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# An intelligent modelling framework for mechanical properties of cemented paste backfill

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ABSTRACT

The mechanical properties of cemented paste backfill (CPB) are particularly important for its application in the minerals industry. In practice, a large number of cumbersome and time-consuming experiments are required to generate the design data. To facilitate the CPB design, this study proposes an intelligent modelling framework for the mechanical properties prediction using machine learning (ML) algorithms and genetic algorithm (GA). Three advanced ML algorithms, including decision tree (DT), gradient boosting machine (GBM), and random forest (RF), were used and compared for the mechanical properties modelling while GA was used for the hyper-parameters tuning. A total of 1077 uniaxial compressive strength (UCS) tests and 231 uniaxial tensile strength (UTS) tests were performed for the dataset preparation. Mechanical properties evaluated were the UCS, the yield strength (YS), the Young's modulus (E) and the UTS. Influencing variables for these mechanical properties were chosen to be the physical and chemical characteristics of tailings, the cement-tailings ratio, the solids content, and the curing time. The results show that GA was efficient in the hyper-parameters tuning of the evaluated ML algorithms. The GBM was a good first ML algorithm for the mechanical properties modelling with high accuracy (correlation coefficients between predicted and experimental properties were 0.963, 0.887, 0.866 and 0.899 for UCS, YS, E and UTS respectively). Based on the results, a user-friendly software package, named the intelligent mining for backfill (IMB), was developed in python programming for a wider application in the minerals industry. The proposed modelling framework and the IMB will be useful for CPB design by saving time, reducing trial tests and cutting costs.

## 1. Introduction

Mine tailings is an inevitable by-product during the excavation of mineral resources. A key issue for the minerals industry is the safe disposal of mine tailings to avoid environmental problems. In modern underground mines, tailings is usually used as a main component of cemented paste backfill (CPB). Typically, CPB consists of dewatered tailings (70–85% solids by weight), a hydraulic binder (3–7% by dry paste weight), and mixing water (fresh or mine processed). Apart from the safe disposal of mine tailings, there are other benefits with CPB, including reduced surface subsidence and rehabilitation costs (Kesimal et al., 2002; Yilmaz, 2010). Moreover, CPB can provide secondary ground support for mining operations to improve the underground working environment. All these technical, economic and environmental benefits have led to the wide application of CPB worldwide (Chen et al., 2017; Chen et al., 2018; Cihangir et al., 2015; Cihangir et al., 2012; Fall et al., 2005; Kesimal et al., 2005; Lu et al., 2018; Wu et al., 2015; Yilmaz et al., 2007; Yilmaz and Fall, 2017; Yilmaz et al., 2004b).

The advantages of CPB are dependent on its mechanical stability, economical performance and durability. Once placed, CPB must have certain mechanical properties to remain stable during adjacent stope excavation. Therefore, mechanical properties of CPB are of great significance during its engineering application. The most widely used mechanical property of CPB is the uniaxial compressive strength (UCS) as the UCS tests are relatively simple and economical (Fall et al., 2008; Vergne, 2000). Numerous UCS tests have been performed and tremendous process has been achieved in understanding the relationship between UCS and its influencing variables (Benzaazoua et al., 1999; Kesimal et al., 2003; Yilmaz et al., 2004a). However, the UCS is not the only mechanical property that determines CPB stability (Fall et al., 2010). Other mechanical properties, such as the yield strength (YS; an indication of maximum stress without plastic deformation), the Young's modulus (E; an indication of deformation behaviour and stiffness) and the uniaxial tensile strength (UTS; an indication of resisting cracking ability), are also key design parameters while receive only a limited studies in the literature (Fall et al., 2010). The experimental

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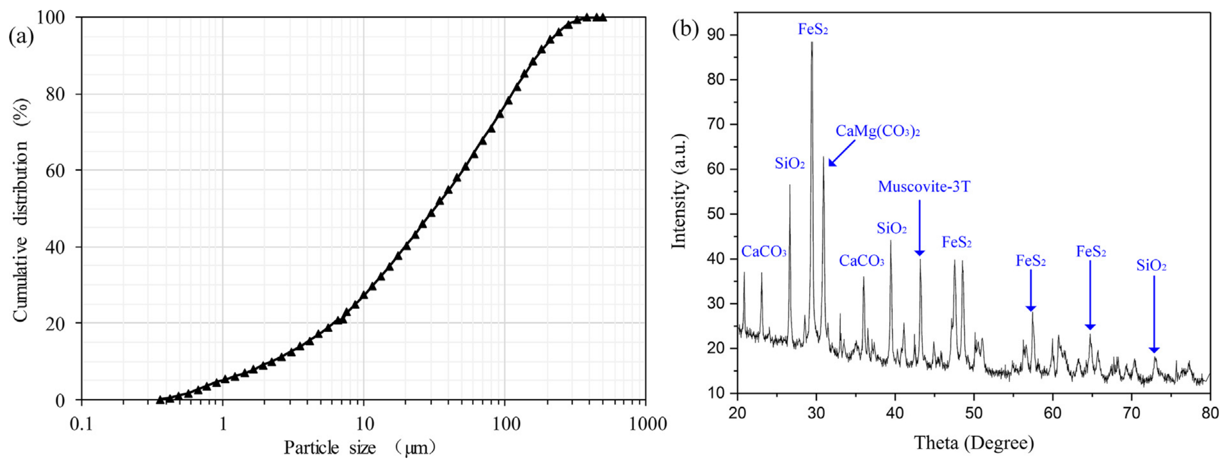


**Fig. 1.** Physical and chemical characteristics of T1: (a) PSD and (b) XRD.

determination of mechanical properties of CPB is cumbersome and time-consuming as it involves lots of mechanical tests for each type of tailings and different testing methods, such as the UCS and the UTS tests. Therefore, a method that can accurately predict CPB mechanical properties is desired.

Mechanical properties of CPB are usually predicted using conventional linear or non-linear regression methods on experimental data (Belem et al., 2000; Fall et al., 2010; Ouellet et al., 2007). However, it is difficult to obtain an accurate regression equation using these empirical-based models. Furthermore, these equations are usually specific to each mine for a given tailings, which means their generalisation capability is unsatisfactory (Benzaazoua et al., 2004). More advanced techniques are needed for the replacement of conventional regression analysis in mechanical properties prediction.

Nowadays, machine learning (ML) algorithms have been applied to model the relationship between inputs and outputs in many areas of minerals engineering, such as forth image analysis (Fu and Aldrich, 2018) and root cause analysis (Groenewald and Aldrich, 2015). Only a small number of studies have used ML algorithms to estimate the mechanical properties of CPB (Orejarena and Fall, 2010a; Orejarena and Fall, 2010b; Qi et al., 2018a). For example, Qi et al. (2018b) proposed a UCS prediction model for CPB using boosted regression trees and particle swarm optimization. Though these studies have great guiding significance, there are some limitations that cannot be neglected: (1) Only the UCS of CPB was predicted using ML algorithms and their feasibilities on other mechanical properties have not been studied. (2) The performance of other advanced ML algorithms, such as random forest (RF), has not been verified and compared on the mechanical properties modelling of CPB. (3) The suitability of genetic algorithm (GA), which is a widely-used optimisation technique, on the hyper-parameters tuning of ML algorithms has not been tested on the mechanical properties modelling. (4) Wider adoption of above ML algorithms in the minerals industry is hampered by the considerable basic knowledge required during model preparation and verification. Therefore, there are still considerable challenges for the prediction of the mechanical properties under different influencing variables.

To compensate for above limitations in the literature, an intelligent modelling framework is proposed to accurately predict the mechanical properties of CPB. For limitation one, four mechanical properties of CPB, including the UCS, the YS, the E and the UTS, were modelled based on a dataset collected from 1077 UCS tests and 231 UTS tests. For limitation two, three advanced ML algorithms, including decision tree (DT), gradient boosting machine (GBM), and random forest (RF), were used and compared on mechanical properties modelling. For limitation three, the suitability of GA for the hyper-parameters tuning of ML algorithms during mechanical properties modelling was investigated. For limitation four, a user-friendly software package was developed that helped store experimental data, perform basic pre-processing, and conduct important prediction.

The main objective of this work is proposing an intelligent modelling framework for the mechanical properties prediction of CPB. Three advanced ML algorithms were compared and a user-friendly modelling software was developed. The presented modelling framework can provide a fast estimation of CPB mechanical properties, and significantly reduce the time and cost allocated for the mechanical properties determination in the minerals industry.

## 2. Experimental program

### 2.1. Materials

The materials used for the preparation of CPB specimens included mine tailings, binders, and water. It needs to note that 'specimen' in this paper represented CPB specimens used during mechanical experiments. By contrast, 'sample' referred to a pair of inputs and output in the dataset used for the implementation of the intelligent modelling framework.

#### 2.1.1. Tailings

Nine types of tailings obtained from different mines in China were used in this study (T1-T9). For each sampling site, the tailings slurry from tailings discharge outlet was filled into the plastic buckets for sedimentation. After 7 days, the upper-layer clarified water was removed and the left dewatered tailings were dried and mixed uniformly for CPB preparation. The specific gravities of these tailings were determined according to the ASTM C642 (ASTM, 2006). The particle size distributions (PSD) were measured using a laser diffraction particle size analyser (Malvern Mastersizer 2000, England) and the chemical composition was measured using the X-ray diffraction (XRD; Bruker SIMENS D500, Germany). The Rietveld method was used to quantify mineralogical composition. The PSD and XRD for T1 are shown in Fig. 1 for illustration and the physical and major chemical characteristics of T1-T9 are given in Table 1.

#### 2.1.2. Binder and water

Based on China's Common Portland Cement Standard (No. GB175-2007), No.325 Portland cement was used as the binder agent. Tap water was used as the mixing water.

### 2.2. CPB preparation

CPB specimens with different tailings, cement-tailings ratio, solids content and curing time were prepared. The mine tailings, binder agent and tap water were mixed in a concrete mixer (JJ-5, Hongda, Hebei