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Evaluation of process technologies for sustainable mining using interval rough number based heronian and power averaging functions

Dragan Pamucar [a,b,c], Muhammet Deveci [d,e,f], Ilgin Gokasar [g], Pablo R. Brito-Parada [e], Luis Martínez [h,*]

[a] Faculty of Organizational Sciences, University of Belgrade, Belgrade 11000, Serbia
[b] College of Engineering, Yuan Ze University, Taoyuan City, Taiwan
[c] Department of Computer Science and Mathematics, Lebanese American University, Byblos, Lebanon
[d] Department of Industrial Engineering, Turkish Naval Academy, National Defence University, Tuzla 34942, Istanbul, Turkey
[e] Royal School of Mines, Imperial College London, London SW7 2AZ, UK
[f] Department of Electrical and Computer Engineering, Lebanese American University, Byblos, Lebanon
[g] Department of Civil Engineering, Bogazici University, Bebek 34342, Istanbul, Turkey
[h] Department of Computer Science, University of Jaén, Jaén 23071, Spain

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ABSTRACT

The mining sector is vital for the world's economy and provides an important source of wealth for various countries. The mines of the future must adhere to sustainable principles, which rely on applying the right technologies. This study evaluates various alternatives for choosing the best process technology, for sustainable mining, by using an interval rough decision-making model, considering four main criteria (cost, efficiency, environmental, and social) and fifteen sub-criteria. The interval rough approach was used to treat uncertainty and imprecision in information, which enabled objective processing of uncertainty in information. A novel approach that makes use of hybrid Heronian and Power Averaging (HPA) functions based on interval rough number is developed to assess different process technologies for sustainable mining. Nonlinear interval rough HPA functions were used to see the criteria's mutual influence and eliminate the impact of extreme and unreasonable arguments in the initial decision matrix. A case study is used to illustrate the feasibility of the proposed model and a sensitivity analysis is conducted to examine the effects of criteria weights in ranking. The results show that the proposed methodology is a powerful tool for objective decision-making.

1. Introduction

The mining industry provides the metals and minerals required for essential products, not least the technologies required for the green energy transition. Yet, the environmental and socio-economic impacts associated with mining are typically large and require mitigation. Mitigation strategies are often framed as Environmental, Social, and Governance (ESG) policies to stakeholders [1]. ESG policies have also become a crucial investment appraisal element for investors [1,2].

The mining industry is a driving force in a country's economic development. While it has made significant contributions to humanity, it also has the potential to cause severe environmental damage [3]. Schwab [4] identified some motivations that have led various industrial sectors to invest in sustainability. Because of these motivations, various researchers and organizations have identified the key features of sustainable development [3]. The mining industry is not the exception and policymakers should, therefore, take the required measures to ensure sustainability in the sector.

Technology selection in the mining industry is of paramount importance as it has cost and benefits implications, including those related to sustainability. Indeed, the impact that the adoption of different technologies in mining operations has on reaching sustainable development goals is an important field of research [5,6]. The technology selection process requires the decision-maker to consider multiple criteria [7,8]. This is not an easy task, and it is particularly challenging when new technologies are being considered. The selection of the most suitable technology alternative on the basis of relevant criteria is a multi-criteria decision-making (MCDM) problem.

* Corresponding author.
E-mail addresses: muhammetdeveci@gmail.com (M. Deveci), martin@ujaen.es (L. Martínez).

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Decision-making in dynamic systems requires the processing of uncertain and inaccurate information. That is why conventional decision-making models face increasingly demanding requirements that need to be met in real-time. In recent years, researchers have explored the possibility of extending traditional MCDM models using uncertainty theories [9–12]. Examples include the development of MCDM models using a fuzzy approach [13], rough theory [14], and neutrosophic theory [15]. In particular, significant efforts have been placed in the last few years to develop new MCDM models based on the application of rough theories [16–19] introduced rough numbers based on the concept of rough sets. The use of interval rough numbers regarding other interval concepts for processing uncertainty introduces the advantage of the adaptability of the rough boundary interval (RBI). It means the adjustment of the width of the interval depending on the degree of uncertainty in the internal information. In this paper, it is proposed to improve the traditional concept of rough numbers [19]. The proposed concept allows for defining rough numbers' lower and upper limits by applying nonlinear hybrid Dombi-Bonferroni functions. By introducing Dombi-Bonferroni functions for defining the lower and upper limit of interval rough numbers, it is possible to a) see the mutual relations between the set of objects under consideration and b) flexibly generate RBI and define the degree of risk depending on the dynamic conditions of the environment. In this study, the authors present a new approach for generating interval rough numbers based on uncertainties and inaccuracy in the information. The novel interval rough approach is implemented in a multi-criteria decision framework based on hybrid Heronian [20] and Power Averaging [21] (HPA) functions. Hybrid HPA functions have been used to generate weighted alternative strategies. The application of HPA functions in a multi-criteria decision framework enabled (*i*) an understanding of the interactions between decision attributes; (*ii*) considering the interrelationships between the criteria in the home matrix; and (*iii*) considering the degree of support between the input arguments. The effectiveness of the presented methodology was tested to deal with uncertainty and inaccuracy in a case study for mining process technology selection.

The rest of the study is summarised as follows: Section 2 provides the case study considered. Sections 3 and 4 present the proposed multi-criteria decision framework and its results. Sections 5 and 6 discuss managerial and policy implications, and the results and discussion, respectively. Section 7 presents the conclusions and indicates possible

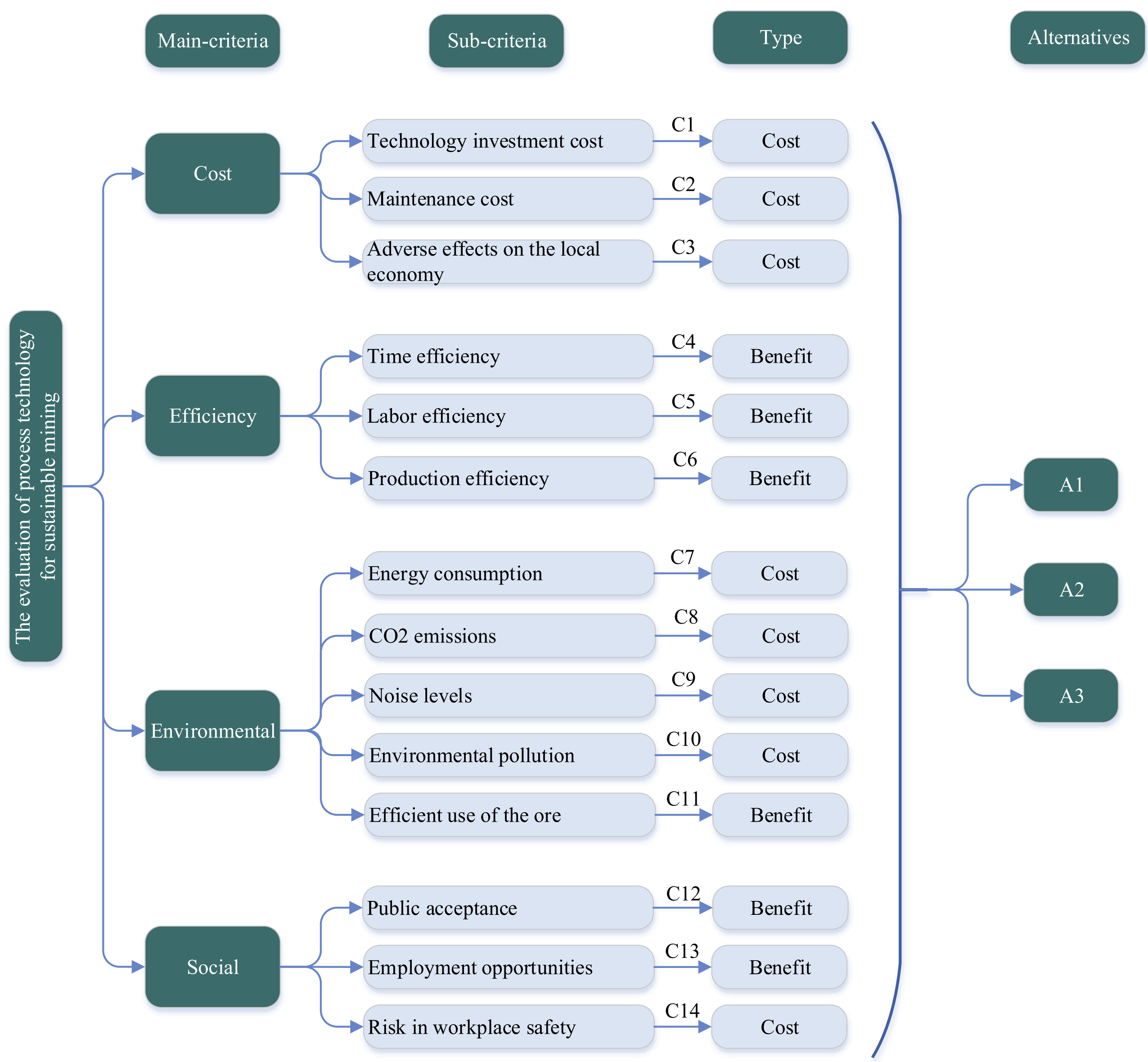

Fig. 1. The decision hierarchy for the selection of process technology for sustainable mining.

future research directions.

2. Problem definition

Mining has the potential to play an important role in community advancement and population welfare [22]. Many of the materials for equipment we use every day, from aluminum to microchips in computers, are supplied by the mining industry. Mining and mineral processing activities generate a large volume of waste materials while utilizing substances that can be damaging to the environment if not treated adequately. Mining is one of the industrial activities with the most widespread environmental and social consequences [22].

According to the literature, there are some alternatives that decision-makers should consider when selecting technology for sustainable mining. These alternatives are discussed below, and the decision hierarchy of the problem is shown in Fig. 1.

2.1. Definition of alternatives

A_1: Fully autonomous systems: The rising use of automation technologies is gradually transforming the mining industry. Automation is defined as the intelligent management of a system through the use of advanced tools so that it can operate without human intervention [23,24]. The agricultural industry pioneered the widespread use of autonomous vehicle technology [25]. Within the mining industry, there is a real push to develop and implement automation technology. Nevertheless, new sensing capabilities are needed to construct rich models of mines for autonomous systems to work efficiently in this field. As mining processes become more automated, sensor technologies for detecting and classifying geological features are becoming increasingly important. Important work has been done on the automation of vehicles in mining. Although it is essential for advanced activities in the mining process, the use of automation has received little attention. Gamma detection sensors are used effectively to manage such high-dimensional data in a robotics setting, and innovative methods are required [26]. Autonomous systems can help geologists in their tasks by determining mine face geology with greater spatial and spectral resolution while providing the operator's safety [26].

A_2:Semi-autonomous with human personnel: The majority of automation efforts are focused on providing semi-autonomous operation and assistance technologies, such as collision avoidance systems for mobile mining equipment [27,28]. Major device manufacturers have tested technologies for equipment maintenance, and truck manufacturers have tested driver-assisted systems to better position trucks for loading [29]. While rapid adoption of automation has frequently been pursued, human activities and staff skilling to assist this automation have not proceeded at the same rate as the technology. To help these technologies, new operational or maintenance skills are required. An automation skills gap, defined as a lack of workers with the technical knowledge, skills, and abilities to encourage current and future workforce requirements, is expected to be a significant impediment to the adoption of automation technologies [23]. The employees who are most affected by automation adoption are those who work in the most difficult areas. Human factors issues must be researched and understood for the mining industry to adopt automation integration and techniques that include a shift management program must be inserted in place to discuss the impact of automation on enhanced security and workplace conditions [30–32].

A_3:System continues with its current technology (labor-intensive): Mining is highly known as one of the most dangerous industries [33], and miners regard it as more dangerous and hazardous than other industries [34]. Moreover, in addition to the potentially dangerous environment, situations, and equipment found in mines, there are a variety of physical and psychosocial risks that have the potential to impact miners' health and safety [35]. There are several challenges in both underground and surface mines [36]. Economic shifts coincided with a transition from labor-intensive underground mining to capital-intensive surface mining. Underground mines typically employed large workforces who performed intensive manual work in unsafe conditions [37].

2.2. Definition of criteria

The aspects and criteria are determined after conducting a comprehensive review of the relevant literature. The criteria for selecting the process technology for sustainable mining include four main criteria and fifteen sub-criteria. These criteria are defined as follows:

(i) *Cost Aspect*

C_1: Technology investment cost: The importance of modern technology in achieving competitiveness in the mining industry has long been known [38]. Parallel to the increasing and accumulating new technologies, technological firms, and most high-tech governmental bodies must deal with the issues and challenges of budget limits and targeted creative projects. Since a lot of organizations have limited funds, launching all projects at the same time is not an option. It should be aimed at various Tech-graphs with more reasonable costing [39]. Traditional capital budgeting procedures have been chastised for stifling company competitiveness, particularly when assessing new technologies. Because of the unpredictability of its consequences, integrating new technology poses different obstacles [38].

C_2: Maintenance cost: Manufacturers are under constant pressure to reduce their manufacturing costs. Maintenance expenditures, which can range from 15 to 70 percent of manufacturing costs depending on what type of company, are one of the major expenses for these businesses [40]. Due to the higher attention on lean production in today's competitive climate, maintenance management has found some extra energy and goals in enhancing system capacity and capability [41]. There are drawbacks to using any of the methodologies for determining the best maintenance strategy. The approach's outcomes are based on the conceptual opinions of experts. The specialists who perform the comparisons must know the maintenance procedures and criteria. It is vital to categorize various equipment and machinery in a corporation based on performance and capabilities [42].

C_3: Adverse effects on the local economy: The economic importance of mining in a host country is also determined by the connections between mining and other sectors, such as equipment manufacturers, downstream processes, and service industries [43]. Mining investments, profit taxes, and income taxation are the primary public financial advantages of mining in Finland [44,45]. Property owners are also compensated with royalties. Minerals-related, construction-related, and metal-related activities, in particular, have already benefited from mining activity [46]. While the economic consequences of mining can be seen at the national, provincial, and local levels, environmental and societal concerns are mostly felt at the local level.

(ii) *Efficiency Aspect*

C_4: Time efficiency: Automation can release humans from time-consuming and labor-intensive duties, as well as decrease misuse, increase speed operations, ramp up production scores, broaden an operation to an extended shift or even production runs, minimize inefficiency, enhance physical specifications, and provide stability. Automation creates extra time and opportunities for the operators [32].

C_5: Labor efficiency: The human activities approach contends that for automated systems to be effective, they must consider the human aspect through user-centered design and execution. There is a presumption that people are more adaptable, responsive, and innovative than automated systems, which is one consideration that should be prevented [32].

C_6: Production efficiency: Automation is usually regarded to be more quick, reliable, and correct than a human operator [32].

(iii) *Environmental Aspect*

C_7*: Energy consumption:* Because crushing and grinding are the most energy-consuming and least energy-efficient stages of the mineral processing activity, using these systems before grinding and crushing equipment can considerably improve the efficiency of the comminution process and minimize energy costs [47].

C_8*:* CO_2 *emissions levels*: Autonomous systems have the power to magnify the industry and increase production and productivity, reducing human labor exposed to dangerous processes and the environment, improving productivity, lowering environmental footprint through diminished energy and fuel consumption, and implementing best practices [48]. Nearly 11% of the world's power is consumed by the mining industry. The mining sector is focused on increasing power efficiency and lowering GHG emissions. The long-term plan for addressing energy-efficiency challenges in mining is heading toward automation. Autonomous excavators are considered being critical in achieving this goal [49].

C_9*: Noise levels:* The Kalman filter technique can calculate acceleration. As a result, a considerable quantity of sensor noise and movement acquired during mining activities can be eliminated [50]. Unless the light is bright, it might generate disturbance in the frame, fooling the sensor into believing there's constant movement in the frame, preventing video compression from working. By minimizing noise, good illumination results in higher-quality, clearer images. It enables the use of video compression techniques and aids in bandwidth reduction [51].

C_{10}: *Environmental pollutant (*e.g. *solid waste) levels*: The aim should be to ensure a sustainable energy future that will provide long-term environmental benefits. The advancement of automated technologies has influenced the industry. Longwall mining techniques with more precise selected material recovery have reduced environmental damage and rehabilitation costs. To overcome the absence of full information about the specific location and type of resources, equipment, and facilities must be developed that are adequately well-integrated to extract resources effectively while minimizing the damage [3,52,53].

C_{11}: *Efficient use of the ore:* The increasing output of mining businesses leads to a growing effect of technological processes [54]. The energy efficiency challenge and resource-saving management must consider both ecological and economic factors in this respect. The cost price and power consumption reduction of raw iron ore and processing technology processes are crucial indicators of success [54–56]. Some technological regimes must be reconfigured, which affect the efficiency of ore beneficiation operations. The features of iron ore raw materials and their operational control at various stages of processing using modern methods have been investigated. As a result, it is recommended that ore processing automated control efficiency be investigated, considering energy, environmental, and economic concerns [54].

(iv) *Social Aspect*

C_{12}: *Public acceptance:* Stakeholder theory, sustainable development, and so on are just a few of the fields investigating the social aspects of mining and its significance to ongoing operations. Automation will eventually transform the way mines interact with persons and the communities in which they operate if it is to change the character of mining [52,57]. Early examination of potential social elements aids in the detection of unintended effects and societal benefits, allowing for educated management of both. The acceptance of these technological advances by the public will be influenced by labor relations. Sometimes unions, as representatives of workers, have refused to support automation in other industries [58]. The Construction, Forestry, Mining, and Energy Union (CFMEU) has already highlighted worries about autonomous vehicles' safety dangers and job creation consequences [51,59].

C_{13}: *Employment opportunities:* According to the International Council on Mining and Metals, over 2.5 million people are employed in legitimate (licensed large-scale) mining around the world [60,61]. Mine automation is projected to have a considerable impact on employment in resource-rich countries [62]. In deteriorating reserve quality, autonomous and remote operation technologies are being pursued to improve efficiency and productivity, alleviate the labor crisis, and improve health and safety, as well as working conditions. Predictions of the impact of automation on the workforce range from huge reductions in mining staff to a continued requirement for on-site employment that will grow with industry expansion (Grad, 2010). Other demographic groups may participate in the mining industry because of autonomous and remote operation technologies, spreading the benefits of mining, and expanding labor participation in the mining sector [57,63].

C_{14}: *Workplace safety*: The development of remote and automated mining technology has been a critical component of this strategy for creating safer, more efficient, and environmentally friendly coal mining systems. Re-manufacturing has been unsatisfactory, and worker health and safety have been a concern due to the complexity of manually operating equipment of this magnitude. As a result, the organizational environment and safety of coal mine staff have improved, resulting in a reduction in the number of accidents and deaths, saving mining companies millions of dollars each year. Mining automation technology can provide meaningful answers to this dilemma by allowing for more precise mining methods, adding sensors to optimize equipment management, and increasing crew security through remote process operation [53].

3. Proposed multi-criteria decision framework

In this section of the paper, a decision-making model is presented (see Fig. 2). The first module presents the novel IRN methodology for determining the weighting coefficients of the criteria, which is based on the application of additive logarithmic functions. The second module is based on applying hybrid IRN HPA functions that were used to evaluate alternatives and define weighted strategies. Within the second module, a novel approach to the standardization of information was implemented.

The concept based on the IRN presented in this paper enables the appreciation and treatment of imprecision and uncertainty in expert assessments. Each expert assessment is represented by an ordered pair $(\varrho_i;\varrho_j)$, where the values ϱ_i and ϱ_j represent values from a predefined scale. If there is no uncertainty in the expert assessment, the condition that $\varrho_i=\varrho_j$ is met. Then the expert assessment is not considered as an IRN but as a crisp number. In case of uncertainty in the information, the condition that $\varrho_i>\varrho_j$ is met. Then the assessments of other experts are compared and inaccuracies in the assessments are analysed. If there is a consensus in expert assessments, then all expert assessments are equal and are represented by crisp values. Therefore, as the imprecision in expert judgments increases, the width of the RBI increases. Thus, inaccuracies are expressed by the width of the lower and upper rough boundary intervals, while uncertainties are described by the distance between the upper and lower rough boundary intervals. This enables the preservation and treatment of inaccuracies and uncertainties that were presented in the original data.

The preservation of information in expert judgments will be presented in the next example. Let's assume that the experts defined their assessments using a five-point scale as follows: $E1=(2;3)$, $E2=(3;4)$, $E3=(4;5)$ and $E4=(5;5)$. Based on the values presented, we can conclude that there are uncertainties among all experts except for expert E4 since all experts had a dilemma when choosing a value from a five-point scale. Also, there are inaccuracies in the assessments since all experts used different values from the scale to describe the same attribute.

The processing of expert assessments $E1=(2;3)$, $E2=(3;4)$, $E3=(4;5)$, and $E4=(5;5)$ in the classic way would imply arithmetic averaging, which would give us the values 3.5 and 4.25. These values are represented in Fig. 3 by the shaded part and dashed line.

Also, such information can be represented by trapezoidal fuzzy numbers $C=(c_1, c_2, c_3, c_4)$, where c_2 and c_3 represent modal values, while c_1 and c_4 represent limit values. So for our example we can define four

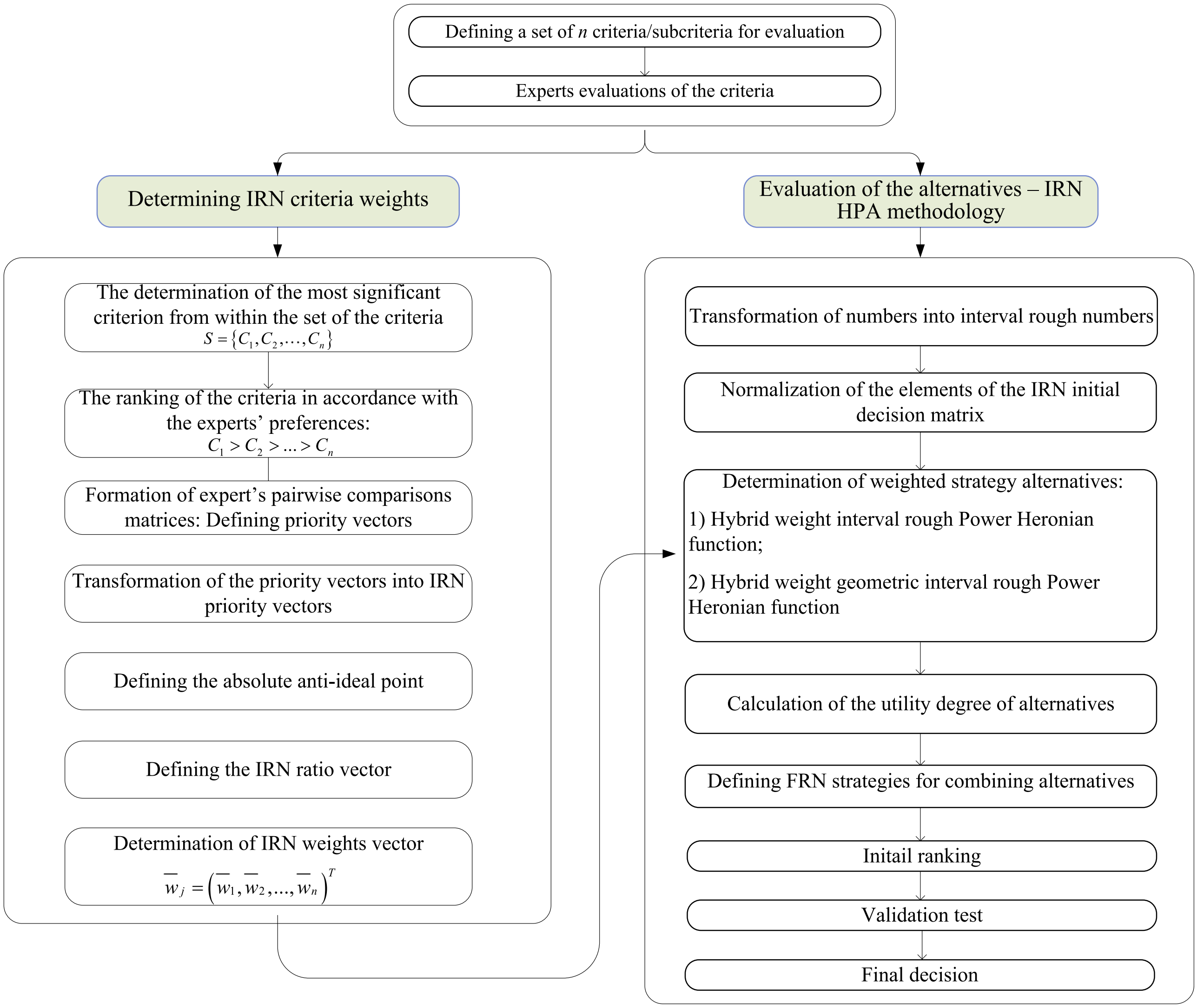

Fig. 2. Interval rough HPA framework.

fuzzy values C(E1)=(1,2,3,4), C(E2)=(2,3,4,5), C(E3)=(3,4, 5,5) and C (E4)=(4,5,5,5). The graphic representation of this information is presented in Fig. 3, where the darker shade of the fuzzy numbers (see Fig. 3) represents the elements of the fuzzy set that belong to the fuzzy set with 100%, while the lighter shade represents the elements that belong to the fuzzy set with a lower degree. By analyzing the results, it is observed that only two membership functions (C(E2) and C(E3)) partially or completely include the expected values, while the membership functions of the remaining fuzzy sets include the expected values with a degree of membership that is less than 0.5. On the other hand, all IRN concepts include expected values across all four interval rough numbers.

Suppose that in a case study, it is necessary to evaluate m alternatives Δ_i ($i=1,2,\ldots,m$) under n criteria Y_j ($j=1,2,\ldots,n$). Also, suppose that the research involves $E_e(e=1,2,\ldots,b)$ experts who should evaluate alternatives under the defined set of criteria. Then we propose a multi-criteria decision framework (see Fig. 2) that is implemented through the following steps:

Step 1. Forming a home matrix. The elements of the home matrix are defined based on expert estimates. Experts express their preferences based on a predefined linguistic scale. Evaluation of alternatives per each criterion by k ($1\le k\le b$) expert is denoted as $(\partial_{ij}^{k};\partial_{ij}^{k'})$, where $i=1,\ldots,m$; $j=1,\ldots,n$; ∂_{ij}^{k} and $\partial_{ij}^{k'}$ represent values from a defined linguistic scale.

Based on expert estimates, we can form two initial matrices $\Re^{k(l)}=[\partial_{ij}^{k(l)}]_{m\times n}$ and $\Re^{k(u)}=[\partial_{ij}^{k(u)}]_{m\times n}$. Suppose that universe G contains all objects from the home matrix $\Re^{k(l)}$ and $\Re^{k(u)}$. Also, suppose v is an arbitrary criterion from set G; R and is a set of b classes $(\partial_{ij}^{1(l)};\partial_{ij}^{2(l)};\ldots;\partial_{ij}^{b(l)})$ and R^* is a set of b classes $(\partial_{ij}^{1(u)};\partial_{ij}^{2(u)};\ldots;\partial_{ij}^{b(u)})$, which include all qualitative criteria from U. If classes are ordered as $\partial_{ij}^{1(l)}<\partial_{ij}^{2(l)}<\ldots<\partial_{ij}^{b(l)}$ and $\partial_{ij}^{1(u)}<\partial_{ij}^{2(u)}<\ldots<\partial_{ij}^{b(u)}$, and $\forall v\in U, \partial_{ij}^{q(l)}\in R$, $\partial_{ij}^{q(u)}\in R*$, ($1\le q\le b$) then the lower and upper approximation $\underline{Apr}(\partial_{ij}^{q(l)})$, $\underline{Apr}(\partial_{ij}^{q(u)})$, $\overline{Apr}(\partial_{ij}^{q(l)})$ and $\overline{Apr}(\partial_{ij}^{q(u)})$ can be presented as follows:

$$\begin{aligned}
\underline{Apr}\left(\partial_{ij}^{q(l)}\right) &= \bigcup_{1\le q\le b}\left\{v\in U \middle/ R(v)\le \partial_{ij}^{q(l)}\right\}\\
\underline{Apr}\left(\partial_{ij}^{q(u)}\right) &= \bigcup_{1\le q\le b}\left\{v\in U \middle/ R*(v)\le \partial_{ij}^{q(u)}\right\}\\
\overline{Apr}\left(\partial_{ij}^{q(l)}\right) &= \bigcup_{1\le q\le b}\left\{v\in U \middle/ R(Y)\ge \partial_{ij}^{q(l)}\right\}\\
\overline{Apr}\left(\partial_{ij}^{q(u)}\right) &= \bigcup_{1\le q\le b}\left\{v\in U \middle/ R*(Y)\ge \partial_{ij}^{q(l)}\right\}
\end{aligned} \quad (1)$$

Then the ordered pair $(\partial_{ij}^{k};\partial_{ij}^{k'})$ can be represented as the interval rough number $\widehat{\partial}_{ij}^{q}$, which is defined based on the corresponding lower and upper limits $(\underline{\partial}_{ij}^{q(l)},\underline{\partial}_{ij}^{q(u)},\overline{\partial}_{ij}^{q(l)}$ and $\overline{\partial}_{ij}^{q(u)})$ as follows:

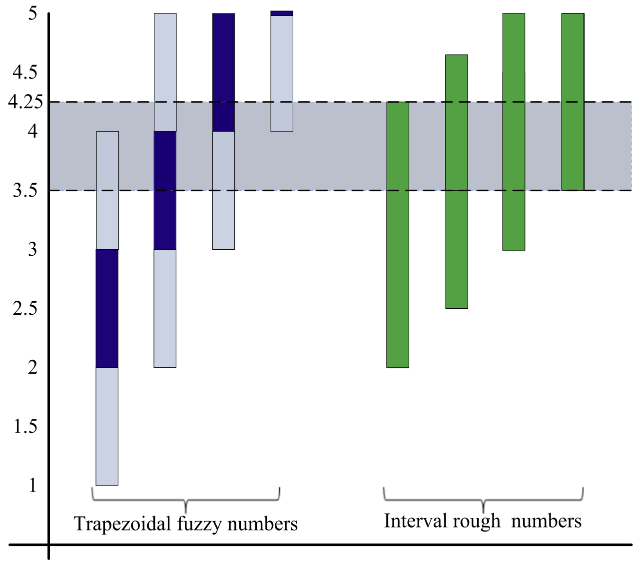

Fig. 3. Representation of information using IRN and fuzzy concept.

$$\underline{\partial}_{ij}^{q(l)} = \frac{\sum_{t=1}^{e}\partial_{ijt}^{q(l)}}{1+\left\{\frac{e(e-1)(\beta_1+\beta_2)^{-1}}{\sum_{\substack{x,y=1\\ x\neq y}}^{e}\left(\beta_1\left(\left(1-z_1^l\right)/z_1^l\right)^{\alpha}+\beta_2\left(\left(1-z_2^l\right)/z_2^l\right)^{\alpha}\right)^{-1}}\right\}^{1/\alpha}}\Bigg|\partial_{ij}^{(x)(l)},\partial_{ij}^{(y)(l)}\in\underline{Apr}\left(\partial_{ij}^{q(l)}\right) \tag{2}$$

$$\underline{\partial}_{ij}^{q(u)} = \frac{\sum_{t=1}^{e}\partial_{ijt}^{q(u)}}{1+\left\{\frac{e(e-1)(\beta_1+\beta_2)^{-1}}{\sum_{\substack{x,y=1\\ x\neq y}}^{e}\left(\beta_1\left(\left(1-z_1^u\right)/z_1^u\right)^{\alpha}+\beta_2\left(\left(1-z_2^u\right)/z_2^u\right)^{\alpha}\right)^{-1}}\right\}^{1/\alpha}}\Bigg|\partial_{ij}^{(x)(u)},\partial_{ij}^{(y)(u)}\in\underline{Apr}\left(\partial_{ij}^{q(u)}\right) \tag{3}$$

$$\overline{\partial}_{ij}^{q(l)} = \frac{\sum_{t=1}^{e}\partial_{ijt}^{q(l)}}{1+\left\{\frac{e(e-1)(\beta_1+\beta_2)^{-1}}{\sum_{\substack{x,y=1\\ x\neq y}}^{e}\left(\beta_1\left(\left(1-z_1^l\right)/z_1^l\right)^{\alpha}+\beta_2\left(\left(1-z_2^l\right)/z_2^l\right)^{\alpha}\right)^{-1}}\right\}^{1/\alpha}}\Bigg|\partial_{ij}^{(x)(l)},\partial_{ij}^{(y)(l)}\in\overline{Apr}\left(\partial_{ij}^{q(l)}\right) \tag{4}$$

$$\overline{\partial}_{ij}^{q(u)} = \frac{\sum_{t=1}^{e}\partial_{ijt}^{q(u)}}{1+\left\{\frac{e(e-1)(\beta_1+\beta_2)^{-1}}{\sum_{\substack{x,y=1\\ x\neq y}}^{e}\left(\beta_1\left(\left(1-z_1^u\right)/z_1^u\right)^{\alpha}+\beta_2\left(\left(1-z_2^u\right)/z_2^u\right)^{\alpha}\right)^{-1}}\right\}^{1/\alpha}}\Bigg|\partial_{ij}^{(x)(u)},\partial_{ij}^{(y)(u)}\in\overline{Apr}\left(\partial_{ij}^{q(u)}\right) \tag{5}$$

Where $z_1^l = f(\partial_{ij}^{(x)(l)}), z_2^l = f(\partial_{ij}^{(y)(l)}), z_1^u = f(\partial_{ij}^{(x)(u)})$ and $z_2^u = f(\partial_{ij}^{(y)(u)})$.

Thus we can define the interval rough number $\widehat{\partial}_{ij}^{q} = \left(\left[\underline{\partial}_{ij}^{q(l)},\overline{\partial}_{ij}^{q(l)}\right],\left[\underline{\partial}_{ij}^{q(u)},\overline{\partial}_{ij}^{q(u)}\right]\right)$ ($1 \le q \le b$). By fusing rough values of $\widehat{\partial}_{ij}^{q}$ we obtain an aggregated home matrix $\Re = [\widehat{\partial}_{ij}]_{m\times n}$.

Step 2. Home matrix standardization. Since the elements of the home matrix $\Re = [\widehat{\partial}_{ij}]_{m\times n}$ are described by different types of criteria, it is necessary to standardize the data and transform them into a unified criterion range. We obtain a standardized matrix $\Re^s = [\widehat{\partial}_{ij}]_{m\times n}$ by applying Eqs. (6) and (7), respectively.

a) For benefit type of criteria:

$$\widehat{\partial}_{ij} = \left(\left[\frac{\underline{\partial}_{ij}^{(l)}}{\partial_j^{+}},\frac{\overline{\partial}_{ij}^{(l)}}{\partial_j^{+}}\right],\left[\frac{\underline{\partial}_{ij}^{(u)}}{\partial_j^{+}},\frac{\overline{\partial}_{ij}^{(u)}}{\partial_j^{+}}\right]\right) \tag{6}$$

Table 1
The evaluation criteria and their types.

Aspect	Criteria	Type
Cost Aspect		
C_1	Technology investment cost	C
C_2	Maintenance cost	C
C_3	Adverse effects on the local economy	C
Efficiency Aspect		
C_4	Time efficiency	B
C_5	Labor efficiency	B
C_6	Production efficiency	B
Environmental Aspect		
C_7	Energy consumption	C
C_8	CO2 emissions levels	C
C_9	Noise levels	C
C_{10}	Environmental pollutant (e.g. solid waste) levels	C
C_{11}	Efficient use of the ore	B
Social Aspect		
C_{12}	Public acceptance	B
C_{13}	Employment opportunities	B
C_{14}	Workplace safety	C

*C: Cost, and B: Benefit.

b) For cost type of criteria:

$$\widehat{\partial}_{ij}=\left(\begin{array}{c}\left[-\frac{\underline{\partial}_{ij}^{(l)}}{\partial_j^{+}}+\max_{1\le i\le m}\left(\frac{\underline{\partial}_{ij}^{(l)}}{\partial_j^{+}}\right)+\min_{1\le i\le m}\left(\frac{\underline{\partial}_{ij}^{(l)}}{\partial_j^{+}}\right),-\frac{\overline{\partial}_{ij}^{(l)}}{\partial_j^{+}}+\max_{1\le i\le m}\left(\frac{\overline{\partial}_{ij}^{(l)}}{\partial_j^{+}}\right)+\min_{1\le i\le m}\left(\frac{\overline{\partial}_{ij}^{(l)}}{\partial_j^{+}}\right)\right],\\ \left[-\frac{\underline{\partial}_{ij}^{(u)}}{\partial_j^{+}}+\max_{1\le i\le m}\left(\frac{\underline{\partial}_{ij}^{(u)}}{\partial_j^{+}}\right)+\min_{1\le i\le m}\left(\frac{\underline{\partial}_{ij}^{(u)}}{\partial_j^{+}}\right),-\frac{\overline{\partial}_{ij}^{(u)}}{\partial_j^{+}}+\max_{1\le i\le m}\left(\frac{\overline{\partial}_{ij}^{(u)}}{\partial_j^{+}}\right)+\min_{1\le i\le m}\left(\frac{\overline{\partial}_{ij}^{(u)}}{\partial_j^{+}}\right)\right]\end{array}\right) \tag{7}$$

where $\partial_j^{+}=\max_{1\le i\le m}\left(\underline{\partial}_{ij}^{(l)},\underline{\partial}_{ij}^{(u)},\overline{\partial}_{ij}^{(l)},\overline{\partial}_{ij}^{(u)}\right)$.

Step 3. Determination of weight coefficients of criteria. Experts $E_e(e=1,2,...,b)$ evaluate the criteria using a predefined scale.

Step 3.1. Based on expert comparisons $(\varpi_j^k;\varpi_j^{k'})$ $(1\le k\le b; j=1,2,...,n)$, the comparative significance of the criteria is determined, where $(\varpi_j^k;\varpi_j^{k'})$ represents an expert's assessment of the significance of the criteria. Expert assessments of the significance of the criteria are transformed into interval rough assessments by applying the methodology presented in *Step 1*, i.e., by applying Eqs. (1)-(5). Thus we obtain the interval rough priority for each expert $\aleph^k=(\widehat{\wp}_1^k,\widehat{\wp}_2^k,..,\widehat{\wp}_n^k)$ $(1\le k\le b)$. Arithmetic averaging for each criterion gives an aggregate priority vector $\aleph=(\widehat{\wp}_1,\widehat{\wp}_2,..,\widehat{\wp}_n)$, where $\widehat{\wp}_j=\left(\left[\underline{\wp}_{ij}^{(l)},\overline{\wp}_{ij}^{(l)}\right],\left[\underline{\wp}_{ij}^{(u)},\overline{\wp}_{ij}^{(u)}\right]\right)$.

Step 3.2. Express the absolute anti-ideal point (ϑ_{AIP}) using Eq. (8).

$$\vartheta_{AIP}<\min\left(\widehat{\wp}_1,\widehat{\wp}_2,..,\widehat{\wp}_n\right) \tag{8}$$

Step 3.3. Defining the interval rough relation vector $D=(\widehat{\varphi}_1,\widehat{\varphi}_2,..,\widehat{\varphi}_n)$ using Eq. (9).

$$\widehat{\varphi}_j=\frac{\widehat{\wp}_j}{\vartheta_{AIP}}=\left(\left[\frac{\underline{\wp}_{ij}^{(l)}}{\vartheta_{AIP}},\frac{\overline{\wp}_{ij}^{(l)}}{\vartheta_{AIP}}\right],\left[\frac{\underline{\wp}_{ij}^{(u)}}{\vartheta_{AIP}},\frac{\overline{\wp}_{ij}^{(u)}}{\vartheta_{AIP}}\right]\right) \tag{9}$$

where $\widehat{\wp}_j=\left(\left[\underline{\wp}_{ij}^{(l)},\overline{\wp}_{ij}^{(l)}\right],\left[\underline{\wp}_{ij}^{(u)},\overline{\wp}_{ij}^{(u)}\right]\right)$ represents the element of interval rough priority vector $\aleph$.

Step 3.4. Find the interval of the rough vector of weight coefficients $\overline{\Omega}_j=(\overline{\Omega}_1,\overline{\Omega}_2,...,\overline{\Omega}_n)^T$ using Eq. (10) as follows:

$$\overline{\Omega}_j=\frac{\ln\left(\widehat{\varphi}_j\right)}{\ln\left(\widehat{\mathbb{Q}}\right)}=\left(\left[\frac{\underline{\varphi}_{ij}^{(l)}}{\overline{\mathbb{Q}}_{ij}^{(u)}},\frac{\overline{\varphi}_{ij}^{(l)}}{\underline{\mathbb{Q}}_{ij}^{(u)}}\right],\left[\frac{\underline{\varphi}_{ij}^{(u)}}{\overline{\mathbb{Q}}_{ij}^{(l)}},\frac{\overline{\varphi}_{ij}^{(u)}}{\underline{\mathbb{Q}}_{ij}^{(l)}}\right]\right) \tag{10}$$

where $\widehat{\varphi}_j=\left(\left[\underline{\varphi}_{ij}^{(l)},\overline{\varphi}_{ij}^{(l)}\right],\left[\underline{\varphi}_{ij}^{(u)},\overline{\varphi}_{ij}^{(u)}\right]\right)$ represent elements of the relation vector D, and $\widehat{\mathbb{Q}}=\prod_{j=1}^{n}\widehat{\varphi}_j=\left(\left[\prod_{j=1}^{n}\underline{\varphi}_{ij}^{(l)},\prod_{j=1}^{n}\overline{\varphi}_{ij}^{(l)}\right],\left[\prod_{j=1}^{n}\underline{\varphi}_{ij}^{(u)},\prod_{j=1}^{n}\overline{\varphi}_{ij}^{(u)}\right]\right)$.

Step 4. Determination of weighted strategy options. Based on arithmetic operations with interval rough numbers [64,65] and Definitions A1, A2, and A3, in Appendix 1 we can define hybrid functions to calculate weighted strategy alternatives: (*1*) hybrid weight interval rough Power Heronian function $(\mathbb{N}_i^{\rho_1,\rho_2})$ and (*2*) hybrid weight geometric interval rough Power Heronian function $(\mathbb{Z}_i^{\rho_1,\rho_2})$, Eq. (11) and (12).

$\widehat{\partial}_{ij}$ denotes a set of elements of $\Re^s=[\widehat{\partial}_{ij}]_{m\times n}$, and $\overline{\Omega}_j=(\overline{\Omega}_1,\overline{\Omega}_2,...,\overline{\Omega}_n)^T$ denotes the vector of weight coefficients of the criteria, we can then express the weighted alternative strategies by:

a) The first weighted strategy $(\mathbb{N}_i^{\rho_1,\rho_2})$:

$$\mathbb{N}_i^{\rho_1,\rho_2}=\left(\begin{array}{c}\left[\begin{array}{c}\left(\frac{2}{n(n+1)}\sum_{x=1}^{n}\left(n\underline{\Omega}_1^{(l)}\underline{\widehat{\partial}}_i^{(x)(l)}\right)^{\rho_1}\sum_{y=x}^{n}\left(n\underline{\Omega}_2^{(l)}\underline{\widehat{\partial}}_j^{(y)(l)}\right)^{\rho_2}\right)^{\frac{1}{\rho_1+\rho_2}},\\ \left(\frac{2}{n(n+1)}\sum_{x=1}^{n}\left(n\overline{\Omega}_1^{(l)}\overline{\widehat{\partial}}_i^{(x)(l)}\right)^{\rho_1}\sum_{y=x}^{n}\left(n\overline{\Omega}_2^{(l)}\overline{\widehat{\partial}}_j^{(y)(l)}\right)^{\rho_2}\right)^{\frac{1}{\rho_1+\rho_2}}\end{array}\right],\\ \left[\begin{array}{c}\left(\frac{2}{n(n+1)}\sum_{x=1}^{n}\left(n\underline{\Omega}_1^{(u)}\underline{\widehat{\partial}}_i^{(x)(u)}\right)^{\rho_1}\sum_{y=x}^{n}\left(n\underline{\Omega}_2^{(u)}\underline{\widehat{\partial}}_j^{(y)(u)}\right)^{\rho_2}\right)^{\frac{1}{\rho_1+\rho_2}},\\ \left(\frac{2}{n(n+1)}\sum_{x=1}^{n}\left(n\overline{\Omega}_1^{(u)}\overline{\widehat{\partial}}_i^{(x)(u)}\right)^{\rho_1}\sum_{y=x}^{n}\left(n\overline{\Omega}_2^{(u)}\overline{\widehat{\partial}}_j^{(y)(u)}\right)^{\rho_2}\right)^{\frac{1}{\rho_1+\rho_2}}\end{array}\right]\end{array}\right) \tag{11}$$

b) The second weighted strategy $(\mathbb{Z}_i^{\rho_1,\rho_2})$

$$\mathbb{Z}_i^{\rho_1,\rho_2}=\frac{1}{\rho_1+\rho_2}\left(\begin{array}{c}\left[\begin{array}{c}\prod_{\frac{x=1,}{y=x}}^{\chi}\left(\rho_1\underline{\widehat{\partial}}_i^{(x)(l)n\underline{\Omega}_1^{(l)}}+\rho_2\underline{\widehat{\partial}}_j^{(y)(l)n\underline{\Omega}_2^{(l)}}\right)^{\frac{2}{n(n+1)}},\\ \prod_{\frac{x=1,}{y=x}}^{\chi}\left(\rho_1\overline{\widehat{\partial}}_i^{(x)(l)n\overline{\Omega}_1^{(l)}}+\rho_2\overline{\widehat{\partial}}_j^{(y)(l)n\overline{\Omega}_2^{(l)}}\right)^{\frac{2}{n(n+1)}}\end{array}\right],\\ \left[\begin{array}{c}\prod_{\frac{x=1,}{y=x}}^{\chi}\left(\rho_1\underline{\widehat{\partial}}_i^{(x)(u)n\underline{\Omega}_1^{(u)}}+\rho_2\underline{\widehat{\partial}}_j^{(y)(u)n\underline{\Omega}_2^{(u)}}\right)^{\frac{2}{n(n+1)}},\\ \prod_{\frac{x=1,}{y=x}}^{\chi}\left(\rho_1\overline{\widehat{\partial}}_i^{(x)(u)n\overline{\Omega}_1^{(u)}}+\rho_2\overline{\widehat{\partial}}_j^{(y)(u)n\overline{\Omega}_2^{(u)}}\right)^{\frac{2}{n(n+1)}}\end{array}\right]\end{array}\right) \tag{12}$$

Where in Eqs. (11) and (12) $\underline{\Omega}_1^{(l)}=\frac{n\widehat{\underline{\Omega}}_i^{(l)}\underline{\Omega}_i^{(l)}}{\sum_{t=1}^{n}\widehat{\underline{\Omega}}_t^{(l)}\underline{\Omega}_t^{(l)}}$, $\underline{\Omega}_2^{(l)}=\frac{n\widehat{\underline{\Omega}}_i^{(l)}\underline{\Omega}_j^{(l)}}{\sum_{t=1}^{n}\widehat{\underline{\Omega}}_t^{(l)}\underline{\Omega}_i^{(l)}}$, $\overline{\Omega}_1^{(l)}=\frac{n\widehat{\overline{\Omega}}_i^{(l)}\overline{\Omega}_i^{(l)}}{\sum_{t=1}^{n}\widehat{\overline{\Omega}}_t^{(l)}\overline{\Omega}_t^{(l)}}$, $\overline{\Omega}_2^{(l)}=\frac{n\widehat{\overline{\Omega}}_i^{(l)}\overline{\Omega}_j^{(l)}}{\sum_{t=1}^{n}\widehat{\overline{\Omega}}_t^{(l)}\overline{\Omega}_i^{(l)}}$, $\underline{\Omega}_1^{(u)}=\frac{n\widehat{\underline{\Omega}}_i^{(u)}\underline{\Omega}_i^{(u)}}{\sum_{t=1}^{n}\widehat{\underline{\Omega}}_t^{(u)}\underline{\Omega}_t^{(u)}}$, $\underline{\Omega}_2^{(u)}=\frac{n\widehat{\underline{\Omega}}_i^{(u)}\underline{\Omega}_j^{(u)}}{\sum_{t=1}^{n}\widehat{\underline{\Omega}}_t^{(u)}\underline{\Omega}_i^{(u)}}$, $\overline{\Omega}_1^{(u)}=\frac{n\widehat{\overline{\Omega}}_i^{(u)}\overline{\Omega}_i^{(u)}}{\sum_{t=1}^{n}\widehat{\overline{\Omega}}_t^{(u)}\overline{\Omega}_t^{(u)}}$, $\overline{\Omega}_2^{(u)}=\frac{n\widehat{\overline{\Omega}}_i^{(u)}\overline{\Omega}_j^{(u)}}{\sum_{t=1}^{n}\widehat{\overline{\Omega}}_t^{(u)}\overline{\Omega}_i^{(u)}}$ and $\widehat{\Omega}_t=\frac{(1+T(\widehat{\partial}_{ij}))}{\sum_{j=1}^{n}(1+T(\widehat{\partial}_{ij}))}$, while $T(\widehat{\partial}_{ij})=\sum_{\substack{x=1\\ y\neq x}}^{\chi}Sup(\widehat{\partial}_i^{(x)},\widehat{\partial}_j^{(y)})$ and $Sup(\widehat{\partial}_i^{(x)},\widehat{\partial}_j^{(y)})$

Step 5. Calculation interval rough score functions $(\mathfrak{I}_i)$, Eq. (13).

$$\mathfrak{S}_i = \frac{\mathbb{N}_i^{\rho_1,\rho_2} + \mathbb{Z}_i^{\rho_1,\rho_2}}{1 + \left\{ \psi \left(\frac{1-\mathbb{N}_i^{\rho_1,\rho_2}}{\mathbb{N}_i^{\rho_1,\rho_2}} \right)^{\alpha} + (1-\psi) \left(\frac{1-\mathbb{Z}_i^{\rho_1,\rho_2}}{\mathbb{Z}_i^{\rho_1,\rho_2}} \right)^{\alpha} \right\}}; \ \alpha, \psi \geq 0 \tag{13}$$

The coefficient $\psi \in [0,1]$ is defined based on the consensus of decision-makers. It is recommended that $\psi = 0.5$ it be adopted to calculate the initial values score functions. This allows the equal influence of weighted alternative strategies ($\mathbb{N}_i^{\rho_1,\rho_2}$ and $\mathbb{Z}_i^{\rho_1,\rho_2}$) on the decision-making process.

4. Proposed model results

In the case study, three alternatives were evaluated: *A_1-Fully autonomous systems, A_2-Semi-autonomous with human personnel,* and *A_3-System continues with its current technology (labor-intensive)*. Fourteen criteria grouped within four clusters were used to evaluate alternatives, Table 1.

4.1. Ranking results

Step 1: The alternatives are evaluated by four experts using a nine-point scale: 1– Absolutely Low, 2 – Very Low, 3 – Low, 4 – Medium Low. 5 – Equal, 6 – Medium High, 7 –High, 8 – Very High, 9 – Absolutely High. Based on expert assessments of alternatives, a home matrix has been defined $\Re^k = [(\partial_{ij}^k; \partial_{ij}^{k'})]_{3\times 14}$as given in Table 2.

Based on Table 2, we note that the experts evaluated the alternatives using pairs of estimates $(\partial_{ij}^k; \partial_{ij}^{k'})$, $1 \leq k \leq 4$. The level of uncertainty and inaccuracy in expert assessments were presented with the help of assessment pairs. Assessment pairs were used to represent uncertainty and inaccuracy in expert assessments. If $\partial_{ij}^k = \partial_{ij}^{k'}$, uncertainty in the expert's assessment does not exist, while if $\partial_{ij}^k \neq \partial_{ij}^{k'}$ then there is a certain level of uncertainty and imprecision. The level of uncertainty is determined using the assessment interval $\varsigma_{ij} = \partial_{ij}^{k'} - \partial_{ij}^k$. It is clear that if $\partial_{ij}^k = \partial_{ij}^{k'}$, then $\varsigma_{ij} = 0$. If $\partial_{ij}^k \neq \partial_{ij}^{k'}$, then $\varsigma_{ij} \neq 0$. Higher values ς_{ij} indicate greater uncertainty and vice versa. Based on data from the home matrix (see Table 2), we note a significant level of uncertainty in experts' assessments.

Using Eqs. (1)-(5), the pairs of estimates from Table 2 were transformed into interval rough numbers. *Appendix 2* presents the procedure for transforming estimation pairs from Table 2 at position A_2—C_1. The remaining values were transformed similarly. Using the interval rough Dombi-Bonferroni operator (1)-(5), the rough interval values from the experts' correspondent matrices were aggregated into the final home matrix $\Re = [\widehat{\partial}_{ij}]_{3\times 14}$ given in Table 3.

Step 2: Elements from the home matrix (see Table 3) were normalized using Eqs. (6) and (7), and standardized matrix values were obtained, which are presented in Table 4.

The normalization of the element at position A_1—C_1 in the standardized matrix is presented below:

$$\widehat{\partial}_{11} = \left(\begin{bmatrix} -\frac{1.00}{7.98} + \max\limits_{1\leq i\leq 3}\left(\frac{1.00}{7.98}, \frac{2.21}{7.98}, \frac{3.67}{7.98}\right) + \min\limits_{1\leq i\leq 3}\left(\frac{1.00}{7.98}, \frac{2.21}{7.98}, \frac{3.67}{7.98}\right), \\ -\frac{1.00}{7.98} + \max\limits_{1\leq i\leq 3}\left(\frac{1.00}{7.98}, \frac{3.11}{7.98}, \frac{7.71}{7.98}\right) + \min\limits_{1\leq i\leq 3}\left(\frac{1.00}{7.98}, \frac{3.11}{7.98}, \frac{7.71}{7.98}\right) \end{bmatrix}, \begin{bmatrix} -\frac{1.04}{7.98} + \max\limits_{1\leq i\leq 3}\left(\frac{1.04}{7.98}, \frac{2.51}{7.98}, \frac{5.09}{7.98}\right) + \min\limits_{1\leq i\leq 3}\left(\frac{1.04}{7.98}, \frac{2.51}{7.98}, \frac{5.09}{7.98}\right), \\ -\frac{1.33}{7.98} + \max\limits_{1\leq i\leq 3}\left(\frac{1.33}{7.98}, \frac{3.35}{7.98}, \frac{7.98}{7.98}\right) + \min\limits_{1\leq i\leq 3}\left(\frac{1.33}{7.98}, \frac{3.35}{7.98}, \frac{7.98}{7.98}\right) \end{bmatrix} \right)$$

$$= ([0.460, 0.966], [0.638, 1.00])$$

The standardization of the remaining elements from Table 4 was performed similarly.

Step 3: The evaluation of the criteria was performed by four experts using the nine-point scale defined in *Step* 1. The expert opinions of the criteria are given in Table 5.

Step 3.1: The expert estimates in Table 5 were transformed into interval rough values using the methodology presented in *Step 1*. Arithmetic averaging is used to define the aggregate interval rough priority vector given in Table 6.

Step 3.2: The absolute anti-ideal point ϑ_{AIP} is defined based on the condition $\vartheta_{AIP} < \min(\widehat{\wp}_1, \widehat{\wp}_2, .., \widehat{\wp}_n)$. The value of $\vartheta_{AIP} = ([0.5, 0.5], [0.5, 0.5])$ was arbitrarily adopted.

Step 3.3: Using Eq. (9), the interval rough relation vectors are defined in Table 7.

Step 4: By applying Eq. (10), we obtain the interval rough vectors of the weight coefficients of the criteria as given in Table 8.

Fig. 3(a) shows the values of the weighting coefficients of the criteria. Then, global criterion values were used to evaluate alternatives as shown in Fig. 4(b).

Step 4: Using Eqs. (11) and (12), the weighted alternative strategies are defined as follows:

a) The first weighted strategy ($\mathbb{N}_i^{\rho_1,\rho_2}$):

$$\mathbb{N}_i^{\rho_1=\rho_2=1} = \begin{array}{c} A1 \\ A2 \\ A3 \end{array} \begin{bmatrix} ([0.483, 0.839], [0.527, 0.905]) \\ ([0.480, 0.801], [0.545, 0.845]) \\ ([0.398, 0.597], [0.435, 0.649]) \end{bmatrix}$$

b) The second weighted strategy ($\mathbb{Z}_i^{\rho_1,\rho_2}$):

Table 2
Home matrix.

Criteria	A_1				A_2				A_3			
	E_1	E_2	E_3	E_4	E_1	E_2	E_3	E_4	E_1	E_2	E_3	E_4
C_1	(1;1)	(1;1)	(1;1)	(1;2)	(3;3)	(2;3)	(4;4)	(2;2)	(8;8)	(7;8)	(9;9)	(2;3)
C_2	(1;1)	(1;2)	(2;2)	(1;1)	(3;3)	(4;5)	(4;4)	(2;3)	(8;8)	(7;8)	(9;9)	(3;3)
C_3	(1;1)	(3;3)	(2;2)	(4;5)	(2;2)	(5;6)	(4;5)	(5;5)	(3;3)	(8;9)	(7;8)	(5;6)
C_4	(9;9)	(9;9)	(8;8)	(9;9)	(8;8)	(7;8)	(7;7)	(8;9)	(8;8)	(2;3)	(3;4)	(7;8)
C_5	(9;9)	(2;2)	(9;9)	(1;1)	(8;8)	(4;5)	(6;7)	(7;8)	(7;7)	(7;8)	(2;3)	(9;9)
C_6	(9;9)	(2;2)	(7;7)	(8;9)	(7;7)	(4;5)	(6;7)	(8;8)	(8;8)	(8;8)	(3;3)	(7;8)
C_7	(1;1)	(3;3)	(2;2)	(1;1)	(2;2)	(5;6)	(3;4)	(1;2)	(3;3)	(7;8)	(7;8)	(2;3)
C_8	(1;1)	(2;2)	(1;1)	(1;1)	(2;2)	(4;4)	(2;2)	(1;2)	(3;3)	(8;8)	(8;9)	(4;4)
C_9	(7;7)	(4;4)	(3;4)	(1;1)	(2;2)	(5;5)	(4;4)	(1;2)	(1;1)	(3;3)	(7;7)	(3;3)
C_{10}	(9;9)	(1;1)	(2;3)	(3;3)	(9;9)	(3;3)	(3;4)	(2;3)	(9;9)	(7;8)	(8;8)	(1;2)
C_{11}	(8;8)	(8;9)	(8;8)	(1;1)	(8;9)	(3;4)	(7;7)	(2;2)	(9;9)	(7;7)	(3;3)	(2;3)
C_{12}	(1;1)	(8;9)	(3;4)	(4;5)	(1;1)	(7;8)	(5;6)	(5;6)	(2;2)	(4;5)	(8;8)	(8;9)
C_{13}	(8;8)	(2;3)	(1;2)	(1;2)	(8;8)	(4;4)	(3;4)	(6;7)	(9;9)	(7;7)	(9;9)	(9;9)
C_{14}	(1;2)	(1;1)	(2;2)	(4;5)	(1;1)	(2;3)	(3;4)	(1;2)	(1;1)	(5;5)	(6;7)	(1;1)

Table 3
Aggregate interval rugh home matrix.

Criteria	A_1	A_2	A_3
C_1	([1.00,1.00], [1.04,1.33])	([2.21,3.11], [2.51,3.35])	([3.67,7.71], [5.09,7.98])
C_2	([1.04,1.33], [1.19,1.68])	([2.62,3.67], [3.22,4.14])	([4.57,7.86], [5.09,7.98])
C_3	([1.52,3.05], [1.53,3.39])	([2.95,4.57], [3.29,5.16])	([4.10,6.77], [4.40,7.67])
C_4	([8.55,8.93], [8.55,8.93])	([7.24,7.74], [7.56,8.39])	([2.86,6.14], [4.10,6.79])
C_5	([2.15,6.53], [2.15,6.53])	([5.02,7.07], [6.09,7.62])	([4.02,7.35], [4.57,7.86])
C_6	([3.67,7.71], [3.90,7.97])	([5.02,7.07], [6.00,7.30])	([4.66,7.40], [5.28,7.55])
C_7	([1.17,2.03], [1.17,2.03])	([1.53,3.39], [2.34,4.06])	([3.02,5.73], [3.82,6.25])
C_8	([1.04,1.33], [1.04,1.33])	([1.49,2.61], [2.08,2.66])	([4.10,6.79], [3.95,7.22])
C_9	([1.81,4.65], [2.23,4.79])	([1.60,3.73], [2.32,3.74])	([1.89,4.08], [1.89,4.08])
C_{10}	([1.57,4.26], [1.91,4.46])	([2.61,4.63], [3.32,5.33])	([2.58,7.54], [4.33,7.84])
C_{11}	([3.78,7.24], [3.50,7.67])	([2.86,6.14], [3.12,6.79])	([2.88,6.51], [3.59,6.38])
C_{12}	([1.82,4.92], [2.05,5.90])	([2.54,5.38], [2.87,6.28])	([3.34,6.65], [3.37,7.31])
C_{13}	([1.21,2.87], [2.28,4.12])	([3.78,6.25], [4.51,6.48])	([8.06,8.86], [8.06,8.86])
C_{14}	([1.19,2.29], [1.51,2.85])	([1.17,2.03], [1.52,3.05])	([1.36,3.75], [1.37,4.04])

Table 4
Standardized home matrix.

Criteria	A_1	A_2	A_3
C_1	([0.460,0.966], [0.638,1.00])	([0.308,0.702], [0.454,0.748])	([0.125,0.125], [0.130,0.167])
C_2	([0.573,0.984], [0.638,1.00])	([0.376,0.691], [0.382,0.691])	([0.130,0.167], [0.148,0.210])
C_3	([0.534,0.882], [0.574,1.00])	([0.347,0.684], [0.346,0.769])	([0.198,0.398], [0.200,0.442])
C_4	([0.957,1.00], [0.957,1.00])	([0.81,0.866], [0.846,0.939])	([0.320,0.687], [0.459,0.760])
C_5	([0.274,0.831], [0.274,0.831])	([0.639,0.900], [0.775,0.969])	([0.512,0.935], [0.582,1.00])
C_6	([0.460,0.967], [0.489,1.00])	([0.630,0.887], [0.752,0.916])	([0.584,0.928], [0.663,0.946])
C_7	([0.483,0.917], [0.612,1.00])	([0.425,0.700], [0.425,0.675])	([0.188,0.325], [0.188,0.325])
C_8	([0.568,0.941], [0.548,1.00])	([0.505,0.764], [0.404,0.815])	([0.144,0.185], [0.144,0.185])
C_9	([0.350,0.778], [0.415,0.78])	([0.395,0.970], [0.395,1.00])	([0.333,0.896], [0.485,0.928])
C_{10}	([0.333,0.962], [0.553,1.00])	([0.200,0.915], [0.373,0.888])	([0.204,0.544], [0.244,0.569])
C_{11}	([0.493,0.944], [0.456,1.00])	([0.373,0.800], [0.407,0.885])	([0.376,0.849], [0.468,0.831])
C_{12}	([0.249,0.673], [0.28,0.806])	([0.348,0.736], [0.393,0.859])	([0.456,0.909], [0.461,1.00])
C_{13}	([0.137,0.324], [0.257,0.465])	([0.427,0.705], [0.509,0.731])	([0.910,1.00], [0.910,1.00])
C_{14}	([0.333,0.863], [0.341,1.00])	([0.337,0.928], [0.339,0.949])	([0.290,0.503], [0.376,0.705])

$$\mathbb{Z}_i^{\rho_1=\rho_2=1} = \begin{array}{c} A1 \\ A2 \\ A3 \end{array} \begin{bmatrix} ([0.448, 0.832], [0.502, 0.899]) \\ ([0.452, 0.797], [0.512, 0.841]) \\ ([0.345, 0.550], [0.384, 0.599]) \end{bmatrix}$$

For calculating the functions $\mathbb{N}_i^{\rho_1,\rho_2}$ and $\mathbb{Z}_i^{\rho_1,\rho_2}$, the values $\rho_1=\rho_2=1$ were adopted. An example of the calculation of the function $\mathbb{N}_i^{\rho_1,\rho_2}$, Eq. (11), for alternative A_1 is shown below:

Table 5
Evaluation of criteria.

Criteria	Expert 1	Expert 2	Expert 3	Expert 4
MC_1	(9;9)	(9;9)	(6;6)	(6;5)
MC_2	(8;9)	(8;9)	(8;8)	(8;8)
MC_3	(9;9)	(6;7)	(5;5)	(9;9)
MC_4	(8;8)	(7;7)	(4;4)	(7;8)
MC_1: Cost Aspect				
C_1	(7;7)	(8,8)	(8;8)	(9;9)
C_2	(8;8)	(7;8)	(6;6)	(6;6)
C_3	(9;9)	(6;6)	(5;5)	(7;7)
MC_2: Efficiency Aspect				
C_4	(7;7)	(8;9)	(7;8)	(7;8)
C_5	(8;8)	(8;8)	(5;6)	(8;9)
C_6	(9;9)	(8;9)	(8;8)	(8;8)
MC_3: Environmental Aspect				
C_7	(8;9)	(9;9)	(6;6)	(8;8)
C_8	(8;9)	(6;7)	(7;7)	(9;9)
C_9	(7;7)	(6;7)	(3;3)	(5;5)
C_{10}	(9;9)	(7;8)	(4;5)	(8;9)
C_{11}	(8;8)	(8;8)	(8;8)	(6;6)
MC_4: Social Aspect				
C_{12}	(6;6)	(8;8)	(4;4)	(8;8)
C_{13}	(7;7)	(5;6)	(5;5)	(7;7)
C_{14}	(9;9)	(8;9)	(8;9)	(7;8)

Table 6
Aggregated interval rough priority vector.

Criteria	Interval rough priority vector
MC_1	([6.63,8.12],[6.04,8.17])
MC_2	([8.00,8.00],[8.24,8.74])
MC_3	([6.04,8.17],[6.27,8.36])
MC_4	([5.39,7.20],[5.42,7.51])
	MC_1: Cost Aspect
C_1	([7.56,8.39],[7.56,8.39])
C_2	([6.24,7.19],[6.44,7.44])
C_3	([5.71,7.60],[5.71,7.60])
	MC_2: Efficiency Aspect
C_4	([7.06,7.42],[7.56,8.39])
C_5	([6.51,7.77],[7.01,8.31])
C_6	([8.06,8.42],[8.24,8.74])
	MC_3: Environmental Aspect
C_7	([7.01,8.31],[7.11,8.62])
C_8	([6.68,8.18],[7.45,8.45])
C_9	([3.98,6.05],[4.18,6.32])
C_{10}	([5.36,7.98],[6.47,8.53])
C_{11}	([7.05,7.86],[7.05,7.86])
	MC_4: Social Aspect
C_{12}	([5.23,7.34],[5.23,7.34])
C_{13}	([5.43,6.43],[5.68,6.70])
C_{14}	([7.56,8.39],[8.55,8.93])

1) Normalized functions are calculated for each rough sequence ($\underline{\mathbb{N}}_1^{(l)}, \overline{\mathbb{N}}_1^{(l)}, \underline{\mathbb{N}}_1^{(u)}$ and $\overline{\mathbb{N}}_1^{(u)}$). The following section presents the calculation of normalized functions for $\underline{\mathbb{N}}_1^{(l)}$:

$$\begin{aligned} f\left(\widehat{\underline{\partial}}_{11}\right) &= \frac{0.460}{0.460+0.573+...+0.333} = 0.074;\ f\left(\widehat{\underline{\partial}}_{12}\right) \\ &= \frac{0.573}{0.460+0.573+...+0.333} = 0.092;\ ...;\ f\left(\widehat{\underline{\partial}}_{1,14}\right) \\ &= \frac{0.033}{0.460+0.573+...+0.333} = 0.054. \end{aligned}$$

2) Calculating the degree of support:

$$\begin{aligned} Sup\left(f\left(\widehat{\underline{\partial}}_{11}\right), f\left(\widehat{\underline{\partial}}_{12}\right)\right) &= 0.018;\ Sup\left(f\left(\widehat{\underline{\partial}}_{11}\right), f\left(\widehat{\underline{\partial}}_{13}\right)\right) \\ &= 0.012;\ Sup\left(f\left(\widehat{\underline{\partial}}_{11}\right), f\left(\widehat{\underline{\partial}}_{14}\right)\right) \\ &= 0.080;\ ...;\ Sup\left(f\left(\widehat{\underline{\partial}}_{1,13}\right), f\left(\widehat{\underline{\partial}}_{1,14}\right)\right) = 0.032. \end{aligned}$$

Table 7
Interval rough relation vectors.

Criteria	Interval rough relation vector
MC_1	([13.26,16.24],[12.09,16.33])
MC_2	([16.00,16.00],[16.48,17.48])
MC_3	([12.09,16.33],[12.54,16.71])
MC_4	([10.79,14.41],[10.84,15.03])
	MC_1: Cost Aspect
C_1	([15.11,16.78],[15.11,16.78])
C_2	([12.49,14.38],[12.88,14.88])
C_3	([11.41,15.21],[11.41,15.21])
	MC_2: Efficiency Aspect
C_4	([14.12,14.84],[15.11,16.78])
C_5	([13.03,15.54],[14.03,16.62])
C_6	([16.12,16.84],[16.48,17.48])
	MC_3: Environmental Aspect
C_7	([14.03,16.62],[14.22,17.25])
C_8	([13.36,16.37],[14.90,16.89])
C_9	([7.96,12.11],[8.36,12.64])
C_{10}	([10.72,15.97],[12.93,17.05])
C_{11}	([14.10,15.71],[14.10,15.71])
	MC_4: Social Aspect
C_{12}	([10.46,14.68],[10.46,14.68])
C_{13}	([10.87,12.86],[11.37,13.40])
C_{14}	([15.11,16.78],[17.09,17.87])

That's how we get values: $T\left(f\left(\widehat{\partial}_{11}\right)\right)=0.312$, $T\left(f\left(\widehat{\partial}_{12}\right)\right)=0.417$, $T\left(f\left(\widehat{\partial}_{13}\right)\right)=0.365,\ldots,\ T\left(f\left(\widehat{\partial}_{1,14}\right)\right)=0.358$

1) By applying Eq. (11), we calculate $\underline{\mathbb{N}}_1^{(l)\rho_1,\rho_2}$:

$$\underline{\mathbb{N}}_1^{(l)\rho_1=\rho_2=1}=$$

$$=\frac{2}{14(14+1)}\left(\begin{array}{l}\left(14\cdot\frac{0.076\cdot(1+0.312)}{0.076\cdot(1+0.312)+0.071\cdot(1+0.417)+0.068\cdot(1+0.365)+\ldots+0.071\cdot(1+0.358)}0.460\right)^{1}\cdot\\ \left(14\cdot\frac{0.076\cdot(1+0.312)}{0.076\cdot(1+0.312)+0.071\cdot(1+0.417)+0.068\cdot(1+0.365)+\ldots+0.071\cdot(1+0.358)}0.460\right)^{1}+\\ \left(14\cdot\frac{0.076\cdot(1+0.312)}{0.076\cdot(1+0.312)+0.071\cdot(1+0.417)+0.068\cdot(1+0.365)+\ldots+0.071\cdot(1+0.358)}0.460\right)^{1}\cdot\\ \left(14\cdot\frac{0.071\cdot(1+0.417)}{0.076\cdot(1+0.312)+0.071\cdot(1+0.417)+0.068\cdot(1+0.365)+\ldots+0.071\cdot(1+0.358)}0.573\right)^{1}\\ +\ldots+\\ \left(14\cdot\frac{0.071\cdot(1+0.358)}{0.076\cdot(1+0.312)+0.071\cdot(1+0.417)+0.068\cdot(1+0.365)+\ldots+0.071\cdot(1+0.358)}0.33\right)^{1}\cdot\\ \left(14\cdot\frac{0.071\cdot(1+0.358)}{0.076\cdot(1+0.312)+0.071\cdot(1+0.417)+0.068\cdot(1+0.365)+\ldots+0.071\cdot(1+0.358)}0.33\right)^{1}\end{array}\right)^{\frac{1}{1+1}}$$

$$=0.483$$

Similarly, the remaining rough sequences $\overline{\mathbb{N}}_i^{(l)}$,$\underline{\mathbb{N}}_i^{(u)}$ and $\overline{\mathbb{N}}_i^{(u)}$are calculated, and we obtain the interval rough value $\mathbb{N}_1^{\rho_1=\rho_2=1}=([0.483,0.839],[0.527,0.905])$.

The value of the function $\mathbb{Z}_i^{\rho_1,\rho_2}$ for alternative A_1, Eq. (12), is obtained as follows:

$$\underline{\mathbb{Z}}_1^{(l)\rho_1=\rho_2=1}=$$

$$=\frac{1}{1+1}\left(\begin{array}{l}\left(\begin{array}{l}1\cdot 0.460^{\frac{0.076\cdot(1+0.312)}{0.076\cdot(1+0.312)+0.071\cdot(1+0.417)+0.068\cdot(1+0.365)+\ldots+0.071\cdot(1+0.358)}}+\\ 1\cdot 0.460^{\frac{0.076\cdot(1+0.312)}{0.076\cdot(1+0.312)+0.071\cdot(1+0.417)+0.068\cdot(1+0.365)+\ldots+0.071\cdot(1+0.358)}}\end{array}\right)\cdot\\ \left(\begin{array}{l}1\cdot 0.460^{\frac{0.076\cdot(1+0.312)}{0.076\cdot(1+0.312)+0.071\cdot(1+0.417)+0.068\cdot(1+0.365)+\ldots+0.071\cdot(1+0.358)}}+\\ 1\cdot 0.573^{\frac{0.071\cdot(1+0.417)}{0.076\cdot(1+0.312)+0.071\cdot(1+0.417)+0.068\cdot(1+0.365)+\ldots+0.071\cdot(1+0.358)}}\end{array}\right)\\ \cdot\ldots\cdot\\ \left(\begin{array}{l}1\cdot 0.33^{\frac{0.071\cdot(1+0.358)}{0.076\cdot(1+0.312)+0.071\cdot(1+0.417)+0.068\cdot(1+0.365)+\ldots+0.071\cdot(1+0.358)}}+\\ 1\cdot 0.33^{\frac{0.071\cdot(1+0.358)}{0.076\cdot(1+0.312)+0.071\cdot(1+0.417)+0.068\cdot(1+0.365)+\ldots+0.071\cdot(1+0.358)}}\end{array}\right)\end{array}\right)^{\frac{2}{14(14+1)}}$$

$$=0.448$$

Similarly, the remaining rough sequences $\overline{\mathbb{Z}}_1^{(l)}$,$\underline{\mathbb{Z}}_1^{(u)}$ and $\overline{\mathbb{Z}}_1^{(u)}$, are calculated. Thus we obtain the interval rough value $\mathbb{Z}_1^{\rho_1=\rho_2=1}=([0.448,0.832],[0.502,0.899])$.

Step 5: The interval rough score functions ($\mathfrak{I}_i$) is obtained by applying the Eq. (13):

$$\mathfrak{I}_i^{\alpha,\psi}=\begin{array}{c}A1\\A2\\A3\end{array}\begin{bmatrix}([0.432,1.397],[0.530,1.628])\\([0.434,1.276],[0.559,1.421])\\([0.275,0.656],[0.334,0.777])\end{bmatrix}$$

When calculating the interval rough score functions alternative, the coefficients ψ=0.5 and α=1 were adopted. This allows both strategies ($\mathbb{N}_i^{\rho_1,\rho_2}$ and $\mathbb{Z}_i^{\rho_1,\rho_2}$) to have the same impact on defining interval rough score functions alternatives. Since the alternative should have the highest possible value $\mathfrak{I}_i$, the following rank was obtained $A_1>A_2>A_3$.

4.2. Checking the stability of the results

In this section, the robustness of the initial solution is analyzed. So

Table 8
Vector of weight coefficients of criteria.

Criteria	Local	Global
MC_1	([0.231,0.273],[0.226,0.273])	–
C_1	([0.329,0.366],[0.331,0.367])	([0.076,0.100],[0.075,0.100])
C_2	([0.306,0.346],[0.311,0.352])	([0.071,0.094],[0.070,0.096])
C_3	([0.295,0.353],[0.297,0.355])	([0.068,0.096],[0.067,0.097])
MC_2	([0.248,0.272],[0.254,0.280])	–
C_4	([0.312,0.331],[0.329,0.353])	([0.077,0.090],[0.084,0.099])
C_5	([0.302,0.336],[0.320,0.352])	([0.075,0.091],[0.081,0.098])
C_6	([0.327,0.346],[0.339,0.358])	([0.081,0.094],[0.086,0.100])
MC_3	([0.223,0.274],[0.229,0.275])	–
C_7	([0.191,0.222],[0.195,0.231])	([0.043,0.061],[0.045,0.064])
C_8	([0.188,0.220],[0.198,0.229])	([0.042,0.060],[0.045,0.063])
C_9	([0.150,0.197],[0.156,0.206])	([0.033,0.054],[0.036,0.057])
C_{10}	([0.172,0.218],[0.188,0.230])	([0.038,0.060],[0.043,0.063])
C_{11}	([0.192,0.217],[0.194,0.223])	([0.043,0.059],[0.045,0.062])
MC_4	([0.213,0.261],[0.216,0.265])	–
C_{12}	([0.288,0.353],[0.291,0.361])	([0.061,0.092],[0.063,0.096])
C_{13}	([0.292,0.335],[0.302,0.348])	([0.062,0.088],[0.065,0.092])
C_{14}	([0.333,0.370],[0.352,0.387])	([0.071,0.097],[0.076,0.103])

far, several approaches have been proposed in the literature to analyze the robustness of the results of multi-criteria decision models [66–71]. Most approaches have a single view because robustness analysis depends on the specifics of the methodology used in the mathematical model. Many authors [21,72–74] believe that it is necessary to analyze the impact of subjectively defined input parameters on the initial results of the model. Keeping in mind the mentioned recommendations, the robustness analysis was conducted in this study.

The multi-criteria decision framework presented in this study has several parameters (ρ_1, ρ_2, α, ψ and ϑ_{AIP}) that are defined based on the consensus of decision-makers. In the following section, the strength of the initial results in the conditions of variation of the parameters ρ_1, ρ_2, α, ψ and ϑ_{AIP} is analyzed.

a) *Influence of parameters ρ_1 and ρ_2*

To define the initial solution, the values of the parameters $\rho_1=\rho_2=1$

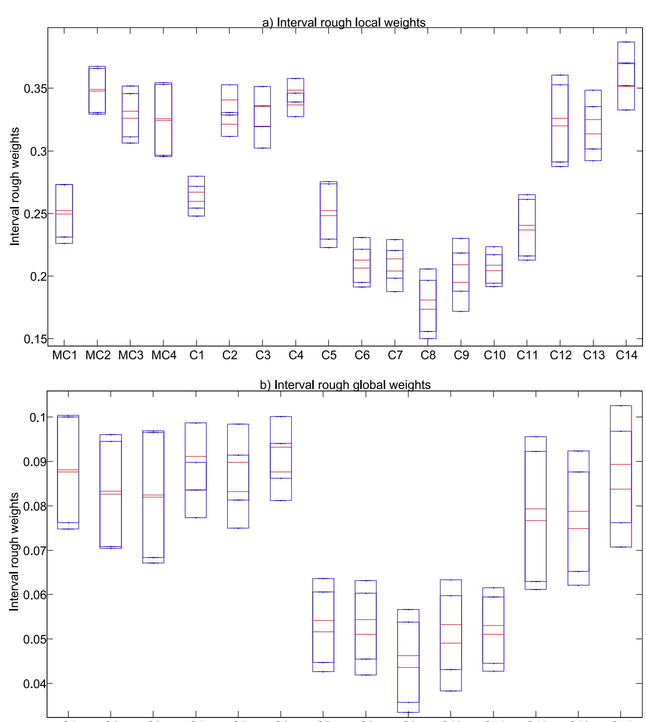

Fig. 4. Interval rough criteria weights.

were adopted. These parameters play a significant role in defining weighted alternative strategies, Eqs. (11) and (12) and thus affect the final ranking results. Therefore, $1\leq\rho_1,\rho_2\leq100$ is simulated. Fig. 5 shows the dependence of interval rough score function alternatives on the mentioned parameters' change.

Fig. 5 (a-c) shows the influence of the parameters ρ_1 and ρ_2 on the individual interval rough score functions of alternatives A_1, A_2, and A_3. Based on the presented results (Fig. 5 (a-c)), it can be noticed that the model is sensitive to changes in the stated parameters.

From Fig. 5 (a-d), $1\leq \rho_1,\rho_2\leq100$ causes increasing interval rough score functions of all three alternatives. Also, changing these parameters causes an increase in the gap between the integrated score functions of the alternatives (see Fig. 5(d)). Based on their preferences, decision-makers can define different values of the parameters ρ_1 and ρ_2. However, the results in Fig. 5(d) indicate that the values of ρ_1 and ρ_2 should not be lower than two, i.e., it is recommended to be between nine and fifteen. Therefore, there was no change in the initial solution during the presented simulation, i.e., the initial rank of alternatives was confirmed ($A_1> A_2> A_3$).

a) *Influence of parameters α and ψ*

The α and ψ parameters were used to fuse weighted alternative strategies and define the initial rank, Eq. (13). As previously emphasized, the values of the parameters $\alpha=1$ and $\psi=0.5$ were defined when defining the initial solution. The parameter ψ takes values from the interval [0,1], while the parameter α can have any value that $\alpha> 0$. Fig. 6 (a) shows the dependence of interval rough score functions alternatives on changing the parameter $1\leq\alpha\leq100$, while Fig. 6(b) shows the influence of the parameter $0\leq\psi\leq1$.

Analyzing the results from Figs. 6(a) and 6(b), we notice a dependence of the model on the change of these parameters. Also, the results show that the initial solution is stable and that the change in the values of the parameters α and ψ does not cause changes in the initial solution.

a) *Influence of parameter ϑ_{AIP}*

The value ϑ_{AIP} is defined in the model for determining the interval rough weights of the criteria and affects the definition of the rough relation vector. Based on the conditions for defining the value ϑ_{AIP}, the absolute anti-ideal point can have values from the interval $0.01\leq\vartheta_{AIP}\leq1$. Based on the consensus of experts, the value $\vartheta_{AIP}= 0.5$ was introduced in this study. In the following section, the influence of ϑ_{AIP} on the change in the values of the criteria' weighting coefficients and the alternatives' initial rank is analyzed. Twenty scenarios were formed in the next experiment. Therefore, twenty new vectors of weight coefficients of the criteria are formed in Fig. 7.

Based on the results from Fig. 7 (a-d), it can be noticed that changes in the values of the absolute anti-ideal point affect the change in the rough boundary interval of the weighting coefficients of the criteria. Fig. 8 shows the influence of new vectors of weight coefficients on the ranking results.

From Fig. 7, the results show that increasing ϑ_{AIP} leads to increasing interval rough score functions ($\mathfrak{I}_i$). However, these changes do not violate the initial solution, so the evidence shows that the initial rank $A_1> A_2> A_3$ is confirmed.

a) *Comparisons with other decision-making models*

In the following section, a comparison of the HPA methodology with other similar approaches from the literature is presented. Multi-criteria models for comparison were selected based on aggregation functions used in the considered models, as well as based on the concept applied to treat uncertainty. Based on defined criteria, the following models were selected for comparison: fuzzy WASPAS (Weighted Aggregated Sum Product Assessment) model [75]; rough CoCoSo (Combined

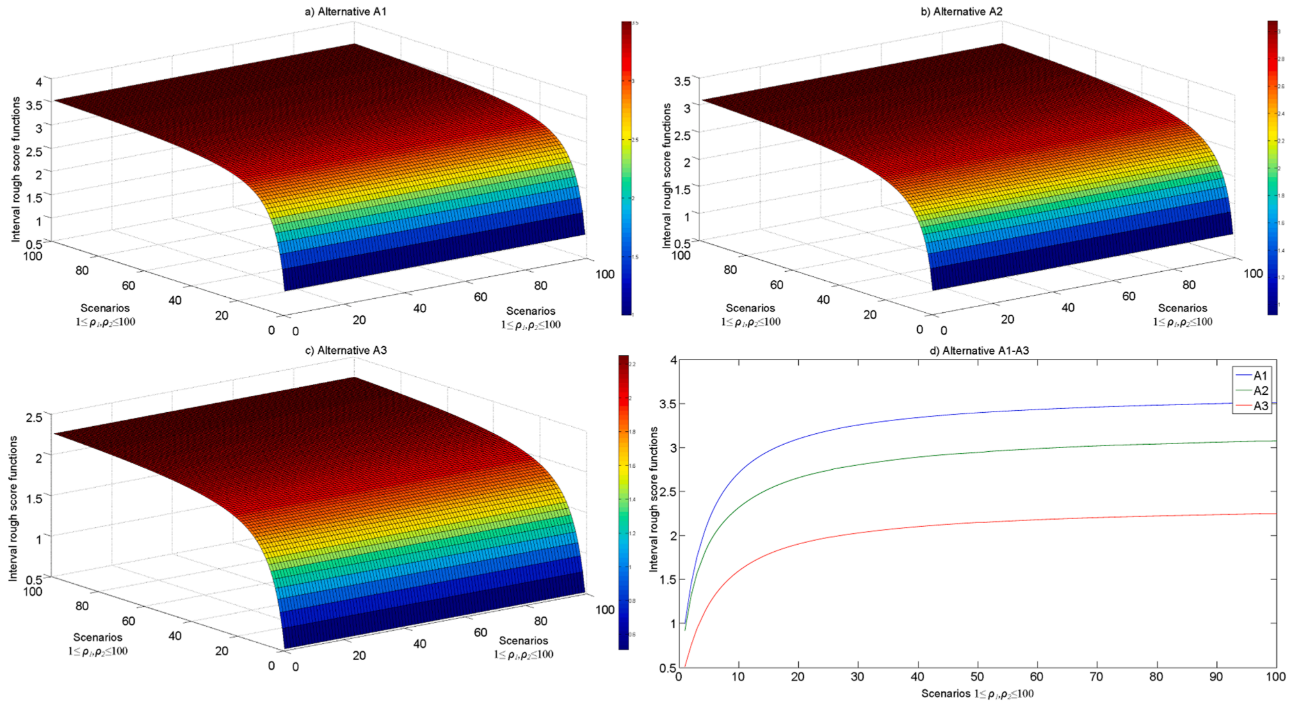

Fig. 5. Influence of parameters ρ_1 and ρ_2 on change of interval rough score functions alternative.

Compromise Solution) model [76], interval rough MAIRCA (Multi-Attributive Ideal-Real Comparative Analysis) model [77] and rough MARCOS model (Measurement of Alternatives and Ranking according to COmpromise Solution) [78]. All used models were applied under the same conditions and using the same input data. When applying the fuzzy WASPAS model, the input parameters were fuzzified using the fuzzy scale proposed by Rudnik et al. [75]. The results of the comparison of multi-criteria techniques are presented in Fig. 9.

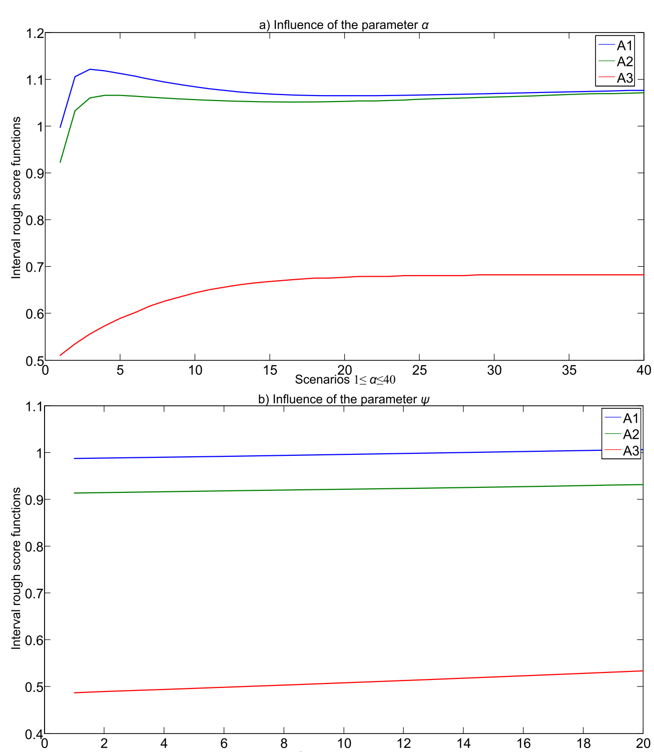

Fig. 6. The analysis of the influence of the parameters α and ψ.

The results presented in Fig. 9 indicate a high correlation of results between the considered techniques. Smaller deviations exist when applying the fuzzy WASPAS model since fuzzy numbers ignore a certain aspect of the original inaccuracies in the information, depending on the defined limit interval values. Minor differences also appeared in the rough CoCoSo and rough MARCOS methods. Such deviations are the result of the approximation of the input parameters and adaptation to the information that is necessary for the application of rough techniques. Because of the approximation of the input parameters, a certain degree of uncertainty in expert assessments was neglected, which consequently led to deviations in the final values. However, these findings are not statistically significant, as they refer to the non-dominant alternative (last in rank). In contrast, the rank of the dominant alternative is confirmed in all considered models.

In addition to the consistent results, it is necessary to emphasize the methodological advantages of the IRN HPA model relative to the considered models. The rough models are not subject to further adjustments, which makes it impossible to consider additional scenarios in which the risk in information would be simulated [17]. The original concept of interval rough numbers is based on the definition of the lower and upper limit of the rough boundary interval (RBI) using arithmetic averaging [77]. However, this concept has anomalies associated with the limitations of arithmetic averaging. On the other side, the application of hybrid nonlinear Dombi-Bonferroni functions enables the generation of adaptive limit intervals of IRNs that are adaptable depending on the dynamic conditions of the environment. The Dombi-Bonferroni functions were used because they enable the visualization of mutual relationships between decision attributes and provide the possibility of adaptive representation of RBI threshold values. Furthermore, adaptive parameters of the Dombi-Bonferroni function enable the simulation of different degrees of risk depending on the conditions in the decision-making problem. While in the fuzzy WASPAS model, the interval values are defined based on subjective assessments, which can affect the final values of the criterion functions.

The IRN HPA multi-criterion framework has stabilization parameters that are defined based on expert assessments, which enable flexible decision-making. Also, the HPA algorithm has an algorithm that considers mutual connections between rough sequences and enables

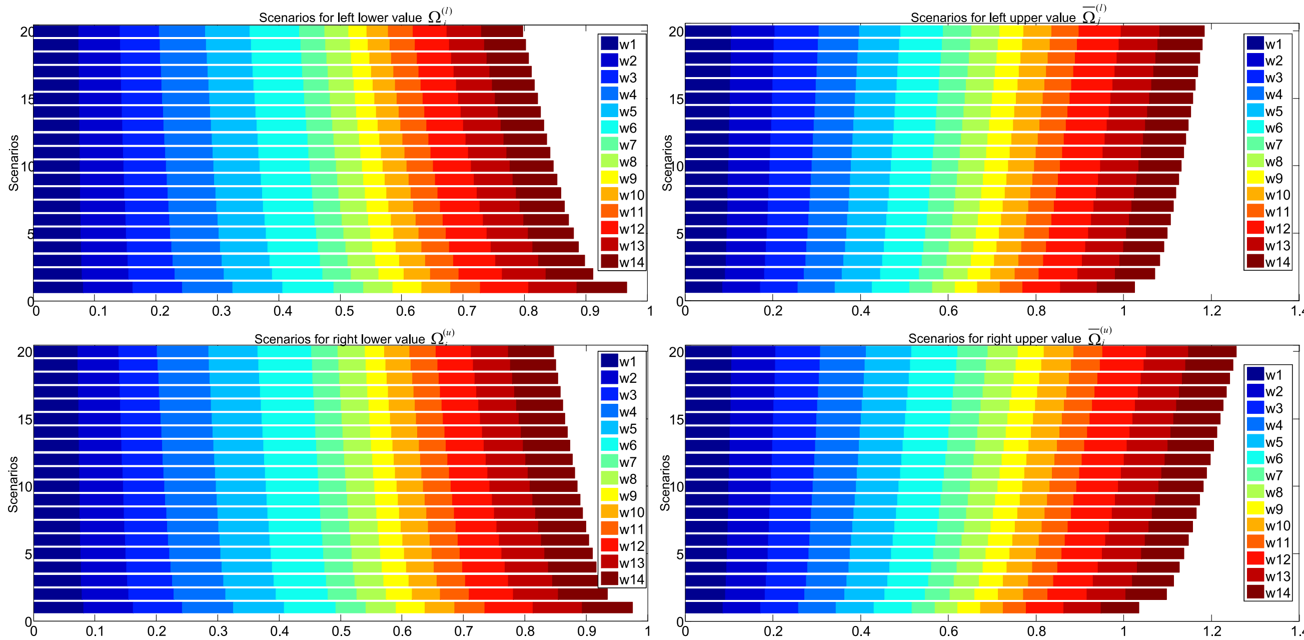

Fig. 7. Influence of ϑ_{AIP} on the change of rough boundary interval of weight coefficients.

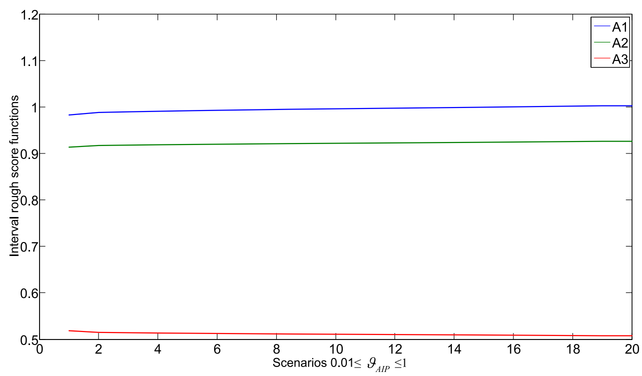

Fig. 8. The analysis of the influence of the parameter ϑ_{AIP}.

rational and objective reasoning while eliminating extreme and unreasonable arguments. On the other hand, the other considered models have linear weighted aggregation functions that depend linearly on the input parameters. In the event of the appearance of extreme and incomprehensible arguments in the initial matrix, models based on linear functions can lead to a violation of the information structure, which can result in making wrong decisions.

5. Results and discussion

A survey was generated after the alternatives and criteria were determined. The survey questionnaire was then completed by experts, and the advantages of the three alternatives were prioritized based on their responses. According to the results, it was seen that a labor-intensive system is the least advantageous, followed by a semi-autonomous with human personnel. Finally, fully autonomous systems are the best alternative among others.

At the point of decision-making, decision-makers should try to evaluate the harmfulness of the mining industry for both the environment and miners' health and security. With the help of autonomous devices, a greener and safer environment is possible.

Among the alternatives, a labor-intensive system is the least effective way to make the mining industry sustainable. Although people have to

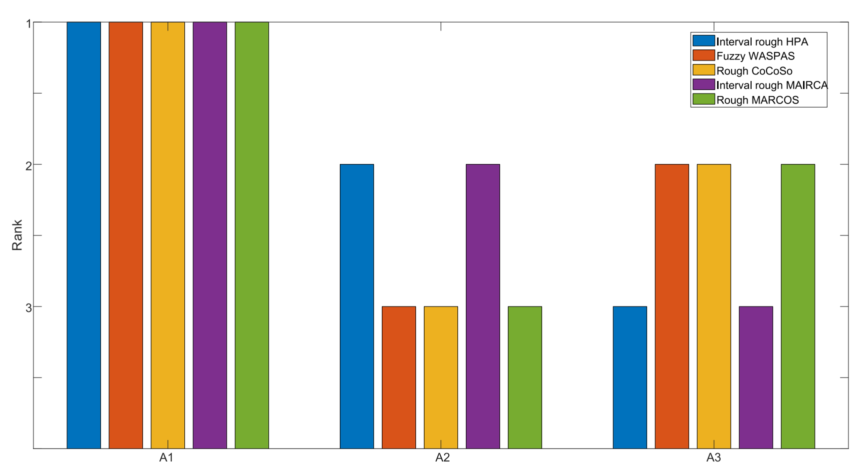

Fig. 9. Comparisons of multi-criteria models.

work there, it is not sustainable for the environment and their health conditions. With these work conditions, miners' health is under threat by heavy metals. The current system is not enough to create a safer and more sustainable environment.

Semi-autonomous with human personnel systems are seen to be the second most advantageous alternative. For the mining sector to implement automation integration, human factors concerns must be explored and understood, and approaches such as a shift management program must be put in place to examine the impact of automation on increased security and workplace conditions [30,32]. Mine conception is still insufficient. Especially when mine disasters occur on a regular basis, resulting in massive loss of ownership and lives. Well-being is a genuine concern of mine, which has gradually evolved into an involved concern of society. The coal issue failures are caused by the multifaceted quality of mine conditions and the variety of mine work states. Therefore, it is critical to screen mine workplace. Because of the regular development of abusing territories and profundity in the mining industry, it is critical to screen drowsy zones, where masses of concealed threats are ready (Sukmaningtyas, 2018). So, applying the semi-autonomous system in the mining industry can be helpful, but it is not enough to create a safe and sustainable environment.

Fully autonomous systems are the most advantageous way to ensure a safe and environmentally friendly environment. Since the 1980s, there has been a lot of focus on developing autonomous vehicles that can perform navigation tasks with minimal human intervention [79]. The mining industry intends to use self-driving trucks in underground mines to extract humans from dangerous environments, resulting in increased safety and efficiency [80]. Automation can boost the mining process. To minimize the effects of weather, the technology could allow infrastructure to work through shift changes. The strategy will be the most effective one for mining projects in remote locations [25].

6. Managerial and policy implications

Automation is increasingly being adopted by the mining industry as a safety and productivity enabler, as well as a critical factor in making future mining methods sustainable [81]. Implementing autonomous systems can be advantageous: it can reduce accidents, increase output efficiency, and reduce operating costs. Decision-makers must use supporting technology when implementing autonomous equipment. These must be identified and incorporated into the operational preparedness strategy and deployment process. The business case should take into account how technology evolves, including prospective new technologies and knowledge of the capabilities. The decision-makers must also understand the current state to determine whether the planned development, and the investment related to implementing autonomous systems follow their sustainability targets. Sometimes autonomous systems are not feasible, or a fully automated process is not feasible, in which case a hybrid approach is preferable. Hence, the current understanding and autonomous implementation competence of the operation, as well as the organization's current capacity and capability, may become critical factors.

7. Conclusions

There are a lot of things written and practiced about the societal importance of industrial minerals and metals [82,83]. It is an industry where social issues are significant, as well as stakeholder pressures [84]. Research should not be limited to the industrialized world, but should include considering the impact of mining on developing and underprivileged countries.

Environmental issues are acquiring traction around the globe and are playing a larger role in the design of innovation strategies. In reality, The Limits to Growth [85] theory predicts that the industrial system will collapse at some point if the exponential growth in demand is not balanced with the availability of resources. This projection has been the subject of significant examination since its publication, with the major argument relying on a lack of tolerance for technological advancement, and it is the same for mineral resources [86,87]. Sustainability has not been consistently comprehended by all organizational and personal stakeholders, which has frequently resulted in rushed actions and discrepant behaviors that fail to consider long-term effects [84,88–90]. A few of these indicators are based on skewed assessments of the ecological consequences of certain business activities, many of which are in the primary industry of production [87]. Sustainable development is impossible without wealth, and the latter will always depend on a strong economy that relies heavily on industrial jobs.

In addition to the above-mentioned advantage, the rough HPA methodology is an original inverse sorting algorithm for the normalization of cost criteria, which enables the preservation of the disposition of normalized values on the measurement scale. However, in addition to the advantages of the rough HPA methodology shown, there are some limitations. One of the limitations is the complex methodology for transforming the crisp elements of the home matrix into interval rough numbers. Also, one of the limitations is the mathematical complexity of the functions used to calculate weighted alternative strategies. This characteristic is especially pronounced in the case of increasing the number of criteria in the multi-criteria model. To overcome these limitations, it is necessary to implement the proposed methodology in a user-oriented decision support system. Also, further research should be directed towards improving the adaptability of the interval rough HPA methodology by implementing Dombi [91], Einstein [92], and Hamacher norms [93]. Furthermore, an exciting direction for future research is the implementation of neutrosophic [15] and grey sets [94] in the HPA multi-criteria framework.

There will undoubtedly be changes to industry methods as a result of the ongoing trend of industrialization evident in the last three decades. Adjusting societal consumption patterns will be needed [87]. Policy-makers and firms should take the necessary precautions to reduce environmental and health problems caused by the mining industry.

CRediT authorship contribution statement

Dragan Pamucar: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Formal analysis. **Muhammet Deveci:** Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Conceptualization. **Ilgin Gokasar:** Writing – review & editing, Writing – original draft, Visualization, Validation, Resources, Investigation, Data curation, Conceptualization. **Pablo R. Brito-Parada:** Writing – review & editing, Writing – original draft, Visualization, Validation, Conceptualization. **Luis Martínez:** Writing – review & editing, Writing – original draft, Validation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

Appendix A1

The following section presents the definitions of Heronian weight operators and Power averaging (PA) operators that are used to create a multi-criteria framework.

Definition A1. [74]: Let $\rho_1, \rho_2 \geq 0$ and let $(\partial_1, \partial_2, ..., \partial_n)$ represent a set of non-negative numbers, and Ω_j represent a set of weight coefficients, then the weight Heronian operator (WHM) can be defined using expression (A1).

$$WHM^{\rho_1,\rho_2} = \left(\frac{2}{n(n+1)} \sum_{x=1}^{n} \left(n\Omega_i \partial_i^{(x)} \right)^{\rho_1} \sum_{y=x}^{\chi} \left(n\Omega_j \partial_j^{(y)} \right)^{\rho_2} \right)^{\frac{1}{\rho_1+\rho_2}} \tag{A1}$$

Definition A2. [74]: Let $\rho_1, \rho_2 \geq 0$ and let $(\partial_1, \partial_2, ..., \partial_n)$ represent a set of non-negative numbers, and Ω_j represent a set of weight coefficients, then the weight geometric Heronian operator (WGHM) can be defined by an expression (A2).

$$WGHM^{\phi,\varphi} = \frac{1}{\rho_1 + \rho_2} \left(\prod_{\substack{x=1,\\ y=x}}^{\chi} \left(\rho_1 \partial_i^{(x)n\Omega_i} + \rho_2 \partial_j^{(y)n\Omega_j} \right)^{\frac{2}{n(n+1)}} \right) \tag{A2}$$

Definition A3. [21]: Let $(\partial_1, \partial_2, ..., \partial_n)$represent a set of non-negative numbers, then the PA operator can be defined using an expression (A3).

$$PA = \sum_{i=1}^{n} \partial_i \cdot \frac{\sum_{i=1}^{n} (1 + T(f(\partial_i)))f(\partial_i)}{\sum_{i=1}^{n} (1 + T(f(\partial_i)))} \tag{A3}$$

where $f(\partial_i) = \partial_i / \sum_{i=1}^{n} \partial_i$, while $T(f(\partial_i)) = \sum_{\substack{j=1\\ j\neq i}}^{\chi} Sup(f(\partial_i), f(\partial_j))$. With $Sup(f(\partial_i), f(\partial_j))$ we denote the degree of support that ∂_i receives from ∂_j.

Appendix 2

The following section presents the procedure for transforming estimation pairs from Table 1 at position A_2—C_1. Based on the data from Table 1 and pairs of estimates (3;3), (2;3), (4;4), and (2;2) we can distinguish two classes of objects $\partial_{21} = \{3, 2, 4, 2\}$ and $\partial'_{21} = \{3,3,4,2\}$. By applying Eqs. (1)-(5), we form rough sequences $\left[\underline{\partial}_{21}^{k(l)}, \overline{\partial}_{21}^{k(l)}\right]$ and $\left[\underline{\partial}_{21}^{k(u)}, \overline{\partial}_{21}^{k(u)}\right]$ defined object classes.

a) For the first class of objects $\partial_{21} = \{3, 2, 4, 2\}$, using Eqs. (1), (2), and (4), we define rough sequences $\left[\underline{\partial}_{21}^{k(l)}, \overline{\partial}_{21}^{k(l)}\right]$ as follows:

$$\underline{\partial}_{21}^{2(l)}(2) = \underline{\partial}_{21}^{4(l)}(2) = 2.00$$

$$\underline{\partial}_{21}^{1(l)}(3) = \frac{2+2+3}{1 + \left\{ \frac{1}{1+1} \frac{3(3-1)}{\left(\frac{1}{2.5}+\frac{1}{2.5}\right)^1 + \left(\frac{1}{2.5}+\frac{1}{1.33}\right)^1 + \left(\frac{1}{2.5}+\frac{1}{2.5}\right)^1 + ... + \left(\frac{1}{1.33}+\frac{1}{2.5}\right)^1 + \left(\frac{1}{1.33}+\frac{1}{2.5}\right)^1} \right\}^{1/1}} = 2.27$$

$$\underline{\partial}_{21}^{3(l)}(4) = \frac{3+2+4+2}{1 + \left\{ \frac{1}{1+1} \frac{4(4-1)}{\left(\frac{1}{4.5}+\frac{1}{4.5}\right)^1 + \left(\frac{1}{4.5}+\frac{1}{2.67}\right)^1 + \left(\frac{1}{4.5}+\frac{1}{1.75}\right)^1 + ... + \left(\frac{1}{1.75}+\frac{1}{4.50}\right)^1 + \left(\frac{1}{1.75}+\frac{1}{2.67}\right)^1} \right\}^{1/1}} = 2.62$$

$$\overline{\partial}_{21}^{2(l)}(2) = \overline{\partial}_{21}^{4(l)}(2) = \frac{3+2+4+2}{1 + \left\{ \frac{1}{1+1} \frac{4(4-1)}{\left(\frac{1}{4.5}+\frac{1}{4.5}\right)^1 + \left(\frac{1}{4.5}+\frac{1}{2.67}\right)^1 + \left(\frac{1}{4.5}+\frac{1}{1.75}\right)^1 + ... + \left(\frac{1}{1.75}+\frac{1}{4.50}\right)^1 + \left(\frac{1}{1.75}+\frac{1}{2.67}\right)^1} \right\}^{1/1}} = 2.62$$

$$\overline{\partial}_{21}^{1(l)}(3) = \frac{3+4}{1 + \left\{ \frac{1}{1+1} \frac{2(2-1)}{\left(\frac{1}{1.33}+\frac{1}{0.75}\right)^1 + \left(\frac{1}{0.75}+\frac{1}{1.33}\right)^1} \right\}^{1/1}} = 3.43$$

$$\overline{\partial}_{21}^{3(l)}(4) = 4.00.$$

b) For the first class of objects $\partial_{21}^{'} = \{3, 3, 4, 2\}$, using Eqs. (1), (3), and (5), we define rough sequences $\left[\underline{\partial}_{21}^{k(u)}, \overline{\partial}_{21}^{k(u)}\right]$ as follows:

$$\underline{\partial}_{21}^{4(u)}(2) = 2.00$$

$$\underline{\partial}_{21}^{1(u)}(3) = \underline{\partial}_{21}^{2(u)}(3) = \frac{2+3+3}{1+\left\{\frac{1}{1+1}\frac{3(3-1)}{\left(\frac{1}{3}+\frac{1}{1.67}\right)^{1}+\left(\frac{1}{3}+\frac{1}{1.67}\right)^{1}+\left(\frac{1}{1.67}+\frac{1}{3}\right)^{1}+\ldots+\left(\frac{1}{1.67}+\frac{1}{3}\right)^{1}+\left(\frac{1}{1.67}+\frac{1}{1.67}\right)^{1}}\right\}^{1/1}} = 2.62$$

$$\underline{\partial}_{21}^{3(u)}(4) = \frac{3+3+4+2}{1+\left\{\frac{1}{1+1}\frac{4(4-1)}{\left(\frac{1}{5}+\frac{1}{3}\right)^{1}+\left(\frac{1}{5}+\frac{1}{3}\right)^{1}+\left(\frac{1}{5}+\frac{1}{2}\right)^{1}+\ldots+\left(\frac{1}{2}+\frac{1}{3}\right)^{1}+\left(\frac{1}{2}+\frac{1}{3}\right)^{1}}\right\}^{1/1}} = 2.91$$

$$\overline{\partial}_{21}^{4(u)}(2) = \frac{3+3+4+2}{1+\left\{\frac{1}{1+1}\frac{4(4-1)}{\left(\frac{1}{5}+\frac{1}{3}\right)^{1}+\left(\frac{1}{5}+\frac{1}{3}\right)^{1}+\left(\frac{1}{5}+\frac{1}{2}\right)^{1}+\ldots+\left(\frac{1}{2}+\frac{1}{3}\right)^{1}+\left(\frac{1}{2}+\frac{1}{3}\right)^{1}}\right\}^{1/1}} = 2.91$$

$$\overline{\partial}_{21}^{1(u)}(3) = \overline{\partial}_{21}^{2(u)}(3) = \frac{3+3+4}{1+\left\{\frac{1}{1+1}\frac{3(3-1)}{\left(\frac{1}{2.33}+\frac{1}{2.33}\right)^{1}+\left(\frac{1}{2.33}+\frac{1}{1.5}\right)^{1}+\left(\frac{1}{2.33}+\frac{1}{2.33}\right)^{1}+\ldots+\left(\frac{1}{1.5}+\frac{1}{2.33}\right)^{1}+\left(\frac{1}{1.5}+\frac{1}{2.33}\right)^{1}}\right\}^{1/1}} = 3.29$$

$$\overline{\partial}_{21}^{3(u)}(4) = 4.00.$$

Based on the obtained rough sequences, we can create interval rough numbers as follows:

$\overset{\frown}{\partial}{}_{21}^{1} = ([2.27, 3.43], [2.62, 3.29]);$
$\overset{\frown}{\partial}{}_{21}^{2} = ([2.00, 2.62], [2.62, 3.29]);$
$\overset{\frown}{\partial}{}_{21}^{3} = ([2.62, 4.00], [2.91, 4.00]);$
$\overset{\frown}{\partial}{}_{21}^{4} = ([2.00, 2.62], [2.00, 2.91]).$

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