The training set is used to establish the nonlinear relationship between input and output in the neural network. After deriving the optimal BP network model from the training set, the trained model was predicted using the test set. It is used to measure the trained model performance and classification ability.

Table 12: BP neural network samples

| N | Volume (%) | Mass (kg) | Water-cement ratio | Cement (kg) | Sand(kg) (kg) | Coarse aggregate(kg) | Tap water(kg) | Fly ash(kg) | Water reducing agent(kg) |
|---|---|---|---|---|---|---|---|---|---|
| C50 | - | - | - | 500 | 700 | 1000 | 200 | 50 | 10 |
| B6-0.2 | 0.2 | 5.23 | 0.66 | 500 | 700 | 1000 | 200 | 50 | 10 |
| B6-0.4 | 0.4 | 10.52 | 0.66 | 500 | 700 | 1000 | 200 | 50 | 10 |
| B6-0.6 | 0.6 | 15.45 | 0.66 | 500 | 700 | 1000 | 200 | 50 | 10 |
| B12-0.2 | 0.2 | 5.23 | 0.66 | 500 | 700 | 1000 | 200 | 50 | 10 |
| B12-0.4 | 0.4 | 10.52 | 0.66 | 500 | 700 | 1000 | 200 | 50 | 10 |
| B12-0.6 | 0.6 | 15.45 | 0.66 | 500 | 700 | 1000 | 200 | 50 | 10 |
| B18-0.2 | 0.2 | 5.23 | 0.66 | 500 | 700 | 1000 | 200 | 50 | 10 |
| B18-0.4 | 0.4 | 10.52 | 0.66 | 500 | 700 | 1000 | 200 | 50 | 10 |
| B18-0.6 | 0.6 | 15.45 | 0.66 | 500 | 700 | 1000 | 200 | 50 | 10 |

### IV. A. 2) Analysis of validation results

The reliability and accuracy of the intrinsic network model of recycled concrete with steel fiber admixture is judged by using the test set to predict the results based on the trained model, and by comparing the data obtained from the experiments, with the predicted data. Figure 1 demonstrates the compressive strength curves of some test values and the predicted values of the BP neural network, where (a) ~ (h) are C50, B18-0.2, B6-0.2, B12-0.4, B18-0.6, B6-0.6, B12-0.2, B18-0.4, respectively. it can be seen that the predicted values of the BP neural network and the experimental results are in good agreement, which illustrates the reliability and accuracy of the recycled concrete intrinsic network model for the steel-fiber-adulterated The concrete intrinsic network model is trained to predict the compressive strength of steel-fiber-adulterated recycled concrete under different loading conditions very well, and has a strong generalization and promotion ability.

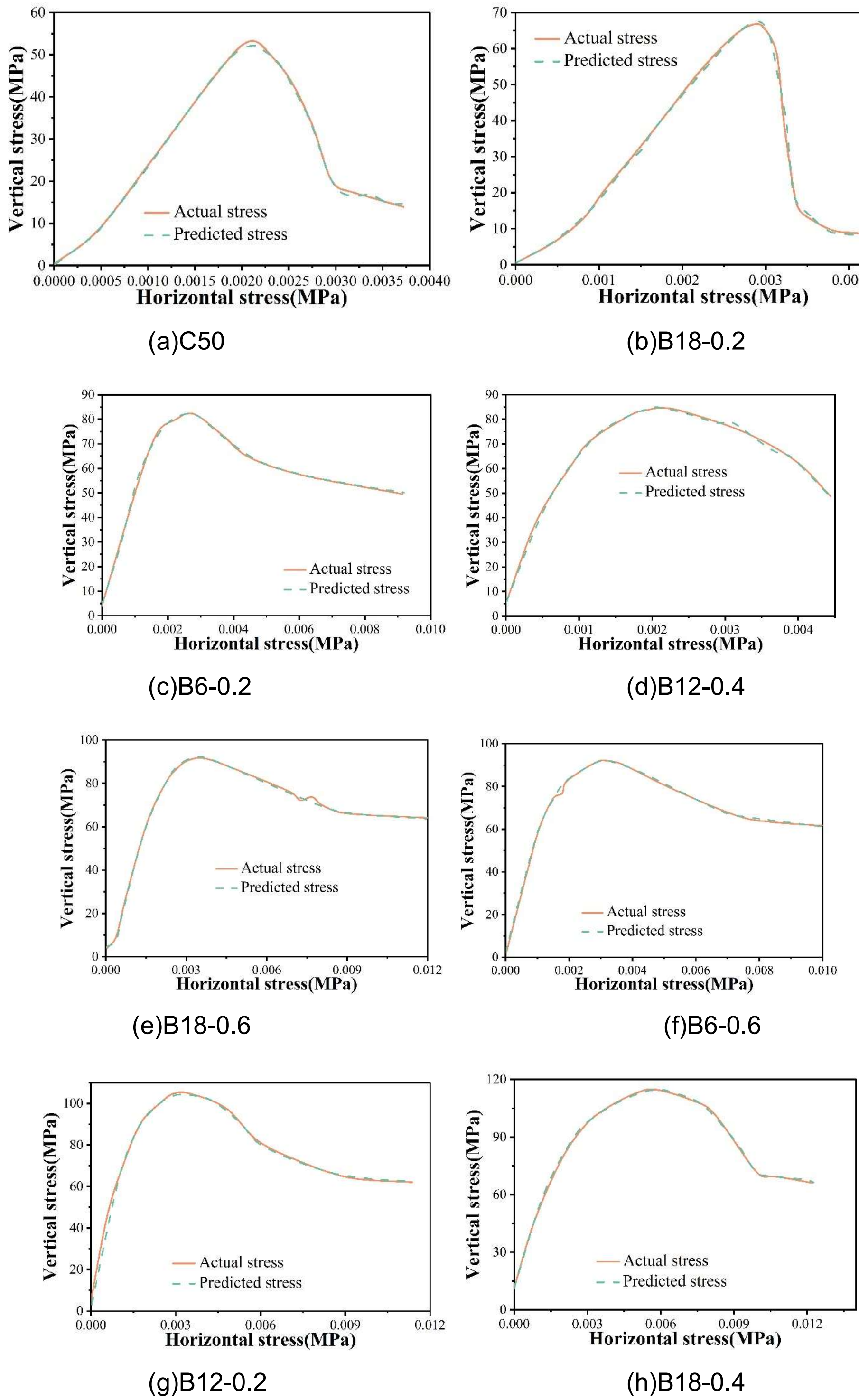


Figure 1: The compressive strength curve of the test value and the predicted value

In order to further verify the accuracy of BP neural network prediction, RMSE (Root Mean Square Error) is generally used to reflect the precision of prediction, and the smaller the value of RMSE, the better the prediction of the model. The calculation formula is as follows:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(y_i^* - y_i\right)^2}{n}} \tag{3}$$

where $y_i^*$ makes the predicted value, $y_i$ makes the actual value, and $n$ is the sample size.

Using the established BP neural network, 10 sets of test samples were used as inputs and the predicted values obtained were used for calculation as shown in Table 13. The average value of the overall root mean square error was found to be 0.8671%. It is further demonstrated that the intrinsic network model of recycled concrete with steel fiber admixture can accurately and reliably predict the magnitude of compressive strength. It reflects the compressive strength-strain relationship of steel-fiber-adulterated recycled concrete under different loading conditions more accurately than the traditional constitutive equation. Especially for large-scale industrialized concrete production bases (e.g., commercial concrete mixing plant), the mix ratio and its performance of concrete produced on weekdays can be continuously added as samples to improve the network model and continuously improve the network accuracy. Through the learning simulation analysis, the successful application of BP neural network to predict the compressive strength of recycled concrete mixed with steel fibers, the model established in this paper can still have a high prediction accuracy, the back propagation neural network system for solving the complex, fuzzy, uncertainty problems in practice to find a way out of the problem, and has a certain degree of practical significance.

Table 13: Error analysis of the BP network model

| Test sample number | Root mean square error(RMSE)/% |
|---|---|
| C50 | 0.7824 |
| B6-0.2 | 0.7803 |
| B6-0.4 | 0.8895 |
| B6-0.6 | 0.8777 |
| B12-0.2 | 0.9692 |
| B12-0.4 | 0.8655 |
| B12-0.6 | 0.9543 |
| B18-0.2 | 0.7816 |
| B18-0.4 | 0.8243 |
| B18-0.6 | 0.9463 |
| Total | 0.8671 |

## *IV. B. Analysis of model applications*

### IV. B. 1) Effect of aggregate type and substitution rate on strength

From the application of the BP neural network based compressive strength prediction model for admixed steel fiber recycled concrete, it can be seen that the BP neural network has good prediction accuracy for each input variable of the admixed steel fiber recycled concrete, which varies within the dosage range of each constituent raw material of the training samples, and predicts the compressive strength of the admixed steel fiber recycled concrete with less error from the test values. Therefore, we can use the established BP neural network model to predict the mechanical strength of steel-fiber-adulterated recycled concrete with a given mix ratio, and analyze the influence of the type of recycled coarse aggregate and substitution rate on the compressive strength of steel-fiber-adulterated recycled concrete at the corresponding age. In order to study the influence of aggregate type and substitution rate on the compressive strength of steel fiber-adulterated recycled concrete, Table 12 shows that the water-cement ratio of steel fiber-adulterated recycled concrete is 0.66 (given above, and will not be repeated), and the four major components of the raw materials, fly ash and water reducing agent are equal in dosage. The type of recycled coarse aggregate (simple crushing, particle shaping) and coarse aggregate substitution rate were selected as variables, and the established BP neural network model was used to predict the 3d, 28d and 56d compressive strength values of steel fiber-adulterated recycled concrete, and the prediction error of the BP neural network is shown in Fig. 2, and the prediction results of the strength of the recycled concrete based on the recycled concrete are shown in Fig. 3. From the trend graph of the effect of aggregate type and substitution rate on the strength of recycled coarse aggregate concrete, it can be seen:

(1) When the water-to-cement ratio is 0.66, with the increase of the substitution rate of recycled coarse aggregate, the compressive strength of recycled concrete mixed with steel fibers at all ages shows a decreasing trend as a whole, which may be attributed to the increase of water absorption by the mortar attached to the surface of recycled

coarse aggregate, which reduces the ease of the concrete and thus affects the compressive strength of the recycled concrete under the condition of determining the water-to-cement ratio.

(2) The strengths of simple crushed recycled coarse aggregate concrete are lower than the compressive strength of granular shaped recycled coarse aggregate concrete, which is consistent with the realization of the actual situation.

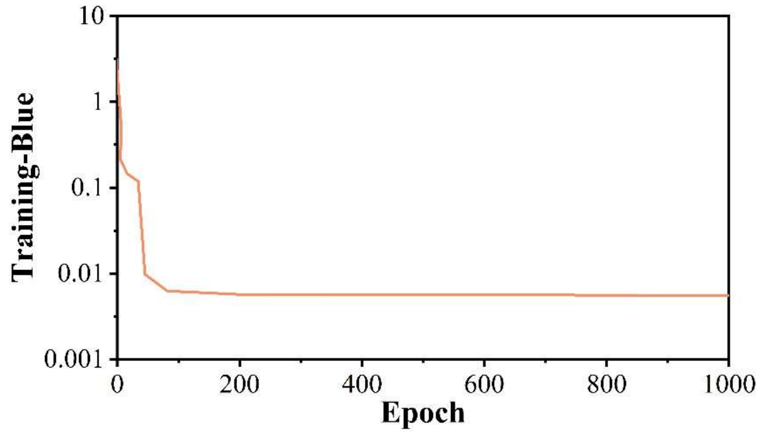


Figure 2: The prediction error of BP neural network

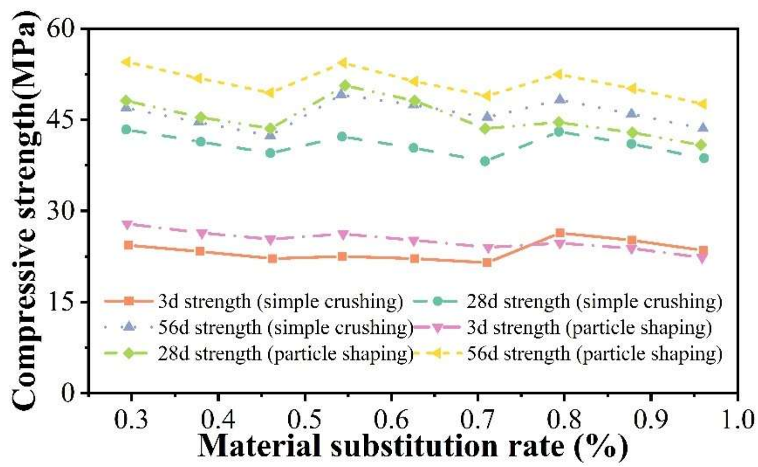


Figure 3: The influence of aggregate types and substitution rates on strength

#### IV. B. 2) Effect of water cement ratio and aggregate type on strength

Similarly, in order to investigate the effect of water cement ratio on the compressive strength of steel fiber-added concrete with different coarse aggregate types, it is assumed that the replacement rate of recycled coarse aggregate in the proportion of steel fiber-added concrete is 55%. Only the type of recycled coarse aggregate (simple crushing, particle shaping) and water-cement ratio are selected as variables, and the established BP neural network model is used to predict the 28d compressive strength value of the admixed steel fiber concrete, in which the prediction error of the BP neural network is shown in Fig. 4, and the prediction results of the compressive strength of the concrete made from the admixed steel fiber are shown in Fig. 5. Through the water cement ratio and aggregate type on the impact of the compressive strength of admixed steel fiber concrete trend graph, analyze the water cement ratio, aggregate type on the impact of the compressive strength of admixed steel fiber concrete law:

(1) The optimal water-cement ratio of 0.45 for simple crushed admixed steel fiber concrete is higher than the optimal water-cement ratio of 0.4 for particle shaping admixed steel fiber concrete, which indicates that the water absorption rate of the simple crushed recycled coarse aggregate after shaping treatment is significantly reduced, which is in line with the actual situation.

(2) With the increase of the water cement ratio, the compressive strength of each age of steel fiber concrete showed a trend of first increase and then decrease, particle shaping steel fiber concrete water cement ratio in the range of 0.35 to 0.4 compressive strength is greater.

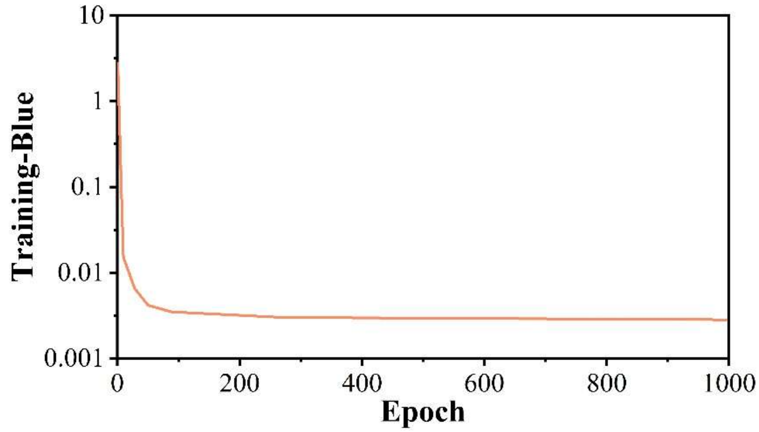


Figure 4: The prediction error of BP neural network

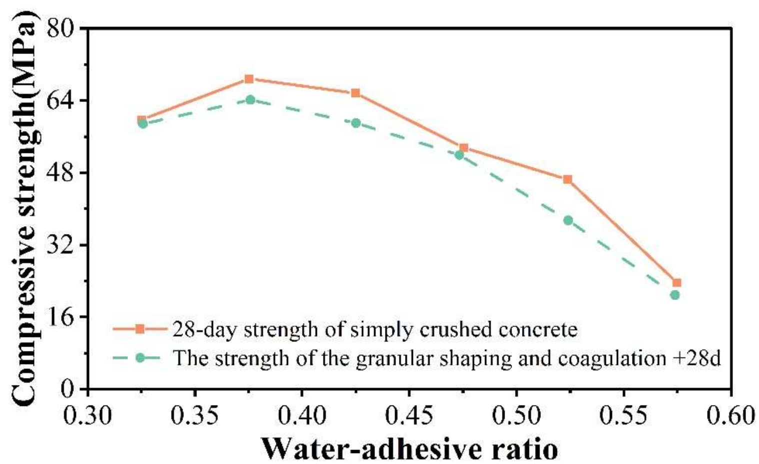


Figure 5: The influence of water-binder ratio and aggregate type on strength

## V. Conclusion

The compressive strength prediction model of steel fiber recycled concrete under different loading conditions is established by BP neural network technology, and the following conclusions are drawn:

The BP neural network model based on the 7-20-3 network structure can accurately predict the compressive strength of steel fiber recycled concrete, and the predicted values are in good agreement with the test values, and the overall root mean square error is only 0.8671%. Among them, the prediction error of C50 specimen is the smallest, which is 0.7824%; the prediction error of B12-0.2 specimen is the largest, which is 0.9692%. The model achieves high-precision prediction of unknown samples by learning the nonlinear mapping relationship in the samples, showing good generalization ability.

The water-cement ratio and recycled aggregate properties have a significant effect on the compressive strength of steel fiber recycled concrete. Under the condition of water-to-cement ratio of 0.66, the increase of recycled coarse aggregate substitution rate leads to the decrease of compressive strength at all ages. The compressive strength of particle shaped recycled coarse aggregate concrete was generally higher than that of simply crushed recycled coarse aggregate concrete, which confirms the importance of aggregate quality on concrete performance.

There are differences in the optimal water-cement ratios of different types of recycled aggregates. The optimal water-to-cement ratio of 0.45 for simple crushed steel fiber recycled concrete is higher than that of 0.4 for granular shaped steel fiber recycled concrete, indicating that the shaping treatment effectively reduces the water absorption of recycled aggregates. The compressive strength of granular shaped steel fiber recycled concrete reaches the maximum value in the range of water-to-cement ratio of 0.35~0.4.

The established BP neural network model has practical value and is suitable for large-scale industrialized concrete production, which can continuously optimize the network accuracy by adding the ratio and performance data of the production process to the training samples. This intelligent prediction method provides an efficient solution to complex engineering problems and is of great significance for improving the application level of steel fiber recycled concrete and resource utilization efficiency.

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