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Review article

A review of soft computing technology applications in several mining problems

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ABSTRACT

Soft computing (SC) is a field of computer science that resembles the processes of the human brain. While conventional hard computing is run based on crisp values and binary numbers, SC uses soft values and fuzzy sets. In fact, SC technology is capable of address imprecision and uncertainty. The application of SC techniques in the mining industry is fairly extensive and covers a considerable number of applications. This paper provides a comprehensive overview of the published work on SC applications in different mining areas. A brief introduction to mining and the general field of SC applications are presented in the first section of the paper. The second section comprises four review chapters. Mining method selection, equipment selection problems and their applications in SC technologies are presented in chapters one and two. Chapter three discusses rock mechanics-related subjects and some of representative SC applications in this field. The last chapter presents rock blasting related SC applications that include blast design and hazards. The final section of the paper comments on the use of SC applications in several mining problems and possible future applications of advanced SC technologies.

Contents

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1. Introduction

Mining[1] is one of the earliest primary industries of human civilisation [1]. It is considered a key industry for many countries, and it has huge ripping effects on other industries. In comparison to past centuries, the efficiency of modern mining has been dramatically improved through the development of associated technologies. Many innovative mining methods and theories have been developed by a multitude of scholars and engineers. Advanced high-tech computing technologies with improved machineries have significantly contributed to the development of the mining industry. In fact, modern mining is an advanced amalgamation of all the fundamental sciences.

In the case of actual mining activities, the mining manager frequently encounters many complex decision-making problems without sufficient data or precise information available to overcome them. An inappropriate decision could endanger people's lives and cause irreversible damage to the mining economy, considering the huge size of the capital of mining. The main causes of difficulties in the decision-making processes in mining can be categorised as follows:

- Uncertainties in commodity markets
- Geological and geotechnical uncertainties of rock mass
- Lack of clarity of qualitative and linguistic expressions of mining-associated factors
- Subjectivity of individual decision makers
- Uncertain effect of weights of single, multiple, and mutual relationships of mining-related factors
- Possibility of undefined mechanisms of rock mass behaviours under particular conditions

To overcome these difficulties, many researchers have employed soft computing (SC) technologies in mining-related subjects. The definition of soft computing is '*a collection of methodologies that aim to exploit tolerance for imprecision and uncertainty to achieve tractability, robustness, and low solution cost*' [2]. The principal SC technologies can be categorised as fuzzy algorithms, neural networks, supporting vector machines, evolutionary communication, machine learning, and probabilistic reasoning. McCulloch and Pitts [3] introduced an initial model of an artificial neural network (ANN), which was recognised as the first study of artificial intelligence. Since then, a significant amount of ANN-related research has been conducted. In 1994, SC became a formal area of computer science [4] and many new and hybrid algorithms, e.g., ANFIS [5], DENFIS [6], swarm intelligence and bio-inspired computations [7], computational intelligence aided design (CIAD) [8], were introduced with the help of advanced computer technology. SC's advantages in treating imprecision and uncertainty have fascinated engineers and scientists, and it has propagated rapidly to other industries. So far, SC has achieved meaningful progresses in many industries. However, its history of use in mining industry is rather short. The purpose of this review is to generate constructive discussion of employing SC technology in the mining industry by reviewing previous applications of SC technologies in several mining problems.

2. Mining process and applications of soft computing technologies

Normally, there are five stages of a mining application: prospecting, exploration, development, production, and reclamation. The location, geometry, extent and worth of the mineral deposit can be estimated with in the prospecting and exploration stage. If the deposit has minable value, then appropriate mining methods can be selected for development and exploitation. Based on the method selected, the mining process used for the removal of valuable minerals can be executed. Such process includes drilling, blasting, loading, and hauling of the materials in the production phase. At the end of a mine's life, the mine will be closed through reclamation processes. During the process of mining, several problems can be addressed using SC techniques. The issues that can be addressed using SC technologies are reviewed in this section, which is comprised of four review chapters. Mining method selection, equipment selection problems and previous applications of SC technologies are presented in chapters one and two, respectively. Rock mechanics-related subjects and some SC applications are discussed in chapter three. The final chapter presents rock blasting-related SC applications, including blast design and blast hazards.

2.1. Mining method selection

Mining method selection (MMS) is a crucial issue in the planning process of mining, and choosing the most appropriate mining method for a given mineral deposit among available alternatives is the goal of MMS. In fact, MMS significantly influences the economics, safety, and productivity of mine. Furthermore, MMS is recognised as a multiple-attribute decision-making (MADM) problem that requires concerning numerous factors, such as technical and industrial problems, financial concerns, and mining related policies, environmental and social issues. Fig. 1 demonstrates a conceptual frame work of MMS.

As shown in Fig. 1, not only numerous main criteria but also their sub-criteria need to be in the consideration of MMS processes. For instance, Nicholas [9] categorised the factors considered in MMS process, i.e., the 3D features of the deposit, geological and geotechnical surroundings, environmental and economic considerations, and other industrial factors. In addition, political and social limitations, machinery, and workforce supply conditions are also important factors. Besides, it is rather difficult to delimit the ranges of criteria which have a huge influence on the selection process. In addition, there are a few mines that can be mined by a single mining method, but the majority of them require the use combinations of two or more feasible methods.

2.1.1. Conventional MMS methods

A few researchers have worked to develop an effective MMS model. In 1973, a mining method classification system had demonstrated by Boshkov and Wright [10] which recognised as the one of first quantitative approaches. The first quantitative ranking system for MMS analysis presented by Nicholas [11], but the proposed system had a critical defect in that all criteria were considered equally important. Nicholas [9] modified the initial MMS method by adopting weighting factors for the criteria, but this modification received negative reviews because of the narrow ranges of score disturbs the optimum selection. Later, Miller-Tait et al. [12] reformed the Nicholas method by extending the maximum and minimum scoring domain.

2.1.2. MMS using soft computing technologies

Although conventional mining method classifications and quantitative and qualitative ranking systems are very convenient for MMS processes, the possibility of subjective effects by decision makers remains. Thus, with the intention of solving this complex problem, different SC approaches have been designed by various researchers.

[1] In this review paper, 'mining' is associated with all activities that extract mineral resources both above and below ground, not including petroleum and natural gas.

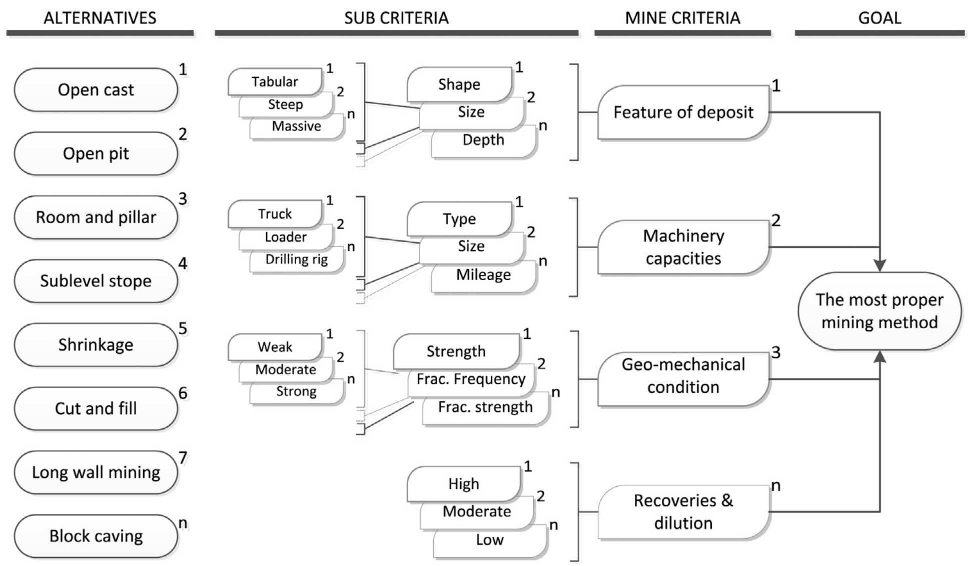

Fig. 1. Conceptual frame work of mining method selection.

Yun and Huang [13] applied a fuzzy algorithm [14] to MMS. The algorithm consisted with three stages. In the first stage, fuzzy relation equations calculating hamming distances between the geological requirements of candidate mining methods and the geological characteristics of the mine to be planned were formulated. In the second stage, the system estimated the technical and economic values of each candidate mining method using data from mines with similar conditions. In the last stage of the system, multiple objective decisions were made based on the results from the first and second stages.

Guray et al. [15] developed a MMS expert system for underground mining. The study developed 13 different virtual experts for 13 different underground mining methods. It used base knowledge systems from Nicholas's [9] quantitative ranking method. The system contained additional criteria such as capital cost, operating cost, productivity, surface subsidence, spontaneous combustion, and lake presence factor, which were not included in Nicholas's method. One merit of the system is a tutorial tool for MMS for inexperienced engineers.

Bitarafan and Ataei [16] introduced a method to assign weights to different criteria. A fuzzy multiple-attributes decision-making method based on Yagar's method [17] and a fuzzy dominance method proposed by Hipel [18] were utilised in the proposed system. One noticeable feature was that the system used exponential scalars to represent the importance of the given criteria, which could dramatically increase the value of the criteria that have similar conditions to the target deposit. Otherwise, the value would be greatly reduced. The method was successfully applied in MMS in one of the anomalies at the Gol-e-Gohar iron mine in Iran, and the block caving method was chosen as the best mining method.

Ataei et al. [19] used analytical hierarchy process (AHP) [20] to solve the MMS problem of the Golbini No. 8 deposit in Jajarm, Iran. The authors formulated the AHP architecture with 13 criteria with 6 alternatives, and 17 experts from various operations were elected to make the pairwise comparison matrixes. As a result of the study, cut and fill mining method was chosen as the most suitable method among six alternatives.

One of the drawbacks of the AHP is that the decision makers intuition will expressed as exact values [21]. Another shortcoming of AHP is the improper handling of intrinsic vagueness in the pairwise comparison process and the judgement scale biases [22]. To overcome these demerits, Naghadehi et al. [23] applied the fuzzy analytical hierarchy process (FAHP) [24] to MMS. In the FAHP system, the weights of the main criteria was decided by a fuzzy algorithm and six candidate-mining methods were ranked by the AHP. The suggested system was employed to the Jajarm Bauxite mine in Iran, and the conventional cut and fill method was chosen as the most appropriate mining method.

The underground mining method selection (UMMS) was developed by Alpay and Yavuz [25] by utilising AHP and Yager's method [17]. Thirty-six MMS-related criteria were selected for the programme, obtained from a study of Hartman and Mutmansky [1]. Rankings of the alternatives were generated by the UBC ranking system [12]. One of the merits of the system is a sensitivity analysis of the final ranking process of all alternatives so that users can recognise the significance of each criterion. The system was applied to the Eskisehir-Karaburun underground chromite mine in Turkey, and the square set stoping method was chosen as the most preferred method for the mine.

Azadeh et al. [26] modified Nicholas's [9] quantitative ranking method, and the vagueness of decision maker's judgements were expressed by trapezoidal fuzzy numbers. The system was composed of two AHP models that were categorised as 'technical operation' and 'economic'. A case study was carried out on the northern anomaly of the Choghart iron mine in Iran to validate the developed system and compared with the Nicholas method.

Namin et al. [27] presented a fuzzy mining method selection with interrelation criteria (FMMSIC), which is a hybrid decision-support system combining FANP [28] and fuzzy entropy (FUE) [29]. The initial weighting processes were carried out with the FANP and FE, and a modified Fuzzy TOPSIS [30] was used for the MMS ranking process. To verify the validity of the FMMSIC, a case study was carried out at the Gol-e-Gohar deposit in southern Iran. Eleven underground mining methods with 16 MMS-related parameters were considered candidate methods and criteria for the selection process, respectively. Ultimately, the block caving method was chosen as the most appropriate mining method for this mine, which was backed by several experts' opinions. Some of representative references of the use of SC in MMS problems are tabulated in Table 1.

In spite of significant effort by researchers, there is still no MMS system that can cover the entire range of the MMS problem. Recent MMS studies have mostly focused on assigning weight factors to criteria and tried to simulate the exact thought process of decision makers. To reduce the scale of MMS, candidate-mining methods can be set before running the MMS system, but then the

Table 1
Summary of representative studies of MMS with SC technologies and MCDM methods.

Author	Soft computing technologies					MCDM methods	
	EXS	FUA	ANN	YAM	FUE	AHP	TOPSIS
Yun and Huang [13]		●					
Bandopadhyay and Venkatasubramanian [31]	●						
Gershon et al. [32]	●						
Yiming et al. [33]	●		●				
Guray et al. [15]	●						
Bitarafan and Ataei [16]		●		●			
Ataei et al. [19]		●				●	
Alpay and Yavuz [25]				●		●	
Naghadehi et al. [23]							
Azadeh et al. [26]		●				●	
Namin et al. [27]		●			●	●	●
Gupta and Kumar [34]						●	
Yavuz [35]				●		●	

EXS, expert system; FUA, fuzzy algorithm; ANN, artificial neural network; YAM, Yagar's method; FUE, fuzzy entropy; MCDM, multiple criteria decision making; AHP, analytic hierarchy process; TOPSIS, technique for order performance by similarity to ideal solution.

application of a very subjective process is inevitable. On the other hand, given that many mines are switching to underground mining after completing the surface exploitation, none of the developed MMS systems can address such multiple sequential choices of open pit to underground mining.

2.2. Mining equipment selection problem

Excavation, loading and hauling are fundamental activities in mine development and exploitation which utilise significant number of equipment. Selecting the proper size, type, and number of equipment has significant effects on mine profitability because the cost of mine equipment is over several million dollars and maintenance costs are high. For example, the operating costs for haul trucks alone may account for one-third to one-half of the total mining operation costs, and poor selection will directly result in higher costs and significantly lower economic performance of the mining operation [36]. Given the significant influence of the equipment selection problem (ESP) on the mine productivity, the goal is to optimise efficient material transfer systems from a set of origins to destinations considering the unique mine plans and features of the mine in question so that the total mining cost will be minimised by optimising the equipment selection over the life of the mine. Some of typical surface and underground mining equipment is shown in Fig. 2.

2.2.1. Characteristics of traditional approaches to the ESP

In spite of the importance of selecting proper equipment of a mining project, the ESP is one of the most difficult tasks in the mine-planning process. To select a suitable combination of equipment for a certain mining project, the decision-making engineer and/or a team should consider various factors during the selection process, such as the climate of the region, geological and geotechnical characteristics, environmental constraints, hauling distance, production requirement, site-specific conditions, types, sizes, numbers, and homogeneity of equipment, possible combination of equipment fleets, and so on. The applicable equipment differs between surface and underground mining. Therefore, most ESP projects are limited in their selection scope to either surface or underground processes. Furthermore, there is no an ESP programme that can cover all ESP-related conditions. The difficulties of the ESP are not only due to the numerous possible alternatives and criteria that have to be considered but also to the ambiguous and linguistic expression of variables. Thus, many mining companies rely on the information from previous events and their intuition to select the right pieces of equipment. In fact, the task of ESP is generally left to knowledgeable experts [38].

Various methods have been applied to the ESP, and some of the methods are briefly enumerated in this chapter. Samanta et al. [39] and Markeset and Kumar [40] employed the Life Cycle Costing (LCC) method to the ESP. LCC analysis is an appropriate method for determining the cost per hours of equipment over the entire span of a mine's life, but one should note that it only considers cost parameters so other parameters are not reflected. Some important mining concepts were also utilised for the ESP. Smith et al. [41] and Burt and Caccetta [42] applied the matching factor ratio, which is the relation between muck loading time and truck influx to loading point. Queuing theory was also employed in the ESP by Farid and Koning [43], Ercelebi and Bascetin [44]. Further information about conventional ESP solutions and mining concepts is available in the cited references.

2.2.2. The ESP with soft computing technologies

In the late 1980s, mining researchers and engineers directed attention to adapting SC technology to the ESP. Fuzzy algorithms, expert systems, genetic algorithms (GA) [45], and hybrid systems have been successfully utilised to solve the ESP. Some mathematical and psychological decision-making methods, such as AHP and Yager's method, were adapted with fuzzy algorithms, and postoptimality analysis strongly supported the reliability of the results. The Visekriterijumsko Kompromisno Rangiranje (VIKOR) method [46,47] was also utilised to solve the ESP, and the details of the application can be found in Aghajani Bazzazi et al. [48]. Since the ESP needs to consider numerous factors with alternative transfer systems, adopting SC technology with MCDM methods show meaningful solution than conventional ESP approaches. Fig. 3 briefly demonstrates processes of ESP through SC technologies with MCDM methods and conventional approach with mining experts.

The following reviews are some representative SC approaches to typical ESP studies. Bandopadhyay and Venkatasubramanian [49] adopted a semantic tree type of expert system for a surface ESP. The process of the programme was simplified by selecting certain alternatives from a given set of alternatives, which satisfies the given goals and objectives. A final decision would be made by considering alternative evaluations based on the decision makers' knowledge of the expert system.

A rule base ESP expert system, named VP-Expert, was developed by Amirkhanian and Baker [38]. The system included 930 rules that interpreted ground conditions, operational performances, and the prerequisite operations of a given mining project. Several ESP experts provided their knowledge through questionnaires, and the required equipment specifications were obtained from performance handbooks of major equipment manufacturing companies. VP-Expert consisted of four sub-knowledge bases depending on the

Fig. 2. Typical surface and underground mining equipment.
Referred photos from Caterpillar [37].

equipment requirements for different sizes of projects, which is a scope limitation of the proposed expert system. Three actual ESPs were evaluated with VP-Expert. As a result, the equipment selected by company was analogous to VP-Expert's selection. One defect of the programme is that it only counts new equipment. Therefore, the calculated productivity is bigger than the actual selection, which could only be adjusted by changing the factors for soil condition and operation inside the system.

Bascetin and Kesimal [50] conducted a study on selecting optimum coal-hauling systems from an open-cast coal mine to a power plant. In view of the advantages of treating ambiguous linguistic explanations of a fuzzy algorithm, it was considered a useful method compared to the linear programming and expert systems. Three alternatives were suggested by the initial transfer system analysis, and 21 operational attributes were set as criteria. The membership grades of each criterion were defied by decision makers, and the reciprocal matrixes of the criteria were constructed to express the importance of each criterion.

Haidar et al. [51] developed a ESP support system using a hybrid method of the knowledgebase system and the GA for open-cast mining. The system was formulated with two connected parts. The first knowledgebase system defined the general type of equipment considering mine parameters, characteristics of overburden, and operation conditions of the mine. Then, the optimum configurations of models, numbers, and the operating life of the equipment were defined by the GA. To validate the system, postoptimality analysis was conducted on the GA by adding four different rules. Four case studies were conducted to compare the results of the four developed systems based on postoptimality analysis given the actual equipment selection for the mines. The system selected almost the same types of equipment as used at the compared mines, and the total costs of the proposed selections were even less than the actual operating systems of two mines.

Marzouk and Moselhi [52] demonstrated a programme to select earthmoving equipment fleets using a computer simulation engine and GA. The computer simulation programme was developed to estimate the fitness of the chromosomes generated in the proposed GA. According to one scenario of mine conditions, chromosomes and genes were generated to define the fleet configuration and the number of equipment types, respectively.

Ganguli and Bandopadhyay [53] established an expert system for a surface mining ESP. In the system, the surface ESP was divided

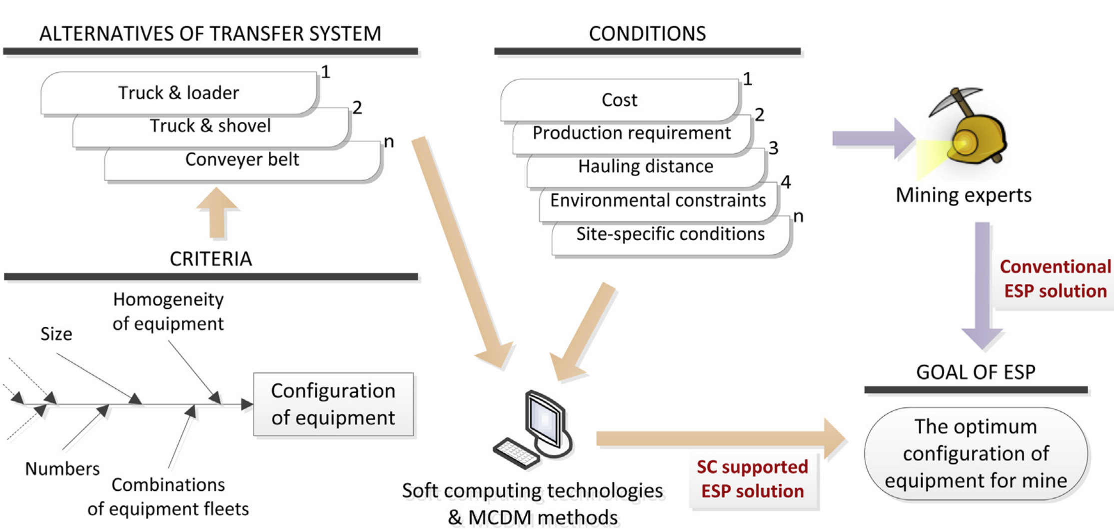

Fig. 3. Comparison of conventional and soft computing (SC) supported ESP solution.

Table 2
Summary of representative studies of ESPs using SC technologies and MCDM methods.

Author	SC technologies				MCDM methods			Auxiliary methods
	EXS	FUA	GA	YAM	AHP	TOPSIS	VIKOR	
Bandopadhyay [56]		●						
Bandopadhyay and Venkatasubramanian [49]	●							
Denby and Schofield [57]	●	●						
Clarke et al. [58]	●							
Amirkhanian and Baker [38]	●							
Haidar and Naoum [59]			●					
Bascetin and Kesimal [50]		●		●	●			
Haidar et al. [51]			●					
Ganguli and Bandopadhyay [53]	●							
Marzouk and Moselhi [52]			●					Simulation
Bascetin [54]		●			●			
Marzouk and Moselhi [60]			●					Pareto optimality
Iphar and Goktan [61]		●						
Li and Song [62]			●			●		
Aghajani Bazzazi et al. [48]	●	●			●		●	Entropy method

EXS, expert system; FUA, fuzzy algorithm; GA, genetic algorithm; MCDM, multiple criteria decision making; YAM, Yagar's method; AHP, analytic hierarchy process; TOPSIS, technique for order of preference by similarity to ideal solution; VIKOR, Visekriterijumsko kompromisno rangiranje method.

into seven different tasks, and the user was asked to input conditions to specify relative importance of each factor for the chosen task. Then, the listed equipment would be evaluated and ranked based on the conditions given by the user. The expert system was validated at the Malanjkhand Copper Mine in India, and the recommended equipment fleets from the expert system and the actual employed equipment were analogous. However, the system had limitations and defects. The system suggests a type of equipment, but the production requirements of the applied mine are not clearly related. Additionally, the weight of the factors assigned by the user can be very subjective, which seriously decreases the creditability of the system.

Bascetin [54] used the AHP to select an ore transportation system for an open-pit coal mine in Turkey. Four transportation systems were proposed as alternatives, and the cost of operational-technical requirements was identified as a major factor that was composed of several sub-criteria. The reciprocal matrixes were constructed by experts.

Aghajani Bazzazi et al. [48] modified the VIKOR and AHP methods to rank and select a set of alternatives in a condition with conflicting criteria in a surface mining ESP. Authors chose VIKOR to rank the attributes of alternatives that were based on their 'closeness' to the positive ideal solution (PIO). In spite of the many advantages of VIKOR, it was not able to address uncertainties and the vagueness of the decision maker's subjective perception because the rating was quantified in crisp values. To mitigate this problem, triangular fuzzy numbers were adopted in VIKOR. After creating normalised decision-making matrixes using VIKOR modified with triangular fuzzy numbers, AHP and the entropy method [55] were used to calculate an initial mean value of fuzzy and interval numbers for weighting criteria. An imaginary iron open pit mine was used to evaluate the proposed system with contributions by six evaluation experts of real case ESP.

SC technologies have been successfully applied to the ESP in mining, and they have been practically utilised in actual ESP. However, because the ESP is a part of mine production planning, it would be beneficial to include mine production scheduling as well. Further discussions are required to include equipment salvage and service for long- and short-term equipment purchasing strategies. Some representative ESP studies adopting SC technologies are listed in Table 2.

2.3. Rock mechanics

Geological and geotechnical information are essential for all mining activities. Particularly in hard rock mining, rock mechanics are of vital importance because all the plans and activities deal with rock and rock masses. To generate an appropriate mine design and plan for a certain mineral deposit, collecting geological data and estimating basic characteristics of the rock masses are fundamental requirements. However, anisotropic and heterogeneous attributes of rock masses and complex geological features are not easy to analyse. Furthermore, the explorable outcrops are usually highly limited. Laboratory rock sample tests are broadly executed at the preliminary stage of a mining project, but they represent a very small portion of the entire rock mass. In addition, the test results of specimens that survived sample collection and test processes could be highly biased [63]. To provide proper guidelines for rock engineering, many rock classification methods have been introduced, such as the rock mass rating (RMR) system [64,65], Q-system [66], and Geological Strength Index (GSI) [67]. Through the contribution of developed technologies and practical tools of rock mechanics, mine design and planning became very systematic and assisted in maintaining a safe working environment. However, there are still many areas that can be improved and innovated because mining and rock mechanics deal with the complexity and uncertainty of rock masses.

2.3.1. Difficulties of rock mechanics and soft computing applications

Rock mechanics is a subject that addresses uncertainties. Since the 1960s, numerous scientists and engineers have endeavoured to understand the characteristics and behaviour of rock masses. Many empirical theories and methods have been published on this area.

Along with advanced computing technologies, numerical analyses have been widely used to simulate the behaviour of rock masses. Many different types of numerical analytic methods are frequently used as a preliminary process of rock engineering design, and some of representative methods are shown in Fig. 4.

In fact, modern rock mechanics have been greatly enhanced by numerical analytic methods and advanced computing technologies [70]. However, numerical analyses are expensive and time-consuming tasks. Furthermore, they are always implemented under certain restricted conditions, and exact modelling of in situ rock masses is still not possible. From this point of view, SC technologies are relatively inexpensive and much faster than numerical analysis. The ability to handle uncertainties and insufficient data of SC technologies can be very beneficial tools for rock mechanics. Fig. 5 demonstrates an example of underground stope stability analysis via artificial neural network and empirical and numerical analysis.

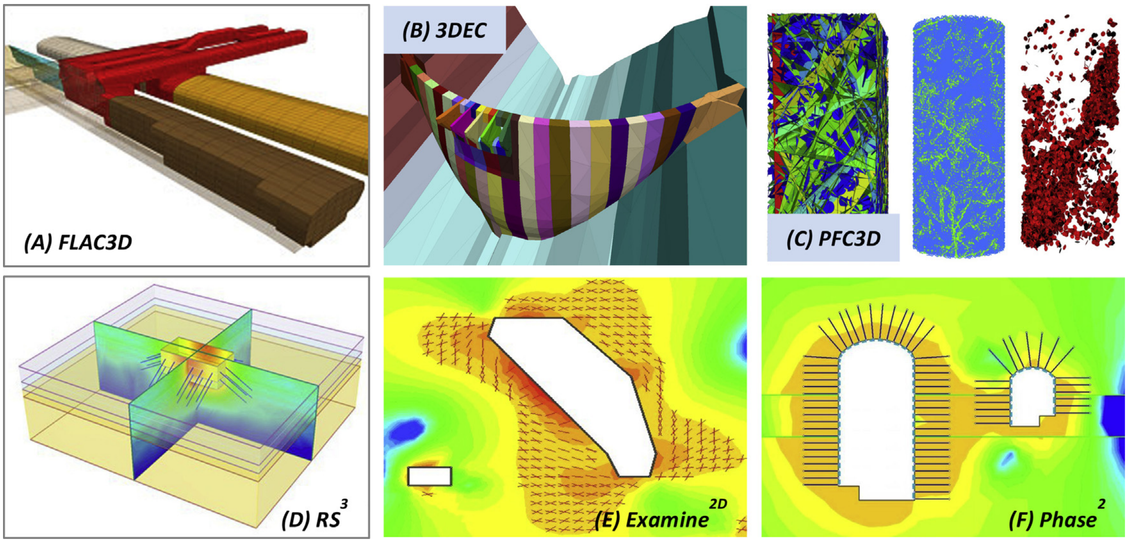

Fig. 4. Representative numerical analysis methods. (A) FLAC3D: 3D continuum modelling analysis, (B) 3DEC: 3D distinct element analysis, and (C) PFC3D: 3D dis-continuum particle flow analysis from Itasca consulting group [68]. (D) RS^3: 3D finite element stress analysis, (E) $Examine^{2D}$: Boundary element analysis, and (F) $Phase^2$: Elasto-plastic finite element stress analysis from Rocscience [69].

As shown in Fig. 5, the feature of the nature rock mass is anisotropic and heterogeneous. Therefore, defining the influential factors to stability of underground stope and their effective weights are very difficult and ambiguous. In this point of view, ANN could be a reliable method to analysis the stability of underground stope with respect to the strength of treating unclearness and uncertainty. Since the mid-1980s, SC technologies have been utilised to assess broad aspects of rock mechanics subjects, and this chapter will review the topics of identifying strengths and the deformation modulus, predicting rock mass performances, estimating stability, and classifying rocks. Given the vast body of research on rock mechanics, more detailed subjects and explanations can be found in the cited references.

2.3.2. *Identifying strengths and deformation modulus*

One of the essential parameters of rock mechanics is the unconfined compressive strength (UCS). Normally, the UCS is determined by a laboratory test and/or published USC related indexes. The laboratory UCS test requires very careful experimental setups because the results are highly sensitive to the test conditions. Index tests are inexpensive but limited only when the properties are realised in any laboratory [71]. Another crucial parameter for rock mechanics is the deformation modulus. The in situ test to determine the deformation modulus requires considerable cost, so various empirical equations have been suggested [72–74]. However, the empirical equations are problematic due to uncertainties of the heterogeneous nature of the rock, the variability of rock types, and limited data availability [75]. To identify the rock strength properties and deformation modulus, some researchers adopted SC technologies to overcome these difficulties.

Meulenkamp and Grima [76] predicted UCS using ANN. The Levenberg–Marquardt algorithm was used as a training function, and the ANN structure consisted of two hidden layers. Equotip-determined hardness, density, porosity, grain size, and rock types were the input parameters, and UCS was set as the output. The performance of prediction and generalisation of the proposed ANN was validated by using 34 rock samples. As a result, the ANN system predicted USC more accurately than the conventional multi-regression analysis predictions. Instead of ANN, Alvarez Grima and Babuška [77] employed the Takagi-Sugeno (TS)-type [78] fuzzy model to predict the unconfined compressive strength of rock samples. The performance of the proposed fuzzy model was compared with the multiple regression analysis and showed better results.

Kayabasi et al. [75] adopted a rule-based fuzzy inference system to predict the deformation modulus. Five existing empirical equations and measured values were compared with the developed

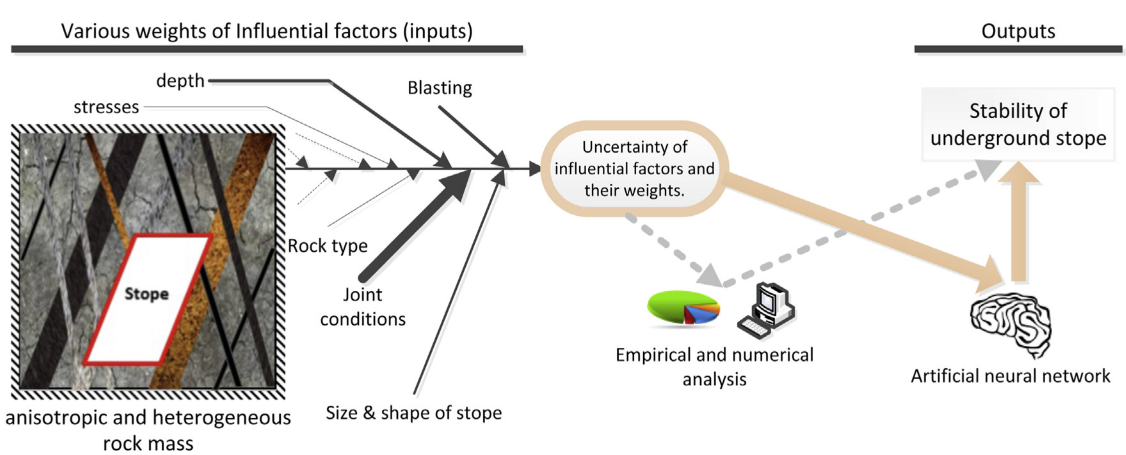

Fig. 5. An example of underground stope stability analysis via ANN and empirical and numerical analysis.

Table 3
Summary of representative studies identifying the strengths and the deformation modulus of rock masses with SC technologies and auxiliary methods.

Author	Object	Soft computing technologies						Auxiliary methods	
		EXS	FUA	ANN	NEF	GA	GEP		
Lee and Sterling [79]	FM			●					
Meulenkamp and Grima [76]	UCS			●				EHT	RA
Alvarez Grima and Babuška [77]	E_d		●					EHT	RA
Singh et al. [80]	I_s, UCS, σ_t			●				VIDSIII	
Kayabasi et al. [75]	E_d		●						RA
Gokceoglu et al. [81]	E_d				●				
Sonmez et al. [82]	UCS, E_{el}		●						RA
Sonmez et al. [83]	E_{el}			●					
Feng et al. [84]	VEM					●		PSO	
Majdi and Beiki [85]	E_d			●		●		PCA	
Beiki et al. [86]	E_d			●			●	SA	
Vardakos et al. [87]	E_{el}, σ_v, σ_h, ν, ϕ					●		FDM	RA
Rafiai et al. [88]	FC			●					
Rezaei et al. [89]	UCS		●					RA	SA
Bagheripour [90]	R_p			●		●		PCA	

EXS, expert system; FUA, fuzzy algorithm; ANN, artificial neural network; NEF, neuro fuzzy system; GA, genetic algorithm; GEP, genetic programming; FM, failure modes; UCS, unconfined compressive strength; E_d, modulus of deformation; I_s, point load strength; σ_t, tensile strength; E_{el}, modulus of elasticity; VEM, viscoelastic mode; σ_v, vertical stress; σ_h, horizontal stress; ν, Poison ratio; ϕ, friction angle; FC, failure criteria; R_p, rock permeability; EHT, equotip hardness tester; VIDSIII, a high resolution semi-automatic image analysis system; PSO, particle swarm optimisation; PCA, principal component analysis; SA, sensitivity analysis; FDM, finite difference method; RA, simple and/or multiple regression analysis.

fuzzy inference model. The fuzzy inference system was much better at predicting performance than the empirical equations, but it was limited in the applicable rock types because of the small number of input datasets. Some of representative references are given in Table 3 to show the rage and tendency of applications of SC technologies to identify the strength and deformation modulus of rock masses.

2.3.3. Predicting rock mass performance and estimating stability

The geotechnical monitoring of rock mass performances have a vital importance through both the development and exploitation stages of mining because identifying rock mass structures and characteristics are important tasks at the initial stage of a mining project. The initial mine design and procedure is generally adjusted by the assessment of the monitored values of rock mass performance to ensure the safety and profitability of the mine. The main reasons for geological monitoring are summarised as follows [91]:

- To note the values and important changes of geotechnical parameters
- To maintain safety through the entire operation processes
- To validate initially assumed factors and parameters for models
- To organise proper ground and environment treatment and remedial work

Improper rock performances, such as slope sliding, subsidence, rock burst, roof and wall failure, and inappropriate stress convergence can cause major disasters that cause loss of life and property damage. Thus, predicting rock performance is an essential task in mining activities. Several empirical methods for various rock performances have been presented by scholars, but generally, the proposed methods are only valid in the investigated area. Generally, theoretical and numerical analyses are widely used to predict rock performance and estimate stability. However, determining all the parameters, ranking their weights, and clarifying their relative effects are very difficult tasks to accomplish. Additionally, with respect to the complexity and uncertainty of geological conditions, some assumptions are inevitable in theoretical and numerical analysis. Detailed information about the empirical and theoretical methods used to predict rock performances and estimate stability can be found in publications by Goodman [71] and Hoek [63].

To overcome the previously described difficulties, several researchers applied SC technologies to predict rock mass performances and estimate stability. Yang and Zhang [92] employed ANN to predict the stability states of an underground opening. The key point was to check the importance of each input parameter in the operation of ANN, and the Relative Sensitivity of Effect (RSE) was defined for input units on output units, which can represent the relative importance of the effect of input parameters on output units. The RSE was applied to coal mine roadway data from Sheorey [93]. In that study, stability states were set as the output, and the span and depth of roadway, USC, RQD, J_n, J_r, J_a, J_w, SRF, dry density, rock type, and joint orientation were set as the inputs. As a result, RQD and rock type appeared to be the most sensitive parameters to the stability of the roadway. Darabi et al. [94], Rafiai and Moosavi [95], and Mahdevari and Torabi [96] studied tunnel convergence estimation with ANN. Darabi et al. [94] predicted convergence and subsidence at a tunnel in the Tehran No. 3 subway line using several empirical models, numerical analysis (FDM: finite difference method), regression analysis, and ANN. The data for ANN were obtained from 50 subways in Iran and Turkey that have similar conditions to the studied tunnel. The results were compared with the observed values. ANN has stronger predictive ability than other methods. Rafiai and Moosavi [95] showed the limitations of elastic behaviour and isotropic in situ fields of former analytical solutions and applied ANN to overcome those defects. Initial data were generated by simulating FLAC [97], which is a finite difference method numerical analysis programme. The design of experiments technique (DOE) [98] was adopted to reproduce data sets. Mahdevari and Torabi [96] indicated the problem of TBM jamming while it is excavating through a weak rock area and emphasised the importance of predicting tunnel convergence. Conventional ANN and radial-based ANN were employed, and predictive capabilities were compared with regression analysis. These studies validated the ANN-based solution by comparing it to conventional analytical solutions and numerical analysis. Some representative references that applied SC technologies to predicting rock mass performance and estimating stability are summarised in Table 4.

2.3.4. Rock classification

Rock mass classification systems provide substantial benefits to the feasibility and preliminary stages of mine design even with insufficiently detailed information on the rock masses [63]. A few studies attempted to classify the rock masses along with the history of mining and rock mechanics. Several representative rock classifications are briefly introduced in this chapter, and further

Table 4
Summary of representative studies predicting rock mass performance and estimating stability with SC technologies and auxiliary methods.

Author	Object	Soft computing technologies						Auxiliary methods	
		EXS	FUA	ANN	NEF	GA	GEP		
Yang and Zhang [92]	ES			●				RSE	
Deng and Lee [99]	DG			●		●		FEM	
Kim et al. [100]	DG			●				RSE	SA
Li et al. [101]	DG		●	●					
Li et al. [102]	DG		●			●	●		
Alimoradi et al. [103]	RMR			●				TSP230	
Darabi et al. [94]	TC, SS			●				FDM	RA
Rafiai and Moosavi [95]	TC			●				FDM	DOE
Mahdevari and Torabi [96]	TC			●				SA	RA
Li et al. [104]	DG		●					MWC	RAC
Yurdakul et al. [105]	SE_{CUT}				●			ANFIS	DENFIS
Ghasemi et al. [106]	Pillar sizing		●						
Choobbasti et al. [107]	DG			●				PSO	
Guo et al. [108]	DG			●				WIPS	

EXS, expert system; FUA, fuzzy algorithm; ANN, artificial neural network; NEF, neuro fuzzy system; GA, genetic algorithm; GEP, genetic programming; ES, engineering state (either stable or unstable); DG, displacements and/or ground settlement; SE_{CUT}, specific cutting energy; RMR, rock mass rating; TC, tunnel convergence; SS, subsidence; RSE, relative strength of effects; FEM, finite element method (numerical analysis); TSP230, tunnel seismic prediction; FDM, finite difference method; SA, sensitivity analysis; MWC, modified Wiebols–Cook criterion; RA, simple and/or multiple regression analysis; DOE, design of experiments technique; RAC, Rafiai criterion; ANFIS, adoptive network based fuzzy inference system; DENFIS, dynamic evolving neuro-fuzzy inference system; PSO, particle swarm optimisation; WIPS, wavelet intelligence prediction system.

information can be found in the cited references. Terzaghi et al. [109] proposed a rock load classification that was used to determine the steel support system in a tunnel. It was one of the first practical rock classification systems, but it received critical reviews because the qualitative assessments of classification were quite general, which could hinder an objective evaluation of rock masses. Later, the Rock Quality Designation (RQD) was developed by Deere [110], and the rock structure rating (RSR) was developed by Wickham et al. [111]. The RQD provides quantitative values of rock mass from the drilling core logs, and the RSR is known as one of the earliest quantitative classifications with rating values for the parameters. More recently, the rock mass rating (RMR) system [64,65], Q-system [66], and Geological Strength Index (GSI) [67] were developed, and currently, these are generally adopted in mining and construction projects.

Although there are considerable benefits to the developed rock mass classification systems, several drawbacks are often discussed among engineers. For instance, in the classifying process, determining the rate of each parameter is difficult, and it can be very subjective because the complex geological features are refractory to exact quantitative values. The classification results are often significantly different among individuals. Thus, the decision relies heavily on experts who have sufficient experience in mining and rock classification. To surmount these difficulties, several researchers attempted to adopt SC technologies for rock mass classifications. Hamidi et al. [112] applied a fuzzy algorithm to rock mass classification. In that system, the rock mass excavability (RME) [113] was used as the reference classification structure. The Mamdani fuzzy inference system (FIS) with seven input variables was applied with triangular and trapezoidal membership functions. Arithmetically, 15,750 if-then rules were generated, but 9300 rules were eliminated by the authors due to consideration of the fundamental attributes of rock masses. The fuzzy algorithm was applied two water-transfer tunnels in Iran whose excavation was to be performed by a tunnel-boring machine (TBM). The average rate of advance (ARA) was calculated with respect to the conventional formulas and the proposed fuzzy algorithm, and then these values were compared with the measured ARA. As a result, the study verified the applicability of the fuzzy algorithm to the rock mass classification problem. Some typical studies of rock mass classification using SC technologies are listed in Table 5.

Typical rock mechanics subjects such as identifying strength properties and deformation modulus, predicting rock mass performance, estimating stability, and rock mass classification using SC technologies are reviewed in this chapter. SC technologies have an important role in rock mechanics, and their ability to address uncertainties, insufficient information, and ambiguous linguistic expressions stand out when dealing with complex natural rock masses.

2.4. Identifying blasting design parameters and hazards

Blasting is one of the core activities in the development and exploitation stages of hard rock mining. Often there are different goals for different design provisions, but commonly, the objects are safety, obtaining a specific fragmentation and distribution, future ease of handling, and stability of the mine and surface [124]. This chapter will briefly introduce the general idea of blasting in mining and the difficulties in blasting design. Some representative early applications of SC technologies in blasting-related subjects are reviewed. More detailed knowledge on blasting related subjects can be found in Persson et al. [125] and Hustrulid [126].

2.4.1. General information about blasting in mining

In hard rock mining, blasting is the breaking of rock using explosives to obtain desired fragment sizes and distributions under the control of engineers. It has an important role in the mining industry and is still recognised as the most economical method to excavate ore. The exothermic chemical reaction of the explosive generates extraordinarily high pressure in the range of 1–20 GPa, and the detonation waves generated travel into the surrounding materials at several thousand metres per second. The surrounding rock will be melted, pulverised, crushed, and fractured by the exposure to such energies. The dynamic performances of objects are influenced by numerous parameters, such as the type and magnitude of explosives, blasting geometries, geological and geotechnical characteristics of rock masses, climate of the region, and so on. Moreover, the mutual interactions of these influencing parameters are even more complex because they are dynamically activated within several milliseconds. Images of the moment of bench blasting and an underground face-drilling machine are shown in Fig. 6.

2.4.2. Applying soft computing technologies to blasting-related subjects

Rock blasting is an uncertain activity in an indistinct rock mass. The exact geological and geotechnical data are practically impossible to obtain and organise, but rock blasting activities are planned based on this insufficient information. Furthermore,

Table 5
Summary of representative studies of rock mass classification using SC technologies and auxiliary methods.

Author	Reference classification method	Soft computing technologies						Auxiliary methods	
		EXS	FUA	ANN	NEF	GA	GEP		
Nguyen [114]	RMR		●						
ShengFeng et al. [115]	–		●						
Zhang et al. [116]	GU	●							
Juang and Lee [117]	RMR	●	●						
Butler and Franklin [118]	RMR, Q	●							
Juang and Lee [119]	RMR		●					FWA	
Habibagahi and Katebi [120]	RMR		●						
Aydin [121]	RMR		●						
Liu and Chen [122]	–		●					FDAHP	LDA
Hamidi et al. [112]	RME		●						
Jalalifar et al. [123]	RMR		●					RA	

EXS, expert system; FUA, fuzzy algorithm; ANN, artificial neural network; NEF, neuro fuzzy system; GA, genetic algorithm; GEP, genetic programming; RMR, rock mass rating system; GU, Gu's rock classification; Q, Q-system; RME, rock mass excavability; FWA, fuzzy weighted average; FDAHP, fuzzy delphi analytic hierarchy process; LDA, linear discriminant analysis; RA, simple and/or multiple regression analysis.

the rock blasting mechanism of generating blasting-induced gases and shock wave performance are still debated among blasting engineers, illustrating the lack of knowledge of the underlying mechanisms. Therefore, SC technologies could overcome these difficulties and several studies have been performed on this topic. For instance, Fig. 7 shows a typical ANN model configuration of peak particle velocity (PPV) prediction.

As shown in Fig. 7, the propagation of peak particle velocity (PPV) in this ANN model is a function of explosive, geometry of blasting plan, regional geological feature, and site specific factors such as distance, level, etc. However, practically, the actions and/or reactions of causative parameters of PPV are extremely complex under the conditions of the insufficient information on rock masses and uncertainties of rock blasting.

To overcome the difficulties on rock blasting, many researchers applied SC technologies. Chakraborty et al. [128] studied a new approach to predict blasting-induced vibration by adopting an on-line feature selection net (FSMLP) [129] and a fusion ANN network. The FSMLP was used to improve the predictability of the conventional ANN by selecting important features among those initially chosen as features influencing blasting-induced vibration. After training, the FSMLP only activates important features by increasing their attenuators, and minor features are eliminated from the feature set. The study focused on predicting PPV (peak particle velocity). Twelve blasting parameters with five empirical models were initially chosen as features, but only twelve superior features were selected out of seventeen for the estimation of blasting vibration. The architecture of the fusion networks was rather similar to the conventional multi-layer perceptron (MLP), because hidden neurons in hidden layers were substituted by MLP models. The results of the study showed that the performance of the fusion network was consistently better than empirical PPV prediction models

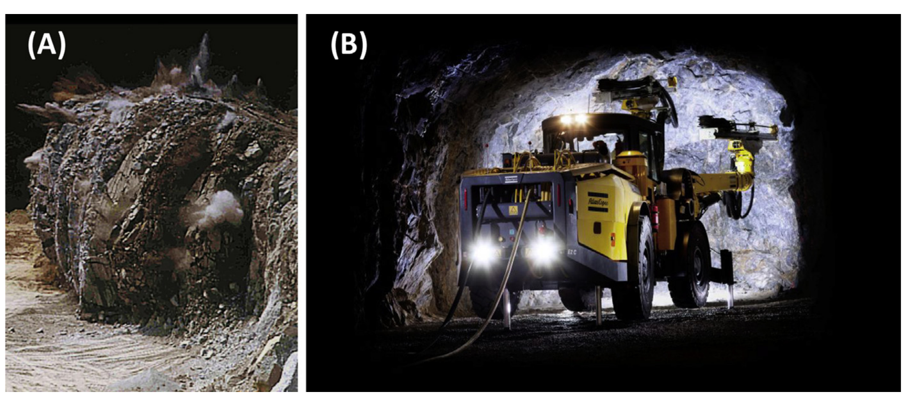

Fig. 6. Bench blasting (A) and undergrounding face drilling machine (B).
Referred photos from Atlas Copco [127].

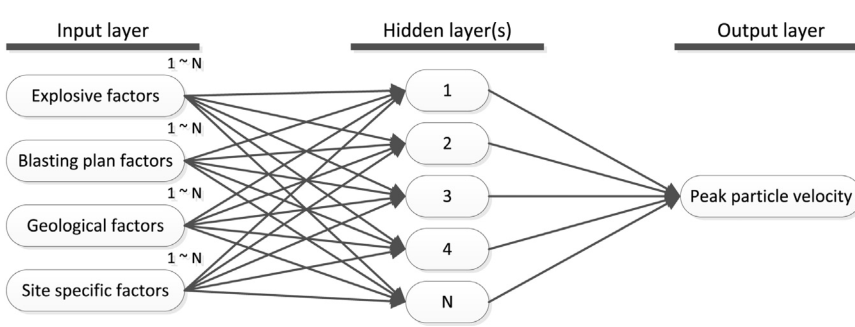

Fig. 7. An example of PPV prediction ANN model.

Table 6
Summary of representative studies Identifying blasting design parameters and hazards with SC technologies and auxiliary methods.

Author	Objects	Soft computing technologies						Auxiliary methods	
		EXS	FUA	ANN	NEF	GA	SVM		
Chakraborty et al. [128]	PPV			●				FSMLP	RA
Singh [150]	PPV			●				RA	
Singh et al. [130]	PPV, BFQ			●				RA	
Manoj and Singh [147]	BAO			●				RA	
Lu [131]	PPV, PPA, BFQ, FBF			●				NH-A	
Monjezi et al. [138]	BFR, MPL, TEX			●				RA	
Remennikov and Rose [151]	AF_p, AF_i			●					
Monjezi and Dehghani [141]	BBB			●					SA
Manoj and Singh [132]	PPV, BFQ			●				RA	SA
Monjezi et al. [152]	PPV			●				RA	SA
Kulatilake et al. [145]	BRF			●				RA	
Azimi et al. [153]	BD		●						
Monjezi et al. [140]	BP, BFQ, BBB			●		●		RA	
Dehghani and Ataee-Pour [154]	PPV			●					SA
Bahrami et al. [146]	BRF			●				RA	SA
Rezaei et al. [137]	BFR		●					RA	SA
Fişne et al. [135]	PPV		●					RA	
Monjezi et al. [155]	PPV			●				RA	SA
Ghasemi et al. [156]	BFR							MC	
Álvarez-Vigil et al. [133]	PPV, BFQ			●				RA	
Monjezi et al. [134]	BFQ, BBB			●		●			SA
Esmaeili et al. [142]	BBB				●			RA	
Ataei and Kamali [136]	PPV				●			ANFIS	
Verma and Singh [157]	PWV				●			ANFIS	
Manoj and Monjezi [158]	BFR						●	RA	
Manoj and Monjezi [143]	BBB						●	RA	
Sun et al. [149]	BOB			●					
Jang and Topal [148]	BOB			●				RA	
Lapčević et al. [159]	PPV			●					
Ghasemi et al. [160]	BFR		●	●					
Hajihassani et al. [161]	BAO			●				PSO	

EXS, expert system; FUA, fuzzy algorithm; ANN, artificial neural network; NEF, neuro fuzzy system; GA, genetic algorithm; SVM, support vector machine; ANFIS, adoptive network based fuzzy inference system; PPV, peak particle velocity; PPA, peak particle acceleration; PWV, P-wave velocity; FBF, frequency bandwidth factor; BFQ, blasting-induced frequency; BBB, blasting-induced backbreak; BFR, blasting-induced flyrock; BRF, blasting-induced rock fragmentation; BP, blasting parameters; BAO, blasting-induced air overpressure; BOB, blasting-induced overbreak; MPL, muck pile ratio; TEX, total explosive required; BD, blastability designation; AFp, air pressure pulse AFi, air pressure impulse; RA, simple and/or multiple regression analysis; FSMLP, on-line feature selection net; SA, sensitivity analysis; MC, Monte Carlo simulation; NH-A, nonlinear hydrocodone–autodyn; PSO, particle swarm optimisation.

and the conventional MLP. A few other studies attempted to predict PPV with SC technologies. Singh et al. [130] attempted to predict the blast-induced vibration and its corresponding frequency with two separate ANNs. Lu [131], Manoj and Singh [132], Álvarez-Vigil et al. [133], and Monjezi et al. [134] attempted to predict PPV and frequency in one ANN model, whereas Fişne et al. [135] employed a fuzzy algorithm, and Ataei and Kamali [136] utilised the adaptive neuro-fuzzy inference system (ANFIS) to predict PPV.

Rezaei et al. [137] employed the Mamdani Fuzzy Model to develop a flyrock-predicting system. Four hundred ninety flyrock datasets were collected at the Gol-e-Gohar iron mine in Iran, and 450 datasets were used to develop the fuzzy model. Burden, spacing, hole depth, specific drilling, stemming, charge per delay, rock density, and powder factor were set as inputs, and the flyrock range was set as the output. The proposed fuzzy model consisted of 390 fuzzy if–then rules, and the performance of the developed fuzzy model was much better than that of conventional statistical models. In addition, Monjezi et al. [138,139] attempted to predict flyrock with an ANN.

To overcome the difficulties in blasting design, Monjezi et al. [140] attempted to optimise open-pit blasting parameters using an ANN and a GA. The idea of the study was to optimise the blasting geometries that can minimise flyrock and backbreak of open-bench blasting. ANN was used to find an optimum formulation of blasting geometries that can minimise flyrock and backbreak and used as a fitness function of the GA. At the end of the GA process, a chromosome was selected the lowermost flyrock and backbreak.

Several researchers attempted to predict the backbreak phenomenon in an open-pit mine blast. Monjezi and Dehghani [141] utilised ANN, Esmaeili et al. [142] employed ANN and an adoptive network based fuzzy inference system (ANFIS), and Manoj and Monjezi [143] adopted a support vector machine (SVM) [144] to predict the backbreak. Kulatilake et al. [145] and Bahrami et al. [146] attempted to predict fragmentation using ANN, and an air over pressure predictive ANN model was built by Manoj and Singh [147]. Recently, Jang and Topal [148] and Sun et al. [149] utilised ANN to predict overbreak on a tunnel blasting excavation. Some representative studies of blasting-related topics applying SC technologies are tabulated in Table 6.

3. Discussion and conclusion

Applications of SC technologies to various mining-related subjects are reviewed in this paper. Furthermore, their applications and potential solutions to difficulties in mining engineering have been discussed.

Many types of SC technologies have been applied to MMS problems including expert system, fuzzy algorithm, ANN, Yagar's method, fuzzy entropy combined with AHP, and TOPSIS. Most of the studies focused on setting weight factors for each criterion and tried to simulate the exact thought process of decision makers. To narrow down the scale of the MMS problem, setting the candidate mining methods before running an MMS system could still be a very subjective activity. On the other hand, given that many mines are switching to underground mining after the surface exploitation, none of the developed MMS systems can handle the multiple sequential choices required in the transition from open pit to underground mining.

As with the MMS problem, the expert system and fuzzy algorithms were successfully applied to the ESP in combination with other MCDM and auxiliary methods. In addition, GA was recently practically utilised in the actual ESP. However, because the ESP is a part of mine-production planning, it would be useful to include mine production scheduling as well. Additionally, further discussions are required to include equipment salvage and services for long- and short-term equipment purchasing strategies.

Typical rock mechanics subjects that use SC technologies were reviewed in the second section of chapter three. ANN was consistently applied to identify strengths and the deformation modulus of rock masses, predict rock mass performance, and estimate their stability. Fuzzy algorithms and GAs were often employed with various auxiliary methods. Fuzzy algorithms were principally utilised in the rock mass classification problem. In some cases, the expert system was also applied. As discussed, the SC technologies have taken an important role in rock mechanics, and their abilities to address uncertainties, insufficient information, and ambiguous linguistic expressions stand out in treating complex natural rock masses.

Rock blasting is an uncertain activity in indistinct rock masses. To overcome the difficulties, several studies consistently employed ANN to predict some important blasting-related effects. Fuzzy algorithms, GAs, neuro-fuzzy algorithms, and support vector machine technologies were often adopted as well. The superiority of SC technologies has been verified by comparing results from SC applications with conventional statistical and mathematical prediction methods.

Each soft computing technology has advantages and disadvantages. For instance, ANN normally shows excellent nonlinear approximation performance but it is hard to enlighten the inputs and outputs relationship as often it called as 'black box'. As well as each mining conundrum has a different aspect of problem and solution. For example, mining method selection (MMS) can be recognised as a multiple-attribute decision-making (MADM) problem that can be efficiently handled by a method that can represent significance and ranking of criteria. From this point of view, fuzzy algorithm is much more suitable algorithm than ANN for MMS. Thus, it is important to cautiously concern the attribute of a problem to amplify the advantages of applied soft computing method.

Precise data and information is expensive, and exact geological and geotechnical data are practically impossible to obtain and organise. In addition, the weighted effects of associated factors of certain mining problems are still unclear. Their mutual interactions increase the complexity of problems. However, mining engineers frequently encounter many decision-making problems due to all the uncertainties and impreciseness previously described. A remedy for those problems may be to adopt advanced SC technology, which may play a large role in mining engineering.

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