



Research article

Prediction of crack coalescence stress in rock-like specimens with non-persistent joints under direct shear test based upon machine learning algorithms

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Keywords

**Non-persistent joint
Rock bridge
Crack coalescence stress
Grey wolf optimizer (GWO)
Gene expression programming (GEP)**

English Extended Abstract

Summary

Concretes frequently contain joints and microcrack fractures, and the failure mechanism of these fractures is highly dependent on the pattern of crack coalescence between pre-existing flaws. Determining the non-persistent joints' failure behavior is an engineering challenge that incorporates several factors, including the ratio of the joint surface to the total shear surface, normal stress, and the mechanical characteristics of the concrete. This paper aims to utilize grey wolf optimizer (GWO) and gene expression programming (GEP) algorithms for the prediction of the crack coalescence stress (CCS). For this purpose, 8 input parameters affecting the CCS including jointing coefficient (JC), normal stress (σ_n), uniaxial compressive strength (σ_c), tensile strength (σ_t), Poisson's ratio (ν), modulus of elasticity (E), cohesion strength (C) and internal friction angle (φ) were selected based on the results of 450 direct shear tests conducted on specimens including 2 sets of non-persistent joints made of gypsum, cement, and water. The GWO and GEP techniques were then implemented. Three performance indicators of determination coefficient (R²), root mean square error (RMSE), and mean absolute error (MAE), were employed for the training and testing phases to evaluate the efficiency of the suggested models. The R² values for GWO and GEP for the training phase were 0.962 and 0.938, respectively, while for the testing phase were 0.996 and 0.981, indicating that the GWO algorithm is more efficient than GEP. Moreover, the findings reveal that the GWO algorithm exhibits lower RMSE and MAE values in both the training and testing phases compared to the GEP method. However, it can be professed that the two methods used have high reliability and accuracy. Also, based on the GEP method, a formula was derived and presented for prediction of CCS. At last, according to the sensitivity analysis, it was found that the normal stress (σ_n) and jointing coefficient (Cu) have the greatest and least influence on CCS, respectively.

Introduction

It is known that the low strength of the concrete mass is usually due to the presence of joints. In certain exceptional cases, there is a possibility that the concrete failure is confined to a single discontinuity. Generally, multiple discontinuities of varying sizes may be present in a rock/ concrete mass. The areas situated between the adjacent discontinuities are referred to as the bridge area [1-3]. As a result of applying loads (compressive and shearing) to materials with discontinuities, cracks are created at the tips of these discontinuities in the bridge area and propagate over time, and finally connect. In general, there are two types of crack patterns in

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the rock bridge area, including wing cracks and secondary cracks. Tensile wing cracks first initiate at the tip of the joint and propagate continuously in a curved path in the direction of the applied axial load, while secondary cracks appear later and are generally described as shear cracks or shear zones [1]. Understanding the initiation, propagation, and coalescence of cracks is an important aspect in fracture mechanics. Crack propagation and coalescence processes may form a shear surface in rock/ concrete mass and therefore cause failure in structures such as dams, foundations, slopes, and tunnels [1].

The determination of the failure behavior of non-persistent joints, which is the result of cracks' coalescence, is affected by several parameters including mechanical properties of materials, normal stresses, and the ratio of joint surface to total shear surface.

So far, many experimental studies have been carried out to investigate the impact of the above-mentioned parameters on the initiation, propagation, and coalescence of cracks under uniaxial and biaxial compression test conditions [2-10]. However, a more limited number of laboratory studies in this field have been conducted on rock-like specimens with coplanar and non-coplanar joints under direct shear test [11-16]. On the other hand, most of the previous studies focused on the effect of configuration, length considering, orientation of the bridge, the orientation of joint-segment, and spacing between the joint rows on the mechanisms of crack initiation, propagation, and coalescence in the bridge area, while the simultaneous effects of Normal stresses, the mechanical properties of the model materials, and the ratio of joint length to bridge length on CCS have not been investigated. Also, the use of experimental results to consider the simultaneous effects of the aforementioned parameters is difficult for the prediction of CCS. so, in this paper, using two artificial intelligent methods of grey wolf optimizer (GWO) and gene expression programming (GEP), CCS in rock-like specimens with two non-persistent joints is predicted. The obtained results indicated that GWO and GEP algorithms are very useful tools that can predict CCS with high accuracy and reliability.

Methodology and Approaches

In this study, based on GWO and GEP algorithms, CCS in rock-like specimens including 2 non-persistent joints was predicted. For this purpose, 450 datasets related to the results of direct shear tests on gypsum/ cement specimens were taken into account. The datasets composed of 8 effective input parameters on CCS including jointing coefficient (JC), normal stress (σ_n), uniaxial compressive strength (σ_c), tensile strength (σ_t), Poisson's ratio (ν), modulus of elasticity (E), adhesion strength (C) and internal friction angle (φ). The 450 datasets are randomly divided into training (360 series) and testing (90 series) datasets. Based on the training datasets, optimum GWO and GEP models are developed to predict CCS. Finally, the developed models are evaluated and verified using the testing datasets.

Results and Conclusions

To achieve the optimal version of GWO and GEP models for predicting CCS, their performances are evaluated throughout the training and testing phases by utilizing three performance indicators: determination coefficient (R²), root mean square error (RMSE), and mean absolute error (MAE). Through the use of the trial and error methodology, the optimal GWO and GEP models are achieved. The values of the aforesaid indicators for the training and test phase data are shown in Table 1. Also, Figure 1 displays the acquired relationship between the measured and predicted values of CCS from both the GWO and GEP models within the training and testing stages. As illustrated in Fig. 1, the GWO and GEP models exhibit R² values of 0.962 and 0.938, respectively, when predicting CCS during the training phase. In the testing phase, these models yield R² values of 0.996 and 0.981, respectively. Moreover, the findings reveal that the GWO algorithm exhibits lower RMSE and MAE values in both the training and testing phases compared to the GEP method. This suggests that the GWO algorithm exhibits lower error and higher reliability and accuracy when compared to the GEP model. From the obtained results, it can be inferred that the GWO algorithm demonstrates greater reliability and heightened accuracy when compared to the GEP model in its ability to predict CCS. However, the GEP method also has relatively high accuracy, and based on this method, relationship (1) was presented for the prediction of CCS. Furthermore, the GWO and GEP results reveal a strong correlation with the measured data and align closely with the actual values. Consequently, it can be deduced that the GWO and GEP algorithms serve as suitable tools for the prediction of CCS.



Based on the important study method, the impact of values of 8 input variables on CCS derived from the GWO and GEP algorithms are computed and presented in Fig. 2. It is evident that normal stress (σ_n) holds the highest importance in determining CCS. Conversely, the jointing coefficient (JC) is of the least importance in modeling CCS.

Table 1. Values of statistical indicators in training and testing phases of GWO and GEP models

| index | Train phase | | Test phase | |
|-------|-------------|-------|------------|-------|
| | GWO | GEP | GWO | GEP |
| R2 | 0.962 | 0.938 | 0.996 | 0.981 |
| RMSE | 3.47 | 4.53 | 1.35 | 3.35 |
| MAE | 2.63 | 3.41 | 1.08 | 2.79 |

$$CCS = (\sigma_t + 7.554)\varphi - \frac{(v + 0.71)}{(v - 3.55)} + \sigma_n[1 + 115.9v(\sigma_c - 8.88)/\sigma_c] + (\sigma_t - 4.344) - JC(\sigma_t + \varphi + 3.583) + \left(\frac{\sigma_t - \sigma_c}{E + C - v - 4.185}\right) \quad (1)$$

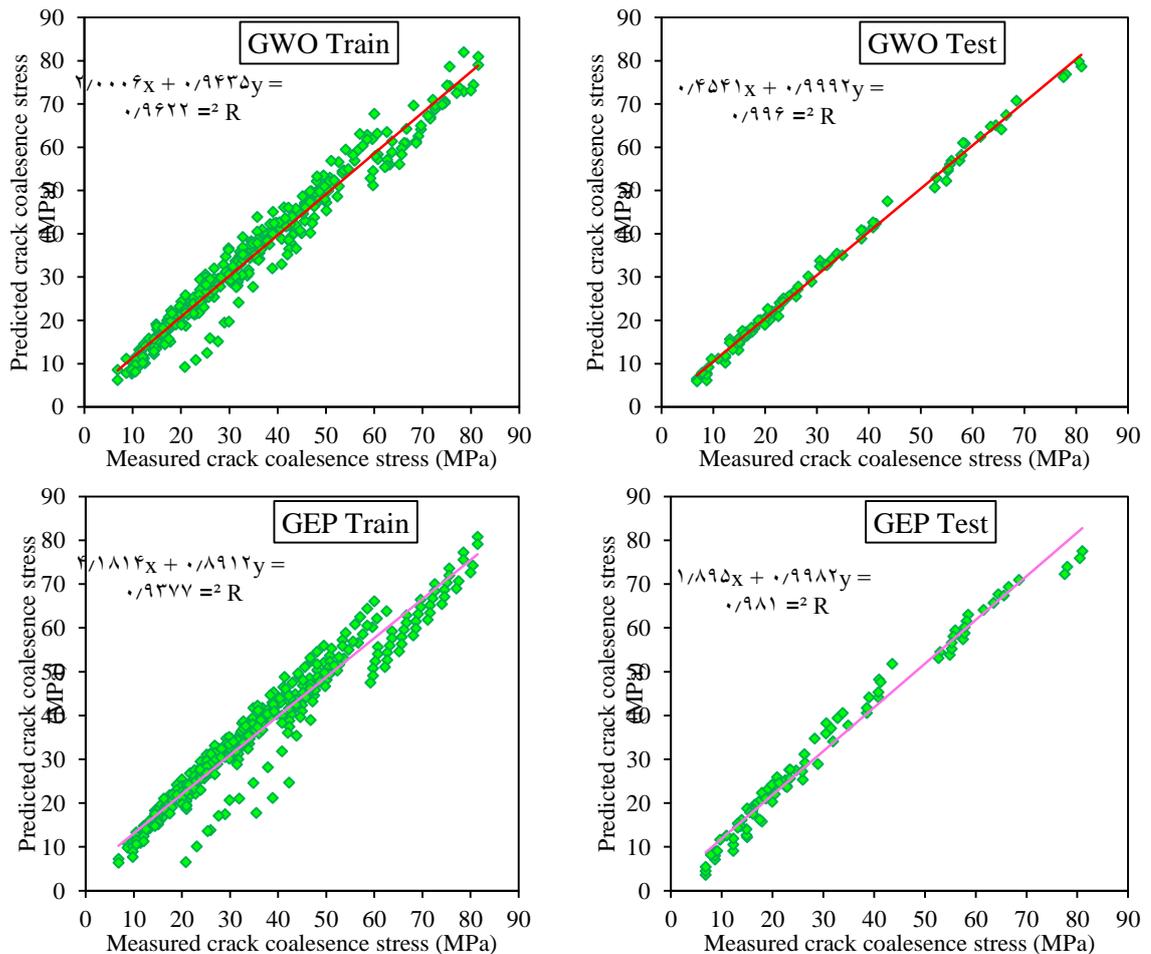


Fig. 1. Relationship of measured and predicted values of CCS in training and testing phases of GWO and GEP models

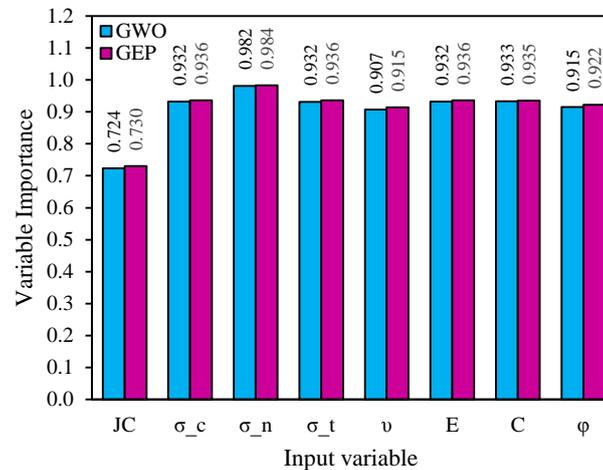


Fig. 2 .The results of the importance study for CCS modeling

Conclusion

In this study, prediction of CCS was carried out using GWO and GEP techniques and the obtained results from these models were compared with each other as well as with the measured values. For this purpose, 450 datasets related to the results of direct shear tests on rock-like specimens including 8 input parameters were considered to develop, evaluate, and verify the GWO and GEP models. The results indicated that R2 value obtained from the GWO algorithm in the training and testing phases are higher than the corresponding values from the GEP model, while the RMSE, and MAE values obtained from the GWO algorithm in the training and testing phases are lower than the corresponding values from the GEP model. This comparison showed the higher efficiency and superiority of GWO technique compared to the GEP model. However, the GEP method also has relatively good accuracy for the prediction of CCS. Eventually, variable importance analysis discovered that the most and least important variables in CCS modeling in both the GWO and GEP algorithms are σ_n and JC, respectively.

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