Type of the Paper (state-of-the-art review)

Multi-criteria Decision-making Methods for Sustainable Decisionmaking in the Mining Industry (A Comprehensive Study)

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Abstract: The mining industry operates in a complex and dynamic environment, and faces many challenges that can negatively affect sustainable development goals. To avoid these effects, mining needs to adopt strategic decisions. Therefore, it requires effective decision-making processes for resource optimization, operational efficiency, and sustainability. Multicriteria decision-making methods (MCDMs) have been considered valuable decision-support tools in the mining industry. This article comprehensively examines the MCDM methods and their applications in the mining industry. This article discusses the basic principles and concepts of the MCDM methods including the ability to prioritize and weigh conflicting, multiple criteria, and support decision-makers in evaluating diverse options. According to the results, 1579 MCDM articles in mining have been published from the beginning to April 15, 2023, and a scientometric analysis was done on these articles. In another part of this article, 19 MCDM methods, among the most important MCDM methods in this field, have been examined. The process of doing work in 17 cases of the reviewed methods is presented visually. Overall, this paper is a valuable resource for the researchers, mining industry professionals, policy-makers, and decision-makers that can lead to a deeper understanding of the application of the MCDM methods in mining. By facilitating informed decision-making processes, the MCDM methods can potentially increase operational efficiency, resource optimization, and sustainable development in various mining sectors, ultimately contributing to mining projects' long-term success and sustainability.

Keywords: Multicriteria decision-making, Sustainable development, Mining industry; Scientometric analysis, MCDM.

1. Introduction

The mining industry is one of the most important sectors for a nation's economic development and growth [1, 2]. The industry is critical in providing essential raw materials and resources for various industries such as construction, manufacturing, and energy. However, the mining industry faces several challenges including environmental concerns, resource depletion, social responsibility, and fluctuating commodity prices [3].

All the written challenges can be attributed to one of the sustainable development indicators. In general, sustainable development is a process during which the people of a country meet their needs and improve their living standards without consuming resources belonging to future generations and wasting future capital to meet immediate needs. Therefore, development is called sustainable when it is not destructive and provides the possibility of preserving resources (including water, soil, air, etc.) for the future [4-6]. At the core of sustainable development lies the fundamental principle of preserving our natural resources, ensuring that future generations can meet their needs and thrive to at least the same extent as the present generation. Sustainable development sets its primary objective as fulfilling basic human needs, elevating living standards universally, stewarding and enhancing ecosystems, and forging a path toward a secure and prosperous future. The term "sustainable" paints a vision of a world where the harmonious coexistence of humans and nature persists. This coexistence hinges on considering present needs alongside the rights of future generations, all while safeguarding the environment from profound and irreversible harm. Sustainable development entails crafting socio-economic solutions that preempt challenges such as unchecked population growth, poverty, resource and environmental depletion, disruptions to Earth's delicate ecosystems, and the subsequent fallout from environmental degradation. Pursuing economic and social objectives ensures the enduring preservation of resources, safeguarding the environment, and promoting human health and well-being [7, 8]. Consequently, numerous challenges encountered in diverse spheres of human life, most notably in industries such as mining, are intimately entwined with the principles and imperatives of sustainable development [5].

To address these challenges, mining companies must simultaneously make complex decisions considering multiple criteria or attributes. Various decision methods in the mining context involve exploring the approaches and techniques used to make critical decisions within the mining industry [9].

Various types of decision methods commonly used in mining include:

- Multi-Criteria Decision Making (MCDM): Consider multiple factors such as environmental, social, and economic aspects to make complex decisions.
- Cost-Benefit Analysis (CBA): Evaluate the economic feasibility of mining projects by comparing costs and benefits.
- Simulation modeling: Use computer simulations to model mining scenarios and assess outcomes.
- Geostatistics: Incorporate spatial data and statistical techniques to estimate mineral reserves.
- Risk assessment: Analyze the risks associated with mining operations and develop risk mitigation strategies.
- Machine learning and artificial intelligence: Utilize advanced algorithms to optimize mining processes and predict outcomes.

The advantages and disadvantages of types of decision methods are shown in Table 1 [10].

Table 1. Advantages and disadvantages of types of decision methods.

Advantages of types of decision methods	Disadvantage of types of decision methods
❖ It improved decision quality and accuracy. ❖ Enhanced resource allocation and project planning. ❖ Better risk management and reduced uncertainty. ❖ It has increased efficiency and cost-effectiveness. ❖ Compliance with regulatory and environmental standards.	❖ Data and information limitations. ❖ Complexity and resource-intensive nature. ❖ Potential for biases in decision-making. ❖ Difficulty in quantifying certain factors (e.g. environmental and social impacts). ❖ Technological and expertise requirements.

The decision-making process in the mining industry involves a wide range of variables including geological, technical, economic, social, and environmental factors [11]. The complexity of these variables makes the decision-making process in the mining industry challenging and time-consuming. To simplify the decision-making process, Multicriteria Decision Making (MCDM) and Multi-Attribute Decision Making (MADM) techniques are used [12]. MCDM techniques are used to rank alternatives based on multiple criteria, while MADM techniques are used to choose the best alternative based on a set of attributes. MCDM techniques in the mining industry have become increasingly popular in the recent years. These techniques provide a systematic approach to decision-making that enables mining companies to make informed decisions based on multiple criteria or attributes [13]. Using MCDM techniques, mining companies can identify the most critical criteria or attributes and assign weights based on their relative importance. This approach enables companies to evaluate and compare various alternatives based on their performance against multiple criteria, leading to a better understanding of each alternative's trade-offs and potential risks. There are various applications of MCDM techniques in the mining industry including selecting the best location for a mine, selecting the optimal extraction method, and determining the most cost-effective way to manage waste [14, 15]. The benefits of using MCDM techniques in the mining industry are numerous. These techniques allow mining companies to make more objective, consistent, and transparent decisions. In addition to the benefits mentioned above, using MCDM techniques can contribute to more sustainable and responsible mining practices. Mining companies can use these techniques to evaluate the environmental impact of different mining practices, consider social and economic factors, and identify opportunities to reduce waste and improve resource efficiency [16]. Finally, using MCDM techniques in the mining industry can improve decision-making processes and contribute to more sustainable and responsible mining practices. The mining industry faces many challenges, and using these techniques provides a systematic approach to decision-making that enables mining companies to make informed decisions based on multiple criteria or attributes [11, 12].

Decision methods in mining should provide a balanced view of their utility, acknowledging their strengths and weaknesses, while emphasizing the importance of informed decision-making in the mining industry [17, 18]. Thus one of the most important decision types is MCDM. Because of that, in this paper, all articles published in the field of MCDM and mining have been analyzed from the beginning to April 15, 2023, and then the most important MCDM methods were reviewed in summary form. Finally, the discussion and results of this article are presented.

2. Scientometrics Analysis of MCDM and Mining Articles

Scopus has meticulously compiled a comprehensive database encompassing all articles published at the intersection of Multicriteria Decision-Making (MCDM) and the mining domain. Our analysis reveals that from 1977 to April 15, 2023, 1,579 articles have been published, collectively employing MCDM methodologies within the mining context. Leveraging the Scopus platform with the VOS viewer software, we have successfully extracted valuable insights and data using MCDM techniques in this domain.

The evolving landscape of scholarly publications related to applying Multicriteria Decision-Making (MCDM) methods in mining reveals a noteworthy pattern. Until the year 2019, the utilization of these methods exhibited a relatively stable trajectory, occasionally experiencing fluctuations. However, in the wake of technological advancements and the synergistic integration of hybrid MCDM approaches, a substantial resurgence has occurred since 2019. This resurgence has rekindled significant interest among researchers, marking a distinct and vigorous revival in adopting MCDM methods within the mining domain (Figure 1).

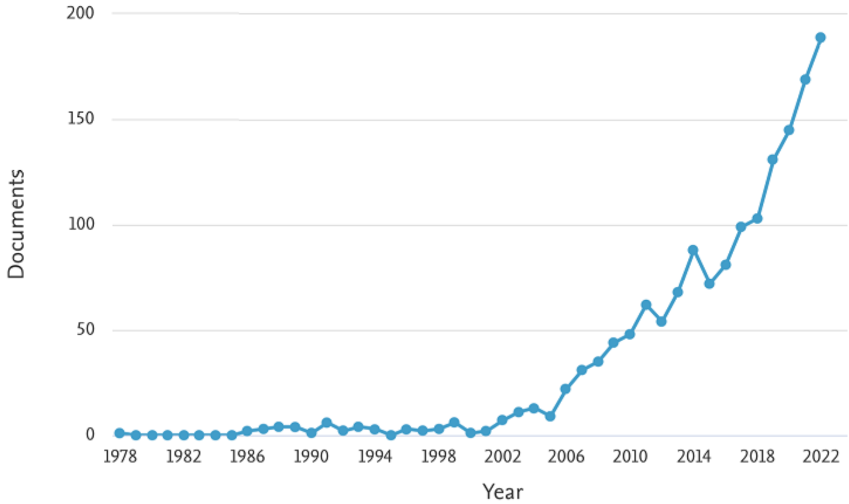

Figure 1. The trend of published MCDM articles in mining from the beginning to 2022 (time of receiving information: April 15, 2023).

An analysis of the 1,579 extractive articles under scrutiny has unveiled a notable trend in utilizing Multicriteria Decision-Making (MCDM) methods within the mining domain. Specifically, Chinese and Iranian researchers have emerged as active contributors to this field, surpassing their counterparts from other nations' research output. Additionally, the cooperative endeavors between Chinese and Iranian researchers have been more extensive than collaborations involving researchers from different countries, as depicted in Figures 2 and 3.

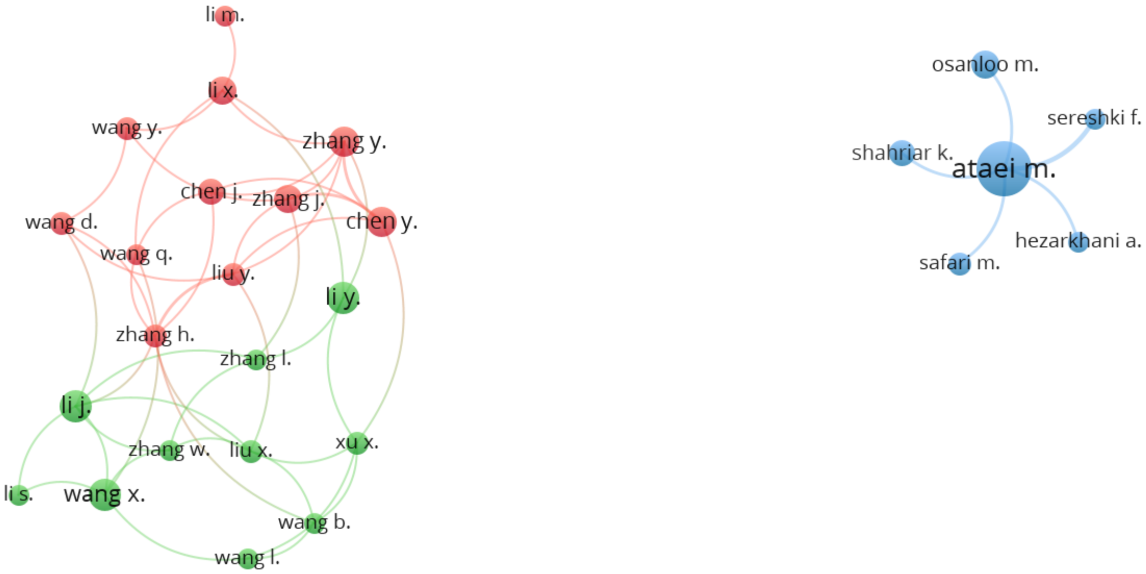

Figure 2. The authors were working on writing a paper on using MCDM. Circle size indicates the number of articles presented in the mentioned field by the researchers, and the link between the data indicates the frequency of collaboration between two researchers in writing MCDM articles in mining (limitation of this data: having at least five articles in the mentioned field and ten references to the articles of these researchers in the field of MCDM in mining).

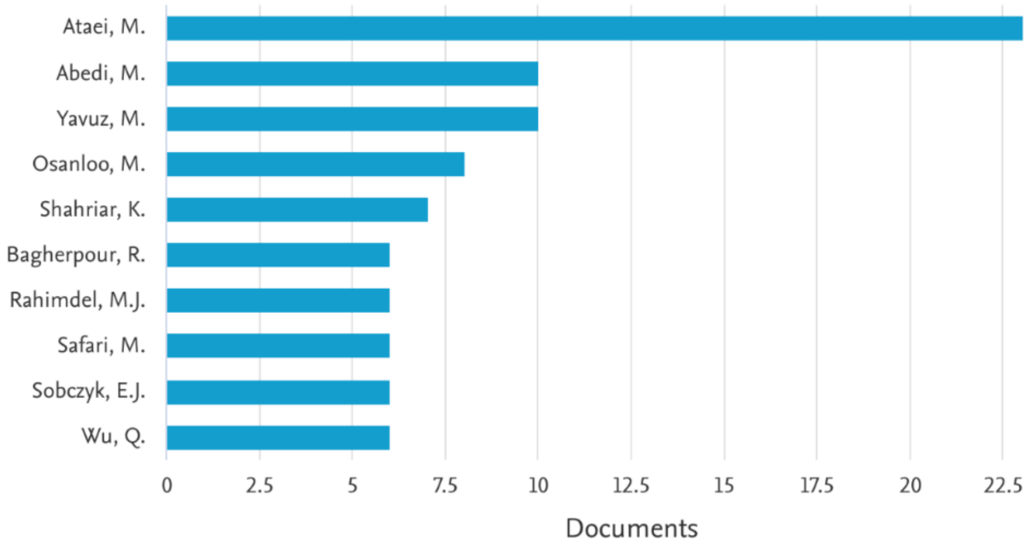

Figure 3. Researchers with the most published articles in the field of MCDM and mining from the beginning of 2023 (data received April 15, 2023).

Examining the global landscape concerning adopting Multicriteria Decision-Making (MCDM) methods within the mining domain highlights Iran and China as frontrunners in this field, a finding substantiated by Figures 4 to 5. However, a noteworthy shift has emerged in the recent years. This shift can be attributed to a change in the research focus of scholars in these leading countries. 133 134

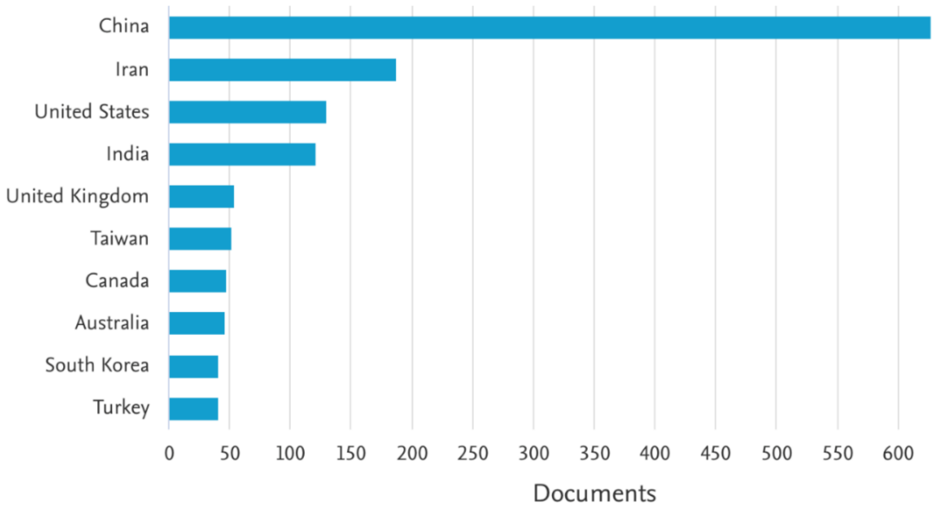

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Figure 4. The leading countries in publishing articles in the field of MCDM and mining from the beginning to 2023 (time of receiving information April 15, 2023). 136 137

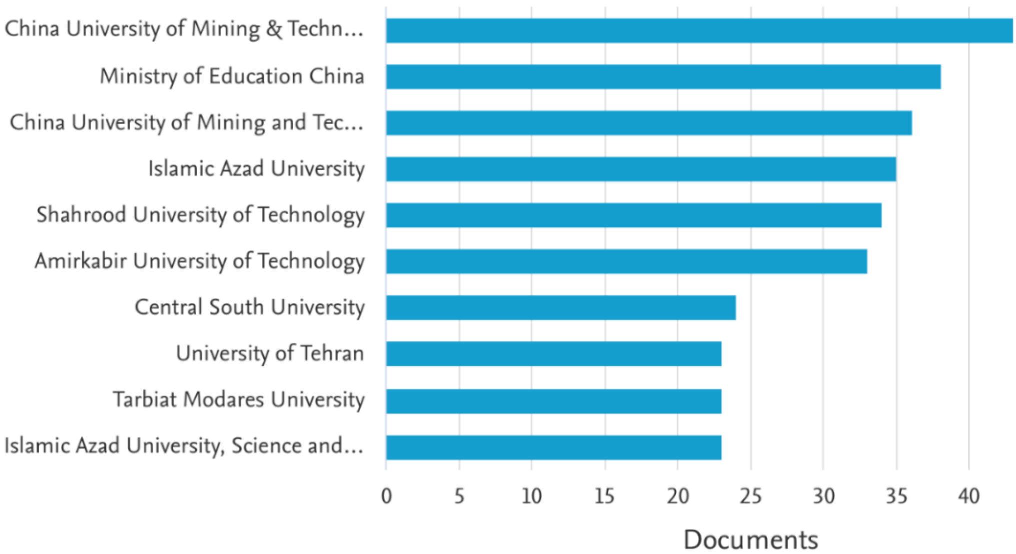

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Figure 5. The most active academic institutions in publishing articles in the field of MCDM and mining from the beginning to 2023 (data received April 15, 2023). 139 140

Figure 6 examines various MCDM techniques extensively applied within the mining domain. A comprehensive data analysis derived from Scopus (as detailed in Table 2) underscores the widespread adoption of these techniques across various facets of the mining sector. Researchers have employed these methodologies to publish many articles spanning different mining disciplines. 141 142 143 144
Figure 6 visually represents the prevalent keywords employed in these articles, shedding light on the specific terminologies and concepts frequently explored within the context of MCDM in mining research. 145 146

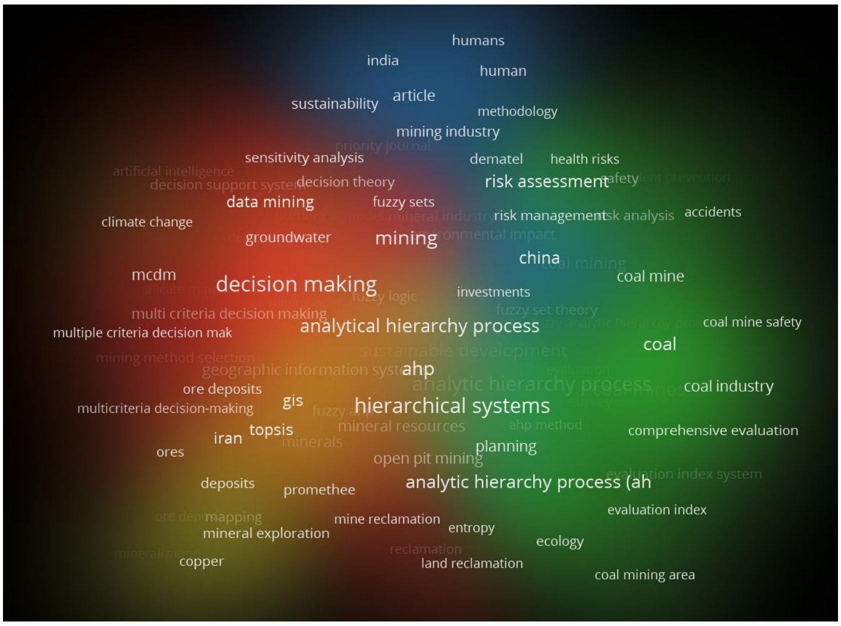

Figure 6. The important keywords used by researchers in the mining field are related to MCDM.

Table 2. Number of words used as keywords in articles from the beginning to April 15, 2023 (Limitation: at least 20 repetitions).

Keyword	Occurrences	Keyword	Occurrences
Multicriteria decision-making	31	Decision-making	163
Coal mine	30	Hierarchical systems	130
Minerals	29	Analytic hierarchy process	118
MCDM	28	Mining	100
Mineral resources	28	Coal mines	90
Planning	28	Analytical hierarchy process	88
Coal deposits	27	AHP	79
Coal industry	27	Coal	72
Open-pit mining	27	Analytic hierarchy process (AHP)	68
Geographic information systems	25	Sustainable development	66
Environmental protection	24	Risk assessment	57
Fuzzy AHP	23	China	44
Mining industry	23	Multicriteria analysis	40
Groundwater	21	Data mining	38
Multicriteria decision-making	21	GIS	37
Economics	20	Coal mining	35
Remote sensing	20	Fuzzy mathematics	35
Sustainability	20	TOPSIS	35
Environmental impact	20	Iran	33

Figure 7 provides a comprehensive breakdown of the data sources in the context of using MCDM methods in mining. Notably, it reveals that a substantial majority, amounting to 69.2 percent, of the reviewed data is disseminated through articles, while conference papers constitute the remaining 30.8 percent.

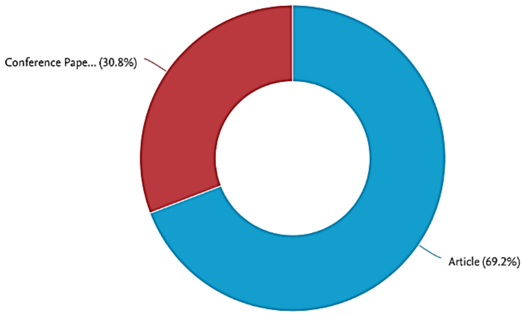

Figure 7. Distribution of the type of documents published in the field of MCDM and mining from the beginning to 2023 (data received April 15, 2023).

To put it briefly, our comprehensive analysis of the intersection of Multicriteria Decision-Making (MCDM) methods and the mining domain, facilitated by Scopus and the VOS viewer software, has yielded valuable insights into the evolving research landscape in this field.
Over the years, we have witnessed a notable trajectory in the publication of MCDM-related articles in mining, with a stable trend until 2019. Subsequently, a resurgence in interest and research activity has been observed, driven by technological advancements and the integration of hybrid MCDM methodologies.
Chinese and Iranian researchers have emerged as prolific contributors, spearheading this domain with remarkable research output and collaboration. However, a noteworthy shift has occurred in recent years, with developing nations such as Saudi Arabia, the UAE, Nigeria, and Nepal actively engaging in MCDM research, further enriching the global research landscape.
We have observed diverse applications of MCDM techniques across various facets of the mining sector, emphasizing their versatility and utility. Additionally, our analysis of keywords employed in research articles has shed light on the prevalent terminologies and concepts central to MCDM in mining research.
Citation patterns have provided insights into research articles' evolving impact and interconnectivity, while co-citation analysis has illuminated the shared knowledge base and collaborative networks within the field.
Lastly, the distribution of document types has revealed that articles dominate the dissemination of research findings, constituting 69.2 percent of the reviewed data, while conference papers account for the remaining 30.8 percent. This comprehensive analysis is a valuable resource for researchers, policy-makers, and industry professionals, offering a deep understanding of the state of MCDM research within the mining domain. It also highlights the dynamic nature of this field, underlining the critical role of collaboration, technological advancements, and emerging research trends in shaping its future trajectory.

3. MCDM

MCDM is a vital approach in decision analysis to tackle choices involving multiple, often conflicting, criteria. In various real-world scenarios, a single factor cannot adequately capture decisions. Instead, they depend on several dimensions: cost, benefit, risk, time, and sustainability. MCDM provides a methodical framework to handle these complexities, aiding decision-makers in systematically evaluating alternatives and arriving at well-informed choices. By considering a range of criteria and their relative importance, MCDM helps ensure decisions align closely with the objectives and preferences of the decision-makers.
According to the analysis of the published articles that used MCDM in mining areas, 19 of the most important techniques used MCDM have been reviewed in this section.

3.1. Analytic Hierarchy Process (AHP)

The AHP is a structured approach to decision-making that facilitates the resolution of complex decisions by breaking them down into more manageable components. This methodology is highly effective because it enables decision-makers to consider qualitative and quantitative factors systematically. One of the key strengths of AHP is its ability to incorporate the preferences and viewpoints of multiple stakeholders in the decision-making process. However, it should be noted that the proper implementation of AHP demands considerable effort and expertise, especially in accurately defining the decision problem and constructing precise pairwise comparison matrices [19-22]. The AHP process is shown in Figure 8.

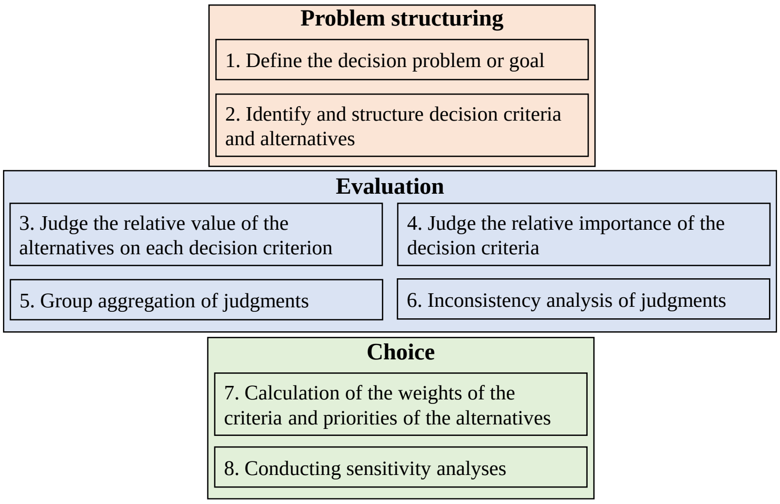

Figure 8. Steps of the AHP method.

3.2. Analytic Network Process (ANP)

The ANP is an extension of the AHP that allows decision-makers to model and analyze complex decision problems that involve interdependent criteria and alternatives. ANP is particularly useful when the decision problem involves feedback loops, interdependence, and mutual influences between criteria and alternatives. It enables decision-makers to evaluate the relative importance of criteria and their interactions. This is achieved by representing the decision problem as a network of clusters and elements, with clusters representing criteria and elements representing alternatives [11, 23]. The ANP process is shown in Figure 9. ANP allows decision-makers to model the interactions between criteria and alternatives more sophisticatedly than AHP. However, it can be more complex and time-consuming to implement than AHP, requiring more expertise and data input [13, 16, 24].

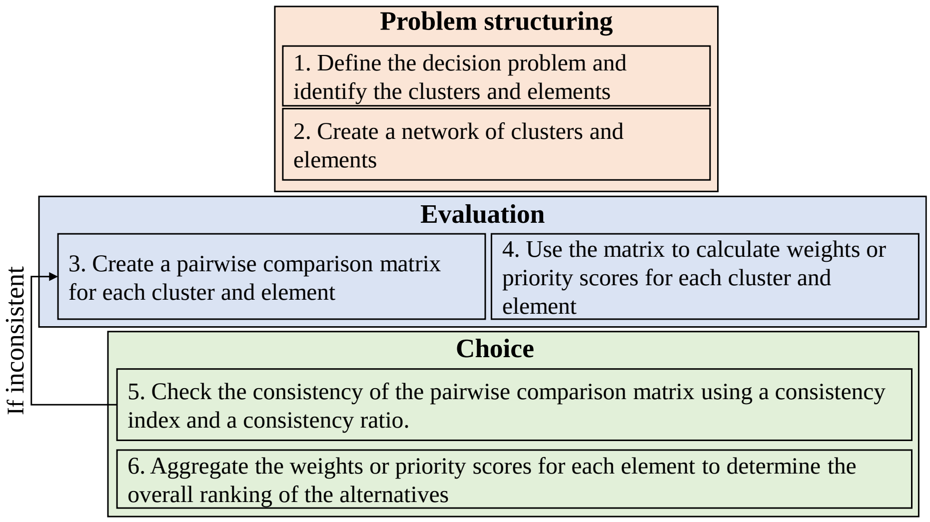

Figure 9. Steps of the ANP method.

3.3. Best Worst Method (BWM)

The BWM is a decision-making technique that helps decision-makers identify the most important and least important criteria or alternatives in a given decision problem. The BWM is a simple and intuitive method for identifying the most important and least important criteria or alternatives in a given decision problem. It allows decision-makers to focus on the most critical factors and to make informed decisions based on their relative importance. However, it does not consider the interactions between criteria or alternatives, which may be important in some decision problems [25, 26]. The BWM process is shown in Figure 10 [27, 28].

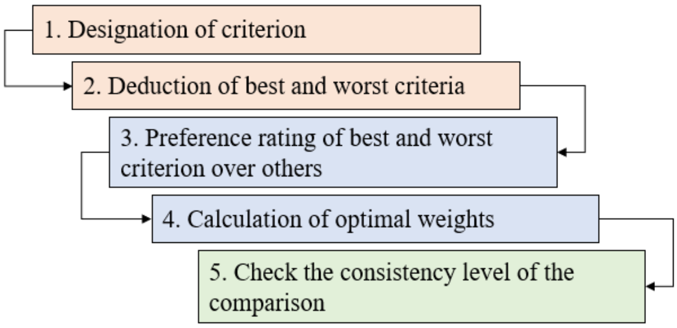

Figure 10. Steps of the BWM method.

3.4. Choquet Integral (CI)

The CI is a non-linear aggregation function used in multicriteria decision-making to combine criteria with different levels of importance or uncertainty. The CI is based on the idea that decision-makers have preferences that are not necessarily additive, meaning that a combination of criteria cannot simply be calculated by adding up the values of each criterion. Instead, the CI considers the interactions between criteria and the degree of importance or uncertainty associated with each criterion [29]. The CI provides a flexible and powerful way to aggregate criteria with different levels of importance or uncertainty. It allows decision-makers to capture the interactions between criteria and make decisions based on their importance. However, it can be computationally intensive and requires significant data input and expertise to implement properly [30, 31].

1. Define the decision problem and identify the criteria that will be used to evaluate the alternatives.
2. Specify the weighting function, which assigns a weight to each subset of criteria based on its degree of importance or relevance. This function is represented by a set function, which maps from subsets of criteria to real numbers between 0 and 1.
3. Calculate the weighted average of the criteria, where the weighting function determines the weights. This involves taking the average value of each subset of criteria, weighted by the corresponding weight.
4. Aggregate the weighted averages of the criteria using the CI formula. This involves taking a weighted sum of the weighted averages, where the weighting function determines the weights.

3.5. Compromise Programming (CP)

CP is a multicriteria decision-making technique that involves finding a compromise solution that satisfies multiple objectives simultaneously. The CP approach allows decision-makers to identify a solution that balances the trade-offs between multiple objectives or criteria. It considers each objective or criterion's relative importance and target values and provides a systematic way to evaluate and compare alternatives [32, 33]. However, it can be sensitive to the choice of compromise function and requires careful consideration of the objectives and criteria involved [34, 35]. The CP process is shown in Figure 11.

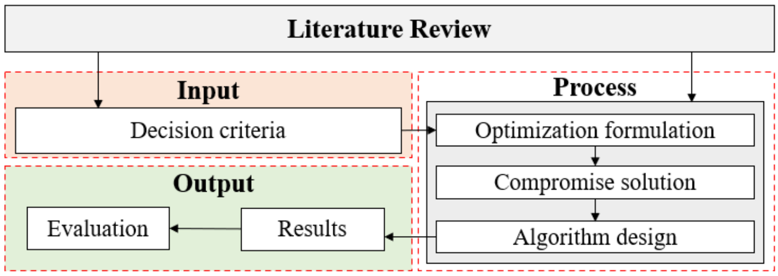

Figure 11. Steps of the CP method.

3.6. Data Envelopment Analysis (DEA)

DEA is a non-parametric method used to measure the efficiency of decision-making units (DMUs) in a given system. DEA provides a flexible and powerful way to measure the efficiency of DMUs and to identify best practices and improvement opportunities. It allows decision-makers to evaluate multiple DMUs' performance and compare their efficiency scores relative to each other [36, 37]. However, it can be sensitive to the choice of the DEA model and requires careful consideration of the inputs and outputs involved [38, 39]. The DEA flowchart is shown in Figure 12.

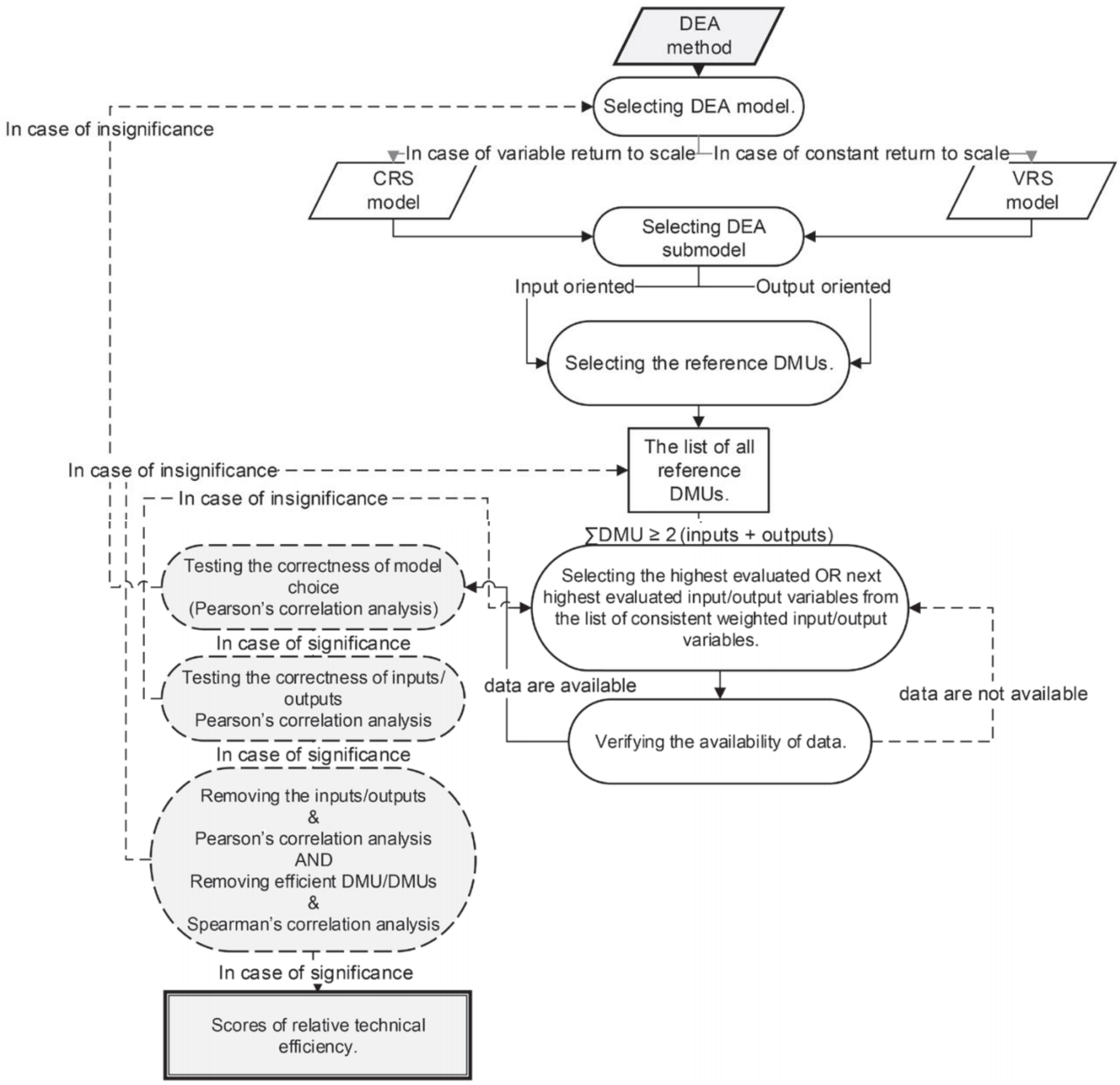

Figure 12. Flowchart of DEA method [40].

3.7. Electre (Elimination and Choice Expressing Reality)

Electra is one of the MCDM methods. It is a widely used method for solving decision problems involving multiple conflicting criteria. Electro is a flexible and powerful method that allows decision-makers to consider multiple criteria and preferences simultaneously. It provides a systematic and transparent way to evaluate and compare alternatives, considering each criterion's relative importance and performance [41]. However, it can be sensitive to the choice of preference structure and weights, and it requires a significant amount of data input and expertise to implement properly [42, 43]. The Electre flowchart is shown in Figure 13.

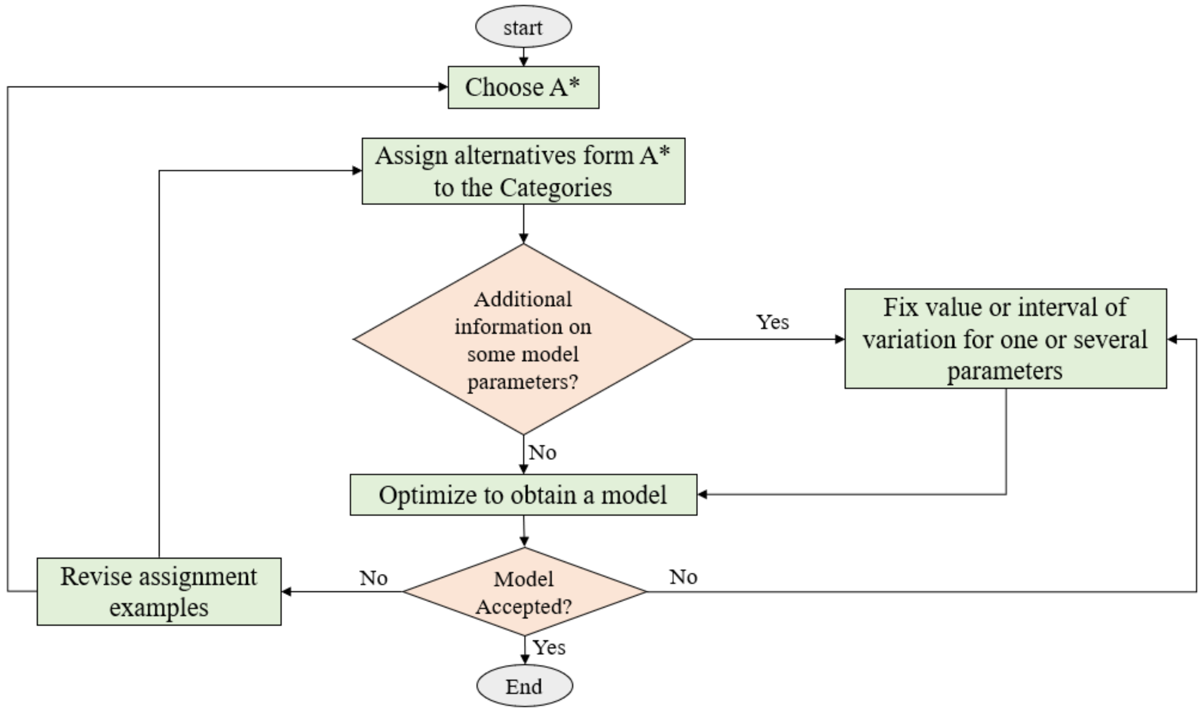

Figure 13. Flowchart of Electre method.

3.8. Evaluation based on Distance from Average Solution (EDAS)

EDAS is used in MCDM. It is a variation of the Technique for Order of Preference by Similarity to the Ideal Solution (TOPSIS) method and ranks alternatives based on their performance across multiple criteria. EDAS offers a straightforward and transparent approach by assessing alternatives' proximity to the average solution, representing each criterion's ideal performance. This method enables decision-makers to systematically and objectively consider multiple criteria and their relative importance [44, 45]. However, it is important to note that EDAS assumes equal importance among criteria and considers the average solution as the ideal performance, which may not always align with the decision context [46, 47]. The EDAS process is shown in Figure 14.

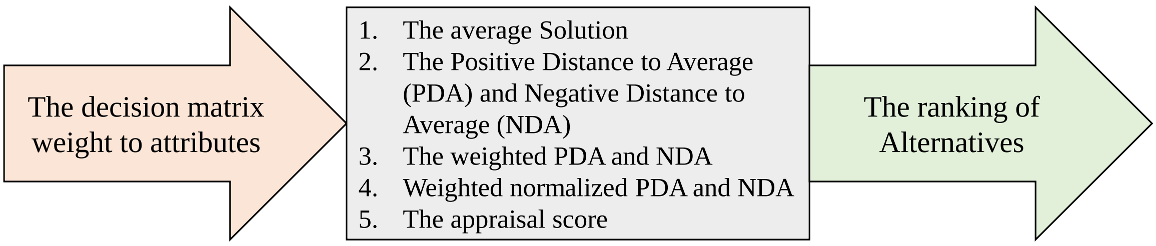

Figure 14. Steps of the EDAS method.

3.9. Fuzzy Analytic Hierarchy Process (FAHP)

The FAHP is an enhanced version of the traditional AHP, extending its capabilities in multicriteria decision-making. FAHP effectively incorporates linguistic variables and fuzzy sets to address uncertainty and vagueness inherent in decision-making processes. By utilizing linguistic variables and fuzzy sets, decision-makers can handle and represent preferences and performance flexibly and powerfully [48]. FAHP offers a systematic and transparent approach for evaluating and comparing alternatives, considering each criterion's relative importance and performance. It is important to note that FAHP implementation requires substantial data input and expertise, and its effectiveness can be influenced by the choice of preference structure and weights [3, 49]. FAHP flowchart is shown in Figure 15.

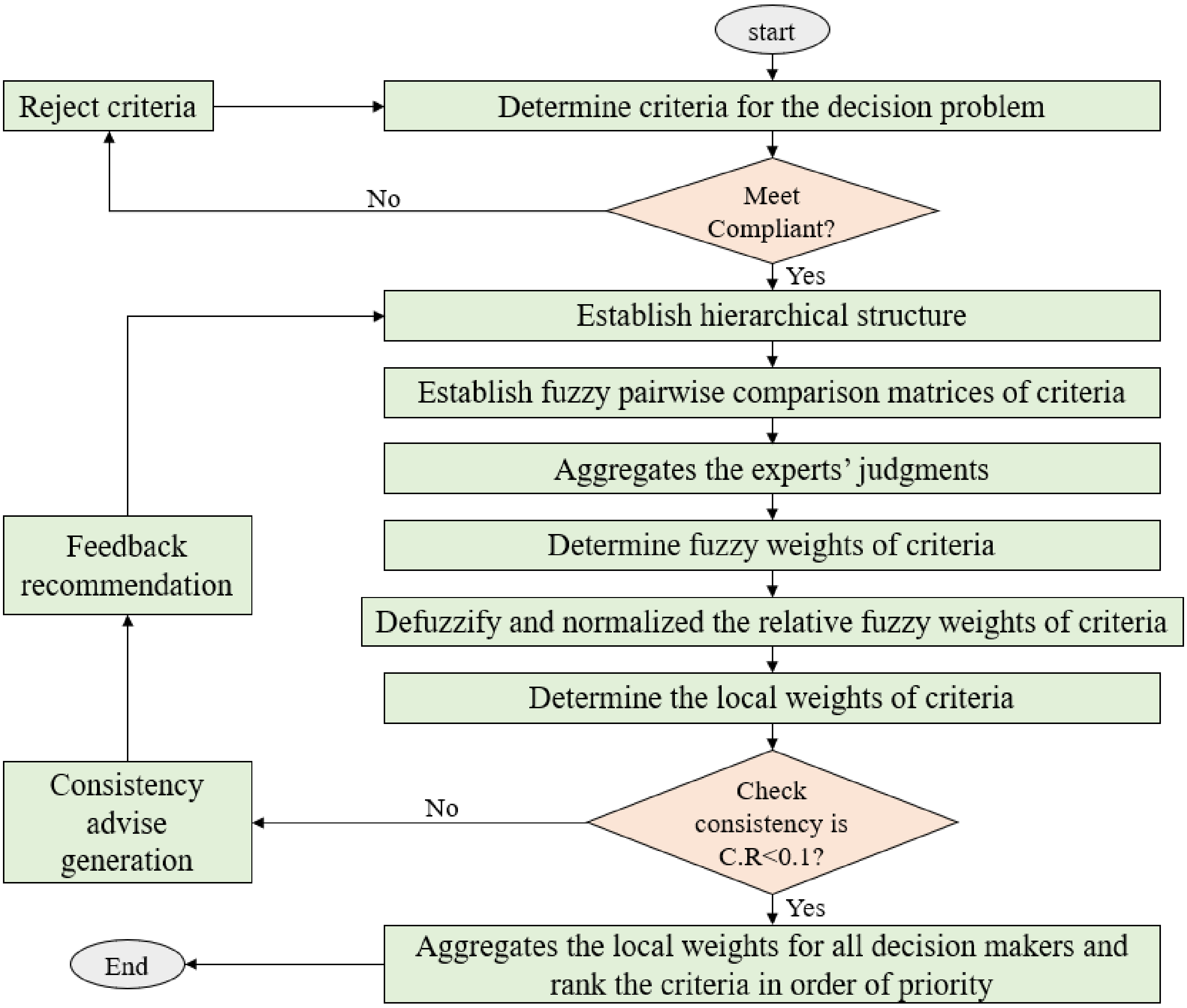

Figure 15. *Flowchart of FAHP method 3.10. Fuzzy Linguistic Quantifier (FLQ).*

FLQ is a mathematical tool used in fuzzy logic to quantify and measure linguistic terms commonly used to express subjective opinions and perceptions. FLQs are used to translate natural language expressions into quantitative measures that can be processed by computers or used in mathematical models. FLQs use fuzzy sets to represent the degree of membership of a linguistic term in a set, usually expressed using a membership function. FLQs can be categorized into different types based on their properties and characteristics, such as absolute, relative, and modifier quantifiers. FLQs are used in various applications, such as decision-making, control systems, and information retrieval. They provide a flexible and powerful way to handle linguistic expressions and subjective opinions while allowing mathematical operations and computations [50]. However, using FLQs requires a significant amount of expertise in fuzzy logic and mathematics, and the choice of FLQs can affect the results and outcomes of the analysis [51, 52]. The FLQ process is shown in Figure 16.

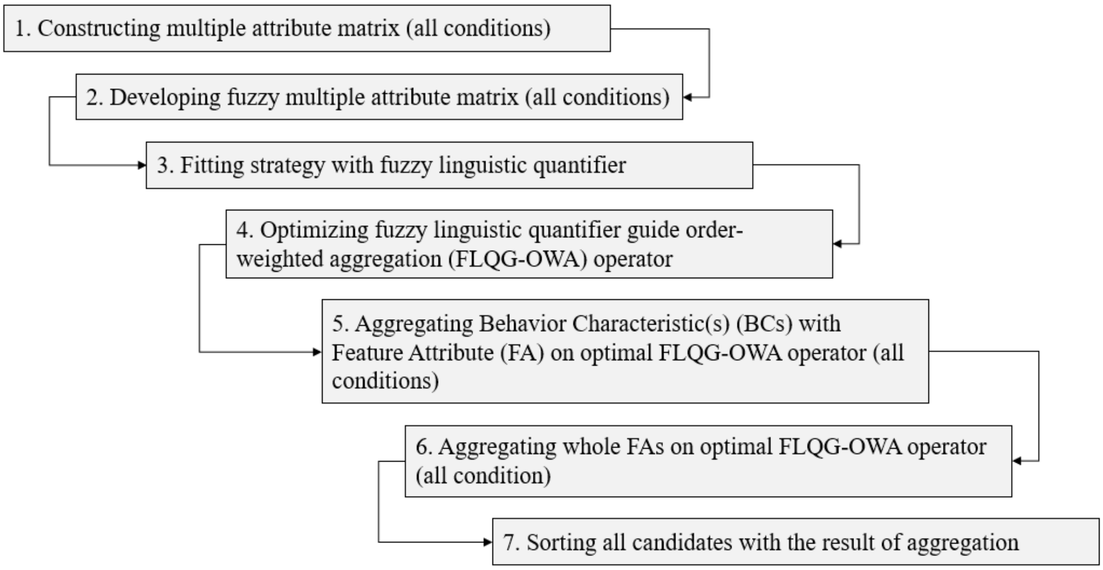

Figure 16. Steps of the FLQ method.

3.11. Grey Relational Analysis (GRA)

GRA is a method for analyzing the relationship between input and output variables in a system. GRA involves converting numerical data into dimensionless grey numbers, representing the similarity between the input and output variables. Grey numbers consist of a black part and a white part, respectively, representing the variable's ideal and actual values. The closer a grey number's black and white parts are, the higher the similarity between the ideal and actual values. GRA can be used to identify the most influential input variables on the output variable and to evaluate the effectiveness of different scenarios or strategies. It can also be used for optimization and decision-making purposes. One of the advantages of GRA is that it is suitable for analyzing systems with incomplete or limited data [53, 54]. However, GRA has limitations, such as its sensitivity to the selection of reference series and the difficulty in determining the appropriate weighting of input variables. Therefore, it is recommended to use GRA in combination with other methods for a more comprehensive analysis [55, 56]. The GRA flowchart is shown in Figure 17.

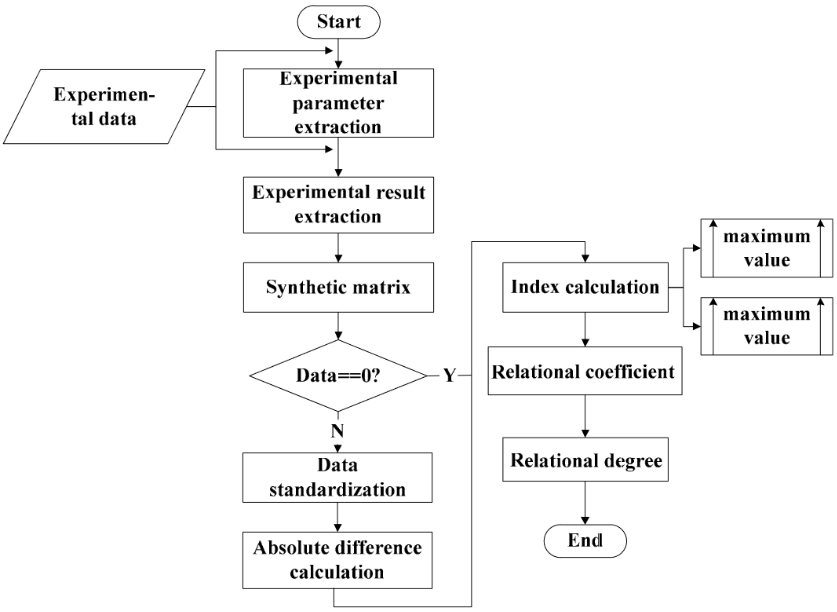

Figure 17. Flowchart of GRA method [57].

3.12. Multi-Attribute Utility Theory (MAUT)

MAUT is a decision-making framework that helps individuals or organizations make complex decisions involving multiple attributes or criteria. It is a formal method for evaluating and ranking options based on their perceived utility or value, considering the decision-maker's preferences. In MAUT, decision-makers identify and evaluate the attributes or criteria important to them in the decision-making process. These attributes can be qualitative or quantitative and may include cost, risk, quality, and time. Decision-makers establish a value or weight scale for each attribute that reflects their relative importance. MAUT provides a structured and transparent approach to decision-making, and it can handle a wide range of decision-making problems involving multiple criteria [58, 59]. It allows decision-makers to consider their preferences and priorities explicitly and incorporate objective and subjective information in decision-making [60, 61]. The MAUT process is shown in Figure 18.

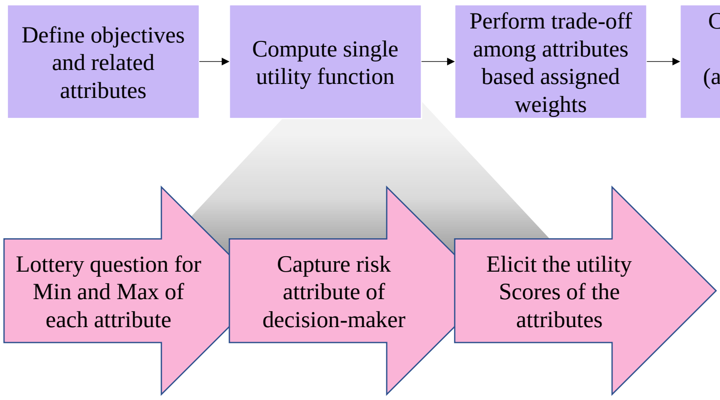

Figure 18. Steps of the MAUT method [62].

3.13. Multiple Criteria Decision Analysis (MCDA)

MCDA is a family of methods to evaluate and prioritize alternatives based on multiple criteria or objectives. MCDA allows decision-makers to consider multiple criteria and objectives simultaneously and provides a systematic and transparent approach to decision-making. MCDA methods help decision-makers to structure, compare, and evaluate different options and make informed decisions. MCDA methods can be used in various decision-making problems, such as project selection, risk assessment, and environmental impact assessment. Identifying and prioritizing the relevant criteria and assigning accurate weights to each criterion can be challenging [63, 64].

Some MCDA methods can also be computationally complex, especially when dealing with many criteria or alternatives. Finally, MCDA methods rely on the accuracy of the data used in the evaluation, and the results can be sensitive to errors or uncertainties in the data [65-67]. MCDA flowchart is shown in Figure 19.

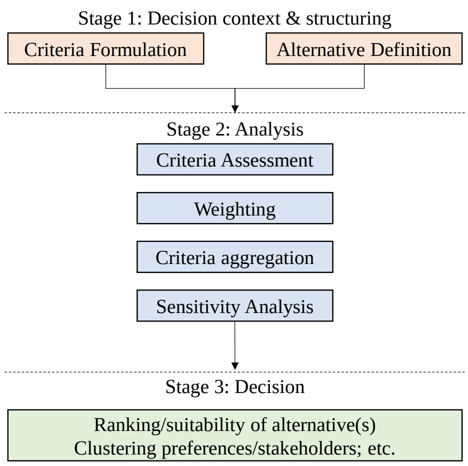

Figure 19. Flowchart of MCDA methods.

3.14. Preference Ranking Organization Method for Enrichment Evaluations (PROMETHEE)

PROMETHEE is a multicriteria decision-making (MCDM) technique that ranks alternatives based on multiple criteria. As an outranking method, PROMETHEE compares alternatives pairwise to assess their relative performances. In PROMETHEE, preference measures are considered: preference functions and indifference thresholds. Preference functions quantify the degree of preference between two alternatives, indicating how much one alternative is preferred. On the other hand, indifference thresholds gauge the degree of indifference between two alternatives, reflecting situations where the decision-maker perceives them as equally favorable. For each criterion, preference functions and indifference thresholds are defined and can be either linear or nonlinear. These functions allow for capturing various degrees of preference and indifference based on the decision-maker's evaluations [68, 69]. By incorporating preference functions and indifference thresholds, PROMETHEE offers a systematic approach to rank alternatives while considering multiple criteria in decision-making [70, 71]. To rank the alternatives, PROMETHEE calculates the net preference flow for each alternative, which is the difference between the positive and negative preference flows. The positive preference flow measures the number of alternatives that are preferred to the given alternative. In contrast, the negative preference flow measures the number of alternatives that are inferior to the given alternative. The net preference flow reflects the degree of preference for an alternative compared to the other alternatives. After calculating the net preference flows, PROMETHEE ranks alternatives based on their values. PROMETHEE can also provide sensitivity analysis to investigate the effects of changes in the criteria weights or parameters on evaluating alternatives [72]. PROMETHEE has been widely used in practice for various decision-making problems, such as supplier selection, location analysis, and environmental management. It is a flexible and efficient method for dealing with multiple criteria and can provide valuable insights into complex decision problems [73, 74].

3.15. Technique for Order Preference by Similarity to Ideal Solution (TOPSIS)

The TOPSIS is a well-known MCDM technique to evaluate alternatives based on multiple criteria. The main objective of TOPSIS is to identify the alternative closest to the ideal solution and furthest from the negative ideal solution. TOPSIS can handle nonlinear relationships between criteria, enabling a more flexible assessment of alternatives. Additionally, it can incorporate uncertainty by utilizing fuzzy sets, allowing for a more nuanced representation of imprecise or vague information. However, it is important to note that TOPSIS may not always provide an optimal solution due to its methodology. The rankings generated by TOPSIS can be sensitive to the choice of weights assigned to the criteria and the normalization methods employed in the evaluation process [75, 76]. These factors can influence the outcome and should be carefully considered during applying TOPSIS [77-79]. The TOPSIS process is shown in Figure 20.

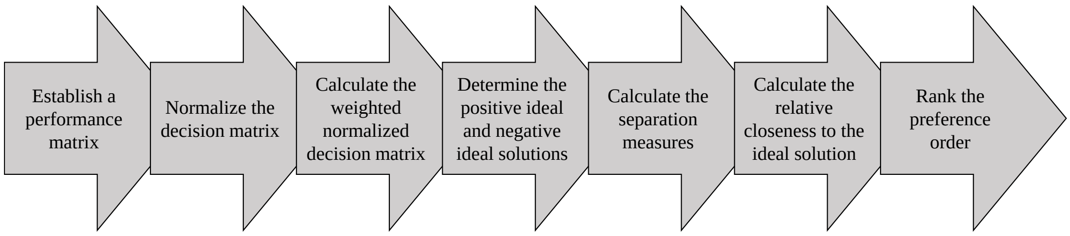

Figure 20. Steps of TOPSIS method.

3.16. VIKOR (VlseKriterijumska Optimizacija I Kompromisno Resenje)

VIKOR is a multicriteria decision-making method developed in Yugoslavia in the 1980s. It is designed to provide a compromise solution when conflicting criteria are considered. The VIKOR method differs from other multicriteria decision-making methods in considering the best and worst solutions for each criterion and the compromise solution [80, 81]. This allows for a more balanced assessment of alternatives, especially when conflicting criteria cannot be fully optimized [82-84]. The VIKOR process is shown in Figure 21.

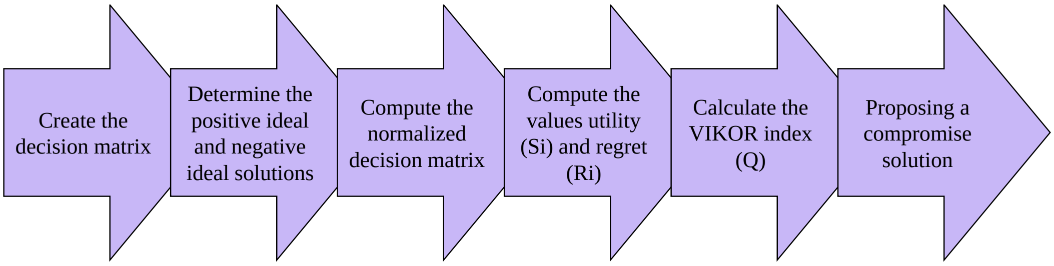

Figure 21. Steps of the VIKOR method.

3.17. Multiobjective Optimization by Ratio Analysis (MOORA)

It extends Simple Additive Weighting (SAW) principles and Weighted Product Model (WPM) methods. MOORA ranks alternatives based on their performance across multiple criteria by maximizing benefits and minimizing costs relative to other alternatives. In MOORA, decision-makers can express their preferences and priorities by assigning weights to the decision criteria. This allows for a tailored and customized evaluation of alternatives. MOORA can handle both quantitative and qualitative data, making it suitable for scenarios where criteria have different units or scales of measurement. However, one potential limitation of MOORA is its assumption of independence between the positive and negative performance ratios of each alternative [85]. This assumption may not always hold in real-world decision-making situations, which should be considered when applying the method [86, 87]. The MOORA process is shown in Figure 22.

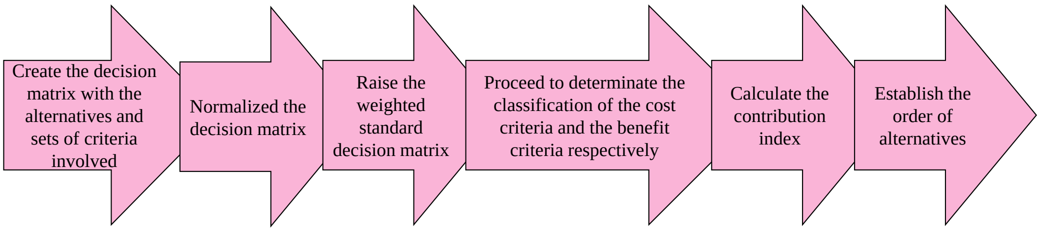

Figure 22. Steps of MOORA method.

3.18. Complex Proportional Assessment (COPRAS)

COPRAS is a popular MCDM technique to tackle complex decision-making problems. COPRAS employs ratio-based criteria weights and compensatory aggregation to determine the overall performance score of alternatives. COPRAS is particularly valuable when dealing with decision-making scenarios that involve multiple criteria and where the criteria weights are not predetermined. It offers a systematic approach to evaluate alternatives and rank them based on their performance scores. By employing ratio-based criteria weights, COPRAS allows decision-makers to consider the relative importance of each criterion in a flexible manner [88]. The compensatory aggregation process enables the integration of the various criteria and their weights to obtain an overall performance score for each alternative. COPRAS is an effective method for complex decision-making problems, providing a structured framework to evaluate alternatives and make informed choices based on their performance scores [89, 90]. The COPRAS process is shown in Figure 23.

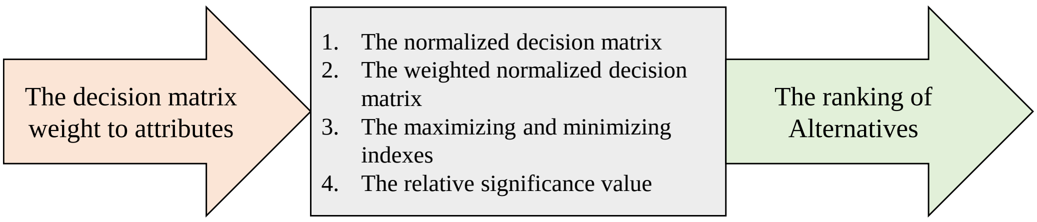

Figure 23. Steps of the COPRAS method.

3.19. Decision-making Trial and Evaluation Laboratory (DEMATEL)

DEMATEL is a valuable MCDM method designed to analyze and comprehend the intricate relationships between criteria and decision alternatives. DEMATEL operates on the premise that decision problems are interconnected networks of factors and sub-factors. By utilizing DEMATEL, decision-makers can gain insights into the causal relationships among criteria and identify critical factors that significantly influence decision-making. The method is particularly beneficial in navigating complex social, economic, and environmental systems. It aids decision-makers in comprehending the interdependencies and interrelationships between various factors, facilitating a more informed decision-making process [91]. DEMATEL has been successfully applied in various domains, including project management, financial management, and environmental management. Its ability to uncover causal relationships and highlight critical factors makes it a valuable tool for tackling complex decision-making challenges [92-94]. DEMATEL flowchart is shown in Figure 24.

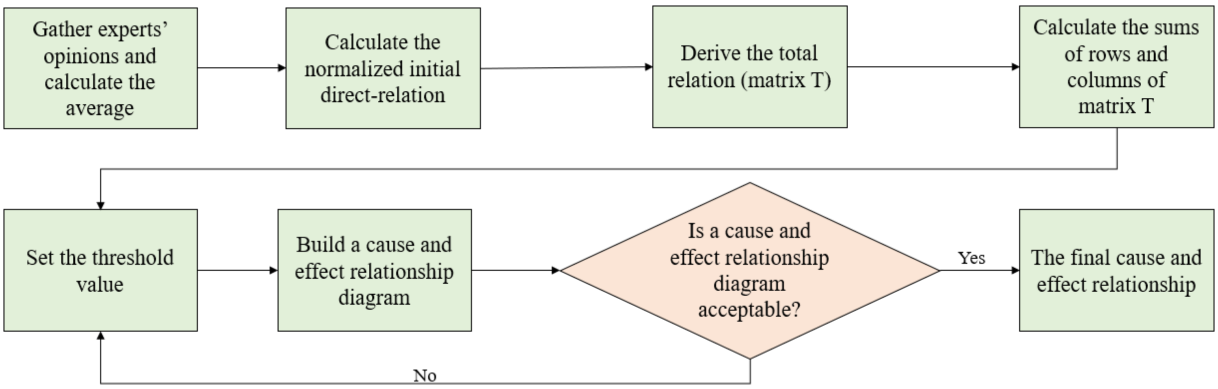

Figure 24. Flowchart of DEMATEL method.

4. Discussion

Analyzing and discussing these 19 Multiple Criteria Decision Making (MCDM) methods can provide valuable insights into their applicability, advantages, disadvantages, and recommendations for mining scenarios. Here is a summary of the discussion for each method is shown in Table 3.

Table 3. Advantages, disadvantages, and recommendation of 19 MCDM methods.

Method	Advantage	Disadvantage	Recommendation	Input	Output
AHP	Systematic consideration of qualitative and quantitative factors, incorporation of multiple stakeholders' preferences.	Requires effort and expertise in defining the decision problem and constructing precise pairwise comparison matrices.	Suitable for mining decisions involving multiple stakeholders and diverse criteria.	Environmental impact, cost, safety, and geological considerations.	Overall ranking or score of alternatives based on their weighted priorities.
ANP	Addresses complex decision problems with interdependent criteria and alternatives.	More complex and time-consuming than AHP, it requires expertise and data input.	Ideal for mining decisions with interdependencies among criteria and alternatives.	Defining clusters of criteria, specifying criteria and sub-criteria, establishing network relations with pairwise comparisons, and assigning priority weights to assess interdependencies and influences comprehensively.	Priority vector for criteria and sub-criteria, reflecting their relative importance and overall rankings or scores for alternatives based on their weighted priorities.
BWM	Simple and intuitive for identifying critical factors.	Doesn't consider interactions between criteria or alternatives.	Useful for quickly identifying important criteria or alternatives in straightforward mining decisions.	Identifying criteria, specifying alternatives, and conducting pairwise comparisons to determine the best and worst elements within each criterion facilitate decision-making.	Priority order for alternatives within each criterion, highlighting the best and worst choices.
CI	Flexibly aggregates criteria with different importance levels.	Computationally intensive, it requires significant data input and expertise.	Suitable for mining decisions involving non-additive preferences and	Defining fuzzy measures to capture interactions between criteria, specifying the fuzzy capacities representing the importance of subsets, and	Aggregated scores for alternatives reflect the comprehensive consideration of interactions and dependencies.

Method	Advantage	Disadvantage	Recommendation	Input	Output
			Interactions among criteria.	Utilizing these measures to model complex decision contexts.	
CP	Balances trade-offs between multiple objectives.	Sensitive to the choice of compromise function requires careful consideration of objectives.	Effective for mining decisions with conflicting objectives.	Defining decision criteria, establishing their relative importance, and setting acceptable compromise levels to find solutions that balance conflicting objectives within the mining context.	A solution that represents a balanced compromise among conflicting objectives in mining engineering, providing a feasible and acceptable outcome based on the specified compromise levels for decision criteria.
DEA	Measures efficiency of decision-making units and identifies best practices.	Sensitive to the choice of DEA model requires careful consideration of inputs and outputs.	Useful for assessing efficiency in mining operations and benchmarking.	Identifying input and output variables and quantifying their efficiencies to assess and improve the overall performance of mining operations.	Provides efficiency scores for each mining unit, identifying benchmarks and highlighting areas for improvement in resource utilization, aiding decision-makers in optimizing performance.
Electre	Addresses multiple conflicting criteria transparent evaluation.	Sensitive to preference structure and weights, data-intensive.	Suitable for mining decisions with conflicting criteria and the need for transparency.	Defining criteria, assigning weights to criteria, and specifying preference thresholds to assess and rank alternatives based on their performance against the established criteria.	A ranking of alternatives, emphasizing those that meet preference thresholds and revealing viable choices based on the defined criteria in mining engineering.
EDAS	Straightforward and objective approach.	Assumes equal importance among criteria and considers the average solution as ideal.	Appropriate for mining decisions with equal-weighted criteria and straightforward evaluations.	Defining criteria, specifying weights for criteria, and evaluating alternatives based on their proximity to the average solution, facilitating decision-making by assessing performance against established criteria.	A ranking of alternatives, highlighting those with closer proximity to the average solution, aiding decision-makers in selecting mining engineering options based on the established criteria and their performance against the average benchmark.
FAHP	Handles uncertainty and vagueness in decision-making.	Requires substantial data input and expertise.	Effective for mining decisions in uncertain environments or when linguistic variables are involved.	Defining criteria, establishing their fuzzy pairwise comparison matrices, and determining the weights of criteria to assess and prioritize alternatives under uncertainty.	Fuzzy priority vector for criteria and alternatives, offering a nuanced and flexible decision-making framework in mining engineering by considering uncertainties and preferences in the prioritization process.
FLQ	Translates linguistic terms into quantitative measures.	Requires expertise in fuzzy logic and mathematics.	Useful for handling subjective opinions and linguistic expressions in mining decisions.	Defining linguistic variables, specifying fuzzy membership functions, and establishing fuzzy quantifiers to model imprecise information and enhance decision-making.	Quantified fuzzy values allowing for a more nuanced representation of imprecise information in mining engineering decision-making, aiding in capturing and managing uncertainties effectively.
GRA	Measures the relationship between input and output variables.	Sensitive to the selection of reference series, difficulty in determining input variable weights.	Useful for assessing the influence of input variables on mining outcomes.	Defining evaluation criteria, normalizing data, and establishing reference sequences to assess and rank alternatives based on their relationships.	Grey relational grades, highlighting the closeness of alternatives to the reference sequence, aiding in decision-making in mining engineering by identifying relationships and rankings based on evaluated criteria.
MAUT	Evaluate and rank options based on perceived utility and consider decision-maker's preferences.	Identifying criteria and assigning weights can be challenging.	Suitable for mining decisions involving multiple attributes and subjective preferences.	Defining decision criteria, assigning weights to criteria, and quantifying the preferences or utility values for alternatives, facilitating a systematic evaluation of complex decision scenarios.	A utility score for each alternative, aiding in the systematic ranking and selection of mining engineering options based on the assigned weights and preferences for decision criteria, allowing for a comprehensive evaluation.
MCDA	Provides a systematic and transparent approach to evaluate and compare alternatives.	Challenges in prioritizing criteria and handling data inaccuracies.	Effective for mining decisions with multiple criteria and objectives.	Defining decision criteria, specifying their weights, and evaluating alternatives against these criteria to facilitate a structured decision-making process.	A ranking or scoring of alternatives, assisting in decision-making within mining engineering by considering multiple criteria and their weighted importance, resulting in a more informed and balanced choice.

Method	Advantage	Disadvantage	Recommendation	Input	Output
PROMETHEE	Rank alternatives based on pairwise comparisons consider preferences and indifference.	Rankings are sensitive to weights and normalization methods.	Suitable for mining decisions with well-defined preferences and pairwise comparisons.	Defining criteria, assigning preference functions, and comparing alternatives to establish rankings based on their relative performance.	Provides a preference ranking of alternatives, highlighting their suitability based on assigned preferences and criteria, aiding decision-makers in mining engineering to choose optimal solutions.
TOPSIS	Identifies alternatives closest to the ideal solution and handles nonlinear relationships.	Rankings are sensitive to criteria weights and normalization methods.	Effective for mining decisions with nonlinear relationships and well-defined criteria.	Defining criteria, normalizing data, and calculating the Euclidean distances to determine the proximity of alternatives to the ideal solution, facilitating a systematic ranking process.	Provides a ranking of alternatives based on their closeness to the ideal solution and farthest from the negative ideal solution, aiding decision-makers in mining engineering to identify the most favorable options.
VIKOR	Provides a compromise solution for conflicting criteria.	Rankings influenced by criteria weights are not suitable for all scenarios.	Useful for mining decisions with conflicting criteria and the need for compromise.	Defining criteria, assigning weights, and determining preference functions to assess and rank alternatives based on their overall performance, providing a compromise solution.	Provides a compromise ranking of alternatives, considering both maximum group utility and individual regret, aiding in decision-making in mining engineering by offering a balanced solution that considers multiple criteria and preferences.
MOORA	Customized evaluation with ratio-based criteria weights.	Assumes independence between positive and negative ratios.	Suitable for mining decisions with flexible criteria weights.	Defining decision criteria, determining their importance weights, and comparing alternatives to establish rankings based on the calculated ratios facilitates a systematic decision-making process.	Provides a ranking of alternatives based on the calculated scores, aiding in mining engineering decision-making by identifying the most favorable options considering multiple criteria and their assigned weights.
COPARS	Systematic evaluation with ratio-based criteria weights.	Assumes independence between positive and negative ratios.	Effective for mining decisions requiring a structured evaluation process.	Defining criteria, specifying preference values, and establishing decision matrix elements to systematically evaluate and rank alternatives based on their performance.	A comprehensive ranking of alternatives, considering both positive and negative aspects, aids decision-makers in mining engineering by offering a balanced assessment that captures various criteria and preferences.
DEMATEL	Analyzes causal relationships between criteria and identifies critical factors.	It focuses on relationships and may not provide a direct ranking of alternatives.	Suitable for mining decisions where understanding causal relationships is crucial.	Defining criteria, conducting pairwise comparisons to establish the cause-and-effect relationships, and determining the influence strength, facilitating a structured analysis of interdependencies.	A visualized influence network and impact scores, aiding decision-makers in understanding and managing the cause-and-effect relationships among criteria in mining engineering, enhancing the decision-making process.

Certainly, each of these MCDM methods offers distinct advantages and has its own set of limitations. The specific characteristics and demands of the mining decision in question should guide the selection of the most suitable method. It is important to recognize that there is no one-size-fits-all approach, and the choice of method should be tailored to the unique circumstances of each mining scenario. To make the best-informed decision, engaging with domain experts with experience in the mining industry is often beneficial. Their insights can help identify the most relevant criteria and guide the weighting of those criteria, ultimately enhancing the accuracy of the decision-making process. A hybrid approach that combines multiple MCDM methods may be advantageous in some cases. This allows decision-makers to harness different techniques' strengths while mitigating their weaknesses. Such an approach can lead to more robust and reliable outcomes, particularly in complex mining decisions.

The choice of the most commonly used (standard) method can vary significantly depending on the practices and preferences of the mining company or organization. It is advisable to consider industry standards, best practices, and the specific context of the decision to determine which method best aligns best with the organization's goals and requirements. Ultimately, the goal is to ensure a comprehensive and dependable decision-making process in the dynamic and multifaceted mining industry.

5. Conclusions

Multicriteria Decision-Making (MCDM) techniques within the mining industry confer many advantages, underlining their pivotal role in enhancing decision-making processes. MCDM methodologies offer a systematic framework for evaluating and selecting alternatives founded on multiple criteria, empowering decision-makers to navigate intricate mining scenarios with insight and confidence. Mining engineers benefit significantly from MCDM methods, as they facilitate the simultaneous consideration of various factors spanning economic, environmental, social, and technical dimensions. This holistic approach provides a robust foundation for evaluating mining projects, allowing decision-makers to incorporate diverse stakeholders' perspectives and interests. One of the standout features of MCDM is its capacity to tackle the inherent uncertainty and risks entwined with mining operations. By doing so, MCDM aids in the identification of resilient solutions that exhibit reduced sensitivity to uncertainties, bolstering the decision-making process and its efficacy. Moreover, MCDM methods make substantial contributions to fostering sustainable mining practices. By integrating environmental and social criteria into the decision-making framework, mining engineers can meticulously evaluate mining projects' ecological consequences, societal impacts, and long-term sustainability prospects. This holistic perspective allows MCDM to identify challenges, proffer environmentally and socially harmonious solutions, and safeguard natural resources, biodiversity, and the well-being of local communities. Additionally, the integration of MCDM methods into resource allocation processes stands out as a critical benefit. Mining engineers can efficiently allocate limited resources by simultaneously considering multiple objectives and constraints, enhancing resource management, cost reduction, and heightened operational efficiency. The synergy between MCDM methods and advanced technologies opens up new horizons for cutting-edge decision-making in mining engineering. These interdisciplinary approaches facilitate the seamless integration of diverse datasets, fostering more precise, dynamic, and agile decision-making processes.

Incorporating MCDM techniques in mining engineering offers a structured and systematic framework for evaluating alternatives, mitigating risks, advancing sustainability objectives, optimizing resource allocation, and harnessing technological advancements. Embracing these methodologies empowers stakeholders within the mining industry to engage in informed decision-making processes that harmonize economic priorities with environmental responsibility and social considerations. This, in turn, lays the foundation for the cultivation of mining practices characterized by enhanced sustainability and heightened social and environmental responsibility.

References

1. Pouresmaieli, M. *et al.*, *Building ecological literacy in mining communities: A sustainable development perspective.* Case Studies in Chemical and Environmental Engineering, 2023: p. 100554.
2. Pouresmaieli, M. *et al.*, *Integration of renewable energy and sustainable development with strategic planning in the mining industry.* Results in Engineering, 2023. **20**: p. 101412.
3. Azadeh, A., M. Osanloo, and M. Ataei, *A new approach to mining method selection based on modifying the Nicholas technique.* Applied Soft Computing, 2010. **10**(4): p. 1040-1061.
4. Pouresmaieli, M. *et al.*, *Recent Progress on Sustainable Phytoremediation of Heavy Metals from Soil.* Journal of Environmental Chemical Engineering, 2022: p. 108482.
5. Pouresmaieli, M., M. Ataei, and A.N. Qarahasanlou, *A scientometrics view on sustainable development in surface mining: Everything from the beginning.* Resources Policy, 2023. **82**: p. 103410.
6. Pouresmaieli, M., M. Ataei, and A. Taran, *Future mining based on internet of things (IoT) and sustainability challenges.* International Journal of Sustainable Development & World Ecology, 2022: p. 1-18.
7. Ekrami, E. *et al.*, *Nanotechnology: a sustainable solution for heavy metals remediation.* Environmental Nanotechnology, Monitoring & Management, 2022: p. 100718.

8. Ekrami, E. *et al.*, *A review on designing biosensors for the detection of trace metals.* Applied Geochemistry, 2021: p. 104902.
9. Mardani, A. *et al.*, *A review of multi-criteria decision-making applications to solve energy management problems: Two decades from 1995 to 2015.* Renewable and Sustainable Energy Reviews, 2017. **71**: p. 216-256.
10. Gupta, S.K. *et al.*, *Data Mining Processes and Decision-Making Models in the Personnel Management System*, in *Designing Workforce Management Systems for Industry 4.0*. 2023, CRC Press. p. 85-104.
11. Mohammadi, S. *et al.*, *A New Roof Strata Cavability Index (RSCi) for longwall mining incorporating new rating system.* Geotechnical and Geological Engineering, 2019. **37**: p. 3619-3636.
12. Masir, R.N., M. Ataei, and A. Motahedi, *Risk assessment of flyrock in surface mines using a FFTA-MCDM combination.* Journal of Mining and Environment, 2021. **12**(1): p. 191-203.
13. Mohammadi, S. *et al.*, *Prediction of the main caving span in longwall mining using fuzzy MCDM technique and statistical method.* Journal of Mining and Environment, 2018. **9**(3): p. 717-726.
14. Pazand, K., A. Hezarkhani, and M. Ataei, *Using TOPSIS approaches for predictive porphyry Cu potential mapping: A case study in Ahar-Arasbaran area (NW, Iran).* Computers & Geosciences, 2012. **49**: p. 62-71.
15. Rahimdel, M.J. and M. Ataei, *Application of analytical hierarchy process to selection of primary crusher.* International Journal of Mining Science and Technology, 2014. **24**(4): p. 519-523.
16. Norouzi Masir, R., M. Ataei, and A. Mottahedi, *Risk assessment of Flyrock in Surface Mines using a FFTA-MCDM Combination.* Journal of Mining and Environment, 2021. **12**(1): p. 191-203.
17. Pouresmaieli, M. and M. Osanloo. *Establishing a Model to Reduce the Risk of Premature Mine Closure*. in *IOP Conference Series: Earth and Environmental Science*. 2019. IOP Publishing.
18. Pouresmaieli, M. and M. Osanloo. *A Valuation Approach to Investigate the Sustainability of Sorkhe-Dizaj Iron Ore Mine of Iran*. in *International Symposium on Mine Planning & Equipment Selection*. 2019. Springer.
19. Ataei, M., et al., *Mining method selection by AHP approach.* Journal of the Southern African Institute of Mining and Metallurgy, 2008. **108**(12): p. 741-749.
20. Ataei, M., H. Shahsavany, and R. Mikaeil, *Monte Carlo Analytic Hierarchy Process (MAHP) approach to selection of optimum mining method.* International Journal of Mining Science and Technology, 2013. **23**(4): p. 573-578.
21. Bascetin, A., *A decision support system using analytical hierarchy process (AHP) for the optimal environmental reclamation of an open-pit mine.* Environmental Geology, 2007. **52**: p. 663-672.
22. Chakraborty, S. *et al.*, *A comprehensive and systematic review of multi-criteria decision-making methods and applications in healthcare.* Healthcare Analytics, 2023: p. 100232.
23. Azimi, R. *et al.*, *Ranking the strategies of mining sector through ANP and TOPSIS in a SWOT framework.* Journal of business economics and management, 2011. **12**(4): p. 670-689.
24. Selvan, S.U. *et al.*, *Toward multi-species building envelopes: A critical literature review of multi-criteria decision-making for design support.* Building and Environment, 2023: p. 110006.
25. Ataei, M., A. Divsalar, and M. Saberi, *The bi-objective orienteering problem with hotel selection: An integrated text mining optimisation approach.* Information Technology and Management, 2022: p. 1-29.
26. Bahrami, Y., H. Hassani, and A. Maghsoudi, *Spatial modeling for mineral prospectivity using BWM and COPRAS as a new HMCDM method.* Arabian Journal of Geosciences, 2022. **15**(5): p. 394.
27. Pamučar, D. *et al.*, *Application of improved best worst method (BWM) in real-world problems.* Mathematics, 2020. **8**(8): p. 1342.
28. Rezaei, J., *Best-worst multi-criteria decision-making method.* Omega, 2015. **53**: p. 49-57.

29. Bonab, S.R. *et al.*, *Logistic autonomous vehicles assessment using decision support model under spherical fuzzy set integrated Choquet Integral approach.* Expert Systems with Applications, 2023. **214**: p. 119205.
30. Bajpayee, T. *et al.*, *Blasting injuries in surface mining with emphasis on flyrock and blast area security.* Journal of Safety Research, 2004. **35**(1): p. 47-57.
31. Boateng‐Okrah, E. and F. Appiah Fening, *TQM implementation: a case of a mining company in Ghana.* Benchmarking: An International Journal, 2012. **19**(6): p. 743-759.
32. Hosseinzadeh, A. *et al.*, *A new multi‐criteria framework to identify optimal detention ponds in urban drainage systems.* Journal of Flood Risk Management, 2023: p. e12890.
33. Mena, R. *et al.*, *Multi-objective two-stage stochastic unit commitment model for wind-integrated power systems: A compromise programming approach.* International Journal of Electrical Power & Energy Systems, 2023. **152**: p. 109214.
34. Baloyi, V.D. and L. Meyer, *The development of a mining method selection model through a detailed assessment of multi-criteria decision methods.* Results in Engineering, 2020. **8**: p. 100172.
35. Kemmar, A. *et al*. *Mining relevant sequence patterns with cp-based framework*. in *2014 IEEE 26th International Conference on Tools with Artificial Intelligence*. 2014. IEEE.
36. Emrouznejad, A. *et al.*, *A review of inverse data envelopment analysis: origins, development, and future directions.* IMA journal of management mathematics, 2023: p. dpad006.
37. Kyrgiakos, L.S. *et al.*, *A systematic literature review of data envelopment analysis implementation in agriculture under the prism of sustainability.* Operational Research, 2023. **23**(1): p. 7.
38. Zuo, Z. *et al.*, *A two-stage DEA evaluation of Chinese mining industry technological innovation efficiency and eco-efficiency.* Environmental Impact Assessment Review, 2022. **94**: p. 106762.
39. Rabbani, M., H. Farrokhi-Asl, and N. Manavizadeh, *Using Robust-DEA optimization approach to analyze performance and efficiency of a mine in north of Iran.* Management Science Letters, 2017. **7**(2): p. 97-110.
40. Bajec, P., M. Kontelj, and A. Groznik, *Assessment of logistics platform efficiency using an integrated delphi analytic hierarchy process–data envelopment analysis approach: a novel methodological approach including a case study in Slovenia.* 2020.
41. Taherdoost, H. and M. Madanchian, *A Comprehensive Overview of the ELECTRE Method in Multi Criteria Decision-Making.* Journal of Management Science & Engineering Research, 2023. **6**(2).
42. Akbari, A., S. Zare, and M. Ataei, *Ranking the Risk of Mechanized Tunnel construction in Large Cross Section by Fuzzy Multi Criteria Decision Making Methods in Western Alborz Tunnel.* Journal of Mineral Resources Engineering, 2020. **5**(2): p. 43-65.
43. Fahliani, Z.R. *et al.*, *Application of electre method for election of optimum support system for access tunnel in Gooshfill mine.* International Multidisciplinary Scientific GeoConference: SGEM, 2011. **1**: p. 693.
44. Agarwal, R. and A.K. Nishad, *A Fuzzy Mathematical Modeling for Evaluation and Selection of a Best Sustainable and Resilient Supplier by using EDAS Technique.* Process Integration and Optimization for Sustainability, 2023: p. 1-10.
45. Torkayesh, A.E. *et al.*, *A state-of-the-art survey of evaluation based on distance from average solution (EDAS): Developments and applications.* Expert Systems with Applications, 2023: p. 119724.
46. Maksimović, M. *et al.*, *An approach for evaluation the safety and quality of transport at the open pit mines, based on the EDAS method.* Mining and Metallurgy Engineering Bor, 2017(3-4): p. 139-144.
47. Ye, J., S. Du, and R. Yong, *Mine safety evaluation method using correlation coefficients of consistency linguistic neutrosophic sets in a linguistic neutrosophic multivalued environment.* Soft Computing, 2023: p. 1-11.

48. Darms, I., *Fuzzy Analytic Hierarchy Process Utilization in Government Projects: A Systematic Review of Implementation Processes.* 2023.
49. Tahernejad, M., M. Ataei, and R. Khalokakaie, *Selection of the best strategy for Iran's quarries: SWOT-FAHP method.* Journal of Mining and Environment, 2012. **3**(1): p. 1-13.
50. Zarghami, M., *Soft computing of the Borda count by fuzzy linguistic quantifiers.* Applied Soft Computing, 2011. **11**(1): p. 1067-1073.
51. Flegg, A.T. *et al.*, *A new approach to modelling the input–output structure of regional economies using non-survey methods.* Journal of Economic Structures, 2021. **10**(1): p. 1-31.
52. Flegg, A.T. and T. Tohmo, *The Regionalization of national input–output tables: a review of the performance of two key non-survey methods.* Applications of the input-output framework, 2018: p. 347-386.
53. Chakraborty, S., H.N. Datta, and S. Chakraborty, *Grey Relational Analysis-Based Optimization of Machining Processes: a Comprehensive Review.* Process Integration and Optimization for Sustainability, 2023: p. 1-31.
54. Kuo, T., *A review of some modified grey relational analysis models.* The Journal of grey system, 2017. **29**(3): p. 70-78.
55. Abdelrasoul, M.E. *et al.*, *Review on the Development of Mining Method Selection to Identify New Techniques Using a Cascade-Forward Backpropagation Neural Network.* Advances in Civil Engineering, 2022. **2022**.
56. Janovac, T. *et al.*, *Selection of the motivation strategy for employees in the mining industry using the GRA method.* Mining and Metallurgy Engineering Bor, 2018(1-2): p. 157-164.
57. Jung, Y. *et al.*, *Cage-like amine-rich polymeric capsule with internal 3D center-radial channels for efficient and selective gold recovery.* Chemical Engineering Journal, 2022. **438**: p. 135618.
58. Suwitno, S., N.D. Chandra, and B. Daniawan, *Boarding House Provider Information with Multi Attribute Utility Theory (MAUT) Method.* bit-Tech, 2023. **5**(3): p. 155-165.
59. Von Winterfeldt, D. and G.W. Fischer. *Multi-attribute utility theory: models and assessment procedures*. in *Utility, Probability, and Human Decision Making: Selected Proceedings of an Interdisciplinary Research Conference, Rome, 3–6 September, 1973*. 1975. Springer.
60. Kamenopoulos, S., Z. Agioutantis, and K. Komnitsas, *A new hybrid decision support tool for evaluating the sustainability of mining projects.* International Journal of Mining Science and Technology, 2018. **28**(2): p. 259-265.
61. Saki, F. *et al.*, *Determination of the most appropriate tools of multi-criteria decision analysis for underground mining method selection—a case study.* Arabian Journal of Geosciences, 2020. **13**(23): p. 1271.
62. Stipanovic, I., et al., *A multiobjective decision-making model for risk-based maintenance scheduling of railway earthworks.* Applied Sciences, 2021. **11**(3): p. 965.
63. Diaby, V., K. Campbell, and R. Goeree, *Multi-criteria decision analysis (MCDA) in health care: a bibliometric analysis.* Operations Research for Health Care, 2013. **2**(1-2): p. 20-24.
64. Huang, I.B., J. Keisler, and I. Linkov, *Multi-criteria decision analysis in environmental sciences: Ten years of applications and trends.* Science of the total environment, 2011. **409**(19): p. 3578-3594.
65. Riz, G., E.A.P. Santos, and E. de Freitas Rocha Loures. *Interoperability assessment in health systems based on process mining and MCDA methods*. in *Recent Advances in Information Systems and Technologies: Volume 1 5*. 2017. Springer.
66. Stevanović, D. *et al.*, *Application of MCDA in selection of different mining methods and solutions.* Advances in Science and Technology. Research Journal, 2018. **12**(1).
67. Takam Tiamgne, X. *et al.*, *Modelling areas for sustainable forest management in a mining and human dominated landscape: A Geographical Information System (GIS)-Multi-Criteria Decision Analysis (MCDA) approach.* Annals of GIS, 2022. **28**(3): p. 343-357.

68. Behzadian, M. *et al.*, *PROMETHEE: A comprehensive literature review on methodologies and applications.* European journal of Operational research, 2010. **200**(1): p. 198-215.
69. Yu, D., Y. Liu, and Z. Xu, *Analysis of knowledge evolution in PROMETHEE: A longitudinal and dynamic perspective.* Information Sciences, 2023. **642**: p. 119151.
70. Balusa, B.C. and J. Singam, *Underground mining method selection using WPM and PROMETHEE.* Journal of the Institution of Engineers (India): Series D, 2018. **99**: p. 165-171.
71. Namin, F.S., A. Ghadi, and F. Saki, *A literature review of Multi Criteria Decision-Making (MCDM) towards mining method selection (MMS).* Resources Policy, 2022. **77**: p. 102676.
72. Ebrahimabadi, A. *et al.*, *Comparing two methods of PROMETHEE and Fuzzy TOPSIS in selecting the best plant species for the reclamation of Sarcheshmeh copper mine.* Asian Journal of Water, Environment and Pollution, 2018. **15**(2): p. 141-152.
73. Mikaeil, R. *et al.*, *Ranking sawability of dimension stone using PROMETHEE method.* 2015.
74. Mikaeil, R., et al., *Evaluation of dimension stone according to resistance to freeze–thaw cycling to use in cold regions.* Journal of Soft Computing in Civil Engineering, 2022. **6**(1): p. 88-109.
75. Behzadian, M. *et al.*, *A state-of the-art survey of TOPSIS applications.* Expert Systems with applications, 2012. **39**(17): p. 13051-13069.
76. Li, K., C.-Y. Chen, and Z.-L. Zhang, *Mining online reviews for ranking products: A novel method based on multiple classifiers and interval-valued intuitionistic fuzzy TOPSIS.* Applied Soft Computing, 2023. **139**: p. 110237.
77. Ataei, M., et al., *Suitable mining method for Golbini No. 8 deposit in Jajarm (Iran) using TOPSIS method.* Mining Technology, 2008. **117**(1): p. 1-5.
78. Mikaeil, R., M. Ataei, and R. Yousefi, *Evaluating the power consumption in carbonate rock sawing porocess by using FDAHP and TOPSIS techniques.* Efficient Decision Support Systems—Practice and Challenges in Multidisciplinary Domains, 2011: p. 413-436.
79. Safari, M. *et al.*, *Using fuzzy TOPSIS method for mineral processing plant site selection.* Arabian Journal of Geosciences, 2012. **5**(5): p. 1011-1019.
80. Gul, M. *et al.*, *A state of the art literature review of VIKOR and its fuzzy extensions on applications.* Applied soft computing, 2016. **46**: p. 60-89.
81. Mardani, A. *et al.*, *VIKOR technique: A systematic review of the state of the art literature on methodologies and applications.* Sustainability, 2016. **8**(1): p. 37.
82. Hayati, M., R. Rajabzadeh, and M. Darabi, *Determination of optimal block size in Angouran mine using VIKOR method.* Journal of Materials and Environmental Science, 2015. **6**(11): p. 3236-3244.
83. Mijalkovski, S. *et al.*, *Mining method selection for underground mining with the application of VIKOR method.* Podzemni radovi, 2021(39): p. 11-22.
84. Tabasi, S. and G. Kakha, *An application of fuzzy-VIKOR method in environmental impact assessment of the boog mine Southeast of Iran.* International Journal of Engineering, 2021. **34**(6): p. 1545-1556.
85. Chakraborty, S. *et al.*, *A narrative review of multi-objective optimization on the basis of ratio analysis (MOORA) method in decision making.* OPSEARCH, 2023: p. 1-44.
86. Ajrina, A.S. *et al.*, *Mining zone determination of natural sandy gravel using fuzzy AHP and SAW, MOORA, and COPRAS methods.* Int. J. Intell. Eng. Syst, 2020. **13**(5): p. 560-571.

87. Setyono, R.P. and R. Sarno. *Comparative method of Moora and CoprAs based on weighting of the best worst method in supplier selection at ABC mining companies in Indonesia*. in *2019 International Conference on Information and Communications Technology (ICOIACT)*. 2019. IEEE.

88. Stefano, N.M. *et al*., *COPRAS (Complex Proportional Assessment): state of the art research and its applications.* IEEE Latin America Transactions, 2015. **13**(12): p. 3899-3906.

89. Fan, J., R. Cheng, and M. Wu, *R-Set COPRAS (R-COPRAS) Methods-Based Multi-Attribute Decision-Making With RBM and RGBM Operators: A Case Study of Smart Mine Project Safety Assessment.* IEEE Access, 2022. **10**: p. 43481-43500.

90. Fouladgar, M.M. *et al*., *Maintenance strategy selection using AHP and COPRAS under fuzzy environment.* International journal of strategic property management, 2012. **16**(1): p. 85-104.

91. Si, S.-L. *et al*., *DEMATEL technique: A systematic review of the state-of-the-art literature on methodologies and applications.* Mathematical Problems in Engineering, 2018. **2018**: p. 1-33.

92. Ataei, M. and R. Norouzi Masir, *A fuzzy DEMATEL based sustainable development index (FDSDI) in open pit mining–a case study.* Rudarsko-geološko-naftni zbornik, 2020. **35**(1): p. 1-11.

93. Babaeian, M. *et al*., *A new framework for evaluation of rock fragmentation in open pit mines.* Journal of Rock Mechanics and Geotechnical Engineering, 2019. **11**(2): p. 325-336.

94. Mohammadfam, I. *et al*., *Analysis of factors affecting human reliability in the mining process design using Fuzzy Delphi and DEMATEL methods.* Sustainability, 2022. **14**(13): p. 8168.