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Application of support vector machines and relevance vector machines in predicting uniaxial compressive strength of volcanic rocks

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ABSTRACT

The uniaxial compressive strength (UCS) of intact rocks is an important and pertinent property for characterizing a rock mass. It is known that standard UCS tests are destructive, expensive and time-consuming task, which is particularly true for thinly bedded, highly fractured, foliated, highly porous and weak rocks. Consequently, prediction models have become an attractive alternative for engineering geologists. In the last several years, a new, alternative kernel-based technique, support vector machines (SVMs), has been popular in modeling studies. Despite superior SVM performance, this technique has certain significant, practical drawbacks. Hence, the relevance vector machines (RVMs) approach has been proposed to recast the main ideas underlying SVMs in a Bayesian context. The primary purpose of this study is to examine the applicability and capability of RVM and SVM models for predicting the UCS of volcanic rocks from NE Turkey and comparing its performance with ANN models. In these models, the porosity and P-durability index representing microstructural variables are the input parameters. The study results indicate that these methods can successfully predict the UCS for the volcanic rocks. The SVM and RVM performed better than the ANN model. When these kernel based models are considered, RVM model found successful in terms of statistical performance criterions (e.g., performance index, PI values for training and testing data are computed as 1.579 and 1.449). These values for SVM are 1.509 and 1.307. Although SVM and RVM models are powerful techniques, the RVM run time was considerably faster, and it yielded the highest accuracy.

1. Introduction

Uniaxial compressive strength (UCS) of intact rocks is an important and pertinent property for characterizing rock mass. This parameter is widely used in geological, geotechnical, geophysical and petroleum engineering projects. A UCS test requires high-quality core samples with regular geometry. Standard cores cannot always be extracted from weak, highly fractured, thinly bedded, foliated and/or block-in-matrix rocks. In addition, careful execution of this test is destructive, time-consuming, and expensive, as well as involving destructive tests (Gokceoglu and Zorlu, 2004). To overcome this difficulty, various predictive models based on index tests, including mineralogical-petrographic analyses, physical properties, an elastic wave velocity test and basic mechanical tests have been developed by many researchers (Yilmaz, 2009; Zhang et al., 2012; Ceryan et al., 2012; Mishra and Basu, 2012, 2013; Singh et al., 2012a; Yesiloglu-Gultekin et al., 2013a; Nefeslioglu, 2013). Index and basic mechanical tests are easy to perform. Sophisticated instruments are not required for index tests; they can be easily performed in the field (Kumar et al., 2013). These tests and analyses require smaller samples compared the sample quantities necessary to determine the UCS directly, and they are faster and more economical (Ulusay et al., 1994; Singh et al., 2001, 2010; Gokceoglu, 2002; Tiryaki, 2008; Sarkar et al., 2012). However, the index tests always include a certain level of uncertainty. One study observed no consistency between the equations suggested by these methods (Fener et al., 2005). While certain equations exhibit the same trend, others differ (Fener et al., 2005).

Basic mechanical tests, including Schmidt hammer (Miller, 1965), impact strength test (Paone et al., 1969), the point load index (Broch and Franklin, 1972), block punch test (Van der Schrier, 1988), cone indentor (Leite and Ferland, 2001), core strangle index (Yilmaz, 2009), nail penetration test (Kayabali and Selcuk, 2010) and Equotip hardness tester (Gunes Yilmaz, 2013), are often used with empirical equations to estimate the UCS (Yilmaz, 2009; Mishra and Basu, 2012; Yesiloglu-Gultekin et al., 2013a). Serious shortcomings, limitations and problems are related to these testing methods (Yilmaz, 2009; Kayabali and Selcuk, 2010; Nefeslioglu, 2013).

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The mineralogical and textural characteristics of rocks significantly affect their mechanical behavior, including their UCS; these properties were widely used to estimate the UCS (Ulusay et al., 1994; Tugrul and Zarif, 1999; Singh et al., 2001; Gokceoglu, 2002; Jeng et al., 2004; Zorlu et al., 2008; Sabatakakis et al., 2008; Yesiloglu-Gultekin et al., 2013a, 2013b; Tandon and Gupta, 2013). Eliminating the real effects of rock fabric parameters on the mechanical properties of rocks by applying complex fabric coefficients inhibits their practical use in petrography applied to geomechanics. (Přikryl, 2006); these conditions are valid for the aforementioned indices developed for specific rocks. Simple indices, such as slake-durability, elastic wave velocity and physical properties, for rock materials are indicative of petrographic features, including the mineralogical composition, fabric and weathering state. Therefore, these indices are widely used to estimate UCS of rock material (Karakus et al., 2005; Yilmaz and Yuksek, 2009; Ceryan et al., 2012, 2013a).

Most investigations involve determining the individual correlation between an index and the UCS (i.e., a simple regression analysis) (e.g., Koncagul and Santi, 1999; Tugrul and Zarif, 1999; Chang et al., 2006; Kahraman et al., 2008; Sabatakakis et al., 2008; Mishra and Basu, 2013). Certain studies have used models that relate the indices simultaneously with the UCS (i.e., multiple regression analysis) (e.g., Ulusay et al., 1994; Tiryaki, 2008; Zorlu et al., 2008; Kahraman et al., 2008; Dehghan et al., 2010; Yagiz et al., 2012; Mishra and Basu, 2013).

In addition to these conventional methods, new techniques for estimating the UCS have also garnered considerable attention. Several researchers have recently proposed meaningful relationships using a fuzzy inference system (FIS) to characterize rock properties, such as the UCS (e.g., Alvarez Grima and Babuska, 1999; Gokceoglu, 2002; Gokceoglu and Zorlu, 2004; Sonmez et al., 2006; Yilmaz and Yuksek, 2009; Gokceoglu et al., 2009; Jalalifar et al., 2011; Singh et al., 2012b; Yesiloglu-Gultekin et al., 2013a). A neural network can be used to solve problems that are not suitable for conventional statistical methods. Using ANNs, many researchers have attempted to estimate the UCS (e.g., Nie and Zhang, 1994; Meulenkamp and Alvarez Grima, 1999; Kahraman and Alber, 2006; Cobanoğlu and Celik, 2008; Tiryaki, 2008; Zorlu et al., 2008; Yilmaz and Yuksek, 2009; Dehghan et al., 2010; Kahraman et al., 2010; Cevik et al., 2011; Yagiz et al., 2012; Ceryan et al., 2012, 2013a; Yesiloglu-Gultekin et al., 2013a; Majdi and Rezaei, 2013; Yurdakul and Akdas, 2013). The studies show that ANN is superior compared with traditional prediction models. Despite the ANN model's high prediction performance, it is not possible to relate ANN input with its output using an analytical equation. Genetic programming (GP) provides a method for overcoming this problem (Beiki et al., 2010). Few studies have predicted rock strength using GP (e.g., Baykasoglu et al., 2008; Asadi et al., 2011). In addition, a neuro-genetic network (Monjezi et al., 2012) and genetic expression programming (Ozbek et al., 2013) were developed to predict the uniaxial compressive strength of rocks.

In the past decade, a new, alternative kernel-based technique, support vector machines (SVMs), was derived from statistical learning theory (Vapnik, 1998). The SVM model using a sigmoid kernel function is equivalent to a two-layer perceptron neural network. Using a kernel function, SVMs are alternative training methods for polynomials, radial basis functions, and multilayer perceptron classifiers, in which the network weights are generated by solving a quadratic programming problem with linear constraints rather than solving a non-convex, unconstrained minimization problem, as with standard ANN training (Huang et al., 2010). SVM is popular for estimating geological material behaviors due to certain advantages over ANN (Gill et al., 2007; Goh and Goh, 2007; Samui, 2008, 2011; Zhao, 2008; Yao et al., 2008; Pal, 2009; Zhi-xiang et al., 2009; Khandelwal, 2010; Martins et al., 2012; Mohamadnejad et al., 2012; Samui and Karthikeyan, 2013; Ceryan et al., 2013b).

The relevance vector machine (RVM) technique is based on a linear model Bayesian formulation with an appropriate prior that results in sparse representation (Tipping, 2000). This method may be viewed as a probabilistic version of SVM (Scholkopf and Smola, 2002) and be effectively used for regression and classification problems. RVM is based on a hierarchical prior, where an independent Gaussian prior is defined based on the weighted parameters in the first level, and an independent Gamma hyper prior is used for the variance parameters in die second level (Pal, 2009). The major advantages of RVM over SVM include (a) reduced sensitivity to die hyperparameter settings, (b) the ability to use non-Mercer kernels, (c) probabilistic output with fewer relevance vectors for a given dataset and (d) no need to define the parameter C (Pal, 2009). RVM has recently attracted much interest for various rock engineering and geotechnical applications (Samui, 2011, 2012; Kumar et al., 2013).

In this study, the applicability and capability of RVM for predicting the uniaxial compressive strength of the volcanic rock from NE Turkey was examined, and its performance was compared with the ANN and SVM models. Considering that the rock materials consist of a solid and porous portion, intrinsic properties that affect the UCS of rock materials can be divided into two groups; one is pore characteristics, and the second is microstructural variables, consisting of the mineralogical composition and rock texture. These cases were considered using soft-computing models to estimate the UCS of the volcanic rock materials herein. To represent the mineralogical composition and rock texture, the P-durability index, a new engineering index, derived from the P-wave velocity in the solid portion of the rock materials, and the slake durability index were developed. Furthermore, the porosity was used as a characteristic of the porous rock material. The performance index (PI), Nash–Sutcliffe coefficient (NS) and weighted mean absolute percentage error (WMAPE) were used to determine the accuracy of the SVM, RVM, and ANN models developed.

2. Materials and testing procedure

The study area is located in the Eastern Pontides of NE Turkey (Fig. 1). Magmatic rocks of different ages with different emplacement levels within the crust are exposed throughout the Pontide Belt (Fig. 1). The samples used in this study were included volcanic rocks, Late Cretaceous and interbedded sedimentary rocks.

The dasitic and andesitic rock samples investigated are from the excavated slopes throughout the Gumushane-Giresun roadway in NE Turkey (Figs. 1 and 2). The intact rock samples from the tuffs and basalt investigated were obtained from the Iyidere-Ikizdere quarry, Rize NE Turkey. The index and engineering properties of the weathered samples from the stone walls in 1970 for environmental recreation at the Karadeniz Technical University, Trabzon, NE Turkey were from the study performed by Ceryan and Usturbelli (2011).

In this study, 47 block samples, each sample measuring approximately 30 × 30 × 30 cm, were collected in the field for the rock mechanics tests using the core-drilling machine at the Rock Mechanics Laboratory in the Engineering Faculty of Karadeniz Technical University. The core samples were prepared from the rock blocks; they were 50 mm in diameter, and the edges of the specimens were cut parallel and smooth (Fig. 3). The index and mechanical tests on the samples, such as for porosity, P-wave velocity, slake durability, and UCS strength, were performed in the laboratory; these test results are in Fig. 4.

The total porosity (n) of the rock was estimated using the following equations: