Spectrum of Operational Research

Journal homepage: www.sor-journal.org
ISSN: 3042-1470

# Aggregation of Expert Ranking Opinions Using Multi-Criteria Decision-Making Methods

Duško Tešić[1,*], Dragan Pamučar[2,3,4,*], Gülay Demir[5], Adis Puška[6], Darko Božanić[1]

1 Military Academy, University of Defence in Belgrade, Belgrade, Serbia
2 Department of Applied Mathematical Science, College of Science and Technology, Korea University, Sejong 30019, Republic of Korea
3 UNEC Applied Artificial Intelligence Research Center, Azerbaijan State University of Economics (UNEC), Baku, Azerbaijan
4 School of Engineering and Technology, Sunway University, Selangor, Malaysia
5 High School of Health Vocational Services, Sivas Cumhuriyet University, Sivas, Türkiye
6 Department of Public Safety, Government of the Brčko District of Bosnia and Herzegovina, Brčko, Bosnia and Herzegovina

**ARTICLE INFO**

***Article history:***
Received 2 January 2026
Received in revised form 10 February 2026
Accepted 11 March 2026
Available online 15 March 2026

***Keywords:***
MCDM; Group Decision-Making; Aggregation; Expert; MARCOS; COPRAS; ARAS; CoCoSo; EWAA; HWAA; OWA; OWG

**ABSTRACT**

This paper investigates the application of multi-criteria decision-making methods (MCDM) for the aggregation of expert opinions related to ranking, considering the weight coefficients of the experts' competencies. Measurement Alternatives and Ranking according to Compromise Solution (MARCOS), Complex Proportional Assessment (COPRAS), Additive Ratio Assessment (ARAS), and Combined Compromise Solution (CoCoSo) methods, which are traditionally used to select the optimal alternative in MCDM, are applied in this study for the purpose of aggregating the ranks given by experts. The validity of the results was confirmed by comparison with the Einstein weighted arithmetic average (EWAA), Hamacher weighted arithmetic aggregation (HWAA), Ordered Weighted Averaging (OWA), and Ordered Weighted Geometric (OWG) operators, where identical ranks were obtained. The conducted sensitivity analysis based on a Monte Carlo simulation confirms that classical MCDM methods provide stable and reliable results under conditions of perturbations of expert weights and ranks, while aggregation operators show significantly lower robustness and consistency. The aforementioned shows that MCDM methods can be a reliable and practical tool for group decision-making, i.e., the aggregation of expert opinions, with the advantage of generating final ranks without additional post-analysis.

## 1. Introduction

Everyday life requires people to make various decisions, both personal and business. These decisions are made with different goals in mind, which primarily satisfy certain interests, where they choose the one that satisfies them most fully from among the offered options. Goals can be set as personal goals of individuals, while for profit business organizations the goal is always, in essence, higher earnings, both directly and indirectly.

* *Corresponding author.*
*E-mail address: tesic.dusko@yahoo.com*

https://doi.org/10.31181/sor202780

The term "decision" itself has several meanings. Based on the opinions of various authors [1-7] common premises can be observed in all definitions, which are reflected in the following:

1) A decision is a choice between two or more alternatives (options/actions);
2) A decision has as its ultimate result the achievement of a specific goal and
3) A decision is the result of decision-making.

The most general division of decisions in relation to the fact of who makes them, i.e. the number of decision makers [8], is into:

1) Individual (where the decision is made by an individual) and
2) Group (where the decision is made by a group of people).

Since a ʹʹdecisionʹʹ is the result of ʹʹdecision-makingʹʹ, it is necessary to define this term as well. Decision-making can be defined as the process of choosing one alternative from a set of possible alternatives in order to solve a specific problem and achieve a set goal, the final result of which is a decision. Just as decisions can be individual and group, decision-making can also be divided in the same way.

Group decision-making is a process in which several experts participate in the evaluation of criteria or alternatives, with the aim of making a single and as objective decision as possible [9]. In practice, experts often have different attitudes, experiences and levels of competence, leading to heterogeneous rankings and ratings. Without adequate aggregation, this diversity can make it difficult to reach consensus and reduce the reliability of the final decision. Therefore, it is necessary to develop methodologies that enable the unification of expert opinions into a single result, while respecting the weight coefficients that reflect the competencies of each participant.

The weight competences of experts represent one of the most important elements in the MCDM process, because they allow the opinion of each participant to be evaluated in accordance with his knowledge, experience and relevance to a specific problem [10]. In this way, a balance is achieved between different levels of expertise and prevents the opinion of less competent experts from having the same influence as the opinion of leading authorities [10]. The introduction of weights ensures the transparency and fairness of the process, because it is clearly shown on the basis of which the decision was weighted. In addition, the weights contribute to the stability of the model and reduce the variability in the results, thereby increasing the reliability of the opinion aggregation. Competences can be evaluated objectively, based on publications, experience and position, subjectively, through the evaluations of other experts, or hybridly, by combining statistical indicators and expert evaluations [11]. Precisely because of this, correctly defined weight competences of experts form the basis for quality and reliable decision-making in MCDM frameworks. In addition to the MCDM methods that are intended for the selection of the optimal alternative, this is very important when determining the weight coefficients of the criteria using subjective MCDM methods such as, for example, Defining Interrelationships Between Ranked criteria (DIBR) [12], Defining Interrelationships Between Ranked criteria II (DIBR II) [13], Full Consistency Method (FUCOM) [14], because taking into account the competence of experts increases the objectivity of the decision made. The mentioned methods, in one of their first steps, require a comparison of criteria according to importance, that is, their ranking. In most cases, when calculating the weight of the criteria, group decision-making is used, so it is necessary to aggregate expert opinions regarding the ranking of the criteria. The most commonly used traditional approaches for aggregating expert opinions are given in Table 1.

There is a clear difference between methods that do not take into account expert weights (traditional) and those that do (operators, Bayesian approach, ML). Traditional methods are simple but limited, while advanced operators and probabilistic approaches offer greater precision and a more realistic competency model, at the cost of more complex implementation and interpretation.

In other words, the evolution of operators goes from simple and equal approaches to sophisticated methods that balance expertise and data, which is precisely the space in which the proposed approach to MCDM methods naturally fits.

**Table 1**
Comparative overview of some expert opinion aggregation methods regarding ranking

| Method | Working principle | It respects the weight of experts | Advantages | Disadvantages |
|---|---|---|---|---|
| Arithmetic mean | Summing ranks/grades and calculating averages | No | Simple, intuitive, fast | It ignores the competence of experts; all treated equally |
| Geometric mean | Multiplication of ranks and rooting | No | It reduces the impact of extreme values | Ignores expert weights; more complex interpretation |
| Borda count [15] | Ranks are converted into points, added up | No (basic version) | A clear and transparent method | It does not take into account the competence of experts; possible expansion with weights |
| Consensus rank (median) | A median or average rank is taken for each alternative | No | Robust method, resistant to extreme values | Ignores expert weights; it can mask differences of opinion |
| Kendall's tau minimization [16] | It looks for a ranking that minimizes the total difference to all experts | No | Mathematically rigorous; gives the "closest" consensus rank | Computationally demanding; does not take into account the competences of experts |
| Einstein weighted arithmetic average (EWAA) operator [17-19] | Weighted arithmetic mean of ranks | Yes | Respects the weight of experts; flexible application | Decimal results require additional interpretation |
| Hamacher weighted arithmetic aggregation (HWAA) operator [20-22] | Combination of subjective and objective expert weights | Yes | Accepts different types of weights; more robust than EWAA | Decimal results require additional interpretation |
| Ordered Weighted Averaging (OWA) [23] | Aggregation of values according to a predefined order of weights | Yes (implicit) | Flexible operator; can model different views of experts | It is necessary to define a vector of weights; interpretation can be complex |
| Ordered Weighted Geometric (OWG) [24] | The geometric version of the OWA operator | Yes | It reduces the impact of extreme values; flexible | The results require further interpretation; more complex than OWA |
| Bayesian methods [25] | Ranks treated as probabilities; aggregation through the posterior distribution | Yes (implicit) | It respects the uncertainty and expertise of experts through probabilities | Computationally complex; require statistical modeling |
| Machine learning (ML) approaches [26] | Ensemble models (RankNet, BordaFuse) combine the ranks of experts | Yes (can be defined) | Flexible; can learn from data; scalable | They require data and training; complexity of implementation |

Considering that MCDM methods for selecting the optimal alternative, when applied, mainly consider the weights of the criteria, i.e. the magnitude of their influence on the final decision, and that the output of the method is the rank of alternatives, it was concluded that ranking aggregation can also be performed using these methods.

The starting hypothesis of this paper is *that MCDM methods, which are traditionally used for ranking alternatives, can also be used for the aggregation of expert opinions regarding ranking*. The mathematical apparatus of these methods allows expert opinions to be combined into a single result, while respecting the weight coefficients of competencies, and based on the concept presented in [11].

The aim of the study is to:

1) Shows the general framework of application of MCDM methods for aggregation of expert ranks.
2) Validate the application of MCDM methods for this purpose, through comparison with EWAA, HWAA, OWA and OWG operators.
3) Shows that MCDM methods provide final rankings without the need for additional post-analysis, thus facilitating interpretation and increasing practical applicability in group decision-making.

In addition to the Introduction, the paper consists of three more sections. In the second section, the concept of aggregating expert opinions regarding ranking using traditional MCDM methods is presented. The third section shows the application of the mentioned concept with proof of validity, while in the fourth part of the paper, a Sensitivity Analysis was performed. Finally, concluding considerations and directions for future research are given.

## 2. Methodology

In classical MCDM methods, such as, for example, Measurement Alternatives and Ranking according to Compromise Solution (MARCOS) [27, 28], Complex Proportional Assessment (COPRAS) [29, 30], Additive Ratio Assessment (ARAS) [31, 32] and Combined Compromise Solution (CoCoSo) [33, 34], for the selection of the optimal alternative, the alternatives are evaluated according to defined criteria and generally have the steps presented in Table 2.

**Table 2**
Comparative overview of the steps of some MCDM methods

| Step | MARCOS | COPRAS | ARAS | CoCoSo |
|---|---|---|---|---|
| Formation of the initial decision matrix | Yes | Yes | Yes | Yes |
| Normalization of criteria ($C_n$) values (benefit, cost) | Yes | Yes | Yes | Yes |
| Weighting the criterion values for each alternative | Yes | Yes | Yes | Yes |
| Adding ideal and anti-ideal solutions | Yes | No | No | No |
| Calculation of the ratio towards the optimal solution | Yes (ideal/anti-ideal) | Yes (proportional) | Yes (additive) | Yes (combined) |
| Calculation of the compromise index | Yes | No | No | Yes |
| Combining SAW and WASPAS values | No | No | No | Yes |
| Ranking of alternatives ($A_m$) | Yes | Yes | Yes | Yes |

The initial decision matrix ( $X$ ) in these methods has the following form [35]:

$$X = \begin{array}{c} \\ A_1 \\ A_2 \\ \cdots \\ A_m \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \cdots & C_n \end{array} \\ \begin{pmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{pmatrix} \end{array}$$

Each of the criteria is of Benefit or Cost type, i.e. the higher the value the better or the lower the value the better [35]. Considering that each of the criteria has its own weight ( $\omega_i$ ) and that in each of the mentioned methods the weighting of the values according to the criteria for each of the alternatives is carried out, it is concluded that the mentioned weights affects the final decision in a certain percentage, given that $\sum_{i=1}^{n} \omega_i = 1$. In the same way that criteria weights affect the final decision, expert weights ($\omega_i^E$) do the same.

Given that the output in these methods is the rank of alternatives, and that the input values are weighted by certain coefficients (weights of the criteria) as is done in the case of aggregating expert opinions in relation to the rank using the weight coefficient of the expert's competence, the following concept is reached:

1) in the initial decision matrix, instead of criteria (horizontally), experts $E = \{E_1, E_2, \dots, E_e\}$ are defined, and instead of criterion weights, competence weight coefficients ( $\omega_i^E$ ) are defined, while the character of the criteria (experts) is defined as the Cost type (the best rank has the value 1). Instead of alternatives in the initial decision matrix (vertically), criteria $C = \{C_1, C_2, ..., C_n\}$ are defined, which experts are ranked by importance.

$$X = \begin{array}{c c} & \begin{array}{cccc} E_1 & E_2 & \cdots & E_e \end{array} \\ \begin{array}{c} C_1 \\ C_2 \\ \cdots \\ C_n \end{array} & \begin{pmatrix} x_{11} & x_{12} & \cdots & x_{1e} \\ x_{21} & x_{22} & \cdots & x_{2e} \\ \cdots & \cdots & \cdots & \cdots \\ x_{n1} & x_{n2} & \cdots & x_{ne} \end{pmatrix} \end{array}$$

2) by applying the mathematical apparatus of the classical MCDM method, an aggregated rank is reached that takes into account expert competencies.

It is important to note that here one should take into account the consistency of expert opinions, that is, it should be checked using one of the well-known methodologies intended for that, as well as in all other situations where group decision-making is carried out.

In order to prove the validity of the obtained results, the operators EWAA (1), HWAA (2), OWA (3) and OWG (4) will be used in this research, which take into account the expert competence coefficients during aggregation.

$$EWAA\{x_1, x_2, ..., x_e\} = \sum_{i=1}^{e} x_i \frac{\prod_{i=1}^{e}\left(1+f\left(x_i\right)\right)^{\omega_i^E} - \prod_{i=1}^{e}\left(1-f\left(x_i\right)\right)^{\omega_i^E}}{\prod_{i=1}^{e}\left(1+f\left(x_i\right)\right)^{\omega_i^E} + \prod_{i=1}^{e}\left(1-f\left(x_i\right)\right)^{\omega_i^E}} \tag{1}$$

$$HWAA\{x_1, x_2, .., x_e\} = \\ = \sum_{i=1}^{e} z_j \frac{\prod_{i=1}^{e}\left(1+(\eta-1)f\left(x_i\right)\right)^{\omega_i^E} - \prod_{i=1}^{e}\left(1-f\left(x_i\right)\right)^{\omega_i^E}}{\prod_{i=1}^{e}\left(1+(\eta-1)f\left(x_i\right)\right)^{\omega_i^E} + (\eta-1)\prod_{i=1}^{e}\left(1-f\left(x_i\right)\right)^{\omega_i^E}} \tag{2}$$

$$OWA(x_1, \dots, x_e) = \sum_{i=1}^{e} w_i^E x_i \tag{3}$$

$$OWG(x_1, x_2, \dots, x_e) = \prod_{i=1}^{e} x_{(i)}^{\omega_i^E} \tag{4}$$

where are $f(x_i) = \frac{x_i}{\sum_{i=1}^{e} x_i}$, $\eta > 0$, $i \in \{1, 2, \dots, e\}$, $e$ is the number of experts and $\omega_i^E$ expert weights.

The research was conducted according to the algorithm presented in Figure 1.

```
\begin{algorithm}[H]
\caption{Aggregation of Expert Opinions Using Classical MCDM Methods}
\begin{algorithmic}[1]
\State \textbf{Input:} Set of experts E={E_1,E_2,...,E_e} , set of criteria C={C_1,C_2,...,C_n} , competence weight
coefficients ω_i^E , expert rankings of criteria
\State \textbf{Output:} Aggregated ranking of criteria
\State Construct the initial decision matrix:
    \begin{itemize}
        \item Rows: criteria (instead of alternatives)
        \item Columns: experts (instead of criteria)
        \item Weights: competence coefficients of experts (instead of criterion weights)
        \item Expert character: \textit{Cost type} (best rank = 1)
    \end{itemize}
\State Apply classical MCDM methods (MARCOS, COPRAS, ARAS, CoCoSo) to the matrix
\State Obtain aggregated ranking of criteria
\State Check consistency of expert opinions
\State Validate results using operators:
    \begin{itemize}
        \item EWAA
        \item HWAA
        \item OWA
        \item OWG
    \end{itemize}
\State Compare operator-based rankings with MCDM-based rankings
\If{rankings are identical or consistent}
    \State Confirm validity of the approach
    \State \textbf{Conclusion:} Classical MCDM methods can successfully replace complex operators,
producing final rankings directly without additional interpretation.
\Else
    \State Hypothesis is not confirmed
    \State \textbf{Conclusion:} Differences between operator-based and MCDM-based rankings indicate
limitations of the current methodology. Further research is required to refine aggregation
techniques.
\EndIf
\end{algorithmic}
\end{algorithm}
```

**Fig. 1.** Research algorithm

## 3. Results

For a more detailed explanation of the above concept, an example of the above application is given below, with proof of the validity of the results obtained.

Let five experts $E = \{E_1, E_2, \ldots, E_5\}$, with the values of the weight coefficients of the competencies $\omega_i^E = \{0.21, 0.20, 0.23, 0.19, 0.17\}$, ranked five criteria $C = \{C_1, C_2, \ldots, C_5\}$ by importance, where the most important criterion has a value of 1, and the least important 5. The ranking of the criteria by importance, for each of the experts, is presented in Table 3.

**Table 3**
Ranking of criteria by importance by experts

| | E1 | E2 | E3 | E4 | E5 |
|---|---|---|---|---|---|
| C1 | 2 | 1 | 1 | 1 | 1 |
| C2 | 1 | 2 | 3 | 2 | 2 |
| C3 | 3 | 3 | 2 | 3 | 4 |
| C4 | 4 | 4 | 4 | 5 | 3 |
| C5 | 5 | 5 | 5 | 4 | 5 |

In order to use this data in further calculations, it is necessary to aggregate it, i.e. combine it into single values, taking into account the rankings of the criteria defined by each expert, as well as the weights of their competencies. By applying classical MCDM methods to aggregate the ranks defined by experts in Table 3, the final (aggregated) ranks were obtained, presented in Table 4.

**Table 4**
Aggregated criteria rankings using classical MCDM methods

| | MARCOS | COPRAS | ARAS | CoCoSo |
|---|---|---|---|---|
| C1 | 1 | 1 | 1 | 1 |
| C2 | 2 | 2 | 2 | 2 |
| C3 | 3 | 3 | 3 | 3 |
| C4 | 4 | 4 | 4 | 4 |
| C5 | 5 | 5 | 5 | 5 |

To confirm the validity of the obtained results, it is necessary to compare the obtained ranks with the results of other aggregation methodologies. One of the tools that would be used for aggregation are operators. For the purposes of this research, the EWAA, HWAA, OWA and OWG operators were used. By applying the above operators, the following aggregated criteria ranks are obtained, Table 5.

**Table 5**
Aggregated ranks obtained by applying the operator

| | EWAA | | HWAA | | OWA | | OWG | |
|---|---|---|---|---|---|---|---|---|
| | Aggregated Value | Rank | Aggregated Value | Rank | Aggregated Value | Rank | Aggregated Value | Rank |
| C1 | 1.217007 | 1 | 1.22890 | 1 | 1.21000 | 1 | 1.15669 | 1 |
| C2 | 2.029335 | 2 | 2.04768 | 2 | 2.02000 | 2 | 1.89808 | 2 |
| C3 | 2.945434 | 3 | 2.95651 | 3 | 2.94000 | 3 | 2.86985 | 3 |
| C4 | 4.023775 | 4 | 4.03127 | 4 | 4.02000 | 4 | 3.97405 | 4 |
| C5 | 4.811273 | 5 | 4.81393 | 5 | 4.81000 | 5 | 4.79244 | 5 |

As can be seen from the previous table, aggregated rank values were obtained, which are mostly records with multiple decimal places, which then need to be reduced to the final rank. Considering that the aggregated ranks obtained by applying classical MCDM methods (Table 4) are identical to the ranks obtained using operators (Table 5), it can be concluded that classical MCDM methods can be used to aggregate ranks defined by experts, taking into account the weight coefficients of their competencies, thus proving the starting hypothesis and aim of this research.

The advantage of this approach is reflected in the fact that it is the only one that combines mathematical consistency, because the results given by classical MCDM methods correspond to those obtained by existing operators, with practical simplicity, since the final ranking is immediately obtained without the need for additional processing. In addition, the concept is universally applicable because it can be used with any MCDM method to select the optimal alternative, and at the same time it enables a realistic model of experts' competencies through the natural inclusion of their weight coefficients. In other words, this approach represents a bridge between traditional operators and modern MCDM methods, with a clear advantage in interpretation and flexibility

## 4. Sensitivity Analysis

In order to additionally check the robustness of the obtained results, a sensitivity analysis based on Monte Carlo simulation [35] was carried out. The basic idea of this approach is not to observe only one deterministic set of input parameters, but a large number of possible scenarios resulting from controlled perturbations of the input data. In this way, it is examined how stable the obtained ranks are when there are changes in the experts' weights.

In this section, the Monte Carlo analysis is organized so that two types of changes occur in each iteration. First, the experts' weights are perturbed, which simulates the possibility that the relative importance of individual experts is not completely fixed. In this way, the relative importance of experts varies in real decision-making conditions. Second, a controlled change in the rank matrix is introduced through random substitutions of values within the expert assessments. This models the possibility of minor deviations in expert assessments. After each such perturbation, the ranking of alternatives is recalculated for each of the observed models. The analysis of the validation results organized in this way has several goals: 1) It enables the evaluation of whether the first-ranked alternative remains dominant even under changed conditions; 2) It provides an insight into the average stability of the entire ranking, not just the first place and 3) It enables the mutual comparison of different models and shows which models give more stable and resilient results, and which are more sensitive to changes in input parameters. In the following, the most important results of the obtained Monte Carlo sensitivity analysis are presented and interpreted.

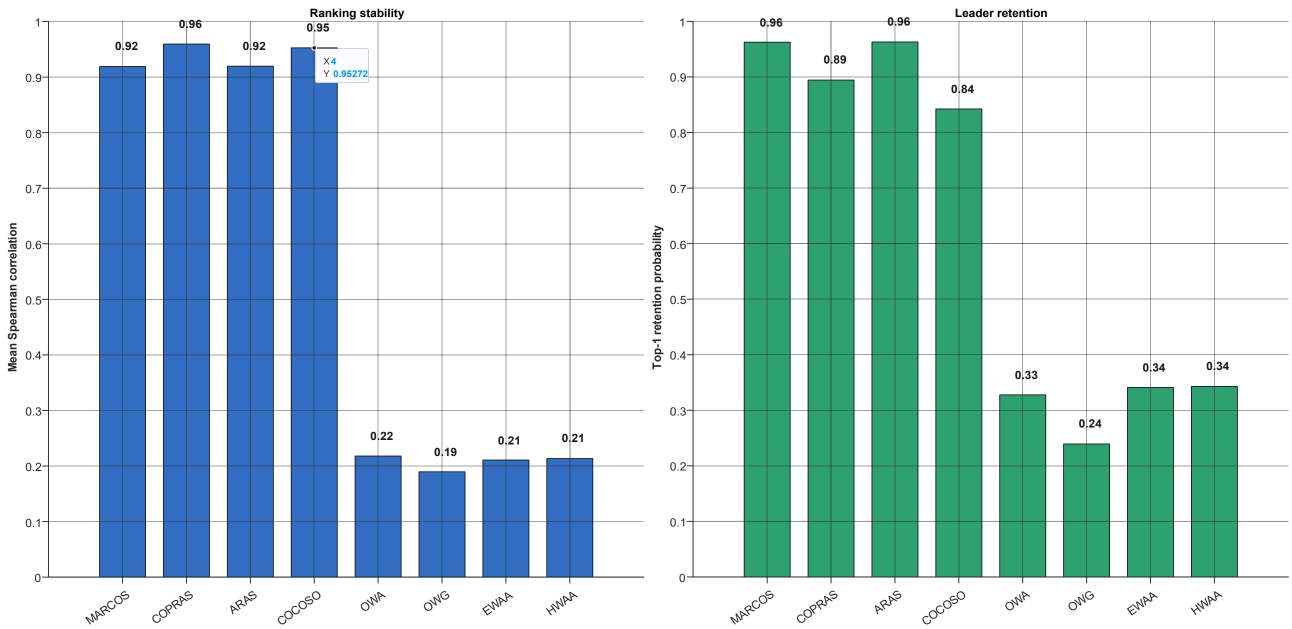


**Fig 2.** Monte Carlo sensitivity summary across all models

Figure 2 provides a summary of the robustness of all considered models through two key indicators: the average Spearman rank correlation and the probability of retaining first place. Ranking stability (Figure 2) shows the average Spearman correlation between the base rank and the ranks obtained in Monte Carlo iterations. High values in MARCOS, COPRAS, ARAS and CoCoSo models indicate that their overall order of alternatives changes very little due to perturbations. COPRAS and CoCoSo stand out in particular, while MARCOS and ARAS also show a very high level of stability. In contrast, the OWA, OWG, EWAA and HWAA operators have significantly lower average correlation values, i.e. their ranks are much more susceptible to change.

Leader retention (Figure 2) shows the retention probability of the first ranked alternative. The results show that in MARCOS and ARAS models, the first ranked alternative remains the same in approximately 96% of simulations, while in COPRAS and CoCoSo this probability is somewhat lower, but still high. With the aggregation operator, that probability is significantly lower. These results confirm that they are more sensitive to changes in experts' weights and changes in input ranks. Based on the results from Figure 2, we can conclude that classical MCDM methods show greater robustness than aggregation operators when applied to the problem of aggregation of expert ranks.

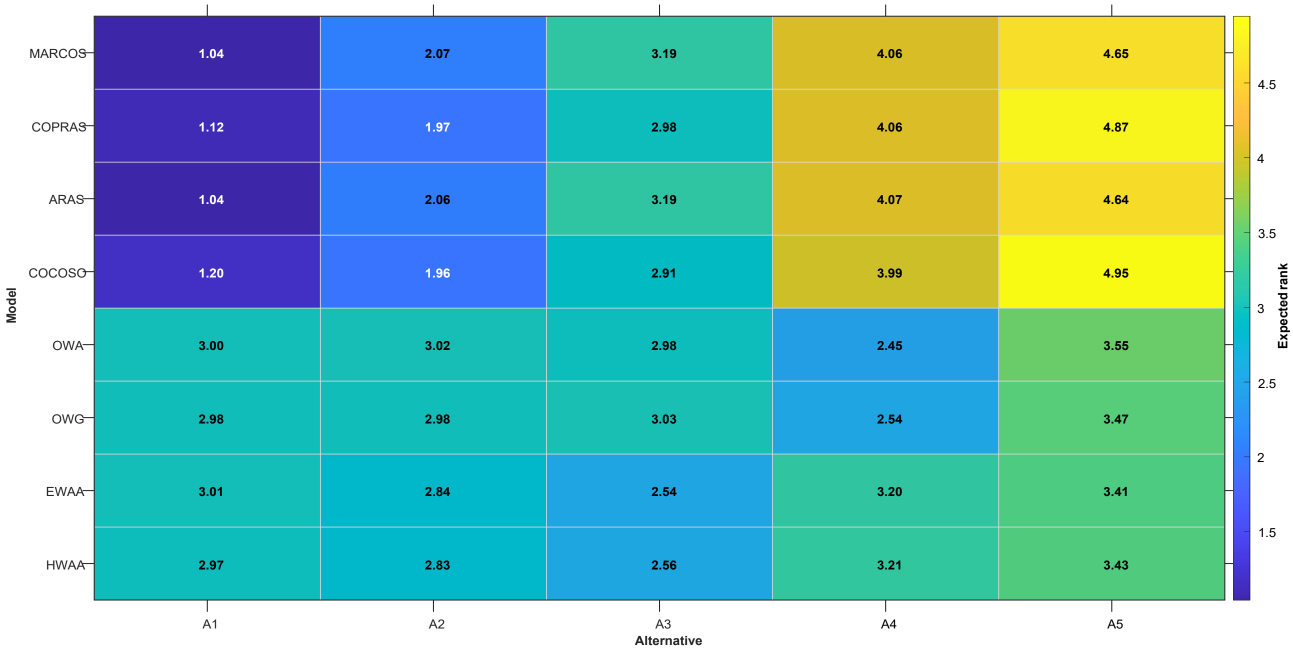


**Fig 3.** Expected rank under Monte Carlo perturbations

Figure 3 presents a map of the expected ranks of the alternatives for each observed model. Each cell shows the average position that a particular alternative occupies during all Monte Carlo simulations. It can be seen from Figure 3 that the MARCOS, COPRAS, ARAS and CoCoSo models have an almost ideal structure. This means that the perturbations do not lead to significant disturbances in the final rank and that the obtained results are stable. With operators OWA, OWG, EWAA and HWAA, the results in Figure 3 are different, that is, there is no pronounced dominance of the same alternative throughout all simulations. Based on this, we conclude that with operators, perturbations more easily change the relative position of alternatives, so the final order is less stable. It should be emphasized that Figure 3 does not only show the stability of the first place, but the stability of the entire ranking list. Therefore, based on it, it can be concluded that MCDM models are more stable in choosing the best alternative.

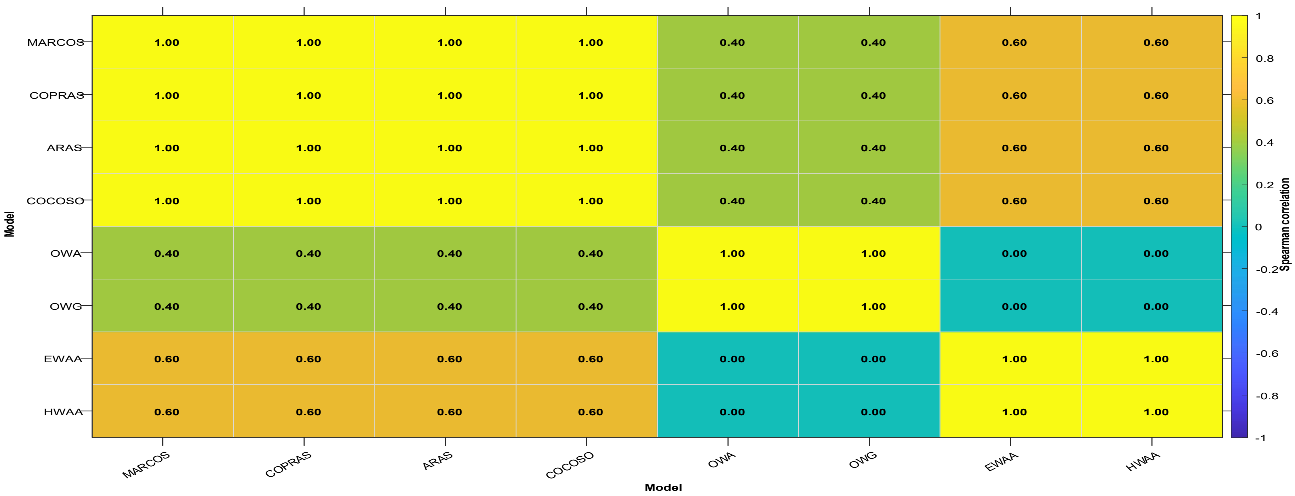


**Fig. 4.** Pairwise agreement of baseline rankings

Figure 4 shows the mutual matching of the base ranks of all considered models, represented by the Spearman correlation. On the diagonal in Figure 4 are, as expected, values equal to 1, since each model is fully correlated with itself. Also, in Figure 4 it can be seen that MARCOS, COPRAS, ARAS and CoCoSo have a complete agreement with each other, i.e. a correlation of 1.00. This means that all four methods give the same basic order of alternatives. This finding is very important because it confirms that, in a given problem, classical MCDM methods behave practically identically from the point of view of final ranking.

On the other hand, Figure 4 shows that the OWA and OWG models also show complete agreement with each other, as do the EWAA and HWAA models. However, the agreement between these two groups of operators and classical MCDM methods is weaker. Correlations of about 0.40 between the MCDM method and the OWA/OWG operator, as well as about 0.60 between the MCDM method and the EWAA/HWAA operator. Such results show that the aggregation operators rely on a different logic to form the final rank.

It is particularly interesting that the correlation between OWA/OWG and EWAA/HWAA is equal to zero, which indicates a distinctly different ranking structure between these two groups of operators. Based on this, it can be concluded that three families of models are clearly distinguished in the analyzed problem: classic MCDM methods, OWA/OWG operators, and EWAA/HWAA operators. Such results in Figure 4 show that robustness is not the only criterion of difference between the models, but that they also differ in the very structure of the base ranking.

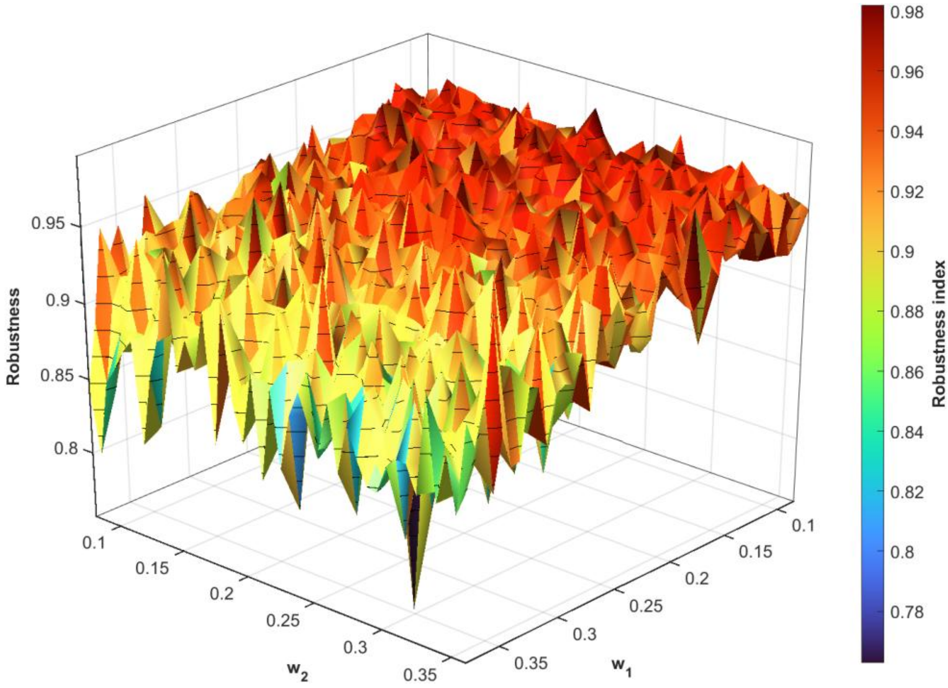


**Fig. 5.** MARCOS robustness landscape

Figure 5 presents a three-dimensional representation of the robustness of the MARCOS model depending on the changes in the experts' weights. The horizontal axes show the weights $w_1$ and $w_2$, while the vertical axis represents the robustness index of the model. The parameters $w_1$ and $w_2$ represent the weights of the first two experts in the group decision-making process. By varying these weights, different scenarios are simulated in which the relative importance of these two experts changes compared to the others. In doing so, the remaining weights of the experts are automatically adjusted and renormalized so that the sum of all weights remains equal to one. In this way, it was analyzed how changes in the structure of expert weights affect the stability of the final ranking.

From Figure 5, it can be seen that the robustness surface in the largest part of the observed space is relatively high and stable. This means that even with significant changes in the weights of the first two experts, the MARCOS model in most cases maintains the same or very similar order of alternatives. Local indentations on the surface indicate zones of slightly higher sensitivity. However, even in those regions, there is no significant disruption of the stability of the ranking. This result confirms that the MARCOS model is very robust in relation to changes in experts' weights. Similar results are obtained for other MCDM models used in this paper.

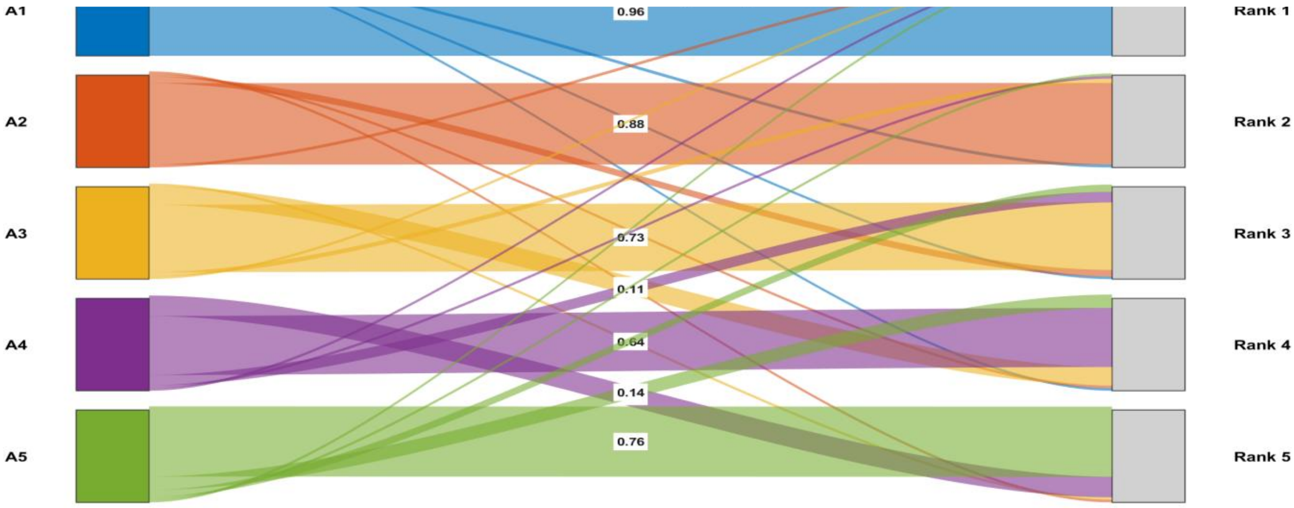


**Fig. 6.** Monte Carlo rank-flow diagram (MARCOS)

Figure 6 shows the rank flow for the MARCOS model. The thickness of each link represents the probability that a certain alternative, under conditions of Monte Carlo perturbations, will end up in a specific ranking position. Based on Figure 6, it can be seen that alternative A1 almost completely remains in first place, with a probability of approximately 0.96. Similarly, the alternative A2 remains in the second position in the majority of cases, while A3 is most often in the third position, although it shows a slightly higher degree of transition to the fourth position. Alternative A4 most often remains in the fourth position, but in part of the simulations it also moves to the fifth place. Alternative A5 dominantly remains in the fifth position.

Figure 6 shows that when rank changes occur, they mostly occur between adjacent ranks, while large deviations are very rare. Such results prove that the MARCOS model is stable, since perturbations do not produce drastic changes in the final order. Similar results were obtained using other MCMD models.

Based on the conducted sensitivity analysis, it can be concluded that the MARCOS, COPRAS, ARAS and CoCoSo models showed a high level of robustness under conditions of perturbations of expert weights and changes in expert ranks. MARCOS and ARAS stand out in particular, where the probability of retaining the first-placed alternative is the highest, while at the same time maintaining a very high correlation with the base rank. COPRAS and CoCoSo also show very stable behavior, although a slightly higher sensitivity is present in CoCoSo.

On the other hand, the operators OWA, OWG, EWAA and HWAA show a significantly lower degree of robustness. Their ranks are more subject to change. The expected ranks of the alternatives are less clearly separated, and the probability of retaining the top-ranked alternative is significantly lower. This indicates that these operators are more sensitive to changes in input parameters and give less stable results in the context of aggregation of expert ranks.

Additionally, the mutual agreement analysis showed that three clearly differentiated groups of methods can be distinguished in the observed problem: classical MCDM methods, OWA/OWG operators and EWAA/HWAA operators. This structure confirms that the choice of method does not only affect the degree of robustness, but also the very logic of forming the final ranking. Overall, the performed sensitivity analysis confirms that classic MCDM methods, and especially the MARCOS model, are very reliable for the problem of aggregation of expert ranks, because they maintain a stable and consistent order of alternatives even in conditions of pronounced input uncertainty.

## 5. Conclusions

Based on the conducted research with five experts and five criteria, it was shown that classic MCDM methods (MARCOS, COPRAS, ARAS, CoCoSo) give identical ranks as advanced operators (EWAA, HWAA, OWA, OWG). This confirms the mathematical consistency and validity of the approach, because the results match regardless of the methodology. The advantage of classic MCDM methods is that they immediately generate final ranks, while operators give decimal values that require additional interpretation, so the process is simpler and more practical to apply.

This concept has proven to be universally applicable, as it can be used with any MCDM method and naturally includes expert weight coefficients, thus realistically modeling their competence. In this way, a bridge between traditional operators and modern MCDM methods is realized, with a clear advantage in interpretation, flexibility and practical use. This confirmed the initial hypothesis that classic MCDM methods can successfully replace complex operators, while preserving the validity of the results and facilitating interpretation.

Based on the conducted Monte Carlo sensitivity analysis, it can be concluded that classic MCDM methods show a high level of robustness and reliability in conditions of perturbations of expert weights and changes in expert ranks. Their results remain stable and consistent, with a high probability of retaining the top-ranked alternative and a strong correlation with the base rank. In contrast, the OWA, OWG, EWAA, and HWAA operators show significantly lower stability and greater susceptibility to change, indicating their limited applicability in the context of expert rank aggregation. The conducted analysis clearly confirms that the choice of method does not only affect the degree of robustness, but also the very logic of ranking formation, whereby classic MCDM methods stand out as the most reliable approach for decision-making in conditions of uncertainty.

This paper represents a contribution to the literature in the field of group decision-making and opens up space for further research, especially in combination with theories that handle imprecision and uncertainty well and hybrid MCDM models.

**Acknowledgement**
This research was not funded by any grant.

**Conflicts of Interest**
The authors declare no conflicts of interest.

## References

[1] Ćosić, P. (2008). *Dictionary of synonyms*. Cornet.
[2] Stevanović, M., & Jonke, L. (1967). *Dictionary of the Serbo-Croatian literary language*. Matica srpska.
[3] Oxford Advanced Learner's Dictionary. (2026). *Decision*. https://www.oxfordlearnersdictionaries.com/definition/english/decision?q=decision
[4] The Britannica Dictionary. (2026). *Decision*. https://www.britannica.com/dictionary/decision
[5] Torres-Pomales, W. (2015). *Considering risk and resilience in decision-making*. Langley Research Center.
[6] Yates, J. F. (2003). *Decision management*. Jossey-Bass.

[7] Pavličić, D. (2007). *Decision theory*. Faculty of Economics, University of Belgrade.
[8] Taherdoost, H., & Madanchian, M. (2023). Multi-criteria decision making (MCDM) methods and concepts. *Encyclopedia, 3*(1), 77–87. https://doi.org/10.3390/encyclopedia3010006
[9] Peniwati, K. (2007). Criteria for evaluating group decision-making methods. *Mathematical and Computer Modelling, 46*(7–8), 935–947. https://doi.org/10.1016/j.mcm.2007.03.005
[10] Tsyganok, V. V., Kadenko, S. V., & Andriichuk, O. V. (2012). Significance of expert competence consideration in group decision making using AHP. *International Journal of Production Research, 50*(17), 4785–4792. https://doi.org/10.1080/00207543.2012.657967
[11] Tešić, D., & Božanić, D. (2024). Model for determining competences of experts in the field of military science. *Vojno Delo, 76*(1), 1–22. https://doi.org/10.5937/vojdelo2401001t
[12] Pamucar, D., Deveci, M., Gokasar, I., Işık, M., & Zizovic, M. (2021). Circular economy concepts in urban mobility alternatives using integrated DIBR method and fuzzy Dombi CoCoSo model. *Journal of Cleaner Production, 323*, Article 129096. https://doi.org/10.1016/j.jclepro.2021.129096
[13] Božanić, D., & Pamucar, D. (2023). Overview of the method defining interrelationships between ranked criteria II and its application in multi-criteria decision-making. In *Lecture Notes in Electrical Engineering* (Vol. 984, pp. 863–873). Springer Nature Singapore. https://doi.org/10.1007/978-981-19-8493-8_64
[14] Pamučar, D., Stević, Ž., & Sremac, S. (2018). A new model for determining weight coefficients of criteria in MCDM models: Full consistency method (FUCOM). *Symmetry, 10*(9), Article 393. https://doi.org/10.3390/sym10090393
[15] Emerson, P. (2013). The original Borda count and partial voting. *Social Choice and Welfare, 40*(2), 353–358. https://doi.org/10.1007/s00355-011-0603-9
[16] Lin, S. (2010). Rank aggregation methods. *WIREs Computational Statistics, 2*(5), 555–570. https://doi.org/10.1002/wics.111
[17] Tešić, D., Božanić, D., Radovanović, M., & Petrovski, A. (2023). Optimising assault boat selection for military operations: An application of the DIBR II-BM-CoCoSo MCDM model. *Journal of Intelligent Management Decision, 2*(4), 160–171. https://doi.org/10.56578/jimd020401
[18] Deveci, M., Pamucar, D., Gokasar, I., Köppen, M., Gupta, B. B., & Daim, T. (2023). Evaluation of Metaverse traffic safety implementations using fuzzy Einstein based logarithmic methodology of additive weights and TOPSIS method. *Technological Forecasting and Social Change, 194*, Article 122681. https://doi.org/10.1016/j.techfore.2023.122681
[19] Jin, Y., Wu, H., Merigó, J. M., & Peng, B. (2019). Generalized Hamacher aggregation operators for intuitionistic uncertain linguistic sets: Multiple attribute group decision making methods. *Information, 10*(6), Article 206. https://doi.org/10.3390/info10060206
[20] Yanhong, L., Ambrin, R., Ibrar, M., & Ali Khan, M. (2022). Hamacher weighted aggregation operators based on picture cubic fuzzy sets and their application to group decision-making problems. *Security and Communication Networks, 2022*, Article 1651017. https://doi.org/10.1155/2022/1651017
[21] Pamučar, D. (2025). *Multiattributive decision making* [Unpublished book manuscript].
[22] Kreinovich, V. (2022). Ordered weighted averaging (OWA), decision making under uncertainty, and deep learning: How is this all related? *Information, 13*(2), Article 82. https://doi.org/10.3390/info13020082
[23] Chiclana, F., Herrera, F., & Herrera-Viedma, E. (2002). The ordered weighted geometric operator: Properties and application in MCDM problems. In *Studies in Fuzziness and Soft Computing* (Vol. 141, pp. 173–183). Springer. https://doi.org/10.1007/978-3-7908-1796-6_14
[24] Vatian, A., Gusarova, N., & Tomilov, I. (2025). Feature ranking on small samples: A Bayes-based approach. *Entropy, 27*(8), Article 773. https://doi.org/10.3390/e27080773
[25] Köppel, M., Segner, A., Wagener, M., Pensel, L., Karwath, A., & Kramer, S. (2025). Pairwise learning to rank by neural networks revisited: Reconstruction, theoretical analysis and practical performance. *Machine Learning, 114*(4), Article 112. https://doi.org/10.1007/s10994-024-06644-6
[26] Stević, Ž., Pamučar, D., Puška, A., & Chatterjee, P. (2020). Sustainable supplier selection in healthcare industries using a new MCDM method: Measurement of alternatives and ranking according to compromise solution (MARCOS). *Computers & Industrial Engineering, 140*, Article 106231. https://doi.org/10.1016/j.cie.2019.106231
[27] Radovanović, M., Jovčić, S., Petrovski, A., & Cirkin, E. (2025). Evaluation of university professors using the spherical fuzzy AHP and grey MARCOS multi-criteria decision-making model: A case study. *Spectrum of Decision Making and Applications, 2*(1), 197-217. https://doi.org/10.31181/sdmap21202518
[28] Zavadskas, E., Kaklauskas, A., & Šarka, V. (1994). The new method of multicriteria complex proportional assessment of projects. *Technological and Economic Development of Economy, 1*(3), 131–139.
[29] Biswas, A., Gazi, K. H., Bhaduri, P., & Mondal, S. P. (2024). Neutrosophic fuzzy decision-making framework for site selection. *Journal of Decision Analytics and Intelligent Computing, 4*(1), 187–215. https://doi.org/10.31181/jdaic10004122024b

[30] Zavadskas, E. K., & Turskis, Z. (2010). A new additive ratio assessment (ARAS) method in multicriteria decision-making. *Technological and Economic Development of Economy, 16*(2), 159–172. https://doi.org/10.3846/tede.2010.10

[31] Saha, A., & Chatterjee, P. (2025). A Fermatean fuzzy decision-making model for manufacturing outsourcing vendor selection: An improved combined compromise solution method. *Spectrum of Mechanical Engineering and Operational Research, 2*(1), 231-247. https://doi.org/10.31181/smeor21202544

[32] Yazdani, M., Zarate, P., Zavadskas, E. K., & Turskis, Z. (2019). A combined compromise solution (CoCoSo) method for multi-criteria decision-making problems. *Management Decision, 57*(9), 2501–2519. https://doi.org/10.1108/MD-05-2017-0458

[33] Mukherjee, A. K., Gazi, K. H., Raisa, N., Momena, A. F., Mukherjee, S. B., Sobczak, A., Salahshour, S., Mondal, S. P., & Ghosh, A. (2025). Review of alternative ranking methods in multi-criteria decision analysis based on WASPAS and CoCoSo methodologies. *Yugoslav Journal of Operations Research*. Advance online publication. https://doi.org/10.2298/YJOR241215037M

[34] Tešić, D. (2025). A machine learning and multi-criteria decision-making framework for student grade prediction. Smart Multi-Criteria Analytics and Reasoning Technologies, 1(1), 22-32. https://doi.org/10.65069/smart1120253

[35] Kaya, A., Gurler, H. E., Karyağdı, N. G., Özçalıcı, M., Akpınar, Y., Koca, N., & Pamucar, D. (2025). Decision-analytics-based enhancing auditor performance evaluation: Application of multi-criteria methodology with Monte Carlo simulation. *Expert Systems with Applications, 291*, Article 128561. https://doi.org/10.1016/j.eswa.2025.128561