Multifactor optimization of MICP base on BP model

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Abstract. Microbial-induced calcite precipitation (MICP) can be used to cement soil and produce new biomaterials. The formation of this material is affected by many factors, such as physical, chemical, biological factors, many studies focused on the effect of a single factor on the strength ignoring the synergy between factors. Back-propagation neural network (BPNN) can be used as a multi-factor nonlinear prediction model and an analysis method. 140 MICP grout tests in the literature were summarized to 15 factors affecting UCS and act as BPNN input data. At last, five key factors were elected based on weight analysis of well-trained BPNN. On this basis, a simple strength model composed of those factors is established, which can well predict the strength of MICP grouting soil with practical convenience. Key factors and strength prediction models help popularize MICP for engineering applications and optimize grouting experiments.

1. Introduction

Microbe-induced calcium carbonate precipitation (MICP) is an environmental-friendly biomaterial. It can be used to cement sand, suppress dust, improve soil strength, and repair cracks[1, 2]. The uniaxial compressive strength (UCS) of these biomaterials are affected by physical, chemical, biological, and environmental factors such as curing temperature and time, injection interval of cementing solution, calcium ion concentration, bacteria concentration, bacterial reinjection, and sand size[3, 4]. Many studies focus on the influence of a single factor on strength, ignoring the synergistic effect of each factor, resulting in the lack of a general strength formula that can be used in different environments[5]. A strength model for predicting the MICP and the key factors for controlling it are required for the application of this material.

To establish a strength prediction model with a universal application function, it is necessary to consider a strong nonlinear model framework, which can take into account the synergistic effects of many factors. BPNN (Back Propagation) was proposed by Rumelhart et al., 1986. Its multi-layer neuron structure and transfer function give BPNN powerful nonlinear learning ability[6, 7]. Based on the robustness, it can meet the need of prediction accuracy when the relationship between input factors and output factors is unknown.
Related experimental data in literature were summarized and used as the database of the BPNN model. The influence of factors on MICP strength can be obtained from weight analysis. Last, the predicted results are explained from the perspective of the mechanism. The results can be helpful for the accurate prediction of MICP applying in the complicated environment and the development of grouting experiments.

2. Method

A BPNN model is composed of input layer, hidden layer, and output layer, which is pictured in Figure 1. The number of hidden layer neurons ($L$) is determined according to the formula (1-3). The output value $Y$ is calculated through the formula (4-6).

$$L_1 = N - 1$$  \hspace{2cm} (1)

$$L_2 = (M + N)^{1/2} + a$$  \hspace{2cm} (2)

$$L_3 = \log_2 N$$  \hspace{2cm} (3)

$$Y = \sum_{j=1}^{L} (\mu_j Q_j - \theta'_j)$$  \hspace{2cm} (4)

$$Q_j = 1/(1 + \exp(-z_j))$$  \hspace{2cm} (5)

$$z_j = \sum_{i=1}^{N} (\omega_{ij}X_i - \theta_j)$$  \hspace{2cm} (6)

Where $\mu_j (j = 1, L)$ is the connection weight between $Y$ and $Q_j$, $\omega_{ij}$ is connection weight between $X_i$ and $Q_j$, $\theta'_j$ and $\theta_j$ is output and hidden neuron bias respectively. The weight and threshold of BPNN are adjusted by negative feedback.

Figure 2 shows that R-squared decreases with the increase of the number of hidden layer and hidden layer neurons. So, a single hidden layer with 5 neurons is set. The learning rate, the number of iterations, allowable error, and exponential decay factor are set to be 0.05, 300, 0.000001, and 0.95 respectively.

Based on connected weight, the sensitivity ($A_i$) of input neuron is analyzed by the "weight product" theory\cite{8} and is presented by \[ A_i = AVG(abs(\sum_j w_{ij} u_{ij})). \]

140 groups of MICP grouted soil experiments data are collected from the literature\cite{9-25}. To accurately predict UCS, quantifiable data of the factors in the above experiments were collected and normalized as input values of the BPNN model. They are the 15 factors listed in Table 1.
Table 1. Influencing factors of MICP grouted soil

| Name (Abbr.)                          | Unit                     | Name (Abbr.)                          | Unit                     |
|--------------------------------------|--------------------------|--------------------------------------|--------------------------|
| bacteria concentration (OD600) (Bc)  | /                        | cementing solution volume per gram of sand sample (Csv) | ml/g                     |
| urease activity (Ua)                 | U/mL                     | ratio of cementation solution to bacterial solution (Rcb) | /                        |
| d50 particle size (D50)              | mm                       | injection rate per gram of soil sample (Irate) | ml/min/g                 |
| coefficient of nonuniformity (Cu)    | /                        | total injection number (Tnum)         | /                        |
| coefficient of curvature (Cc)        | /                        | injection times of bacterial solution (Ibt) | /                        |
| cementing solution concentration (Csc)| ml/L                     | injection times of cementing solution (Ict) | /                        |
| interval injection time (Iit)        | h                        | weight content of CaCO$_3$ (Ccc)      | %                        |
| bacterial solution volume per gram of soil sample (Bsv) | ml/g                     |                                       |                          |

3. Results and Discussion

Figure 3 plots predicted UCS, target UCS and the fitting line, which exhibits good predictability with R-squared 0.85. Figure 4 lists the sensitivities of the factors based on the BPNN prediction model in descending order, with cumulative sensitivities on the right axis. As can be seen from Figure 6, Bc has a maximum of 3.67 and Cu has a minimum of 0.93. According to the sensitivity, four sensitivity degrees and corresponding factor groups are suggested in Figure 4.

Groups 1, 1-2, and 1-3 contain 3, 5, and 10 factors respectively. For validating the results of sensitivity analysis, factors 3, 5, and 10 are successively taken as input data of BPNN. The predicted UCS and target UCS are drawn in Figure 5, and their r-squared and data analysis results are shown in Figure 6 and Table 2. Certainly, predictive performance improves with the amount of input data. Among those combinations, 5 factors have good performance with fewer factors.

Figure 3. R-squared of between predicted UCS and target one
Figure 4. sensitivities and cumulative sensitivities of 15 factors

Table 2. R-squared of MICP grouted based on factors sensitivity classification

| Factors source | Number of factors | Mean R-squared | Variance  |
|----------------|-------------------|----------------|-----------|
| Group I–IV     | 15                | 0.85           | 0.0177    |
| Group I–III    | 10                | 0.88           | 0.0033    |
| Group I–II     | 5                 | 0.86           | 0.0168    |
| Group I        | 3                 | 0.74           | 0.0371    |

predicted UCS $y=0.736x+0.30221$

predicted UCS $y=0.918x+0.13493$
Based on the above sensitivity, \( B_c \), Itare, Tnum, Ccc, Ibt are expected to be the simple and effective factors for the application of the MICP technique in geotechnical engineering. A simple UCS model of MICP grouted soil is suggested with an R-squared of 0.71 and is written as

\[
\text{UCS} = 0.65 \times B_c - 6.9 \times \text{Irate} - 0.02 \times Tnum + 0.01 \times Ccc - 0.065 \times Ibt 
\]  

(7)

The simple UCS model has an acceptable prediction accuracy, though it is slightly poor than the original BPNN nonlinear models. However, it has a relatively simple structure, which can be easily applied in practical engineering applications.
Figure 7. Prediction results of different UCS prediction models ((a)(b) Empirical formula; (c) six-factor simple strength model; (d) BP neural network prediction model)

Empirical models\cite{26, 27} in references show poor prediction ability because the formulas are summarized from the limited number of experiments and their generalization ability is not as good as polynomial and BPNN prediction models. The self-learning and feedback mechanism of BPNN makes it have the best prediction performance in the data set containing complex nonlinear relations. Meanwhile, the complexity of the model makes it difficult to be used in the field of engineering practice. The simple model based on BPNN has higher UCS prediction accuracy than the model with a single factor. This simplifies the complex nonlinear relationship with a slight reduction of USC prediction accuracy, while significantly better than single factors linear models. Therefore, the simple model based on the sensitivity analysis of BPNN has good predictability and convenience.

The calcium carbonate acts as a bridge between the sands, improving the internal friction angle and cohesion of the material. Its formation and distribution are the core of cementation strength formation. Therefore, the factors highly correlated with the formation and distribution of calcium carbonate should be paid attention to. Among the influencing factors of groups 1-2, Bc increased the number of bacteria involved in the reaction, Irate could improve the injection depth and injection volume per unit time, and the distribution uniformity of calcium carbonate increased with Tnum. Therefore, Bc, Irate, Tnum, and Ccc affect the content of calcium carbonate from two aspects of reactant quantity and reaction time.

The research results are only based on the collected 140 series of experimental data of MICP cemented soil, the statistical particle size ranging from 0.06–1.91mm, and the influence of the 15 factors on UCS is preliminarily revealed. However, the influence of PH, soil density, and other factors were not
studied. A more comprehensive understanding of the influencing factors on UCS of MICP cemented soil needs to be executed.

4. Conclusions
140 sets of MICP cemented soil test data were collected and analyzed by a BPNN model. Then, a simple UCS prediction model was established based on sensitivity. The conclusions are as follows:
(1) The R-squared of the BPNN prediction model is 0.85, with the prediction ability of this model being significantly better than a polynomial model and empirical formula.
(2) By sensitivity analysis, the 15 factors are divided into four groups. The optimized 5 factors on MICP cemented soil UCS are suggested to be Bc, Irate, Tnum, Ccc, and Ibt.
(3) The linear model based on these five factors has better predictability and convenience. The BPNN prediction model and a new simple prediction model can be further applied to the MICP experiment grouting ratio design and help to establish the corresponding mix ratio theory.

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