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Analyzing the role of safety level and capital investment in selection of underground metal mining method

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ABSTRACT

It is one of the important tasks to select a suitable mining method for economic and safe extraction of the specific ore deposit. The selection of individual mining methods depends on multiple factors like dip, shape, thickness, depth, grade distribution, RMR (rock mass rating) of ore and adjacent strata, and RSS (rock substance strength) of ore and adjacent strata. The present study aims to analyze the role of two extrinsic factors (safety and capital) in the selection of underground metal mining methods. A fuzzy-AHP decision-making model is developed to analyze the possible changes in the mining method with different levels of safety and capital. The study considers seven alternatives or mining methods (block caving, sublevel stoping, sublevel caving, room and pillar mining, shrinkage stoping, cut and fill stoping, and square set stoping) in the model. The results revealed that the preference level or ranking of different mining method in a particular condition like low safety (SAL), medium safety (SAM), high safety (SAH), low capital (CL), medium capital (CM), and high capital (CH) remains same for different decision-making attitude and uncertainty level.

Keywords: Safety, Capital, Fuzzy-AHP, Sensitivity analyzis, Underground mining methods

1. Introduction

The selection of an appropriate method for underground mining depends on characteristics of ore deposits like dip, shape, thickness, depth from the surface, grade distribution, RMR (rock mass rating), and RSS (rock substance strength) of the ore body and adjacent rocks. The selection of mining methods also depends on external factors like productivity, ore recovery, ore dilution percentage, flexibility, safety, and capital availability. In general, mine planners need to consider all the intrinsic and extrinsic factors during the selection of the most appropriate mining method for the extraction of an ore deposit. But the selection of the appropriate mining method based on the consideration of multiple criteria is a tedious and complex task. At the same time, improper selection of mining methods may lead to the poor recovery of ore, unsafe working conditions, and uneconomical extractions. In the past, many studies have been conducted for the selection of mining methods based on different sets of criteria.

Namin, Shahriar, Ataee-Pour, and Dehghani (2008) proposed TOPSIS (a technique for order preference by similarity to ideal solution) and fuzzy-TOPSIS models for selection of mining method based on the consideration of the intrinsic factors of the ore deposit only. The study considered different geometry and geo-mechanical parameters for the selection of mining methods for both the opencast and underground coal and non-coal mining [1]. Naghedehi, Mikaeil, and Atei (2009) proposed a Fuzzy-AHP (Fuzzy- analytical hierarchy process) based multi-criteria decision making (MCDM) model by considering a limited number of intrinsic and extrinsic parameters for the selection of mining method for Bauxite ore deposit in Iran [2]. Mikaeil, Naghadehi, Ataei, and Khalokakaie (2009) proposed Fuzzy-AHP and TOPSIS models by considering the intrinsic and extrinsic factors for the selection of suitable mining methods for the Bauxite ore deposit in Iran [3]. Alpay and Yavuz (2007) proposed AHP and Yager's model for the selection of underground mining methods based on the considerations of various intrinsic and extrinsic parameters [4]. Gupta and Kumar (2012) proposed an AHP-based MCDM model by considering the various intrinsic and extrinsic parameters for selecting the most suitable underground mining method for metal ore deposits [5]. Yavuz (2015) developed AHP and Yager's MCDM model for the selection of underground coal mining methods by considering the different intrinsic and extrinsic parameters [6]. Dehghani, Siami, and Haghi (2017) proposed Grey and TODIM (Tomada de Decisão Interativa Multicritério) models by considering different intrinsic and extrinsic parameters for the selection of the type of opencast and underground method for mining coal and non-coal [7]. Balusa and Gorai (2018) developed an MCDM model using the fuzzy-AHP technique for the selection of appropriate underground metal mining methods by considering various geometry and geo-mechanical conditions of the ore deposit [8]. Balusa and Gorai (2018) conducted a sensitivity analysis of the fuzzy-AHP MCDM model in the selection of underground metal mining methods. The study examined the robustness of the proposed model through sensitivity analysis [9]. Balusa and Gorai (2018) conducted a comparative study of the decisionmaking results in the selection of mining method using five MCDM models (TOPSIS, VIKOR (viseKriterijumska optimizacijai i kompromisno resenje), improved ELECTRE (The Elimination and Choice Translating Reality), PROMETHEE II (preference ranking organization method for enrichment evaluation), and WPM (weighted product method)) [10]. Balusa and Singam (2018) proposed WPM and PROMETHEE decision-making models for the selection of underground metal mining methods by considering various geometry and geo-mechanical conditions of the ore deposit [11].

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Though numerous underground mining methods have been developed for hard rock extractions in the last few decades, each method has a different level of safety to workers and operational efficiency. Also, the fixed and operational costs for different mining methods are different [12]. Hartman and Mutmansky (2002) analyzed the advantages and disadvantages of different mining methods developed for coal and metal extractions [13]. As per literature, it is yet to explore the effect of different safety levels and capital availability on the selection of mining methods. Thus, the present study attempts to analyze the sensitivity of two extrinsic parameters (safety and capital availability) in the selection of an underground mining method for hard rock deposits. Currently, these two parameters play a vital role in any mining industry for successful operation. Hazard using different mining method vary significantly, and thus the safety of the miners need regular monitoring. Additionally, mining is capital intensive industry and needs a different level of capital for different mining methods. The study will analyze the sensitivity of safety and capital for various underground metal mining methods using a fuzzy-AHP based decision-making model.

2. Methodology

The proposed study aims to determine the role of safety level, and capital availability in the selection of underground metal mining methods assuming the intrinsic characteristics of ore deposit is fixed. The proposed study demonstrates the development of a fuzzy-AHP decision-making model to analyze the sensitivity of safety and capital availability. The proposed work has been carried out with the following steps as represented in the flowchart shown in Fig. 1.



Fig. 1: Flowchart for the working methodology

2.1. Selection of sub-criteria for Safety and Capital, and mining methods

The model considers two criteria (safety and capital) for analyzing the influences on the selection of the mining method. The criteria (safety and capital) are classified into three sub-criteria each [13-14]. Safety (SA) is classified as low safety (SAL), medium safety (SAM), and high safety (SAH), and capital (CAP) is classified as low capital (CAL), medium capital (CAM), and high capital (CAH) in the proposed model. The model analyzed the sensitivity of safety and capital on seven underground metal mining methods (block caving (BC), sublevel stoping (SS), sublevel caving (SC), room and pillar (RP), shrinkage stoping (SH), cut and fill stoping (CF) and square set stoping (SQ)). The hierarchical structure of the model is shown in Fig. 2.

2.2. Formulation of the fuzzy pair-wise comparison matrices using preference scores of mining methods correspond to different subcriteria of safety and capital

The fuzzy pair-wise comparison matrices are constructed based on Saaty's fuzzy scale [15]. The matrices are formulated by assigning the preference scores to each mining method for different sub-criteria of safety and capital. The pair-wise comparison matrices correspond to low safety, medium safety, and high safety are represented by SAL, SAM, and SAH respectively; whereas that of low capital, medium capital, and high capital are represented by CL, CM, and CH respectively.



Fig.2 Sub-criteria of (a) Safety and (b) Capital

												SAL											
	Г ^{ВС}	SS	SC	RP	SH	CF	SQ	1	Г ^{ВС}	SS	SC	RP	SH	CF	SQ	1							
BC	1	$\overline{1}$	1	1	1	1	$\frac{1}{8}$	BC	1	1	1	$\overline{1}$	1	$\frac{1}{7}$	1		ВС гВС	SS	SC	RP	SH	CF	SQ-
SS	$\overline{1}$	1	1	1	1	1	1	SS	1	1	1	$\overline{1}$	1	1	1		$SS = \frac{1}{1}$	$\frac{1}{1}$	$\frac{1}{1}$	$\frac{1}{1}$	$\frac{\overline{1}}{\overline{1}}$	777	8
SC	1	$\overline{1}$	$\overline{1}$	1	$\overline{1}$	$\frac{3}{1}$		SC	1	$\overline{1}$	$\overline{1}$	$\overline{1}$	$\overline{1}$	1	$\overline{1}$	-	$SC \mid \frac{1}{1}$	$\frac{1}{1}$	$\frac{1}{1}$	$\frac{1}{1}$	$\frac{1}{1}$	777	8
= RP	1	$\overline{1}$	$\overline{1}$	1	$\overline{1}$	3 1 		; SAM = _{RP}	1	1	1	1	1	1	$\overline{1}$; SAH =	$= RP \begin{vmatrix} \frac{1}{1} \\ 1 \end{vmatrix}$	$\frac{1}{1}$	$\frac{1}{1}$	$\frac{1}{1}$	$\frac{1}{1}$	7	8
SH	1	$\overline{1}$	1	1	1	3 1 2	0 1	SH	1	1	1	1	1	1	1		SH = 7	7 1	7 1	7 1	7 1	1 1	3
CF SO	3	3	3	3	3	$\frac{3}{1}$	0 1 7		7	7	7	7	7	$\frac{7}{1}$	7			8	8	8	8	3	1
SQ	$\lfloor \frac{1}{8} \rfloor$	8	8	8	8	7	$\frac{7}{1}$	3Q	lī	1	1	1	ī	7	1		зų						



	гВС	SS	SC	RP	SH	CF	SO T	1											BL	33	30	RP	3H	CF	SQ
BC	-	1	1	1	1	1	1		BC	гBС	SS	SC	RP	SH	CF	SQ-	1	ВС	1	7	7	7	8	7	8
SS	1	3	3	3	8	3	8		SS	1	1	1	1	$\overline{1}$	1	$\frac{1}{1}$		SS	$\frac{1}{7}$	1	1	1	3	1	3
SC	3	1	1	1	$\frac{1}{7}$	1	$\frac{1}{7}$		sc	7	$\frac{7}{1}$	$\frac{7}{1}$	$\frac{7}{1}$	7	$\frac{7}{1}$	7		sc	1	1	1	$\overline{1}$	3	$\overline{1}$	3
CL = RP	3	1	1	1	$\frac{1}{7}$	1	$\frac{1}{\overline{7}}$; CM =	= RP	777	$\frac{\overline{1}}{1}$	$\frac{\overline{1}}{1}$	$\frac{\overline{1}}{1}$	$\frac{7}{7}$	$\frac{\overline{1}}{1}$	777	; CH =	= RP	1	$\overline{1}$	1	$\overline{1}$	3	$\overline{1}$	3
SH	3	1	1	1	1	1	1		SH	$\frac{1}{1}$	1	1	1	$\frac{1}{1}$	1	$\frac{1}{1}$		SH	7	1	1	1	1	1	1
511	8	7	7	7	$\frac{7}{1}$	7	$\frac{7}{1}$		011	7	$\frac{7}{1}$	$\frac{7}{1}$	$\frac{7}{1}$	7	$\frac{7}{1}$	7		011	8	3	3	3	-	3	-
CF	$\frac{3}{3}$, 1	, 1	, 1	1	, 1	1		CF	$\frac{1}{1}$	1	1	1	$\frac{1}{1}$	1	$\frac{1}{1}$		CF		1	1	1	3	1	3
SQ	$\left\lfloor \frac{8}{8} \right\rfloor$	7	7	7	$\frac{\overline{7}}{1}$	7	$\frac{\overline{7}}{1}$		SQ	L	7	7	7	-	7		I	SQ	$\frac{1}{\overline{8}}$	$\frac{1}{\overline{3}}$	$\frac{1}{\overline{3}}$	$\frac{1}{\overline{3}}$	1	$\frac{1}{\overline{3}}$	1

The value in the fuzzy pair-wise comparison matrices (\bar{x}_{ij}) represents the preference score. The fuzzy preference score in matrices scores $\bar{3}$, $\bar{5}$, $\bar{7}$, $\bar{8}$ except $\bar{1}$ were converted into lower and upper limit values by considering the level of uncertainty (α -cut) using the equation. (1) [16].

$$\bar{x}_{ij} = [x - \alpha, x + \alpha], \text{ and } \frac{1}{\bar{x}_{\alpha}} = \left[\frac{1}{x + \alpha}, \frac{1}{x - \alpha}\right]$$
 (1)

In equation. (1), the α -cut defines the uncertainty level, i and j represent the value corresponding to the ith row and jth column. The value of α ranges from 0 to 1. The higher value of α represents consideration of higher uncertainty level and vice-versa. In the current study, α is considered as 0, 0.2, 0.4, 0.6, 0.8, and 1 for determining the lower and upper limit of the relative importance. This will help in determining the sensitivity of the model for a different level of uncertainty in the data. From the above fuzzy pair-wise comparison matrices, a new sets of pair-wise comparison matrices (SAL_f, SAM_f,

 $SAH_i, CL_i, CM_i, and CH_i$ were derived which represents the lower limit (x_{ijl}^{α}) and upper limit (x_{iju}^{α}) of the preference scores.

For example, the lower and upper limits $(x_{ijl}^{\alpha} and x_{iju}^{\alpha})$ correspond to 6^{th} row and 1^{st} column of the matrix, SAL, can be determined for $\alpha = 1$ as $x_{61l}^{\alpha} = 3 - 1 = 2$, and $x_{61u}^{\alpha} = 3 + 1 = 4$

Similarly, the lower and upper limit corresponds to 1st row and 6th column value of $\frac{1}{2}$ in the matrix, SAL can be determined for α =1 as

 $x_{16l}^{\alpha} = \frac{1}{3-1} = 0.5$, and $x_{16u}^{\alpha} = \frac{1}{3+1} = 0.25$

The new matrices for each sub-criterion of safety and capital for α equal to 1 are shown in the following matrices. The fuzzy pair-wise comparison matrices for α is 0, 0.2, 0.4, 0.6, and 0.8 are also derived in a similar method but not shown in the text due to the manuscript's size limitation.

$\begin{array}{c} BC\\SS\\SC\\SAL_{c}=BB\\SAL_{c$	<i>SS</i> [1] [1] [1]	SC [1] [1] [1]	RP [1] [1] [1]	SH [1] [1] [1]	<i>CF</i> [0.25,0.5] [0.25,0.5] [0.25,0.5]	<i>SQ</i> [0.11,0.1 [0.11,0.1 [0.11,0.1	[4] [4] [4] [54]	$BC \\ SS \\ SC \\ M_{c} = pp$	BC [1] [1] [1]	<i>SS</i> [1] [1] [1]	SC [1] [1] [1]	RP [1] [1] [1]	SH [1] [1] [1]	<i>CF</i> [0.125,0.16] [0.125,0.16] [0.125,0.16]	SQ [1] [1] [1]
$\begin{array}{c c} SH \\ SH \\ CF \\ \hline $	[1] [1]	[1] [1]	[1] [1]	[1] [1]	[0.25,0.5] [0.25,0.5]	[0.11,0.1 [0.11,0.1	.4] .4]	SH CF	[1] [1]	[1] [1]	[1] [1]	[1] [1]	[1] [1]	[0.125,0.16] [0.125,0.16]	[1] [1]
$SQ \begin{bmatrix} [2,4] \\ [7,9] \end{bmatrix}$	[2,4] [7,9]	[2,4] [7,9]	[2,4] [7,9] BC	[2,4] [7,9]	[1] [6,8] <i>SS</i>	[0.125,0 [1] SC		SQ RP	[0,8] [1]	[0,0] [1] <i>SH</i>	[0,0] [1]	[0,0] [1] <i>CF</i>	[0,0] [1] <i>SQ</i>	[1] [0.125,0.16]	[0,0]
		BC SS SC	[1] [1]		[1] [1]	[1] [1]		[1] [1]		[1] [1]		[6,8] [6,8]	[7,9 [7,9)])]	
	SAH _f	$= \frac{SC}{RP}$ SH	[1] [1] [1]		[1] [1] [1]	[1] [1] [1]		[1] [1] [1]		[1] [1] [1]		[6,8] [6,8] [6,8]	[7,9 [7,9)])])]	
		CF SQ	[0.125,0. [0.11,0.1	16] [4]	[0.125,0.16 [0.11,0.14]	[1] [0.125,0 [0.11,0]).16] [.14]	[0.125,0.10 [0.11,0.14	6] [0.] [0	.125,0.1).11,0.14	6] 4] [0	[1] .25,0.5]	[7,5 [2,4 [1]]]	
		E	$BC\begin{bmatrix} BC\\ [1] \end{bmatrix}$	[0 2	SS 15 0 51 [0 2	SC 25.0.51 [0]	<i>RP</i> 25.0.51	<i>SH</i> [0 11 0	14]	<i>CF</i> [0 25 0	5] [(<i>SQ</i>	₄ı]		
		5	SS [2,4]	[0.2	[1] [1]	[1] [1]	[1] [1]	[0.125,0	.16] .16]	[0. <u>2</u> 0,0. [1] [1]	[0] [0] [0]	.125,0.1 .125,0.1	6] 6]		
		$LL_f = F$	$\begin{bmatrix} P \\ [2,4] \\ H \\ [7,9] \end{bmatrix}$	[([1] 6,8] [[1] 6,8]	[1] [6,8]	[0.125,0 [1]	.16]	[1] [6,8]	[0.	.125,0.1 [1]	6]		
		S	$SQ \begin{bmatrix} [2,4] \\ [7,9] \\ [7,9] \end{bmatrix}$	[([1] 6,8] [\$\$	[1] 6,8] SC	[1] [6,8]	[0.125,0 [1]	.16] גע	[1] [6,8]	[0. CF	.125,0.1 [1] \$0	6]		
			BC [1] SS [6,8	,] [(3]	0.125,0.16] [1]	[0.125,0.1 [1]	[6] [0.	[125,0.16] [1]	[1] [6,8]	[0.12]	25,0.16 [1]] [1] [6,8]			
		<i>CM_f</i> =	$ \begin{array}{c} SC \\ RP \\ SH \end{array} \begin{bmatrix} 6,8 \\ 6,8 \\ 6,8 \end{bmatrix} $	3] 3]	[1] [1]	[1] [1]		[1] [1]	[6,8] [6,8]]	[1] [1]	[6,8] [6,8]			
			$\begin{bmatrix} CF \\ SQ \end{bmatrix} \begin{bmatrix} 1 \\ [6,8] \\ [1] \end{bmatrix}$] [¹ 3]] [¹	[1] [1] 0.125,0.16]	[0.125,0.1 [1] [0.125,0.1	16] [0. 16] [0.	[125,0.16] [1] [125,0.16]	[1] [6,8] [1]	[0.12] [0.12	25,0.16 [1] 25,0.16	j [1] [6,8]] [1]			



BC SS SC $CH_f = RP$ SH	<i>BC</i>	<i>SS</i>	<i>SC</i>	<i>RP</i>	SH	<i>CF</i>	<i>SQ</i>
	[1]	[6,8]	[6,8]	[6,8]	[7,9]	[6,8]	[7,9]
	[0.125,0.16]	[1]	[1]	[1]	[2,4]	[1]	[2,4]
	[0.125,0.16]	[1]	[1]	[1]	[2,4]	[1]	[2,4]
	[0.125,0.16]	[1]	[1]	[1]	[2,4]	[1]	[2,4]
	[0.11.0.14]	[0 25 0 5]	[0 25 0 5]	[0 25 0 5]	[1]	[0 25 0 5]	[1]
$CH_f = RP$	[0.125,0.16]	[1]	[1]	[1]	[2,4]	[1]	[2,4]
SH	[0.11,0.14]	[0.25,0.5]	[0.25,0.5]	[0.25,0.5]	[1]	[0.25,0.5]	[1]
CF SQ	[0.11, 0.14] [0.125, 0.16] [0.11, 0.14]	[0.25, 0.5] [1] [0.25, 0.5]	[0.25,0.5]	[0.25, 0.5] [1] [0.25, 0.5]	[1] [2,4] [1]	[0.25, 0.5] [1] [0.25, 0.5]	[1] [2,4] [1]
, i	L [0.11,0.14]	[0.23,0.3]	[0.23,0.3]	[0.23,0.3]	[1]	[0.23,0.3]	

In the next step, these fuzzy pair-wise comparison matrices were further converted into crisp comparison matrices. These matrices can be used for determining the weights of the different underground mining methods corresponding to each sub-criterion for both safety and capital. The crisp comparison matrices are derived using equation(2) [17].

$$x_{ij}^{a} = \lambda x_{iju}^{a} + (1 - \lambda) x_{ijl}^{a}$$
(2)

In equation. (2), x_{iju}^{α} and x_{ijl}^{α} are the upper and lower limit of \bar{x}_{ij} that are determined in the fuzzy pair-wise comparison matrices. In equation. (2), x_{ij}^{α} is the crisp value correspond to ith row and jth column. In equation. (2), λ represents the decision-making attitude of the mine planners. Generally, the value of λ ranges from 0 and 1. In the present study, the crisp comparison matrices were determined for three λ values (0, 0.5, and 1). The λ values 0, 0.5, and 1 respectively explain the pessimistic, neutral and optimistic decision-making attitude. A new set of crisp comparison matrices ($SAL'_f, SAM'_f, SAH'_f, CL'_f, CM'_f, and CH'_f$) were derived from the respective fuzzy pair-wise comparison matrices ($SAL_t, SAM_t, SAH_t, CL_f, CM_t$, and CH_t). For example, for $\lambda = 0.5$, $x_{61l}^{\alpha} = 2$, and $x_{61u}^{\alpha} = 4$, *the* x_{61}^{α} of matrix SAL_f can be determined as

$$x_{61}^{\alpha} = 0.5 * 2 + (1 - 0.5) * 4 = 3$$

where x_{61}^{α} represents the crisp value of the matrix, SAL'_f correspond to 6th row and 1st column.

The crisp comparison matrices for α equal to 1 and λ equal to 0.5 are represented as SAL'_f , SAM'_f , SAH'_f , CL'_f , CM'_f , and CH'_f . The crisp comparison matrices for all other combinations $[(\lambda = 0, \alpha = 0); (\lambda = 0, \alpha = 0.2); (\lambda = 0, \alpha = 0.4); (\lambda = 0, \alpha = 0.6); (\lambda = 0, \alpha = 0.8); (\lambda = 0, \alpha = 1); (\lambda = 0.5, \alpha = 0.4); (\lambda = 0.5, \alpha = 0.6); (\lambda = 0.5, \alpha = 0.8); (\lambda = 0.5, \alpha = 0.8); (\lambda = 1, \alpha = 0.2); (\lambda = 1, \alpha = 0.2); (\lambda = 1, \alpha = 0.2); (\lambda = 1, \alpha = 0.4); (\lambda = 1, \alpha = 0.4); (\lambda = 1, \alpha = 0.6); (\lambda = 1, \alpha = 0.6); (\lambda = 1, \alpha = 0.8); (\lambda = 1, \alpha = 1)]$ were derived using similar method but not shown in the text due to size constraint of manuscript.

2.3. Checking of consistency of the pair-wise comparison matrices

It is mandatory to examine the consistency of each pair-wise comparison matrix before any inference. The consistencies of the matrices were examined using the consistency ratio (CR). The consistency ratio of the pair-wise comparison matrices can be determined using the equation. (3).

 $CR = \frac{CI}{RI}$ (3)

In the above equation, the CI and RI represent the consistency index and the random index respectively.

$$CI = \frac{\lambda \max - n}{n - 1}$$

where λ_{max} is the maximum eigenvalue of the pair-wise comparison matrix, and n is the size of the matrix.

The value of RI depends on the size of the pair-wise comparison matrix. The value is determined by many researchers using different approaches. The present study uses the RI values derived by [18] for different matrix sizes. These are listed in Table 1.

Table 1: Random index (RI) values for different matrix size

Size of matrix	1	2	3	4	5	6	7
RI	0	0	0.58	0.9	1.12	1.24	1.32

The results of the maximum eigenvalue (λ_{max}), consistency index (CI), and consistency ratio (CR) for different pairwise comparison matrices were determined and listed in Table 2. The matrix is said to be consistent for a CR value less than 0.1. The results in the present cases reveal that CR values are less than 0.1 for all the pair-wise comparison matrices. Thus, all the matrices (SAL, SAM, SAH, CL, CM, and CH) are consistent. For any inconsistencies, the preference score needs to be reassigned to make it consistent.

Table 2. λ_{max} CI, CR of fuzzy pair-wise comparison matrices of sub-criteria of

Sub-criteria	Maximum Eigenvalue	CI	CR
SAL	7.0998	0.0166	0.0126
SAM	7	0	0
SAH	7.0998	0.0166	0.0126
CL	7.1571	0.0261	0.0198
CM	7	0	0
CH	7.1571	0.0261	0.0198

2.4. Determination of the weights of underground mining methods

The weights of the different mining methods were determined from the crisp comparison matrices $(SAL'_{f}, SAM'_{f}, SAH'_{f}, CL'_{f}, CM'_{f}, and CH'_{f})$. The suitability of a mining method has been determined based on the weights. The weights of each mining method correspond to each subcriterion were determined from the crisp comparison matrix based on the geometric mean (GM) concept. The GM of ith row in any crisp comparison matrix was determined using equation. (4).

$$GM_i = \left[\prod_{j=1}^M x_{ij}\right]^{1/M} \tag{4}$$

where x_{ij} represents the value correspond to i^{th} row and j^{th} column of the crisp comparison matrix. M represents the number of columns in the crisp comparison matrix, and this is equal to the number of mining methods.

The weights of ith mining method correspond to each sub-criterion were determined using equation. (5) as shown below.

 $W_i = GM_i / \sum_{i=1}^N GM_i$

(5)

where W_i represents the weight of the ith parameter or mining method The determination of the weights of the different mining methods correspond to SAL condition is explained below.

The GM of each row of the crisp comparison matrix SAL'_{f} was determined as

 $GM_1 = [1*1*1*1*1*0.375*0.125]^{1/7} = 0.6458$ $GM_2 = [1 * 1 * 1 * 1 * 1 * 0.375 * 0.125]^{1/7} = 0.6458$ $GM_3 = [1 * 1 * 1 * 1 * 1 * 0.375 * 0.125]^{1/7} = 0.6458$ $GM_4 = [1 * 1 * 1 * 1 * 1 * 0.375 * 0.125]^{1/7} = 0.6458$ $GM_5 = [1 * 1 * 1 * 1 * 1 * 0.375 * 0.125]^{1/7} = 0.6458$ $GM_6 = [3 * 3 * 3 * 3 * 3 * 1 * 0.14]^{1/7} = 1.6550$ $GM_7 = [8 * 8 * 8 * 8 * 8 * 7 * 1]^{1/7} = 5.8316$

These are represented in matrix GM_{SAL} as follows:

$$GM_{SAL} = \begin{array}{c} BC\\ SS\\ SC\\ O.6458\\ SC\\ O.6458\\ SH\\ O.6458\\ SH\\ O.6458\\ CF\\ 1.6550\\ SQ\\ 58316 \end{array}$$

The weight of each mining method was determined as GM_{PC}

$$W_{BC} = \frac{BC}{\sum_{i=1}^{7} GM_i}$$

0.6458

0.6458 + 0.6458 + 0.6458 + 0.6458 + 0.6458 + 1.655 + 5.83160.6458 = 0.06027

$$W_{SS} = \frac{0.6458}{10.71602} = 0.06027$$
$$W_{SC} = \frac{0.6458}{10.71602} = 0.06027$$
$$W_{RP} = \frac{0.6458}{10.71602} = 0.06027$$
$$W_{SH} = \frac{0.6458}{10.71602} = 0.06027$$
$$W_{CF} = \frac{1.6550}{10.71602} = 0.15440$$
$$W_{SQ} = \frac{5.8316}{10.71602} = 0.54420$$

The weights of different mining method correspond to SAL condition is represented in WSAL matrix.

In a similar way, the weights of the different mining methods correspond to each sub-criterion of safety and capital for α =1 and λ =0.5 are determined and represented in matrices WSAM, WSAH, WCL, WCM, and W_{CH}



3. Results and discussion

The preference scores of each mining method correspond to different safety levels, and capital availability or investment is represented by the weights. Safety is classified into three subcategories viz. low, medium, and high. Similarly, capital is also classified into three subcategories viz. low, medium, and high. The weights of each mining method correspond to different safety levels, and capital investment for maximum uncertainty level ($\alpha = 1$) and neutral decision-making attitude ($\lambda = 0.5$) are shown in the matrices WSAL, WSAM, WSAH, WCL, WCM, and WCH. The mining method which is having a higher weight is more suitable and vice-versa. It can be inferred from the results that the highest weight for SAL condition was assigned to SQ stoping method (0.544201). Hence the most preferred method of ore deposit extraction is SQ for low safety conditions. Similarly, for the SAM conditions, the highest weight was found to be 0.539179 correspond to CF stoping method, and hence the CF method is the highest favorable method for extractions of the ore deposit with a medium level of safety. For SAH working conditions, five mining methods (BC, SS, SC, RP, and SH) are equally preferable as all these methods are having equal weights (0.189668).

Similarly, it can be observed from the W_{CL} matrix that the highest weight is 0.366414 correspond to SH and SQ stoping methods. These two mining methods are most adaptable than the others in case of low capital availability. Similarly, the highest weights found for mediumlevel capital availability condition is 0.226058 correspond to four mining methods (SS, SC, RP, and CF). In case of the high level of capital availability or investment, the BC is the most favorable mining method as the weight of this method is highest (0.525006) for CH condition.

To analyze the sensitivity of the safety and capital parameters on preferences of different mining methods under different uncertainty level and decision-making attitude, the weights are determined using proposed Fuzzy-AHP decision-making model for different combinations of α and λ [(λ = 0, α =0); (λ = 0, α =0.2); (λ = 0, α =0.4); (λ = 0, α =0.6); (λ = 0, α =0.8); (λ = 0, α =1); (λ = 0.5, α =0); (λ = 0.5, α =0.2); (λ = 0.5, α =0.2); (λ = 0.5, α =0.2); (λ = 0.5, α =0.2); (λ = 0.5, α =0.2); (λ = 0.5, α =0.2); (λ = 0.5, α =0.2); (λ = 0.5, α =0.2); (λ = 0.5, α =0.2); (λ = 0.5, α =0.2); (λ = 0.5, α =0.2); (λ = 0.5, α =0.2); (λ = 0.5, α =0.2); (λ = 0.5, α =0.2); (λ = 0.5, α =0.2); (λ =0.5, α =0.2); ({\lambda}=0.5, \alpha=0.2); ({\lambda} 0.5, α =0.4); (λ = 0.5, α =0.6); (λ = 0.5, α =0.8); (λ = 0.5, α =1); (λ = 1, α =0); $(\lambda = 1, \alpha = 0.2); (\lambda = 1, \alpha = 0.4); (\lambda = 1, \alpha = 0.6); (\lambda = 1, \alpha = 0.8); (\lambda = 1, \alpha = 1)].$ In general, $\alpha = 0$ indicates zero levels of uncertainty whereas $\alpha = 1$ indicates the maximum level of uncertainty [9]. The three λ values viz. 1, 0, and 0.5 respectively indicate the optimistic, pessimistic, and neutral decision-making attitude of the mine planner. For each type of decisionmaking attitude (λ), six sets of fuzzification factors (α =0, 0.2, 0.4, 0.6, 0.8, and 1) were considered for determining the weights of different mining methods correspond to each sub-criteria parameter of safety and capital. Here only six fuzzification factors are considered to observe the clear change. The software used to analyze the parameters by changing different values of fuzzification factor (α) and decision-making attitude (λ) in the present works is Origin. The summarized results are



represented in Fig. (3) and Fig. (4) respectively for safety and capital parameter. Fig. 3(a) shows the weights of various mining methods for SAL conditions. The results indicate the order of the preference level is SQ>CF>BC=SS=SC=RP=SH for SAL condition. That is, for any combination of λ and α , the highest weight was found for square set stoping (SQ). It indicates that the ranks or preference levels of different mining methods are unaltered with changes in the values of λ and α . Similarly, Fig. 3(b) shows the weights of various mining methods for SAM condition. The results indicate the order of the preference level is CF>BC=SS=SC=RP=SH=SQ for SAM condition. That is, for any

combination of λ and α , the highest weight was found for cut and fill stoping (CF). Fig. 3(c) shows the weights of various mining methods for SAH condition. The results indicate the order of the preference level is BC=SS=SC=RP=SH>CF>SQ for SAH condition. That is, for any combination of λ and α , the highest weight was found for block caving (BC), sublevel stoping (SS), sublevel caving (SC), room and pillar (RP), and shrinkage stoping (SH). In all the occasions, it is observed that the ranking of different mining methods in particular conditions remains the same for different λ and α values.



Fig. 3: Weights of mining methods for various decision-making attitude (λ) and fuzzification factor (α) (a) low safety condition (SAL) (b) medium safety condition (SAM) and (c) high safety condition (SAH)



Fig. 4: Weights of mining methods for various decision-making attitude (λ) and fuzzification factor (α) (a) low capital investment/availability (CL) (b) medium capital investment/availability (CM) (c) high capital investment/availability (CH).

Similarly, Fig. 4(a) shows the weights of various mining methods for CL conditions. The results indicate the order of the preference level is SH=SQ>SS=SC=RP=CF>BC for CL condition. That is, for any combination of λ and α , the highest weight was found for shrinkage stoping (SH) and square set stoping (SQ). In this case also the ranks or preference level of different mining methods is not changing with changes in the values of λ and α . Similarly, Fig. 4(b) shows the weights of various mining methods for CM conditions. The results indicate the order of the preference level is SS=SC=RP=CF>BC=SH=SQ for CM condition. That is, for any combination of λ and α , the highest weight was found for sublevel stoping (SS), sublevel caving (SC), room and pillar (RP) and cut and fill stoping (CF). Fig. 4(c) shows the weights of various mining methods for CH conditions. The results indicate the order of the preference level is BC>SS=SC=RP=CF>SH=SQ for CH condition. That is, for any combination of λ and α , the highest weight was found for block caving (BC). As in the case of safety, the ranking of different mining methods remains the same for a different level of uncertainty and decision-making attitude in a particular level of capital investment.

4. Conclusions

The present study aims to analyze the influence on the selection of mining methods for a different level of safety and capital investment using the fuzzy-AHP decision-making model. In the current study, the decision-making model considered seven mining methods viz. block caving (BC), sublevel stoping (SS), sublevel caving (SC), room and pillar (RP) and shrinkage stoping (SH), cut and fill (CF), and square set stoping (SQ). The order of the preference level for three safety levels (SAL, SAM, and SAH) are found to be SQ>CF>BC=SS=SC=RP=SH, CF>BC=SS=SC=RP=SH=SQ, and BC=SS=SC=RP=SH>CF>SQ respectively. Similarly, the order of the preference level for three levels of capital investment (CL, CM, and CH) are found to be SH=SQ>SS=SC=RP=CF>BC, SS=SC=RP=CF>BC=SH=SQ, and BC>SS=SC=RP=CF>SH=SQ respectively. Overall, the results indicated that the ranking of different mining methods remains the same irrespective of the level of uncertainty (α) and decision-making attitude (λ) for each sub-criterion condition (SAL, SAM, SAH, CL, CM, and CH).

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