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Technical note

Neural network and particle swarm optimization for predicting the unconfined compressive strength of cemented paste backfill

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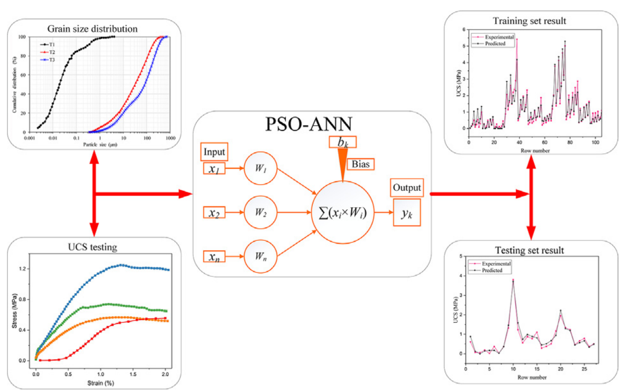
HIGHLIGHTS

- A novel method is proposed for predicting cemented paste backfill (CPB) strength.
- Artificial neural network (ANN) and particle swarm optimization (PSO) are combined.
- Dataset is collected from 396 unconfined compressive strength tests.
- PSO was efficient in the architecture-tuning of the ANN.
- The optimum ANN model was accurate at predicting CPB strength with $R = 0.979$.

GRAPHICAL ABSTRACT



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ABSTRACT

Cemented paste backfill (CPB) has been widely used to prevent and mitigate hazards produced during the excavation of underground stopes. In practice, the strength of CPB is often an essential parameter for successful stope design. We propose an intelligent technique in this study for predicting the unconfined compressive strength (UCS) of CPB. This intelligent technique is a combination of the artificial neural network (ANN) and particle swarm optimization (PSO). The ANN was used for non-linear relationships modelling and PSO was used for the ANN architecture-tuning. Inputs of the ANN were selected to be the tailings type, the cement-tailings ratio, the solids content, and the curing time. A total of 396 CPB specimens under different combination of influencing variables were tested for the preparation of the dataset. The results showed that PSO was efficient for the ANN architecture-tuning. Also, comparison of the predicted UCS values with experimental values showed that the optimum ANN model was very accurate at predicting CPB strength.

1. Introduction

Cemented paste backfill (CPB) is a mine composite material produced with filtered tailings, hydraulic binders and mixing water and it has many operational, environmental and financial benefits. Given safety regulations and environmental concerns, CPB provides ground support for mining operations, reduces ore dilution and allows safe disposal of tailings. Moreover, the surface subsidence can be minimized, thereby rehabilitation costs are reduced.

The advantages of CPB are dependent on its ability to remain stable during the extraction of adjacent stopes. In practice, the unconfined compressive strength (UCS) is usually utilised to estimate the mechanical stability of CPB as UCS tests are simple, eco-

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nomical and have been successfully correlated with accepted stability over many years of experience. Many researchers have studied the effects of influencing variables on the UCS of CPB, such as the tailings type, the binder content and the curing time [1–7]. However, experimental UCS determination is cumbersome and costly when lots of UCS tests are required. This has driven the search for easy and reliable methods to predict the UCS of CPB specimens.

One method that may be useful for the UCS estimation of CPB specimens is the utilisation of non-destructive methods such as ultrasonic pulse velocity (UPV) and electrical resistivity (ER) tests. Previous researchers [2,3,8–10] suggested the use of UPV and ER tests, as a non-destructive, low cost, less time-consuming and easy method in both the field and laboratory, for the assessment of the UCS properties of CPB instead of the conventional UCS test. Though it is very promising to use non-destructive methods for CPB strength estimation, a general correlation between the UCS and corresponding UPV values has not been established. Moreover, the availability of UPV and ER equipment in laboratory and mine site needs to be considered during the application of these methods.

Another method is predicting the UCS of CPB directly from its influencing variables using the artificial neural network (ANN) approach, which has been widely used to model non-linear relationships between inputs and outputs in construction and building materials [11–13]. The main advantage of the ANN is that non-linear relationships between inputs and outputs are not pre-assumed before the training is carried out. Only a limited number of studies have been performed for predicting the UCS of CPB using the ANN method [14–16]. Also, there is no ANN-based tool for predicting the UCS of CPB specimens under the combined effect of the tailings type, the cement-tailings ratio, the solids content and the curing time. Moreover, a limitation to the large-scale application of the above studies is that the architecture of ANN was determined using empirical formulae, which may affect the performance of ANN models. Particle swarm optimization (PSO) can be used to find the optimum ANN architecture for UCS prediction.

The main objective of this study is to propose an intelligent technique based on the ANN and PSO approaches for predicting the UCS of CPB under the combined effect of four important influencing variables. The PSO-ANN method is a new technique for predicting the UCS of CPB, and there are no studies so far being published in the literature. Also, the combined effect of the tailings type, the cement-tailings ratio, the solids content and the curing time on the UCS of CPB has not been studied using the PSO-ANN method. This study is thus the pioneer work in the application of the ANN and PSO approaches for CPB strength prediction, which is of great significance to the engineering application of CPB.

2. Materials and methods

2.1. Mechanical tests

Three types of tailings were used for the specimen preparation. The grain size distribution was determined using a laser diffraction particle size analyser (Malvern Mastersizer 2000) and the mineralogy of the tailings was determined using X-ray diffraction (XRD; Bruker AXS D8 Advance Diffractometer) as shown in Fig. 1. The mineralogical composition was quantified using the Rietveld method and the physico-chemical characteristics of tailings are summarized in Table 1. Common Portland cement was used as a binder and tap water was used as the mixing water. Based on experience and some trial tests, cement-tailings ratios were prepared at 1:4, 1:6, 1:8 and 1:10. The solids content for three types of tailings (shown in Appendix) was slightly different as very large differences exist in their grain size distributions (Fig. 1). CPB mixtures were fully mixed and poured into plastic moulds (50 mm in diameter and 100 mm in height). These moulds were then sealed and cured for 3, 7 and 28 days at approximately 25 °C and 90% humidity. A total of 396 CPB specimens were prepared. Three replicates of each test were carried out and the dataset for the construction of ANN models utilised the mean UCS values.

The UCS value was obtained according to ASTM C 39 [17]. A WDW-2000 rigid hydraulic pressure servo machine (Ruite, Guilin, China) was used for UCS tests with a deformation rate of 0.5 mm/min.

2.2. ANN

The ANN is a computational paradigm that maps inputs to outputs using a directed set of interconnected neurons. Each neuron is a basic computation unit that performs $y = \max(0, \sum_i w_i x_i + b)$, where $\{x_i\}$ are the neuron inputs, $\{w_i\}$ are the weights, b is bias and y is the neuron output.

All neurons are connected in a layered architecture, where the mapping between inputs and outputs is conducted using the following formula:

$$h_i = \max(0, \mathbf{W}_i \cdot \mathbf{h_{i-1}} + \mathbf{b_i}) \text{ for } 1 \leqslant i \leqslant L, \text{ and } \mathbf{h_0} = \mathbf{x} \quad (1)$$

$$y = \max(0, \mathbf{V} \cdot \mathbf{h_L}) \quad (2)$$

where L is the number of layers, matrices $\mathbf{W_1}, \ldots \mathbf{W_L}, \mathbf{V}$ and vector $\mathbf{b_1}, \ldots \mathbf{b_L}$ are model parameters learned from the dataset.

The ANN was trained using the dataset collected from UCS tests. Inputs of the ANN were the tailing type, the cement-tailings ratio, the solids content, and the curing time while the output was the UCS value. The whole dataset was divided into two parts: the training set (80%) and the testing set (20%). 10-fold cross validation was used as the validation method. The architecture of the ANN was first tuned by PSO before its application based on the mean squared error (MSE), which is defined as:

$$\text{MSE} = \frac{1}{N}\sum\nolimits_{i=1}^{N}(y_i^* - y_i)^2 \quad (3)$$

where N is the number of data samples, y_i^* and y_i are the predicted and experimental UCS values of the *ith* data sample.

2.3. PSO architectures-tuning

PSO is a powerful optimization technique for finding a global optimum in a multi-dimensional searching space [18]. The PSO process started with a randomly generated swarm of particles and each represented a specific ANN architecture. The fitness of particles' position were evaluated by the MSE on the training set. To be more specific, an ANN architecture that achieves a lower MSE will be represented by a particle with higher fitness. The next swarm was generated by the position-update of particles, which considered the swarm best position in history and each particle's best position in history. Swarms of particles progressively moved to the optimum position until the maximum iteration was reached. The position-update formula for particles used in this paper are:

$$V_i^{t+1} = wV_i^t + c_1 r_1(p_{best,i}^t - X_i^t) + c_2 r_2(g_{best,i}^t - X_i^t) \quad (4)$$

$$X_i^{t+1} = X_i^t + V_i^{t+1} \quad (5)$$

where V_i^{t+1} and V_i^t represents the velocity of particle i at iteration t and $t+1$; X_i^{t+1} and X_i^t represent positions of particle i; w, c_1 and c_2 are the inertia parameter, the cognitive influence parameter and the social influence parameter; r_1 and r_2 are random values between 0 and 1; $p_{best,i}^t$ and $g_{best,i}^t$ represent the best position of a particle and