Enhancing Personalized Decision-Making with the Balanced SPOTIS Algorithm

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Abstract: Besides being very useful in solving decision-making problems, classical Multi-Criteria Decision-Making (MCDM) techniques were designed to consider only profit and cost criteria. However, in some cases, it can be necessary to include more complex preferences of decision makers to better fit the problem. In such cases, modern MCDM methods such as Stable Preference Ordering Towards Ideal Solution (SPOTIS) can be used. The SPOTIS method allows for providing the Expected Solution Point (ESP) as input data for the decision problem. However, this approach can lead to unsatisfactory results if provided expert preferences are unreliable. To solve this problem, we propose a novel Balanced SPOTIS method with an ESP confidence parameter, which allows us to obtain a solution that is balanced between objectively ideal solutions and subjective expert preferences. We show how this new approach works in the case study of selecting a used car and provide an in-depth analysis of the problem using the new ESP confidence parameter for sensitivity analysis. Finally, to underline the advantages of the proposed approach, we compare it with the Expected Solution Point - Characteristic Objects Method (ESP-COMET).

1 INTRODUCTION

Multi-Criteria Decision Making (MCDM) is a part of operational research that concentrates on providing comprehensive tools and algorithms for solving and analyzing decision-making problems. Such problems usually involve different criteria and decision alternatives and require some domain knowledge to evaluate them (Torres et al., 2024). MCDM methods can be helpful in aiding the expert or a decision maker in the appropriate and satisfying solution of decision problems based on the input and preferences provided by the expert (Shekhovtsov, 2022).

Most of the MCDM methods concentrate on finding the optimal solution in the set of decision alternatives based on the criteria types and importance weights. However, this narrows the ability to personalize the decision-making process, mostly because most MCDM methods allow only profit (maximization) and cost (minimization) criteria types. However, there are different types of problems in which the type of "target" criterion is involved (Jahan et al., 2012). The target criterion indicates that this criterion should not be maximized or minimized, but our expected (or most suitable) value is somewhere between the minimum and maximum values for this criterion.

There are methods designed to operate on target criteria through the input of the decision maker, such as Stable Preference Ordering toward the Ideal Solution (SPOTIS) (Dezert et al., 2020), Characteristic Objects METhod (COMET) (Shekhovtsov et al., 2023), and Reference Ideal Method (RIM) (Cables et al., 2016). While the COMET method requires the preparation of the pairwise comparison matrix, both SPOTIS and RIM methods allow the definition of the expected (target) solution in the form of the vector of expected values for the different criteria. For example, in material selection decision makers can expect some specific value for material's property, making this an expected solution value. These methods are also notable because of their robustness, as they are resistant to rank reversal by design. Classical MCDM methods can usually be extended with advanced normalization techniques to include target criteria in the

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problem (Jahan et al., 2012), but the potential and usability of such extensions are rather low and limited to concrete decision problems.

In this study, we focus on the SPOTIS method, which is a relatively new decision support method proposed by Dezert et al. (Dezert et al., 2020). This method allows the decision maker to provide the Expected Solution Point (ESP) to personalize the decision-making process to suit the specific needs of the decision maker. However, this approach has some practical limitations. Changes in ESP can have a great impact on the final ranking, which implies that ESP provided by inexperienced or not confident decision makers can lead to an unsatisfactory solution to the problem.

The main contribution of the paper is:

- to propose a Balanced SPOTIS method, which extends the standard algorithm of the SPOTIS method with ESP confidence parameter, which allows for balancing between rankings built towards ideal and expected solutions.
- The usefulness of the method is demonstrated in the case study of choosing a used car based on mileage, price, and year of manufacture.
- We demonstrate how to conduct a solution sensitivity analysis with the new method, which can be used to better understand the problem and the preferences of the decision maker, providing a more reliable and informed decision.
- Additionally, we show the comparison with the ESP-COMET method, as it can handle several ESP points, making these methods comparable.

The rest of the paper is structured as follows. In Section 2, we describe some related works on the topic. In Section 3, we describe the original SPOTIS method, and in Section 3.3, we describe our proposal on the extension of this method. Then, in Section 4, we demonstrate the application of this new method in a practical case study of choosing a used car in Poland and we make the analysis of the decision made depending on the confidence factor chosen by the decision maker. Next, in Section 5, we summarize the research results and propose some possible perspectives.

2 RELATED WORKS

Most popular MCDA methods, such as the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) and the Analytic Hierarchy Process (AHP), suffer from the rank reversal paradox, which can make the results unreliable in certain cases (Chakraborty, 2022; Yulistia et al., 2023). This paradox typically arises when the set of alternatives is modified, causing shifts in the previously established ranking. In such cases, it can be difficult to determine which alternative should be ranked higher due to conflicting results.

To address the rank-reversal problem, many extensions of the affected methods have been proposed (Yulistia et al., 2023). However, it seems more beneficial, in terms of simplicity, to develop methods that are inherently robust to this issue by design. Methods such as RIM (Cables et al., 2016) and SPOTIS (Dezert et al., 2020) rely on data normalization and criteria bounds to create decision models that are resistant to rank reversal. Other approaches, like the COMET and its extension ESP-COMET (Shekhovtsov et al., 2023), use fuzzy logic and rule-based systems to model the full domain of the decision problem.

These methods have demonstrated their applicability and usefulness in practical case studies. For example, Torres successfully applied the SPOTIS method for the selection of unmanned aerial vehicle systems (Torres et al., 2024). Furthermore, Shekhovtsov investigated the possibility of applying the SPOTIS method to personal decision-making problems, incorporating the ESP approach within the SPOTIS framework (Shekhovtsov, 2022).

The RIM was applied by Hsiung et al. in a case study assessing the risk of COVID-19 in hospital screening procedures (Hsiung et al., 2023). To address potential uncertainty in the data, the authors used Single-Valued Trapezoidal Neutrosophic Sets in combination with the Best-Worth Method (BMW), followed by the RIM method, to rank the risk models and identify areas for improvement. Similarly, Patil et al. (Patil and Majumdar, 2021) sought to identify attributes that influence the use of two-wheelers in India and prioritized these attributes using several MCDA methods, including the RIM method.

The COMET method was applied by (Więckowski and Zwiech, 2021) to select the most energy-efficient material. In other work, (Kizielewicz and Dobryakova, 2020) proposed using the COMET method to assess the performance of NBA players. They showed that, even with missing data, it is possible to accurately rank players.

Despite their high applicability, both the COMET and RIM methods have certain limitations. The COMET method suffers from the curse of dimensionality and requires the creation of a pairwise comparison matrix, which can be time consuming. The RIM method, on the other hand, is easier to use and builds a ranking towards a reference ideal interval. However, it is not possible to prioritize solutions in the interval leading to a tie for all alternatives within the reference interval.

Our proposed method, Balanced SPOTIS, addresses these issues. Although it remains as easy to use and understand as the original SPOTIS method, it allows the incorporation of both Ideal Solution Points (ISP) and Expected Solution Points (ESP), along with the ability to adjust the importance of ESP using a confidence parameter α. This approach not only enables the preference of ESP over ISP to some extent but also offers analytical advantages, providing deeper insights into the decision problem and preferences of decision makers.

3 METHODOLOGY

3.1 Stable Preference Ordering Towards Ideal Solution (SPOTIS)

The SPOTIS method is a MCDA method proposed by (Dezert et al., 2020). This method uses reference objects to evaluate decision alternatives. However, in contrast to other methods, which usually deduce reference objects based on the data in the decision matrix, the SPOTIS method requires them to be defined by the decision-maker.

To apply the SPOTIS method, the decision maker must first define the data boundaries that will form reference objects for alternative evaluation. For each criterion C_j ($j \in \{1,2,\ldots,N\}$) the maximum S_j^{max} and minimum S_j^{min} bounds must be defined. Next, the ISP $\boldsymbol{S}^* = \{S_1^*, \ldots S_j^*, \ldots S_m^*\}$ is selected as $S_j^* = S_j^{max}$ for the profit criterion and as $S_j^* = S_j^{min}$ for the cost criterion. The decision matrix is defined as $S = (S_{ij})_{M \times N}$, where S_{ij} is the attribute value of the i-th alternative A_i for the j-th criterion C_j.

The algorithm of the SPOTIS method presented in (Dezert et al., 2020) is as follows:

Step 1. Calculation of the normalized distances to ISP (1).

$$d_{ij}(A_i, S_j^*) = \frac{|S_{ij} - S_j^*|}{|S_j^{max} - S_j^{min}|} \tag{1}$$

Step 2. Calculation of the weighted normalized distances from ISP $d(A_i, \boldsymbol{S}^*) \in [0,1]$, according to (2).

$$d(A_i, \boldsymbol{S}^*) = \sum_{j=1}^{N} w_j d_{ij}(A_i, S_j^*) \tag{2}$$

Step 3. Determine the final ranking by ordering the alternatives by the values $d(A_i, \boldsymbol{S}^*)$. The better alternatives have smaller values of $d(A_i, S^*)$.

The interesting features of this method are its simplicity, its robustness to the rank reversal paradox, and also its ability to use the so-called Expected Solution Point (ESP), which allows the definition of an outcome expected by the decision maker and builds the ranking toward this point instead of the ISP. In order to use the SPOTIS method with selected ESP $\boldsymbol{S}^+$ one should apply the normal SPOTIS procedure, substituting values of Ideal Solution Point S_j^* to values of ESP S_j^+. The decision maker should choose the values of $\boldsymbol{S}^+$ to fit the given decision problem. However, it is essential to ensure that the chosen ESP is within the scope of the problem, i.e., S_j^+ must satisfy $S_j^{min} \leq S_j^+ \leq S_j^{max}$ for every j.

3.2 Expected Solution Point COMET

The Expected Solution Point COMET was developed to address the dimensionality curse present in the COMET method (Shekhovtsov et al., 2023). To overcome this challenge, the ESP-COMET method was introduced as an alternative approach to building the pairwise comparison matrix in the original COMET method. In this approach, the expert or decision maker first defines one or more Expected Solution Points (ESPs) based on their preferences and domain expertise. Each ESP vector contains N values, where N represents the number of criteria in the decision problem.

The short version of the algorithm is defined as follows:

Step 1. Define the criteria for the decision problem and assign fuzzy numbers to represent each criterion. Define ESP points which should be used to build the pairwise comparison matrix.

Step 2. Use the Cartesian product of fuzzy numbers to create a set of Characteristic Objects representing all possible combinations.

Step 3. Use the defined Expected Solution Points to identify pairwise comparison matrix, rather than using manual comparisons. The preference values for the Characteristic Objects then defined based on the identified matrix.

Step 4. Convert each characteristic object and its preference value into a fuzzy rule.

Step 5. Use the fuzzy rule base and Mamdani's inference method to evaluate and rank alternatives. Alternatives with a higher preference value are better.

The complete algorithm of the ESP-COMET method is presented in (Shekhovtsov et al., 2023), while implementation of the method can be found and used in `pymcdm` Python library (Kizielewicz et al., 2023).

3.3 Proposed Approach

The SPOTIS method is quite effective and can be helpful even in complex decision-making problems. If ESP is used in the SPOTIS method it can also be useful in the case of personalized decision-making, where the target criteria appear in the problem (Jahan et al., 2012; Shekhovtsov, 2022). However, this approach has some limitations because the selection of ESP has a critical impact on the final ranking, which can lead to unsatisfactory outcome.

To address this issue, we propose the improvement of the SPOTIS method named Balanced SPOTIS (B-SPOTIS), as well as a sensitive analysis algorithm that can be used to comprehensively analyze the decision problem. This hybrid approach allows users to define the level of confidence (or trust) in ESP, allowing them to perform a finer analysis of the decision problem.

The application of the proposed B-SPOTIS method requires the definition of the criteria bounds S_j^{min} and S_j^{max} for all criteria C_j and the ESP values S_j^+. Next, the decision maker should choose which criteria values are preferred if they are smaller and which are preferred if they are larger than ESP. Based on this information, it is necessary to define the Ideal Solution Point S_j^* as S_j^{min} if the decision maker prefers the values smaller than ESP or as S_j^{max} if larger values are preferred than ESP for the jth criterion. Next, it is required to choose the value of the confidence parameter of the ESP $\alpha \in [0,1]$, which regulates the trust of the decision maker to the provided values.

When all values are defined, the B-SPOTIS procedure can be applied in three steps as follows:

1. Apply the standard SPOTIS algorithm to calculate the weighted normalized distances $d(A_i, \boldsymbol{S}^+)$ from ESP $\boldsymbol{S}^+$. Those values will allow one to choose the closest alternative to ESP.
2. Apply the standard SPOTIS algorithm to calculate the weighted normalized distances $d(A_i, \boldsymbol{S}^*)$ from the ISP $\boldsymbol{S}^*$. Those values will allow one to choose the closest alternative to the ISP.
3. Calculate the final compromise (i.e. balanced) distances $P_i = d(A_i, \boldsymbol{S}^*, \boldsymbol{S}^+, \alpha)$ for each alternative A_i using the convex combination of $d(A_i, \boldsymbol{S}^*)$ and $d(A_i, \boldsymbol{S}^+)$ given in (3):

$$P_i = \alpha \cdot d(A_i, \boldsymbol{S}^+) + (1-\alpha) \cdot d(A_i, \boldsymbol{S}^*) \quad (3)$$

Manipulation of the ESP confidence parameter α can be useful to provide certain information on which alternatives are closer to the objectively chosen Ideal Solution and which are closer to the subjectively selected Expected Solution. This type of analysis can be useful to get a different perspective on the problem and the preferences chosen, which can help to make more deliberate and informed decisions.

4 EXPERIMENTS AND RESULTS

4.1 Case Study

To demonstrate the application of the Balanced SPOTIS, we present the case study of choosing a used car in Poland. In Table 1, we present the primary criteria involved in the decision problem. The criterion C_1 describes the mileage of the car in thousands of kilometers; criterion C_2 is a price and is defined in thousands of Polish złoty (PLN), as the data were collected from the Polish Web pages. The last criterion, C_3, is a production year.

For this example, we consider eight decision alternatives in which the criteria data are within the range of minimum and maximum criteria values (S_j^{min} and S_j^{max}) defined by the decision maker. The importance weights of the criteria presented in Table 1 were identified by the decision maker using the RANking COMparison method (RANCOM), which creates numerical weights based on the importance established by the expert (Więckowski et al., 2023).

Table 1: Criteria description.

C_j	Name	Unit	w_j	Type	S_j^{min}	S_j^{max}
C_1	Mileage	k km	0.33	Min	70	360
C_2	Price	k PLN	0.56	Min	35	70
C_3	Year	Year	0.11	Max	2013	2018

The data collected are presented in Table 2. The alternatives A_1 - A_8 were established based on advertisements for one specific car model, but from different advertisements. We also include the ESP S^+ defined by the decision maker, as well as the Ideal Solution Point S^* defined based on the types and limits of criteria (see Table 1). It can be seen that both ESP and ISP set the criterion C_3 (production year) to 2018, and none of the alternatives considered can satisfy this value. However, ESP and ISP differ in terms of car price and mileage, which presents subjective preferences of the decision maker and an objective ideal solution.

We then calculate three preference vectors and three ranking using the standard algorithm of the SPOTIS method with regard to the Ideal Solution Point (ranking $P_i^{(*)}$ and ranking $R_i^{(*)}$), with regard to

Table 2: Alternatives data (A_i) with ESP S^+ and ISP S^*.

A_i	C_1	C_2	C_3
A_1	94.0	69.9	2017
A_2	297.0	42.0	2013
A_3	205.0	68.9	2015
A_4	360.0	36.9	2014
A_5	86.0	59.9	2017
A_6	79.6	63.8	2017
A_7	113.0	56.9	2015
A_8	171.0	58.0	2016
$\boldsymbol{S}^+$	110.0	45.0	2018
$\boldsymbol{S}^*$	70.0	35.0	2018

Table 3: Preferences P_i and rankings R_i for ESP $(+)$, ISP $(*)$ and Balanced SPOTIS with $\alpha = 0.5$ algorithms.

A_i	$P_i^{(*)}$	$P_i^{(+)}$	$P_i^{(0.5)}$	$R_i^{(*)}$	$R_i^{(+)}$	$R_i^{(0.5)}$
A_1	0.6077	0.4386	0.5232	7	6	7
A_2	0.4803	0.3708	0.4256	4	5	4
A_3	0.7620	0.5565	0.6593	8	8	8
A_4	0.4484	0.5021	0.4752	2	7	6
A_5	0.4386	0.2877	0.3632	1	2	2
A_6	0.4937	0.3574	0.4256	5	4	5
A_7	0.4653	0.2598	0.3626	3	1	1
A_8	0.5269	0.3214	0.4242	6	3	3
$\boldsymbol{S}^+$	0.2055	0.0000	0.1028	-	-	-
$\boldsymbol{S}^*$	0.0000	0.2055	0.1028	-	-	-

the Expected Solution Point ($P_i^{(+)}$ and $R_i^{(+)}$) and using the proposed Balanced SPOTIS algorithm with the confidence parameter ESP α set to 0.5 ($P_i^{(0.5)}$ and $R_i^{(0.5)}$). Those preferences and rankings for all alternatives are presented in Table 3. Keep in mind that both SPOTIS and Balanced SPOTIS evaluate alternatives in terms of distance to the Ideal or Expected Solution. Therefore, smaller values of P_i indicate better alternatives.

To analyze the results presented in Table 3, we will concentrate on the first three ranking positions. As we can see, in the case of ranking $R_i^{(*)}$ built towards ISP, the best alternatives are A_5, A_4 and A_7, however, in the case of both $R_i^{(+)}$ and $R_i^{(0.5)}$ rankings, the order of the best alternatives is A_7, A_5 and A_8. Two alternatives, A_7 and A_5, are especially interesting for our analysis. It can be seen that A_7 is closest to ESP and A_5 is closest to ISP and if we analyze preferences obtained using the Balanced SPOTIS method with $\alpha = 0.5$ (see $P_i^{(0.5)}$) we can see that these two alternatives performed very similar (A_5 got 0.3632 and A_7 0.3626), therefore this can be seen as a tie from a certain point of view. However, the decision maker decided that for his case, alternative A_5 is the best, showing that in addition to being closer to ISP than ESP, it can be a good solution for the personalized decision-making process.

We also add the resulted preference values for the ESP $\boldsymbol{S}^+$ and ISP $\boldsymbol{S}^*$ vectors in Table 3. It can be seen that in the ranking built towards ISP, the ESP preference is 0.2055, and for the ranking built towards ESP, the ISP preference is the same value (0.2055). However, in the results of the Balanced SPOTIS with $\alpha = 0.5$, both ESP and ISP received a preference value equal to 0.1028. This property is derived from the linear behavior of the SPOTIS algorithm and is proved as follows.

Theorem. In the case of using $\alpha = 0.5$ ESP, ISP and all the alternatives places between them will be evaluated equally.

Proof. Consider $N > 2$ criteria C_j $(j = 1, 2, \ldots, N)$ with their importance weights $w_j \geq 0$ $(j = 1, 2, \ldots, N)$, and an alternative A_i with its score vector $\boldsymbol{S}_i = [S_{i1}, \ldots, S_{ij}, \ldots, S_{iN}]$. Suppose that for any criterion C_j the condition $S_j^* \leq S_{ij} \leq S_j^*$ satisfied, where S_j^* is the j-th component of ISP point and S_j^+ is the j-th component of ESP point, which can be written more concisely as $\boldsymbol{S}^* \leq \boldsymbol{S}_i \leq \boldsymbol{S}^+$. The distance of A_i to ISP and the distance of A_i to ESP are respectively given by

$$d(A_i, \boldsymbol{S}^*) = \sum_{j=1}^{N} w_j \frac{|S_{ij} - S_j^*|}{\delta_j} \tag{4}$$

$$d(A_i, \boldsymbol{S}^+) = \sum_{j=1}^{N} w_j \frac{|S_{ij} - S_j^+|}{\delta_j} \tag{5}$$

where $\delta_j \triangleq |S_j^{\max} - S_j^{\min}|$.

The Balanced SPOTIS solution is given by

$$P_i = \alpha \cdot d(A_i, \boldsymbol{S}^+) + (1 - \alpha) \cdot d(A_i, \boldsymbol{S}^*) \tag{6}$$

and for $\alpha = 1/2$ we get

$$P_i = \frac{1}{2} \sum_{j=1}^{N} w_j \frac{|S_{ij} - S_j^+|}{\delta_j} + \frac{1}{2} \sum_{j=1}^{N} w_j \frac{|S_{ij} - S_j^*|}{\delta_j} \tag{7}$$

$$= \frac{1}{2} \sum_{j=1}^{N} w_j \frac{|S_{ij} - S_j^+| + |S_{ij} - S_j^*|}{\delta_j} \tag{8}$$

Because we have the inequality $S_j^* \leq S_{ij} \leq S_j^*$ satisfied, we get $|S_{ij} - S_j^+| = S_j^+ - S_{ij}$ and $|S_{ij} - S_j^*| = S_{ij} - S_j^*$. Therefore $|S_{ij} - S_j^+| + |S_{ij} - S_j^*| = S_j^+ - S_j^*$, whence for any alternative A_i we always have $P_i = \frac{1}{2} \sum_{j=1}^{N} w_j \frac{S_j^+ - S_j^*}{\delta_j}$, which is actually independent of the alternative scores S_{ij}. In this very particular balanced case where $\boldsymbol{S}^* \leq \boldsymbol{S}_i \leq \boldsymbol{S}^+$ with $\alpha = 1/2$ none of the alternatives can be preferred and we have a total uncertain situation showing indifference between all the alternatives. The similar remark holds for the case where the condition $S_j^+ \leq S_{ij} \leq S_j^+$ for $j = 1,2,\ldots,N$ is satisfied (i.e. $\boldsymbol{S}^+ \leq \boldsymbol{S}_i \leq \boldsymbol{S}^*$ holds) because we will get $P_i = \frac{1}{2}\sum_{j=1}^{N} w_j \frac{S_j^* - S_j^+}{\delta_j}$.

This behavior implies that there is no possibility to differentiate or order alternatives between ESP and ISP when $\alpha = 0.5$. This reflects a situation with full uncertainty on which alternative should be preferred as it lies within a range between equally preferred values. To ensure that this paradox does not interfere with the results, it is advisable to always investigate several possible α values or to ensure that there are no alternatives between Expected and Ideal solutions.

Going further with the analysis of the rankings presented in Table 3 we can check the values of the Weighted Spearman correlation coefficient r_w between the rankings (Pinto da Costa and Soares, 2005). The correlation between the rankings $R_i^{(*)}$ and $R_i^{(+)}$ is 0.4709, which implies that these rankings are quite different but not uncorrelated. Then, r_w correlation between $R_i^{(0.5)}$ and $R_i^{(*)}$ is 0.5873, but for pair $R_i^{(0.5)}$ and $R_i^{(+)}$ we got the value 0.9630. This shows that a balanced ranking is much closer to the ranking built toward ESP than ISP. It can be expected that a balanced ranking would have a similar correlation to the ESP and ISP rankings. However, it is very dependent on the decision problem and the correlation coefficient used. In the case of the Weighted Spearman correlation, $R_i^{(0.5)}$ is closer to $R_i^{(+)}$ due to the similar heading of the ranking, as this correlation coefficient puts more weight on the top alternatives.

4.2 Sensitivity Analysis

As mentioned earlier, the ESP confidence parameter, α, can be used to analyze which alternatives are closer to the Expected Solution Point (ESP) and which are closer to the Ideal Solution Point (ISP). This analysis can be performed by gradually changing the value of α within the range $[0,1]$, using a chosen step size. Figure 1 presents the proposed sensitivity analysis algorithm.

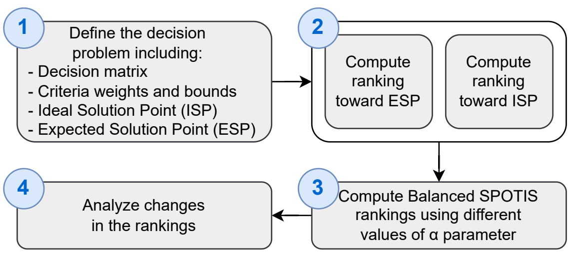

Figure 1: Flowchart of the sensitivity analysis process.

In the current research, we demonstrate the application of this sensitivity analysis framework with step $\Delta\alpha = 0.1$. It is worth mentioning that according to Equation (3), using $\alpha = 0.0$ will provide the same results as ISP SPOTIS, and the use of $\alpha = 1.0$ is the same as applying ESP SPOTIS. The results of the calculations are shown in Figure 2.

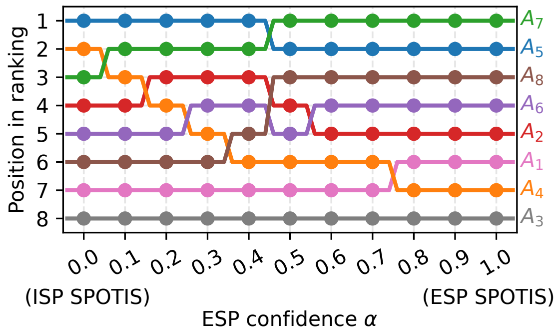

Figure 2: Changes in alternatives' positions in ranking for different values of α parameter.

From the analysis of Figure 2, we can see that there are not many changes in the ranking, because the chosen ESP and ISP are similar. However, there are two interesting cases that we want to discuss in detail, specifically alternatives A_4 and A_8. The alternative A_8 at the sixth position for $\alpha = 0.0$, and the increase of α improved the positions of the alternative A_8, and in the ranking for $\alpha = 1.0$, it took the third position. It is interesting because most of the alternatives do not change their rankings more than one position up or down. If we look closer to Table 2, this change can easily be explained: while A_8 performs relatively poorly with regard to ISP because of the large mileage and price, it is closer to ESP than some other alternatives because ESP allows for a higher price and mileage. However, the alternative A_4 changes its position from seventh in the ranking with $\alpha = 1.0$ to second for $\alpha = 0.0$. At first sight, it can be very strange that this alternative got such a high position, performing badly in mileage and year. However, the most important criterion for the decision-maker is price, and this alternative has the lowest price among all alternatives.

To better explain how the ESP confidence factor α influences the results of the Balanced SPOTIS method, we show in Figure 3 how the preference function changes depending on different values of α. We choose to present the plots only for $\alpha \in \{0.1, 0.5, 0.9\}$, as these three values are most significant in understanding how the ESP confidence factor influences preferences. The three subplots of Figure 3 show the change of preferences for the three α values based on criteria C_1 and C_2 when C_3 is set to

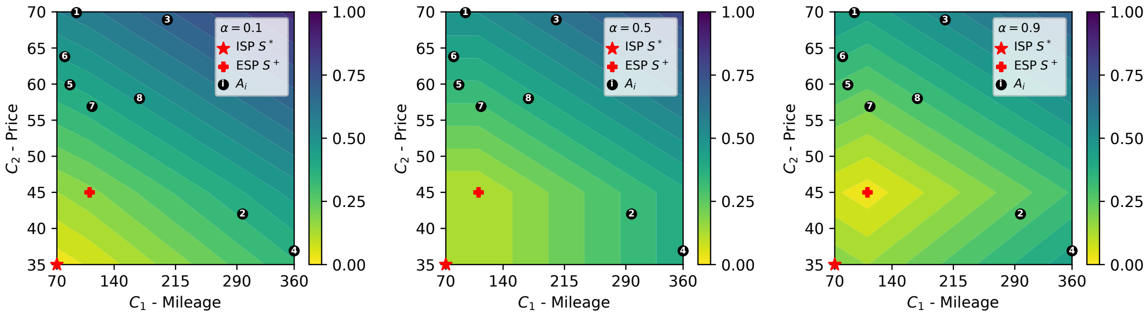

Figure 3: Visualization of the preference function shape for $\alpha \in \{0.1, 0.5, 0.9\}$. For all evaluated points C_3 is set to 2018.

2018 for all the evaluated points. The direction of the criteria and the weights are drawn from Table 1. For each subplot, the ESP is marked with a red plus symbol and the ISP is marked with a red star symbol for convenience. The black circles with white numbers indicate the position of the eight alternatives.

It can be seen that for $\alpha = 0.1$, the yellow region of the smallest distances (more preferred solutions) is placed around ISP, but for $\alpha = 0.9$, the region with the most preferred solutions is located around ESP, which is in agreement with how the ESP confidence parameter is expected to work. However, in the case of $\alpha = 0.5$, it can be observed that there is no yellow region around ISP or ESP, but a light green region that determines the equally preferred alternatives between ESP and ISP, as mentioned earlier in the paper. It is also worth noting that the alternatives A_5 and A_7, which were ranked best for both models, are visually closer to ESP and ISP than the other alternatives. When A_2 appears to be close to both ESP and ISP, it ranked lower than A_5 and A_7 due to the lower value of the criterion C_3 (year).

4.3 Comparison Between Balanced SPOTIS and ESP-COMET

To highlight the advantages of the Balanced SPOTIS method, we also present a comparison with the ESP-COMET method. This method was chosen because of the possibility to provide several expected solution points and build the ranking based on them. However, the procedure of the ESP-COMET doesn't provide the ability to prioritize one or another ESP. Another limitation is that there is no possibility to apply criteria weights in this method.

Equation 9 shows the ranking produced using the ESP-COMET method ($R^{(E)}$). The ESP-COMET ranking takes into account both the ESP and ISP points utilized in the SPOTIS calculations. In the ESP-COMET ranking, the alternative A_5 holds the top position, which is the same as in the SPOTIS ranking toward ISP. However, the alternative A_6, which ranked second in the ESP-COMET method, is lower in the other rankings (see Table 3). This is notable since A_6 has criteria values similar to A_5 and may be seen as a better candidate for second place than A_4.

It is important to note that the SPOTIS method incorporates the criteria weights of Table 1, while the ESP-COMET method treats all criteria equally. Given that Price is the most important criterion, it is reasonable to expect A_4 to rank higher and A_6 lower, as reflected in the SPOTIS results. A similar discrepancy can be observed with A_1.

$$\begin{array}{cccccccccc} & A_1 & A_2 & A_3 & A_4 & A_5 & A_6 & A_7 & A_8 \\ R^{(E)} = & [7 & 4 & 8 & 6 & 2 & 5 & 1 & 3] \end{array} \tag{9}$$

In addition, in Figure 4, we present a visualization of the preference function in the ESP-COMET model for two criteria, with the third criterion held constant. Note that in the COMET method, more preferred alternatives receive higher preference values, so we reversed the colormap for convenience. Brighter, more yellow regions represent more preferred alternatives. The orange dots and lines indicate the grid of Characteristic Objects.

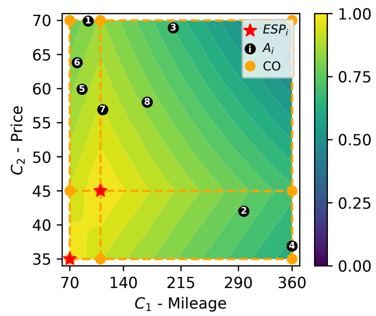

Figure 4: Visualization of the preference function shape for ESP-COMET with two ESP selected. For all evaluated points C_3 is set to 2018.

The region between two ESPs (or an ESP and ISP) in Figure 4 is particularly interesting. It shows that, in addition to the highly preferred yellow region, there are two areas with slightly lower preference values. This situation may seem counterintuitive. While having all alternatives between the ISP and ESP receive the same preference values, as observed in Balanced SPOTIS with $\alpha = 0.5$, seems more intuitive to us, the differing preferences in this area can be harder to justify. With B-SPOTIS, it is possible to evaluate multiple values of α, which is not possible in ESP-COMET. Consequently, when decision-makers encounter cases where two very similar alternatives within the expected/ideal value range have different preference values, it can lead to confusion.

5 CONCLUSIONS

In this paper, we proposed a Balanced SPOTIS method, which can be helpful for personalized decision-making and analysis of the decision problem. The usefulness of the proposed approach was demonstrated in the case study of choosing a used car, where the decision maker provided the ESP but preferred the alternative, which was the best in the ISP ranking. ESP trust (or confidence) parameter α can be very useful in such situations when it is necessary to perform a sensitivity analysis, investigating the decision problem from different perspectives. It can also be useful in cases where we do not have too much confidence in the preferences provided by the expert. We also performed a comparison between the Balanced SPOTIS and ESP-COMET methods, highlighting certain drawbacks of ESP-COMET. Although ESP-COMET allows for the inclusion of any number of ESPs, it faces issues such as the curse of dimensionality and lacks a weighting mechanism, leading to equal treatment of all criteria.

This work opens some interesting future research directions. The Balanced SPOTIS method can be extended further to address the issue of aggregating several ESP or expert preferences to provide a comprehensive compromise solution. We also want to further investigate the properties of the proposed method and compare its performance with different MCDM methods in more real-life case studies. In the future, we also plan to extend B-SPOTIS to handle imprecise data.

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