A new approach to large-scale multi-criteria group decision-making based on the RANCOM method

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Abstract. This paper introduces a novel approach to large-scale group decision-making, addressing the challenge of effectively aggregating diverse expert opinions. By integrating the Ranking Comparison (RANCOM) method into the aggregation process, the approach minimizes the impact of individual inaccuracies on the final results. The study compares six aggregation techniques through simulation experiments and a practical case study on solar panel evaluation. Additionally, it proposes a new fuzzy ranking-based method for aggregating group results. The research highlights the importance of accounting for inaccuracies in individual assessments and subtle differences in expert opinions. Key contributions include an improved method for aggregating expert input and a robust framework for large-scale group decision-making, enhancing the reliability of outcomes in complex multi-criteria scenarios.

Keywords: large-scale group decision-making · multi-criteria analysis · judgment inaccuracy · expert knowledge

1 Introduction

Decision-making is a daily activity undertaken by individuals in various roles [14]. While some decisions carry minimal individual responsibility, others are critical to businesses or public institutions [9]. Multi-criteria problems introduce additional complexity due to conflicting objectives, making it difficult to evaluate alternatives using analytical skills alone. These situations often involve multiple decision-makers, requiring the integration of diverse perspectives [10]. Multi-Criteria Group Decision-Making (MCGDM) approaches offer structured and reliable methods for addressing such challenges [33], enabling the modeling of available information to generate solutions that reflect the collective expertise of the group.

MCGDM methods can be categorized based on the scale of their application. Conventional group decision-making typically involves up to 20 experts,

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whereas large-scale scenarios include 20 or more participants [20]. Incorporating multiple expert opinions enhances decision quality by reducing individual bias and increasing overall reliability [5]. However, a key challenge lies in reconciling differences in expert judgments [17]. To address this, MCGDM methods often utilize Multi-Criteria Decision Analysis (MCDA) techniques and aggregation procedures to achieve consensus among diverse viewpoints.

Effectively aggregating individual judgments is essential in group decision-making, especially when experts hold differing opinions [7]. Addressing inaccuracies in expert assessments is critical, as such errors can compromise the reliability of the final outcome [1]. Minimizing these inaccuracies is particularly important in large-scale group decision-making to ensure robust and trustworthy results. Aggregating input from a large group of experts involves trade-offs and requires careful validation of methods to ensure they accurately capture diverse perspectives [16]. Given the wide range of available approaches, research should focus on evaluating their effectiveness and their ability to reflect expert opinions with sensitivity to subtle differences.

In this paper, we propose a novel approach to large-scale group decision-making by incorporating the Ranking Comparison (RANCOM) method [27]. Numerical simulations were conducted with expert groups of varying sizes ($n = 30, 40, 50$) and differing levels of opinion divergence ($\varepsilon = 0.2, 0.5, 0.8$), comparing the effectiveness of six aggregation procedures. To reduce the impact of potential inaccuracies in individual assessments, the RANCOM method was integrated into the aggregation process. The approach was further validated through a practical case study involving the evaluation of solar panels for photovoltaic farms. Additionally, we introduced a fuzzy ranking-based aggregation method designed to capture nuanced differences in expert preferences. This study addresses key challenges in large-scale group decision-making, particularly those related to the accuracy of expert evaluations and the limitations of traditional aggregation methods. The main contributions of this work are:

- This study extends the RANCOM method for aggregating different expert opinions in large-scale group decision-making effectively.
- Comparative analysis of different aggregation procedures to verify the impact of selected approaches on the robustness of the results.
- A new group results aggregation procedure based on the fuzzy ranking concept was introduced.
- The RANCOM method was integrated into the proposed approach for large-scale group decision-making to minimize the risk of inaccuracy of expert judgments.

The rest of the paper is organized as follows. Section 2 presents the work related to large-scale group decision-making approaches. Section 3 describes the preliminaries of the RANCOM method and the fuzzy ranking aggregation procedure. Section 4 shows the study case with experiments directed toward the comparative analysis of different aggregation procedures and validation of the proposed approach within a practical problem from literature. Section 5 discusses

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the obtained results. Finally, Section 6 concludes the research and indicates future directions.

2 Related works

Multi-Criteria Group Decision-Making (MCGDM) methods are widely used to evaluate complex decision problems by leveraging knowledge from multiple experts [8]. MCGDM approaches can be categorized into standard group decision-making methods involving fewer than 20 experts and large-scale group decision-making methods, which involve more than 20 decision-makers [24]. Various techniques have been proposed to aggregate conflicting expert opinions [13]. Among them, average and geometric mean procedures are popular aggregation techniques [34]. Other approaches utilize fuzzy logic to identify fuzzy sets that represent group preferences, from which crisp values are derived and used in subsequent evaluation steps. Triangular Fuzzy Numbers (TFNs) are commonly applied in aggregation procedures [11], along with other fuzzy-based extensions [2, 23]. Furthermore, several compromise-based methods have been developed to facilitate consensus among conflicting expert preferences or resulting rankings, including Borda [3], rank position methods [3], Half-Quadratic (HQ)[15], and Iterative Compromise Ranking Analysis (ICRA)[19].

Moreover, group decision-making approaches often combine aggregation procedures with various Multi-Criteria Decision Analysis (MCDA) methods to evaluate the considered decision alternatives. Among the numerous developed MCDA techniques, methods such as the Best-Worst Method (BWM)[21], ELimination and Choice Expressing REality (ELECTRE)[2], VIseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR)[6], Technique for Order Preference by Similarity to Ideal Solution (TOPSIS)[36], and COmbinative Distance-based ASsessment (CODAS) [35], among others, have been widely integrated into group-based decision-making methodologies.

MCGDM methods have been applied to a wide range of practical decision problems. Tang and Liao proposed a multi-attribute large-scale group decision-making approach for evaluating circular economy initiatives [25]. Wan, Cheng, and Dong applied the MCGDM concept combined with probabilistic linguistic information to evaluate emergency assistance efforts during the COVID-19 pandemic [26]. Wu et al. utilized a group decision-making approach for portfolio allocation within an interval type-2 fuzzy environment [32]. Nikas, Doukas, and López developed a tool for assessing climate policy risk based on expert group knowledge [18]. These studies highlight the growing importance of group decision-making in addressing complex, multi-criteria problems with conflicting objectives, reinforcing the need to enhance the performance and reliability of methods in this field.

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3 Preliminaries

3.1 The Ranking Comparison method

The RANCOM method offers a novel approach to gathering expert knowledge while considering various decision factors [27]. Through a comparative examination against the Analytic Hierarchy Process (AHP) method, this method demonstrates superior ability in managing discrepancies within expert assessments. The RANCOM method has been applied to several practical problems within the MCDA field [12, 29, 30]. The formal notation and procedural steps of the weights calculation process are presented in [27].

3.2 Fuzzy ranking procedure

The fuzzy ranking concept introduces a novel method for achieving consensus among conflicting rankings [28]. It utilizes fuzzy sets to determine membership degrees, which represent the confidence in assigning specific rank positions to each alternative. The result is a two-dimensional matrix that captures the certainty of recommendations across different rankings, offering decision-makers deeper insights into the uncertainty and reliability of these positions. The formal definition of this matrix, illustrating the membership degrees, is provided in Equation (1).:

$$M = \begin{array}{c} \\ R_1 \\ R_2 \\ R_3 \\ \dots \\ R_m \end{array} \begin{array}{c} \begin{array}{ccccc} A_1 & A_2 & A_3 & \dots & A_m \end{array} \\ \begin{bmatrix} p_{11} & p_{21} & p_{31} & \dots & p_{m1} \\ p_{12} & p_{22} & p_{32} & \dots & p_{m2} \\ p_{13} & p_{23} & p_{33} & \dots & p_{m3} \\ \dots & \dots & \dots & \dots & \dots \\ p_{1m} & p_{2m} & p_{3m} & \dots & p_{mm} \end{bmatrix} \end{array} \tag{1}$$

where p_{ij} represents the frequency of placing $i-th$ alternative within $j-th$ position in ranking.

Furthermore, the matrix M must meet two essential conditions. The first condition ensures that the sum of values in each column equals 1, indicating comprehensive coverage of ranking positions for each alternative (2).

$$\sum_{i=1}^{m} p_{ci} = 1 \tag{2}$$

where c is the column index and m the number of alternatives. The second condition ensures that the sum of values in each row falls within the range [0, m], illustrating the frequency of placing alternatives across ranking positions (3).

$$0 < \sum_{i=1}^{m} p_{ir} < m \tag{3}$$

where r represents the rows' index from the matrix and m represents the number of alternatives.

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Based on the defined M matrix, the fuzzy ranking is established and can be expressed in two ways. The first notation denotes the membership degree (μ) of a given alternative (A_i) concerning ranking positions, defined as (4):

$$\mu_{A_i} = \left\{ \frac{p_{i1}}{R_1}, \frac{p_{i2}}{R_2}, \ldots, \frac{p_{ij}}{R_j}, \ldots, \frac{p_{im}}{R_m} \right\} \tag{4}$$

where A_i represents the i-th alternative, R_j the $j-th$ position, and m the number of alternatives. A higher value for a specific position indicates greater confidence in classifying the alternative there.

The second notation indicates the membership degree (μ) of a given position (R_i) concerning all analyzed alternatives and is defined as (5):

$$\mu_{R_i} = \left\{ \frac{p_{1i}}{A_1}, \frac{p_{2i}}{A_2}, \ldots, \frac{p_{ji}}{A_j}, \ldots, \frac{p_{mi}}{A_m} \right\} \tag{5}$$

where i represents the i-th rank position, A_j the $j - th$ alternative, and m the number of alternatives. A higher value indicates greater reliability in placing alternative A_j in the $i - th$ position.

These ranking representations provide decision-makers with insights into placing alternatives across positions or the likelihood of achieving a specific position, unlike conventional crisp rankings. Employing max normalization is recommended for enhanced stability and comparison, standardizing the fuzzy set within the range $[0, 1]$. The normalization procedure for alternative membership degrees to ranking positions is outlined as (6):

$$p_{ij} = \frac{p_{ij}}{\max p_j} \tag{6}$$

where i is the row index and j the column index in the M matrix. The formula to calculate the normalized ranking membership degree for all analyzed alternatives is presented as (7):

$$p_{ij} = \frac{p_{ij}}{\max p_i} \tag{7}$$

where i stands for the row index and j represents the column index in the M matrix. In this case, normalization should be done for each column.

After computing the fuzzy ranking for each alternative, the next step is to aggregate them into a consolidated ranking that represents the group's consensus. This process merges the individual fuzzy rankings into a single ranking that reflects the overall group preferences. The weighted rank is calculated by multiplying each row of the fuzzy ranking matrix by its corresponding position. This step is expressed in Equation (8):

$$\text{weighted\_rank}_j = \sum_{i=1}^{m} p_{ij} \cdot j \tag{8}$$

where i stands for the row index and j represents the column index in the M matrix.

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The obtained weighted values are then ranked to determine the final crisp positional ranking, where lower values correspond to better positions in the ranking.

4 Study case

The case study was divided into two stages to evaluate the performance of the proposed large-scale group decision-making method based on the RANCOM approach. The first stage involved simulation experiments that modeled varying numbers of experts and different levels of disagreement among their opinions. These simulations compared six selected methods for aggregating expert judgments, including the fuzzy ranking-based approach proposed in this study. The second stage focused on assessing the effectiveness of the proposed method in a practical decision-making scenario—evaluating solar panels for use in photovoltaic farms.

4.1 Simulations

In this study, we propose a large-scale group decision-making approach based on the RANCOM method, which is characterized by strong robustness to individual expert error. Integrating this method into the group decision-making process helps minimize the impact of inconsistent judgments from individual decision-makers, thereby enhancing the reliability and error tolerance of the evaluation procedure. Given the variety of existing approaches for aggregating expert preferences, the study compares six aggregation techniques. Three of these are based on aggregating the relevance rankings of weights, while the remaining three aggregate the actual criteria weights. The newly proposed fuzzy ranking-based aggregation method is compared with compromise-based approaches such as Borda and Rank Position, as well as with traditional aggregation techniques including the arithmetic mean, geometric mean, and TFNs operators. This comparative analysis aims to evaluate the effectiveness of each method in aggregating expert opinions within large-scale group decision-making contexts.

The performance of the proposed method was validated through a simulation-based study, modeling various group sizes and levels of expert opinion disagreement, represented by the parameter ε. Lower values of ε indicated greater alignment among expert opinions. The study considered three group sizes ($n \in 30, 40, 50$) and three levels of disagreement ($\varepsilon \in 0.2, 0.5, 0.8$), resulting in nine distinct test scenarios. Each scenario was evaluated over 1,000 iterations, using decision problems involving 10 alternatives and between 4 and 16 criteria. The complete set of simulations, including all implementation details and visualizations, has been made available in an open-access repository [31].

To illustrate the experimental modeling of expert opinions with varying levels of disagreement, Figure 1 presents the distribution of Weight Similarity Coefficient (WSC) correlation values [22] between experts for a group of 30 and 50 decision-makers, under two levels of disagreement ($\varepsilon = 0.2$ and $\varepsilon = 0.8$). The

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results show a clear distinction in correlation values depending on the degree of disagreement. Specifically, lower ε values result in higher similarity between expert weightings, while higher ε values reflect more diverse opinions. This confirms that the simulation scenarios effectively captured a range of realistic group decision-making situations, from highly consistent to significantly divergent expert judgments.

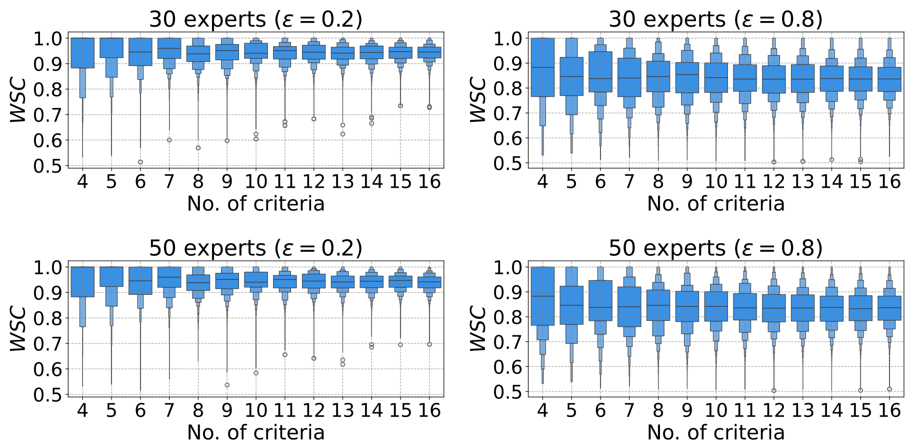

Fig. 1. Comparison of the distribution of Weights Similarity Coefficient (WSC) values for the groups including 30 and 50 experts and two levels of disagreement rates ($\varepsilon = 0.2$, $\varepsilon = 0.8$).

Based on the simulated expert assessments within the study group across 1,000 simulation runs, the criteria weights determined using the RANCOM method were aggregated using six selected techniques. Given the differing computational procedures and assumptions underlying these approaches, it was essential to examine how the aggregated weight vectors influenced the outcomes of the multi-criteria decision analysis. To this end, the resulting weight sets were applied within the TOPSIS method to generate recommendation rankings for the evaluated decision alternatives. For each simulation iteration, the Weighted Similarity (WS) rank coefficient was computed to assess the correlation between rankings obtained from the different aggregation methods. Finally, the average WS values were calculated across all iterations to evaluate the consistency and performance of each aggregation technique.

Figure 2 presents the average WS correlation values obtained for the test scenario involving 50 experts and two levels of opinion disagreement ($\varepsilon = 0.2$ and $\varepsilon = 0.8$). As observed, lower disagreement levels led to slightly higher average ranking correlations across the tested aggregation methods compared to scenarios with more divergent expert opinions. The proposed approach based on the fuzzy ranking concept exhibited slightly lower correlation values relative

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to the other methods. However, all methods achieved strong correlations, with values exceeding 0.80, indicating a high degree of similarity between the resulting rankings. It is noteworthy that the other aggregation techniques produced nearly identical average correlation values, suggesting minimal variation in the final rankings. This consistency implies that these methods, despite computational differences, may not contribute distinct insights to the group preference aggregation process. In contrast, the fuzzy ranking-based method, while still maintaining high correlation levels, demonstrated more noticeable variation in ranking similarity. This could indicate that the method incorporates additional information or captures nuanced differences more effectively, potentially enhancing the consensus-building process in group decision-making contexts.

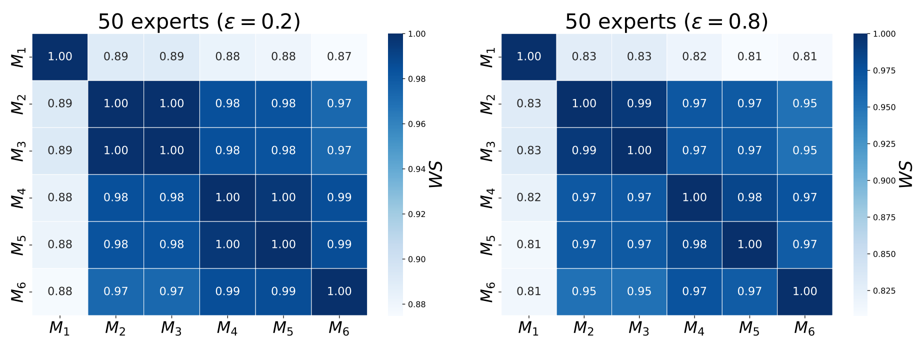

Fig. 2. Comparison of mean Weighted Similarity (WS) rank coefficient values for six selected group weights aggregation approaches and two disagreement levels of $\varepsilon = 0.2$ and $\varepsilon = 0.8$. (M_1: Fuzzy ranking, M_2: Rank position, M_3: Geometric mean, M_4: Borda, M_5: Average mean, M_6: Triangular Fuzzy)

Additional metrics were used in the simulation study to evaluate the accuracy of aggregated group weights in comparison to individual expert weights. Specifically, the Mean Absolute Error (MAE) and Mean Squared Error (MSE) were employed for this purpose. Figure 3 illustrates the distribution of MAE and MSE values for a test scenario involving 50 experts and a high disagreement level ($\varepsilon = 0.8$) across the analyzed aggregation techniques. The results indicate that as the number of criteria in the decision problem increased, the proposed fuzzy ranking-based approach consistently produced lower mean MAE values. The standard deviation of MAE remained comparable across the tested techniques, regardless of the number of criteria. Among all methods, the Triangular Fuzzy Numbers aggregation yielded the most consistent MAE values, showing the lowest variability. In comparison to the other techniques, the proposed method demonstrated values that were generally more aligned with the individual expert weights, especially when evaluated using the MAE metric. These findings suggest that while differences among the methods in terms of MSE

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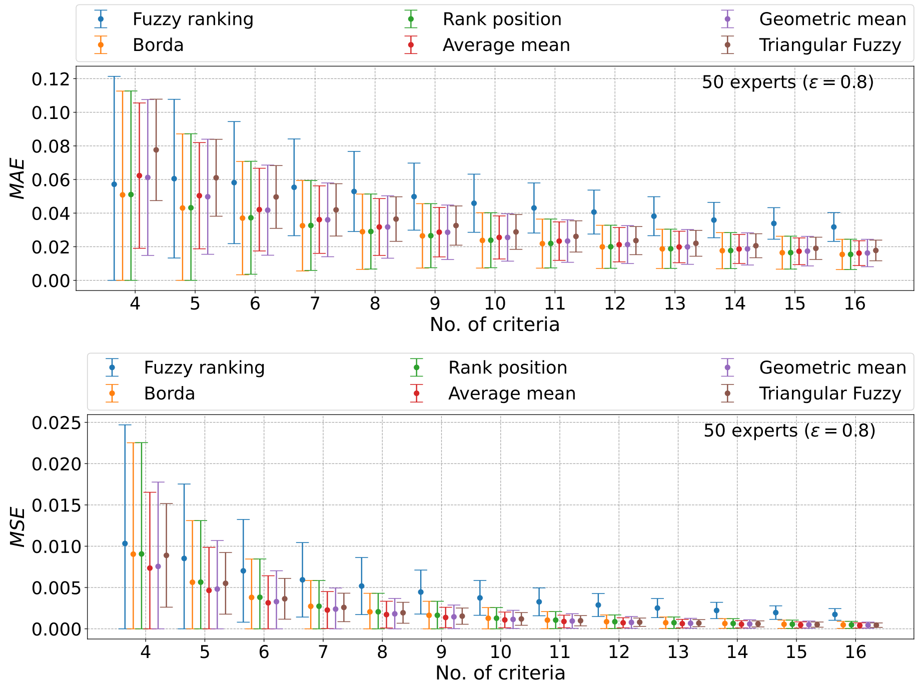

Fig. 3. Comparative analysis of Mean Absolute Error (MAE) and Mean Squared Error (MSE) values for 50 decision-makers and for six selected group weights aggregation procedures for the different number of criteria in the decision problem.

were not substantial enough to cause wide dispersion in values, the fuzzy ranking approach still provided a more accurate and stable representation of group preferences in the presence of significant opinion divergence.

The distribution of WSC values observed in the other analyzed test scenarios closely resembled the distributions shown in Figure 1. For the inconsistency level $\varepsilon = 0.5$, the mean WSC values ranged from 0.90 for problems with 4 criteria to 0.88 for problems with 16 criteria. In contrast, the mean WS correlation values between the rankings obtained using the analyzed group preference aggregation approaches remained relatively consistent across different expert group sizes and levels of disagreement. For simulations involving 30 experts, the mean correlation values were approximately 0.01 higher than those observed with 50 experts.

Differences in the mean and standard deviation distributions for the MAE metric were observed, varying according to the modeled level of disagreement among expert ratings. For $\varepsilon = 0.2$, the MAE values ranged between 0.00 and 0.06, regardless of the number of experts in the group. For $\varepsilon = 0.5$, the range widened slightly, with values between 0.00 and 0.10. In the case of the MSE metric, the values for $\varepsilon = 0.2$ ranged from 0.000 to 0.010, while for $\varepsilon = 0.5$, they extended from 0.000 to 0.020. Across all test scenarios, as the number of criteria

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in the decision problem increased, both MAE and MSE values decreased significantly. The full experimental implementations and accompanying visualizations are available in the open-access repository [31].

4.2 Practical problem

To verify the proposed approach of large-scale multi-criteria group decision-making based on the RANCOM method, the practical problem from the literature was selected. Bączkiewicz et al. addressed the problem of solar panel evaluation in [4]. The authors included 30 alternatives and 6 criteria in the decision problem. The set of criteria determined for the assessment purposes were open circuit voltage (C_1), short circuit current (C_2), module efficiency (C_3), peak power per m^2 (C_4), cost per m^2 (C_5), and weight per m^2 (C_6). The decision matrix and types of criteria used in the performed evaluation with the proposed approach were described by the authors in their work [4].

The decision problem was evaluated using the TOPSIS method for a group of 50 experts, with a disagreement level of $\varepsilon = 0.8$. The reference weights, which served as the basis for modeling expert behavior, were determined using the entropy method. For the group of 50 experts, the relevance of each criterion was assessed and aggregated to evaluate the correlation between the resulting values. The mean weight similarity coefficient was 0.87, with a standard deviation of 0.08.

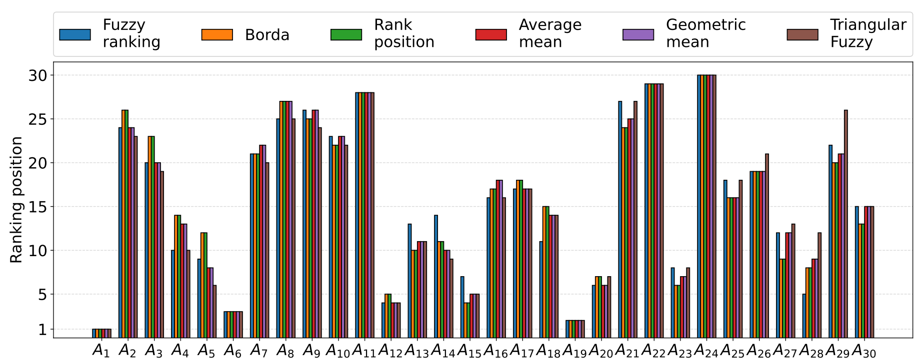

Fig. 4. Comparison of Weighted Spearman (r_W) coefficients values for six selected group weights aggregation approaches, disagreement level ε of 0.8 for the solar panels' evaluation.

Figure 4 presents the rankings of the evaluated solar panels, obtained using six different group aggregation techniques. Several differences were observed among the examined methods. For instance, while some solar panels consistently maintained their positions across all techniques, others exhibited significant variations in their rankings, depending on the aggregation approach used. This sug-

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gests that the choice of aggregation method can influence the final ranking order of the solar panels in the given problem. These discrepancies underscore the importance of carefully selecting an appropriate aggregation technique based on the specific characteristics of the decision-making context.

While some methods consistently rank selected solar panels in the same positions, others place them in different orders. In the top part of the ranking, the most significant discrepancy was observed for alternative A_{28}, which showed a five-position difference across the examined aggregation procedures. Additionally, alternatives A_2, A_{10}, A_{18}, A_{26}, and A_{29} exhibited a four-position difference among the aggregation methods. This variability suggests that depending on the chosen weights aggregation procedure, the order of alternatives in the ranking can differ significantly. Moreover, it highlights the sensitivity of the obtained results to the selected technique.

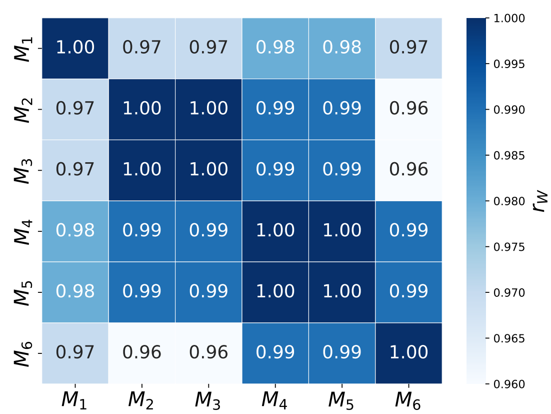

Fig. 5. Comparison of Weighted Spearman (r_W) coefficients values for six selected group weights aggregation approaches, disagreement level ε of 0.8 for the solar panels' evaluation. (M_1: Fuzzy ranking, M_2: Rank position, M_3: Geometric mean, M_4: Borda, M_5: Average mean, M_6: Triangular Fuzzy)

Figure 5 compares the Weighted Spearman (r_W) correlation coefficient values for the rankings shown in Figure 4. The results indicate that the obtained rankings are highly correlated, with r_W values exceeding the threshold of 0.96. Additionally, two pairs of methods (Borda and Rank Position, and Average Mean and Geometric Mean) produced identical rankings. This suggests that despite some variations in the rankings derived from the different weight aggregation methods, the results remain highly consistent in the context of the practical solar panel evaluation problem.

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5 Discussion

The study comprehensively examined the proposed large-scale group decision-making approach based on the RANCOM method through simulation experiments and a practical application in solar panel evaluation for photovoltaic farms. The simulations analyzed various group sizes and expert opinion disagreements, while the practical application validated the approach in a real-world decision-making scenario.

The simulation experiment demonstrated the robustness of the proposed approach in handling diverse expert opinions and aggregating them effectively. By comparing six aggregation techniques, including the new fuzzy ranking-based approach, the study showed the RANCOM-based group decision-making method's ability to reduce the impact of inconsistent judgments. Although variations in rankings were observed across different aggregation methods, the proposed approach consistently yielded reliable and robust results, effectively representing group preferences. The comparative analysis highlighted that depending on the aggregation method, the results could differ, but most techniques produced similar rankings. Minor differences were noted with the fuzzy ranking method, yet the rankings correlation calculated using the WS coefficient showed high similarity across different group sizes and disagreement rates. Despite slight ranking differences, the fuzzy ranking method demonstrated potential in enhancing consensus among differing expert opinions.

In the practical solar panel evaluation, the RANCOM-based approach proved effective in providing consistent and highly correlated rankings across different aggregation techniques. While minor discrepancies were seen in the r_W correlation values, the results remained highly similar, confirming the approach's robustness in real-world decision-making. The study highlighted the advantages of the large-scale group decision-making approach, offering a systematic and reliable framework for aggregating diverse expert opinions and fostering consensus in complex decisions. The method is promising for a wide range of applications, contributing to more informed and effective decision-making. By reducing individual inaccuracies in expert judgments, the RANCOM method enhances the reliability and credibility of aggregated decisions, making them more suitable for critical scenarios where accuracy and consistency are crucial.

While the RANCOM-based approach offers many strengths, it is important to recognize its limitations. It relies on assumptions that may not fully capture the complexities of real-world decision problems, potentially leading to biases or inaccuracies. The approach primarily focuses on aggregating expert opinions based on rankings of criteria weights, without considering factors like expertise level or expert credibility. Ignoring these factors could overlook valuable insights from more experienced experts, affecting decision quality. Addressing these limitations requires ongoing research to refine the approach and improve its performance in practical decision-making contexts.

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6 Conclusion

The proposed RANCOM-based approach to large-scale group decision-making shows promise in effectively aggregating different expert opinions and facilitating consensus building for varied preferences in complex decision-making problems. Through simulation experiments and a practical application in evaluating solar panels for photovoltaic farms, the approach demonstrated robustness and reliability in representing group preferences. Despite minor discrepancies observed across different aggregation techniques, the proposed group decision-making method provided highly correlated rankings, indicating its suitability for real-world decision-making scenarios. The proposed aggregation procedure based on the fuzzy ranking concept showed potential for capturing additional information about group preferences compared to the other techniques examined. This highlights the versatility and effectiveness of the RANCOM-based approach in enhancing consensus among differing expert opinions since the weights aggregation procedures could be integrated into the proposed method interchangeably.

For further research directions, it is worth considering comparing other aggregation procedures to examine whether obtained group criteria weights would differ significantly. Moreover, refining and optimizing the proposed aggregation procedure based on the fuzzy ranking concept would be meaningful to maximize its utility and applicability across various domains, ultimately enhancing the quality and reliability of group decision-making processes. The proposed group decision-making approach based on the RANCOM method should be compared to other methods that aggregate criteria weights based on expert knowledge.

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References

1. Abels, A., Lenaerts, T., Trianni, V., Nowé, A.: Dealing with expert bias in collective decision-making. Artificial Intelligence **320**, 103921 (2023)
2. Akram, M., Alsulami, S., Khan, A., Karaaslan, F.: Multi-criteria group decision-making using spherical fuzzy prioritized weighted aggregation operators. International Journal of Computational Intelligence Systems **13**(1), 1429–1446 (2020)
3. Altuntas, S., Dereli, T., Yilmaz, M.K.: Evaluation of excavator technologies: application of data fusion based MULTIMOORA methods. Journal of Civil Engineering and Management **21**(8), 977–997 (2015)
4. Bączkiewicz, A., Kizielewicz, B., Shekhovtsov, A., Yelmikheiev, M., Kozlov, V., Sałabun, W.: Comparative analysis of solar panels with determination of local significance levels of criteria using the MCDM methods resistant to the rank reversal phenomenon. Energies **14**(18), 5727 (2021)
5. Bang, D., Frith, C.D.: Making better decisions in groups. Royal Society open science **4**(8), 170193 (2017)

6. Çalı, S., Balaman, Ş.Y.: A novel outranking based multi criteria group decision making methodology integrating ELECTRE and VIKOR under intuitionistic fuzzy environment. Expert Systems with Applications **119**, 36–50 (2019)
7. Dong, Y., Li, Y., He, Y., Chen, X.: Preference–approval structures in group decision making: Axiomatic distance and aggregation. Decision Analysis **18**(4), 273–295 (2021)
8. García-Zamora, D., Labella, Á., Ding, W., Rodríguez, R.M., Martínez, L.: Large-scale group decision making: a systematic review and a critical analysis. IEEE/CAA Journal of Automatica Sinica **9**(6), 949–966 (2022)
9. Hartman, L.P., DesJardins, J., MacDonald, C.: Decision making for personal integrity & social responsibility. Business Ethics, McGraw Hill International, New York, NY10020 (2011)
10. Hwang, C.L., Lin, M.J.: Group decision making under multiple criteria: methods and applications, vol. 281. Springer Science & Business Media (2012)
11. Keršulienė, V., Turskis, Z.: An integrated multi-criteria group decision making process: selection of the chief accountant. Procedia-Social and Behavioral Sciences **110**, 897–904 (2014)
12. Korucuk, S., Aytekin, A.: A field study examining barriers to logistics 4.0 using polytopic fuzzy RANCOM. Journal of process management and new technologies **12**(3-4), 90–100 (2024)
13. Labella, Á., Liu, Y., Rodríguez, R., Martínez, L.: Analyzing the performance of classical consensus models in large scale group decision making: A comparative study. Applied Soft Computing **67**, 677–690 (2018)
14. Moe, N.B., Aurum, A., Dybå, T.: Challenges of shared decision-making: A multiple case study of agile software development. Information and Software Technology **54**(8), 853–865 (2012)
15. Mohammadi, M., Rezaei, J.: Ensemble ranking: Aggregation of rankings produced by different multi-criteria decision-making methods. Omega **96**, 102254 (2020)
16. del Moral, M.J., Chiclana, F., Tapia, J.M., Herrera-Viedma, E.: A comparative study on consensus measures in group decision making. International Journal of Intelligent Systems **33**(8), 1624–1638 (2018)
17. Mukherjee, N., Zabala, A., Huge, J., Nyumba, T.O., Adem Esmail, B., Sutherland, W.J.: Comparison of techniques for eliciting views and judgements in decision-making. Methods in Ecology and Evolution **9**(1), 54–63 (2018)
18. Nikas, A., Doukas, H., López, L.M.: A group decision making tool for assessing climate policy risks against multiple criteria. Heliyon **4**(3) (2018)
19. Paradowski, B., Kizielewicz, B., Shekhovtsov, A., Sałabun, W.: The Iterative Compromise Ranking Analysis (ICRA)-The New Approach to Make Reliable Decisions. In: Special Sessions in the Advances in Information Systems and Technologies Track of the Conference on Computer Science and Intelligence Systems. pp. 151–170. Springer (2022)
20. Rodríguez, R.M., Labella, Á., Nuñez-Cacho, P., Molina-Moreno, V., Martínez, L.: A comprehensive minimum cost consensus model for large scale group decision making for circular economy measurement. Technological Forecasting and Social Change **175**, 121391 (2022)
21. Safarzadeh, S., Khansefid, S., Rasti-Barzoki, M.: A group multi-criteria decision-making based on best-worst method. Computers & Industrial Engineering **126**, 111–121 (2018)
22. Shekhovtsov, A.: Evaluating the performance of subjective weighting methods for multi-criteria decision-making using a novel weights similarity coefficient. Procedia Computer Science **225**, 4785–4794 (2023)

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23. Sodenkamp, M.A., Tavana, M., Di Caprio, D.: An aggregation method for solving group multi-criteria decision-making problems with single-valued neutrosophic sets. Applied Soft Computing **71**, 715–727 (2018)
24. Tang, M., Liao, H.: From conventional group decision making to large-scale group decision making: What are the challenges and how to meet them in big data era? A state-of-the-art survey. Omega **100**, 102141 (2021)
25. Tang, M., Liao, H.: Multi-attribute large-scale group decision making with data mining and subgroup leaders: An application to the development of the circular economy. Technological Forecasting and Social Change **167**, 120719 (2021)
26. Wan, S.P., Cheng, W.B.H., Dong, J.Y.: Interactive multi-criteria group decision-making with probabilistic linguistic information for emergency assistance of COVID-19. Applied Soft Computing **107**, 107383 (2021)
27. Więckowski, J., Kizielewicz, B., Shekhovtsov, A., Sałabun, W.: RANCOM: A novel approach to identifying criteria relevance based on inaccuracy expert judgments. Engineering Applications of Artificial Intelligence **122**, 106114 (2023)
28. Więckowski, J., Sałabun, W.: Supporting multi-criteria decision-making processes with unknown criteria weights. Engineering Applications of Artificial Intelligence **140**, 109699 (2025)
29. Więckowski, J., Wątróbski, J., Sałabun, W.: Inaccuracies in expert judgment: Comparative analysis of RANCOM and AHP methods in housing location selection problem. IEEE Access (2024)
30. Więckowski, J., Wątróbski, J., Shkurina, A., Sałabun, W.: Adaptive multi-criteria decision making for electric vehicles: A hybrid approach based on RANCOM and ESP-SPOTIS. Artificial Intelligence Review **57**(10), 270 (2024)
31. Więckowski, J.: Group RANCOM simulation implementation and visualization. https://github.com/jwieckowski/research/tree/main/Group%20Rancom (2025), [Online; accessed 28-February-2025]
32. Wu, Q., Liu, X., Qin, J., Zhou, L.: Multi-criteria group decision-making for portfolio allocation with consensus reaching process under interval type-2 fuzzy environment. Information Sciences **570**, 668–688 (2021)
33. Xia, M., Chen, J.: Multi-criteria group decision making based on bilateral agreements. European Journal of Operational Research **240**(3), 756–764 (2015)
34. Xia, M., Xu, Z., Zhu, B.: Geometric Bonferroni means with their application in multi-criteria decision making. Knowledge-Based Systems **40**, 88–100 (2013)
35. Yeni, F.B., Özçelik, G.: Interval-valued Atanassov intuitionistic Fuzzy CODAS method for multi criteria group decision making problems. Group Decision and Negotiation **28**, 433–452 (2019)
36. Zhang, Z., Li, Z.: Consensus-based TOPSIS-Sort-B for multi-criteria sorting in the context of group decision-making. Annals of Operations Research **325**(2), 911–938 (2023)

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