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Multi-Criteria Personnel Evaluation and Selection Using an Objective Pairwise Adjusted Ratio Analysis (OPARA)

Abstract. *In Human Resource Management (HRM), personnel evaluation and selection is essential because they create the groundwork for developing a skilled and productive staff. Organisations can find people that have the requisite knowledge, abilities, and attitudes to support the aims and objectives of the business by using efficient evaluation and selection procedures. Organisations can evaluate and select individuals for different positions with greater knowledge by applying Multi-Criteria Decision-Making (MCDM) approaches. This ensures a more thorough and comprehensive evaluation process, leading to better selection outcomes. In this study, an Objective Pairwise Adjusted Ratio Analysis (OPARA) is introduced as an approach for multi-criteria personnel evaluation and selection. Unlike traditional decision-making methods, OPARA avoids information loss by not using any normalisation techniques. The method focuses on preserving the original data characteristics to ensure a comprehensive evaluation of each alternative by employing pairwise adjusted ratios. Two adjusting parameters are used in OPARA: the first adjusts the ratios based on the range of each criterion, reducing the impact of high-range criteria, while the second parameter accounts for the linearity of the criterion, mitigating the negative effect of non-linear data. The method is exemplified through an initial illustration, followed by a comparative analysis, an efficiency assessment using simulated data, and a practical example in personnel evaluation and selection, which is examined for credibility through analytical scrutiny. The results show that the proposed method provides reliable results, has stability in presenting results, and is applicable and efficient in dealing with MCDM problems, including the personnel evaluation and selection.*

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1. Introduction

One of the crucial components in human resource management (HRM), essential for the success of an organisation and the achievement of its goals, is personnel selection. Identifying and recruiting the right individuals, enhancing the skills of current personnel, and assembling a proficient team are among the fundamental challenges confronting expanding businesses (Cole, 2004; Robertson and Cooper, 2015; Rothstein and Goffin, 2006). This process plays a significant role in determining the level of quality and efficiency of employees through the accurate recognition of people according to the desired job. Performance evaluation allows managers to optimally use individual talents and abilities and improve employee performance through continuous feedback. The correct selection of people according to the needs and goals of the organisation can increase the productivity and quality of the team's performance (Kerfoot and Knights, 1992; Lundy, 1994).

The evaluation process offers employees an opportunity to enhance job satisfaction by self-assessing and gaining a better understanding of their professional development path. This is directly correlated with increased commitment and participation in organisational goals. (Gunderson, 2001; Hendry and Pettigrew, 1986). Accurately assessing employees' skills and characteristics ensures their proper alignment with desired job requirements, reducing the likelihood of recruitment errors and minimising associated costs. This process plays a vital role in creating a successful work environment. Aligning employee selection with individual and organisational compatibility fosters positive interactions within the organisation (Ferris and Judge, 1991; Oehlhorn et al., 2020). Providing constructive feedback and identifying each employee's strengths and weaknesses allow the organisation to implement tailored training programs, ultimately improving performance quality. Furthermore, this process serves as a key tool in ensuring organisational diversity by considering individual differences, such as experiences, expertise, gender, and culture (Salas-Vallina et al., 2021; Sharma and Publications, 2023).

The evaluation process functions as an effective tool to promote organisational interactions. In addressing the intricate challenges of contemporary human resources, employee evaluation and selection empowers the organisation to dynamically respond to market needs. This process facilitates strategic human resources planning, paving the way for sustainable development (Bril et al., 2021; Lepak et al., 2006; Storey, 1996). The most effective personnel selection directly affects the organisation's performance and production. Using multi-criteria decision-making (MCDM) techniques in this situation is crucial to enhancing the hiring and appraisal process (Gürbüz and Albayrak, 2014; Kosareva et al., 2016).

Using MCDM methods throughout the hiring and evaluation process can be a very effective way to handle the intricate and occasionally unclear decision-making process in this area. (Alguliyev et al., 2015; Bali et al., 2015). In this regard, these methods help managers to select and promote employees more accurately and intelligently. In addition, MCDM as an analytical and systematic method allows for greater productivity of available information due to the complexity of variables and various connections in the evaluation and analysis process (Keshavarz-Ghorabaee, 2023; Keshavarz-Ghorabaee et al., 2022). The evolution of technology has precipitated a continuous improvement in the knowledge and skills of individuals using computers and automation in both the professional and private spheres. This advancement intertwines with the significance of adeptly evaluating and selecting employees using MCDM methods. Such an integration of sophisticated technology and human resource strategies bolsters management practices, thereby enhancing not just organisational performance and productivity, but also improving the work-life quality for employees. This fusion of technological proficiency and strategic employee assessment forms a symbiotic relationship that perpetuates growth and efficiency within modern workplaces. (Filip, 2021; Liang and Wang, 1994; Urosevic et al., 2017).

In this study, an approach called Objective Pairwise Adjusted Ratio Analysis (OPARA) is proposed for multi-criteria personnel evaluation and selection. To avoid potential information loss, the proposed method, unlike most conventional decision-making methods, does not use any normalisation approach. The procedure of the proposed method is designed to circumvent the loss of decision-making information by preserving original data characteristics. Instead of normalisation, the method employs pairwise adjusted ratios, ensuring that the evaluation of each alternative considers the entire decision dataset, not just data specific to that alternative. In the process of OPARA, the pairwise adjusted ratios play a pivotal role in determining the dominance or importance of each alternative in relation to others. These ratios are based on objective data, disregarding subjective judgments or opinions of decision-makers. A notable advantage of OPARA lies in the use of adjusting parameters to determine these ratios, with two parameters at play. The first parameter adjusts the pairwise ratios based on the range of each criterion. This parameter should be defined according to the data related to each criterion, and it helps us to reduce the effect of high-range criteria on determination of pairwise ratios. Another parameter allows the decision-maker to adjust pairwise ratios based on the level of linearity of the criterion. This parameter helps to avoid the negative effect of non-linear data on the evaluation process. These two parameters ensure that the method remains unbiased and equitable. To elucidate the proposed method, an initial illustration is employed, and the steps of its application are explained using a simple example. Subsequently, a comparative analysis between the results of the proposed method and those of some other decision-making approaches is presented based on a numerical example. Furthermore, an analytical assessment of the efficiency of the proposed method is conducted using simulated data. Finally, the application of the proposed method in employee selection is demonstrated through a practical example, and the credibility of its results is scrutinised through analytical examination.

The structure of this paper is as follows: Section 2 delves into recent applications of MCDM techniques in the context of personnel evaluation and selection. The explanation of the methodology, accompanied by an illustrative example, is described in Section 3. Section 4 is dedicated to presenting findings and analyses, including both a numerical example for comparative analysis and a simulation study, as well as an exposition on integrating the OPARA framework into personnel evaluation processes. Section 5 draws the paper to a close with concluding remarks.

2. Literature review

In recent years, the application of MCDM approaches in personnel evaluation and selection has garnered increasing attention in the organisational and human resources management literature. The use of MCDM methods offers a systematic and structured way to consider multiple criteria and attributes when making decisions about personnel, thereby enabling a more comprehensive and informed evaluation of candidates. In this section, we explore some recent studies in this field that utilised various MCDM approaches in personnel evaluation and selection processes.

Sutrisno et al. (2019) examined a company to evaluate potential hires by combining Simple Additive Weighting (SAW) computation method with the fuzzy MCDM approach. The optimal option was chosen using the MCDM approach based on various factors. The weighted sums of performance ratings for each choice on all qualities were found using the SAW method based on each department's requirements. Nabeeh et al. (2019) suggested an approach for people selection that combines Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) and neutrosophic Analytic Hierarchy Process (AHP). They offered a detailed procedure for putting the concept into practice, which included tabulating weights for criteria, turning neutrosophic scales into crisp values, collecting the viewpoints of decision makers, ensuring consistency, and using TOPSIS to rank options. The approach was then used in a real-world case study in Cairo, Egypt, where a manager was needed for a customer service department. Yalçın and Yapıcı Pehlivan (2019) presented a fuzzy Combinative Distance-based Assessment (CODAS) technique based on fuzzy envelopes and hesitant fuzzy linguistic term sets (HFLTSs) for solving people selection challenges. The options were then ranked using the fuzzy CODAS algorithm. Six employees were ranked in a case study, and the stability of the results was confirmed by a sensitivity analysis.

Demirci and Kiliç (2019) developed an integrated methodology for personnel selection using Decision Making Trial and Evaluation Laboratory (DEMATEL), Analytic Network Process (ANP), and Elimination and Choice Translating Reality (ELECTRE) techniques to identify network relationships between selection criteria, determine importance weights, and rank candidates. The approach was applied to an automotive company, contributing a new methodological approach to the literature. Ijadi Maghsoodi et al. (2020) also introduced a hybrid approach called the parallel weighted CLUSter analysis for Multiple Criteria Decision Analysis (W-CLUS-MCDA) to handle multiple big data structured problems simultaneously, using k-means clustering, MULTIMOORA (Multi-Objective Optimisation by Ration Analysis in Full Multiplicative Form) method, and Best-Worst Method (BWM). It was applied to a case study of personnel selection in a large multi-national organisation. Chuang et al. (2020) studied a data-driven MCDM model using rough set theory, DEMATEL-based ANP, and Preference Ranking Organisation Method for Enrichment Evaluation (PROMETHEE) method to solve personnel selection and improvement problems for a Chinese food company, providing management implications.

Ulutaş et al. (2020) proposed a hybrid MCDM model that combined Grey Pivot Pairwise Relative Criteria Importance Assessment (PIPRECIA-G) and Grey Operational Competitiveness Rating (OCRA-G) methods to rank personnel candidates in uncertain environments. A case study demonstrated applying the methods to select a production manager for a textile factory. Krishankumar et al. (2020) introduced the fuzzy intuitionistic fuzzy VIKOR ("VIseKriterijumska Optimizacija I Kompromisno Resenje" in Serbian) method to handle intuitionistic fuzzy (IF) values in multi-criteria personnel selection problems. Their method effectively retained intuitionistic fuzzy information throughout the decision-making process and was validated through a personnel selection problem. Additionally, Sumarno et al. (2021) used MCDM and system dynamics approaches to evaluate the performance of personnel in the Indonesian Ministry of Defense, weighting criteria using AHP and conducting a survey to score the criteria. Their simulation results showed an increase in performance over two years and identified the top five influential sub-criteria.

Popović et al. (2021) and Popović (2021) explored the use of MCDM methods in personnel selection. Popović et al. (2021) used the Stepwise Weight Assessment Ratio Analysis (SWARA) method to determine weights based on the views of 31 respondents, finding it reliable due to its simplicity. Popović (2021) proposed using SWARA to determine criteria weights and rank alternatives using the Combined Compromise Solution (CoCoSo) method, which integrates simple additive weighting and exponential weighted product approaches. Ersoy (2021) studied the use of entropy-based Evaluation Based on Distance from Average Solution (EDAS) and CODAS methods for personnel selection in the software industry, with the aim of selecting the most suitable software personnel for a company. The study provided an application case where these methods were used to select the best candidate.

Li et al. (2022) developed a three-stage framework that combines data analytics algorithms and multi-criteria decision-making methods, utilising both human resource data and expert judgment. They implemented a personnel evaluation system called personnel evaluation and selection (PLEAS) to demonstrate the framework through a real-world case study. Additionally, Nguyen (2022) proposed a novel two-phase approach using a hybrid Genetic Algorithm and Grey Decision-Making Trial and Evaluation Laboratory (GA-GDEMATEL) to determine the best candidates based on subjective weights of recruitment criteria. A genetic algorithm with a new objective function of Minimising Distance to Ideal Solution (MDIS) was used to find the optimal solution and select the best candidates based on the GDEMATEL weights.

Asan and Soyer (2022) presented an approach to assess and select candidates for job positions using asynchronous video interviews (AVIs) and a two-stage method that uses artificial intelligence techniques like machine learning to analyse candidates' video responses and predict their suitability, as well as an extended cumulative belief degree (CBD) approach to effectively combine the AVI scores obtained under multiple criteria. Their approach was designed to make the selection process fully data-driven, objective, and able to handle a large number of candidates. Kalem and Akpinar (2022) developed an entropy-based Multi-Attributive Border Approximation area Comparison (MABAC) methodology for personnel performance evaluation in the food sector. Five candidates were evaluated based on criteria such as initiative, cooperation, imagination, responsibility, and self-confidence. The entropy method was used to determine the criteria weights, and the MABAC method was employed to rank the alternatives.

Khalil et al. (2023) used a fuzzy TOPSIS approach to evaluate medical staff in a healthcare system according to criteria such as skills, experience, and ability to respond to problems. Experts' vague judgments were represented using fuzzy triangular numbers. Additionally, Kiratsoudis and Tsiantos (2024) discussed an analytical decision-making model called ES-MADM (Entropy-based Stakeholder Model Considering Mixed-Attributes of Decision Making) for personnel selection problems, which provided insights into candidate rankings, criteria importance, and decision stability. Yenilmezel and Ertuğrul (2023) focused on the selection of blue-collar personnel for a manufacturing company, identifying six criteria through consultation with decision makers. They used the fuzzy PIPRECIA method to determine criteria weights and the fuzzy Complex Proportional Assessment (COPRAS) method to evaluate and determine the best alternative. The study found professional competence to be the most important criterion.

The abovementioned studies demonstrated application of different MCDM methods in personnel evaluation and selection process. Moreover, these studies aimed to provide valid and job-related selection tools and procedures, and their methodologies were illustrated with numerical examples.

3. Methodology

In this section, the OPARA is proposed for dealing with general MCDM problems. Then an illustrative example is presented to show the procedure of using OPARA.

3.1 OPARA

In this study, we introduce the OPARA, a novel multi-criteria decision-making method, designed as an effective approach for addressing the complex issues of personnel evaluation and selection. The proposed method has its advantages and disadvantages compared to other MCDM approaches, which will be explained to the extent possible below. The methodology proposed in this study does not incorporate the application of normalisation procedures. The use of normalisation methods may lead to information loss. This loss of information can result from the necessary trade-offs between preserving the original data characteristics and achieving a suitable standard scale for analysis. The procedure of the proposed method prevents the loss of decision-making information based on pairwise adjusted ratios. These ratios are obtained according to the objective decision-making data, and we do not need subjective judgments and opinions of decision-makers. The pairwise adjusted ratios are used to involve the data related to all alternatives in the evaluation process. This ensures that the final evaluation of each alternative is based on the entire decision data, not solely on the data specific to that alternative. The pairwise adjusted ratios determine the degree of dominance or importance of each alternative over the other alternatives. Another advantage of the proposed method is the use of adjusting parameters to determine the pairwise adjusted ratios. Two adjusting parameters are employed in this method. The first parameter adjusts the effect related to the range of each criterion, such that the greater the range of a criterion, the more it is adjusted in the pairwise ratios. Another parameter is related to the linearity of a criterion. This parameter is set by the decision-maker and adjusts the impact of non-linear criteria in the calculation of the ratios. One of the disadvantages of the proposed method is the higher computational complexity compared to some of the conventional multi-criteria decision-making approaches. However, this disadvantage is somewhat mitigated by the use of computers in performing decision-making calculations.

Each decision-making method involves steps that ultimately result in the final evaluation of alternatives with respect to several criteria. The proposed method in this study includes the following steps.

Step 1. Determine the decision criteria and their respective weights or importance. Then specify different options for evaluation and construct the decision matrix. It should be noted that all elements of the decision matrix here must be positive. In the absence of this condition, a technique such as the one proposed by Keshavarz-Ghorabaee (2022) should be used to ensure the positivity of the elements of this matrix. Assume that m criteria and n alternatives have been defined at this stage. Then, w_j represents the weight of criterion j, and the decision matrix is defined as follows.

$$X = \begin{bmatrix} x_{11} & \cdots & x_{m1} \\ \vdots & \ddots & \vdots \\ x_{n1} & \cdots & x_{nm} \end{bmatrix} = \left[x_{ij}\right]_{n\times m} \tag{1}$$

Step 2. Obtain the range-based pairwise adjusted ratio (RPAR) of kth alternative to lth alternative. Utilise the following equation to calculate these ratios. In the following equation, BC represents the set of benefit criteria, and NC represents the set of cost criteria.

$$RPAR_{kl} = \sum_{j \in BC} w_j \left(\frac{x_{kj}}{x_{lj}} \right)^{\rho_j} + \sum_{j \in NC} w_j \left(\frac{x_{lj}}{x_{kj}} \right)^{\rho_j} \quad , \quad k, l \in \{1,2,\dots,n\} \tag{2}$$

ρ_j is the adjustment parameter in RPAR, determined using an adjustment function based on the corresponding performance range for each criterion (the minimum and maximum values associated with each criterion). The adjustment function used in this study is defined by the following equation.

$$\rho_j = \begin{cases} \dfrac{(\alpha - 1) \max\limits_i x_{ij} + \min\limits_i x_{ij}}{\alpha \max\limits_i x_{ij}} & if \quad \dfrac{\max\limits_i x_{ij} - \min\limits_i x_{ij}}{\max\limits_i x_{ij} + \min\limits_i x_{ij}} > \beta \\ 1 & otherwise \end{cases} \tag{3}$$

The above-defined function has two parameters, α and β, which are set by the decision-maker (expert) based on the information related to the criterion. In this study, the values of α and β are suggested to be 5 and 0.8, respectively. This function helps prevent the intensification of the relative effect of a criterion in the evaluation process when the difference between the minimum and maximum performance of a criterion is substantial. It is evident that if minimum performance equals maximum performance, then ρ_j will be 1; consequently, ρ_j always falls within the interval $(\frac{\alpha-1}{\alpha}, 1]$ according to Eq. (3).

To understand the RPAR ratio, consider a decision-making process in which the performance of one criterion falls within the range [1, 10], while another criterion lies within the range [1, 100]. Given these ranges, the second criterion can potentially have a more significant impact on evaluations. This phenomenon can manifest itself even in methods that utilise various normalisation approaches. The use of an adjustment function in such cases can be beneficial.

Step 3. Calculate the linearity-based pairwise adjusted ratio (LPAR) of kth alternative to lth alternative. These ratios are similar to the previous ones (RPAR), but their adjustment is based on the linearity of the criteria's performance. The following equation is used for the calculations.

$$LPAR_{kl} = \sum_{j \in BC} w_j \left(\frac{x_{kj}}{x_{lj}} \right)^{\tau_j} + \sum_{j \in NC} w_j \left(\frac{x_{lj}}{x_{kj}} \right)^{\tau_j} \quad , \quad k, l \in \{1,2,\dots,n\} \tag{4}$$

The parameter "τ_j" in these ratios is set by the decision-maker. It is clear that when a criterion has a linear nature, τ_j will be equal to 1. When seeking to intensify LPAR, we consider values greater than 1 for τ_j, and when aiming to abate LPAR, we consider values less than 1 for it. These ratios can assist the decision-maker in adjusting the non-linear effects of criteria for evaluations. For example, this adjustment can be beneficial when the performance related to a criterion is measured on a logarithmic scale.

It should be noted that if $k = l$, then both $RPAR_{kl}$ and $LPAR_{kl}$ will be equal to 1.

Step 4. Obtain the aggregated pairwise adjusted ratios ($APAR_{kl}$) using the following equation.

$$APAR_{kl} = \omega RPAR_{kl} + (1-\omega)LPAR_{kl} \tag{5}$$

In Eq. (5), ω represents the aggregation parameter and it lies within the interval [0,1].

Step 5. Calculate the final score of each alternative. The following equation is used in this step. The alternative with a higher score will be ranked higher.

$$S_i = \frac{1}{n}\left(\sum_{l=1}^{n}\left(\frac{APAR_{il}}{\sum_{k=1}^{n} APAR_{kl}}\right)\right) \tag{6}$$

3.2 Illustrative example

In this section, an example is provided to clarify the usage of the proposed method. In this example, three alternatives and three criteria are considered, and the decision matrix, weight, and type of evaluation criteria are defined in Table 1.

Suppose that the decision-maker set the parameters as follows: α=5, β=0.8, τ_1=0.9, τ_2=1 and τ_3=1.1. According to Eq. (3), the values of ρ_j are calculated. The only criterion that satisfies the threshold condition is C_3, so $\rho_1 = 1$, $\rho_2 = 1$ and $\rho_3 = ((4 \times 10) + 1)/(5 \times 10) = 0.82$.

Table 1. The data of the illustrative example

		Criteria	
Alternatives	C_1/Benefit/w_1=0.3	C_2/Cost/w_2=0.4	C_3/Benefit/w_3=0.3
A_1	10	120	1
A_2	50	80	10
A_3	30	100	7

Source: authors' own contribution.

Now we can calculate the values of $RPAR_{kl}$ and $LPAR_{kl}$ as shown as follows.

$$RPAR_{12} = 0.3\left(\frac{10}{50}\right)^1 + 0.4\left(\frac{80}{120}\right)^1 + 0.3\left(\frac{1}{10}\right)^{0.8} = 0.372$$

$$RPAR_{13} = 0.3\left(\frac{10}{30}\right)^1 + 0.4\left(\frac{100}{120}\right)^1 + 0.3\left(\frac{1}{7}\right)^{0.8} = 0.494$$

$$RPAR_{21} = 0.3\left(\frac{50}{10}\right)^1 + 0.4\left(\frac{120}{80}\right)^1 + 0.3\left(\frac{10}{1}\right)^{0.8} = 4.082$$

$$RPAR_{23} = 0.3\left(\frac{50}{30}\right)^1 + 0.4\left(\frac{100}{80}\right)^1 + 0.3\left(\frac{10}{7}\right)^{0.8} = 1.402$$

$$RPAR_{31} = 0.3\left(\frac{30}{10}\right)^1 + 0.4\left(\frac{120}{100}\right)^1 + 0.3\left(\frac{7}{1}\right)^{0.8} = 2.859$$

$$RPAR_{32} = 0.3\left(\frac{30}{50}\right)^{1} + 0.4\left(\frac{80}{100}\right)^{1} + 0.3\left(\frac{7}{10}\right)^{0.8} = 0.724$$
$$LPAR_{12} = 0.3\left(\frac{10}{50}\right)^{0.9} + 0.4\left(\frac{80}{120}\right)^{1} + 0.3\left(\frac{1}{10}\right)^{1.1} = 0.361$$
$$LPAR_{13} = 0.3\left(\frac{10}{30}\right)^{0.9} + 0.4\left(\frac{100}{120}\right)^{1} + 0.3\left(\frac{1}{7}\right)^{1.1} = 0.480$$
$$LPAR_{21} = 0.3\left(\frac{50}{10}\right)^{0.9} + 0.4\left(\frac{120}{80}\right)^{1} + 0.3\left(\frac{10}{1}\right)^{1.1} = 5.654$$
$$LPAR_{23} = 0.3\left(\frac{50}{30}\right)^{0.9} + 0.4\left(\frac{100}{80}\right)^{1} + 0.3\left(\frac{10}{7}\right)^{1.1} = 1.419$$
$$LPAR_{31} = 0.3\left(\frac{30}{10}\right)^{0.9} + 0.4\left(\frac{120}{100}\right)^{1} + 0.3\left(\frac{7}{1}\right)^{1.1} = 3.837$$
$$LPAR_{32} = 0.3\left(\frac{30}{50}\right)^{0.9} + 0.4\left(\frac{80}{100}\right)^{1} + 0.3\left(\frac{7}{10}\right)^{1.1} = 0.712$$

We can show these values as the following matrices.

$$RPAR = \begin{bmatrix} 1 & 0.372 & 0.494 \\ 4.082 & 1 & 1.402 \\ 2.859 & 0.724 & 1 \end{bmatrix}$$
$$LPAR = \begin{bmatrix} 1 & 0.361 & 0.480 \\ 5.654 & 1 & 1.419 \\ 3.837 & 0.712 & 1 \end{bmatrix}$$

Accordingly the values of $APAR_{kl}$ can be calculated as shown as the following matrix ($\omega = 0.5$).

$$APAR = \begin{bmatrix} 1 & 0.367 & 0.487 \\ 4.868 & 1 & 1.411 \\ 3.348 & 0.718 & 1 \end{bmatrix}$$

Then we can calculate the final scores as follows.

$$S_1 = \frac{1}{3}\left(\frac{1}{1+4.868+3.348} + \frac{0.367}{0.367+1+0.718} + \frac{0.487}{0.487+1.411+1}\right) = 0.151$$
$$S_2 = \frac{1}{3}\left(\frac{4.868}{1+4.868+3.348} + \frac{1}{0.367+1+0.718} + \frac{1.411}{0.487+1.411+1}\right) = 0.498$$
$$S_3 = \frac{1}{3}\left(\frac{3.348}{1+4.868+3.348} + \frac{0.718}{0.367+1+0.718} + \frac{1}{0.487+1.411+1}\right) = 0.351$$

Therefore, the final ranking is $A_2 \succ A_3 \succ A_1$.

4. Results and analyses

In this section, the aim is to conduct analyses on the results of OPARA and evaluate its performance to handle MCDM problems in comparison to other methods. Following that, we will demonstrate its application in a practical problem.

4.1 Comparative analysis

This subsection illustrates the proposed method's performance with an example, comparing it to the outcomes from other methods. Subsequently, an analysis based on simulated data is presented to further examine the results of the proposed approach.

4.1.1 Numerical example

In this subsection, an MCDM example adapted from the study by Keshavarz Ghorabaee et al. (2015) is used to compare the results of OPARA with the outcomes of six other decision-making methods, including SAW, Weighted Aggregated Sum Product Assessment (WASPAS), COPRAS, TOPSIS, VIKOR, and EDAS. The selected methods for comparison are practical and widely used in numerous practical research studies in various scientific and engineering fields. The data for the problem is presented in the Table 2.

In order to address the problem, seven sets of criteria weights have been employed for the criteria, as outlined in the Table 3, and the decision parameters for OPARA are assumed as follows: α=5, β=0.8, τ_j=1 and ω=0.5. The results obtained from various methods under different weight sets are presented in Table 4. In order to facilitate a comparison of the results, the Spearman's correlation coefficient (r_s) has been utilised, and its corresponding values are also provided in Table 4.

As evident in Table 4, all the Spearman's correlation coefficients are greater than 0.8. This indicates a strong correlation between the results obtained from the OPARA method and those of other decision-making methods (Keshavarz Ghorabaee et al., 2016). Additionally, we observe a relative stability in the rankings obtained from OPARA under different weight sets. Therefore, it can be said that, upon preliminary examination, this method exhibits a promising performance and efficiency compared to others. For a more detailed examination of this matter, simulation data will be utilised in the following subsection to assess performance.

Table 2. The data of the numerical example

	Type of criterion						
	Benefit	Benefit	Benefit	Cost	Cost	Cost	Cost
Alternatives	C_1	C_2	C_3	C_4	C_5	C_6	C_7
$\boldsymbol{A_1}$	23	264	2.37	0.05	167	8900	8.71
$\boldsymbol{A_2}$	20	220	2.2	0.04	171	9100	8.23
$\boldsymbol{A_3}$	17	231	1.98	0.15	192	10800	9.91
$\boldsymbol{A_4}$	12	210	1.73	0.2	195	12300	10.21
$\boldsymbol{A_5}$	15	243	2	0.14	187	12600	9.34
$\boldsymbol{A_6}$	14	222	1.89	0.13	180	13200	9.22
$\boldsymbol{A_7}$	21	262	2.43	0.06	160	10300	8.93

	Type of criterion						
	Benefit	Benefit	Benefit	Cost	Cost	Cost	Cost
A_8	20	256	2.6	0.07	163	11400	8.44
A_9	19	266	2.1	0.06	157	11200	9.04
A_{10}	8	218	1.94	0.11	190	13400	10.11

Source: Data presented in Keshavarz Ghorabaee et al. (2015).

Table 3. Different sets of criteria weights for the numerical example

	C_1	C_2	C_3	C_4	C_5	C_6	C_7
Set 1	0.25	0.214	0.179	0.143	0.107	0.071	0.036
Set 2	0.182	0.212	0.182	0.152	0.121	0.091	0.061
Set 3	0.139	0.167	0.194	0.167	0.139	0.111	0.083
Set 4	0.108	0.135	0.162	0.189	0.162	0.135	0.108
Set 5	0.083	0.111	0.139	0.167	0.194	0.167	0.139
Set 6	0.061	0.091	0.121	0.152	0.182	0.212	0.182
Set 7	0.036	0.071	0.107	0.143	0.179	0.214	0.25

Source: Data presented in Keshavarz Ghorabaee et al. (2015).

Table 4. The results of the numerical example

Sets	Method	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8	A_9	A_{10}	r_s
Set 1	OPARA	1	2	6	10	7	8	3	4	5	9	—
	SAW	1	3	6	9	7	8	2	4	5	10	0.98
	WASPAS	1	3	6	10	7	8	2	4	5	9	0.99
	COPRAS	1	3	6	10	7	8	2	4	5	9	0.99
	TOPSIS	1	4	6	10	7	8	2	3	5	9	0.96
	VIKOR	2	5	7	9	6	8	1	3	4	10	0.88
	EDAS	1	4	6	10	7	8	2	3	5	9	0.96
Set 2	OPARA	1	2	6	10	7	8	3	4	5	9	—
	SAW	1	2	6	10	7	8	3	4	5	9	1
	WASPAS	1	2	6	10	7	8	3	4	5	9	1
	COPRAS	1	3	6	10	7	8	2	4	5	9	0.99
	TOPSIS	1	4	6	10	7	8	2	3	5	9	0.96
	VIKOR	2	5	7	10	6	8	1	3	4	9	0.89
	EDAS	1	4	6	10	7	8	2	3	5	9	0.96
Set 3	OPARA	2	1	6	10	7	8	3	4	5	9	—
	SAW	1	2	6	10	7	8	3	4	5	9	0.99
	WASPAS	1	2	6	10	7	8	3	4	5	9	0.99
	COPRAS	1	2	6	10	7	8	3	4	5	9	0.99
	TOPSIS	1	3	9	10	8	7	2	4	5	6	0.84
	VIKOR	2	5	7	10	6	8	1	3	4	9	0.85

Sets	Method	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8	A_9	A_{10}	r_s
	EDAS	1	3	7	10	6	8	2	4	5	9	0.95
Set 4	OPARA	2	1	6	10	7	8	3	5	4	9	—
	SAW	1	2	6	10	7	8	3	4	5	9	0.98
	WASPAS	1	2	6	10	7	8	3	4	5	9	0.98
	COPRAS	1	2	7	10	6	8	3	4	5	9	0.96
	TOPSIS	1	2	9	10	8	7	3	5	4	6	0.87
	VIKOR	1	5	8	10	6	7	2	3	4	9	0.83
	EDAS	1	2	7	10	6	8	3	4	5	9	0.96
Set 5	OPARA	2	1	6	10	7	8	3	5	4	9	—
	SAW	1	2	6	10	7	8	3	4	5	9	0.98
	WASPAS	1	2	6	10	7	8	3	4	5	9	0.98
	COPRAS	1	2	7	10	6	8	3	4	5	9	0.96
	TOPSIS	1	2	9	10	8	7	3	5	4	6	0.87
	VIKOR	1	5	8	10	6	7	2	3	4	9	0.83
	EDAS	1	2	6	10	7	8	3	4	5	9	0.98
Set 6	OPARA	2	1	6	10	7	8	3	5	4	9	—
	SAW	2	1	6	10	7	8	3	4	5	9	0.99
	WASPAS	2	1	6	10	7	8	3	4	5	9	0.99
	COPRAS	1	2	6	10	7	8	3	4	5	9	0.98
	TOPSIS	1	2	9	10	8	7	3	5	4	6	0.87
	VIKOR	1	3	6	9	7	8	2	4	5	10	0.94
	EDAS	1	2	6	10	7	8	3	4	5	9	0.98
Set 7	OPARA	2	1	6	10	7	8	3	5	4	9	—
	SAW	2	1	6	10	7	8	3	4	5	9	0.99
	WASPAS	2	1	6	10	7	8	3	4	5	9	0.99
	COPRAS	2	1	7	10	6	8	3	4	5	9	0.98
	TOPSIS	1	2	9	10	8	7	3	5	4	6	0.87
	VIKOR	1	2	8	10	6	7	3	4	5	9	0.94
	EDAS	1	2	6	10	7	8	3	4	5	9	0.98

Source: authors' own calculations.

4.1.2 Simulation-based analysis

In the previous section, we demonstrated the relative performance of the proposed method using an example and comparing the outcomes of OPARA with other MCDM methods. Here, for a more detailed investigation, we generate a substantial number of MCDM problems using a simulation-based approach. Detailed data are available in Keshavarz-Ghorabaee (2024), under the title "Simulation Data".

By solving these problems with OPARA and the six other methods mentioned in the previous section, we conduct a comparative analysis of their results to assess the efficiency of the proposed method.

For this purpose, we generated nine datasets. The range of values used in each dataset, along with the number of alternatives and criteria in each, are outlined in the Table 5. Through simulation, we generated 500 decision matrices for each dataset.

The weights and criterion types (benefit and cost) in each generated matrix were randomly determined. In total, 4500 decision matrices are employed to evaluate the performance of the proposed method in this section. It is worth noting that the decision parameters for OPARA remain consistent with the previous section (α=5, β=0.8, τ_j=1 and ω=0.5).

Table 5. Datasets of the simulation-based analysis

Dataset No.	Range of values	Number of alternatives	Number of criteria
1	[1, 10]	10	10
2	[1, 10]	15	15
3	[1, 10]	20	20
4	[10, 50]	10	10
5	[10, 50]	15	15
6	[10, 50]	20	20
7	[50, 150]	10	10
8	[50, 150]	15	15
9	[50, 150]	20	20

Source: authors' own contribution.

We solved these 4500 generated MCDM problems using the OPARA method and the six mentioned methods, and analysed the results obtained. To analyse the results, the Spearman's correlation coefficients between the OPARA results and the results of the other methods were calculated for each problem.

For clarity, the average correlation values and confidence intervals (CI) for each dataset are illustrated in Figure 1 (at a 95% confidence level). These values are provided in more detail (including Standard Deviation) in Table 6.

As observed, the average correlation values across all datasets for all methods are greater than 0.6, indicating a strong relationship between the output of the proposed method and the output of the other considered methods.

This underscores the high efficiency of the OPARA method in addressing MCDM problems. Additionally, it can be observed that the level of correlation between the results of OPARA and other methods increases with the range of values used in the generated matrices, demonstrating the high reliability of the proposed method. The analysis was made using Minitab® 19.2 (64-bit).

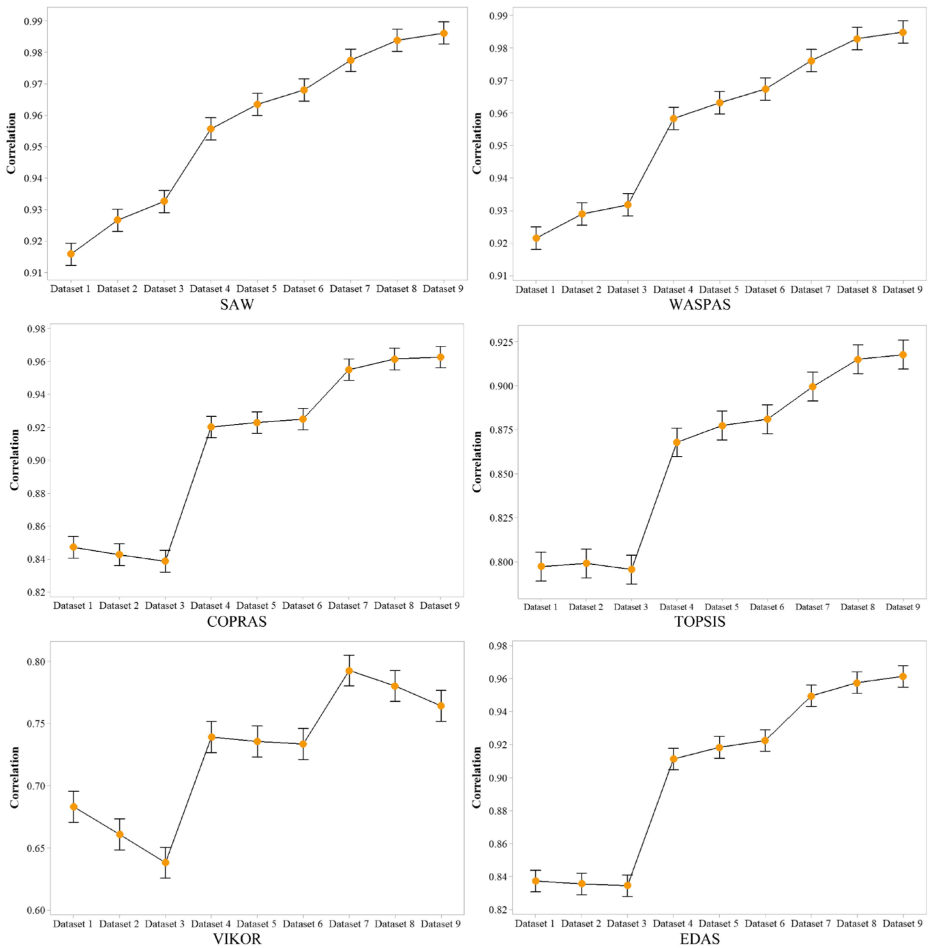

Figure 1. Graphical results of the simulation-based analysis

Source: authors' own calculations.

Table 6. Detailed results of the simulation-based analysis

		Dataset No.								
		1	2	3	4	5	6	7	8	9
SAW	Mean	0.915	0.926	0.932	0.955	0.963	0.968	0.977	0.983	0.986
	StDev	0.077	0.047	0.041	0.047	0.028	0.021	0.027	0.014	0.009
	95% CI	(0.912, 0.919)	(0.923, 0.930)	(0.929, 0.936)	(0.952, 0.959)	(0.959, 0.966)	(0.964, 0.971)	(0.973, 0.981)	(0.980, 0.987)	(0.982, 0.989)
WASPAS	Mean	0.921	0.929	0.932	0.958	0.963	0.967	0.976	0.983	0.985
	StDev	0.075	0.049	0.041	0.044	0.028	0.022	0.028	0.014	0.011
	95% CI	(0.918, 0.925)	(0.925, 0.932)	(0.928, 0.935)	(0.955, 0.962)	(0.959, 0.966)	(0.963, 0.970)	(0.972, 0.979)	(0.979, 0.986)	(0.981, 0.988)
COPRAS	Mean	0.847	0.843	0.839	0.920	0.923	0.925	0.955	0.961	0.962
	StDev	0.128	0.104	0.083	0.082	0.054	0.049	0.048	0.032	0.025
	95% CI	(0.840, 0.853)	(0.836, 0.849)	(0.832, 0.845)	(0.913, 0.926)	(0.916, 0.929)	(0.918, 0.931)	(0.948, 0.961)	(0.954, 0.967)	(0.955, 0.969)

		Dataset No.								
		1	2	3	4	5	6	7	8	9
TOPSIS	Mean	0.797	0.799	0.796	0.868	0.877	0.881	0.900	0.915	0.918
	StDev	0.148	0.116	0.094	0.108	0.073	0.065	0.089	0.058	0.047
	95% CI	(0.789, 0.805)	(0.790, 0.807)	(0.787, 0.803)	(0.859, 0.876)	(0.869, 0.885)	(0.872, 0.889)	(0.891, 0.907)	(0.906, 0.923)	(0.909, 0.926)
VIKOR	Mean	0.683	0.661	0.638	0.739	0.736	0.734	0.793	0.780	0.764
	StDev	0.190	0.156	0.139	0.172	0.132	0.112	0.131	0.115	0.109
	95% CI	(0.670, 0.695)	(0.648, 0.673)	(0.625, 0.650)	(0.726, 0.751)	(0.723, 0.748)	(0.721, 0.746)	(0.780, 0.805)	(0.767, 0.792)	(0.752, 0.777)
EDAS	Mean	0.837	0.836	0.834	0.911	0.918	0.922	0.950	0.958	0.961
	StDev	0.127	0.105	0.084	0.079	0.055	0.049	0.052	0.033	0.026
	95% CI	(0.830, 0.843)	(0.828, 0.842)	(0.827, 0.840)	(0.904, 0.917)	(0.911, 0.924)	(0.915, 0.929)	(0.943, 0.956)	(0.951, 0.964)	(0.955, 0.968)

Source: authors' own calculations.

4.2 Application to personnel evaluation and selection

In this section, the use of the proposed approach in a personnel selection problem is presented. Firstly, the problem is described, and then the proposed method is utilised to provide practical solutions.

4.2.1 Problem description

In addressing the challenge of selecting human resources for internal promotion, a company is obligated to choose three individuals from its pool of 12 employees. This selection process is based on seven fundamental criteria adapted from the study by Demirci and Kiliç (2019). These criteria are enumerated and described below.

Education (C_1): Education refers to an individual's knowledge and abilities acquired through the educational process and the completion of various educational courses.

Experience (C_2): Experience refers to the amount of time spent on practical and scientific activities in different fields.

Personality and Personal Skills (C_3): The measure of personality and personal skills refers to the characteristics, behaviours, and psychological abilities of a person.

Technical Skills and Requirements (C_4): The criterion of technical skills and specialised requirements refers to a person's abilities, knowledge, and expertise in specific and specialised fields.

Foreign Language (C_5): The criterion of foreign language skills refers to a person's ability to effectively use one or more foreign languages to communicate and perform tasks related to work and professional life.

Vocational Flexibility (C_6): The measure of vocational flexibility refers to a person's ability to adapt to the needs and changes in job and labour market demands.

Vocational Exam Results (C_7): The criterion of vocational exam results evaluates a person's achievement or performance in exams and assessments related to their profession or job.

4.2.2 Results of OPARA

In the initial stage, the CEO of the company made an initial screening and conducted the first round of assessment, assigning numerical scores from 1 to 100 for each candidate across each criterion. These scores serve as a valid foundation for subsequent evaluations.

The objective of this selection is not solely to identify individuals excelling in their current roles, but also to gauge their ability and potential for assuming more advanced positions. Furthermore, this selection process, beyond ensuring fairness and transparency, is dedicated to fostering the professional development of individuals. Moreover, the company's objective in conducting this process goes beyond decisions on internal promotions. It aims to instil a sense of trust among employees and promote healthy and professional competition. The significance of these criteria in enhancing the work environment and attracting high-quality talents is firmly emphasised.

According to the evaluation of the CEO and the weights of criteria presented in Demirci and Kiliç (2019), the decision matrix of the problem is defined in Table 7. It should be noted that the decision parameters for OPARA are α=5, β=0.8 and τ_j=1, and all of the criteria are of a beneficial nature.

Table 8 presents the final scores and ranking achieved by OPARA, along with the results of other MCDM methods.

According to Table 8, A_6, A_{12} and A_{11} are the best three candidates among the employees based on the results of OPARA. Moreover, we can see that the results of OPARA are relatively congruent with those of the other MCDM methods.

Table 7. The decision-matrix and criteria information

	C_1	C_2	C_3	C_4	C_5	C_6	C_7
A_1	70	50	50	40	30	40	56
A_2	70	40	50	60	40	40	54
A_3	50	40	60	50	30	50	58
A_4	80	10	70	50	50	60	67
A_5	80	30	70	40	40	50	73
A_6	100	60	60	70	80	70	79
A_7	50	30	50	60	20	40	61
A_8	40	10	60	50	10	40	55
A_9	50	10	50	40	30	60	57
A_{10}	40	20	60	40	30	50	68
A_{11}	70	40	60	60	40	40	51
A_{12}	70	70	50	60	50	60	78
Weights	0.2933	0.2015	0.1669	0.1499	0.0553	0.0343	0.099

Source: authors' own contribution and data presented in Demirci and Kiliç (2019).

Table 8. Final scores and ranking of the alternatives

	OPARA		SAW	WASPAS	COPRAS	TOPSIS	VIKOR	EDAS
	Score	Rank						
A_1	0.0881	5	7	6	6	3	7	6
A_2	0.0877	6	6	5	5	5	6	5
A_3	0.0803	7	8	8	8	8	8	8
A_4	0.0799	8	5	7	7	7	5	7
A_5	0.0883	4	3	3	4	6	2	4
A_6	0.1248	1	1	1	1	1	1	1
A_7	0.0729	9	9	9	9	9	9	9
A_8	0.0554	12	12	12	12	12	12	12
A_9	0.0584	11	11	11	11	11	10	11
A_{10}	0.0638	10	10	10	10	10	11	10
A_{11}	0.0896	3	4	4	3	4	4	3
A_{12}	0.1108	2	2	2	2	2	3	2

Source: authors' own calculations.

4.2.3 Sensitivity analysis of the results

To check the stability of the ranking results obtained from OPARA, a total of 1000 sets of criteria weights were generated, and the problem was solved with the assumption that the remaining parameters remained the same. Figure 2 shows the distribution of the rank of each alternative based on different sets of criteria weights, and Figure 3 represents the distribution of the final scores.

From Figures 2 and 3 it can be seen that A_6 and A_{12} are identified as the top two candidates since both of them have better scores and ranks comparing to the other candidates. However, we cannot find the third-best candidate according to the rank and score distributions. This indicates that the third candidate can be varied with different criteria weights, and we should have specific weights to identify it.

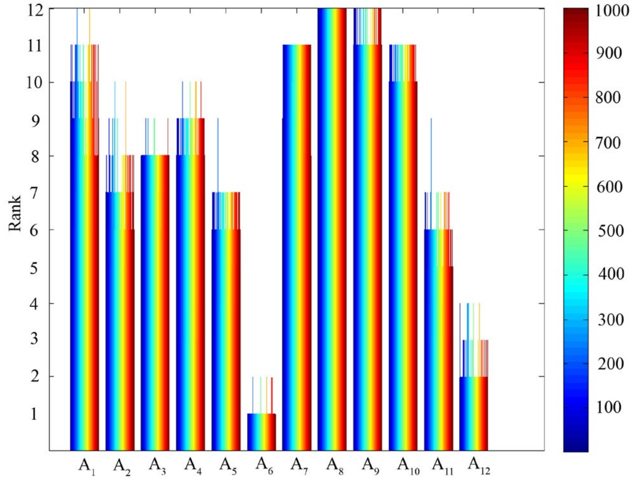

Figure 2. The distribution of the ranks in different sets of criteria weights
Source: authors' own calculations.

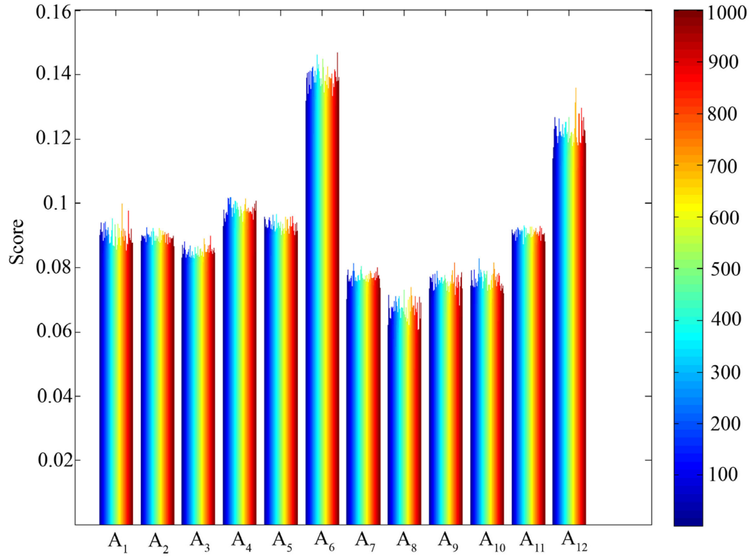

Figure 3. The distribution of the final scores in different sets of criteria weights

Source: authors' own calculations.

5. Conclusions

Effective human resource management requires an efficient process for personnel evaluation and selection. The process of evaluating and selecting individuals to join or advance within an organisation ensures that the right talent is placed in the right positions. It enables companies to identify and recruit individuals with the necessary skills, qualifications, and experience that align with the organisation's goals and objectives. Furthermore, personnel evaluation allows employers to assess current employees' performance, providing the opportunity for feedback, development, and recognition. In this study, an MCDM approach called OPARA has been introduced for the personnel evaluation and selection process. The OPARA method offers a distinct approach to multi-criteria personnel evaluation and selection that preserves the integrity of original data. By focusing on the preservation of original dataset characteristics, OPARA successfully avoids the common issues of information loss associated with normalisation processes in traditional decision-making methods. By implementing pairwise adjusted ratios calculated using objective data, the approach enhances the robustness of alternative evaluations. The unique incorporation of two adjusting parameters further refines the process, allowing decision-makers to mitigate the impacts of range and non-linearity associated with various criteria. The practical application to personnel selection and the subsequent scrutiny of results further demonstrated the method's efficacy and potential for broader application. The OPARA method's robust framework also demonstrates a significant advantage in its capacity to handle different types of data, expanding its applicability in a wide range of MCDM contexts. Exploring the OPARA method presents fertile ground for future research, particularly to examine its applicability across diverse disciplines. The adaptability and efficacy of OPARA can be rigorously tested in varying domains, from engineering and finance to social policy and urban planning, to ascertain its utility and scalability. Further research could also focus on integrating OPARA with other MCDM frameworks, which could lead to the creation of robust hybrid models enhancing the decision-making process. Additionally, the extension of OPARA to operate within uncertain or fuzzy environments would be a significant advancement, offering refined tools for scenarios where data are ambiguous or incomplete.

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