Chapter 88

RADAR: Ranking based on distance and range for multi-attribute decision-making

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88.1 Introduction

Multicriteria decision-making methods can be characterized as a methodological framework designed to support the decision-making process in a mathematically grounded manner. A specific subset of these methods comprises multi-attribute decision-making (MADM) approaches, which are applied to discrete decision problems. Generally speaking, such problems involve a predefined set of feasible alternatives. In other words, the goal is to rank the available alternatives from the most to the least preferred. Additionally, MADM methods can be used for the selection of the best alternative or for classifying alternatives into predefined categories. The resolution of these problems is based on evaluating or comparing alternatives across multiple criteria or attributes. There is also a group of MADM methods specifically developed for determining the relative importance or weight of the evaluation criteria.

This chapter focuses on a method primarily intended for ranking a given set of alternatives based on a predefined set of attributes, the ranking based on distance and range (RADAR) method. Although a large number of MADM methods have been developed and extensively discussed in the literature with various, and in some cases similar, mathematical foundations—none can be considered universally perfect or applicable to every decision-making problem. Each method, including RADAR, has its own advantages and limitations.

Many commonly used MADM ranking methods tend to evaluate alternatives based strictly on their absolute performance with respect to each criterion. In certain decision contexts, such an approach may lead to misleading conclusions. For instance, an alternative that performs exceptionally well on a single, highly weighted criterion, but poorly on several less important ones—may still attain a high position in the overall ranking. In contrast, an alternative that performs consistently above average across most criteria, but without extreme values, may be ranked lower. While this type of outcome may be desirable in some cases, it can be problematic in others, particularly in fields such as risk assessment or reliability analysis.

To address this issue, the RADAR method, first published in (Komatina, 2024), was developed with the aim of finding a balance between alternatives that perform strongly on the most important criteria and those that demonstrate consistent performance across a broader set of attributes. In other words, RADAR relies on proportional relationships between alternative values within each criterion, taking into account the range of variation, thereby providing an opportunity for alternatives with stable, well-rounded performance to attain a favorable ranking.

This chapter, which introduces the fundamentals of the RADAR method, is organized into several sections. Following the introduction, Section 88.2 provides a brief literature overview. Section 88.3 outlines the main steps of the proposed methodology. Sections 88.4 and 88.5 are devoted to numerical case studies, while Section 88.6 presents a comparative analysis with other MADM approaches. The chapter concludes with final observations and recommendations.

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88.2 Literature review

RADAR, as one of the newer MADM methods, has so far been used in only a few scientific publications to solve decision-making problems and has been cited in several research and review papers. Although it was first introduced in (Komatina, 2024), a detailed presentation of the mathematical foundations and characteristics of the method was provided in (Komatina et al., 2026). The basic method, in combination with the best–worst method (BWM), was applied for equipment selection in the automotive industry (Komatina, 2025a).

So far, it has primarily been used in industrial contexts, most often in combination with failure mode and effect analysis (FMEA). For instance, in the paper where it was first mentioned, it was applied within the FMEA framework (Komatina, 2024) for prioritizing failure modes. To solve a similar problem, it was used in (Komatina et al., 2025), where the method was extended through the use of triangular fuzzy numbers. The same approach for modeling uncertainty, combined with the RADAR method, was also applied in (Komatina, 2025b) for assessing risks in football player transfers. In that study, the analytic hierarchy process was used to determine the weights of the criteria. The fuzzy RADAR method was also used in the study (Karjust et al., 2025), where the authors applied it to prioritize key performance indicators in small and medium-sized enterprises.

In the domain of personnel selection, specifically for choosing members of an FMEA team, it was employed in Komatina & Marinković (2025), where the basic RADAR method was extended by incorporating Pythagorean fuzzy numbers.

As a method used in the literature, it was mentioned in a review paper (Aleksić et al., 2025), while it was also highlighted as a potentially applicable method for solving future research problems in (Abdulvahitoğlu, 2025; Marinato et al., 2025), or listed as one of the approaches used in the literature in (Ecer et al., 2025; Mandal et al., 2025; Petrović, Jovanović et al., 2025; Petrović, Tadić et al., 2025; Sandra et al., 2025; Spasenić et al., 2025; Tadić et al., 2025; Więckowski & Sałabun, 2025). As a control method for determining the robustness of the proposed approach, it was applied in (Runic Ristic et al., 2025).

88.3 Methodology

This section presents the steps of the basic RADAR method. Any additional modification, such as RADAR II (Komatina et al., 2026), can be implemented by adjusting the normalization procedure, the method of weighting the values, the application of different approaches for modeling uncertainty, and so on.

In addition to outlining the steps and presenting them through formulas, a brief explanation and the significance of each step are provided. The explanations are adapted from (Komatina et al., 2026), where readers can find a detailed description and mathematical proof for each step.

The basic RADAR method is implemented through the following steps:

Let there be a defined set of alternatives $\{1, \ldots, i, \ldots, I\}$, which need to be evaluated and ranked according to a set of criteria $\{1, \ldots, j, \ldots, J\}$.

Step 1. Formation of the decision matrix:

$$[M_{ij}]_{I\times J}$$

Step 2. The maximum proportion matrix, α:

$$[a_{ij}]_{I\times J}$$

For the benefit-type of criteria:

$$a_{ij} = \frac{\frac{\max_i M_{ij}}{M_{ij}}}{\left(\left(\frac{\max_i M_{ij}}{M_{ij}}\right) + \left(\frac{M_{ij}}{\min_i M_{ij}}\right)\right)}$$

For the cost-type of criteria:

$$\alpha_{ij} = \frac{\frac{M_{ij}}{\min_i M_{ij}}}{\left(\left(\frac{\max_i M_{ij}}{M_{ij}}\right) + \left(\frac{M_{ij}}{\min_i M_{ij}}\right)\right)}$$

Step 3. The minimum proportion matrix, β:

$$[\beta_{ij}]_{I\times J}$$

For the benefit-type of criteria:

$$\beta_{ij} = \frac{\frac{M_{ij}}{\min\limits_i M_{ij}}}{\left(\left(\frac{\max\limits_i M_{ij}}{M_{ij}}\right) + \left(\frac{M_{ij}}{\min\limits_i M_{ij}}\right)\right)}$$

For the cost-type of criteria:

$$\beta_{ij} = \frac{\frac{\max\limits_i M_{ij}}{M_{ij}}}{\left(\left(\frac{\max\limits_i M_{ij}}{M_{ij}}\right) + \left(\frac{M_{ij}}{\min\limits_i M_{ij}}\right)\right)}$$

From the given information, the following rules can be concluded:

- a_{ij} for a benefit-type criterion is calculated in the same way as β_{ij} for a cost-type criterion. The reverse also holds.
- For every considered i, $i = 1, \ldots I$ evaluated according to any $j = 1, \ldots, J$, the following holds: $a_{ij} + \beta_{ij} = 1$.

Explanation: In the RADAR method, the normalization process is carried out in a dual manner, meaning that a single normalized value is not obtained. Instead, the normalized distance from both the maximum (a_{ij}) and minimum (b_{ij}) values of the alternatives within each criterion is calculated.

Step 4. The empty range matrix:

$$[E_{ij}]_{I\times J}$$

where

$$E_{ij} = |\alpha_{ij} - \beta_{ij}|$$

Explanation: The empty range matrix is the result of subtracting the values of the maximum and minimum proportion matrix. The values of this matrix are always within the range from 0 to 1.

Step 5. The relative relationship matrix:

$$[RR_{ij}]_{I\times J}$$

where:

$$RR_{ij} = \frac{\alpha_{ij}}{\beta_{ij} + E_{ij}}$$

Explanation: The relative relationship matrix, like the empty range matrix, falls within the range from 0 to 1. The importance of this step is to highlight alternatives that are above the relative average with respect to a given criterion, while treating those below the relative average equally. This step favors alternatives that demonstrate stable performance across a greater number of criteria.

Step 6. The weighted relative relationship matrix:

$$[WRR_{ij}]_{I\times J}$$

Where:

$$WRR_{ij} = RR_{ij} \cdot \omega_j$$

Explanation: The weighted relative relationship matrix is the step in which the weights of the considered criteria are taken into account. This adds a second dimension to the ranking of alternatives, amplifying the influence of alternatives that perform above average according to the most important criteria.

Step 7. The aggregated ranking index, RI_i:

$$RI_i = \frac{\min \sum_{j=1}^{J} WRR_i}{\sum_{j=1}^{J} WRR_i}$$

The values of RI_i need to be sorted in a nonincreasing order. The best alternative is the one with the highest RI_i value, which is always 1. The lowest-ranked alternative is the one with the smallest value of this coefficient.

88.4 Numerical example 1

A manufacturing company plans to acquire a new metal-cutting machine to improve the production process. There are a total of four options available on the market, which can be designated as alternatives, i, $i = 1, \ldots I$, where $I = 4$. The considered alternatives are evaluated and analyzed based on three criteria: cutting speed expressed in mm/min ($j = 1$), energy efficiency expressed as the number of meters cut per kWh ($j = 2$), and the machine price expressed in euros ($j = 3$). The first two criteria are benefit-type criteria, while the third is a cost-type criterion. Let the company management consider the criterion weights as $\omega_1 = 0.4$, $\omega_2 = 0.25$, and $\omega_3 = 0.35$. The decision matrix, that is, the input data, is given in Table 88.1.

After the decision matrix, which represents the first step in applying the RADAR method, the second and third steps involve calculating the elements of the maximum and minimum proportion matrices, as shown in Tables 88.2 and 88.3.

An example of calculating a single element of the maximum and minimum proportion matrix:

$$a_{11} = \frac{\frac{1300}{1250}}{\left(\left(\frac{1300}{1250}\right) + \left(\frac{1250}{1100}\right)\right)} = 0.478 \quad \beta_{11} = \frac{\frac{1250}{1100}}{\left(\left(\frac{1300}{1250}\right) + \left(\frac{1250}{1100}\right)\right)} = 0.522$$

In Step 4, the empty range matrix is calculated, as presented in Table 88.4.

TABLE 88.1 Decision matrix.

	$j = 1$	$j = 2$	$j = 3$
$i = 1$	1250	45	85000
$i = 2$	1300	42	89000
$i = 3$	1100	48	79000
$i = 4$	1250	51	88000

TABLE 88.2 Maximum proportion matrix.

	$j = 1$	$j = 2$	$j = 3$
$i = 1$	0.478	0.514	0.507
$i = 2$	0.458	0.548	0.530
$i = 3$	0.542	0.482	0.470
$i = 4$	0.478	0.452	0.524

TABLE 88.3 Minimum proportion matrix.

	$j = 1$	$j = 2$	$j = 3$
$i = 1$	0.522	0.486	0.493
$i = 2$	0.542	0.452	0.470
$i = 3$	0.458	0.518	0.530
$i = 4$	0.522	0.548	0.476

TABLE 88.4 Empty range matrix.

	$j = 1$	$j = 2$	$j = 3$
$i = 1$	0.044	0.028	0.014
$i = 2$	0.083	0.097	0.060
$i = 3$	0.083	0.036	0.060
$i = 4$	0.044	0.097	0.048

An example of calculating the first element of the empty range matrix:

$$E_{11} = |0.478 - 0.522| = 0.044$$

In Steps 5 and 6, the elements of the relative relationship matrix and the weighted relative relationship matrix are calculated, as shown in Tables 88.5 and 88.6.

The following section provides an example of calculating one element of the relative relationship matrix and one element of the weighted relative relationship matrix:

$$RR_{11} = \frac{0.478}{0.522 + 0.044} = 0.844 \quad WRR_{11} = 0.844 \cdot 0.4 = 0.337$$

In Table 88.7, according to Step 7 of the RADAR method application, the aggregated ranking index has been calculated and presented.

The first step in calculating the aggregated ranking index is to sum all WRR_{ij} values of the alternative across all criteria:

$$\sum_{j=1}^{J} WRR_1 = 0.337 + 0.250 + 0.350 = 0.937 \quad \sum_{j=1}^{J} WRR_2 = 0.293 + 0.250 + 0.350 = 0.893$$

$$\sum_{j=1}^{J} WRR_3 = 0.400 + 0.217 + 0.279 = 0.896 \quad \sum_{j=1}^{J} WRR_4 = 0.337 + 0.175 + 0.350 = 0.862$$

Then, the formula from the seventh step is applied:

$$RI_1 = \frac{0.862}{0.937} = 0.920 \quad RI_2 = \frac{0.862}{0.893} = 0.965$$

$$RI_3 = \frac{0.862}{0.896} = 0.962 \quad RI_4 = \frac{0.862}{0.862} = 1.000$$

TABLE 88.5 Relative relationship matrix.

	$j = 1$	$j = 2$	$j = 3$
$i = 1$	0.844	1.000	1.000
$i = 2$	0.733	1.000	1.000
$i = 3$	1.000	0.869	0.798
$i = 4$	0.844	0.700	1.000

TABLE 88.6 Weighted relative relationship matrix.

	$j = 1$	$j = 2$	$j = 3$
$i = 1$	0.337	0.250	0.350
$i = 2$	0.293	0.250	0.350
$i = 3$	0.400	0.217	0.279
$i = 4$	0.337	0.175	0.350

TABLE 88.7 The aggregated ranking index.

	$\sum_{j=1}^{J} WRR_i$	Ranking index	Rank
$i = 1$	0.937	0.920	4
$i = 2$	0.893	0.965	2
$i = 3$	0.896	0.962	3
$i = 4$	0.862	1.000	1

After that, the RI_i values are sorted in descending order to obtain the final ranking of the alternatives.

By applying the RADAR method, it was determined that the machine labeled as alternative $i = 4$ is the most suitable solution. A deeper analysis reveals that this alternative ranks second according to the most important criterion, ranks first according to the second criterion (which is the least important), and ranks second or third according to the third criterion, which is slightly less important than the most important one.

The alternative ranked second is $i = 2$. While it ranks first according to the most important criterion, it ranks last for the other two criteria. Out of the two conditions—extreme values for the most important criterion and stability across all criteria—only the first one is satisfied.

Alternative $i = 3$ is in third place. Although it performs worst with respect to the most important criterion, it performs best on the third criterion, which is only slightly less important than the first. For the second, least important criterion, it ranks second.

The last-ranked alternative is $i = 1$. This alternative is not the best according to any of the criteria. It shares second and third place for the first criterion, ranks third for the second, and second for the third. Therefore, it can be said that this alternative shows stability across two criteria, but it is not particularly strong in any of them to stand out as a leading option.

It should be emphasized that the differences between the values of the alternatives for each considered criterion are relatively small, that is, there is only a slight deviation between their values. Therefore, a sensitivity analysis will be conducted to examine how changes in weights affect the ranking of alternatives.

88.5 Numerical example 2

A company engaged in the sale and distribution of home appliances intends to purchase new delivery vehicles. Based on the company's budget and operational needs, a total of seven vehicle models have been shortlisted, denoted as alternatives, i, $i = 1, \ldots I$, where $I = 7$. The management evaluates the considered alternatives according to seven criteria: vehicle payload expressed in kilograms ($j = 1$), esthetic impression rated on a scale from 1 to 10 (assessed by multiple management members) ($j = 2$), fuel consumption expressed in liters per 100 km ($j = 3$), estimated annual maintenance costs expressed in euros ($j = 4$), volume of cargo space expressed in cubic meters ($j = 5$), driver comfort rated on a scale from 1 to 10 (evaluated by multiple drivers) ($j = 6$), and vehicle price expressed in euros ($j = 7$). The criteria $j = \{1, 2, 5, 6\}$ are benefit-type criteria, while the criteria $j = \{3, 4, 7\}$ are cost-type criteria. Let the company management consider the criterion weights as $\omega_1 = 0.18$, $\omega_2 = 0.07$, $\omega_3 = 0.17$, $\omega_4 = 0.13$, $\omega_5 = 0.12$, $\omega_6 = 0.08$, and $\omega_7 = 0.25$. The decision matrix is given in Table 88.8.

In the second and third steps, the elements of the maximum and minimum proportion matrices are determined (see Tables 88.9 and 88.10).

In fourth step, the empty range matrix is calculated, as presented in Table 88.11.

In Steps 5 and 6, the elements of the relative relationship matrix and the weighted relative relationship matrix are calculated, as shown in Tables 88.12 and 88.13.

In Table 88.14, according to Step 7 of the RADAR method application, the aggregated ranking index has been calculated and presented.

Based on the application of the RADAR method, alternative $i = 6$ was ranked first. It performs best according to the most important criterion $j = 7$, and is also the best with respect to criterion $j = 4$, which ranks fourth in importance. It holds second place for criterion $j = 3$, the third most important one. Although it performs below average for the remaining criteria, two of these four have very low, almost negligible importance.

TABLE 88.8 Decision matrix.

	$j = 1$	$j = 2$	$j = 3$	$j = 4$	$j = 5$	$j = 6$	$j = 7$
$i = 1$	1300	7.67	7.8	950	9	8.33	35000
$i = 2$	1250	7.33	7.4	880	8.5	6.67	32000
$i = 3$	1350	9.00	8.1	1000	10.5	9.33	42000
$i = 4$	1200	5.67	7.1	870	8	5.00	30000
$i = 5$	1320	8.00	7.6	920	9.8	7.00	38000
$i = 6$	1180	6.67	7.3	850	7.5	6.33	29000
$i = 7$	1400	6.67	8.3	1050	11	6.67	40000

TABLE 88.9 Maximum proportion matrix.

	$j = 1$	$j = 2$	$j = 3$	$j = 4$	$j = 5$	$j = 6$	$j = 7$
$i = 1$	0.494	0.465	0.508	0.503	0.505	0.402	0.501
$i = 2$	0.514	0.487	0.482	0.465	0.533	0.512	0.457
$i = 3$	0.475	0.387	0.527	0.528	0.428	0.349	0.592
$i = 4$	0.534	0.613	0.461	0.459	0.563	0.651	0.425
$i = 5$	0.487	0.444	0.495	0.487	0.462	0.488	0.542
$i = 6$	0.543	0.534	0.475	0.447	0.595	0.538	0.408
$i = 7$	0.457	0.534	0.539	0.553	0.405	0.512	0.568

TABLE 88.10 Minimum proportion matrix.

	$j = 1$	$j = 2$	$j = 3$	$j = 4$	$j = 5$	$j = 6$	$j = 7$
$i = 1$	0.506	0.535	0.492	0.497	0.495	0.598	0.499
$i = 2$	0.486	0.513	0.518	0.535	0.467	0.488	0.543
$i = 3$	0.525	0.613	0.473	0.472	0.572	0.651	0.408
$i = 4$	0.466	0.387	0.539	0.541	0.437	0.349	0.575
$i = 5$	0.513	0.556	0.505	0.513	0.538	0.512	0.458
$i = 6$	0.457	0.466	0.525	0.553	0.405	0.462	0.592
$i = 7$	0.543	0.466	0.461	0.447	0.595	0.488	0.432

TABLE 88.11 Empty range matrix.

	$j = 1$	$j = 2$	$j = 3$	$j = 4$	$j = 5$	$j = 6$	$j = 7$
$i = 1$	0.011	0.071	0.016	0.006	0.009	0.196	0.003
$i = 2$	0.028	0.026	0.037	0.071	0.066	0.024	0.087
$i = 3$	0.049	0.227	0.054	0.057	0.144	0.302	0.183
$i = 4$	0.069	0.227	0.078	0.082	0.126	0.302	0.150
$i = 5$	0.027	0.113	0.010	0.027	0.076	0.025	0.085
$i = 6$	0.085	0.068	0.050	0.105	0.189	0.076	0.183
$i = 7$	0.085	0.068	0.078	0.105	0.189	0.024	0.136

TABLE 88.12 Relative relationship matrix.

	$j = 1$	$j = 2$	$j = 3$	$j = 4$	$j = 5$	$j = 6$	$j = 7$
$i = 1$	0.956	0.766	1.000	1.000	1.000	0.506	1.000
$i = 2$	1.000	0.904	0.868	0.766	1.000	1.000	0.725
$i = 3$	0.829	0.460	1.000	1.000	0.598	0.366	1.000
$i = 4$	1.000	1.000	0.747	0.736	1.000	1.000	0.586
$i = 5$	0.901	0.663	0.961	0.902	0.753	0.908	1.000
$i = 6$	1.000	1.000	0.825	0.680	1.000	1.000	0.527
$i = 7$	0.728	1.000	1.000	1.000	0.517	1.000	1.000

TABLE 88.13 Weighted relative relationship matrix.

	$j = 1$	$j = 2$	$j = 3$	$j = 4$	$j = 5$	$j = 6$	$j = 7$
$i = 1$	0.172	0.054	0.170	0.130	0.120	0.041	0.250
$i = 2$	0.180	0.063	0.148	0.100	0.120	0.080	0.181
$i = 3$	0.149	0.032	0.170	0.130	0.072	0.029	0.250
$i = 4$	0.180	0.070	0.127	0.096	0.120	0.080	0.146
$i = 5$	0.162	0.046	0.163	0.117	0.090	0.073	0.250
$i = 6$	0.180	0.070	0.140	0.088	0.120	0.080	0.132
$i = 7$	0.131	0.070	0.170	0.130	0.062	0.080	0.250

TABLE 88.14 The aggregated ranking index.

	$\sum_{j=1}^{J} WRR_i$	Ranking index	Rank
$i = 1$	0.936	0.866	7
$i = 2$	0.872	0.930	4
$i = 3$	0.832	0.974	3
$i = 4$	0.819	0.989	2
$i = 5$	0.902	0.898	6
$i = 6$	0.811	1.000	1
$i = 7$	0.893	0.907	5

The second-ranked alternative is $i = 4$. This alternative performs best for criterion $j = 3$ and ranks second for the most important criterion $j = 7$, as well as for the third most important criterion $j = 4$. For the remaining criteria, it ranks either second-to-last or last.

The lowest-ranked alternative is $i = 1$. For as many as five criteria, this alternative does not appear among the top three (i.e., not in the upper half of the ranking). It holds second and third place only for criteria $j = 6$ and $j = 2$, respectively. It is important to note that these two criteria are the least important and have very little influence.

Additional explanation of the obtained ranking in this example, as well as in the numerical example 1, will be provided through a comparative analysis with other MADM methods.

88.6 Comparative and sensitivity analysis

In this section, a comparative analysis was conducted between the results obtained using the RADAR method and those derived from the application of the technique for order of preference by similarity to ideal solution (TOPSIS) (Hwang & Yoon, 1981) and elimination and choice translating reality (ÉLimination Et Choix Traduisant la REalité [ELECTRE]) (Roy, 1968) methods on the same numerical examples.

In addition to being two of the most widely used and well-established MADM methods in the literature, TOPSIS and ELECTRE are based on fundamentally different mathematical principles. The RADAR method combines certain characteristics of TOPSIS, which represents a compensatory type of method, with features of ELECTRE, which belongs to the noncompensatory category. For example, the use of proportional matrices in RADAR aligns with the logic of TOPSIS, as it involves measuring the distance from the best and worst possible solutions. On the other hand, dual normalization, relative dominance of alternatives within each criterion, and the "penalization" of poorly performing alternatives reflect principles found in ELECTRE. For this reason, comparing the results obtained using these three methods on the same numerical examples is particularly insightful.

In addition to the comparative analysis, this section also includes a sensitivity analysis conducted by varying the criteria weights. The comparative analysis is presented in Subsection 88.6.1, while the sensitivity analysis is provided in Subsection 88.6.2.

88.6.1 Comparative analysis

The first comparison of the obtained rankings using the RADAR, TOPSIS, and ELECTRE methods was conducted on numerical example 1. The results obtained by applying these three methods are presented in Table 88.15.

Based on the insights from Table 88.15, it is evident that alternative $i = 4$ is ranked as the best by all three considered methods. This is primarily due to its relatively stable performance across all criteria—it is not ranked last according to any of them.

The most significant difference in this example lies in the ranking of alternatives $i = 1$ and $i = 2$. ELECTRE places them in a tie for second and third place, whereas RADAR and TOPSIS reverse their positions—placing one in second and the other in fourth place. This discrepancy occurs because TOPSIS is a compensatory method, allowing alternative $i = 1$ to be ranked second even though it is not the best in any single criterion.

In contrast, RADAR penalizes alternative $i = 1$ for not being particularly strong in any criterion, especially since it is only tied for second/third place with respect to the most important one. In this case, RADAR favors $i = 2$ because it performs best on the most important criterion, even though it performs worst on the other two. Nevertheless, being the best on the most important criterion was not sufficient for it to achieve the top overall ranking.

Another notable difference in this example is that ELECTRE ranks alternative $i = 3$ last. Apparently, the fact that it performs worst on the most important criterion is considered a significant "penalty" by the ELECTRE method.

Of course, the results should be interpreted with caution, as even small changes in the criterion weights or the decision matrix elements can affect the final ranking. When it comes to numerical example 2, Table 88.16 presents the ranking results obtained by applying the three methods. What follows is an explanation of the results.

As in numerical example 1, in this case as well, one alternative is ranked the best by all three methods ($i = 6$). In fact, this alternative holds the first position for the most important criterion, and ranks first and second in two other important criteria (as explained in Section 88.5). Since all three methods are in agreement on this matter, there is no need for further discussion regarding the position of this alternative.

Significant discrepancies in the results can be observed for several alternatives. First, for alternative $i = 1$, RADAR penalizes it due to its instability. It performs below average in five criteria, which is why it is placed at the very bottom of the ranking. On the other hand, TOPSIS allows for compensation, and good results in the remaining criteria help this

TABLE 88.15 Ranking results for numerical example 1 using RADAR, TOPSIS, and ELECTRE.

	RADAR	TOPSIS	ELECTRE
$i = 1$	4	2	2–3
$i = 2$	2	4	2–3
$i = 3$	3	3	4
$i = 4$	1	1	1

TABLE 88.16 Ranking results for numerical example 2 using RADAR, TOPSIS, and ELECTRE.

	RADAR	TOPSIS	ELECTRE
$i = 1$	7	3	5–6
$i = 2$	4	2	2
$i = 3$	3	4	5–6
$i = 4$	2	6	3–4
$i = 5$	6	5	3–4
$i = 6$	1	1	1
$i = 7$	5	7	7

alternative achieve a better overall rank. Finally, ELECTRE places it around fifth or sixth, as a kind of compromise—acknowledging its strong performance, but mostly in less important criteria.

A major difference is also seen with alternative $i = 4$. RADAR ranks it second, because it is second in the most important criterion and performs well in two other important ones (as also explained in Section 88.5). TOPSIS places it next to last, as it ranks last or second to last in four criteria—one of which is the second most important. ELECTRE recognizes this alternative's dominance, especially in the most important criterion and two others, and thus positions it in the middle of the ranking, around third or fourth place.

Aside from some smaller variations (by one or possibly two positions), there is also a notable discrepancy in the case of alternative $i = 7$. TOPSIS and ELECTRE both place it last, while RADAR ranks it fifth. Although it performs below the relative average in five criteria, it is ranked first in the second most important criterion and in one other. According to RADAR's logic, this was enough to move it from the last to the fifth position.

Thus, it can be concluded that the differences in the mathematical basis and the underlying logic of various MADM methods may lead to different rankings of alternatives. For this reason, a good strategy is to apply multiple methods and seek a compromise solution. Comparative analysis, such as the one presented in this section, enables decision-makers to view the problem from multiple perspectives, allowing them to conduct a better analysis before making a final decision.

88.6.2 Sensitivity analysis

In this subsection, a sensitivity analysis of the obtained solution using the RADAR method was conducted. The aim is to determine how changes in the criteria weights affect potential changes in the ranking of alternatives. Table 88.17 presents numerical example 1 with three new variants of weight values, in which the weight of criterion $j = 1$ is gradually decreased, while the weight of criterion $j = 2$ is increased.

TABLE 88.17 Sensitivity analysis of numerical example 1—gradual decrease of ω_1 and increase of ω_2.

	0.4; 0.25; 0.35	**0.35; 0.3; 0.35**	**0.3; 0.35; 0.35**	**0.25; 0.4; 0.35**
$i = 1$	4	4	4	4
$i = 2$	2	3	3	3
$i = 3$	3	2	2	2
$i = 4$	1	1	1	1

TABLE 88.18 Sensitivity analysis of numerical example 1—gradual decrease of ω_2 and increase of ω_3

	0.25; 0.4; 0.35	**0.25; 0.35; 0.4**	**0.25; 0.3; 0.45**	**0.25; 0.25; 0.5**
$i = 1$	4	4	4	4
$i = 2$	3	3	3	3
$i = 3$	2	2	1	1
$i = 4$	1	1	2	2

Table 88.17 shows that the only change observed across the three newly considered scenarios is the swap between the second and third positions in the ranking. By increasing the value of ω_2 and simultaneously decreasing ω_1, alternative $i = 3$ moved to second place, while $i = 2$ dropped to third. This occurred because alternative $i = 3$ had performed poorly according to the most important criterion, ω_1, but was ranked highly for the other two criteria. As the importance of this criterion decreased, this alternative gained the opportunity to improve its ranking position.

Now, we can focus on the current set of weights (the last scenario): $\omega_1 = 0.25$, $\omega_2 = 0.4$, and $\omega_3 = 0.35$, and gradually decrease the weight of the criterion $i = 2$ while increasing the weight of the criterion $i = 3$ (Table 88.18).

In the first change of criteria weights, there was no alteration in the ranking of alternatives. With the second change, it is observed that the top two alternatives switched places. Alternative $i = 3$ became the top-ranked option because criterion $j = 3$, in which this alternative performs best, became extremely important. Additionally, this alternative ranks second with respect to criterion $j = 2$, which at this point is the second most important criterion. In the final weight adjustment, the ranking remained unchanged, as the first two criteria combined were now equally important as the third criterion, according to which this alternative performs best.

Considering that numerical example 2 has seven criteria, and it is very difficult to closely follow the changes, as was the case with numerical example 1, the sensitivity analysis in this case will be conducted by swapping the weights of the most important and the least important criteria. Thus, $\omega_7 = 0.25$ will now be $\omega_7 = 0.07$, while $\omega_2 = 0.07$ will now be $\omega_2 = 0.25$. The ranking results for these two scenarios are presented in Table 88.19.

Following the aforementioned change in criterion weights, where the most important criterion becomes the least important and vice versa, slight but, in some cases, drastic changes occurred. For alternatives $i = \{1,3,4,7\}$, these changes are reflected in a shift of two positions (either an improvement or a decline). For alternatives $i = 1$ and $i = 7$, these changes were positive, as both alternatives perform better with respect to criterion $j = 2$, which is the most important one in the second scenario.

Furthermore, alternative $i = 3$ jumped from third to first place in the ranking. Simply put, this alternative performs best according to the most important criterion in the second scenario and also ranks highly in three other criteria, including second place with respect to the second most important criterion. In contrast, alternative $i = 4$ dropped from second to fourth place. The main reason lies in the fact that it now ranks last with respect to the most important criterion.

TABLE 88.19 Ranking results after the weight swap between the most and the least important criteria in numerical example 2.

	$\omega_2 = 0.07; \omega_7 = 0.25$	$\omega_2 = 0.25; \omega_7 = 0.07$
$i = 1$	7	5
$i = 2$	4	7
$i = 3$	3	1
$i = 4$	2	4
$i = 5$	6	2
$i = 6$	1	6
$i = 7$	5	3

Alternative $i = 2$ worsened its ranking by three positions, falling from fourth to seventh place. This change occurred because in the first scenario it was ranked third according to the most important criterion, whereas now it is ranked fourth (below the relative average).

Besides these "minor" changes, there were also two drastic shifts in ranking. Alternative $i = 5$ jumped from sixth to second place. In the first scenario, it was fifth with respect to the most important criterion, whereas now it ranks second. Conversely, alternative $i = 6$ significantly dropped in ranking, falling from first to sixth place. This occurred because it was ranked first according to the most important criterion in the first scenario, but now ranks fifth.

88.7 Conclusions

This chapter presented the main characteristics and the application procedure of the RADAR method. The method was illustrated through two numerical examples, and the obtained results were compared with two well-known and reliable methods that are based on different mathematical principles and decision-making logic—TOPSIS and ELECTRE. In addition, a sensitivity analysis of the results was conducted by varying the weights of the criteria.

Through comparison with TOPSIS and ELECTRE, it was shown that these methods were in complete agreement regarding the alternatives that were ranked the highest. However, each method produced slightly different results due to their distinct decision-making logic. In some cases, the results obtained using the RADAR method were more aligned with those from TOPSIS, while in other cases, they were more similar to the results from ELECTRE. As previously mentioned, this is because RADAR combines certain elements of both compensatory and noncompensatory MADM methods. For this reason, in some situations, TOPSIS and ELECTRE may assign the same rank to a particular alternative, while RADAR positions the same alternative noticeably higher or lower in the ranking.

The sensitivity analysis showed that RADAR is responsive to changes in the weights of the criteria, especially in cases where the weights of the most and the least important criteria are swapped. In this way, the method proved to be reliable, as it reacts to changes in the ranking of alternatives in accordance with decision-making logic. Furthermore, it can be said that the method does not automatically favor alternatives with high numerical values, but rather responds dynamically to changes in criterion importance.

The method clearly identifies the weaknesses of alternatives with respect to the most important criteria and does not easily allow for compensation through less important ones. Additionally, it provides an opportunity for alternatives that demonstrate stable performance across multiple, particularly important, criteria to achieve a higher rank.

Based on all the above, it can be concluded that RADAR can serve as a reliable decision-making tool, but care should be taken in choosing the appropriate context for its application. After all, the same holds true for any other MADM method. Ultimately, it is up to the decision-makers to assess which method to use in a given situation or whether to apply multiple methods in order to analyze the problem from different perspectives.

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