Towards Sustainable Decision Making: New Reference Point-Based MCDA Method

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Abstract. Sustainable decision making is a multi-criteria decision analysis (MCDA) problem, often requiring the evaluation of numerous alternatives based on conflicting criteria. Many traditional MCDA methods rely on synthetic ideal and anti-ideal solutions, which may not align with the preferences of decision-makers who simply wish to replace a broken device with a similar one. In this paper, we propose a novel MCDA approach, which ranks alternatives based on their proximity to a reference model target solution, representing the user's preferred characteristics. This method is particularly useful in cases where the decision-maker has prior experience with a product and seeks a comparable replacement. We demonstrate its effectiveness through a case study on washing machine selection. Our findings highlight the practical advantages of the proposed approach over conventional MCDA techniques, offering a more intuitive and user-centered decision process.

Keywords: multi-criteria decision analysis (MCDA) · reference model · decision support systems · Euclidean distance

1 Introduction

The home appliance sector, encompassing household electrical and mechanical devices, is a multi-billion-dollar industry. Global retail sales reached approximately 670 billion U.S. dollars in 2024, with projections exceeding 800 billion dollars by 2028 [14]. However, with the growing complexity of modern appliances, breakdowns have become increasingly common. A 2022 study by Allstate Protection Plans [1] revealed that over 40% of American homeowners experienced a major appliance failure in the past year, with washing machines (29%) being the most frequently affected.

When an essential home appliance fails, consumers are typically under time pressure to replace it quickly. On average, homeowners purchase a replacement within 10.9 days, leaving little time for extensive research and comparison [1].

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Adding to this challenge, modern appliances have shorter lifespans, and manufacturers frequently discontinue models within just a few years [10]. As a result, even if a homeowner was satisfied with their previous appliance, repurchasing the same model is often impossible. A quick search for a washing machine on a Polish online electronics store[4] returns over 450 options, making the selection process overwhelming.

Choosing a new appliance is inherently a multi-criteria decision-making problem. Consumers must evaluate multiple attributes – often conflicting – such as price, energy efficiency, capacity, and brand reliability. Traditional MCDA methods, such as TOPSIS [6] and VIKOR [8], either synthesize multiple criteria into a single utility function or use pairwise comparisons to determine outranking relationships. Typically, product features are classified as benefit criteria (to be maximized) or cost criteria (to be minimized). However, in real-life replacement scenarios, consumers may look for a more sustainable solution. They may have a specific reference point in mind – an ideal set of product attributes that match their previous appliance. Instead of seeking the "best" synthetic alternative, they may prefer an option closest to their prior experience, prioritizing sustainability over theoretical optimization.

To address this challenge, we propose a new sustainable MCDA approach incorporating the decision-maker's reference model into the selection process. Instead of ranking alternatives based on distance from an ideal or anti-ideal synthetic solution, our method prioritizes options that deviate the least from a user-defined target model – even if such a model does not exist. This approach acknowledges that in many real-world scenarios, "good is sometimes good enough," and better is neither needed nor expected [12].

Our proposed approach can be particularly useful for repeat decision-making, such as homeowners seeking a replacement appliance with nearly identical attributes to their previous one. Moreover, in IT-based decision-aiding systems, reference model parameters can be derived from historical data or inferred using machine learning, making this approach even more practical and simple to use.

The remainder of this paper is organized as follows: Section 2 provides the literature review on the topic. Section 3 introduces the methodological foundations of our proposed MCDA approach. Section 4 provides a simple two-dimensional illustrative example. Section 5 presents an empirical study demonstrating the practical application of the proposed approach in selecting a replacement home appliance and compares it to traditional MCDA techniques. Section 6 concludes the paper.

2 Literature Review

In the realm of multi-criteria decision analysis, various methods have been developed to aid decision-makers in evaluating alternatives based on multiple, often conflicting criteria. These methods synthesize diverse criteria into a coherent framework, facilitating informed and balanced decision-making [18].

[4] https://www.mediaexpert.pl/agd/pralki-i-suszarki/pralki

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The MCDA methods can be generally divided into two groups - American and European [13]. The American school with methods such as MAUT [3] or AHP [16] focuses on aggregating all criteria into a single utility function, facilitating a complete ranking of alternatives. In contrast, the European school employs outranking methods, such as ELECTRE [4] and PROMETHEE [15], which compare alternatives pairwise to establish preference relations without necessarily achieving a complete ordering.

In several MCDA methods, distance metrics play a pivotal role, quantifying the closeness of alternatives to ideal or anti-ideal solutions. TOPSIS [6] and WEDBA [11] computes scores based on distances to ideal and anti-ideal solutions. EDAS [9] utilizes positive and negative distances to a computed average solution. CODAS [7] measures Euclidean distance from the worst solution and resolves draws using Taxicab distance. VIKOR [8, 17] uses Taxicab and Chebyshev distance.

Methods such as TOPSIS [6], WEBDA [11], VIKOR [8], EDAS [9] use synthetic best, worst, average alternatives computed based on the available alternatives' performance under various criteria. SPOTIS [2] chooses the ideal solution point based on separately specified criteria bounds.

In scenarios where decision-makers have a specific reference alternative – potentially a past product or experience – they seek options that closely match this target. When replacing household appliances, consumers often prefer a more sustainable approach instead of maximizing all parameters, valuing familiarity in features, dimensions, and performance [5]. The vast array of available options, coupled with frequent product discontinuations, complicates this process [10]. The aforementioned MCDA methods may not sufficiently accommodate the specificity required in such replacement scenarios, as they are designed to identify optimal solutions based on generalized ideal or anti-ideal points rather than prioritizing alternatives based on their resemblance to a user-defined reference model. This constitutes an interesting research gap, which this paper seeks to address with our proposed sustainable reference-based MCDA approach.

3 Methodology

This paper proposes a novel MCDA approach to evaluating multiple similar alternatives when the decision-maker envisions an ideal, possibly non-existent, reference alternative. We refer to this hypothetical alternative as the target solution (A^*).

Step 1. Forming the decision-making matrix. For the given decision-making problem, criterial performance of m alternatives (rows) under n criteria (columns) can be represented in the form of the following matrix X:

$$X = [x_{ij}]_{m \times n} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \tag{1}$$

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where m - number of alternatives, n - number of criteria describing each alternative, x_{ij} - performance value of alternative i in terms of criterion j.

Step 2. Defining the target solution vector. In the proposed approach, the decision-maker is considered an expert in their own needs. Consequently, they likely have an ideal version of the optimal alternative in mind, even if it does not exist in reality. The performance of this hypothetical alternative across all criteria is represented as the vector A^*:

$$A^* = \left[x_{*1}\ x_{*2}\ \cdots\ x_{*n} \right] \tag{2}$$

Step 3. Defining the relative importance weights of criteria. Several approaches can be used to determine the vector of relative importance weights for the criteria. The most common methods include:

1. equal weights - criteria are considered equally important in the given decision problem. This approach is particularly useful for benchmarking and comparing various decision-aiding methods;
2. subjective preferences - the decision-maker assigns weights based on their own judgment. This can be done manually (for a small number of criteria) or using structured methods such as AHP;
3. objective weighting methods - techniques such as entropy weighting and CRITIC determine preference weights solely based on the criteria values for all alternatives, without incorporating the decision-maker's preferences.

In the proposed approach, we recommend following either approach 1 or 2. The weights should be well-founded because they influence the final solution. Ultimately, the preference weight vector is determined:

$$w = \left[w_1\ w_2\ \cdots\ w_j\ \cdots\ w_n \right] \tag{3}$$

where w_j denotes the relative importance weight of criterion j. Notably, the weights are not required to sum to 1.

Step 4. Normalization of the decision matrix (X), target solution (A^*) and weights (w). The values in the decision matrix (X) may have different units and varying ranges across criteria. To ensure comparability, all values in the decision matrix should be normalized to a range between 0 and 1. The normalization process must also include the target solution (A^*) to maintain consistency. Additionally, the weights need to be normalized so that they sum to 1.

Start by combining the matrix X and the vector A^*:

$$X' = [x_{ij}]_{m+1 \times n} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \\ \hdashline x_{*1} & x_{*2} & \cdots & x_{*n} \end{bmatrix} \tag{4}$$

Normalize the X' matrix using the formula:

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$$\overline{X'} = [\overline{x_{ij}}]_{m+1 \times n} \mid \overline{x_{ij}} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \tag{5}$$

Finally, compute the normalized weights vector using the formula:

$$\overline{w} = [w_j]_{1 \times n} \mid \overline{w_j} = \frac{w_j}{\sum_{j=1}^{n} w_j} \tag{6}$$

Step 5 Defining normalized-weighted matrix $\hat{X}$. Each normalized performance value should be multiplied by the corresponding normalized weight to obtain the normalized-weighted matrix:

$$\hat{X'} = [\hat{x_{ij}}]_{m+1 \times n} \mid \hat{x_{ij}} = \overline{x_{ij}} \cdot \overline{w_j} \tag{7}$$

Eventually, separate the normalized-weighted decision matrix $\hat{X}$ and the normalized-weighted target solution $\hat{A}^*$ from the combined matrix $\hat{X'}$.
Step 6 Computing Euclidean distances of all alternatives from the normalized-weighted target solution $\hat{A}^*$. The Euclidean distance between each alternative from $\hat{X}$ and the target $\hat{A}^*$ is computed as follows:

$$d_i = \sqrt{\sum_{j=1}^{n} (\hat{x_{ij}} - \hat{x_{*j}})^2} \tag{8}$$

The ranking of alternatives is obtained by sorting them in ascending order based on their Euclidean distance from the target solution. A smaller distance indicates a closer resemblance to the target solution, implying a more favorable alternative.

4 Basic Two-Dimensional Example

Consider this simple two-dimensional example with ten alternatives A1, A2, ..., A10, evaluated based on two criteria, C1 and C2. Both criteria are measured on a scale from 0 to 10 and are considered equally important (equal weights). The decision-maker seeks an alternative whose performance in both C1 and C2 is closest to 5. This defines the target solution as $A^* = [5, 5]$. A visual representation of the target solution and all considered alternatives is provided in Fig. 1.

Among the given alternatives, none perfectly matches A*. However, the proposed method identifies the alternative closest to A* by computing the Euclidean distance between the target solution and each alternative. In Fig. 1, these distances are represented by red dashed circles. The alternatives are then ranked in ascending order based on their distance from A*. The closest match is A8, followed by A9 and A7. A comparison of their performance relative to other alternatives is illustrated in Fig. 2.

This simple example illustrates the efficiency and clarity of the proposed approach. However, in more complex scenarios, additional dimensions would be considered, and the results would be influenced by the relative importance weights assigned to each criterion.

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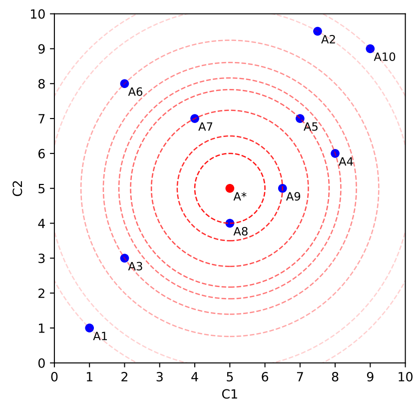

Fig. 1: Visualization of the sample two-dimensional decision problem. A* denotes the target solution, and dashed circles indicate the Euclidean distance between each evaluated alternative to the target solution on the two-dimensional plane.

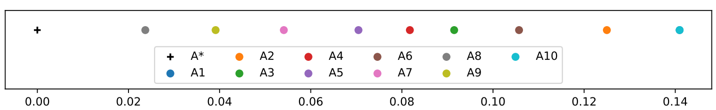

Fig. 2: Visual demonstration of the distance between the target solution (+) and the evaluated alternatives for the example two-dimensional decision problem.

5 Empirical Study

5.1 Decision Problem and Dataset

In this section, we simulate a scenario where our proposed approach proves particularly useful. Suppose a long-serving washing machine has finally broken down. A quick search in a Polish online electronics store yields over 450 available models, priced between PLN 1,000 and 10,000. After narrowing the price range to PLN 1,000–1,500, still 95 options remain. For the sake of brevity, the selection is further reduced to a shortlist of 20 alternatives: A1, A2, ..., A20.

The product specifications were analyzed to construct a decision matrix with 11 criteria, following step 1 from Section 3:

C1 price [PLN];
C2 wash capacity [kg];
C3 energy efficiency class [A-E represented by 1-5 values];
C4 depth [cm] (all 20 alternatives had the same width and height of approximately 60cm and 85 cm respectively);
C5 maximum spin speed [rpm];
C6 noise emission at spin [dB];

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Table 1: Criterial performance of 20 alternatives in the empirical study

Alternative	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11
A1	1098	7	5	52.2	1000	81	45	0	30	205	3
A2	1099	7	4	41	1000	77	41	0	14	208	3
A3	1099	6	1	45	1200	74	43	1	15	198	3
A4	1149.99	7	1	50	1200	74	45	1	15	208	3
A5	1199.99	6	4	40	1200	79	40	0	14	198	2
A6	1299	6	4	41.5	1000	74	36	1	28	197	3
A7	1299	6	4	57.5	1200	80	43	1	30	195	2
A8	1299.99	6	2	41.6	1200	75	43	1	15	198	2
A9	1343.64	7	2	50.1	1400	76	45	1	15	208	2
A10	1348	6	3	42.5	1200	80	43	1	30	198	2
A11	1349	6	3	40	1200	74	43	1	15	198	3
A12	1349	8	1	53	1500	78	44	1	14	218	2
A13	1349.87	6	1	40	1000	72	49	0	15	198	3
A14	1379	9	1	53	1400	78	46	1	14	228	2
A15	1398	7	3	54	1200	76	40	1	14	200	2
A16	1399	8	2	51.8	1200	74	47	1	28	218	2
A17	1399.99	7	3	43.5	1200	74	42	1	15	208	2
A18	1399.99	7	1	41.8	1000	72	43	1	28	207	3
A19	1497	6	3	40	1200	74	43	1	15	198	3
A20	1499	9	1	58	1400	75	36	1	12	228	2

Table 2: Reference model values for the empirical study.

Criterion	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11
Reference	1300	8	1	48	1200	70	35	1	25	180	1

C7 water consumption per washing cycle [L];
C8 inverter motor [1-yes; 0-no];
C9 shortest programme duration [min];
C10 ECO 40-60 programme duration [min];
C11 spin drying efficiency class [A-C represented by 1-3 values].

The criterial performance values for the studied alternatives are presented in Table 1. The data is also available on a GitHub repository[5].

5.2 Target Solution Vector

In the second step, the target solution vector was defined based on expert knowledge. The target performance for each criterion is presented in Table 2.

When constructing the reference model, the noise emission at spin (C6), water consumption per washing cycle (C7) and ECO 40-60 programme duration (C10) were set slightly lower than the minimum observed values among the considered

[5] https://github.com/mcdait/datasets/blob/main/washers202502/washing-machines-ahp.csv

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Table 3: Relative importance weights of criteria, obtained using AHP method.

Criterion	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11
Weights	2	9	21	3	5	15	14	3	6	3	19

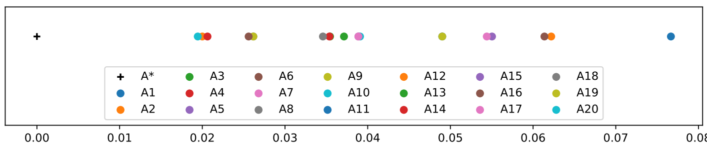

Fig. 3: Visual demonstration of the distance between the target solution (+) and the evaluated alternatives when expert weights are applied.

alternatives. This will result in preferring lower values and penalizing higher values for these criteria.

On the other hand, the shortest programme duration (C9) was set to 25 minutes. Among the 20 analyzed alternatives, the minimum, average, and maximum values were 12, 18.8, and 30 minutes, respectively. Notably, this reference value is close to the maximum, which contrasts with traditional MCDA methods, where criteria are typically classified as either benefits (to be maximized) or costs (to be minimized). In this case, despite 12 minutes being more than twice as fast as the target of 25 minutes, expert judgment and common sense suggest that proper washing cannot be achieved in under 25 minutes. Any duration shorter than this was deemed inefficient by the decision-maker, leading to unnecessary water and energy consumption.

5.3 Subjective Relative Preference Weights

Initially, the AHP method was applied to determine the relative importance of the evaluation criteria (step 3). The resulting weights, presented in Table 3, are expressed as integer values and sum to 100.

With all input data available, steps 4-6 of the proposed approach were executed, resulting in calculating the weighted Euclidean distance for each alternative relative to the target solution. This allowed for ranking the alternatives accordingly. The computed distances and final rankings are presented in Table 4, while a visual representation of the outcomes is provided in Fig. 3.

According to the ranking, A20 is the best alternative, with the distance metric of 0.019. However, when Fig. 3 is analyzed, it can be observed that alternatives A12 (ranked second) and A14 (ranked third) scored very close to the winning one - 0.020 and 0.021, respectively. The rest of the alternatives are aggregated in five clusters - A9, A8, followed by A8, A18, A4, A3, A13, A17, A15, A10, followed by A15, A19, followed by A7, A5, A6, A2 with A1 ranked worst.

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Table 4: Results of the proposed approach compared to VIKOR and TOPSIS.

	Proposed Approach				Verification			
	AHP		Equal Weights		TOPSIS Rank		VIKOR Rank	
	Rank	Distance	Rank	Distance	AHP	Equal	AHP	Equal
A1	20	0.077	20	0.041	20	19	20	15
A2	19	0.062	19	0.037	19	20	19	4
A3	9	0.035	11	0.020	12	12	12	5
A4	8	0.035	9	0.020	11	8	15	10
A5	17	0.055	18	0.035	13	17	10	1
A6	18	0.061	16	0.028	16	9	16	7
A7	16	0.054	15	0.025	15	11	13	16
A8	6	0.026	5	0.017	4	4	1	3
A9	5	0.026	4	0.016	6	5	4	14
A10	13	0.039	8	0.019	10	6	9	13
A11	14	0.049	13	0.025	17	13	17	8
A12	2	0.020	2	0.016	3	10	6	17
A13	10	0.037	17	0.031	14	18	11	2
A14	3	0.021	3	0.016	8	14	7	20
A15	12	0.039	12	0.021	7	3	5	9
A16	4	0.026	1	0.013	2	1	8	19
A17	11	0.039	10	0.020	5	2	3	6
A18	7	0.035	7	0.018	9	7	14	12
A19	15	0.049	14	0.025	18	16	18	11
A20	1	0.019	6	0.017	1	15	2	18

5.4 Ranking Verification

To validate the produced ranking, the same decision problem was analyzed using two popular MCDA methods that also rely on distance metrics: TOPSIS and VIKOR (with $v = 0.5$). Both methods require criteria to be classified as either benefit (where higher values are preferred) or cost (where lower values are preferred). However, this classification is not fully applicable to the given decision problem (see the explanation of criterion C9 in Section 5.2).

To accommodate this limitation, the decision matrix was transformed using the following formula:

$$\mathring{X} = [\mathring{x_{ij}}]_{m\times n} \mid \mathring{x_{ij}} = |x_{*j} - x_{ij}| \tag{9}$$

where $\mathring{X}$ is an $m \times n$ matrix of values $\mathring{x_{ij}}$ produced as the absolute values of the difference between the target solution criterion values x_{*j} and the corresponding evaluated alternative criterion values x_{ij}. Consequently, all criteria were converted to cost criteria for TOPSIS and VIKOR, i.e. the closer to 0, the better.

The resultant ranks for TOPSIS and VIKOR are presented in Table 4. TOPSIS also indicates A20 as the best alternative. On the other hand, VIKOR puts the A20 alternative on rank 2, which is different, but still close. Fig. 4 shows that rankings of all three approaches are highly correlated (0.86 with TOPSIS

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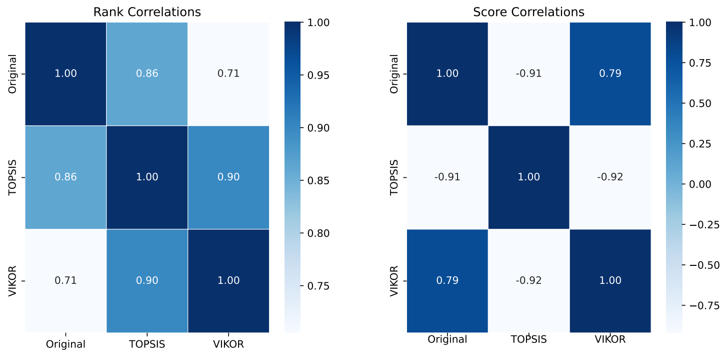

Fig. 4: Correlation between ranks and scores for the proposed approach, TOPSIS and VIKOR with expert weights.

and 0.71 with VIKOR). Regarding scores, there is high positive correlation between the proposed approach and VIKOR (in both methods the lower the metric, the better), and high negative correlation between the proposed approach and TOPSIS (for which the higher the score metric, the better).

This high yet not complete correlation between the proposed approach and other popular MCDA methods confirms the validity of the obtained solution.

5.5 Equal Relative Preference Weights

In the next stage of the study, to further validate the proposed approach, the expert subjective weights were replaced by weights equal to 1 (see step 3 of Section 3):

$$w = [w_j]_{1\times n} \mid \underset{j}{\forall} w_j = 1 \tag{10}$$

As the weight selection impacts the final results of MCDA methods, the scores and ranks were expected to change. The rest of the steps of the proposed method were executed as before. The obtained distance metrics and ranking are presented in Table 4 and visually demonstrated in Fig. 5. Indeed, the results changed, and alternative A16 is now considered best.

Using the same weights vector, also rankings using TOPSIS and VIKOR were generated. They are also presented in Table 4.

There is a high correlation between the rankings with equal weights produced by all three methods (see Fig. 6). This further confirms the validity of the proposed approach.

Nonetheless, the ranks of alternatives differ for the proposed approach depending on which weights vector is used. Therefore, in the next section a sensitivity analysis of how the changes in weights affect the end ranking in our proposed novel approach is presented.

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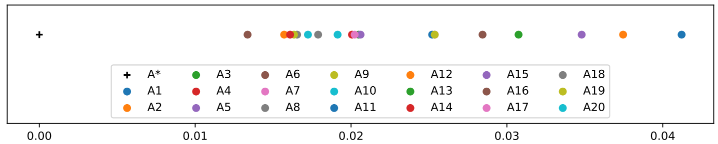

Fig. 5: Visual demonstration of the distance between the target solution (+) and the evaluated alternatives when equal weights are applied.

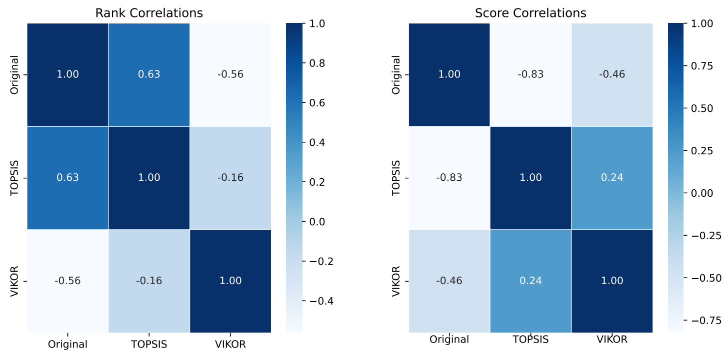

Fig. 6: Correlation between ranks and scores for the proposed approach, TOPSIS and VIKOR with equal weights.

5.6 Sensitivity Analysis

In the last stage of the empirical study, a sensitivity analysis of the proposed approach was performed. At first, the relative importance weights of all criteria were set to an equal value of 50:

$$w = [w_j]_{1\times n} \mid \underset{j}{\forall} w_j = 50 \tag{11}$$

Then, for each criterion, the weight of that criterion was iteratively changed to $1, 2, \ldots, 100$ with the rest of the criteria's weights fixed at 50. In each iteration, new distances were computed for all alternatives. The results were then plotted and are presented in Fig. 7. Note that the Y axis is inverted on all the charts, so the better the alternative, the higher it is plotted. The blue dashed vertical line on each chart indicates where all weights are equal, i.e., the sensitivity analysis starting point.

The analysis of Fig. 7 allows to observe that in the case of only a single criterion changing, the winning alternative A16 is very stable on the first rank. Only changes in criteria C3, C9, or C11 can degrade it to lower ranks. When the rank sensitivity analysis is verified for these three criteria, it can be noticed that they introduce many changes throughout the ranking as their weights change.

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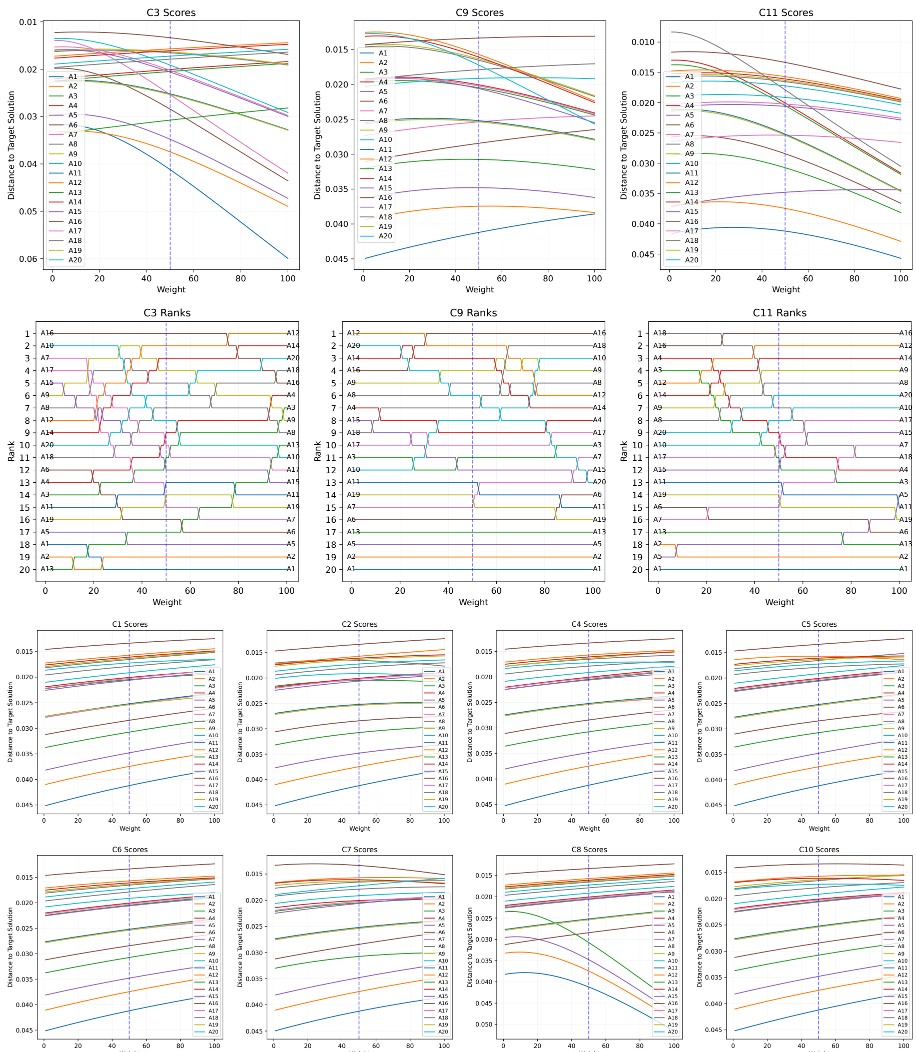

Fig. 7: Sensitivity analysis of the ranking based on equal weights with single criterion weight ranging from 1 to 100.

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Let's consider the chart for criterion C3 ranks. If its weight increases to over 75 (while the weights of the rest of the criteria are fixed at 50), alternative A16 drops to rank 2, and as the weight of C3 rises, it drops even lower down to rank 5. Meanwhile, alternative A12 takes the winner's place when the weight of C3 rises.

This can be interpreted as the energy efficiency class criterion (C3) supporting A12 but conflicting with A16. Indeed, while the target energy efficiency class is A, alternative A16 has class B, whereas A12 has class A.

Similar observations can be made for criterion C9 (shortest programme duration) and C11 (spin drying efficiency class). If the weight of C9 is reduced to below 30, alternative A16 starts dropping until it reaches rank 4; alternative A12 would then be ranked first. The target value for this criterion is 25 min, A16 is 28 min (3 min difference), and A12 is 14 min (11 min difference).

Finally, if the weight of criterion C11 (spin drying efficiency class) was reduced to below 25, A16 (class B) would drop to rank two and would be replaced in the winning position by A18 (class C). Note that the expected spin drying efficiency class was A, yet none of the alternatives reached that target. This might be one of the reasons why none of the analyzed alternatives are plotted perfectly near the target solution on charts in Fig. 3 and Fig. 5.

6 Conclusions

Multi-criteria decision analysis plays a crucial role in helping consumers navigate complex decision-making scenarios, especially in markets with a vast array of choices, such as home appliances. Traditional MCDA methods provide structured approaches to evaluating alternatives based on multiple criteria. Still, they often rely on synthetic best or worst alternatives that may not align with the more sustainable real-world consumer preferences.

This paper addresses the challenge of making multi-criteria decisions when the decision-maker has a specific reference model in mind – one that is often more meaningful and sustainable than generalized ideal or anti-ideal synthetic solutions used in conventional MCDA methods. Existing approaches such as TOPSIS, VIKOR, and EDAS rely on computed best, worst, or average alternatives, which may not align with real-world decision-making scenarios where individuals seek to replace an item with one that closely matches their previous experience. Our proposed approach bridges this gap by ranking alternatives based on their increasing Euclidean distance from a user-defined target solution, allowing for more intuitive and practical decision support.

The primary contributions of this paper include:

- Reference-Based Decision-Making: Unlike conventional MCDA methods that rely on synthetic best or worst alternatives, our approach incorporates a user-defined reference model, which aligns better with real-world decision-making processes where individuals seek to replace products with ones with similar attributes.

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– Application to Home Appliance Selection: By demonstrating the applicability of our method in the selection of washing machines, we highlighted its practical relevance in real-world scenarios where consumers seek to replace discontinued products with similar alternatives.
– Empirical Validation and Sensitivity Analysis: Through empirical testing, we validated the effectiveness of our approach against two established distance-based MCDA methods. Additionally, the sensitivity analysis confirmed that the rankings obtained with the proposed approach are stable under various weight configurations, while still reflecting user preferences.

Our findings contribute to the ongoing development of MCDA methodologies by introducing a consumer-centric perspective that prioritizes familiarity and satisfaction over purely optimal solutions.

Future research could explore extensions of our method, such as integrating non-Euclidean distance metrics or applying machine learning techniques to predict or suggest user preferences more accurately. The proposed reference-based MCDA framework has strong potential for applications beyond home appliance selection, including e-commerce recommendations and product re-purchasing scenarios.

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