Research Article

Assessment of risks of tunneling project in Iran using artificial bee colony algorithm

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Abstract
The soft computing techniques have been widely applied to model and analyze the complex and uncertain problems. This paper aims to develop a novel model for the risk assessment of tunneling projects using artificial bee colony algorithm. To this end, the risk of the second part of the Emamzade Hashem tunnel was assessed and analyzed in seven sections after testing geotechnical characteristics. Five geotechnical and hydrological properties of study zone are considered for the clustering of geological units in front of tunneling project including length of tunnel, uniaxial compressive strength, rock mass rating, tunneling index Q, density and underground water condition. These sections were classified in two low-risk and high-risk groups based on their geotechnical characteristics and using clustering technique. It was resulted that three sections with lithologies Durood Formation, Mobarak Formation, and Ruteh Formation are placed in the high risk group and the other sections with lithologies Baroot Formation, Elika Formation, Dacite tuff of Eocene, and Shear Tuff, and Lava Eocene are placed in the low risk group. In addition, the underground water condition and density with 0.722 and 1 Euclidean distances have the highest and lowest impacts in the high risk group, respectively. Therefore, comparing the obtained results of modelling and actual excavation data demonstrated that this technique can be applied as a powerful tool for modeling risks of tunnel and underground constructions.

Keywords Soft computing · Artificial bee colony · Clustering technique · Tunneling · Risk assessment

1 Introduction

With the expansion and complexity of engineering problems in recent years, the use of optimization methods has faced significant successes. Optimization problems in the real engineering world are becoming increasingly complicated. Therefore, many researchers are using soft computing as a powerful alternative tool in solving these problems [1–6]. The risk assessment of civil and industrial projects is one of the most attractive and practical engineering problems and is inherently uncertain and complex [7–14]. Some researches were conducted on the tunneling projects' risk using different methods such as Fault Tree, Even Tree and Monte Carlo Simulation [15–19]. Nezarat et al. [20] investigated and ranked geological risks in mechanized tunneling by using fuzzy analytical hierarchy process (FAHP). Golab tunnel was considered as a case study in the research work. They found out that squeezing and face tunnel instability had highest level and gas emissions and clogging of clay had the lowest level of risks in this tunnel [20]. The risk assessment of tunneling projects has always faced uncertainty in data analysis due to the geological complexities and nonlinear nature of the projects. Various methods are used for the risk assessment of tunneling projects. In a research, the risk of underground projects in the construction phase (oil depot) was assessed

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by Wang et al. [21] using the fuzzy comprehensive evaluation method. They used geological properties as the risk assessment criteria in order to study the risk. Finally, a proper match was obtained between the risk analysis using the fuzzy logic and the visual results obtained from this underground depot, indicating the suitability of soft methods in the risk assessment of underground projects [21].

Li et al. [22] assessed the geological hazards in the engineering of underground projects using a new quantitative method called Attribute Interval Evaluation Theory. They proposed prioritization for geological hazards using this method. The method proposed in this research is not only capable of risk assessment and prioritization, but it can also assess the validity of results. In this method, the acceptable correlation coefficient is 80%. Finally, after implementing assessments, this method was introduced as a proper numerical method for the risk assessment [22]. The risk assessment of geological hazards in the excavation route of the Ardabil–Miane railway tunnel, kilometer 378 + 021 was conducted by Mikaeil et al. [23] using the harmony search algorithm. Their results showed that harmony search algorithm can assess and predict geological risks in tunneling projects [23]. Haghshenas et al. [24] conducted the geological risk assessment of the Ghomrud tunnel. They determined three effective parameters in the design and excavation of tunnels, namely, overburden (H), internal friction angle (φ), and cohesion (C), and used them in the clustering of geological units in the tunnel route. Their results were validated with the drilling rate index (DRI), which indicated the high ability of the fuzzy c-means (FCM) algorithm in the clustering of geological units in tunneling projects and the appropriate provision of the condition of the region for evaluating the risk management in the project [24]. Esmailzadeh et al. [25] carried out technical analysis of collapse in tunnel excavation. Based on their results, they made some recommendations in order to stabilize of tunnel crown [25]. Haghshenas et al. evaluated tunneling projects risks using the fuzzy analytical hierarchy process. In this research, 11 risks and 3 criteria were selected for investigation and ranking of Toyserkan Doolayi tunnel's risks. The results showed that the risk of swelling of rock had the highest rank [26]. Sun et al. [27] investigated tunnel collapse risk using multistate fuzzy Bayesian networks. The results showed that this method was very suitable for evaluating of the collapse probability of the Yu Liao Tunnel [27]. Xiong et al. [28] proposed a method for 3D multi-scale geology modeling for tunnel engineering risk assessment. Based on their results, they made some recommendations for a case study, railway tunnel engineering of the Yuelongmen tunnel in China [28]. A risk assessment model is proposed by Xia et al. [29]. They used fuzzy logic and similarity measure theory. The results clearly showed the capability of the proposed model for evaluating of risk this case study [29]. Li and Yang [30] used improved attribute mathematical theory to propose risk assessment model of tunnel water inrush. Finally, based on their results, the proposed model was reliable [30]. Mikaeil et al. [31] evaluated the risks of tunneling project using two soft computing techniques. Based on their results, they made some recommendations for risk assessment based upon applications of intelligent approaches [31]. A non-parametric bayesian network have been developed to evaluate tunneling risk analysis by Wang et al. [32]. Their results indicated that the new developed model is a reliable model for evaluating of tunneling risk analysis [32]. In another study, risks of Beijing subway tunnel construction investigated by Xu et al. [33]. They used the new Austrian tunneling method to investigate and, they found out that this approach can be applied as a powerful tool for evaluating of Beijing subway tunnel excavation [33]. Bakhtavar and Yousefi [34] analyzed ground vibration risks on the infrastructures located inside a mining area using a developed hybrid approach based on fuzzy failure mode and effects analysis (FMEA) and a fuzzy slack-based measure model [34].

The identification and assessment of geological hazards are two of the most important parts of risk management because they involve the clustering of geological units [35]. This paper aims to develop a new model for the risk assessment of the second part of the Emamzade Hashem tunnel project. It is worth mentioning that ABC algorithm has not been used in previous studies for investigating of risk assessment. There are always complex and unpredicted conditions in evaluating of tunneling projects' risk, hence in order to investigate these conditions, ABC algorithm as a stochastic algorithm can be more useful in comparison with classic modelling. Different parameters and criteria affect the geological structures in this project, including the geotechnical and hydrological properties of the tunnel implementation scope, such as uniaxial compressive strength (UCS), rock mass rating (RMR), tunneling index Q, and density and underground water condition. Therefore, these criteria and parameters are determined for data analysis and geological units' clustering through laboratory methods or using previous studies for collecting influential parameters in the behavior of the geological structures in the seven sections of the tunnel route. Then, the results obtained from these sections are analyzed and classified using the artificial bee colony (ABC) algorithm as one of the meta-heuristic algorithms. Finally, after validation, the results are classified into two groups of high-risk and low-risk sections.

2 Case study

The mechanized tunneling projects are one of the most important constructional infrastructures in which the ranking and assessment of risk are used as one of most important and influential parameters in designing and implementation of such projects [36, 37]. Hence, one of the most strategic tunneling projects in north of Iran is considered for risk assessment. The second part of the Emamzade Hashem tunnel is one of the most important and strategic tunneling projects in Iran. The total length of the tunnel is approximately 5.6 (km), which includes the second part (approximately 3200 m). This tunnel is located in the northeast of Tehran and at the boundary of Mazandaran in an entirely rocky environment and is a part of the mountainous region of the Alborz mountain range. The maximum and minimum overburden thicknesses of the tunnel crest are 450 m and 50 m, respectively. The lithologies of the region under study and the project implementation include the Durood Formation (H-3), the Mobarak Formation (H-16), the Ruteh Formation (H-16), the Shear Tuff and Lava Eocene (H-4), the Dacite tuff of Eocene (H-1), the Elika Formation (H-11), and the Baroot Formation (H-15). Figure 1 shows the tunnel implementation route from the beginning of excavation to the end of the route in different formations [35, 38].

Table 1 shows that the geotechnical properties are the criteria for the data analysis and clustering of the geological units of the sections under study [35, 38].

3 Methodology

In order to assess uncertain problems, soft computing techniques can be applied with a satisfactory performance for modeling some problems involved in engineering [39–46]. The ABC algorithm is one of the most widely used evolutionary methods in the area of soft computing. In fact, the algorithm's performance is inspired by the honey bee colony [47, 48]. This algorithm was first introduced by Karaboga who used it for the optimization of different problems in the industry, transportation systems, and traffic.

The honey bee colony is generally composed of three sections, namely, food sources, worker bees, and non-worker bees. Non-worker bees are further divided into two sections: onlooker and scout bees. Honey bees use a complex communication system. The relationship among bees is established through a dance language. The dance language includes a set of continuous

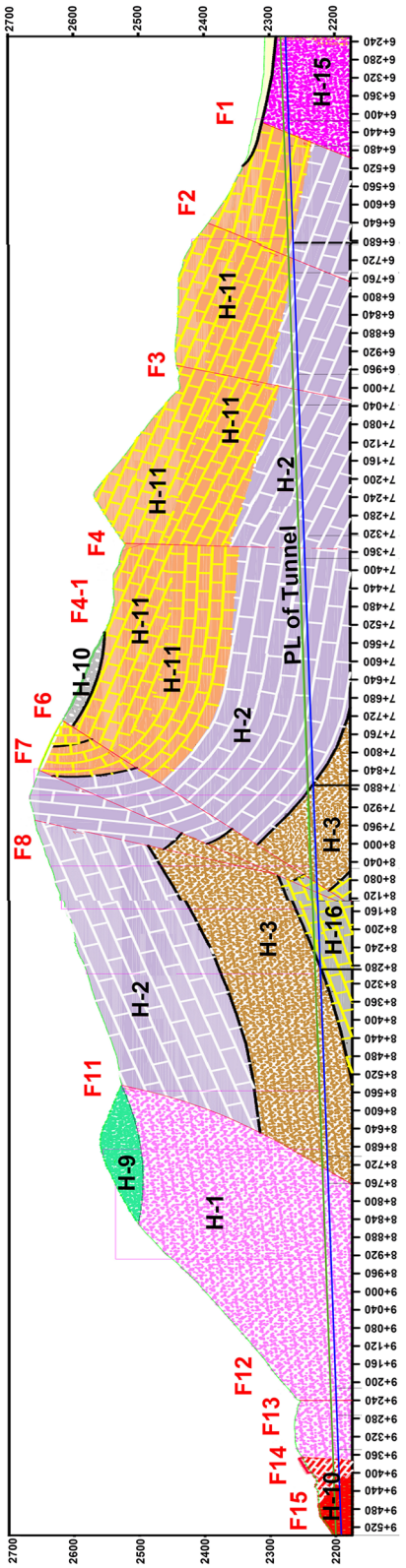

Fig. 1 The route of Tunnel in different formations [35]

Table 1 The results obtained from field and laboratory studies on the second part of Emamzade Hashem Tunnel

Section name	Lithology	Length (m)	UCS (Mpa)	RMR	Average groundwater table (m)	Q	Density (g/cm^3)
H-4	Shear Tuff and Lava Eocene	130	35	19	35	0.02	2.6
H-1	Dacite Tuff of Eocene	600	55	43	125	0.49	2.6
H-3	Durood Formation	520	120	63	265	9	2.6
H-16	Mobarak Formation	140	75	55	270	1.95	2.6
H-2	Ruteh Formation	1020	110	59	195	8	2.6
H-11	Elika Formation	180	40	44	70	2.52	2.6
H-15	Baroot Formation	130	30	50	25	2	2.6

motions performed by bees. This dance, called waggle dance, contains information on the quality of source, location, and position of bees. First, a set of food sources is randomly selected. Worker bees move toward the sources and compute the amount of honey. Then, these bees return to the hive and share their information with onlooker bees. In the second step, after the exchange of information, each worker bee moves toward the source and may select a new source near the previous one based on the information in its mind. Scout bees search the surrounding environment for new food sources. When the food source runs dry or bees leave and move toward a new source, the fitness of the new source (solution) is first investigated based on the previous sources (solutions). If the fitness of the new source is better than those of the previous sources, the new source (solution) is maintained in the memory of the bee; otherwise, the fitness of the new food source is added as another criterion for assessing the least and best sources. This process continues until all the requirements are satisfied by finding the most optimal solution. Equation (1) represents the process of finding a new location for each bee [49].

$$\begin{aligned} &v_{ij} = x_{ij} + \phi_{ij}(x_{ij} - x_{kj}) \\ &k \in \{1, 2, \ldots, BN\}, \quad i \neq k,\ j \in \{1, 2, \ldots, D\} \end{aligned} \tag{1}$$

where υ_{ij} is the position of the initial bee, and x_{ij} and x_{kj} are the positions of the initial and the other bees (neighbor bees), respectively. The lower the value of $x_{ij} - x_{kj}$ is, the lesser the deviation from x_{ij} will be. Values k and j are randomly selected, and BN is the number of worker bees, which is equal to food source number (SN). In addition, variable k is different from variable i. ϕ_{ij} is a random number between interval [− 1, 1], and this variable controls the production of food sources around x_{ij}. Equation (1) attempts to move the initial position toward or against the value of index ϕ_{ij} in the next movements [47, 48]. After the search operations, the observers assess and study the data obtained from the worker bees, and considering the data obtained about the food sources with possibilities, a food resource is selected based on Eq. (2) [50].

$$p_i = \frac{fit_i}{\sum_{n=1}^{SN} fit_n} \tag{2}$$

where P_i indicates the proper probability for the food source. SN is the number food sources (the number of existing solutions). fit_i is the fitness function of food sources, which corresponds to the ith bee. If a food source runs dry and or lacks proper quality, worker bees leave and turn into scout bees [51]. This means that if in the fitness model a point is not improved after several iterations, the local optimal point should be abandoned and a new

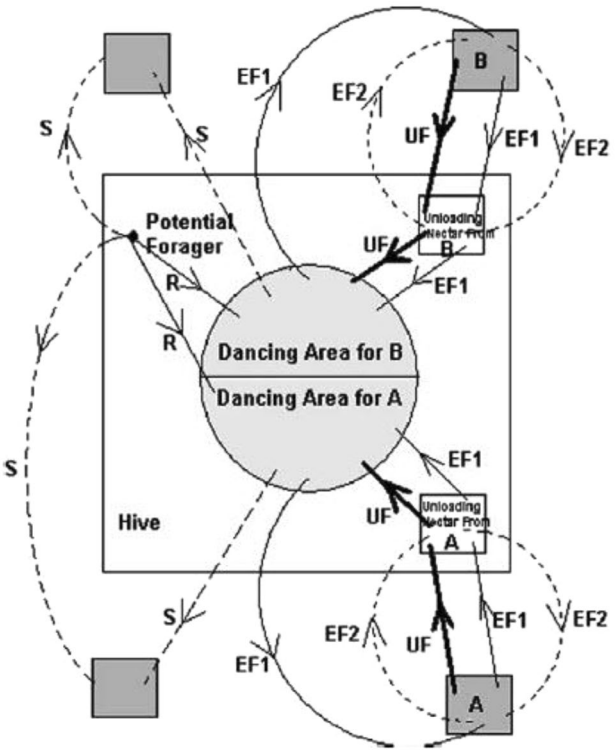

Fig. 2 Behaviour of honeybee foraging for nectar [52]

Table 2 The control parameters for artificial bee colony algorithm

The control parameters	Maximum number of iterations	Minimum acceptable error	Colony size	Number of onlooker bees
Value	250	0.00001	100	100

random point selected. Behaviour of honeybee foraging for nectar is indicated in Fig. 2.

It is worth mentioning that artificial bee colony can be a powerful tool for identifying and assessing variety of the real world problems under uncertain conditions, and unlike some evolutionary algorithms, the advantage of this algorithm is that less control parameters are required. In this study, given that risk in tunneling projects is uncertain and unpredictable, the ABC algorithm, which is one of the most widely used soft computing methods in the rock mechanics, geotechniques, and mining fields, is used for solving complex problems of risk for its high ability and random techniques [53].

4 Modeling and discussion

To study and evaluate the field and laboratory results obtained in this study, one of the most important applications of the ABC algorithm optimization in data clustering is used. In the first step of modeling, after preparing the pseudo-code of the algorithm in MATLAB software, the control parameters of the algorithm are adjusted based on the previous studies and the opinions of skilled experts in Table 2 [54–56]. Then, the data in Table 1 are normalized based on Table 3 to be introduced into the algorithm.

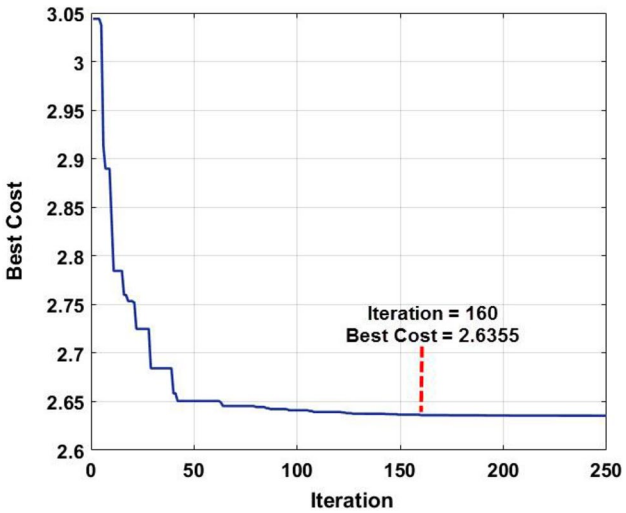

Fig. 3 The process of determining the best cost

After the implementation of the algorithm and the optimization process, the output data are analyzed. Table 4 shows the results of data analysis of the minimum error. In addition, Figs. 3 and 4 illustrates the process of determining the best cost value in each replication and the distance of each criterion from the class under study, respectively.

Based upon Fig. 4, each criterion that has the lowest distance from each class, it has the most effect on that class. For instance in comparison between two classes for C_1 (UCS), it has more influence on the sections H-4, H-1, H-11, and H-15 that are placed in the first class, in comparison with the sections H-2, H-3, and H-16 that are placed in

Table 3 The normalized value of geotechnical and hydrological properties

Section name	Lithology	UCS (C_1)	RMR (C_2)	Average groundwater table (C_3)	Q (C_4)	Density (C_5)
H-4	Shear Tuff and Lava Eocene	0.292	0.301	0.141	0.002	1
H-1	Dacite tuff of Eocene	0.458	0.682	0.463	0.058	1
H-3	Durood Formation	1	1	0.981	1	1
H-16	Mobarak Formation	0.625	0.873	1	0.217	1
H-2	Ruteh Formation	0.917	0.937	0.722	0.889	1
H-11	Elika Formation	0.333	0.698	0.259	0.28	1
H-15	Baroot Formation	0.25	0.283	0.093	0.222	1

Table 4 The process of determining the minimum acceptable error

	Step (n)	$\tilde{U}^{(n-1)}$	$\tilde{U}^{(n)}$	$\varepsilon_L = \tilde{U}^{(n)} - \tilde{U}^{(n-1)}$	Result
Minimum acceptable error	159	2.6366	2.6355	0.0001 > 0.00001	Continue
	160	2.6355	2.6355	0 < 0.00001	Continue
	250	2.6355	2.6355	0 < 0.00001	Stop

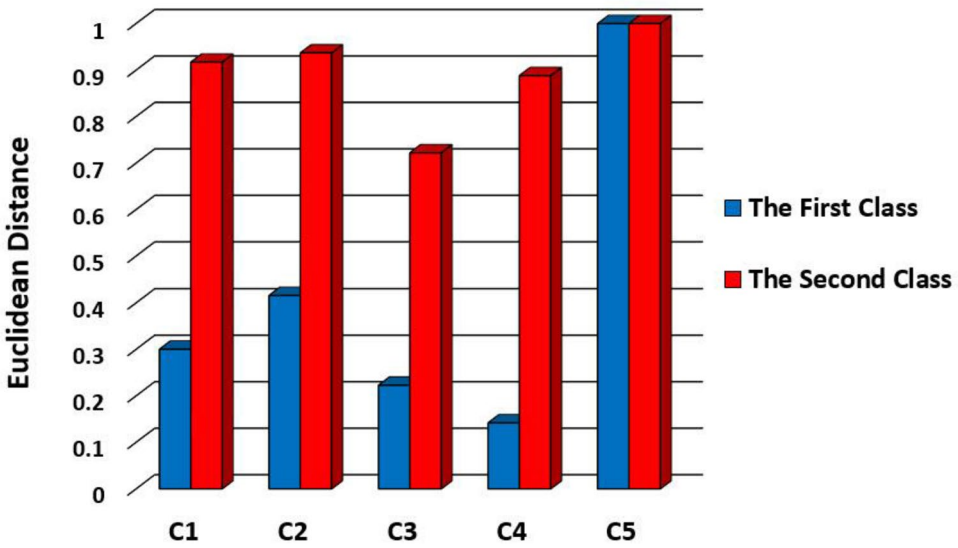

Fig. 4 The distance of each criterion from each class

Table 5 Optimization and clustering of sections by ABC algorithm

Section name	Optimum partition	Optimum partition	Clustering	Clustering
H-4	0.199	1.385	First class	H-4
H-1	0.824	1.019		H-1
H-3	1.275	0.3		H-11
H-16	0.961	0.786		H-15
H-2	1.208	0.0003	Second class	H-3
H-11	0.318	0.992		H-16
H-15	0.208	1.309		H-2

the second class. In addition, C_5 (Density) has same role in both classes with equal distances. On the other hand, in comparison between criteria in each class, C_4 (tunneling index Q) and C_3 (Average Groundwater Table) with 0.142 and 0.722 Euclidean distances have the most effect on the first and second classes, respectively. According to Table 4, the best cost value from replication 159 reaches the minimum allowable error and is fixed until the 250th replication. This reflects the high convergence of the ABC algorithm in optimizing clustering problems.

In the final step of analysis, the optimum partition value of each section is determined to be two groups. Based on the values, sections are classified into two groups according to Table 5. This clustering clearly shows that three sections with lithologies Durood Formation, Mobarak Formation, and Ruteh Formation are placed in the group with close geological properties and four sections with lithologies Shear Tuff and Lava Eocene, Dacite tuff of Eocene, Elika Formation, and Baroot Formation are placed in the group with different properties but the same category.

According to Table 5, sections H-4, H-1, H-11, and H-15 are placed in the first class and sections H-2, H-3, and H-16 are placed in the second class. Finally, for the validation of results, Table 6 shows the comparison of the results obtained from the conducted analyses with the results of a study conducted on the sections in the tunneling project [31, 35].

The sections are correctly placed in two groups in terms of risk, that is, high-risk and low-risk groups. This clustering result can be used by designers and contractors in the design and implementation phases and reduce the costs of geological risks in the project. The comparison of the validation results with previous studies including the Particle Swarm Optimization (PSO), Fuzzy C-means (FCM) clustering approach and the Failure Modes and Effects Analysis (FMEA), shows the high accuracy and convergence of the bee algorithm, which can be a suitable solution for other highly complex and uncertain problems in tunnel engineering and geotechnic [35]. The results of this study provide a new attitude

Table 6 Comparison of results of ABC algorithm with FEMA, PSO and FCM

Section name	H-4	H-1	H-3	H-16	H-2	H-11	H-15
Value of risk using FMEA	9.42	9.42	162	162	160.8	0.49	14.18
Clustering using particle swarm optimization	1	1	2	2	2	1	1
Clustering using fuzzy C-means	1	1	2	2	2	1	1
Clustering using artificial bee colony algorithm	1	1	2	2	2	1	1

in tunneling projects which may lead engineers toward a more reliable design and planning for future risk mitigation.

5 Conclusions

The use of meta-heuristic algorithms in risk assessment and analysis based on uncertain and unpredicted conditions has shown significant progress. The risk analysis of underground projects has always been faced with complex and uncertain conditions. Tunneling projects are one of the most important projects that require risk analysis and investigation at the beginning of the project due to different complicated criteria. Risk assessment in tunneling projects based on the geology of the region before the design and implementation of tunneling projects is one of the most important steps of project management. Thus, a study was conducted on the second part of the Emamzade Hashem tunnel using the ABC algorithm. In this research, seven sections in the route of project with different lithologies are selected, and their geotechnical properties are assessed and tested. Then, an optimized clustering (weak and strong risk classes) of the sections is conducted. Finally, three sections Durood Formation, Mobarak Formation, and Ruteh Formation are placed in the high risk group and four sections Baroot Formation, Elika Formation, Dacite tuff of Eocene and Shear Tuff, and Lava Eocene are placed in the low risk group. It is worth mentioning that C_3 (Average Groundwater Table) with Euclidean distance equal 0.722 has the most effect on three sections Durood Formation, Mobarak Formation, and Ruteh Formation in the high risk group (The second class). In addition, C_4 (tunneling index Q) with Euclidean distance equal 0.142 has the most effect on four sections Baroot Formation, Elika Formation, Dacite tuff of Eocene and Shear Tuff, and Lava Eocene in the low risk group (The first class). Finally, after validation, the results indicated that there was a full compliance between the results of this analysis and previous study. Consequently, it can be concluded that this novel approach is able to tackle for risk assessment of tunneling projects. For future study, it is recommended to use other intelligent algorithms such as gray wolf, Bat and fire fly algorithms and support vector machine for risk assessment of tunneling project.

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Compliance with ethical standards

Conflict of interest On behalf of all authors, the corresponding author states that there is no conflict of interest.

References

1. Aalianvari A, Katibeh H, Sharifzadeh M (2012) Application of fuzzy Delphi AHP method for the estimation and clustering of Ghomrud tunnel from groundwater flow hazard. Arab J Geosci 5(2):275–284. https://doi.org/10.1007/s12517-010-0172-8
2. Bakhtavar E, Shirvand Y (2019) Designing a fuzzy cognitive map to evaluate drilling and blasting problems of the tunneling projects in Iran. Eng Comput 35(1):35–45. https://doi.org/10.1007/s00366-018-0581-y
3. Manouchehrian A, Gholamnejad J, Sharifzadeh M (2014) Development of a model for analysis of slope stability for circular mode failure using genetic algorithm. Environ Earth Sci 71(3):1267–1277. https://doi.org/10.1007/s12665-013-2531-8
4. Rad MY, Haghshenas SS, Haghshenas SS (2014) Mechanostratigraphy of cretaceous rocks by fuzzy logic in East Arak, Iran. In: The 4th international workshop on computer science and engineering-summer, WCSE
5. Haghshenas SS, Mikaeil R, Haghshenas SS, Naghadehi MZ, Moghadam PS (2017) Fuzzy and classical MCDM techniques to rank the slope stabilization methods in a rock-fill reservoir dam. C.E.J 3(6):382–394
6. Faradonbeh RS, Taheri A (2019) Long-term prediction of rockburst hazard in deep underground openings using three robust data mining techniques. Eng Comput 35(2):659–675. https://doi.org/10.1007/s00366-018-0624-4
7. Mohammadi J, Ataei M, Kakaei RK, Mikaeil R, Haghshenas SS (2018) Prediction of the production rate of chain saw machine using the multilayer perceptron (MLP) neural network. C.E.J 4(7):1575–1583
8. Mikaeil R, Haghshenas SS, Haghshenas SS, Ataei M (2018) Performance prediction of circular saw machine using imperialist competitive algorithm and fuzzy clustering technique. Neural Comput Appl 29(6):283–292. https://doi.org/10.1007/s00521-016-2557-4
9. Salemi A, Mikaeil R, Haghshenas SS (2018) Integration of finite difference method and genetic algorithm to seismic analysis of circular shallow tunnels (Case study: Tabriz urban railway tunnels). KSCE J Civ Eng 22(5):1978–1990. https://doi.org/10.1007/s12205-017-2039-y
10. Bakhtavar E, Yousefi S (2018) Assessment of workplace accident risks in underground collieries by integrating a multi-goal cause-and-effect analysis method with MCDM sensitivity analysis. Stoch Environ Res Risk Assess 32:3317–3332. https://doi.org/10.1007/s00477-018-1618-x
11. Yagiz S, Ghasemi E, Adoko AC (2018) Prediction of rock brittleness using genetic algorithm and particle swarm optimization techniques. Geotech Geol Eng 36(6):3767–3777. https://doi.org/10.1007/s10706-018-0570-3
12. Aryafar A, Mikaeil R, Doulati Ardejani F, Shaffiee Haghshenas S, Jafarpour A (2019) Application of non-linear regression and soft computing techniques for modeling process of pollutant adsorption from industrial wastewaters. JME 10(2):327–337
13. Dormishi AR, Ataei M, Khaloo Kakaie R, Mikaeil R, Shaffiee Haghshenas S (2019) Performance evaluation of gang saw using hybrid ANFIS-DE and hybrid ANFIS-PSO algorithms. JME 10(2):543–557
14. Mikaeil R, Haghshenas SS, Ozcelik Y, Gharehgheshlagh HH (2018) Performance evaluation of adaptive neuro-fuzzy inference system and group method of data handling-type neural network for estimating wear rate of diamond wire saw. Geotech Geol Eng 36(6):3779–3791. https://doi.org/10.1007/s10706-018-0571-2
15. Dormishi A, Ataei M, Mikaeil R, Khalokakaei R, Haghshenas SS (2019) Evaluation of gang saws' performance in the

carbonate rock cutting process using feasibility of intelligent approaches. Jestech. https://doi.org/10.1016/j.jestch.2019.01.007
16. Hosseini SM, Ataei M, Khalokakaei R, Mikaeil R, Haghshenas SS (2019) Investigating the role of coolant and lubricant fluids on the performance of cutting disks (case study: hard rocks). RGN Zbornik 34(2):13–24. https://doi.org/10.17794/rgn.2019.2.2
17. Amigun B, Petrie D, Görgens J (2011) Economic risk assessment of advanced process technologies for bioethanol production in South Africa: Monte Carlo analysis. Renew Energy 36(11):3178–3186
18. Vílchez JA, Espejo V, Casal J (2011) Generic event trees and probabilities for the release of different types of hazardous materials. J Loss Prevent Proc 24(3):281–287
19. Hyun KC, Min S, Choi H, Park J, Lee IM (2015) Risk analysis using fault-tree analysis (FTA) and analytic hierarchy process (AHP) applicable to shield TBM tunnels. Tunn Undergr Sp Technol 49:121–129
20. Nezarat H, Sereshki F, Ataei M (2015) Ranking of geological risks in mechanized tunneling by using Fuzzy Analytical Hierarchy Process (FAHP). Tunn Undergr Sp Technol 50:358–364
21. Wang Z, Qiao L, Li S, Bi L (2016) Risk assessment for stability and containment property of an underground oil storage facility in construction phase using fuzzy comprehensive evaluation method. ASCE-ASME J Risk Uncertain Eng Syst Part A Civil Eng 2(4):04016009. https://doi.org/10.1061/AJRUA6.0000885
22. Li SC, Zhou ZQ, Li LP, Lin P, Xu ZH, Shi SS (2016) A new quantitative method for risk assessment of geological disasters in underground engineering: Attribute Interval Evaluation Theory (AIET). Tunn Undergr Sp Technol 53:128–139. https://doi.org/10.1016/j.tust.2015.12.014
23. Mikaeil R, Haghshenas SS, Shirvand Y, Hasanluy MV, Roshanaei V (2016) Risk assessment of geological hazards in a tunneling project using harmony search algorithm (case study: Ardabil-Mianeh railway tunnel). C.E.J 2(10):546–554
24. Haghshenas SS, Haghshenas SS, Barmal M, Farzan N (2016) Utilization of soft computing for risk assessment of a tunneling project using geological units. C.E.J 2(7):358–364
25. Esmailzadeh A, Shirzad PJ, Haghshenas SS (2017) Technical analysis of collapse in tunnel excavation and suggestion of preventing appropriate applicable methods (case study: sardasht dam second diversion tunnel). C.E.J 3(9):682–689. https://doi.org/10.21859/cej-03095
26. Haghshenas SS, Ozcelik Y, Haghshenas SS, Mikaeil R, Moghadam PS (2017) Ranking and assessment of tunneling projects risks using fuzzy mcdm (case study: Toyserkan Doolayi Tunnel). In: 25th International mining congress and exhibition of Turkey, pp 289–297
27. Sun J, Liu B, Chu Z, Chen L, Li X (2018) Tunnel collapse risk assessment based on multistate fuzzy Bayesian networks. Qual Reliab Eng Int 34(8):1646–1662
28. Xiong Z, Guo J, Xia Y, Lu H, Wang M, Shi S (2018) A 3D multiscale geology modeling method for tunnel engineering risk assessment. Tunn Undergr Sp Technol 73:71–81. https://doi.org/10.1016/j.tust.2017.12.003
29. Xia Y, Xiong Z, Lu H, Wen Z, Ma C (2018) Fuzzy risk assessment of a deeply buried tunnel under incomplete information. R Soc Open Sci 5(10):180305. https://doi.org/10.1098/rsos.180305
30. Li TZ, Yang XL (2018) Risk assessment model for water and mud inrush in deep and long tunnels based on normal grey cloud clustering method. KSCE J Civ Eng 22(5):1991–2001. https://doi.org/10.1007/s11771-018-3744-5
31. Mikaeil R, Haghshenas SS, Sedaghati Z (2019) Geotechnical risk evaluation of tunneling projects using optimization techniques (case study: the second part of Emamzade Hashem tunnel). Nat Hazards 97(3):1099–1113. https://doi.org/10.1007/s11069-019-03688-z
32. Wang F, Li H, Dong C, Ding L (2019) Knowledge representation using non-parametric Bayesian networks for tunneling risk analysis. Reliab Eng Syst Saf. https://doi.org/10.1016/j.ress.2019.106529
33. Xu W, Liu B, Fu C, Han Y, Ren X (2019) Risk management for Beijing subway tunnel construction using the New Austrian tunneling method: a case study. In: International conference on transportation and development 2019: smarter and safer mobility and cities. ASCE, Reston, VA, pp 423–435. https://doi.org/10.1061/9780784482575.040
34. Bakhtavar E, Yousefi S (2019) Analysis of ground vibration risk on mine infrastructures: integrating fuzzy slack-based measure model and failure effects analysis. Int J Environ Sci Technol 16(10):6065–6076. https://doi.org/10.1007/s13762-018-2008-0
35. Sedaghati Z (2015) Fuzzy analysis and management of geotechnical risks in second part of Emamzade Hashem tunnel. Master of Science Thesis, Urmia University of Technology, Urmia
36. Jalilvand P, Haghshenas SS, Haghshenas SS, Javan MH (2014) Evaluation of dynamic resistance of the Toyserkan Doolayi Tunnel by rock bolt and reinforced shotcrete composite system. In: Geo-Shanghai. http://dx.doi.org/10.1061/9780784413449.037
37. Jalilvand P, Haghshenas SS (2013) The study stability of Toyserkan Doolayi Tunnel using reinforces shotcrete and rock bolt under static condition. In: The 23rd international mining congress and exhibition of Turkey, pp. 1299–1305
38. Haghshenas SS, Haghshenas SS, Mikaeil R, Sirati Moghadam P, Haghshenas AS (2017) A new model for evaluating the geological risk based on geomechanical properties—case study: the second part of Emamzade Hashem Tunnel. EJGE 22(01):309–320
39. Pirouz B, Maiolo M (2018) The role of power consumption and type of air conditioner in direct and indirect water consumption. J Sustain Dev Energy Water Environ Res 6(4):665–673. https://doi.org/10.13044/j.sdewes.d6.0202
40. Palermo SA, Talarico VC, Pirouz B (2019) Optimizing rainwater harvesting systems for non-potable water uses and surface runoff mitigation. Numer Comput Theory Algorithms NUMTA 2019:84
41. Pirouz B, Palermo SA, Turco M, Piro P (2019) New mathematical optimization approaches for LID systems under fuzzy environment. Numer Comput Theory Algorithms NUMTA 2019:85
42. Janković R, Ćosović M, Amelio A (2019) Time series prediction of air pollutants: a case study for Serbia, Bosnia and Herzegovina and Italy. In: 2019 18th International symposium INFOTEH. IEEE, pp 1–6
43. Amelio A, Janković R, Tanikić D, Draganov IR (2019) Predicting the usability of the dice CAPTCHA via artificial neural network. In: Italian research conference on digital libraries, pp. 44–58. https://doi.org/10.1007/978-3-030-11226-4_4
44. Haghshenas SS, Faradonbeh RS, Mikaeil R, Haghshenas SS, Taheri A, Saghatforoush A, Dormishi A (2019) A new conventional criterion for the performance evaluation of gang saw machines. Measurement 146:159–170. https://doi.org/10.1016/j.measurement.2019.06.031
45. Faradonbeh RS, Haghshenas SS, Taheri A, Mikaeil R (2019) Application of self-organizing map and fuzzy c-mean techniques for rockburst clustering in deep underground projects. Neural Comput Appl. https://doi.org/10.1007/s00521-019-04353-z
46. Karaboga D (2005) An idea based on honey bee swarm for numerical optimization. Technical report-tr06, Erciyes University, Engineering Faculty, Computer Engineering Department, pp 1–10, 200
47. Mikaeil R, Bakhshinezhad H, Haghshenas SS, Ataei M (2019) Stability analysis of tunnel support systems using numerical and intelligent simulations (case study: Kouhin Tunnel of

Qazvin-Rasht Railway). RGN Zbornik 34(2):1–10. https://doi.org/10.17794/rgn.2019.2.1
48. Karaboga D, Gorkemli B, Ozturk C, Karaboga N (2014) A comprehensive survey: artificial bee colony (ABC) algorithm and applications. Artif Intell Rev 42(1):21–57. https://doi.org/10.1007/s10462-012-9328-0
49. Mikaeil R, Haghshenas SS, Hoseinie SH (2018) Rock penetrability clustering using artificial bee colony (ABC) algorithm and self-organizing map. Geotech Geol Eng 36(2):1309–1318. https://doi.org/10.1007/s10706-017-0394-6
50. Kumar D, Kumar B (2013) Optimization of benchmark functions using artificial bee colony (ABC) algorithm. Optimization 3(10):9–14
51. Karaboga D, Akay B (2009) A comparative study of artificial bee colony algorithm. Appl Math Comput 214(1):108–132
52. Karaboga D, Akay B (2011) A modified artificial bee colony (ABC) algorithm for constrained optimization problems. Appl Soft Comput 11(3):3021–3031. https://doi.org/10.1016/j.asoc.2010.12.001
53. Karaboga D, Basturk B (2007) Artificial bee colony (ABC) optimization algorithm for solving constrained optimization problems. In: International fuzzy systems association world congress. Springer, Berlin, pp 789-798. https://doi.org/10.1007/978-3-540-72950-1_77
54. Mikaeil R, Shaffiee Haghshenas S, Ozcelik Y, Shaffiee Haghshenas S (2017) Development of intelligent systems to predict diamond wire saw performance. JSCCE 1(2):52–69. https://doi.org/10.22115/SCCE.2017.49092
55. Aryafar A, Mikaeil R, Haghshenas SS, Haghshenas SS (2018) Application of metaheuristic algorithms to optimal clustering of sawing machine vibration. Measurement 124:20–31. https://doi.org/10.1016/j.measurement.2018.03.056
56. Aryafar A, Mikaeil R, Shafiee Haghshenas S (2018) Utilization of soft computing for evaluating the performance of stone sawing machines, Iranian Quarries. IJMGE 52(1):31–36. https://doi.org/10.22059/IJMGE.2017.233493.594673