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Preliminary communication

Simultaneous Evaluation of Criteria and Alternatives for Mining Method Selection (Case studies: Gol-E-Gohar No. 3 Iron ore and Chahar-Gonbad Copper ore)

Farhad Samimi Namin[1]; Abbas Amou[2]

[1] *Mining Engineering Department; University of Zanjan, Zanjan, Iran, http://orcid.org/0000-0002-7953-4843*

[2] *Mining Engineering Faculty, Amirkabir University of Technology, Tehran, Iran, https://orcid.org/0009-0002-4141-8000*

Abstract

Selecting a mining method is an essential step in the initial phases of mining. The selection of an inappropriate mining method can have consequences, such as the potential loss of a portion of the ore deposit. Sometimes, changing the mining method can result in high costs that render the entire project economically unfeasible. For the past two decades, qualitative patterns and numerical scoring have been replaced by multi-criteria decision-making methods. In this study, the Simultaneous Evaluation of Criteria and Alternatives (SECA) multi-criteria decision analysis method was introduced for the first time in the selection of mining methods. The SECA was used to select the mining method in two ore bodies: Gol-E-Gohar No. 3 Iron ore and Chahar-Gonbad Copper ore. The final ranking compared with the results obtained from the fuzzy TOPSIS decision-making method. The satisfactory results indicated that the open-pit method was selected as the appropriate approach for both cases. The SECA method has lower computational complexity because it does not require the use of weight vectors as inputs. However, it does require a precise decision matrix. This method can be considered the foundation of artificial intelligence for selecting a mining method.

Keywords:

mining method selection; multi criteria decision analysis; SECA; Chahar-Gonbad Copper mine; Gol-E-Gohar Iron mine

1. Introduction

Mining Method Selection (MMS) is a critical and strategic issue in the mining engineering process. Choosing an inappropriate method that is not compatible with the deposit's characteristics can hinder ore exploitation and sometimes prove to be uneconomical. Therefore, the mining method for existing reserves should be chosen based on economic, technical, and safety considerations (**Samimi Namin et al., 2009**). The selection of a mining method is influenced by numerous controllable and uncontrollable parameters, which should be assessed through scientific and technical studies for each ore deposit. After selecting a mining method for a deposit, changing the technique is typically very challenging and can be costly in some instances, rendering the entire project uneconomical.

Approaches for selecting a mining method can be divided into four main categories: qualitative models, numerical scoring, decision-making based techniques, and artificial intelligence models. There is significant overlap between the last two groups, as they both rely on the expert system as their foundation. Nevertheless, the learning capability of the model is crucial in artificial intelligence approaches. Several researchers, such as Bashkov and Wright, Morrison, and Hartman, have proposed qualitative patterns for selecting a mining method (**Boshkov and Wright, 1973; Morrison, 1976; Hartman, 1992**). Numerical scoring methods introduced by Nicholas and Miller are used as numerical scoring models (**Labscher, 1981; Nicholas 1981; Miller, 1995**). The mentioned methods have limitations in terms of the number of influential parameters and do not employ a compensatory approach. This means that the strength of one parameter cannot compensate for the weakness of another parameter (**Samimi Namin et al., 2012**). In the past two decades, the use of multi criteria decision analysis (MCDA) models has become prevalent. MCDA models have found application in the field of mining engineering for the purpose of selecting various equipment, such as transportation and support systems (**Yetkin et al., 2016; Bouhedja et al., 2020; Malli et al., 2021; Kiani., 2021**). The purpose of using multi criteria decision analysis methods is to identify the most suitable mining method that aligns best with the relevant criteria (**Samimi Namin et al., 2022**). Artificial intelligence encompasses all models that mimic human cognition and possess the ability to undertake problem-solving and learning tasks. The fundamental principle of artificial intelligence lies in comprehensively defining human intelligence and its operational mechanisms, enabling models to seamlessly incorporate and effectively execute as-

Corresponding author: Farhad Samimi Namin
e-mail address: f.samiminamin@znu.ac.ir

Figure 1: The process of using mining method selection models in literature

Table 1: Brief background of multi criteria decision analysis in selecting a mining method in last decade

Number	Multi criteria decision analysis models	Reference
1	TODIM (an acronym in Portuguese of interactive and multiple attribute decision making)	**(Saki et al., 2020)**
2	Fuzzy analytic hierarchy process	**(Sanja Bajić, 2020)**
3	Fuzzy technique for order preference by similarity of an ideal solution & Fuzzy analytic hierarchy process	**(Banda, 2020)**
4	Analytic hierarchy process	**(Balt and Goosen, 2020**
5	Pivot Pairwise Relative Criteria Importance Assessment (PIPRECIA)	**(Popović et al., 2019)**
6	Analytic hierarchy process	**(Yetkin and Özfırat, 2019)**
7	Fuzzy technique for order preference by similarity of an ideal solution	**(Kangwa and Mutambo, 2019)**
8	Fuzzy theory & TODIM (an acronym in Portuguese of interactive and multiple attribute decision making)	**(Wei-zhang et al., 2019)**
9	Fuzzy analytic hierarchy process	(Balusa & Gorai, 2019)
10	Analytic hierarchy process	(Stevanović, et al., 2018)
11	Fuzzy analytic hierarchy process	**(Chander et al., 2018)**
12	Technique for order preference by similarity of an ideal solution	(Asadi Ooriad et al., 2018)
13	weighted product model & Preference ranking organization method for enrichment evaluation	(Balusa and Singam, 2017)
14	Fuzzy technique for order preference by similarity of an ideal solution	(Javanshir and Safari, 2017)
15	Fuzzy analytic hierarchy process	(Karimnia and Bagloo, 2015)
16	Fuzzy analytic hierarchy process	(Ghazikalayeh et al., 2014)
17	Analytic hierarchy process	(Nolan and Kecojevic, 2014)
18	Analytic hierarchy process & VIKOR (an acronym in Serbian of multi-criteria optimization and compromise solution)	**(Gelvez and Aldana, 2014)**
19	Monte Carlo analytic hierarchy process	(Ataei et al., 2013)
20	Fuzzy analytic hierarchy process & Fuzzy technique for order preference by similarity of an ideal solution	**(Shariati et al., 2013)**
21	Fuzzy analytic hierarchy process	**(Ozdirat et al., 2012)**
22	Analytic hierarchy process & Preference ranking organization method for enrichment evaluation	**(Bogdanovic et al., 2012)**
23	Fuzzy analytic hierarchy process	**(Azadeh et al., 2010)**

signed tasks. Historically, artificial intelligence has not garnered significant attention in the realm of MMS. However, recent advancements indicate that the time has arrived to develop artificial intelligence systems capable of making informed choices regarding mining methods. These systems should rely on decision-making models and expert systems to ensure optimal outcomes. This article aims to introduce the SECA method, which facilitates the development of an intelligent decision-making system for MMS.

Figure 1 displays the changing trends in mining method selection models. The major emphasis of the MMS articles is depicted in **Figure 1**. The boundary illustrated in the figure is non-existent in actuality. The aforementioned classification highlights that recent research efforts have predominantly concentrated on the selection of mining methods based on a decision support system. It is important to acknowledge that, even today, the industry continues to employ numerical or qualitative scoring methods, similar to those utilized in the past. **Table 1** provides an overview of various studies conducted in the past decade, focusing on the selection of mining methods using a decision support system, especially artificial intelligence approaches.

Below, the calculation basics of method Simultaneous Evaluation of Criteria and Alternatives (SECA) will be

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presented first. Then, the SECA decision-making method for the mining method in two mines in Iran will be evaluated. The results obtained from implementing the SECA have been analyzed to select the mining method for the Gol-E-Gohar (GEG) No. 3 iron ore mine and the Chahar-Gonbad copper ore mine in Iran. At the end, the results will be presented and the limitations of the method will be presented for the mining method.

2. Simultaneous Evaluation of Criteria and Alternatives

Simultaneous Evaluation of Criteria and Alternatives (SECA) is a multi-criteria decision analysis method that involves the simultaneous evaluation of multiple criteria and alternatives. This approach enables decision-makers to consider all the relevant criteria and options simultaneously, rather than evaluating them individually. SECA can help streamline the decision process and ensure that all important considerations are taken into account when making a choice.

This method is often utilized in complex decision-making situations where there are multiple criteria and alternatives to consider. The purpose of SECA is to provide a comprehensive and systematic approach to decision-making that takes into account multiple criteria and their potential impacts on various aspects of the decision. By evaluating the alternatives simultaneously, SECA enables decision-makers to make informed and balanced decisions that consider the complex interplay of social, economic, and environmental factors. SECA helps to ensure that decisions are well-rounded and considerate of the diverse range of impacts that may result from different courses of action.

The main objective of the SECA is to simultaneously determine the ranking of alternatives and the weight of criteria. A multi-objective mathematical model must be developed to achieve this goal. A mathematical model includes two types of reference points for criterion weights. The first type is based on information about the variation within each criterion, which is determined using the standard deviation. The second type is related to variations between criteria and is determined based on the correlation of the criteria. Multi-objective models aim to maximize the performance of each option while minimizing the deviation of weights from reference points. To maximize the performance of each option, a weighted sum model can be used as the objective. Additionally, the sum of squared deviations from reference points must be used to define other objectives of the model.

The steps for SECA for decision-making include identifying criteria, collecting data, simultaneously evaluating, and finally ranking. The first step is to identify the relevant criteria that will be used to evaluate the potential impacts of the decision. The second step is to collect data to assess the potential impacts of each alternative course of action on the identified criteria (decision matrix). The third step is to evaluate the potential impacts of each alternative course of action on the identified criteria simultaneously, rather than sequentially. This may involve using tools such as decision matrix analysis to compare and prioritize the alternatives based on their impacts on the criteria. The final step is to make an informed decision that takes into account the simultaneous evaluation of criteria and alternatives. The SECA mathematical model has been described as follows (**Keshavarz-Ghorabaee et al., 2018**):

Formation of the decision matrix

If the multi attribute decision problem involves n alternatives and m criteria, the decision matrix will be formed as **Equation 1**, where X is decision matrix and X_{ij} represents the performance of alternative i relative to criterion j.

$$X=\begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1j} & \cdots & x_{1m} \\ x_{21} & x_{22} & \cdots & x_{2j} & \cdots & x_{2m} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{i1} & x_{i2} & \cdots & x_{ij} & \cdots & x_{im} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nj} & \cdots & x_{nm} \end{bmatrix} \quad (1)$$

Where:

X – Decision Matrix,

X_{ij} – represents the activity of the i^{th} row alternatives when compared to the j^{th} column of criteria,

m – Number of criteria,

n – Number of alternatives (mining methods).

Normalizing decision matrix

The next step is normalysing the decision matrix. **Equation 2** has been used for normalizing the decision matrix.

$$r_{ij}=\begin{cases} \dfrac{x_{ij}}{\max_k x_{kj}} \text{if } j\in BC \\ \dfrac{\min_k x_{kj}}{x_{ij}} \text{if } j\in NC \end{cases} \quad (2)$$

Where:

r_{ij} – Normalized element of X_{ij},

BC – Positive criteria set and

NC – Negative criteria set.

The collection of r_{ij} constitutes the standard (normal) decision matrix. **Equation 3** depicts the normalized decision matrix.

$$r=\begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1j} & \cdots & r_{1m} \\ r_{21} & r_{22} & \cdots & r_{2j} & \cdots & r_{2m} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ r_{i1} & r_{i2} & \cdots & r_{ij} & \cdots & r_{im} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ r_{n1} & r_{n2} & \cdots & r_{nj} & \cdots & r_{nm} \end{bmatrix} \quad (3)$$

Where:

- r – Decision normalysed matrix,
- r_{ij} – represents the normalysed performance of alternative i relative to criterion j,
- m – Number of criteria and
- n – Number of alternatives (mining methods).

Standard deviation and degree of conflict between elements

The standard deviation (σ_j) must be used to obtain information about the internal variability of matrix. Furthermore, the correlation between each pair of matrices can be used to capture information about the variability among different matrices. **Equation 4** illustrates the degree of conflict (π_j) between the j^th vector and the others.

$$\pi_j = \sum_{l=1}^{m} (1 - r_{jl}) \tag{4}$$

Where:

- r_{jl} – The correlation between j^{th} and l^{th} vectors (j and l $\in \{1, 2, \ldots, m\}$),
- π_j – Degree of conflict and
- m – Number of criteria.

Normalization of standard deviation values and degree of correlation

An increase in the variation within the vector of a criterion (σ_j), as well as an increase in the degree of conflict between a criterion and the other criteria (π_j), intensifies the objective importance of that criterion. **Equations 5** and **6** demonstrate the normalized values of standard deviation (σ_j^N) and degree of correlation (π_j^N).

$$\sigma_j^N = \frac{\sigma_j}{\sum_{l=1}^{m} \sigma_l} \tag{5}$$

$$\pi_j^N = \frac{\pi_j}{\sum_{l=1}^{m} \pi_l} \tag{6}$$

Where:

- σ_j and σ_l – Variation within the vector of a criterion in normalised decision matrix j and $l \in \{1, 2, \ldots, m\}$,
- π_j and π_l – Degree of conflict,
- σ_j^N – Normalized values of standard deviation and
- π_j^N – Normalized values degree of conflict.

Final programming model

The programming model (**Equation 7**) is derived from the explanations provided earlier. In **Equation 7**, it is assumed that the value of β is 0.1. Then, this value increases until the rankings of alternatives and weight values do not change as β increases.

$$Max\, Z = \lambda_a - \beta(\lambda_b + \lambda_c) \tag{7}$$

s.t $\quad \lambda_a, \lambda_b \text{ and } \lambda_c$

$$S_i = \sum_{j=1}^{m} w_j r_{ij}$$

$$\forall i \in \{1, 2, \ldots, n\}$$

$$\lambda_b = \sum_{j=1}^{m} (w_j - \sigma_j^N)^2$$

$$\lambda_c = \sum_{j=1}^{m} (w_j - \pi_j^N)^2$$

$$\sum_{j=1}^{m} w_j = 1$$

Where:

- Z – Objective function,
- β – Incremental coefficient and β ≥ 0,
- λ_a, λ_b *and* λ_c component of objective function,
- wj – Weights of criteria of criteria,
- S_i – Summation of the weighted normalized values,
- σ_j^N – Normalized values of standard deviation and
- π_j^N – Normalized values degree of conflict.

Based on the objective function of **Equation 7**, the minimum of the overall performance score of alternatives (ƛa) is maximized. Since the deviations from reference points should be minimized, they are subtracted from the objective function with a coefficient β ($\beta \geq 0$). This coefficient affects the importance of reaching the reference points of criteria weights. The overall performance score of each alternative (S_i) and the objective weight of each criterion (w_j) are determined by solving **Equation 7**.

3. Mining method selection with SECA

The objective of this section is to assess the feasibility of utilizing the SECA for the selection of the mining method. To achieve this objective, two mines in Iran, namely the Gol-E-Gohar (GEG) No. 3 iron ore mine and the Chahar-Gonbad copper ore mine, were taken into

Figure 2: The location of Gol-E-Gohar No. 3 Iron ore and Chahar-Gonbad copper ore

Table 2: Defining of the main criteria for mining method selection (n)

Criterion	Symbol	Criterion	Symbol	Criterion	Symbol
Recovery	C11	**Rock mass rating of hanging wall**	C6	**Ore body shape**	C1
Access to skilled labor	C12	**Rock mass rating of ore**	C7	**Ore grade distribution**	C2
Production rate	C13	**Rock mass rating of foot wall**	C8	**Ore plunge/dip**	C3
RQD of Hanging wall	C14	**Rock Substance Strength of Ore**	C9	**Ore thickness**	C4
Production costs	C15	**Rock Substance Strength of hanging wall**	C10	**Depth below the surface**	C5

Table 3: Alternatives for mining method selection (m)

Alternatives	Symbol	Alternatives	Symbol	Alternatives	Symbol
Sublevel caving	A9	**Room & pillar**	A5	**Block caving**	A1
Sublevel stoping	A10	**Shrinkage stoping**	A6	**Over hand Cut and fill**	A2
Vertical crater retreat	A11	**Underhand cut and fill**	A7	**Long wall**	A3
		Stop and pillar	A8	**Open pit**	A4

Table 4: The specifications of No. 3 Gol-E-Gohar Iron ore mine (**Samimi Namin et al., 2008**)

	INDEX	Description
Ore	Shape of ore body	Tabular
	Thickness	40 meters
	Plunge/Dip	20 degrees
	Ore grade distribution	Gradual
	Depth below the surface	300 meters
	Rock Quality Designation	75%
	Rock Substance Strength	8.9
	Rock Mass Rating	60-80
	Ore reserve	643 Million Tons
	Rock Joints Condition	Filled with low strength
Hanging wall	Rock Quality Designation	38%
	Rock Substance Strength	6
	Rock Mass Rating	60-80
	Rock Joints Condition	Clean and smooth surface
Foot wall	Rock Quality Designation	15%
	Rock Substance Strength	6.5
	Rock Mass Rating	60-80
	Rock Joints Condition	Rough and clean surface

consideration. The location of Gol-E-Gohar and the Chahar-Gonbad mine is shown in **Figure 2**. Subsequently, the SECA will be employed to determine the mining method for both of these mines after their introduction. The research evaluates the performance of 11 mining methods (m) based on 15 criteria (n). The initial evaluated criteria are listed in **Table 2**, while **Table 3** provides the alternatives.

Gol-E-Gohar No. 3 Iron ore mine

The Gol-E-Ghardar iron ore mine is situated 50 kilometers southwest of Sirjan. As a result of the exploitation, six iron ore deposits with reserves of more than one billion tons have been identified in the Gol-E-Gohar area. No. 3 Iron ore (GEG No.3) is the largest deposit in this area. The Gol-E-Gohar iron ore deposit is situated on the periphery of the Sanandaj-Sirjan transform zone. The primary mineral found in this deposit is magnetite at deeper levels, while hematite is predominant at shallower depths. Other important minerals in the deposit include magnetite, hematite, and pyrite, which alternate with chert and quartzite carbonates. The rocks containing the mineral mass are schist, amphibolite, gneiss, and marble, with an estimated age ranging from Upper Precambrian to Lower Paleozoic. Additionally, the transformation event has been attributed to the Middle Jurassic period.

The Gol-E-Gohar iron deposit can be classified as an epigenetic type. Furthermore, the metamorphic rocks in the area are younger than the deposit, indicating that the metamorphic event has significantly influenced the accumulation and density of magnetite ore. Analysis of the the Gol-E-Gohar mine reveals that the majority of included rocks fall within the range of andesite, andesite basalt, rhyolite, and dacite, which may be associated with andesites resulting from volcanic activity. The specifications of GEG No. 3 are summarized in **Table 4**. Each alternative was evaluated based on specific criteria, and **Table 5** was created to display the decision matrix.

To solve the program described in **Equation 7**, **Equations 2 to 6** have been used to calculate the required values. Variations in the criteria and alternatives have been calculated for various values of β. **Figure 3** illustrates the changes in the criteria, while **Figure 4** presents the variations in the alternatives. In **Figure 3,** the C1, C2, ..., C15 are the mining method selection criteria and in **Figure 4,** A1, A2, ..., A11 are the alternatives according to **Table 2** and **Table 3** respectively.

As shown in **Figures 3** and **4**, when the value of β is 100, increasing this value does not significantly change the weights of the criteria or the ranking of the alternatives. The final weights of the criteria are provided in **Table 6**, and the final ranking of the alternatives is presented in **Table 7**. According to the results obtained from the open pit, block caving, and sublevel caving methods, they are ranked as 1, 2, and 3, respectively. The criteria for production rate, thickness, and skilled labour requirements have been given the highest priority.

Table 5: Decision matrix used for Gol-E-Gohar No. 3 Iron ore

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15
A1	5	5	5	6	6	6	3	7	5	5	5	5	6	6	6
A2	7	6	6	4	6	7	6	6	4	7	6	6	4	6	7
A3	7	4	3	1	5	7	5	1	9	7	4	3	1	5	7
A4	5	6	6	7	3	7	6	6	6	5	6	6	7	3	7
A5	7	5	3	1	6	6	9	3	3	7	5	3	1	6	6
A6	7	5	3	1	6	5	6	3	4	7	5	3	1	6	5
A7	4	4	6	3	4	4	3	7	6	4	4	6	3	4	4
A8	7	6	5	6	6	6	9	3	3	7	6	5	6	6	6
A9	7	5	4	7	5	6	4	7	6	7	5	4	7	5	6
A10	7	7	4	7	7	6	7	3	5	7	7	4	7	7	6
A11	5	4	5	5	4	5	4	7	5	5	4	5	5	4	5

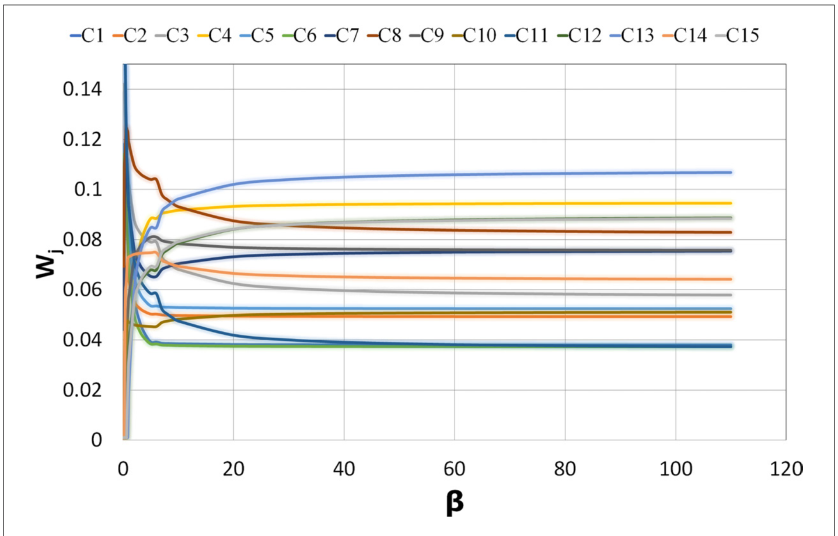

Figure 3: Weighting the criteria for different values of β for Gol-E-Gohar No. 3 Iron ore

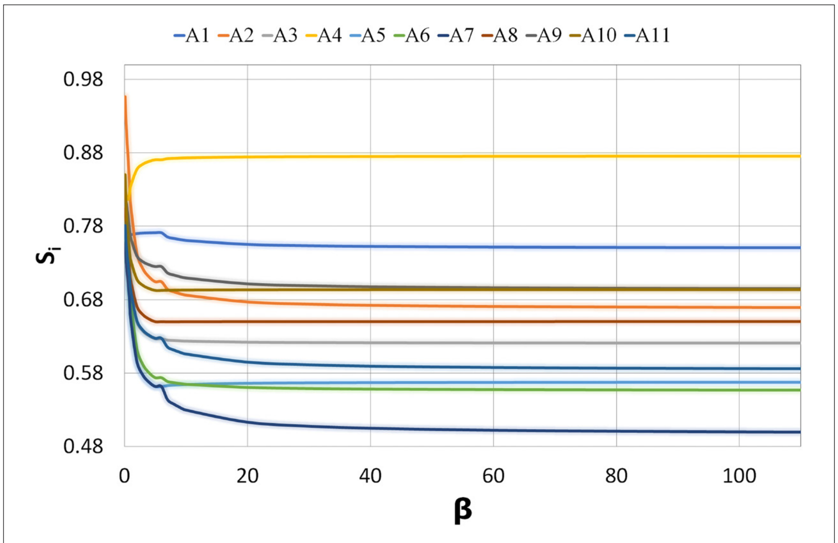

Figure 4: Ranking the alternatives for various values of β for Gol-E-Gohar No. 3 Iron ore

Table 6: The criteria weight for Gol-E-Gohar No. 3 Iron ore

Criteria	Weight	Criteria	Weight	Criteria	Weight
C1	0.038	**C6**	0.037	**C11**	0.037
C2	0.049	**C7**	0.075	**C12**	0.089
C3	0.058	**C8**	0.083	**C13**	0.107
C4	0.094	**C9**	0.076	**C14**	0.062
C5	0.052	**C10**	0.052	**C15**	0.088

Table 7: The final ranking of options for Gol-E-Gohar No. 3 Iron ore

Alternatives	Rank	Alternatives	Rank	Alternatives	Rank
A1	2	**A5**	9	**A9**	3
A2	5	**A6**	10	**A10**	4
A3	7	**A7**	11	**A11**	8
A4	1	**A8**	6		

Table 8: The specifications of the Chahar-Gonbad copper mine (**Samimi Namin et al., 2008**)

	INDEX	Description
Ore	Shape of ore body	Plate
	Thickness	85 meters
	Plunge/Dip	70 degrees
	Ore grade distribution	Sudden Alteration
	Depth below the surface	Less than 100 meters
	Rock Quality Designation	75%
	Rock Substance Strength	8.7
	Rock Mass Rating	60-80
	Ore reserve	700 Million Tons
	Rock Joints Condition	Filled with low strength material
Hanging wall	Rock Quality Designation	38%
	Rock Substance Strength	15.63
	Rock Mass Rating	60-80
	Rock Joints Condition	Smooth and Clean Surface
Foot wall	Rock Quality Designation	15%
	Rock Substance Strength	9.1
	Rock Mass Rating	40-60
	Rock Joints Condition	Rough and clean surface

Chahar-Gonbad copper mine

The Chahar-Gonbad region is located in the southwest of Kerman and northeast of Sirjan city. The Chahar-Gonbad copper deposit is estimated to exceed four million tons in quantity. The geological formations in the region consist of various types of rocks, including ophiolitic rocks, volcanic rocks, intrusive masses, and sedimentary rocks. Along the Chahar-Gombad Fault, mineralization has occurred in andesite rocks, basaltic andesite, and andesite tuffs in the form of veins. Sulfide mineralization in ore-bearing rocks can be observed in three forms: diffuse, veined, and veinlet. The most significant sulfide minerals in these formations are pyrite and chalcopyrite. The study area also exhibits different alterations, such as argillic, phyllic, and propylitic alterations. In addition to these formations, intrusive masses like granite and porphyry quartzdiorite, which are of Oligo-Miocene age, have intruded volcanic rocks including basalt andesite, trachyandesite, and dacite from the Eocene period. The rocks in this region have a porphyritic and granular texture, and their main mineral constituents are plagioclase, quartz, alkali feldspar, pyroxene, and amphibole. The distribution pattern of rare earth elements in all igneous rocks in the region is nearly identical.

The geometric and mechanical specifications of the Chahar-Gonbad copper mine are presented in **Table 8**. Using these specifications, a decision matrix was created as previously and is presented in **Table 9**. In the previous scenario, the variations in numbers and alternatives for various values of β have been examined.

Figure 5 illustrates the changes in criteria, while **Figure 6** depicts the changes in alternatives. In Figure 5, the C1, C2, ..., C15 are mining method selection criteria and In Figure 6, A1, A2, ..., A11 are the alternatives according to **Table 2** and **Table 3** respectively. The mining method for the Chahar-Gonbad copper mine was selected based on the highest weights assigned to production criteria, skilled labor requirements, and cost. Open-pit mining ranked first, followed by sub-level stoping and sub-level caving methods, which ranked second and third. As shown in **Figures 5** and **6**, when the value of β is set to 140, increasing this value does not result in sig-

Table 9: The matrix used for the Chahar-Gonbad copper mine

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15
A1	5	5	7	3	5	6	3	5	5	5	90	1	90	9	12.5
A2	7	7	7	7	5	7	6	7	4	5	100	5	30	7	32.5
A3	7	3	1	3	5	7	5	5	9	6	95	5	40	9	15
A4	5	5	4	6	7	7	6	7	6	7	100	9	90	7	11.5
A5	7	3	1	4	6	6	9	5	3	5	60	6	35	4	20
A6	7	5	7	3	6	5	6	6	4	6	85	6	12	9	27.5
A7	4	6	5	5	4	4	3	4	6	3	100	1	8	7	77.5
A8	7	6	5	6	6	6	9	3	3	5	60	4	40	4	19
A9	7	5	7	3	6	6	4	5	6	5	85	4	35	9	26
A10	7	6	7	6	6	6	7	7	5	6	85	6	45	3	23.5
A11	5	4	3	3	5	5	4	5	6	4	95	5	10	7	42.5

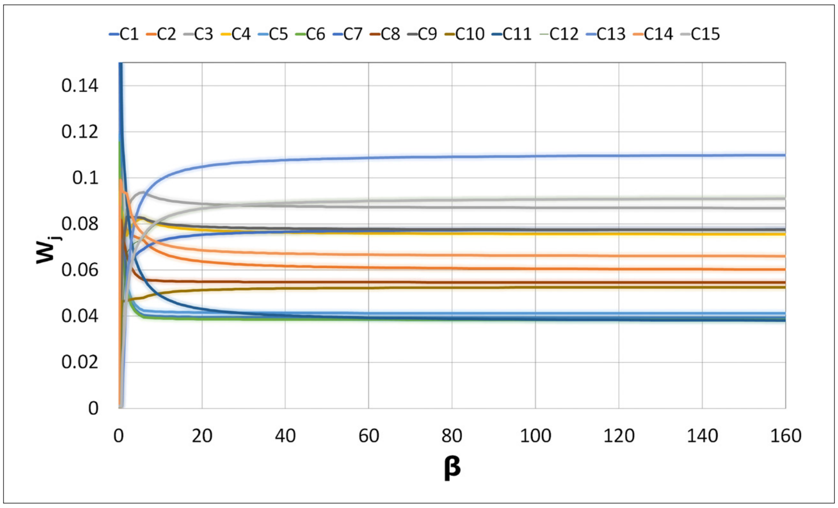

Figure 5: The weights of the criteria for different values of β in the Chahar-Gonbad copper mine

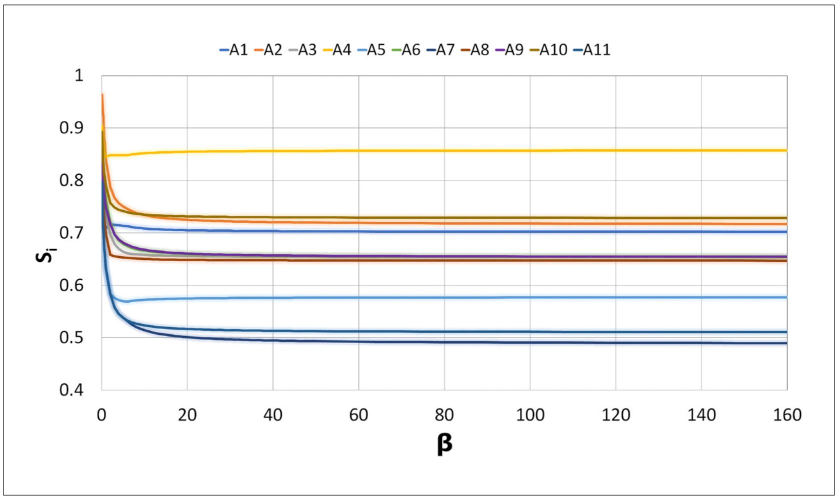

Figure 6: The ranking of alternatives for different values of β in the Chahar-Gonbad copper mine

Table 10: The final ranking of criteria for the Chahar-Gonbad copper mine

Criteria	Weight	Criteria	Weight	Criteria	Weight
C1	0.039	**C6**	0.038	**C11**	0.038
C2	0.060	**C7**	0.076	**C12**	0.091
C3	0.087	**C8**	0.055	**C13**	0.110
C4	0.076	**C9**	0.077	**C14**	0.066
C5	0.041	**C10**	0.052	**C15**	0.091

Table 11: The final ranking of alternatives for Chahar-Gondad

Alternatives	Rank	Alternatives	Rank	Alternatives	Rank
A1	4	**A5**	9	**A9**	5
A2	3	**A6**	6	**A10**	2
A3	7	**A7**	11	**A11**	10
A4	1	**A8**	8		

nificant changes in the weights of the indices, nor does it affect the ranking of the alternatives. The final weights of the criteria are provided in **Table 10**, and the final ranking of the alternatives is shown in **Table 11**.

4. Results and Discussion

Samimi Namin and colleagues investigated the mining methods of two studied mines in 2008 using the Fuzzy TOPSIS method. The results obtained from the SECA and Fuzzy TOPSIS methods are presented in **Table 12**. As shown in **Table 12**, the preferred option in the SECA method for both mines studied was consistent with the fuzzy TOPSIS method, which is open-pit mining. In the case of the Chehar-Gonbad copper mine, the SECA method does not differ from the fuzzy TOPSIS method in the second and third rankings. But in the case of Gol-E-Gohar No. 3 Iron ore, it is different and offers various options.

Advantages of simultaneous evaluation of criteria and alternatives (SECA) include:

Table 12: Comparison of SECA and Fuzzy TOPSIS

	Method	Rank1	Rank 2	Rank 3	Rank 4
Gol-E-Gohar No. 3	SECA FDM	A4 A4	A1 A10	A9 A1	A10 A9
Chahar-Gonbad	SECA FDM	A4 A4	A10 A10	A2 A2	A1 A6

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1 – Comprehensive decision-making: SECA allows for a more holistic and thorough evaluation of all the relevant criteria and alternatives, leading to more informed and balanced decisions.

2 – Consideration of interdependencies: SECA enables decision-makers to consider the interrelationships and trade-offs between different criteria and alternatives, leading to a more nuanced understanding of the decision-making process.

3 – Wider range of impacts and factors: SECA allows for the consideration of a broader range of impacts and factors, including social, economic, environmental, and cultural considerations, leading to more sustainable and responsible decision-making.

Disadvantages of simultaneous evaluation of criteria and alternatives (SECA) may include:

1 – Complexity: SECA can be more complex and time-consuming compared to other decision-making techniques, requiring a greater investment of resources and expertise.

2 – Data and information requirements: SECA may require a significant amount of data and information to effectively evaluate multiple criteria and alternatives simultaneously, which could pose challenges in certain contexts.

3 – Subjectivity: The simultaneous evaluation of criteria and alternatives may introduce subjectivity and biases into the decision-making process, requiring careful consideration and management.

The main difference between SECA and other decision-making techniques lies in the simultaneous evaluation of criteria and alternatives. While other techniques may focus on evaluating criteria and alternatives separately, SECA integrates both process into a comprehensive and holistic approach to decision-making. This allows the decision-maker to consider the interdependencies and trade-offs between different criteria and alternatives, leading to more informed and balanced decisions. Additionally SECA also allows for the consideration of wider range of impacts and factors compared to other decision-making techniques. Overall, SECA provides a more comprehensive and systematic approach to decision-making that takes into account the complex interplay of multiple criteria and alternatives, such as mining method selection problems.

5. Conclusions

This article investigates the effectiveness of the SECA programing in MMS. The SECA relies entirely on the decision matrix and therefore necessitates an accurate decision matrix. The SECA offers several benefits. First, it is easy to put in place, making it convenient. Second, it has low computational complexity and does not require extensive computing power. Unlike other methods, SECA does not depend on weight vectors as input, simplifying the decision-making process. The SECA method demonstrated good performance in selecting the mining method for two mines. In the case of the Chahar-Gonbad copper mine, its performance ranking resembled that of fuzzy TOPSIS. Additionally, in both mines under study, the superior option showed a significant difference compared to the second option. In general, if a robust decision matrix is in place and there is a substantial disparity between the top rank and the second rank, as evidenced in this study, one can have confidence in the SECA method's results for selecting the mining method. The SECA method was employed to investigate the mining method selection in two copper and iron mines in Iran. The findings from both mines indicated that the open pit mining method is the most suitable option, aligning with the actual conditions. In the Gol-E-Gohar mine, the production rate and ore thickness were identified as the most influential factors, collectively contributing to approximately 20% of the evaluation. On the other hand, in the Chahar-Gonbad mine, the production rate and access to skilled personnel were identified as the key parameters, accounting for around 20% of the criteria's weight.

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SAŽETAK

Simultana evaluacija kriterija i alternativa za odabir metode eksploatacije (studije slučaja: željezna ruda Gol-E-Gohar br. 3 i bakrena ruda Chahar-Gonbad)

Odabir metode eksploatacije bitan je korak u početnim fazama otkopavanja. Odabir neprikladne metode eksploatacije može rezultirati neiskorištavanjem dijela rudnoga ležišta. U određenim slučajevima promjena metode eksploatacije može rezultirati visokim troškovima koji cijeli projekt čine ekonomski neisplativim. U posljednja dva desetljeća kvalitativni obrasci i numeričko bodovanje zamijenjeni su višekriterijskim metodama odlučivanja. U ovome je istraživanju prvi put uvedena metoda višekriterijske analize simultane procjene kriterija i alternativa (SECA) u odabiru metoda eksploatacije. SECA je korištena za odabir metode eksploatacije u dvama rudnim tijelima: željezna ruda Gol-E-Gohar br. 3 i bakrena ruda Chahar-Gonbad. Konačni poredak uspoređen je s rezultatima dobivenim neizrazitom TOPSIS metodom odlučivanja. Zadovoljavajući rezultati upućuju na to da je površinska eksploatacija odabrana kao odgovarajući pristup za oba slučaja. Metoda SECA ima manju računsku složenost jer ne zahtijeva korištenje težinskih vektora kao ulaznih podataka. Međutim, to zahtijeva preciznu matricu odlučivanja. Ova se metoda može smatrati temeljem umjetne inteligencije za odabir metode eksploatacije.

Ključne riječi:
odabir metode eksploatacije, višekriterijska analiza odluka, SECA, rudnik bakra Chahar-Gonbad, rudnik željeza Gol-E-Gohar

Authors' contribution

Farhad Samimi Namin (Mining Engineering Assoc. Prof in University of Zanjan): Supervision and administration, conceptualization, investigation resources, data validation, writing – review & editing.
Abbas Amou (M.Sc Student, Mining Engineering, Amirkabir University of Technology) Formal analysis, data collection and processing, provided the original draft.