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Predicting tensile strength of rocks from physical properties based on support vector regression optimized by cultural algorithm

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Abstract
The tensile strength (TS) of rocks is an important parameter in the design of a variety of engineering structures such as the surface and underground mines, dam foundations, types of tunnels and excavations, and oil wells. In addition, the physical properties of a rock are intrinsic characteristics, which influence its mechanical behavior at a fundamental level. In this paper, a new approach combining the support vector regression (SVR) with a cultural algorithm (CA) is presented in order to predict TS of rocks from their physical properties. CA is used to determine the optimal value of the SVR controlling the parameters. A dataset including 29 data points was used in this study, in which 20 data points (70%) were considered for constructing the model and the remaining ones (9 data points) were used to evaluate the degree of accuracy and robustness. The results obtained show that the SVR optimized by the CA model can be successfully used to predict TS.

Keywords: *Tensile Strength (TS) of Rocks, Support Vector Regression (SVR), Cultural Algorithm (CA), Physical Properties.*

1. Introduction

The tensile strength (TS) of rocks is often a significant mechanical parameter in the engineering practice in/on rocks [1]. It governs the failure of rock masses in problems such as the stability of mining roofs, galleries, and drilling and blasting [2]. There are basically two approaches used for determining TS of rocks, one of which is to collect and test rock specimens in the laboratory (direct methods), and the other one is to use the empirical relationships developed between the TS and the index parameters of rocks (indirect methods) [3]. The direct standard methods are difficult, time-consuming, and expensive, especially with highly porous, highly fractured, weak, and inhomogeneous rocks [4]. Hence, different relationships have been presented between the TS and the various physical/mechanical properties of rocks [5]. The estimator variables used for predicting TS are the mineralogical composition and the intrinsic rock properties such as the grain size, aspect ratio, form factor [6], electrical resistivity [7], strength ratio, unconfined compressive strength, tensile crack initiation stress [8], total porosity [9], point load strength [5, 9], and Schmidt hammer value [9]. Many researchers have developed various predictive models that employ the empirical approach [8], conventional statistical models [5, 7, 10], soft computing techniques based on genetic programming [3, 9, 11], and artificial neural networks (ANNs) [6, 12-16]. In spite of their advantages, some soft-computing-based models like ANNs may suffer from drawbacks including getting trapped in local minima, over-training, subjective determination of model parameters, random initialization of the weights in each simulation, and complex structures (i.e. hidden layers, number of neurons in the hidden layers, activation function type, etc.) [3, 17-20].

In the past decade, a new kernel-based technique called a support vector regression (SVR) has been found popular in modeling studies due to its

advantages over ANN. This method is a powerful alternative that overcomes some of the basic weaknesses related to ANN, while retaining all the strengths of ANN [19-23]. SVR is a potent data mining model, which was developed by Vapnik and co-workers [24] based on the statistical learning theory for solving problems encountered in petroleum industry. Although this method is powerful for modeling different phenomena, it suffers from some shortcomings, which limit its application. In every SVR modeling, there is a series of parameters whose values are required to be set precisely by the user. An incorrect input of the aforementioned parameters can lead to erroneous and even deceptive results. Hence, it is crucial to employ a potent optimization algorithm for searching the proper values for these parameters [25, 26]. In the present study, a fast, robust, and easy-to-use method called cultural algorithm (CA) was applied as the strategy of searching the optimal value of the SVR controlling parameters. The integration of the SVR model and CA method produced a model, which can predict the TS of rocks with good precision.

2. A brief review of methods used

2.1. Support vector regression

The method of support vector machines (SVMs), introduced as a machine learning technique by Vapnik [24], has received so much attention due to its promising capabilities in minimizing the prediction error since its development [27-29]. The underlying concept of SVR is to map the original data into a higher-dimensional feature space and to fit a linear function with a least reasonable complexity to the feature space [30, 31]. The latter stage is carried out to make the function as flat as possible in order to reduce the complexity, and it means a better generalization to a considerable extent.

Let the training samples be denoted as $XY = \{(x,y)\,|\,(x_1,y_1),...,(x_n,y_n)\}$, where n is the number of training samples. In SVR, the ultimate goal is to find a linear relation between the n-dimensional input vectors $x \in R^n$ and the output variables $y \in R$, as follows:

$$f(x) = w^T x + b \tag{1}$$

where b and w are the offset of the regression line and the slope, respectively. For determining the values for b and w, it is necessary to minimize the following equation:

$$R = \frac{1}{2}\|w\|^2 + \frac{C}{l}\sum_{i=1}^{l}|y_i - f(x_i)|_{\varepsilon} \tag{2}$$

The first term in Eq. (2), employing the concept of maximizing the distance between two separated training data, is used to regularize weight sizes, to penalize large weights, and to maintain the regression function flatness. The second term penalizes training errors of *f(x)* and *y* using the ε-insensitive loss function. The loss function, utilized in SVR is ε-insensitive, has been proposed by Vapnik (1995) [24] as follows:

$$|y_i - f(x_i)|_{\varepsilon} = \begin{cases} 0 & if \quad |y_i - f(x_i)| \le \varepsilon \\ |y_i - f(x_i)| - \varepsilon & Otherwise \end{cases} \tag{3}$$

This problem can be reformulated in a dual space by:

$$\begin{aligned} &Maximize\, L_p(\alpha_i, \alpha_i^*) = \\ &-\frac{1}{2}\sum_{i,j=1}^{l}(\alpha_i - \alpha_i^*)(\alpha_j - \alpha_j^*)x_i^T x_j \\ &-\varepsilon\sum_{i=1}^{l}(\alpha_i + \alpha_i^*) + \sum_{i=1}^{l}(\alpha_i - \alpha_i^*)y_i \end{aligned} \tag{4}$$

$$Subject\ to \begin{cases} \sum_{i=1}^{l}(\alpha_i - \alpha_i^*) = 0 \\ 0 \le \alpha_i \le C, \quad i = 1,...,l \\ 0 \le \alpha_i^* \le C, \quad i = 1,...,l \end{cases}, \tag{5}$$

where $\alpha_i, \alpha_i^* \ge 0$ are positive Lagrange multipliers, and C is the regulated positive parameter that determines the trade-off between the approximation error and the weight vector norm $\|w\|$. After calculation of the Lagrange multipliers α_i and α_i^*, the training data points that meet the condition $\alpha_i - \alpha_i^* \ne 0$ will be used to construct the decision function. Hence, the best linear hyper surface regression is given by:

$$f(x) = w_0^T x + b = \sum_{i=1}^{l}(\alpha_i - \alpha_i^*)x_i^T x + b \tag{6}$$

in which the desired weight vector of the regression hyper plane is given by:

$$w_0 = \sum_{i=1}^{l}(\alpha_i - \alpha_i^*)x_i \tag{7}$$

In a non-linear regression, the kernel function is applied for mapping the input data onto a higher dimensional feature space in order to generate a linear regression hyper plane. In the case of the non-linear regression, the learning problem is again formulated in the same way as in a linear

case, i.e. the non-linear hyperplane regression function becomes:

$$f(x)=\sum_{i=1}^{l}\left(\alpha_i-\alpha_i^*\right)K(x_i,x)+b \qquad (8)$$

where $K(x_i,x)$ is the kernel function, defined as follows:

$$K(x_i,x_j)=\Phi^T(x_i)\Phi(x_j) \qquad i,j=1,...,l, \qquad (9)$$

where $\Phi(x_i)$ and $\Phi(x_j)$ are the projections of x_i and x_j in the feature space, respectively.

One may choose any arbitrary kernel function such as the linear kernel function, $K(x_i,x_j)=(x_i,x_j)$, radial basis function (RBF), $K(x_i,x_j)=\exp(-\|x_i-x_j\|/2\sigma^2),\sigma>0$, and polynomial kernel function, $K(x_i,x_j)=((x_i,x_j)+1)^d,d>0$. In highly non-linear spaces, the RBF kernel usually yields more promising results in comparison with the other mentioned kernels [32]. Thus we only used the RBF kernel function in this study.

2.2. Cultural algorithm

CA [33, 34] involves acquiring the belief space from the evolving population space and then exploiting that information to guide the search. Figure 1 presents the CA components. CA can be described in terms of the two basic components belief space and population space. The belief space is the information repository, in which the individuals can store their experiences for other individuals in order to learn from them indirectly. In CA, the information acquired by an individual can be shared with the entire population, unlike most evolutionary techniques, in which the information can be shared only with the offspring of the individual. The population space comprises a set of possible solutions to the problem, and can be modeled using any population-based approach. The belief space and the population space are linked using a scheme that states the rules governing the individuals of the population space that can contribute to the belief space based on its experiences (according to the acceptance function), and the belief space can influence the new individuals of the population space (according to the influence function).

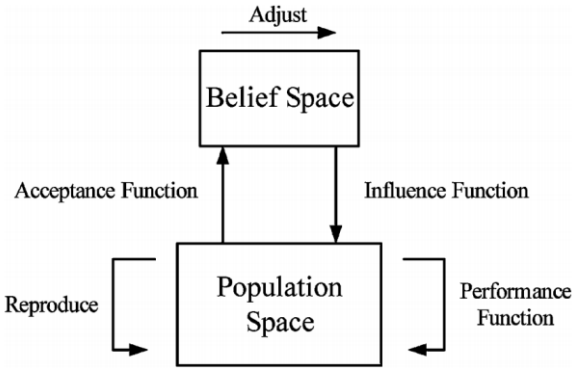

Figure 1. Framework of CA [35].

3. SVR parameter optimization using CA

The generalization ability of SVR is extremely dependent upon its learning parameters, i.e. the RBF kernel parameter $\sigma\in\left[2^{-5},2^{5}\right]$, the error margin $\varepsilon\in[0.01,0.6]$, and the regularization parameter $C\in\left[2^{-5},2^{15}\right]$, to be set correctly. Finding the best combination of the hyper-parameters is often troublesome due to the highly non-linear space of the model performance with respect to these parameters. Although an exhaustive search method could be utilized to tune these hyper-parameters, it suffers from the main drawbacks of being very time-consuming and lacking a guarantee of convergence to the globally optimal solution. The real-value genetic algorithm (GA) was employed to determine the optimal parameters of SVR, which were then applied to construct the SVR model, referred to as SVR-GA [36-38]. ACO has also been used by several researchers to select the model parameters of SVR [39-41]. Recently, the harmony search (HS) has also been utilized to choose the SVR model parameters [42].

In this paper, we adopted CA for choosing the optimal values for the SVR parameters in order to improve the runtime and efficiency of the learning procedure.

4. Data source and data structure

To establish a SVR-CA model in order to predict TS, providing an appropriate dataset is the most important requirement. To achieve this, the datasets given in the previous work were borrowed [13]. A database composed of the measured TS values and physical properties were established using the data collected from a formation around Khouzestan Province, Iran. The specimens of fresh sandstone blocks were cored in the laboratory. Each dataset contained the parameters porosity (%), specific gravity (G_s), dry

unit weight (kN/m^3), saturated unit weight (kN/m^3), and measured TS (MPa). The TS values for the rock samples were determined using the Brazilian tensile strength tests. The Brazilian test is widely used as a satisfactory technique for determining the TS values for many rocks [43-45]. The test measures TS indirectly by developing tension across the diameter of a rock disc that is subjected to compression through a vertical load [5]. The testing procedures for this method have been standardized by the International Society for Rock Mechanics (ISRM) [46]. In the resource [13], the Brazilaian tests were performed according to the ISRM suggested method. A detailed description of the database can be found in the refered resource [13].

The data was randomly divided into two subsets: 70% of the total data (20 cases) was allotted to the training data for the SVR-CA model construction, and 20% of the total data (9 cases) was allocated to the test data used to assess the reliability of the developed model. The partial dataset used in this study is presented in Table 1. Table 2 shows the statistical description of the datasets used in this study.

Table 1. Partial dataset used for constructing SVR-CA model [13].

Input parameters				Output parameter
Porosity (%)	**Specific gravity (G_s)**	**Dry unit weight (KN/m^3)**	**Saturated unit weight (KN/m^3)**	**Tensile strength (MPa)**
18.35	26.68	21.78	23.54	3.85
5.74	24.33	22.86	23.45	8.64
12.51	24.62	21.58	22.76	4.31
5.05	24.92	23.64	24.13	10.18
14.05	24.13	20.7	22.17	2.45

Table 2. Statistical description of dataset utilized for construction of SVR-CA model.

Parameter	Min.	Max.	Average
Porosity (%)	4.19	25.27	11.50
Specific gravity (G_s)	22.76	26.68	24.71
Dry unit weight (KN/m^3)	16.97	24.62	21.90
Saturated unit weight (KN/m^3)	19.42	25.11	23.04
Tensile strength (MPa)	0.19	13.23	5.90

5. Prediction of tensile strength of rocks from physical properties

5.1. Pre-processing of data and evaluation criteria

In the data-driven system modeling methods, some pre-processing steps are usually implemented prior to any calculations in order to eliminate any outliers, missing values or bad data. This step ensures that the raw data retrieved from database is perfectly suitable for modeling. In order to soften the training procedure and improve the accuracy of estimation, all data samples are normalized to adapt to the interval [-1, 1] according to the following linear mapping function [47]:

$$x_M = 2\left(\frac{x - x_{\min}}{x_{\max} - x_{\min}}\right) - 1 \quad (10)$$

where x is the original value for the dataset, x_M is the mapped value, and x_{max} (x_{min}) denotes the maximum (minimum) raw input values, respectively.

Furthermore, to verify the performance of the model, the five statistical criteria mean squared error (MSE), variance account for (VAF), root mean squared error (RMSE), squared correlation coefficient (R^2), and mean absolute percentage error (MAPE) were chosen to be the measures of accuracy [48-51]. Let t_k be the actual value, $\hat{t}_k$ be the predicted value for the k^{th} observation, and n be the number of observations. Then RMSE, MSE, VAF, R^2, and MAPE could be defined, respectively, as follow:

$$MSE = \frac{1}{n}\sum_{k=1}^{n}(t_k - \hat{t}_k)^2 \quad (11)$$

$$VAF = \left(1 - \frac{\mathrm{var}(t_k - \hat{t}_k)}{\mathrm{var}(t_k)}\right) \quad (12)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{k=1}^{n}(t_k - \hat{t}_k)^2} \quad (13)$$

$$R^2 = \frac{(\sum_{k=1}^{n} t_k \hat{t}_k - n\mu_t\mu_{\hat{t}})^2}{(\sum_{k=1}^{n} \hat{t}_k^{\,2} - n\mu_t^{\,2})^2 (\sum_{k=1}^{n} \hat{t}_k^{\,2} - n\mu_{\hat{t}}^{2})^2} \quad (14)$$

$$MAPE = \frac{1}{n}\sum_{k=1}^{n}\left|\frac{t_k - \hat{t}_k}{t_k}\right| \times 100, \quad (15)$$

where μ_t ($\mu_{\hat{t}}$) denotes the mean value for μ_k ($\mu_{\hat{k}}$), $k = 1,...,n$.

5.2. Results

In this paper, a hybrid SVR-CA model was proposed to predict TS. The parameters porosity (%), specific gravity (G_s), dry unit weight (kN/m^3), and saturated unit weight (kN/m^3) were considered as the input parameters of the SVR-CA model, and TS was the output.

Furthermore, the generalization ability of SVR is highly dependent upon its learning parameters, i.e. $\{C, \sigma, \varepsilon\}$. Therefore, CA was used to find the optimal values for these parameters. A 10-fold cross-validation performance measure was applied to the training dataset along with SVR-CA to achieve reliable results. CA with a population size of 20, acceptance ratio = 0.35, number of accepted individuals = 7, alpha = 0.25, and beta = 0.5 was executed for 100 iterations to find the optimal values for the SVR parameters. The adjusted values for the parameters $\{C, \sigma, \varepsilon\}$ with maximal accuracy were selected as the most appropriate ones. Then the optimized parameters were used to train the SVR model. The SVR parameters optimized by CA are presented in Table 3.

A comparison between the values for TS predicted by the SVR-CA model, and the measured values for 29 datasets at the training and testing phases are shown in Figures 2 and 3. As it can be seen, the results of the SVR-CA modeling compared with the actual data show a good precision. The performance analysis of the SVR-CA model for predicting TS is shown in Table 4. The performance indices tabulated in this table indicate a high performance of the SVR-CA model that can be successfully used in the prediction of TS.

Table 5 compares our results with the results obtained by Ghobadi et al. [13]. This table contains the results obtained for the three methods linear regression model (MLR), ANN, and SVR optimized by the CA model. As it can be seen, the SVR-CA model indicates a better performance compared to the previously published models, taking all the criteria into account .

The flexibility of the kernel functions in modeling linear and non-linear relationships allows SVR to search for a wider range of solution space compared to MLR and ANNs [52]. Moreover, ANNs is a black-box approach suffering from a computationally expensive training process [53].

Table 3. Values for SVR parameters optimized by CA.

Optimal value for σ	Optimal value for C	Optimal value for ε
2.2467	862.2191	0.3995

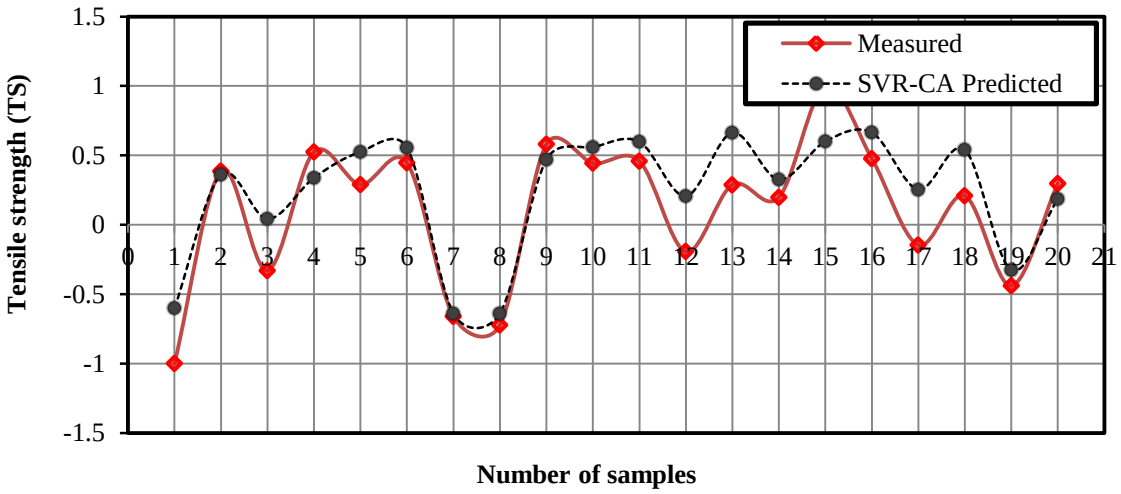

Figure 2. Comparison between measured and predicted TS values for training data points.

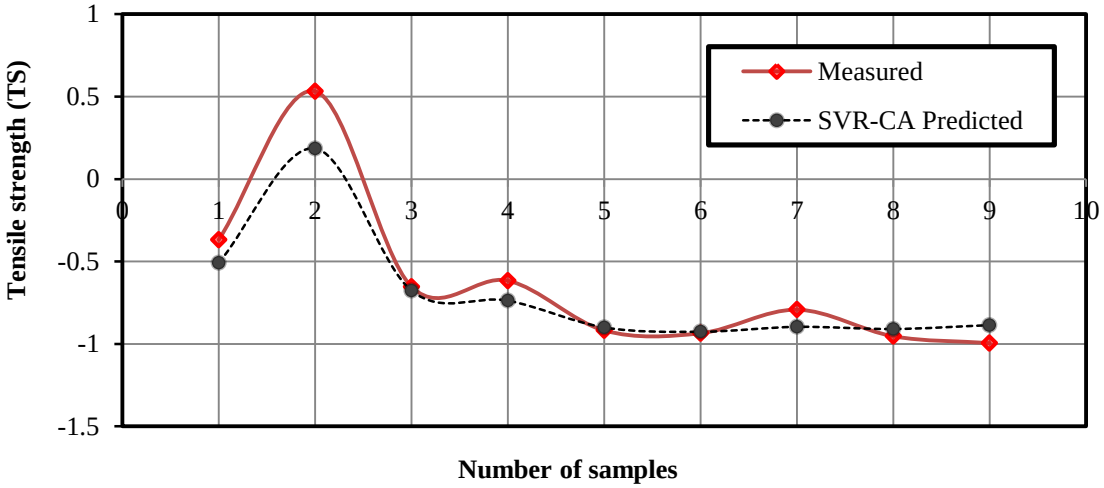

Figure 3. Comparison between measured and predicted TS values for testing data points.

Table 4. Performance of model for predicting TS.

Description	R^2	MSE	RMSE	VAF	MAPE
Training datasets	0.8180	0.032	0.1787	76.41	28.04
Testing datasets	0.9826	0.020	0.1415	93.10	17.57

Table 5. Comparison of performance of proposed model and previously presented models.

Description		R^2	MSE	RMSE	VAF	MAPE
SVR-CA	Training datasets	0.81	0.032	0.1787	76.41	28.04
(Proposed in this study)	Testing datasets	0.98	0.020	0.1415	93.10	17.57
ANN	Training datasets	...	...	...	...	...
(Proposed in Ghobadi et al. [13])	Testing datasets	0.99	...	...	...	...
MLR	Training datasets	...	...	...	...	...
(Proposed in Ghobadi et al. [13])	Testing datasets	0.94	...	...	...	...

6. Conclusions

Since the direct methods used for measuring the tensile strength (TS) of rock materials are associated with difficulties and even uncertainties in some cases, the indirect determination of this parameter is a topic of interest in rock mechanics. In this paper, the idea of relating TS of rocks to their index characteristics was followed. Due to the highly complicated nature of rocks, a soft-computing approach was used in this work. Soft computing is an extension of natural heuristics, and is capable of dealing with complex systems since it does not require strict mathematical definitions and distinctions for the system components. Soft computing, in spite of hard computing, is tolerant of imprecision, uncertainty, and partial truth. Several soft computing techniques have been presented, each of which can be used separately. However, if they are used together, they can produce solutions to problems that are too complex or inherently noisy to tackle with the conventional mathematical methods.

In this paper, a new approach combining SVR with CA was presented to predict TS of rocks from their physical index properties. The inputs of the model were porosity, specific gravity, dry unit weight, and saturated unit weight. In the proposed methodology, CA was used as a tool for determining the optimal value for the SVR controlling parameters. Some statistical measures of performance (i.e. RMSE, MSE, VAF, R^2, and MAPE) were employed to assess the model. The results obtained indicate that SVR optimized by CA successfully predicts TS, and shows a better performance than MLR and ANN do. In terms of accuracy, the SVR-CA model resulted in lower RMSE and MSE values, and higher VAF and R^2 values. Application of the hybrid SVR-CA model in other areas of rock mechanics and rock engineering is suggested as a topic of future studies.

References

[1]. Basu, A., Ghosh, N. and Das, M. (2012), Categorizing weathering grades of quartzitic materials and assessing Brazilian tensile strength with reference to assigned grades. Int J Rock Mech Min Sci, 49: 148-155.

[2]. Coviello, A., Lagioia, R. and Nova, R. (2005). On the measurement of the tensile strength of soft rocks. Rock Mech Rock Eng. 38 (4): 251-273.

[3]. Baykasoğlu, A., Güllü, H., Çanakçı, H. and Özbakır, L. (2008). Prediction of compressive and tensile strength of limestone via genetic programming. Expert Syst Appl. 35 (1): 111-123.

[4]. Ceryan, N., Okkan, U. and Kesimal, A. (2012). Application of generalized regression neural networks in predicting the unconfined compressive strength of carbonate rocks. Rock Mech Rock Eng. 45 (6): 1055-1072.

[5]. Heidari, M., Khanlari, G., Torabi Kaveh, M. and Kargarian, S. (2012). Predicting the uniaxial compressive and tensile strengths of gypsum rock by point load testing. Rock Mech Rock Eng. 45 (2): 265-273.

[6]. Singh, V., Singh, D. and Singh, T. (2001). Prediction of strength properties of some schistose rocks from petrographic properties using artificial neural networks. Int J Rock Mech Min Sci. 38 (2): 269-284.

[7]. Kahraman, S. and Yeken, T. (2010). Electrical resistivity measurement to predict uniaxial compressive and tensile strength of igneous rocks. B Mater Sci. 33 (6): 731-735.

[8]. Cai, M. (2010). Practical estimates of tensile strength and Hoek–Brown strength parameter m i of brittle rocks. Rock Mech Rock Eng. 43 (2): 167-184.

[9]. Karakus, M. (2011). Function identification for the intrinsic strength and elastic properties of granitic rocks via genetic programming (GP). Comput Geosci. 37 (9): 1318-1323.

[10]. Kumar, B.R., Vardhan, H. and Govindaraj, M. (2011). Prediction of uniaxial compressive strength, tensile strength and porosity of sedimentary rocks using sound level produced during rotary drilling. Rock Mech Rock Eng. 44 (5): 613-620.

[11]. Hossein Alavi, A. and Hossein Gandomi, A. (2011). A robust data mining approach for formulation of geotechnical engineering systems. Eng Computation. 28 (3): 242-274.

[12]. Çanakci, H. and Pala, M. (2007). Tensile strength of basalt from a neural network. Eng Geol. 94 (1): 10-18.

[13]. Ghobadi, M.H., Mousavi, S., Heidari, M. and Rafie, B. (2015). The Prediction of the Tensile Strength of Sandstones from their petrographical properties using regression analysis and artificial neural network. Geopersia. 5 (2): 177-187.

[14]. Alavi, A.H. and Gandomi, A.H. (2011). Prediction of principal ground-motion parameters using a hybrid method coupling artificial neural networks and simulated annealing. Comput Struct. 89 (23): 2176-2194.

[15]. Tiryaki, B. (2008). Predicting intact rock strength for mechanical excavation using multivariate statistics, artificial neural networks, and regression trees. Eng Geol. 99 (1): 51-60.

[16]. Dehghan, S., Sattari, G., Chelgani, S.C. and Aliabadi, M. (2010). Prediction of uniaxial compressive strength and modulus of elasticity for Travertine samples using regression and artificial neural networks. Min Sci Tech. 20 (1): 41-46.

[17]. Samui, P., Sitharam, T. and Kurup, P.U. (2008). OCR prediction using support vector machine based on piezocone data. J Geotech Geoenviron. 134 (6): 894-898.

[18]. Samui, P. and Sitharam, T. (2010). Site characterization model using least-square support vector machine and relevance vector machine based on corrected SPT data (Nc). In J Numer Anal Met Geomech. 34 (7): 755-770.

[19]. Yan, K. and Shi, C. (2010). Prediction of elastic modulus of normal and high strength concrete by support vector machine. Constr Build Mater. 24 (8): 1479-1485.

[20]. Khandelwal, M., Kankar, P. and Harsha, S. (2010). Evaluation and prediction of blast induced ground vibration using support vector machine. Min Sci Tech. 20 (1): 64-70.

[21]. Zhi-xiang, T., Pei-xian, L., Li-li, Y. and Ka-zhong, D. (2009). Study of the method to calculate subsidence coefficient based on SVM. Procedia Earth and Planetary Science. 1 (1): 970-976.

[22]. Samui, P. and Sitharam, T. (2011). Machine learning modelling for predicting soil liquefaction susceptibility. Nat Hazards Earth Syst Sci. 11 (1): 1-9.

[23]. Okkan, U. (2012). Performance of least squares support vector machine for monthly reservoir inflow prediction. Fresen Environmen Bull. 21 (3): 611-620.

[24]. Vapnik, V. (1999). The nature of statistical learning theory. Springer.

[25]. Üstün, B., Melssen, W., Oudenhuijzen, M. and Buydens, L. (2005). Determination of optimal support vector regression parameters by genetic algorithms and simplex optimization. Anal Chim Acta. 544 (1): 292-305.

[26]. Meysam Mousavi, S., Tavakkoli-Moghaddam, R., Vahdani, B., Hashemi, H. and Sanjari, M. (2013). A new support vector model-based imperialist competitive algorithm for time estimation in new product development projects. Robot Cim-Int Manuf. 29 (1): 157-168.

[27]. Al-Anazi, A. and Gates, I. (2010). Support vector regression for porosity prediction in a heterogeneous

reservoir: A comparative study. Comput Geosci. 36 (12): 1494-1503.

[28]. Jiang, B. and Zhao, F. (2013). Combination of support vector regression and artificial neural networks for prediction of critical heat flux. Int J Heat Mass Tran. 62: 481-494.

[29]. Wu, Q. and Law, R. (2010). Fuzzy support vector regression machine with penalizing Gaussian noises on triangular fuzzy number space. Expert Syst Appl. 37 (12): 7788-7795.

[30]. Gunn, S.R. (1998). Support vector machines for classification and regression. ISIS technical report 14.

[31]. Vapnik, V., Golowich, S.E. and Smola, A. (1997). Support vector method for function approximation, regression estimation, and signal processing. Adv Neur In. pp. 281-287.

[32]. Geem, Z.W. (2009). Music-inspired harmony search algorithm: theory and applications. Vol 191. Springer Verlag.

[33]. Reynolds, R.G. (1994). An introduction to cultural algorithms. In: Proceedings of the third annual conference on evolutionary programming. Singapore.

[34]. Jin, X. and Reynolds, R.G. (1999). Using knowledge-based evolutionary computation to solve nonlinear constraint optimization problems: a cultural algorithm approach. In: Evolutionary Computation, 1999. CEC 99. Proceedings of the 1999 Congress on IEEE.

[35]. Lin, C.J., Chen, C.H. and Lin, C.T. (2009). A hybrid of cooperative particle swarm optimization and cultural algorithm for neural fuzzy networks and its prediction applications. IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews). 39 (1): 55-68

[36]. Wu, C.H., Tzeng, G.H. and Lin, R.H. (2009). A Novel hybrid genetic algorithm for kernel function and parameter optimization in support vector regression. Expert Syst Appl. 36 (3): 4725-4735.

[37]. Chen, K.Y. and Wang, C.H. (2007). Support vector regression with genetic algorithms in forecasting tourism demand. Tourism Manage. 28 (1): 215-226.

[38]. Huang, C.L. and Wang, C.J. (2006). A GA-based feature selection and parameters optimizationfor support vector machines. Expert Syst Appl. 31 (2): 231-240.

[39]. Zheng, L., Zhou, H., Wang, C. and Cen, K. (2008). Combining support vector regression and ant colony optimization to reduce NOx emissions in coal-fired utility boilers. Energ Fuel. 22 (2): 1034-1040.

[40]. Hong, W.C., Chen, Y.F., Chen, P.W. and Yeh, Y.H. (2007). Continuous ant colony optimization algorithms in a support vector regression based financial forecasting model. In: Natural Computation, 2007. ICNC 2007. Third International Conference on IEEE. pp. 548-552.

[41]. Zheng, L. and Yu, M. (2008). Support vector regression and ant colony optimization for combustion performance of boilers. In: Natural Computation. ICNC'08. Fourth International Conference on IEEE. pp. 178-182.

[42]. Fattahi, H., Gholami, A., Amiribakhtiar, M.S. and Moradi, S. (2015). Estimation of asphaltene precipitation from titration data: a hybrid support vector regression with harmony search. Neural Comput Appl. 26 (7): 789-798.

[43]. Palchik, V. and Hatzor, Y. (2004). The influence of porosity on tensile and compressive strength of porous chalks. Rock Mech Rock Eng. 37 (4): 331-341.

[44]. Chou, Y.C. and Chen, C.S. (2008). Determining elastic constants of transversely isotropic rocks using Brazilian test and iterative procedure. In J Numer Anal Met Geomech. 32 (3): 219-234.

[45]. Bohloli, B. and Hovén, E. (2007). A laboratory and full-scale study on the fragmentation behavior of rocks. Eng Geol. 89 (1): 1-8.

[46]. International Society for Rock Mechanics (ISRM). (1978). Suggested methods for determining tensile strength of rock materials. Suggested method for determining indirect tensile strength by brazilian test. Commission on standardization of laboratory andfield tests.

[47]. Fattahi, H. (2016). Indirect estimation of deformation modulus of an in situ rock mass: an ANFIS model based on grid partitioning, fuzzy c-means clustering and subtractive clustering. Geosciences Journal. 20 (5): 681-690.

[48]. Fattahi H (2016) Application of improved support vector regression model for prediction of deformation modulus of a rock mass. Engeering with Computer. 32 (4): 567-580.

[49]. Wackerly, D., Mendenhall, W. and Scheaffer, R.L. (2007). Mathematical statistics with applications. Nelson Education.

[50]. Papoulis. A. (1990). Probability & statistics, Vol 2. Prentice-Hall Englewood Cliffs.

[51]. Steel, R.G. and James, H. (1960). Principles and procedures of statistics: with special reference to the biological sciences. New York. US: McGraw-Hill.

[52]. Kwon, Y., Omitaomu, O.A. and Wang, G.N. (2008). Data mining approaches for modeling complex electronic circuit design activities. Comput Ind Eng. 54 (2): 229-241.

[53]. Haykin, S. (1994). Neural networks, a comprehensive foundation. Upper Saddle River, NJ: Prentice Hall.

پیش‌بینی مقاومت کششی سنگ‌ها با استفاده از مشخصات فیزیکی و روش رگرسیون بردار پشتیبان بهینه‌شده توسط الگوریتم فرهنگی

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چکیده:

مقاومت کششی سنگ‌ها یکی از پارامترهای مهم در طراحی انواع سازه‌های مهندسی از جمله معادن سطحی و زیرزمینی، پی سدها، انواع تونل‌ها و فضاهای زیرزمینی و دیواره‌ی چاه‌های نفتی است. از طرفی، خصوصیات فیزیکی یک سنگ بر رفتار مکانیکی آن تأثیرگذار است. در این تحقیق با استفاده از یک روش ترکیبی جدید به نام روش «رگرسیون بردار پشتیبان بهینه شده توسط الگوریتم فرهنگی» مقاومت کششی سنگ‌ها از روی خواص فیزیکی‌شان پیش‌بینی شده است. در این روش، الگوریتم فرهنگی برای تنظیم پارامترهای رگرسیون بردار پشتیبان استفاده شده است. داده‌های استفاده شده در این تحقیق شامل ۲۹ داده است که ۷۰ درصد آن‌ها جهت مدل‌سازی و مابقی جهت بررسی دقت و عملکرد مدل بکار گرفته شده است. نتایج به دست آمده در این تحقیق نشان می‌دهد که روش مذکور توانایی بالایی در پیش‌بینی مقاومت کششی سنگ‌ها با استفاده از مشخصات فیزیکی‌شان را دارد.

کلمات کلیدی: مقاومت کششی سنگ‌ها، رگرسیون بردار پشتیبان، الگوریتم فرهنگی، مشخصات فیزیکی.