Abstract: A data set of cemented sand and gravel (CSG) mix proportion and 28-day compressive strength was established, with outliers determined and removed based on the Boxplot. Then, the distribution law of compressive strength of CSG was analyzed using the skewness kurtosis and single-sample Kolmogorov-Smirnov tests. And with the help of Python software, a model based on Back Propagation neural network was built to predict the compressive strength of CSG according to its mix proportion. The results showed that the compressive strength follows the normal distribution law, the expected value and variance were 5.471 MPa and 3.962 MPa respectively, and the average relative error was 7.16%, indicating the predictability of compressive strength of CSG and its correlation with the mix proportion.

Keywords: Cemented sand and gravel; Compressive strength; Boxplot; Normal distribution; BP neural network

1 Introduction

In contemporary society, the harmonious coexistence between man and nature is a prerequisite for healthy and sustainable development. The relationship between dams and ecological environment is receiving more and more attention, and the construction of environmentally-friendly dams has become a mainstream trend [1]. CSG dam is a new type of dam derived from the pursuit of high efficiency, low cost and minimal impact on the natural environment. CSG dam was first proposed by Raphael J M and Londe P [2, 3], which was developed based on Roller Compacted Concrete (RCC) dam and Concrete Face Rockfill (CFR) dam. The CSG dam building material is a new type of dam material obtained by mixing a small amount of cementing materials (mainly cement and fly ash), water, raw gravel of the riverbed or excavated waste materials with simple equipment [4, 5], in line with the new concept of “The dam structure is optimized in order to make better use of local materials” and “Proper materials can be selected for the different parts of the dam in order to realize better function of structures” [1, 6]. As a structural material, CSG needs to be strong enough to withstand different loads, thus ensuring the safety and reliability of the project.

Yang et al. [7] made a uniaxial compressive test and found that for every 10 kg/m\(^3\) increase in cement content, the compressive strength increased by 15% to 20%, and the economic and optimal amounts of fly ash were 40% and 50% of the total cementing materials (mainly cement and fly ash). Guo et al. [8] concluded a linear relationship between CSG cube compressive strength and split strength through strength tests, and the split strength was 7% to 12% of the compressive strength. Yang et al. [9] studied the effect of cement content on the deformation characteristics of CSG materials, and the results showed that with the increase of cement content, the failure strain of CSG materials decreases, the brittleness increases, and the initial modulus grows exponentially. Takashi et al. [10], based on the Nagashima sand blocking dam project, carried out a study on the effect of water consumption per unit on...
CSG performance, and suggested that it was appropriate to control VC values from 5s to 20s in practical application. Feng et al. [11] conducted a research on the effect of sand ratio, water-binder ratio, cement content and fly ash content on the strength, and it was recommended that the sand ratio in actual projects should range from 18% to 32%, water-binder ratio should range from 0.7 to 1.3, and CSG minimum cement content should be not less than 30 kg/m$^3$. Although these researches on CSG performance have achieved some positive results and provided theoretical guidance for the application of practical engineering, most of them are based on the analysis of the test results of variable factors, which does not reflect the potential law of CSG material performance from a statistical perspective, and lacks the multi-factor correlation analysis based on data prediction. To this end, based on the results of previous CSG tests, this paper conducted a study on CSG compressive strength performance using statistical and predictive methods, which provides reference for CSG’s mix proportion design and innovative applications.

2 Data processing and analysis

The basic purpose of data processing is to extract valuable and meaningful data from the original data, form the data analysis style, and ensure the consistency and validity of the data, which is of great significance to the subsequent data analysis. Data analysis is to analyze the collected data and extract valuable information through appropriate analysis methods and tools, so as to get effective conclusions. In the established data set, the data is relatively multi-source, so it is hard to form a continuous whole with other data points due to the lack of data and the large dispersion of data points, which has an impact on the statistics and prediction analysis of data and could lead to wrong conclusions. Therefore, these data points are called “outliers” and eliminated in subsequent analysis.

2.1 Source and analysis of data

The test data was divided into two parts according to its source. One part was based on the CSG material performance test conducted in accordance with the Test Code

![Figure 1: Specimen preparation process](image)

![Figure 2: Data set of CSG 28d compressive strength](image)
for Hydraulic Concrete (SL352-2006) and the Specification of Soil Test (SL-237-1999), with the test process shown in Figure 1 and the specific method shown in the literature [2]. In order to ensure the universality and authenticity of the data while improving the processing capacity and prediction effect of statistical model analysis, another part cited the results of literature [11, 26, 27] to form a data set of the CSG’s 28-day compressive strength (Figure 2). There were 99 sets of compressive strength data in the data set, in which the minimum value is 1.00 MPa and the maximum is 17.7 MPa. The data were mainly concentrated in 1-10 MPa, accounting for about 96% of the total sample number.

In addition, the CSG mix proportion was another basic data needed for the research in this article. In the selection of the mix proportion corresponding to the compressive strength data, the cement content ranged from 30 kg/m$^3$ to 60 kg/m$^3$, which met the requirements of CSG as a super lean cementing material although several mix proportions were slightly greater than 60 kg/m$^3$. The range of fly ash content was 0-80 kg/m$^3$, the range of water-binder ratio was 0.5-3.0, the range of sand-gravel content was 1,278-2,081 kg/m$^3$, and the range of sand ratio was 0.10-0.45.

### 2.2 Identification and removal of outliers

Due to many data sources and differences in the mix proportion and test process corresponding to different strengths, some values may be “abnormal” and should be rejected. This article adopted Boxplot to identify and remove such abnormal values. Boxplot, as an effective data visualization tool, is not only intuitive, easy to understand, but also has no requirement for the distribution form, and no limitation for the data, which is more suitable for analyzing the CSG compressive strength with the distribution law unknown [12]. The implementation of this method was shown in Figure 3 [13]:

1. Set five statistics in the CSG compressive strength values: minimum value, first quartile $Q_L$ (lower quartile), second quartile $Q_M$ (median), third quartile $Q_U$ (upper quartile) and maximum value, where $Q_L$, $Q_M$, and $Q_U$ were the numbers arranged in ascending order at the 25%, 50%, and 75% of the sample data respectively, $Q_L$ and $Q_U$ were approximate estimates of the two quartiles of the data set.

2. Calculate the interquartile range (IQR), namely the distance between $Q_U$ and $Q_L$.

3. Calculate the internal limits, namely $Q_L - 1.5\text{IQR}$ and $Q_U + 1.5\text{IQR}$.

4. Identify outliers, namely values less than $Q_L - 1.5\text{IQR}$ or greater than $Q_U + 1.5\text{IQR}$.

The Boxplot of these 99 sets of compressive strength data was shown in Figure 4. The Boxplot of 28d compressive strength was flat in shape, and the square box was basically symmetrical around the median, indicating that the data distribution was concentrated and the skewness was weak. Three abnormal values were obtained and directly rejected, which were 17.7 MPa, 16.9 MPa and 15.6 MPa respectively.

### 3 Statistical analysis

According to the data processing results, the statistics of the remaining data was calculated, with the results shown in Table 1.

It can be seen from Table 1 that the expected value, variance, and standard deviation of the 28-day compressive strength sample data were: 5.471 MPa, 3.962 MPa, and
Table 1: Statistics of 28d compressive strength sample data

| Statistics             |   |
|------------------------|---|
| Number of cases        | 96 |
| Average value          | 5.471 |
| Standard deviation     | 1.990 |
| Skewness               | -0.032 |
| Kurtosis               | -0.232 |
| Minimum                | 1.00 |
| Maximum                | 10.49 |

Table 2: Single-sample K-S test results

| Summary of hypothesis testing |   |
|-------------------------------|---|
| Null hypothesis               | Test | Significance | Decision makers |
| The 28d compressive strength data showed normal distribution, with an average value of 5.471 and a standard deviation of 1.990. | Single-sample Kolmogorov-Smirnov test | 0.200 | Keep the null hypothesis |

Note: It showed progressive significance with a significance level of 0.05.

1.990 MPa respectively. According to the skewness kurtosis test, \(|-0.032 \div 0.246| = 0.130\), and \(|-0.232 \div 0.488| = 0.475\), which were all less than 1.96, indicating that the 28d compressive strength sample data was normalized. In order to further prove that it obeys the law of normal distribution, a single-sample Kolmogorov-Smirnov (K-S) test was performed, with results shown in Table 2.

According to the results of skewness kurtosis test and K-S test, it can be considered that the compressive strength data of CSG material obeys the normal distribution law.

The normal distribution probability density function is [15]:

\[ f(x) = \frac{1}{\sigma \sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \]  (1)

Where, \( f(x) \) is the probability density function, \( \sigma \) is the standard deviation, and \( \mu \) is the sample mean.

According to the normal “3\( \sigma \)” principle, the normal distribution function can be applied to obtain the probability \( P \) of the samples falling into the interval \((a, b)\). The distribution function is:

\[ P(a < x < b) = \frac{1}{\sigma \sqrt{2\pi}} \int_{b}^{a} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \, dx \]  (2)

According to formula (2), the probability that the 28d compressive strength sample data fell in the interval \((\mu - \sigma, \mu + \sigma)\), \((\mu - 2\sigma, \mu + 2\sigma)\), and \((\mu - 3\sigma, \mu + 3\sigma)\) was: 68.26\%, 95.44\%, and 99.74\% respectively. According to formulas (1) and (2), the statistical distribution characteristics of 28d compressive strength data were obtained, the normal distribution curve was drawn, and the interval frequency was determined, as shown in Figure 5.

4 Predictive analysis

4.1 BP neural network

In the 1980s, D. E. Rumelhart et al. [16, 17] proposed a multi-layer feedforward network trained by the error back-propagation algorithm (Back-Propagation Network, BP network for short), which is currently the most widely used and mature artificial neural network algorithm. BP neural network is a supervised learning algorithm based on the least square method, and features high accuracy and high versatility. Its topology includes three parts: the
input layer, the hidden layer, and the output layer. All neurons in adjacent layers are interconnected, while each neuron in the same layer is independent with each other. When the output value of the output layer does not match the expected value, the weights and thresholds of the network will be modified through error backpropagation, to ensure that the squared error between the output value and the expected value within the threshold range [18, 19].

At present, this method has been successfully applied to the study of the cement-based materials. For example, Liang et al. [20] applied the BP neural network to build a multi-factor model and predict the compressive strength of concrete in dry and wet environments, with an average error of 1.09%; Chen et al. [21] applied the BP neural network to establish a prediction model of the performance of the recycled aggregate permeable concrete based on the permeability and strength properties, with the average relative error within 10%. This article attempted to use this method to predict the compressive strength of CSG.

### 4.2 Sample data

After removing outliers, the 96 sets of sample data involved in the prediction were divided into training group (78 sets, accounting for 71.25%) and prediction group (18 sets, accounting for 18.75%). The data were randomly allocated to ensure that the predictive analysis is representative. The training and prediction data were shown in Tables 3 and 4.

### 4.3 Construction of network model

A prediction model of CSG compressive strength was established with 8 parameters namely cement content, fly ash content, water content, sand content, sand-gravel content, biggest size of sand and gravel, sand ratio and water-binder ratio as the input layer, and 28d compressive strength as the output layer. In addition, there was also one hidden layer, with the number of hidden nodes determined by cut-and-try method [22]:

$$h = \sqrt{m + n + a}$$

Where, $h$ is the number of nodes in the hidden layer; $m$ is the number of nodes in the input layer; $n$ is the number of nodes in the output layer; $a$ is an adjustment constant taken from 1 to 10.

After several trials, when $a$ was 10, the training effect reached the best; thus an 8-13-1 prediction model was constituted. The topology of the network model was shown in Figure 6.

The network model training was achieved with the help of Python software. The `logsig` function was used as the hidden layer transfer function, the `purelin` function

| Table 3: BP neural network training sample data |
|-----------------------------------------------|
| Training group | Cement (kg/m³) | Fly ash (kg/m³) | Water consumption (kg/m³) | Sand (kg/m³) | Gravel material (kg/m³) | The biggest size (mm) | Sand ratio (%) | Water-binder ratio | Compressive strength (MPa) |
|----------------|----------------|-----------------|---------------------------|-------------|------------------------|----------------------|---------------|---------------------|-----------------------------|
| 1              | 40             | 40              | 56                        | 594         | 1847                   | 150                  | 0.25          | 0.70                | 9.20                        |
| ……             | ……             | ……              | ……                        | ……          | ……                     | ……                   | ……            | ……                  | ……                          |
| 3              | 40             | 40              | 88                        | 573         | 1783                   | 150                  | 0.25          | 1.10                | 4.20                        |
| ……             | ……             | ……              | ……                        | ……          | ……                     | ……                   | ……            | ……                  | ……                          |
| 5              | 50             | 0               | 65                        | 478         | 1982                   | 150                  | 0.20          | 1.30                | 8.90                        |
| ……             | ……             | ……              | ……                        | ……          | ……                     | ……                   | ……            | ……                  | ……                          |
| 78             | 60             | 30              | 90                        | 434         | 1736                   | 40                   | 0.20          | 1.00                | 4.60                        |

| Table 4: BP neural network prediction sample data |
|-----------------------------------------------|
| Prediction group | Cement (kg/m³) | Fly ash (kg/m³) | Water consumption (kg/m³) | Sand (kg/m³) | Gravel material (kg/m³) | The biggest size (mm) | Sand ratio (%) | Water-binder ratio | Compressive strength (MPa) |
|-----------------|----------------|-----------------|---------------------------|-------------|------------------------|----------------------|---------------|---------------------|-----------------------------|
| 1               | 40             | 40              | 82                        | 462         | 1915                   | 150                  | 0.194         | 1.025               | 4.50                        |
| ……              | ……             | ……              | ……                        | ……          | ……                     | ……                   | ……            | ……                  | ……                          |
| 3               | 50             | 40              | 100                       | 864         | 1296                   | 40                   | 0.4           | 1.11                | 3.75                        |
| ……              | ……             | ……              | ……                        | ……          | ……                     | ……                   | ……            | ……                  | ……                          |
| 5               | 30             | 0               | 60                        | 484         | 2007                   | 150                  | 0.2           | 2.00                | 5.20                        |
| ……              | ……             | ……              | ……                        | ……          | ……                     | ……                   | ……            | ……                  | ……                          |
| 18              | 40             | 40              | 90                        | 436         | 1744                   | 40                   | 0.2           | 1.13                | 5.36                        |
was used as the output layer function, and the `train` function in the BP algorithm was used as the training function. The number of iterations, the learning rate, and the correction coefficient were set to 15,000 times, 0.05, and 0.10 respectively.

A large difference in the input parameter range may affect the initialization of the network, and cause imbalance in the pattern classification. Similarly, if data with a large range was directly input into the network, the weight would become abnormally large after an accumulator, making it difficult for the network to converge. In addition, considering that the range of the non-linear activation function in the BP neural network was limited to \([-1, 1]\) or \([0, 1]\), the target data for network training should also be mapped to the range of the activation function [23] so that the discrimination of the activation function can be used fully to achieve a better prediction effect. Therefore, in order that the network can converge faster and more accurately, the data was normalized according to the formula (4).

\[
y = \frac{x - x_{\min}}{x_{\max} - x_{\min}}
\]

(4)

Where, \(y\) is the normalized value; \(x_{\max}\) and \(x_{\min}\) are the maximum and minimum values of the data column; \(x\) is the original sample data.

### 4.4 Analysis of prediction results

As seen from Table 5, the absolute error range of predicted values of CSG 28d compressive strength was from 0.024 to 1.096 MPa, with the average value of 0.39 MPa and the relative error range was from 0.52 to 20.45%, with the average value of 7.16%. The measured value of the CSG compressive strength was in good agreement with the predicted value, indicating that the prediction effect was good.

Figure 7 showed the comparison between the measured values and predicted values of the CSG 28d compressive strength, and Figure 8 showed the relative errors. From them, the error of most prediction results was less than or slightly larger than the average value, but there were still data points with a large error, such as Groups 5 and 18, whose average relative errors reached 13.73% and 20.45% respectively, about 2 times and 3 times of the average relative error.

After analysis, it is found that: (1) Some data was estimated or missed in the process of collection, causing a certain random error. (2) The limitation of the BP network model itself led to a certain system error. (3) Due to different sources of test samples, there was a large difference in
production processes and material ratios. For example, the same compressive strength value may have different material ratios, which brought about certain difficulties to the training of BP neural network. The training sample data and factors considered may not be comprehensive enough. If data or factors were added, this error may be reduced.

In general, the CSG compressive strength prediction model based on the BP neural network has higher accuracy.

5 Conclusions

In this paper, the data sets of the mix ratio and compressive strength of CSG were established through different data sources, and the box plot method was used to test and eliminate possible outliers in them. On this basis, the non-parametric test method and BP neural network were adopted to analyze and study the distribution and predictability of the compressive strength of CSG, and the conclusions are as follows:

1. A data set of CSG mix proportion and 28d compressive strength was established, with the range of cement content is 30-60kg/m³ and the range of compressive strength is 1-10MPa. Based on the Boxplot method, it was concluded that the CSG 28d compressive strength data was relatively concentratively distributed and weakly skewed, and three outliers were excluded, namely 15.6 MPa, 16.9 MPa, and 17.7 MPa.

2. With the help of skewness kurtosis test and single-sample K-S test, it was founded that the compressive strength of CSG follows the normal distribution law while the expected value, variance and standard deviation were: 5.471MPa, 3.962MPa, and 1.990MPa respectively.

3. A CSG compressive strength prediction model was established based on the BP neural network to predict the compressive strength using its mix proportion, and results showed that the predicted value was in good agreement with the measured value as the average relative error and absolute error were 7.16% and 0.39 MPa respectively, which proved the predictability of CSG compressive strength and a high correlation between the compressive strength and the mix proportion. In addition, it also showed that the BP neural network model can be used as a method for predicting the compressive strength of CSG, providing a reference for the design of the CSG mix proportion.

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