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Review Article

Review on the Development of Mining Method Selection to Identify New Techniques Using a Cascade-Forward Backpropagation Neural Network

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The most crucial event in a mining project is the selection of an appropriate mining method (MMS). Consequently, determining the optimal choice is critical because it impacts most of the other key decisions. This study provides a concise overview of the development of multiple selection methods using a cascade-forward backpropagation neural network (CFBPNN). Numerous methods of multicriteria decision-making (MCDM) are discussed and compared herein. The comparison includes several factors, such as applicability, subjectivity, qualitative and quantitative data, sensitivity, and validity. The application of artificial intelligence is presented and discussed using CFBPNN. The Chengchao iron mine was selected for this investigation to pick the optimum mining method. The results revealed that cut and fill stoping is the most appropriate mining method, followed by sublevel and shrinkage stoping methods. The least appropriate method is open-pit mining, followed by room and pillar and longwall mining methods.

1. Introduction

Mining methods are techniques for extracting mineral resources from the Earth's surface. Owing to the difficulties associated with the lithological and mechanical properties of mineral deposits, a unique exploitation technique cannot be employed to extract all of them. When extracting ore deposit, it is critical to employ either technique that has the greatest conceptual coherence with the geomechanical and lithological conditions of that mineral deposit. For the employed extraction method, it eventually has to be cost effective compared with alternative methods [1]. The selection of the mining method (MMS) refers to the procedure for picking an ideal extraction technique for mineral deposit. It is hard to switch the picked method, manipulate, and/or swap it with another after the MMS process has been finalized, and the mining of ore deposit has begun using the proposed approach [2]. Because this alternative is typically expensive, the entire project may become uneconomical. Therefore, the selection of the mining method, MMS, seems to be an irrevocable step in mine planning [3]. However, choosing an extraction method for ore deposit is entirely reliant on the resource's ambiguous lithological and geomechanical properties. Due to such ambiguity, no positive value can be ascribed to any of these attributes. For example, mineral resources might not be allocated a positive slope or volume if precise numbers are used [4]. The basic goal in selecting how to mine ore deposits is to develop an ore extraction technique that is fully appropriate within the given conditions. Before deciding on an exploitation technique, it is crucial to know the important characteristics that each mining method requires. MMS is primarily influenced by several factors, including ore deposit geometry (e.g., size, shape, and dip), subsurface properties (e.g., mineral composition, lithology, homogeneity, deformation, and erosional), geomechanical characteristics of rocks and ore (e.g., elastic deformation, in situ stresses, consolidation, competency, and various physical properties), economical aspects (e.g., stockpile weight, rate of production, and mine life) [5].

MMS requires the study, assessment, and evaluation of selection factors, a duty which is frequently completed by engineers according to their mining knowledge, expertise, and intuition. Because of the complexity of the assignment, it can be accomplished significantly more effectively by someone who has a thorough understanding of the subject. It is critical to imitate a human expert's judgment and comprehension. The MMS problem is a comprehensive system from the standpoint of system theory. The characteristics of this system are as follows [6]:

(1) There are multiple attributes to consider while choosing a mining method.
(2) The popularity of the orebody, product demand, enterprise index, and other factors influences the choice of the mining approach.
(3) Relationships between components are intricate. These components are linked to excessive ambiguity, both in structures and in content.
(4) There are multiple dimensions in choosing a mining strategy. The MMS system comprises subsystems, each of which has its own set of subsystems. Mining machines, ore-dressing machines, and processing machines, for example, are all parts of the running machine. Consequently, the MMS system is a massive system with multiple dimensions.
(5) An open machine is the mining strategy of choice. This type of system communicates with external systems regularly by exchanging materials, energy, and statistics.
(6) Information is often ambiguous. Statistics in the technology, economy, geology, and other fields are usually unclear in the exploitation system.
(7) Environmental factors must be considered during the manufacturing process. The main factor is the complex geology of the orebody; as a result, the exploitation system is difficult to explain using a mathematical model.
(8) The machine is in a state of flux. The specifications of the machine, in terms of area and time, often change.

When deciding on an appropriate mining method for ore deposits, various criteria must be considered. Numerous techniques, such as the Nicholas, modified Nicholas, and UBC methods, were designed to assess the appropriate method for ore extraction. Unfortunately, none of such methods consider the weight values for every factor that influences the MMS. Thus, this study aims to provide a review of the development of MMS tools explaining the advantages and disadvantages of each one and provides a new technique based on the application of a cascade-forward backpropagation neural network (CFBPNN), which is adopted as a case study in the Chengchao iron mine.

The rest of the paper is structured as follows. Section 2 focuses on the development of MMS tools. Multicriteria decision-making (MCDM) methods are discussed in Section 3. In Section 4, the MMS employing soft computing and artificial intelligence is discussed. Section 5 discusses the MMS using the application of CFBPNN (Chengchao iron mine case study). Finally, in Section 6, conclusions, recommendations, and suggestions for future work are presented, respectively.

2. Development of MMS Tools

Researchers have investigated the challenges of MMS. Numerous techniques have been generated to evaluate the appropriate extraction strategies for mineral deposits with respect entirely to their natural and geomechanical characteristics. The first qualitative classification scheme for underground method selection was developed by Boshkov and Wright [4]. Consequently, their system assumes that surface mining is no longer an option. Morrison proposed a system based on the width of ore, guide type, and strain energy accumulation [7]. Nicholas and Mark [1, 8] proposed a quantitative device. The device is based on a series of steps, categorized as follows:

- The geometry and mineral composition of the ore
- The characteristics of the ore zone and host rocks (e.g., hanging wall (HW) and footwall (FW))
- A numerical rating based entirely on the addition of scores
- Applying a weighting factor to the categories

Hartman and Mutmansky [6], Laubscher [9], Marano and Everitt [10], Bandopadhyay and Venkatasubramanian [11], Agoshkov et al. [12], Mutagwaba and Terezopoulos [13], Miller-Tait et al. [14], Hamrin [15], Tatiya [16], Basu [17], Kahriman and Karadogan et al. [18, 19], Kesimal and Bascetin [20], Clayton et al. [21], Guray et al. [22], Wei et al. [23], Shahriar et al. [24], Mihaylov [25], Miranda and Almeida [26], and Bascetin [27] have written several papers on MMS. MMS techniques are classified into three categories: qualitative techniques, numerical rating techniques (scoring), and decision-making models. Table 1 provides a brief history of proposed approaches to MMS and their main issues.

Despite the perceived advantages of these approaches, a scientific method for MMS that links subjective and objective decision-making is still lacking. Hence, a few MMS choices are primarily based entirely on experience, wherein

Table 1: Summary of the existing mining method selection (MMS) techniques and main issues associated with them.

Author(s)	Year	Characteristics	Drawbacks
Peele, Church	1941	Uses broad descriptions of thickness, dip, and strength of ore and strength of rock	Only used when there are similar situations in popular methods
Morrison	1976	The criteria for selecting a mining method are overall descriptors of ore size, type of rock support, and buildup of strain energy	The preference for one method over another is determined by various combinations of ground conditions
Nicholas	1981	Numerically rates the characteristics of ore deposit based on lithological and geomechanical properties of ore and host rocks	The chosen mining method is the result of combining evaluation and high ranking
Laubscher	1981	Based on a rock mass classification system that takes into account expected mining effects on rock mass strength	The preferred method is solely determined by the rock mass classification system
Hartman	1987	The decision is made based on the lithological and geomechanical characteristics of ore deposits	A flow chart must be created to define the mining method
Loubscher	1990	If the area available for undercutting is large enough, this method can be modified to include the hydraulic radius, making it feasible for more competent rock	The classification must be altered in order to link rock mass rating to hydraulic radius
Nicholas	1993	Altering the selection procedure by incorporating a weighting factor [28]	
Miller, Pakalnis, and Poulin	1995	The Nicholas approach has been modified to demonstrate more emphasis on stoping methods, better portraying typical Canadian mining design practices	Insufficient and inadequate for conducting accurate and robust MMS process

the outcome of the technique used is the only much like the deposit without absolutely catering to the distinctiveness of the deposit in question. Consequently, the mining industry cannot gain sufficient confidence in the previously implemented approaches. Most of the choices cannot be quantified; consequently, there is a need for a scientific method to select the mining technique. Table 1 lists the existing MMS methods and their main drawbacks.

3. Methods of Multicriteria Decision-Making (MCDM)

A modern method for MMS uses MCDM tools for resources within the process [29]. MCDM is efficient at enabling selection; nevertheless, its use really has not gained widespread acceptance in the mining industry, primarily in MMS [30]. MCDM methods are widely used in a wide range of industries, including manufacturing, management of water resources, quality assurance, mass transit, and product innovation, and they provide a platform for further MMS research [31].

The following decision-making strategies have been used within the MMS process: AHP, PROMETHEE, TOPSIS, TODIM, VIKOR, ELECTRE, and GRA. However, they are no longer widely used within the mining industry, and recent work extends on available research of MCDM methods because they allow for similar exploration in MMS [32]. Furthermore, OCRA, ARAS, COPRAS, CP, and SAW are supplemental decision-making techniques, since no recent evidence could encounter their application within the mining industry [32, 33]. MCDM methods have been used to entail final choice. To acknowledge importance of MCDM methods, their contributions to various decision-making processes must be emphasized. The availability of a technique allows for the use of a variety of MCDM approaches. These tools, regrettably, can be unaffordable and are not always tailored to certain situations. Furthermore, acquiring a tool is only cost effective if it will be used multiple times. Furthermore, no unique strategy is appropriate for all situations, and each approach has benefits and drawbacks that vary depending on the context. Table 2 lists the various MCDM approaches.

4. MMS Using Soft Computing (SC) and Artificial Intelligence

Several studies on MMS have been conducted using MCDM methods. However, some of these studies failed to account for parameter uncertainty. Fuzzy logic could be employed to counteract this uncertainty [31, 96, 97]. Yun and Huang have integrated a fuzzy scheme into the MMS [98, 99]. This technique is broken down into three steps. During the first phase, fuzzy relation equations are derived to calculate Hamming intervals between both the lithological design for the proposed mining method and the geotechnical qualities of the mine that had been built. The technical and economic values of each suggested mining methods are approximated in the second phase employing statistical data from mines with similar circumstances. In the last phase, several goal decisions will be determined based entirely on the outcomes of the first and second stages [100].

Bitarafan and Ataei proposed a method for assigning weights to distinguishing criteria [101]. In the proposed method [102], Yager's technique is used wholly in a fuzzy various ruling method [103] and a fuzzy primacy technique introduced by Hipel has been used. One unique aspect is that the technique adopted accelerating primitives to reflect the relevance of the criteria provided, that can substantially raise the quality of the metrics having equivalent requirements to the ore deposit. Alternatively, it may be decreased drastically [104]. Such technique has been effectively implemented in MMS in one of the anomalies in Iran's GoleGohar iron mine,

Table 2: Summary of the various MCDM methods.

MCDM method	Description	Advantages	Disadvantages
AHP	Saaty created it to enable the decision-makers make more organized decisions [34, 35]. A multilevel hierarchical structure of objectives, criteria and alternatives is used [36]. Evaluate the significance of key measurements before correlating possible options with regard to each factor. Eventually, calculate the utmost preference of each decision option and also the overall score of the decision options [37]	Simple to be adopted, and its scale can be adapted to meet the needs of various decision-making situations [38]. Its popularity arises from the belief that it requires less data than other MCDM methods and can manage evaluation criteria [39]. When data are measured on different scales, it can be normalized and aggregated later [40]. It is accurate in taking decisions because of its potential to prove the consistency of the independent expert assessment [41]	As the list of considerations to be matched grows, calculations can become challenging. The ultimate determination (overall score of options) may be impacted by increasing the scale of relative importance [38]. As stated earlier in the section, AHP is only valid with positive reciprocal matrices [40]
PROMETHEE	In 1982, it was firstly created by Brans and Vincke [42]. The PROMETHEE, for each alternative, calculates both positive and negative flows (Φ+, Φ−), respectively, based on the weight assigned to each criterion [43]. PROMETHEE I through VI was created to serve as outranking methods. In each criterion, alternatives are compared in pairs [44]	Can compare a finite set of alternatives to competing criteria [45]. Pair-wise comparison is no longer necessary once options are removed or provided during the assessment. It is employed to select the optimal underground ore transportation and mining method [46]. Calculations are very complicated; therefore, the method is only suitable for experts	Because of the scarcity of selection guidelines, decision-makers find it hard to set up preference limits and thresholds [47]. The uncertainty of the set up limits is also not wholly responsible for, despite the fact that a parametric analysis is then conducted [48]. The subjective input of preferences adds to the uncertainty [49]
TOPSIS	In 1981, Hwang and Yoon addressed TOPSIS, which stands for order preferences by similarity to ideal solution [50]. Ranks the alternatives according to the distance between the ideal positive and negative solutions [51, 52]. The TOPSIS method's best alternative is the one that comes closest to the positive ideal solution [53, 54]	TOPSIS allows to reach the right solution faster than most MCDM methods. Its logic is sound and easy to grasp. Furthermore, the significance of weight vectors could be incorporated into the comparative process [55]. A polyhedron could be used to depict the effectiveness of options and metrics, and the estimation process is then straightforward [56]. The method is suitable when the indicators of alternatives do not vary very strongly	TOPSIS lacks a component that checks for inconsistency between judgment and expressed preferences [57]. Because TOPSIS cannot elicit weights, it must focus solely on alternative measuring strategies such as AHP [58]. TOPSIS application might be invalid if the weights are not accurate [59]. Simple computational steps, solid mathematical foundations, and a method that is simple to understand [60]
TODIM	Tomada de Decisao interactive multicriteria have been developed in the early 1990s by Gomes and Lima to assist throughout the list of options in which the selection should successfully maintain a choice in the event of a crisis [61]. Main idea has to use the overall value to determine each alternative's dominance over the others and then evaluate and rank the alternatives [62]	In terms of behavioral decision-making, it is effective since it considers the decision-psychological maker's virtues and therefore can catch damage and lack of certainty [63]. The attenuation parameter, that would be adjusted, will portray the decision-maker's risk tolerance [64]. Even professionals with no prior knowledge of MCDM describe the method as an easy-to-implement tool [65, 66]	Inability to acknowledge the uncertainty associated and imprecision in decision-making [67]. In the TODIM method, any two alternatives must be compared, which results in high computational complexity [68]. Interactive attributes can be used with positive or negative criteria interactions and crisp values [69]
VIKOR	Opricovic [70] proposed this method to solve situations with contradictory and quasi requirements [71]. Presuming that agreement is reasonable for dealing with conflict, the selection seeks the fairly close answer to the perfect, and all defined requirements are used to take active steps [72, 73]	It is very simple because it has the fewest steps for calculating the ranking order [74]. Could go with the expansion functionality of the "most of" and the least specific remorse of the "competitor" [75, 76]. A helpful aid, especially once the choice has not yet addressed his or her priorities at the outset of the method [77]. Enables to calculate the distance between the second-best option and the first	Looking for a compromise ranking order, i.e., a compromise between pessimistic and expected solutions. Another flaw is the use of complex-linear normalization in the calculation formula [78]. The use of complex normalization is required for all of the matrix's elements, which typically have different metrics, to be obtained as dimensionless units [79]

Table 2: Continued.

MCDM method	Description	Advantages	Disadvantages
ELECTRE	Roy invented it in 1968. Various ELECTRE methods have since been developed [80] used to classify a number of options by analyzing data in a decision matrix [81]. In the pair-wise correlation of alternatives, consistency and disharmony are used [82]	Capable of dealing with both qualitative and quantitative criteria [83]. ELECTRE was employed in civil and environmental engineering [84]. Examples of these applications include power efficiency, sustainable use of natural resources, environment protection, nutrition, security, healthcare, design, and mechatronics. To select the best surface mining technology [85]	ELECTRE occasionally fails to sort the alternatives into different ranks [86]. The weakness of ELECTRE's normal ranking arises from the need of supplemental limit, and the ranking of the alternative is dependent on the size of this limit, so there is no "correct value" [87]
GRA	Deng proposed it in 1982 to find solutions involving uncertainty and missing information [88]. Grey prediction model, grey relational analysis (GRA), grey decision, grey programming, and grey control are the five components of the grey prediction model [89]. This method treats each alternative as a data sequence. It then looks at how similar each alternative is to the reference sequence [90]	The analyzed results are reliant on the raw data, and the calculation procedure is simple and straightforward [91, 92]. There are no restrictions on sample size or normally distributed data, and the computational method is simple [93]. Ability to provide methods for ranking alternatives that do not necessitate a large sample size or any sample distribution. Very popular and useful tools for analyzing various relationships among discrete information and making decisions in various situations	There is a lack of mathematical principles to discuss its history, rules, and restrictions [94]. The most relative relational degree from the probabilistic linguistic positive ideal solution is used to select an alternative [95]
OCRA, ARAS, COPRAS, SAW, CP		Rapid development of methods for dealing with real-world problems [32]	The method has seen limited application in mining engineering [32]

and the block-caving technique has been selected as the optimal mining technique. Ataei et al. adopted the analytic hierarchy process (AHP) to resolve MMS issue in Golbini No. 8 deposit in Jajarm, Iran [39]. They developed an AHP structure of 13 metrics and six alternatives, and 17 professionals from different tasks were selected to create pairs contrast matrices. According to the findings, the reduce-and-fill mining approach has been opted as the most appropriate approach out of six alternatives [105].

One disadvantage of the AHP is that the decision-making instinct may be expressed as a genuine value. Yet another flaw of the AHP is the incorrect treatment of inherent ambiguity within the pair-wise contrast procedure, as well as judgment size prejudices [106]. To eliminate such disadvantages, Naghadehi et al. [106] employed the fuzzy analytical hierarchy process (FAHP) to MMS [107, 108]. Weights of primary criteria in the FAHP system were determined using a fuzzy set of rules, and six suggested mining techniques have been listed using the AHP [33]. The suggested technique has been adopted in Jajarm Bauxite mine in Iran, and the traditional reduce-and-fill method was chosen as the most suitable extraction technique [109, 110]. Azadeh et al. [28] developed Nicholas' [111] quantitative rating approach, and the ambiguity of the decision-makers' judgments was expressed using trapezoidal fuzzy numbers. The method comprised AHP models labeled as "technical" and "economic" operation. A case study has been adopted at the northern anomaly of the Choghart iron mine in Iran to confirm the advanced method and compare it with the Nicholas method [112].

Namin et al. [113] proposed a fuzzy mining approach with interrelation criteria (FMMSIC), which is a hybrid decision-support system that combines the fuzzy analytic network process (FANP) [114] and fuzzy entropy (FE) [115]. The FANP and FE were used for preliminary weighting [50], and a revised fuzzy method for ordering priorities matching to the optimal situation (TOPSIS) [116] has been employed for the MMS ranking procedure. A case study of the Gole Gohar deposit in southern Iran was conducted to confirm the validity of the FMMSIC [117]. 11 underground mining strategies and 16 MMS-related conditions have been taken into account as proposed strategies and requirements for the choice process [118]. Finally, the block-caving method has been selected as the best suitable mining technique for this mine, which has been supported by numerous expert opinions. Table 3 summarizes relevant studies on MMS using SC technologies and MCDM methods and includes some guiding references for using SC in MMS.

Despite significant efforts by researchers, no MMS system can address the entire scope of the MMS issues. Latest MMS research has typically concentrated on allocating weight elements to standards and attempting to model the precise notion techniques of decision-makers [106]. To cut a size of the MMS, proposed mining strategies

Table 3: Summary of first representative MMS studies using SC technologies and MCDM methods.

Author	Soft computing technologies					MCDM methods	
	EXS	FUA	ANN	YAM	FUE	AHP	TOPSIS
Yun and Huang [98]		✓					
Bandopadhyay and Venkatasubramanian [11]	✓						
Gershon et al. [119]	✓						
Xiaohua [120]	✓		✓				
Guray et al. [22]	✓						
Bitarafan and Ataei [101]		✓					
Ataei et al. [39]		✓		✓			
Yavuz [121]						✓	
Naghadehi et al. [106]				✓		✓	
Azadeh et al. [28]		✓					
Namin et al. [113]		✓			✓	✓	✓
Gupta and Kumar [122]						✓	
Yavuz [121]				✓		✓	

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.

might be suggested prior to executing the MMS system. However, this results in the software of a completely subjective technique. In addition, because many mines are transitioning from surface to underground mining after completing surface exploitation, neither of the evolved MMS structures can manage more than one sequential transition from open pit to underground mining.

Artificial intelligence (AI) or computing intelligence (CI), which has been used in the discovery of minerals recently, has improved over the years. Moreover, the use of statistics is also becoming popular. The importance of relevant information retrieval through massive data collection was emphasized [123]. As the demand for extensive data grows, so does the recognition of statistical processing fields such as statistics mining, massive statistics, machine learning, and synthetic intelligence [124].

Artificial neural networks (ANNs) are a class of massively parallel architectures that can be used to study and generalize from experience in order to provide significant solutions to problems, even if the input data contain mistakes and are imperfect. As a result, the use of ANNs is an effective approach for solving a variety of technically challenging issues. Primarily, the processing elements of a neural network are similar to the neurons within the brain, which include many simple computational elements organized in layers. A neural network has to be trained on the experimental results associated with material in order to predict its behavior. Therefore, if these findings have adequate information relevant to that material behavior, then the trained neural network will not only replicate these results but also approximate the results of different material.

An ANN is a technique that mimics the human mind's analyzing and problem-solving abilities. It is adaptable, highly parallel, reliable, and tolerant to fix faults [125]. In the implementation of synthetic neural networks, expertise is addressed as numeric weights that can be employed to extract correlations within data that are hard to express analytically. This iterative manner adapts the network parameters to reduce the sum of squared approximation errors. Neural networks could be applied to simulate sophisticated relationships rather than using simplified assumptions, which are likely to be employed in linear approaches.

The specific benefits of ANNs are their capabilities to address every linear and nonlinear relationship, their applicability to directly observe these relationships from the data used, the fact that they no longer need to maintain an in-depth record of structures and interactions within the systems, and that they are regarded as final black-box models. For prediction employing the trained network, ANN systems can be used to repeat experiments several times, which can be useful considering that experiments are difficult and in some cases impossible [126, 127]. Since the 1980s, there was a remarkable rise in the use of neural networks to solve a variety of problems [128, 129]. The multilayer perceptron (MLP), radial basis functions (RBFs), recurrent neural networks (RNNs), and echo state networks (ESNs) [130] are among the neural networks that can be used [131, 132]. Lv and Zhang [133] established the TCSMMPM-ANN to decide the suitable thick coal seam mining method to overcome the problems of traditional MMS and address economic and technical index predictions. Chen and Shixiang [134] designed a genetic algorithm ANN to optimize the connection weights and thresholds in the optimal BP network and established a nonlinear relation between the mining method and geological conditions in a thin coal seam working face. However, due to the small sample size and highly advanced background, the BP network built in this study should be improved on a regular basis. Özyurt and Karadogan [135] developed a model using ANN and game theory, which provides solutions if ANNs are continuously trained, benefiting from technological developments and new findings without requiring expert opinion or detailed research in the relevant publication.

ANN models can recognize patterns that link input variables to their corresponding outputs in complex biological systems for prediction. Methods for improving the network performance include determining the optimal network architecture and suitable number of training cycles using different input combinations. One of them is cascade-forward backpropagation.

5. MMS Using CFBPNN (Case Study)

As illustrated in Figure 1 [136], the CFBP model is similar to feedforward (FF) networks; nevertheless, two-layer FF networks could be used to monitor any input-output relationship, whilst FF networks with more layers could be used to visualize intricate interactions more quickly. In terms of using the BP algorithm for the weight update, the CFBPNN model is analogous to the FFBPNN model. However, a key feature of this network is that each layer of neurons is linked to the ones before it [137]. A CFBPNN, like other FF networks, contains a single or multiple interrelated hidden layers and activation functions. Neurons have private biases, and their connections have different weights. A set of modified weights should be determined in ANN modelling in such a way that the estimator error is kept to bare essentials [138].

When using the BP algorithm to update weights, a CFBPNN is similar to an FFBPNN. Most crucial component, however, is each layer of neurons is linked to the layers before it. To maximize the response of the CFBPNN, the characteristics of tan-sigmoid transfer, log-sigmoid transfer, and pure linear limit have all been determined. The mean squared error (MSE) in equation (1), the root mean squared error (RMSE) in equation (2), and R^2 in equation (3) were calculated to demonstrate the effectiveness of the algorithms.

$$\mathrm{MSE} = \left[\sum_{1}^{n} \left((\mathrm{Qexp} - \mathrm{Qcal}) \mid n \right)^2 \right], \tag{1}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{2} \sum_{1}^{n} \left[\left((\mathrm{Qexp} - \mathrm{Qcal}) \mid n \right)^2 \right]}, \tag{2}$$

$$R^2 = \sum_{1}^{n} \left[\left((\mathrm{Qexp} - \mathrm{Qcal}) \mid n \right)^2 \right], \tag{3}$$

where Qexp represents the measured value, Qcal represents the computed values, and n counts the set of observations.

CFBPNN models are like FFBPNN models in which they incorporate a weighted link from an input to every layer as well as from each layer to the subsequent layers. In some circumstances, the CFBP approach outperforms the FFBP method according to Mitra et al. [130].

$$\mathrm{f}\left(\mathrm{net_j}\right) = \frac{1}{\left(1 + \mathrm{e}^{-\mathrm{netj}}\right) \sum_{1}^{n} \left[\left((\mathrm{Qexp} - \mathrm{Qcal}) | n \right)^2 \right]},$$
$$\mathrm{f}\left(\mathrm{net_j}\right) = \mathrm{net}. \tag{4}$$

The yield of the chosen mining tactics was predicted using a schematic of a trainable CFBP. As previously discussed, the training level is critical. Backpropagation and quick-propagation training strategies are widely common employed strategies. Consequently, the backpropagation approach was adapted to be implemented at the training level according to the method of Lashkarbolooki et al. [139] and its benefits in the current study. Specifically, the Levenberg–Marquardt backpropagation technique has been utilized due to its speed and accuracy. As a result, the proposed ANN model is transformed into one trained with the Levenberg–Marquardt algorithm [140]. The number of concealed layers is reduced and improved at the next level. As Cybenko [140] stated, a network with only a single concealed layer may mimic nearly every nonlinear relation; thus, for the proposed ANN model, just one concealed layer is used. The second essential criterion is the optimal number of neurons in the hidden layer. The number of neurons in the hidden layer is difficult to determine due to a limited number of neurons results in a network with low precision, whereas a larger number results in overfitting and poor interpolation quality because the risk of overtraining increases as the number of neurons increases [141]. There are four steps in the proposed technique for MMS using CFBPNN:

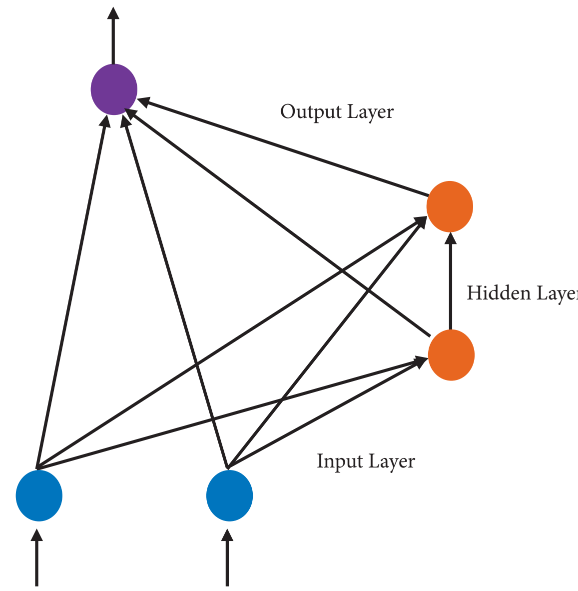

Figure 1: Cascade correlation neural network.

Step 1. The ANN's weight (W) and bias (b) values, as illustrated in Figure 2, were calculated using the MATLAB toolbox's trainable cascade-forward backpropagation and then entered in an Excel sheet.

Step 2. Equation (5) is used to calculate the output of the first layer (K) in the Excel spreadsheet function, and the results are shown in Section 5.2.

$$K1 = \frac{2}{(1 + \mathrm{EMP}(-2 \times (\mathrm{SUM}(O1))))} - 1. \tag{5}$$

Step 3. Equation (6) is used to determine the output of the second layer (rank of the selection technique) in the Excel sheet.

Figure 2: Subsidence features at China's Chengchao iron ore mine. Image courtesy of Google Earth, taken in 2018.

$$R = \mathrm{SUM}\,(\mathrm{Column02}) + K \times \mathrm{W21W1} + b2. \quad (6)$$

Step 4. The approach is chosen, and its name is shown in the Excel sheet by changing approximation rank values to integer values using the V function.

Table 4: Characteristic of underground mining rock.

Characteristics of ore		
Geometry/form	T, tabular	
Width of ore, m	N, thin 17.5	Characterization Amplitude
Dip angle of ore, degrees	70°	
Allocation of grade levels	G, gradational G, gradational	Characterization Amplitude
Depth below surface, m	SH, shallow 210, m	Characterization Amplitude
Ore	M, medium 60	Characterization Amplitude
Hanging wall	VW, very weak 45	Characterization Amplitude
Footwall	VW, very weak 45	Characterization Amplitude
Ore	VW, very weak 40	
Hanging wall	W, weak 35	
Footwall	W, weak 40	

5.1. Gathering Data and Site Investigation. Chengchao iron mine is a major iron ore and pellet ore production base for the Wuhan Iron and Steel Group Company and thus a huge identified underground iron mine in China. Between the Huaiyang Shield and Jiangnan Ancient Land, the Chengchao mining area is situated west of the lower Yangtze depression. It is a part of the western wing of the frontal arc of the Huaiyang epsilon structure. As indicated in Figure 2, the mining area is located near the East-West structural belt, which includes Mufushan as the major orebody in the south, the Liangzi Lake depression with a Neocathaysian structure in the west, and the South Huaiyang fault in the north.

The mining industry has a complex structure. Sedimentary, magmatic, and metamorphic rocks have been found in the Chengchao mining area. Anhydrite deposits were found in the contact zone between marble and granite, iron ores are found near the contact zone between diorite and granite, and skarns, which are in the shape of a pulse or a lens, are found near the contact zone between hornfels and granites. The eastern and western mining zones of the mine are separated by the geological exploration line 15. There are numerous ore deposits in the mining areas. Numbers I, II, III, IV, V, VI, VII, and others are the most typical iron ore bodies. Numbers II, III, VI, and VII are large-scale iron ores. The orebodies are mainly irregular lenticular in shape and slanted southward. Branching, compounding, expansion, and contraction are common occurrences in orebodies and ore sections. Table 4 summarizes the main geomechanical properties of the rock and ore in a mine case study.

5.2. Results. To maximize the CFBPNN response, the tan-sigmoid transfer, log-sigmoid transfer, and pure linear limit characteristics are first determined. This is illustrated in Figure 3. The UBC criteria were converted to weights, and the load was determined using mining techniques (benefits are given the most weight, while risks are given the least, as in the mining methods). Table 5 summarizes the findings.

Table 6 summarizes the output of the first CFBPNN stage, which involves utilizing the MATLAB toolbox to compute the ANN weight (W) and bias (b) values using trainable CFBP. Table 7 presents the MMS results and findings based on the CFBPNN application. Ten mining methods were used to select the best method based on the assigned weights (w) and bias (b), as listed in Table 7. These parameters were calculated using a number of input parameters, including ore shape, thickness, dip angle, depth below surface, rock mass classification systems (such as RQD), and rock structure rating (RSR). CFBPNN was used to estimate the rank of each parameter in relation to the mining method. According to the findings, the cut and fill stopping method is the most effective.

5.3. Discussion. The following layer properties have been employed based on the findings, which represent the integration of the method specifications and the real layer set: a dip of 70°, underground depth of 210 m, and RQD of 60 (moderate) and 45 (very weak) in the hanging wall. The cut and fill stoping method was superior to the other methods due to its suitability for all previous layer specifications. Figure 4 depicts the main design of the cut and fill stoping mining technique, which is the ideal mining method.

The Chengchao iron mine has been extracted using a sublevel caving method that eliminated the need for sill pillars. This is a type of bulk mining technique in which the

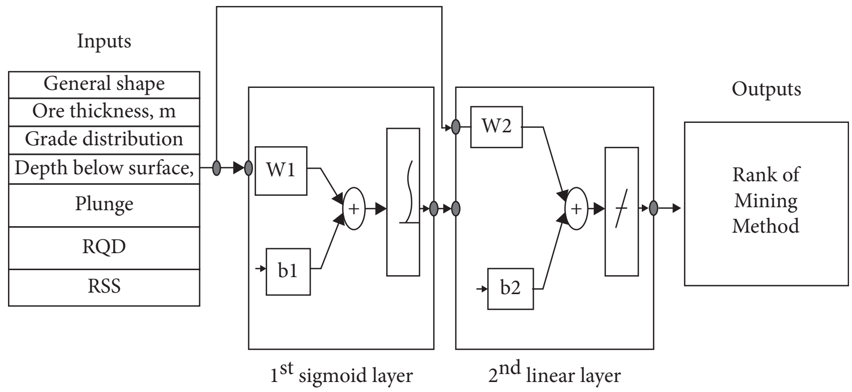

Figure 3: Trainable cascade-forward backpropagation ANN adopted to decide the suitable mining method.

Table 5: Weights of the various parameter assignments based on the mining methods.

	Parameter/mining methods		Open pit	Block caving	Sublevel stoping	Sublevel caving	Longwall	Room and pillar	Shrinkage stoping	Cut and fill stoping	Top slicing	Square set stoping
1	General shape		0.8	0.8	0.6	0.6	0	0	0	0.2	0.2	0
2	Ore thickness, m		0.8	0.8	0.6	0.8	0	0	0	0	0.2	0
3	Grade distribution		0.6	0.6	0.8	0.6	0.8	0.8	0.6	0.4	0.4	0
4	Depth, m		0.8	0.4	0.6	0.6	0.4	0.6	0.6	0.4	0.4	0.2
5	Plunge		0.2	0.8	0.8	0.8	0	0	0.8	0.8	0	0.4
6	RQD	Ore zone	0.6	0	0.8	0	0.4	0.9	0.6	0.6	0	0
7		Hanging wall	0.8	0.4	0.8	0.4	0.6	0.9	0.8	0.6	0.6	0
8		Foot wall	0.8	0.4	0.6	0.6	0	0	0.6	0.4	0.4	0
9	RSS	Ore zone	0.6	0	0.8	0.4	0.2	0.9	0.8	0.6	0	0
10		Hanging wall	0.8	0	0.6	0.25	0.4	0.9	0.8	0.4	0.4	0
11		Foot wall	0.8	0.2	0.6	0.4	0	0	0.6	0.4	0.25	0

Table 6: Values for weight (W) and bias (b) derived from the MATLAB toolbox.

Property/input	w1	w21 w2	b1	b2
General shape	5.4438	3.4113	8.803278	6.128579
Thickness of ore	12.4184	0.0339		
Distribution of grade levels	−12.5975	−5.4184		
Subsurface depth	−0.1821	−1.4329		
Dip angle	11.1132	0.301		
Rock quality designation (RQD) index	6.8993	2.6115		
Rockmass Structure Rate (RSR)	−22.7358	0.7069		
		−2.78847		

movement of blasted ore and caved waste rock is controlled by gravity. To relieve ground pressure, backed down rock masses from overlying country rock have been used to replace mined-out regions caused by ore extraction [142]. The caved zone, which is composed of caved rock masses, can come as a result above the mined-out area, inferring vertical caving. In addition, above the fallen rock mass, a joint may be developed. Consequently, this type of mass underground mining can cause severe ground surface disruption. As the excavation of the subterranean orebody continues, the caving of the overlying country rock caves ultimately propagates to the ground surface, causing it to collapse [143]. According to Zhang et al. [144], the movement of strata at the Chengchao iron mine can be classified into six categories: vertical subsidence, toppling slip, toppling, deformation, deformation accumulation, and undisturbed areas. As a result, when a large-scale orebody is mined, large-scale collapse at the ground surface is common. According to the CFBPNN rank presented in Table 8, sublevel caving is ranked No. 4. According to the overall score assigned to all ore attributes, the findings reveal metrics for selection to use when deciding between different mining processes.

Table 7: Results of using CFBPNN for MMS with the given parameters.

Mining method	No.			O2	O1	b2	b1	w21 w2	w1	Properties/ input
		Rank	2.72904	4.35504	6.128579	8.803278	3.4113	5.4438	0.8	
Open-pit mining	1		7.933731	0.01356	4.96736			0.0339	12.4184	0.4
Block caving	2	**Method 8 Cut and fill stoping**		−3.25104	−7.5585			−5.4184	−12.5975	0.6
Sublevel stoping	3			−0.85974	−0.10926			−1.4329	−0.1821	0.6
Sublevel caving	4			0.0301	1.11132			0.301	11.1132	0.1
Longwall mining	5			0.26115	0.68993			2.6115	6.8993	0.1
Room and pillar	6			0.42414	−13.6415			0.7069	−22.7358	0.6
Shrinkage stoping	7			7.933731	−1.38231			−2.78847		
Cut and fill stoping	8				−0.88147					
Top slicing	9									
Square set stoping	10									

The bold value means the optimal selected mining method.

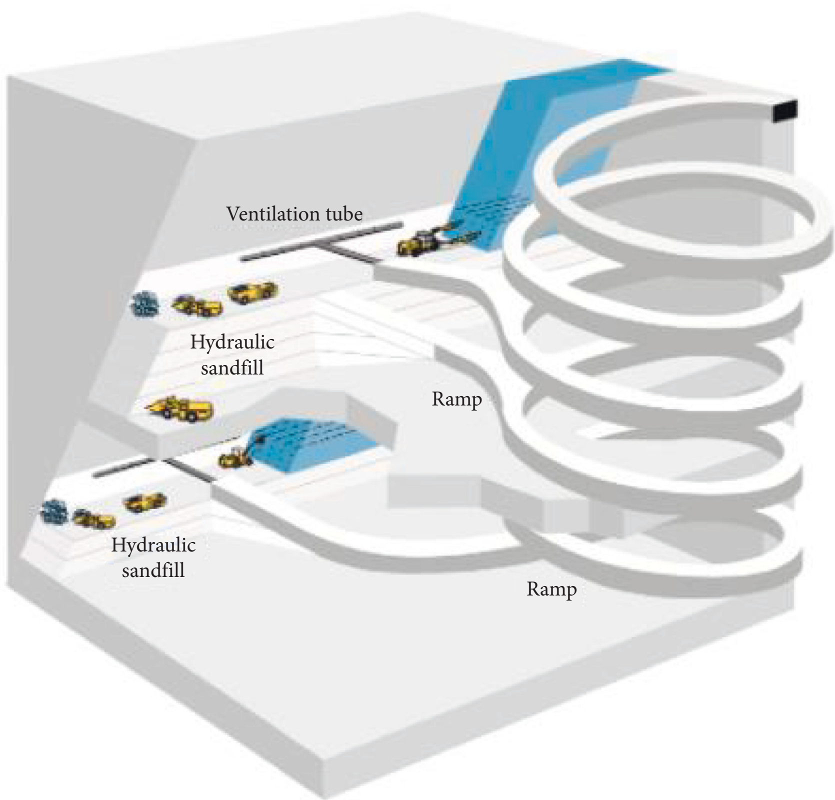

Figure 4: Cut and fill stoping.

Table 8: Ranking of all mining methods using CFBPNN.

Mining method	Final Rank
Open pit	10
Block caving	5
Sublevel stoping	2
Sublevel caving	4
Longwall mining	8
Room and pillar	9
Shrinkage stoping	3
Cut and fill stoping	**1**
Top slicing	6
Square set stoping	7

The bold means the best mining method based on the results.

6. Conclusions

Various criteria must be considered when deciding on an appropriate mining method for ore deposits. Several techniques, including the Nicholas, modified Nicholas, and UBC methods, were created to investigate the appropriate mining methods for mineral deposits. Unfortunately, none of these methods consider the weight values for every factor that influences the MMS. As a result, this study takes into account the weight values for each parameter that influences the mining method selection. In comparison to other studies, this is the first to try a new technique called CFBPNN, which was implemented in the Chengchao iron ore mine to select the most appropriate (safe) mining method. The findings of this study can be summarized as follows:

(1) The primary goal of this review is to study in detail the development of different tools that are earlier used in decision-making for MMS and their application, functionality, advantages, and disadvantages.

(2) A newly proposed technique for MMS based on the application of CFBPNN was presented and illustrated, which is easier to apply and more accurate than traditional tools.

(3) The CFBPNN method is used in this paper to determine appropriate mining methods for the Chengchao iron mine under various conditions. The most effective mining method is cut and fill stoping.

(4) Based on the total score assigned to all ore properties, the results offer metrics that could be used to select among various mining methods.

Users should understand the MMS tools described and recognize that the suggested method is a simplified approach and will only be helpful if the theoretical background behind ANN is understood. If the factors and methods in the results section are not sufficient, an appropriate criteria and alternatives could be included to the database for the investigated problem. For effective and reliable results, changes in the final rank have to be monitored and recorded using at least two MMS tools in the suggested way.

The suggested model was introduced without correlation to other MMS methods, which is a limitation. As a result, future research could look into other MMS tools and their impact on final rankings. The second limitation is that some of the publications have been translated into English. As a result, in the future, more publications will need to be reviewed to learn more about MMS tools. CFBPNN algorithms for selecting a proper MMS can be developed in future research once the problem has been described and organized, so determining the optimal method will be convenient.

Abbreviations

AHP:	Analytic hierarchy process
AI:	Artificial intelligence
ANN:	Artificial neural network
ARAS:	Additive ratio assessment approach
CFBPNN:	Cascade forward backpropagation neural network
CI:	Computing intelligence
COPRAS:	Complex proportional assessment approach
CP:	Constraint programming
ELECTRE:	ELimination Et Choix Traduisant la REalité (elimination and choice translating reality)
GRA:	Grey relational analysis
MCDM:	Multicriteria decision-making
MMS:	Mining method selection
OCRA:	Operational competitiveness rating analysis
PROMETHEE:	Preference ranking organization method for enrichment evaluation
SAW:	Simple additive weighting
TODIM:	Portuguese acronym for interactive multicriteria decision-making
TOPSIS:	Technique for order of preference by the similarity to ideal solution
VIKOR:	Vlsekriterijumska Optimizacija I Kompromisno Resenje (multicriteria optimization and compromise solution).

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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