Exploring relationships between mechanical properties of marl core samples by a coupling of mutual information and predictive ensemble model

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Abstract

Inappropriate evaluation of uniaxial compression indexes (E and UCS) of rocks in high seismic intensity areas such as dam regions can lead to underestimation of the load, and possible settlement of the structure. Indirect assessments of these rock mechanical indexes based on non-destructive experiments and by using intelligent models is a well-accepted method to overcome associated limitations with laboratory tests of E and UCS. This study introduces the mutual information (MI) method as a unique system for variable importance measurement (VIM) and feature selection. Conducting MI-VIM assessments between various analyses of marl core samples (depth, density, ultrasonic tests (ν_d , V_p and V_s), Brazilian test (σ_t), triaxial compression test (C and ϕ) and point load test ($I_s(50)$) indicated that V_s and σ_t had the highest importance for E and UCS prediction. adaptive boosting–neural network ensemble (Adaboost–NNE) was used for the prediction of E and UCS. Testing of the generated Adaboost–NNE indicated that this model could accurately predict UCS and E with correlations of determinations 0.98 and 0.92, respectively. These results showed that VIM of MI coupled with Adaboost–NNE could develop a robust model that can be used for the prediction and modeling of other indexes of rocks.

Keywords Marls · Dam · Variable importance · Maintenance · Brazilian test · Mutual information

Introduction

The study of geotechnical and mechanical properties of rocks would be critical keys for the construction, control, and maintenance of high seismic intensity regions such as dam areas. Seydoon dam (Khoozestan Province, south-west of Iran) has been constructed over a series of marls, shale and sandstones. Among these rocks, marls are particularly important due to their specific properties. Marls are composed of clay and carbonate minerals in different proportions and their characters mainly depend on the

type and percentage of carbonate and clay minerals (Bellair and Pomerol 1980; El Amrani et al. 1998). It is well accepted that the force load in dam areas has a large effect on the mechanical properties of rocks, such as elasticity and strength (Abrams 1917; Watstein 1953; Malvar and Ross 1998; Yan and Lin 2006). Uniaxial compressive strength (UCS) and Young's modulus (E) can be used to determine the durability of rocks against weathering agents and their fabrics. UCS and E are also can be used to determine their deformation and bearing capacity (Dehghan et al. 2010; Matin et al. 2017). Therefore, the determination of UCS and E for marls from the ground of the dam can play an essential role in understanding their mechanical properties and help to do appropriate maintenance for the site.

American Standards for Testing Materials (ASTM) and International Society for Rock Mechanics (ISRM) have been introduced as standard procedures for the determination of UCS and E . However, direct determinations of these indexes based on ASTM and ISRM approaches in the laboratory have few drawbacks (complex sample preparation, expensive and time consuming process) (Sousa 2014; Jamshidi et al. 2016a, b; Armaghani et al. 2016a, b). For solving limitations

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associated with laboratory tests, various investigations were performed for the indirect determination of UCS and E , based on non-destructive index experiments. In those studies, mineral properties (composition, porosity and density), ultrasonic tests [P-wave velocity (V_p) and S-wave velocity

(V_s)] and other standard indexes were used to predict UCS and E by regression or other intelligent computing methods [i.e., artificial neural networks (ANNs) or the adaptive neuro-fuzzy inference system (ANFIS)] (Demirdag et al. 2010; Ersoy and Kanik 2012; Armaghani et al. 2016a, b).

Table 1 Various experiments on core of marls and their representative UCS and E

Depth (m)	Index properties		Point load test	Brazilian test	Uniaxial compression test		Ultrasonic test			Triaxial test	
	Density (kN/cm ³)	$I_{s(50)}$	σ_t (MPa)		UCS (MPa)	E_d (GPa)	V_p (m/s)	V_s (m/s)	ν_d	c (MPa)	ϕ (°)
12.3–12.7	2.4	0.4	1.02		1.91	0.84	2204	1155	0.31	1.389	31.021
12.7–13.2	2.45	0.18	1.75		3.98	1.1	2680	1287	0.35	0.623	49.865
13.6–14.2	2.5	0.21	2.65		7.95	0.95	2113	1237	0.24	1.513	28.448
15.1–15.4	2.43	0.05	0.78		6.47	1.2	2412	1414	0.24	1.687	29.784
16.7–17.35	2.36	0.06	0.96		0.27	0.97	2213	1281	0.25	1.235	30.382
17.35–17.75	2.41	0.05	1.23		0.31	1.21	2991	1351	0.37	1.408	34.678
18.7–19.1	2.41	2.12	2.24		3.16	1.02	2669	1244	0.36	0	38.949
19.1–19.5	2.42	0.08	0.82		5.57	1.12	2298	1380	0.22	0.485	49.882
21.75–22.25	2.54	3.57	1.12		5.29	1.35	3036	1395	0.366	0.057	38.807
23–23.27	2.51	4.23	1.6		5.29	1.11	2187	1369	0.18	1.721	24.387
23.27–23.6	2.48	2.75	3.39		10.79	1.52	2621	1592	0.21	0.733	49.874
23.72–24.09	2.47	0.08	0.94		4.81	1.19	2610	1351	0.32	1.15	33.654
25.35–25.75	2.43	1.87	0.48		2.73	0.97	3672	1174	0.44	1.324	37.824
28.3–28.65	2.43	3.81	2.62		4.03	1.15	2741	1322	0.35	0.985	39.689
29.25–29.49	2.5	7.92	2.5		16.29	2.02	3188	1781	0.27	1.213	53.214
29.84–30.11	2.59	8.74	9.95		38.57	3.41	3700	2416	0.13	0.213	54.125
30.5–30.8	2.52	0.51	0.67		1.47	1.05	2848	1226	0.39	1.101	41.518
30.8–31.1	2.48	7.1	4.65		10.79	1.8	3088	1675	0.29	1.146	38.452
32.65–32.9	2.53	8.35	10.4		36.99	3.91	4043	2587	0.15	0.134	60.391
32.85–33.35	2.5	8.76	6.84		20.9	2.45	3607	1947	0.294	1.11	38.257
33.55–33.85	2.51	8.79	8.86		38.34	3.98	4123	2607	0.17	0.068	60.366
35–35.4	2.52	1.98	3.54		15.67	1.83	2950	1708	0.248	1.567	49.061
39.6–40	2.47	0.12	2.4		5.48	1.28	3002	1377	0.367	0.847	42.212
40–40.35	2.58	7.96	3.02		17.4	1.71	2840	1623	0.26	0.43	46.243
40.52–41	2.46	6.9	5.44		24.12	2.8	3567	2175	0.2	0.062	58.078
46.15–46.38	2.55	5.35	1.42		6.42	1.31	2605	1412	0.29	1.014	38.315
46.38–46.88	2.62	1.44	5.64		16.6	2.06	3000	1793	0.22	0.435	53.143
50–50.2	2.54	8.23	7.66		30.56	2.93	3521	2216	0.17	0.035	60.032
51.55–52.15	2.47	0.13	0.79		3.83	1.19	3128	1315	0.39	1.253	30.443
52.15–53.05	2.54	7.2	4.12		12.191	1.79	2825	1705	0.214	0	39.318
55.5–55.77	2.5	0.57	1.96		4.15	1.19	2746	1327	0.35	1.374	29.547
55.9–56.4	0.77	0.62	2.48		11.95	0.52	3030	1619	0.3	0.834	47.525
56.2–56.5	2.26	0.92	1.32		2.35	0.97	2680	1259	0.36	1.163	33.471
56.4–56.8	1.25	5.96	3.84		7.96	0.72	2885	1470	0.32	0.601	49.984
56.8–57.15	0.53	1.74	1.81		14.53	0.4	3124	1716	0.28	0.258	54.023
57.7–57.92	2.46	7.58	6.53		28.09	2.91	3618	2223	0.2	0.638	43.601
66.3–66.65	0.58	0.82	2.06		11.44	0.38	3011	1600	0.3	0.285	52.225
67.3–67.68	2.38	0.76	1.48		7.98	1.36	2886	1470	0.32	1.104	34.241
69.6–70.18	0.45	1.17	3.1		4.64	0.22	2764	1345	0.34	0.993	40.276

Fig. 1 Dependency measurement among input variables by MI for the prediction of UCS and E and E

For generating a robust predictive model, it is essential to build a highly accurate system based on the most relevant parameters (inputs). Development of a model which can explore inter-correlations through various variables, detect and select the most effective ones [variable importance measurement (VIM)], and use them as inputs of a precise predictive model has several advantages: as irrelevant variables make noises in modeling, by VIM redundant variables can be removed (save time and reduce cost of analyses) and outliers (influential points) identified (Chehreh Chelgani et al. 2016a, b; Matin and Chelgani 2016; Matin et al. 2016; Shahbazi et al. 2017).

Mutual information (MI) is an intelligent computer method which can explore both the linear and nonlinear relationship between wide ranges of inputs and rank them based on their influences. In other words, MI provides a decision-making system that can be used to select the most effective inputs (variables which can represent the influence of other ones) and reduce the noises for the development of a model (Chelgani et al. 2018). In a predictive modeling problem, various researches indicated that combination of intelligent predictor models and development of an ensemble of predictors (experts) can construct an accurate model to deal with complicated problems (Masoudnia et al. 2012; Hadavandi et al. 2015, 2016). One of the popular ensemble methods is the neural network ensemble (NNE) (Hansen and Salamon 1990) and an efficient approach for creating an NNE model is Adaptive Boosting (Adaboost) that can adaptively improve the probability of sampling cases for accurate training experts for the NNE model. This approach

can develop a model by using a wide distribution of inputs and reduce the prediction errors by considering the information of previous experts (Hansen and Salamon 1990; Freund and Schapire 1996; Solomatine and Shrestha 2004; Masoudnia et al. 2012; Tian et al. 2012; Zhai et al. 2012). Although the last decade has witnessed increasing applications of MI and Adaboost–NNE models, they have not yet been used in the exploration and prediction of earth science sectors. This work explores the relationships between the mechanical properties of marls (from the cores of Seydoon dam) to predict UCS and E based on various analyses (depth, density, ultrasonic tests, Brazilian test, point load test, etc.). The interpretation of variables was evaluated by using MI and Adaboost–NNE predictive models. The results of this investigation would be useful for the maintenance of the dam and could introduce a unique model for the prediction of other rock and geomechanical indexes.

Materials and methods

Database

Thirty-nine core marl samples were collected from the Sydoon dam area by drilling exploration boreholes to different depths during geotechnical studies. The density of samples was determined by the weighting of cores. All sample analyses were based on ISRM and ASTM procedures. Core marls were highly weathered and weak against water and cutting blade; therefore, a high-speed thin cutting blade was

used for sample preparation. Dynamic Poisson ratio (ν_d), S-wave (V_s) and P-wave (V_p) velocities were measured by 200 and 1000 kHz ultrasonic transducers through core samples. Brazilian test σ_t (MPa) was performed by using a 15 ton jack and a pump to generate forces to a cylindrical specimen between Brazilian frames. Point load test ($I_s(50)$) core sample was subjected to a comprehensive load between two conical platens and, as a result of tension, the broke point was recorded. UCS and triaxial compression test [cohesion of rock material (C (MPa)) and friction angle of rock material (ϕ (°))] of samples were performed by an MTS machine. These tests were done using different confining pressures (1–6 MPa). The results of various experiments and their representative UCS and E are reported in Table 1.

Mutual information

Mutual information (MI) as a powerful VIM tool can quantify the inter-dependency between random variables. In other words, MI is the amount of shared information between model inputs. The MI ($0 \ll I(X;Y) \ll 1$) between two variables (X and Y) is defined based on the joint probability distribution $p(x,y)$ and the product distribution $p(x)p(y)$:

$$I(X;Y) = E_{p(x,y)} \left[\log \frac{p(x,y)}{p(x)p(y)} \right] = \sum_x \sum_y p(x,y) \log \frac{p(x,y)}{p(x)p(y)}, \quad (1)$$

where E_p is the mathematical expectation. MI can reduce the prediction error by the maximization scheme between input variables and targets. In other words, MI can consider the information of more than single input to predict an output. This system detects the most relative variables, ranked them based on VIM and feed them to the predictive model. Variable selection by MI reduces learning algorithm time, increases the size of the search space and prevents overfitting in the predictive model

(Kerroum et al. 2010; Lee and Kim 2013; Han et al. 2015; Hansen and Salamon 1990; Freund and Schapire 1996; Solomatine and Shrestha 2004; Masoudnia et al. 2012; Tian et al. 2012; Zhai et al. 2012).

Adaptive boosting

One approach for modeling complicated relationships is generating an ensemble system by combining the single prediction models (based on components) and exploiting the different local behavior of these base models to improve the performance of the overall prediction model (Masoudnia et al. 2012). The neural network ensemble (NNE) is a popular ensemble model that is developed based on a combination of neural network experts (Masoudnia et al. 2012; Tian et al. 2012; Zhai et al. 2012). The sequential manipulating of instances to train an individual neural network is one of the typical methods for the construction of NNEs that is called boosting method (Freund and Schapire 1996). For the last two decades, boosting as one of the most powerful ensemble methods was generated with a high learning capability. Adaptive boosting (Adaboost) changes the distribution of training set based on the performance of the previous NN components which is added in an ensemble model (Adaboost–NNE) (Tian et al. 2012; Zhai et al. 2012). Adaboost–NNE adaptively increases the probability of instances, which have higher prediction errors, by the previous components. The main idea in an Adaboost–NNE model is filtering out examples with the relative prediction error higher than the pre-set threshold value, and then following the Adaboost procedure (Hansen and Salamon 1990; Solomatine and Shrestha 2004). In this study, for prediction of rock mechanic indexes, an Adaboost–NNE model was developed in T iterations (T is the number of multi-layered perceptron neural network experts in the ensemble model). The training model is presented in algorithm 1:

Algorithm 1. The Adaboost-NNE training algorithm**Inputs :**

S: A set of training instances $\{(X_n, Y_n) | X_n \in X, Y_n \in Y, 1 \leq n \leq N\}$ with original input space $X = (x_1, x_2, \dots, x_D)$

T: Number of experts in Adaboost-NNE model (that are MLP models)

Initialize:

The threshold $\mathcal{G}$ for demarcating correct and incorrect predictions

$t=1$

Distribution $w_t(i) = \frac{1}{N}$ for all i (instances)

Error rate $\varepsilon_t = 0$

While ($t \leq T$)

Sampling with replacement from data with distribution w_t

Training MLP neural network (expert t) using selected dataset and Backpropagation algorithm

Calculate the error rate of MLP_t : $\varepsilon_t = \sum_{n=1}^N w_t(n) \mathbb{I}\left(\left|\frac{y_n - MLP_t(X_n)}{y_n}\right| > \mathcal{G}\right), \mathbb{I}(true) = 1$

Set $b_t = \varepsilon_t^2$

Update $w_{t+1}(n) = w_t(n) \begin{cases} b_t & \text{if } \left|\frac{y_n - MLP_t(X_n)}{y_n}\right| \leq \mathcal{G} \\ 1 & \text{Otherwise} \end{cases}$

Set $t=t+1$

end

Output: The Adaboost-NNE model which predicts the output using the following formula:

$$Adaboost - NNE_{ens}(X_n) = \sum_{t=1}^T g_t MLP_t(X_n) \text{ Where } g_t = \frac{\log(1/b_t)}{\sum_{t=1}^T \log(1/b_t)}$$

Results and discussions

Variable selection

For making a robust system, before generating Adaboost–NNE model for the estimation of UCS and E , VIMs by MI (MI-VIM) is applied through all measured variables (ν_d , V_p , V_s , $I_s(50)$, σ_t , depth, density, C and ϕ) to evaluate their importance for the prediction, and as a result select the most effective inputs. MI-VIM results (Fig. 1) indicated that there are complicated interactions among variables, although σ_t and V_s showed a direct correlation with the outputs. On the other hand, MI ranked variables based on their importance and results illustrated that V_s and σ_t have the highest effectiveness for the prediction of UCS and E , respectively (Fig. 2). These outcomes demonstrated that V_s and σ_t can represent the correlation of other variables for the generation of predictive models and can be selected as input variables. There is a good agreement with these VIMs and

theoretical studies where Castagna et al. (1985) and Pickett (1963) indicated that increasing the percentage of porosity would decrease the strength of rock. Therefore, the velocity of sonic waves (P or S) would be lower during passing through voids; therefore, results of ultrasonic tests potentially could be a good indicator of the mechanical properties of rocks. Moreover, several investigations demonstrated that sonic waves (V_p or V_s) can be strong predictors of UCS and E (Yasar and Erdogan, 2004a, b). On the other hand, the dependency evaluation of these indexes with Brazilian tensile strength (σ_t) (as an independent variable) showed that σ_t can be an appropriate predictor for UCS and E modeling (Jamshidi et al. 2016a, b; Fereidooni 2016).

The complex interactions of selected variables with the outputs are illustrated in Fig. 3. Linear correlations (Pearson correlation) between the MI selected variables and outputs (Table 2) indicate that there are significant positive correlations between them. To develop comprehensive Adaboost–NNE models (with 6 MLP experts) for the prediction

Fig. 2 Variable importance measurements by MI and ranking inputs for the prediction of UCS and E

of UCS and E based on MI-VIM selected variables, approximately 75% of records from the dataset were randomly applied for the training stage and the remaining 25% of the samples for the testing stage of the models. After training, the model was tested and the results of the testing phase showed that the Adaboost–NNE models could accurately predict the outputs, with the correlation of determination values (R^2) of 0.92 and 0.98 for the E and UCS, respectively.

The differences (Fig. 4) between laboratory measured variables (actual values) and Adaboost–NNE predicated ones showed that models could provide high satisfaction in the prediction of E and UCS. These results indicated the potential of MI coupled with Adaboost–NNE in the prediction of geomechanical indexes, and that these systems can be used for the assessment of other complicated variables in rock mechanics and other related disciplines.

Fig. 3 Topographic relationship between selected variables by MI with UCS and E

Table 2 Pearson correlation between VIM selected variables and UCS- E

Variables	σ_t	V_s
UCS	0.93	0.98
E	0.87	0.90

Conclusion

Uniaxial compressive strength (UCS) and Young's modulus (E) indexes can play critical roles for the control and maintenance of high seismic intensity regions such as dam areas. This study has introduced a new method [mutual information (MI)] for feature selections through rock properties based on variable importance measurements (VIMs) to predict UCS and E of marls from the Sydoon dam (Iran) by a powerful ensemble method called Adaboost–NNE (adaptive boosting–neural network ensemble). MI-VIM can assess the impact of each rock index individually and also in multivariate interactions with other variables. Based on MI-VIM results, the most effective features could be detected and selected to generate an unbiased and broadly applicable Adaboost–NNE model. Various rock mechanic analyses were performed [depth, density, ultrasonic tests (V_p and V_s), Brazilian test (σ_t), and point load test], MI-VIM through provided variables indicated that V_s and σ_t have the highest importance for the prediction of both UCS and E among other measured parameters. These two variables were selected to generate predictive Adaboost–NNE models. Testing results of the developed models indicated that Adaboost–NNE could predict UCS and E quite accurately with the correlation of determination values of 0.98 and 0.92, respectively. These results demonstrated that variable selection by MI and prediction by Adaboost–NNE make a robust system which can be used for expanding the knowledge surrounding modeling of rock and geomechanical indexes, and powerful tools for control and maintenance of other embankments.

Fig. 4 Relationship between predicted and actual value of UCS and E , and their differences

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References

- Abrams DA (1917) Effect of rate of application of loading on the compressive strength of concrete. *J ASTM* 17:364–377
- Armaghani DJ, Mohamad ET, Hajihassani M, Yagiz S, Motaghedi H (2016a) Application of several non-linear prediction tools for estimating uniaxial compressive strength of granitic rocks and comparison of their performances. *Eng Comput* 32:189–206
- Armaghani DJ, Mohamad ET, Momeni E, Monjezi M, Narayanasamy MS (2016b) Prediction of the strength and elasticity modulus of granite through an expert artificial neural network. *Arab J Geosci* 9(48):1–16
- Bellair M, Pomerol L (1980) *Tratado de Geología*. Limusa, Mexico
- Castagna JP, Batzle ML, Eastwood RL (1985) Relationships between compressional-wave and shear-wave velocities in clastic silicate rocks. *Geophysics* 50(4):571–581
- Chelgani SC, Matin SS, Hower JC (2016a) Explaining relationships between coke quality index and coal properties by random forest method. *Fuel* 182:754–760
- Chelgani SC, Matin SS, Makaremi S (2016b) Modeling of free swelling index based on variable importance measurements of parent coal properties by random forest method. *Measurement* 94:416–422
- Chelgani SC, Shahbazi B, Hadavandi E (2018) Support vector regression modeling of coal flotation based on variable importance measurements by mutual information method. *Measurement* 114:102–108
- Dehghan S, Sattari Gh, Chehreh Chelgani S (2010) Prediction of uniaxial compressive strength and modulus of elasticity for Traver-tine samples using regression and artificial neural networks. *J Min Sci Technol* 20:41–46
- Demirdag S, Tufekci K, Kayacan R, Yavuz H, Altindag R (2010) Dynamic mechanical behavior of some carbonate rocks. *Int J Rock Mech Min Sci* 47:307–312
- El Amrani Paaza N, Lamas F, Irigaray C, Chaco'n J (1998) Engineering geological characterisation of neogene marls in the southeastern Granada Basin, Spain. *Eng Geol* 50:165–175
- Ersay H, Kanik D (2012) Multicriteria decision-making analysis based methodology for predicting carbonate rocks' uniaxial compressive strength. *Earth Sci Res J* 16(1):65–74
- Fereidooni D (2016) Determination of the geotechnical characteristics of hornfelsic rocks with a particular emphasis on the correlation between physical and mechanical properties. *Rock Mech Rock Eng* 49(7):2595–2608
- Freund Y, Schapire RE (1996) Experiments with a new boosting algorithm. In: *Thirteenth International Conference on Machine Learning—ICML*, pp 148–156

- Hadavandi E, Shahrabi J, Shamsirband S (2015) A novel boosted-neural network ensemble for modeling multi-target regression problems. *Eng Appl Artif Intell* 45:204–219
- Hadavandi E, Shahrabi J, Hayashi Y (2016) SPMoE: a novel subspace-projected mixture of experts model for multi-target regression problems. *Soft Comput* 20(5):2047–2065
- Han M, Ren W, Liu X (2015) Joint mutual information-based input variable selection for multivariate time series modeling. *Eng Appl Artif Intell* 37:250–257
- Hansen LK, Salamon P (1990) Neural network ensembles. *IEEE Trans Pattern Anal Mach Intell* 12:993–1001
- Jamshidi A, Nikudel MR, Khamsehchiyan M, Sahamieh RZ (2016a) The effect of specimen diameter size on uniaxial compressive strength, P-wave velocity and the correlation between them. *Geomech Geoeng* 11(1):13–19
- Jamshidi A, Reza Nikudel M, Khamsehchiyan M (2016b) A novel physico-mechanical parameter for estimating the mechanical strength of travertines after a freeze–thaw test. *Bull Eng Geol Environ* 76:1–10
- Kerroum MA, Hammouch A, Aboutajdine D (2010) Textural feature selection by joint mutual information based on Gaussian mixture model for multispectral image classification. *Pattern Recognit Lett* 31:1168–1174
- Lee J, Kim DW (2013) Feature selection for multi-label classification using multivariate mutual information. *Pattern Recognit Lett* 34(3):349–357
- Malvar LJ, Ross CA (1998) Review of strain rate effects for concrete in tension. *ACI Mater J* 95(6):735–739
- Masoudnia S, Ebrahimpour R, Arani SAAA (2012) Combining features of negative correlation learning with mixture of experts in proposed ensemble methods. *Appl Soft Comput* 12:3539–3551
- Matin SS, Chelgani SC (2016) Estimation of coal gross calorific value based on various analyses by random forest. *Fuel* 177:274–278
- Matin SS, Hower JC, Chelgani SC (2016) Explaining relationships among various coal analyses with coal grindability index by random forest. *Int J Miner Process* 155:140–146
- Matin SS, Farahzadi L, Makaremi S, Chelgani SC, Sattari Gh (2017) Variable selection and prediction of uniaxial compressive strength and modulus of elasticity by Random Forest. *Appl Soft Comput* 70:980–987 (**in press**)
- Pickett GR (1963) Acoustic character logs and their applications in formation evaluation. *J Petrol Technol* 15(6):659–667
- Shahbazi B, Chelgani SC, Matin SS (2017) Prediction of froth flotation responses based on various conditioning parameters by random forest method. *Coll Surf A Physicochem Eng Asp* 529:936–941
- Solomatine DP, Shrestha DL (2004) AdaBoost. RT: a boosting algorithm for regression problems. In: *Neural networks, 2004. Proceedings. 2004 IEEE International Joint Conference*, pp 1163–1168
- Sousa LMO (2014) Petrophysical properties and durability of granites employed as building stone: a comprehensive evaluation. *Bull Eng Geol Environ* 73:569–588
- Tian J, Li M, Chen F, Kou J (2012) Coevolutionary learning of neural network ensemble for complex classification tasks. *Pattern Recogn* 45:1373–1385
- Watstein D (1953) Effect of straining rate on the compressive strength and elastic properties of concrete. *ACI Mater J* 49:729–744
- Yan DM, Lin G (2006) Dynamic properties of plain concrete in direct tension. *Cem Concr Res* 36:1371–1378
- Yasar E, Erdogan Y (2004a) Correlating sound velocity with the density, compressive strength and Young's modulus of carbonate rocks. *Int J Rock Mech Min Sci* 41:871–875
- Yasar E, Erdogan Y (2004b) Estimation of rock physicommechanical properties using hardness methods. *Eng Geol* 71:281–288
- Zhai J, Xu H, Wang X (2012) Dynamic ensemble extreme learning machine based on sample entropy. *Soft Comput* 16:1493–1502

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