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ORIGINAL PAPER

Prediction of rockburst risk in underground projects developing a neuro-bee intelligent system

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Abstract
The prediction of the risk of rockbursts in burst-prone grounds is turned into a challenging and vital mission for most underground projects that attract great interest from engineers and researchers. In this study, a hybrid technique, the artificial neural network (ANN) and artificial bee colony (ABC), neuro-bee model, was considered to create the sophisticated relationship between the risk of rockbursts in burst-prone grounds and its influencing factors. The establishment and validation of ANN models were implemented via a data set extracted from previous works, and the database covers 246 reliable rockburst cases. Six influencing factors were selected as input variables. Five-fold cross validation were adopted to tune hyper-parameters of ABC-ANN models, and the performance of ANN models was evaluated by correlation coefficient (R^2) and root mean square error (RMSE). Observational experiment results indicated that the ABC-ANN algorithm can be utilized as an effective tool for predicting the risk of rockbursts in burst-prone grounds. The R^2 and RMSE values between the predicted and actual rockburst values were 0.9656 and 0.1281, respectively. Sensitivity analyses implemented by the response surface method revealed that the maximum tangential stress of the cavern wall and the elastic strain index parameters have a greater effects on rockburst compared with other input parameters. As a result, the proposed hybrid method outperforms the other models for rockburst prediction in terms of the prediction accuracy and the generalization capability.

Keywords Rockburst · ABC-ANN · ANN · Prediction · Risk

Introduction

Rockburst is one of the dynamic and geological disasters that occurs in underground hydropower caverns, tunnels, and hard rock mines. The phenomenon of rockbursts is attributable to the abrupt release of potential energy in the rock mass under some certain condition (Cook 1965; Kaiser et al. 1996; Wang et al. 2006; Gong et al. 2018; Zhou et al. 2018). The occurrence of rockbursts usually causes immeasurable damage to equipment and/or infrastructure and may even lead to fatalities due to the fact that rockbursts occur suddenly and intensely (Zhou et al. 2016a, 2016b). In contrast with the past, the geotechnical activities usually are carried out under the great-depth condition, and with the increase of geotechnical activities, the occurrence of rockburst is likely to become more frequent and severer (Zhou et al. 2016a, 2018; Tao et al. 2017, 2019; Wang et al. 2018a, 2018b, 2019a, 2019b). Consequently, the prediction of rockburst with high accuracy is imperative for disaster prevention and control.

In spite of much research on rockburst mechanics in the past decades, the approach to rockburst prediction is still based on empirical results and lacks well-rounded theory based on fundamental mechanics. Although the accurate prediction of rockburst is a complicated technique in the process of excavation, many valuable achievements on this task have been reported in the past several decades by many researchers

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aiming at different aspects such as the triggering mechanism, the micro-gravity method, the rebound method, the microseismicity method, the drilling-yield test, the electromagnetic radiation method, and the probabilistic methods (Zhou et al. 2012, 2018; Afraei et al. 2018). Far-reaching rockburst research has been carried out in South Africa, Australia, Canada, China, and many other countries (Kaiser et al. 1996; Ortlepp 2005; Zhou et al. 2018). These corporate achievements have enormously enriched the comprehension of rockbursts. Moreover, various types of empirical criteria (i.e., Turchaninov criterion, Barton criterion, Russense criterion, Hoek criterion, strain energy storage index, and burst potential index) for estimating and predicting rockbursts have been developed since the 1960s and often applied in practice, as summarized in Zhou et al. (2012, 2018). These criteria have been examined with laboratory tests and local monitoring data to investigate the mechanical responses of rockbursts. Nevertheless, the phenomenon of rockburst is site-specific to a large extent and lies on many factors such as the strength of rock mass, the geometry shape of the underground opening, the magnitude and direction of in situ stresses and excavation methods (Li et al. 2017c). It is, therefore, rather troublesome to unify feasible rockburst criteria for accuracy estimation of the potential of rockbursts.

Besides the aforementioned work, various techniques for rockburst prediction have been implemented by means of different statistical machine learning approaches since the seminal work of Feng and Wang (1994), as tabulated in Table 1. These studies apply linear classification techniques such as discriminant analysis (Gong and Li 2007; Zhou et al. 2010) and logistic regression classifier (Li and Jimenez 2018); nonlinear classification approaches such as neural networks (Feng and Wang 1994; Xia-ting et al. 1998) and support vector machine (Zhao 2005), classification trees and rule-based models such as classification and regression trees (Zhou et al. 2016a) and decision tree (DT)–based C4.5 algorithm (Faradonbeh and Taheri 2018), and hybrid models such as Zhou et al. (2012) combined support vector machines with the heuristic algorithms (i.e., GA and PSO) for the establishment of the classification model of long-term rockburst for underground projects. Adoko et al. (2013) proposed a rockburst intensity prediction model integrating fuzzy inference system with adaptive neuro-fuzzy inference systems. Recently, a data set of 246 rockburst incidents was sorted out by Zhou et al. (2016a) for establishing rockburst classification model using ten supervised learning methods. Lin et al. (2018) proposed a cloud model with a rough set to predict rockbursts. Although many rockburst prediction models have already been depicted and analyzed by several authors (Feng and Wang 1994; Xia-ting et al. 1998; Shi et al. 2010; Adoko et al. 2013; Liu et al. 2013; Zhou et al. 2012, 2016a, 2016b, 2018), there no exists a comprehensive model which can perform well aiming to different problems of rockbursts according to the "No Free Lunch" theorem. Every approach has its advantages and disadvantages. For support vector machine (SVM), for example, it can be used to classify complex nonlinear data, performs well with high dimensional small data sets, but is time-consuming, difficult to interpret, and restricted to pairwise classification (Zhao 2005; Zhou et al. 2016a). As for artificial neural network (ANN), it works well with nonlinear relationship; no assumptions are required on probability density and distribution but it is susceptible to irrelevant features, high computational time, over-fitting, and prone to sub-optimal local minima (Guo et al. 2019; Koopialipoor et al. 2019e). In addition, the over-fitting condition tends to occur once the hidden layers or nodes are determined mistakenly (Koopialipoor et al. 2018d; Zhou et al. 2018; Armaghani et al. 2019; Zhou et al. 2019a). Adaptive neuro-fuzzy inference system (ANFIS) combined of artificial neural networks and fuzzy inference systems but it costs excessive computational time and is not transparent. Therefore, it still poses enormous challenge for understanding, predicting, and controlling rockbursts in underground openings (Zhou et al. 2016a). On the other hand, a large number of models for predicting the rockburst can provide valuable and useful information for work in mining and geological engineering. During these years, more and more researchers have set about ensemble learning techniques, which integrate the outputs of few basic classification techniques to generate a composite output, in order to enhance classification accuracy (Trevor et al. 2009; Zhou et al. 2019c; Li et al. 2020; Koopialipoor et al. 2017, 2018b). However, for the domain of rockburst classification, few scholars take ensemble methods into consideration; thus, it is imperative to implement more in-depth and extensive research in this area.

To compensate the research in this area blank, this paper investigates the suitability of a hybrid artificial bee colony-based neural network for the prediction of rockbursts in underground geotechnical engineering. To achieve this goal, 246 data from the events of this phenomenon were collected in deep tunnels and mines. After initial analysis, using artificial intelligence, relationships between different variables were identified. At the end, these models were used to evaluate the phenomenon of rockburst.

Methodology

Artificial neural network

ANN, as a popular intelligence mathematical technique, was proposed by McCulloch and Pitts (1943) and exhibited the capacity to mimic the complex nonlinear relationship between input and output variables based on different environment. Inspired by the working mechanism of the brain, the ANN can be considered an effective parallel processing architecture

Table 1 Summary of pre-existing supervised machine learning techniques work on rockburst classification with influence factors and accuracy values (modified from Zhou et al. 2018)

Algorithm/technique	Input parameters	Accuracy	Data	Authors (year)
Mahalanobis distance discriminant analysis	σ_θ/σ_c, σ_c/σ_t, W_{et}	100%	15	Gong and Li (2007)
Bayes discriminant analysis	σ_θ/σ_c, σ_c/σ_t, W_{et}	100%	21	Gong et al. (2010)
Fisher linear discriminant analysis	σ_θ/σ_c, σ_c/σ_t, W_{et}	100%	15	Zhou et al. (2010)
Fisher linear discriminant analysis	H, σ_θ, σ_c, σ_t, σ_θ/σ_c, σ_c/σ_t, W_{et}	48.4–55.9%	246	Zhou et al. (2016a)
Quadratic discriminant analysis	H, σ_θ, σ_c, σ_t, σ_θ/σ_c, σ_c/σ_t, W_{et}	48.4–60.9%	246	Zhou et al. (2016a)
Partial least-squares discriminant analysis	H, σ_θ, σ_c, σ_t, σ_θ/σ_c, σ_c/σ_t, W_{et}	45.3–57.5%	246	Zhou et al. (2016a)
SVM	σ_θ, σ_c, σ_t, W_{et}	100%	16	Zhao (2005)
SVM	H, σ_θ, σ_c, σ_t, σ_θ/σ_c, σ_c/σ_t, W_{et}	51.7–67.2%	246	Zhou et al. (2016a)
GSM-SVM	H, σ_θ, σ_c, σ_t, σ_θ/σ_c, σ_c/σ_t, W_{et}	66.67–88.9%	132	Zhou et al. (2012)
GA-SVM	H, σ_θ, σ_c, σ_t, σ_θ/σ_c, σ_c/σ_t, W_{et}	66.67–80%	132	Zhou et al. (2012)
PSO-SVM	H, σ_θ, σ_c, σ_t, σ_θ/σ_c, σ_c/σ_t, W_{et}	66.67–90%	132	Zhou et al. (2012)
ANFIS	σ_θ, σ_c, σ_t, σ_θ/σ_c, σ_c/σ_t, W_{et}	66.5–95.6%	174	Adoko et al. (2013)
ANN	σ_θ, σ_c, σ_t, W_{et}	100%	10	Feng and Wang (1994)
ANN	H, σ_θ, σ_c, σ_t, σ_θ/σ_c, σ_c/σ_t, W_{et}	50–67.5%	246	Zhou et al. (2016a)
Adaptive boosting	σ_θ, σ_θ/σ_c, σ_c/σ_t, W_{et}	87.8–89.9	36	Ge and Feng (2008)
k-nearest neighbors	H, σ_θ, σ_c, σ_t, σ_θ/σ_c, σ_c/σ_t, W_{et}	53.2–67.2%	246	Zhou et al. (2016a)
Gradient boosting machines	H, σ_θ, σ_c, σ_t, σ_θ/σ_c, σ_c/σ_t, W_{et}	61–76.6%	246	Zhou et al. (2016a)
Gradient boosting machines	E_1, E_2, E_3, E_4, PPV	61.22%	254	Zhou et al. (2016b)
Naive Bayes	H, σ_θ, σ_c, σ_t, σ_θ/σ_c, σ_c/σ_t, W_{et}	53.9–67.2%	246	Zhou et al. (2016a)
DT	σ_θ, σ_c, σ_t, W_{et}	73–93%	132	Pu et al. (2018)
Logistic regression	H, σ_θ, σ_c, σ_t, W_{et}	80.2–90.9%	135	Li and Jimenez (2018)
Bayesian network	H, σ_θ, σ_c, σ_t, W_{et}	91.75%	135	Li et al. (2017a)
GA and extreme learning machine	σ_θ, σ_c, σ_t, W_{et}	100%	30	Li et al. (2017b)
Emotional neural network (ENN)	σ_θ, σ_c, σ_t, W_{et}	85.19%	134	Faradonbeh and Taheri (2018)
Gene expression programming (GEP)	σ_θ, σ_c, σ_t, W_{et}	85.16%	134	Faradonbeh and Taheri (2018)
DT-based C4.5 algorithm	σ_θ, σ_c, σ_t, W_{et}	81.48%	134	Faradonbeh and Taheri (2018)
Cloud model with rough set	σ_θ, σ_c, σ_t, σ_θ/σ_c, σ_c/σ_t, W_{et}	71.05%	246	Lin et al. (2018)

which consists of at least one hidden layer, inputs, and outputs. It has the strong power to handle fuzzy information, whose functional relations are concealed (Mandal and Singh 2009; Koopialipoor et al. 2018a). In ANN systems, by training the previous experiences and samples, the models are established, that is to say, according to different training data, the patterns used for gathering the neurons and the outputs are mutative. For the ANNs, the fundamental units are neurons, which determine the organization networks. These neurons build up the layer and contextual layers connect with each other by interconnection weights. Among the many ANN patterns, feed-forward back-propagation (BP) is feasible and has been applied successfully by some scholars (Engelbrecht 2007; Koopialipoor et al. 2019a; Zhou et al. 2020). Each neuron consists of different inputs and these inputs generate an output during a training process. In the network, the neurons are fully associated with each other, and an output of each unit element is employed as an input for the next unit element. Multiple neurons build up the layers, where the first layer transmits the information to the next layer during the process of training and the last layer generates network response. The layers between input and output layers are named hidden or intermediate layers (Haykin and Network 2004). Among all the algorithms in ANN, the BP is the most popular to interpret the modification behavior of network (Koopialipoor et al. 2019c; Le et al. 2019; Zhao et al. 2019; Zhou et al. 2020). The BP algorithm are generally keeping with the error correction learning law where the propagating of errors is responsible for the adjustment of the weights of the connections to minimize the sum of the mean squared error in the output layer. In other words, the learning propagation is comprised of two phases: forward phase and back phase. For the forward phase, the transmission of layer inputs provides a series of outputs. As for the forward stage, synaptic weights will be achieved. Two statistical indicators including the root mean square error (RMSE) and coefficient of determination (R^2) have been suggested as the quality measures to benchmark the performance of the aforementioned model results.

Artificial bee colony

In nature, many species live depending on a colony have demonstrated great efficient productivity. Without any supervised coordination mechanism, their behaviors are spontaneous and methodical. Take the honey bee colonies for example, a circulation of foraging practice needs to be manipulated by employed, onlooker, and scout bees (Badem et al. 2018; Ghaleini et al. 2018; Le et al. 2019).

The employed bees are in charge of exploiting the already discovered sustenance source and fetch the nectar. Each employed bee contacts with a corresponding onlooker bee. When they return to the hive, they transmit the message about the quality and location of the nectar to the onlooker bees by dancing. The onlooker bees obtain the information by observing the different duration and frequency dances (Wenner et al. 1967; Gordan et al. 2018). Once the nourishment source is exhausted, the so-called scout bees start to search for new promising flower patches arbitrarily.

The ABC algorithm is a metaheuristic optimization method established by Karaboga (2005) which gets inspired from the behaviors of bees foraging. In the ABC algorithm, the position of nectar sources can be regarded as the solution of the problem, and thus the number of the nectar sources represents the rationality of the associated solution. The main search procedure of the ABC algorithm can be divided into four phases as follows.

Initialization phase

The initialization of the ABC algorithm is to generate a random population of the food source positions (called SN solutions) as below:

$$\delta_{ab} = \mathrm{rand}(0,1)\left(\delta_b^{\max} - \delta_b^{\min}\right) + \delta_b^{\min} \tag{1}$$

where δ_{ab} is defined as the b_{th} optimal variable of the a_{th} solution; a and b is in the range of [1, SN] and [1, D]; both a and b are integers. SN shows the number of solutions and D indicates the number of optimization parameters. Additionally, $\delta_b^{\min}$ and $\delta_b^{\max}$ denote the lower and upper bounds of the b_{th} optimal variable, respectively, and rand(0, 1) denotes a random well-distributed number ranging from [0, 1].

Employed bee phase

In this phase, the employed bees aim to explore a more suitable nourishment candidate by integrating their previously obtained position information with a random nectar source location in the neighborhood as below:

$$v_{ab} = \delta_{ab} + \eta_{ab}(\delta_{kb} - \delta_{ab}) \tag{2}$$

where η_{ab} is generated randomly in the range of [− 1, 1], k and b are randomly selected from $\{1, 2, \ldots, SN\}$ and [1, D] respectively, also $k \neq b$ (Kumbhar and Krishnan 2011). After generating the new position v_a, the goodness of the new nutrition source v_a will be compared with the previously one δ_a by employed bees. According to the greedy selection, the old information δ_a will be replaced by the better food source information v_a. Otherwise, the previous position δ_a still is kept by employed bees (Nourani et al. 2012).

Onlooker bees phase

When the employed bees reach the hive, they transmit the information associated with the quality and location of the nourishment sources to the onlooker bees. After that, the onlooker bees pick out the available information and select the new nectar source according to the probability values expressed by fitness values. Here, the mathematical expression of probability values is given as below:

$$p_a = \frac{\mathrm{fitness_a}}{\sum_{a=1}^{\mathrm{SN}} \mathrm{fitness_a}} \tag{3}$$

Here, $\mathrm{fitness}_a$ denotes the fitness value of the a_{th}-solution. And then, the roulette wheel (Dhahri et al. 2012) selection is introduced to evaluate the p_a. A random real number between [0, 1] can be obtained by the roulette wheel selection for each position. If all the random number is less than the probability value p_a corresponding to the position δ_a, it proves that a good nourishment source is found nearby. For the new generated solution v_a, it is compared with the current solution δ_a by applying greedy selection. If v_a is more advanced than δ_a, it is retained in the population. On the contrary, δ_a is retained (Kisi et al. 2012; Koopialipoor et al. 2019b).

Scout bees phase

When the source of nourishment is close to be exhausted, the employed bees convert to the scout bees. The mission of these scout bees is to search for new promising nectar source in the vicinal area randomly (Karaboga 2005). In other words, when the existing solution is unable to reach the threshold (called limit) defined by manipulators, the new source position is computed as in "Initialization phase" until the requirements of the nourishment source are met (Kurban and Beşdok 2009). Then, the best-optimal food source is obtained.

Data collection

The performance of the ABC-ANN models was measured utilizing the data collected from the original Zhou et al. (2016a) database which contains a total of 246 rockburst cases. In addition, the sources are verified and include documents published between 1994 and 2013among which half of the documents are published between 2009 and 2013. The general database consists of data collected from at least 20 underground projects (i.e., road and railway tunnels, hydropower station tunnels, nuclear cooling tunnels, coal mines, and hard rock metal mines) from different countries (i.e., China, Norway, Sweden, Japan, Italy, and Russia) and includes 246 cases of rockburst events. Six potential indicators are included in this database and investigated in this work which are coalescent between the internal and external factors and a comprehensive consideration including geotechnical and constructive factors. They are the maximum tangential stress of the cavern wall (σ_θ = MTS), the uniaxial compressive strength (UCS or σ_c) of rock, the uniaxial tensile strength (UTS or σ_t) of rock, stress concentration factor (SCF or σ_θ/σ_c), rock brittleness index ($B = \sigma_c/\sigma_t$), and the elastic strain index (EEI or W_{et}). Those indicators are considered the major parameters to quantitatively characterize the occurrence of rockburst. Table 2 displays the relevant input indicators used to establish the potential of rockburst prediction model range with their range, mean, standard deviation, and skew, respectively. The proportion of four types of rockburst as described by Zhou et al. (2012) and Zhou et al. (2016a) in this database was categorized as heavy rockburst (H, 44 cases), moderate rockburst (M, 81 cases), low rockburst (L, 78 cases), and none rockburst (N, 43 cases). Correlations, boxplot, bar graphs, and scatterplots of rockburst database as illustrated by the GGally function (Schloerke et al. 2011) in Fig. 1, and all bivariate combinations of a single set of indicators are depicted as a plot matrix that allows for a mixture of both discrete and continuous indicator types using the ggplot2 plotting framework (Wickham 2016). Particularly, the scatterplot matrix in the upper panel demonstrates the pairwise relationship between parameters with corresponding correlation coefficients showing in the lower panel (i.e., the parameter W_{et} is notably correlated with MTS), whereas the marginal frequency of each kind of rockburst parameter exhibits on the diagonal distribution.

Table 2 Descriptive statistics values of various parameters of rockburst case histories with their range, mean, standard deviation, and skew for the ABC-ANN modeling

Parameter	Range	Mean	Standard deviation	Skew	Kurtosis
MTS/Mpa	2.60~297.80	58.00	54.075	2.924	9.432
UCS/Mpa	20.00~304.20	111.54	42.661	0.777	1.815
UTS/Mpa	1.30~22.60	7.17	4.182	0.888	0.579
SCF	0.10~4.87	0.59	0.672	3.819	16.543
B	0.15~80.00	20.54	14.241	2.037	4.947
W_{et}	0.81~30.00	5.16	4.156	3.247	13.817

Result and discussion

In this section, various artificial intelligence models are developed to predict the rockburst phenomenon. As mentioned in the previous section, 6 parameters were used to investigate this phenomenon (Table 2). These parameters were selected by reviewing the abovementioned previous studies. Using these parameters, four intensities are predicted for the occurrence of this phenomenon in underground mines. ANN and ABC-ANN are the prediction models used in this research. In fact, these models are employed to predict the exact occurrence of this phenomenon in underground mines, as well as improving the performance of intelligent models by means of optimization algorithms.

Multi-variable regression

The purpose of regression analyses is to design a model which is able to create a relationship between the dependent and independent variables (Koopialipoor et al. 2018d, 2019d). The multi-variable regression (MVR) method is employed to establish a relationship between dependent and independent variables. This method established a linear relationship between the parameters to find their best-suited function considering the least error. In this study, the parameters of Table 2 and rockburst were used as the inputs and output of the model, respectively. The MVR method suggests the following equation for rockburst:

$$\text{Rockburst} = 0.0062 \times \text{MTS} + 0.0013 \times \text{UCS} + 0.0141 \times \text{UTS} + 0.0664 \times \text{SCF} + 0.0097 \times B + 0.0824 \times W_{et} + 1.2369 \quad (4)$$

The correlation (R^2) of the above equation is 0.409 with the RMSE of 0.7524, indicating a poor relationship between the

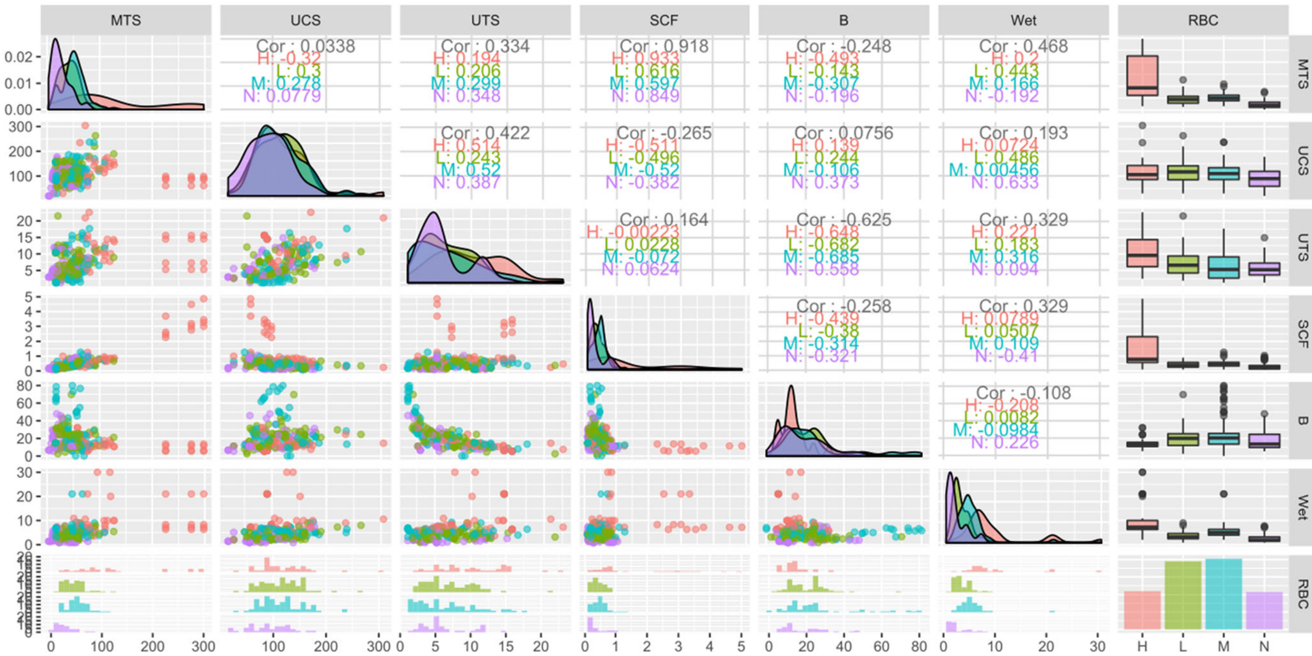


Fig. 1 Generalized pairs plot of rockburst database. Each color represents a different rockburst type

input and output parameters with very low accuracy. Consequently, this method cannot be used to predict rockburst in underground mines.

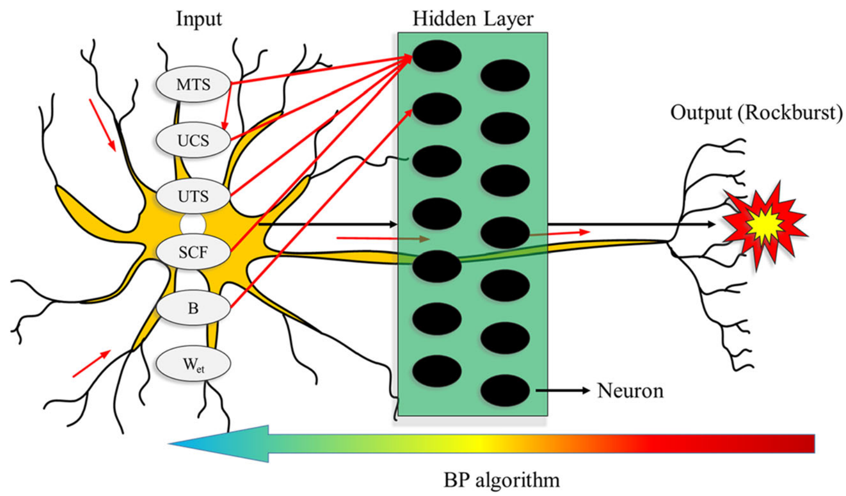
ANN

In this section, the ANN model is designed and developed to predict rockburst. Proper use of the input data is one of the most significant parts needed in designing intelligent systems. Considering the literature review of the researchers in the previous section, parameters affecting the rockburst phenomenon have been identified. Table 2 has been used for the input data of this system. Intelligent networks have two fundamental parts: the training part, which creates a nonlinear relationship between dependent and independent parameters and then assessed by the testing part. Therefore, from the totally 246 available data, some part should be allocated to the training part as well as the testing part. Many researchers have suggested that the number of training data should be larger and about 70–80% of the total data (Khandelwal and Singh 2009; Koopialipoor et al. 2018c; Liao et al. 2019; Xu et al. 2019). Also in this study, 80% of the data was allocated to the training part and 20% to the testing part.

Various algorithms are employed to train the ANN, among which, the Levenberg-Marquardt (LM) method has been used and recommended by different researchers (Jahed Armaghani et al. 2015; Ghaleini et al. 2018). Given its ability, this algorithm can be used appropriately in the field of mining and civil engineering issues (Mohamad et al. 2019; Yang et al. 2019; Zhou et al. 2019b, 2020). Three layers are used in this model. The first and third layers are related to the input data and output data (rockburst), respectively. The past researchers have also referred to the use of a hidden layer, by which, many linear and nonlinear engineering problems can be solved (Koopialipoor et al. 2018a). In this study, a hidden layer has been used, too. Figure 2 depicts the structure presented by this research for the ANN.

The ANN model aims for finding the proper performance for predicting the intelligent systems. The results of the ANN model are influenced by the two parameters of the number of neurons and iterations. In other words, the number of neurons in the hidden layer can contribute to the determination of the minimums of computational space. This search goes ahead to the stages that the problem's initial condition has been set for it. When the initial conditions are not obtained, the system will progress according to the number of the specified iterations. Various researchers have suggested methods to determine the appropriate number of hidden layer's neurons. Some researchers have proposed several formulas to determine the number of neurons (Jahed Armaghani et al. 2015; Koopialipoor et al. 2017). However, various researches have been conducted in the engineering fields, and various numbers of data have been used, indicating that the intelligent models reach their best function in each computational space with a certain number of neurons (Monjezi et al. 2013; Gordan et al. 2018). Therefore, in this study, it has been tried to use between 1 and 16 neurons, and in order to specify the best performance, each sample has been run several times. It is noteworthy that the conventional neuron number for a hidden layer has been reported about 5–15 (Monjezi et al.

Fig. 2 The proposed structure for the prediction of rockburst



2013; Gordan et al. 2018). In addition, a full analysis of 10 to 100 iterations was carried out for the sake of determining the number of iterations. The two statistical indices of R^2 and RMSE were used aiming at assessing the performance of the developed models. Figures 3 and 4 illustrate the effect of the number of neurons on the performance of the prediction model. As shown in Fig. 3, the R^2 and RMSE change diagram is ascending and descending, respectively. A good performance is provided in the number of 10 neurons. It should be noted that some next neurons have a much better performance, however, it caused the model had high runtime. For this reason, since the goal is to find the best conditions for optimal model implementation, the number of 10 neurons that have a lower implementation time is chosen as optimal conditions. The same reasons are similar to the number of iterations for choosing the best condition (see Fig. 4).

Eventually, the results of the best model obtained by 60 iterations and 10 hidden-layered neurons are presented in Table 3. The values of rockburst prediction for the total data are plotted in Fig. 5. As observed, the performance of this neural model (R^2) for the total data is 0.8334, suggesting that the developed neural model can have a better performance than the MVR model in predicting rockburst in underground mines and deep tunnels.

ABC-ANN

Different researchers have used optimization algorithms to improve the performance of an ANN (Ghaleini et al. 2018; Koopialipoor et al. 2018c). One of the problems with neural networks is being trapped in the local minimum. In this case, the model presents the result to the system, and since the system's minimum error is not available, the performance appropriate for it is presented and cannot be improved, while optimization algorithms find the lowest system error with the best performance and more accurately through searching the computational space. Some researchers have proposed various hybrid networks that, with developing them and the help of neural models, they have aimed to find a more acceptable performance. In this study, the ABC optimization algorithm has been used for the part of ANN training. In this case, the ABC-ANN hybrid algorithm is modeled. Figure 6 illustrates an overview of the operating system in this model. Given the importance of rockburst in underground mines and tunnels, its better prediction can decrease the risks caused by it as well as providing the required preparations for the design of tunnels. In the following, the more effective parameters in this modeling will be assessed.

Number of bees

The number of bees is one of the important parameters affecting the results of this hybrid system. Indeed, the bees replace the hidden-layered neurons in the neural network. They search the computational space according to the ABC algorithm rules. Many researchers consider the number of particles in the optimization algorithms as the most effective factor in the result of the prediction models (Ghaleini et al. 2018; Koopialipoor et al. 2018c). Nevertheless, the selection of high number of particles will increase the program runtime. In this case, finding appropriate algorithms or techniques providing acceptable performance with a low number is favored. For example, using their hybrid algorithms, some researchers have reported their best performance in a population of 200–500 particles (Ghaleini et al. 2018; Koopialipoor et al. 2018c). It

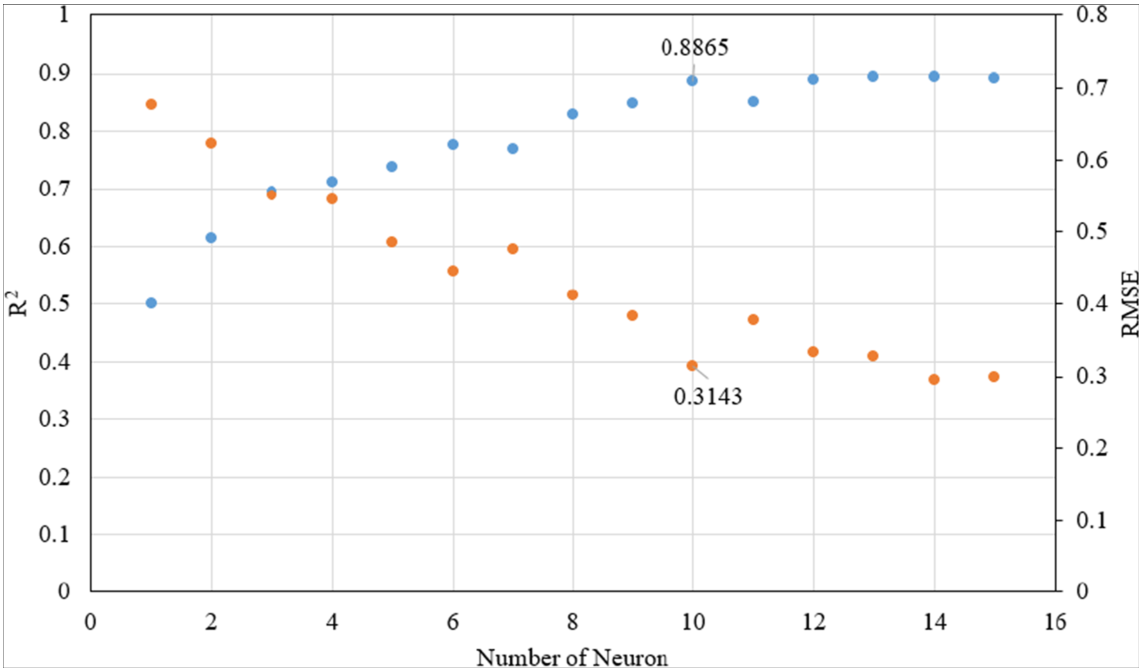


Fig. 3 Investigate the effect of neuron on ANN models

should be noted that the technique used in this research is of the kind of new methods. Some studies on this method have declared that acceptable results can be obtained regarding the continuous search feature of the ABC algorithm (Ghaleini et al. 2018; Koopialipoor et al. 2018c). In these researches, 10 to 100 bees were the largest number of bees in which were used and they received proper performance (Ghaleini et al. 2018; Koopialipoor et al. 2018c). Also in this study, 10 to 100 bees were used. As mentioned, an ANN performance is improved by this method. Hence, a structure similar to the best selected ANN of previous section (10 neurons) was used in order to compare the results, and only its training section was learnt by the ABC algorithm. Figure 7 illustrates the effect of number of bees on the rockburst prediction model. As can be seen, the results of model performance are closed to steady state after 80 bees. Therefore, 80 bees are selected as optimal.

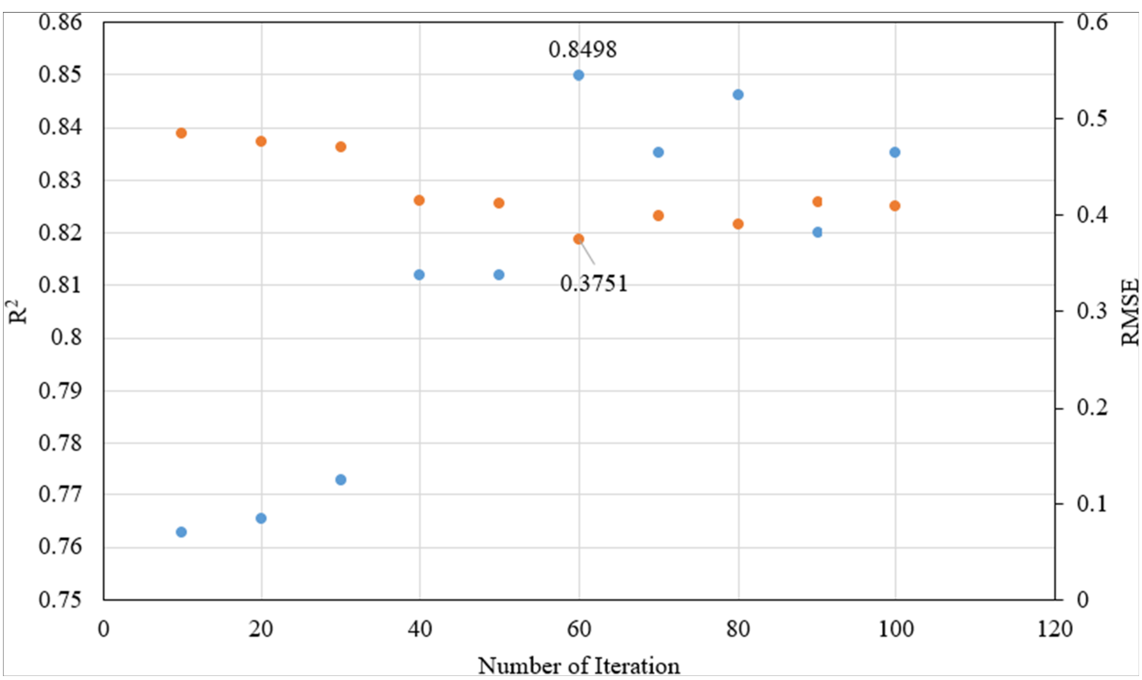


Fig. 4 Investigate the effect of iteration on ANN models

Table 3 The results of the optimum ANN model

Training		Testing	
R^2	RMSE	R^2	RMSE
0.8982	0.3137	0.8015	0.4206

Number of iterations

The number of iterations is another parameter affecting the performance of the prediction system. It is the same as the iteration parameter in the ANN. In addition, here in their hybrid networks, some researchers have reported the effectiveness of the number of iterations in their prediction models (Ghaleini et al. 2018; Koopialipoor et al. 2018c). They usually have their best system performance at 300 to 600 iterations, while researchers who have used the ABC method have achieved proper performance in the range of 150–250 (iterations) (Ghaleini et al. 2018; Koopialipoor et al. 2018c). In this case, the number of iterations from 50 to 500 was analyzed in order to determine the effect of this parameter. Moreover, due to the comparison, the used structure is the same as the ANN structure. Figure 8 illustrates the effect of the number of iterations on the rockburst prediction model. As can be seen, the results of the model performance in the repetition number of 300 are at an acceptable level. Also, the runtime of this number is less than the subsequent iterations.

Ultimately, a model with 80 bees and 300 iterations was chosen as the best model in terms of runtime reduction to predict rockburst in the intelligent system. Table 4 shows the results of the best model made with this technique. Figure 9 illustrates the values of rockburst prediction for the total data. The ABC-ANN model offers better performance than the previous two models for the prediction of rockburst in deep tunnels and underground spaces.

Sensitivity analysis

In this research, the response surface method is used aiming to optimize the model and search the largest contribution of the model's input parameters. By specifying the number of variables and the maximum and minimum limits set for each variable, this method designates the test matrix. Therefore, the number of tests and levels of each variable are determined in each test. When numerous variables need to be analyzed, this method is fully preferable to high-volume procedures such as a complete factorial. The test design is such that reliable statistical results are obtained even without a retest. Thus, this method will facilitate the research process as well as reducing time and costs. It is worth noting that in this analysis, the range of changes is between − 1 and 1, indicating the direct and inverse relationship between the changes. The more the line of variation becomes vertical, the lower the impact of that parameter will be.

Here, the perturbation graph is presented. It allows comparing the effect of all parameters at a specific point in the design space. The reference point is placed at the midpoint of all factors determined by the zero code. The steep of a parameter indicates the response sensitivity to that parameter. The relatively smooth line indicates the insensitivity of the

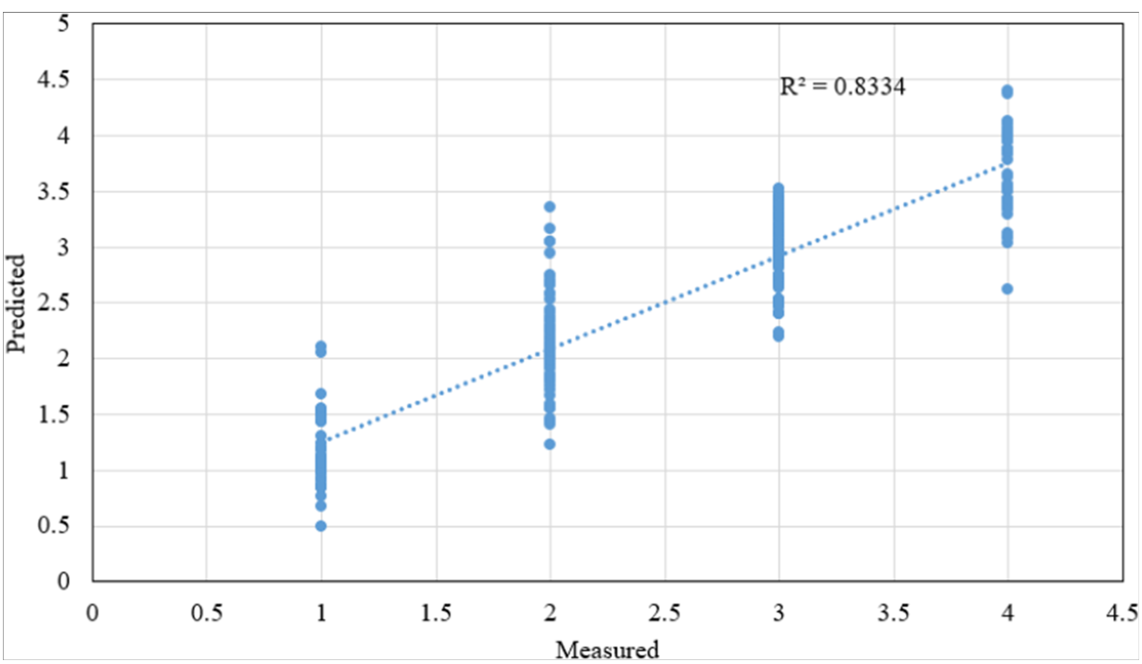


Fig. 5 Results of R^2 for all data using the ANN model

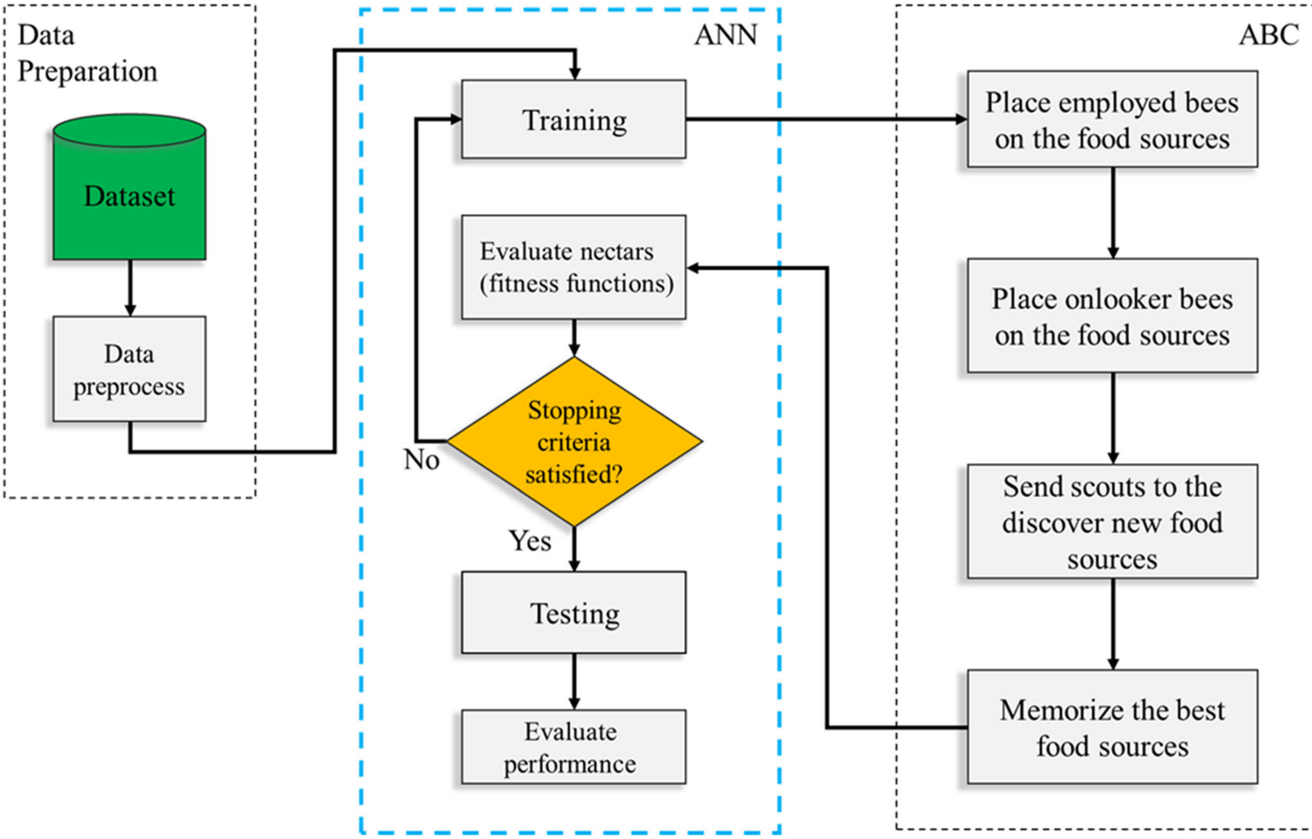


Fig. 6 A total structure of ABC-ANN for the prediction of rockburst

response to the change in that particular agent. It is noteworthy that the effect of interactions is not visible in this graph.

Here, the variables A, B, C, D, E, and F are MTS, UCS, UTS, SCF, B, and W_{et}, respectively. As observed in Fig. 10,

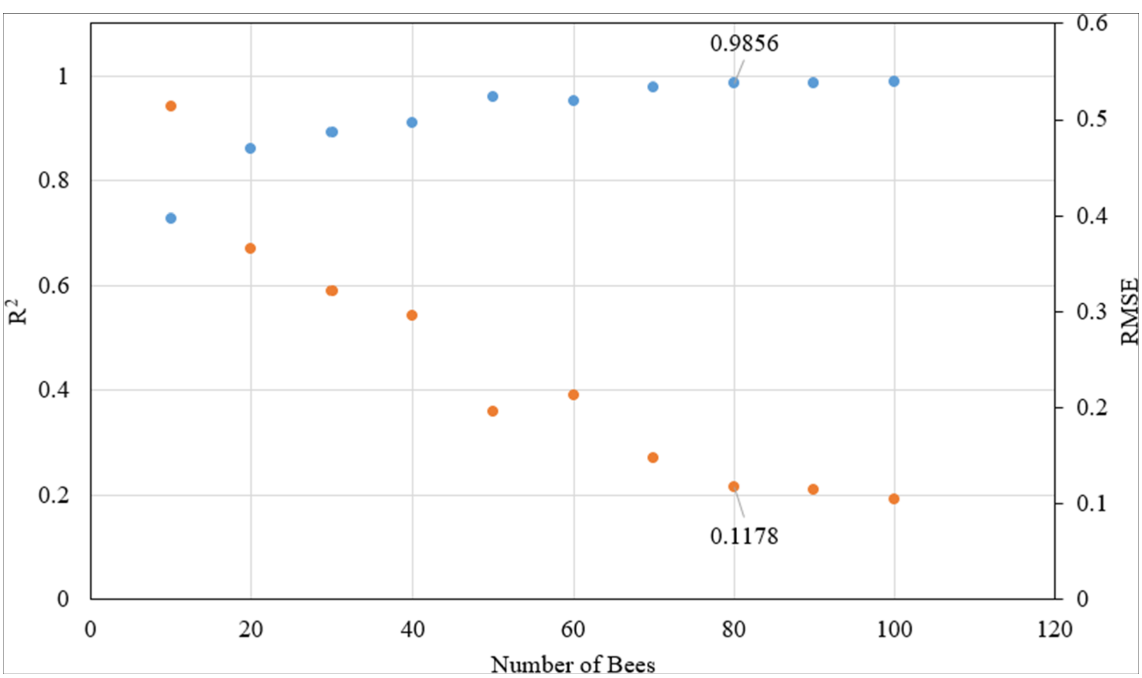


Fig. 7 The effect of bee numbers on results of rockburst prediction

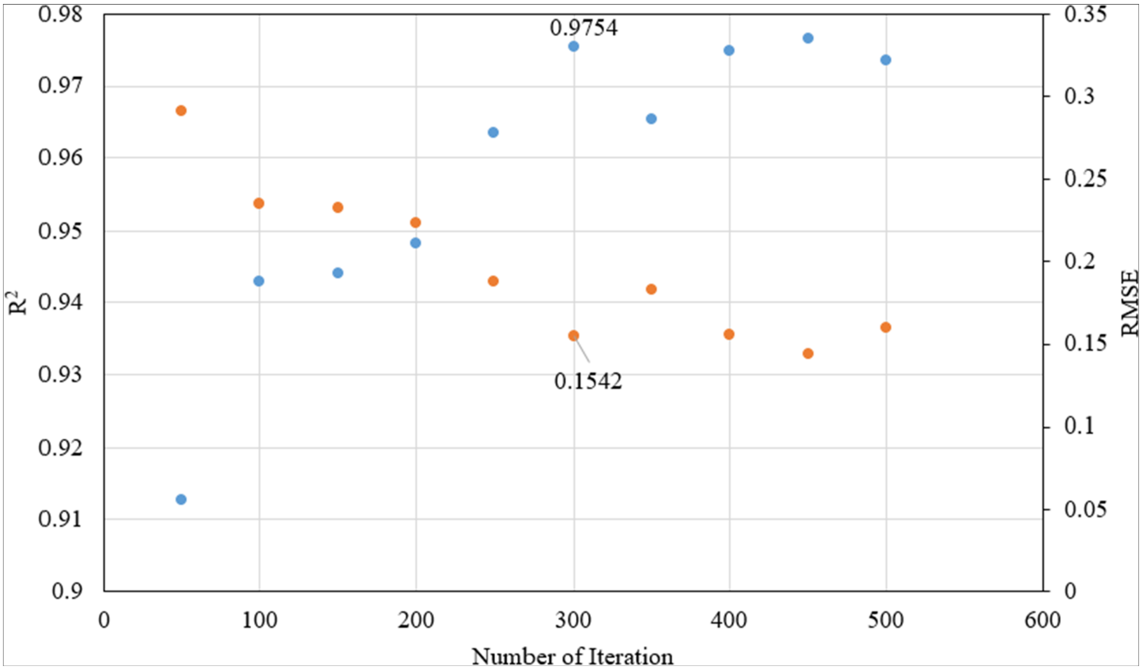


Fig. 8 The effect of iteration numbers on results of rockburst prediction

the MTS and W_{et} parameters have a greater effect, while compared with other parameters, the UCS parameter has a lesser effect on rockburst.

Application of prediction methods

Rockburst is one of the dangerous phenomena occurring in tunnels and mines, particularly at deep areas. This phenomenon can cause damage to the facilities. Rockburst is categorized into four different levels based on its intensity. The precise prediction of this phenomenon can significantly help designers and engineers of underground structures to mitigate the risk of rockbursts.

To assess the performance of the models proposed in this study, 50 events which occurred in underground mines and tunnels were randomly selected. In terms of intensity, rockburst was divided into four levels for these cases. The results of the three methods of MVR, ANN, and ABC-ANN were used in order to compare the outcomes with the actual results. Figure 11 simply shows the application of rockburst prediction methods with real data. As observed, each model shows some values of the prediction for this phenomenon. In this figure, the ABC-ANN model accurately predicts rockburst based on the four levels. As can be seen, 46 samples of rockburst events are predicted accurately by the ABC-ANN method. This is despite the fact that only 27 samples are correctly determined by the ANN method. Therefore, it is possible to control the dangers in these areas carefully using the proposed ABC-ANN model.

Table 4 The results of the optimum ANN model

Training		Testing	
R^2	RMSE	R^2	RMSE
0.9987	0.1073	0.9656	0.1281

Conclusions

Rockburst is one of the dangers occurring in deep underground mines and tunnels. Precise understanding of this phenomenon can reduce or control its destructive effects. The use of models which is able to predict the behavior of this phenomenon accurately is a matter for experts in this field. For the same reason, in this research, rockburst has been assessed and predicted based on real data in tunnels and underground mines using artificial intelligence and its development technique. In the present study, 246 samples of rockburst events of various intensity of risk were collected. The data used to predict this phenomenon included the following: MTS (σ_θ), UCS (σ_c), UTS (σ_t), SCF (σ_θ/σ_c), B (σ_c/σ_t), and W_{et} (EEI). Two intelligent models were implemented and developed in this study. First, the ANN model was designed at different conditions and developed to its maximum capacity in predicting rockburst. Then, a new model was developed in this field using the ABC optimization algorithm. By ABC, the previous model was trained and its various conditions were investigated. The results of the new hybrid model ABC-ANN indicated

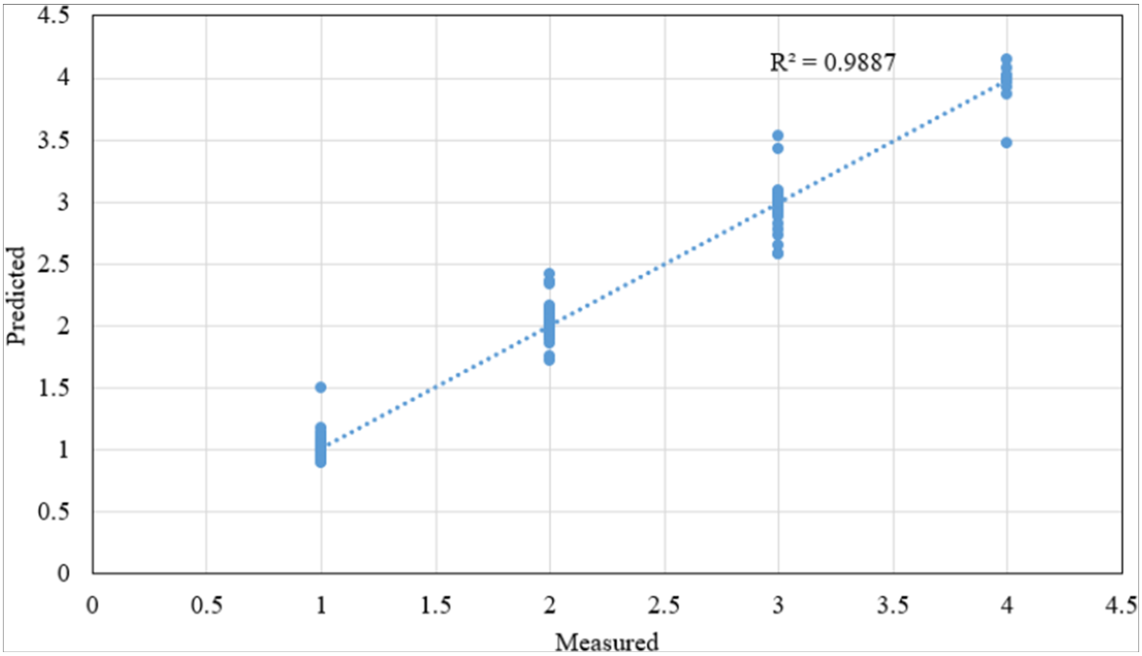
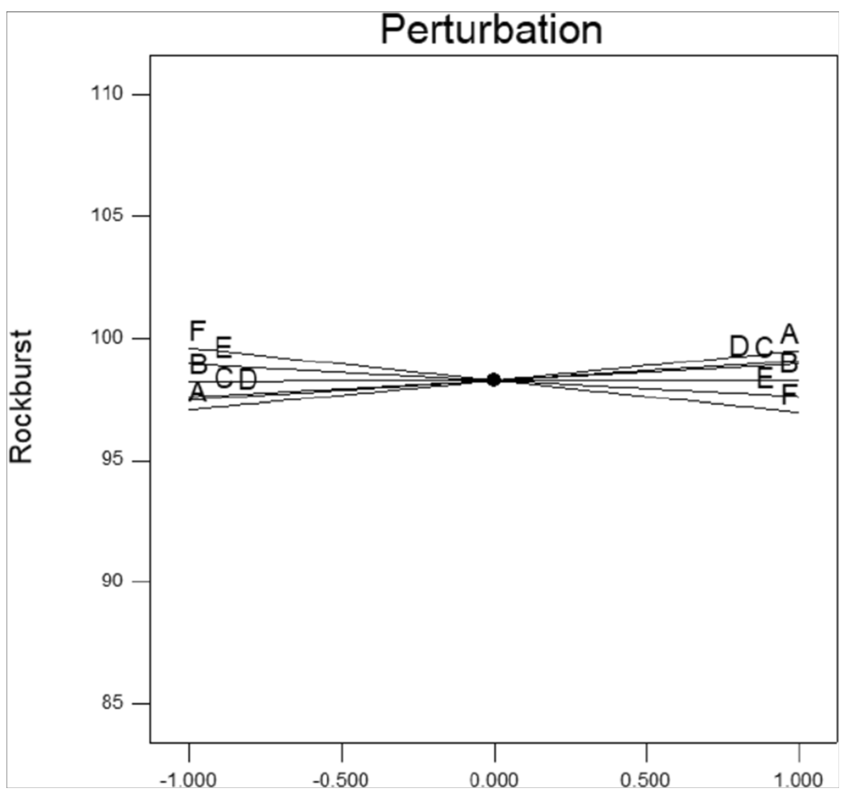


Fig. 9 Results of R^2 for all data using the ABC-ANN model

a proper improvement in the performance of the prediction systems of rockburst phenomenon. Finally, a comparison was eventually made between different models to examine the four risk levels of this phenomenon in tunnels and underground mines, indicating that newly developed models were able to predict accurately and assess risk levels of rockburst which allow designers and specialists to investigate and control the hazards.

Fig. 10 Parameters effects on the probability of rockburst



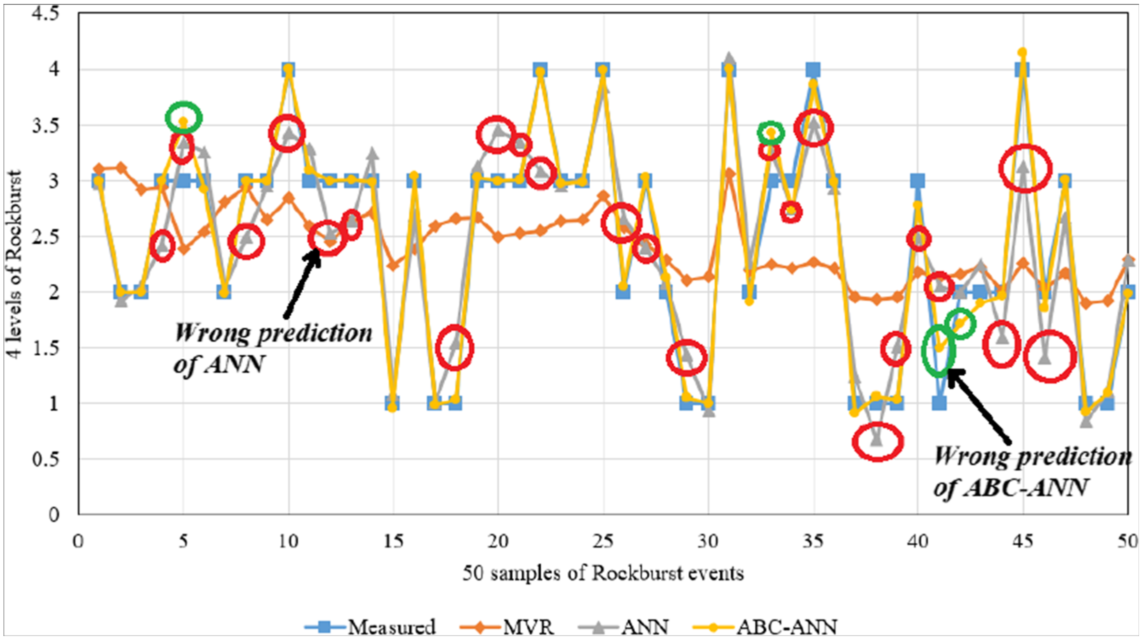


Fig. 11 A comparison between developed models for the prediction of rockburst

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