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A New Multi-Criteria Approach for Sustainable Material Selection Problem

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Abstract: Sustainable material selection is a crucial problem given the new demands of society and novel production strategies that consider the concepts of sustainability. Multi-criteria decision-making methods have been extensively used to help decision-makers select alternatives in different fields of knowledge. Nonetheless, these methods have been criticized due to the rank reversal problem, where the independence of the irrelevant alternative principle is violated after the initial decision problem is changed. Over the course of this study, we observed that the solutions that are proposed for this problem, in the context of sustainable material selection, are insufficient. Thus, we present a new material selection approach that is based on the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) method, which is immune to rank reversal. We also demonstrate the causes of rank reversal in the TOPSIS method, how the R-TOPSIS method was designed to solve them, and how it can be applied to sustainable material selection.

Keywords: multi-criteria decision-making; TOPSIS; R-TOPSIS; rank reversal; sustainable material selection

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1. Introduction

Sustainability has become a strategic imperative, due to the accelerated depletion of natural resources and enormous ecological destruction, which have gravely affected global economic growth, social welfare, and improvements in human health in this century [1,2].

The term sustainability has been traditionally defined as "design that meets the needs of the present without compromising the ability of future generations to meet their own needs" and involves an interaction between three pillars: environment, economic, and society [3,4]. Given that sustainability is a significant concern in modern life, its transformations are essential changes in the cultures, structures, and practices that foster sociotechnical systems toward more sustainable production and consumption [5–8].

In this respect, materials are considered a key factor in a product's sustainability, since they play an important role in the full design and manufacturing process. As such, improper material selection may result in adversities or failures of an assembly and significantly decrease product performance, thereby negatively affecting the profitability, productivity, and reputation of an organization [7,9,10].

Material selection is vital in product design and development, and critical to the success and competitiveness of the manufacturers. Sustainable material selection (SMS) is an important step for industry to enhance material properties and promote sustainable development [11]. In this case, the needs of a sustainable material selection problem involve not only economic and technical aspects, but also social and environmental features [12]. Thus, the material selection problem can be understood as an intricate multi-criteria decision-making (MCDM) problem [13], whose primary objective is to help decision-makers solve real problems by comparing, classifying, or ranking alternatives using multiple conflicting criteria [14].

Mousavi-Nasab and Sotoudeh-Anvari [13] described the strengths and limitations of MCDM methods in material selection (MS). The authors found that Complex Proportional Assessment (COPRAS) [15] and Technique for Order of Preference by Similarity to Ideal Solution (TOP- SIS) [16] were the best methods to solve material selection problems. In another study, Mousavi-Nasab and Sotoudeh-Anvari [12] considered the impact of the Rank Reversal Problem (RRP) on MCDM methods for SMS.

The RRP was initially associated with a modification in ranking of the alternatives; for example, after adding or deleting an alternative. Since the groundbreaking study by Belton and Gear [17], a number of RRP approaches have been analyzed in the literature. Aires and Ferreira [18] performed a literature review on the issue, considering a sample of 138 articles that were extracted from journals in the main scientific databases. A literature review that was carried out during the present study (see Section 2 for more details) identified a number of limitations that need to be investigated in future SMS research, including (i) not presenting a solution for the RRP, (ii) limiting assessment of rank reversal cases to the addition/removal of alternatives, and (iii) presenting new di-cult-to-operationalize methods for practical applications.

With respect to the first two cases, since the study by Mousavi-Nasab and Sotoudeh-Anvari [12] did not aim to solve RRP, but limited itself to assessing SMS problems in relation to adding and removing alternatives, future research could propose a new SMS approach using multiple criteria, as well as their validity in terms of the different RRP cases that are presented by Aires and Ferreira [18], including the transitivity property and decomposing the problem into sub-problems. In regard to the third case, the method that is proposed by Mousavi-Nasab and Sotoudeh-Anvari [12] requires long and complex operationalization because it involves a hybrid model that considers three approaches. In this case, the TOPSIS method may be a good alternative, since it has been extensively used in the literature and is recognized as an easy-to-use intuitive method that is applicable in different areas (see, for example, Bilbao-Terol et al. [19], Chmielarz and Zborowski [20], Mao et al. [21], and Wang et al. [22]), individually or in conjunction with other techniques [23].

Thus, the aim of the present study was to present a new approach, called R-TOPSIS, for SMS using MCDM concepts and the classic TOPSIS method (see Algorithm 1). Aires and Ferreira [24] demonstrated that R-TOPSIS is immune to the main RR cases that are proposed in the literature, but needs to be analyzed in specific contexts, given that most of the experiments were conducted with simulated decision problems. We, therefore, used the data that were reported by Mousavi-Nasab and Sotoudeh-Anvari [12] to illustrate the potential of R-TOPSIS in solving the different RR cases that were presented in the literature, as well as demonstrate its simple use in sustainable material selection based on the ideas that made the TOPSIS method one of the most traditional in MCDM. These studies were selected to validate and demonstrate the effectiveness of R-TOPSIS in real situations that were not created in the laboratory.

In summary, the contributions of this paper were as follows: (i) demonstrate the use of a new approach for SMS using MCDM concepts, (ii) describe an algorithm that can be applied to assess different RR cases using multicriteria decision-making methods, (iii) demonstrate the causes of RR in the TOPSIS method based on real decision-making problems, and (iv) demonstrate how R-TOPSIS solves the RR problems that are presented.

The remainder of this study is organized as follows: Section 2 presents a review of the literature on SMS and RRP, in addition to related studies; Section 3 presents the TOPSIS and R-TOPSIS methods and the experimental designs that were used with the MCDM methods in the context of SMS; Section 4 shows the results that were obtained; and finally Section 5 draws some conclusions and makes suggestions for future lines of research.

2. Background

2.1. Sustainable Material Selection and Multi-Criteria Decision-Making

It is increasingly necessary that companies adopt sustainable practices in their processes, even in a scenario of environmental protection initiatives [25,26].

In a recent study on how environmental sustainability interferes in the organizational routines of the plastic transformation industry, da Silva et al. [27] observed that the companies that were analyzed experienced legal and market pressures to implement new routines, but those that adopted a proactive attitude were more competitive and active in local and global markets.

However, this is not an easy task for companies. Given a series of significant pressures, such as global climate change [28], the rise in population [29], and the scarcity of resources, sustainable development is one of the emerging strategies that addresses these issues [30].

Sustainable development has been a significant concern for countries, especially developing nations [11], and a response to the negative social and environmental impacts of rampant economic development [31].

In this respect, including a careful consideration of which materials to use is essential, since there is no "sustainable material" without understanding the context of where and how it is used [32]. Selecting sustainable materials is an essential aspect of sustainable development and one of the critical factors for administrators [11,33,34]. It plays a vital role in reducing the consumption of resources and recycling materials for subsequent use [34].

However, material selection is a complicated task involving several criteria and causes significant concern in guaranteeing the competitiveness of organizations [33,35,36]. Few materials meet all the criteria and these conflicting criterion selection problems can be treated as a multicriteria decision-making (MCDM) problem [11,31,34,37,38].

Thus, in recent decades, several researchers have concentrated on this area, given that they can easily and successfully resolve complex assessment problems [33].

Mahmoudkelaye et al. [39] presented a model for selecting the best sustainable materials for building construction based on the life cycle and analytic network process (ANP) for multicriteria decision-making. Manjunatheshwara and Vinodh [36] analyzed the selection of sustainable materials for tablet device enclosures using Grey decision-making, while Khoshnava et al. [40] used the Decision-Making Trial and Evaluation Laboratory (DEMATEL) and a fuzzy ANP-based approach for selecting sustainable materials for construction.

Roy et al. [33] proposed a model that was based on the combinative distance assessment (CODAS) model containing intuitionistic fuzzy numbers with a range of values. For example, the authors conducted a real case study on brick selection in sustainable building construction projects.

Chatterjee et al. [41] applied a mathematical model for entropy and multi-attributive ideal real comparative analysis (MAIRCA), integrated with entropy weights to select lightweight environment friendly materials (LWEFMs) from a set of alternative candidates in the automotive sector.

Finally, Agrawal [34] assessed the selection of sustainable additive manufacturing (AM) materials based on four techniques: Simple additive weighting (SAW), multi-objective optimization based on ratio analysis (MOORA), TOPSIS, and Vlsekriterijumska Optimizacija I Kompromisno Resenje (VIKOR). Moreover, the author also considered the effect of rank reversal in his analysis, given the relevance of the problem.

2.2. The Rank Reversal Problem in Decision-Making

MCDM is a collection of methods and procedures to support decision-makers (DM) when multiple criteria should be taken into consideration [42,43]. Based on the DM preferences, MCDM presents a structure to assist in obtaining information to resolve dilemmas during a complex process [44]. For this reason, MCDM has become one of the most important subfields of Operations Research and Management Science [45].

However, many methods have serious problems of rank reversal, which leads to the unreliability of the evaluation process [46]. Rank reversal is related to the change in ranking that is obtained after the addition, removal, or substitution of one of the alternatives. That is, the DM preferences ordering between alternatives changes according to the aforementioned situations [18,24].

To further clarify this problem, consider that we are assessing five alternative materials. An MCDM method is used to assess these alternatives and the ranking obtained is A1 > A2 > A3 > A4 > A5, that is, A1 is the best alternative. Next, alternative A2 is substituted by another with a worse performance called A6. In this case, since A2 > A6 and the other alternatives (A1, A3, A4, and A5) remained unchanged, and considering a rational decision-maker, the following initial ranking properties are also expected to remain unaltered: (i) indication of the best alternative (A1) does not change and (ii) there is no change in the remaining DM preferences, namely A3 > A4 > A5.

However, if conditions (i) and (ii) were not preserved, rank reversal occurred. This is an extremely undesirable problem, primarily in dynamic decision-making environments [47], such as selecting materials and suppliers, where alternatives can be added and removed according to the restrictions of the problem and preferences of the decision-maker.

The first discussions on rank reversal were described in the pioneering papers of Belton and Gear [17], Saaty and Vargas [48], and Saaty and Vargas [49] on the Analytic Hierarchy Process (AHP) method. Since then, numerous studies on the issue have been published and it is now possible to characterize five different rank reversal topologies in the literature, as described in Aires and Ferreira [18].

According to Aires and Ferreira [18], Type #1 is the most widely used in the literature. These authors also classify the studies into five clusters according to their research goal: survey, application, problem solution, simulation, and problem identification. Most of the studies (61.54%) were related to identifying the problem, while only 14.62% presented new approaches to solve the RRP and only three of the 130 articles (2.30%) dealt with the RRP in TOPSIS.

During this study, we updated the literature review that was conducted by the authors and found new articles on the subject: Mufazzal and Muzakkir [50], Senouci et al. [51], Cables et al. [52], Mousavi-Nasab and Sotoudeh-Anvari [12], Sałabun [53], Dezert et al. [54], Munier [55], Wątróbski et al. [56], Yang et al. [57], Kizielewicz et al. [58], and Aires and Ferreira [24].

Mufazzal and Muzakkir [50] proposed a new method to minimize the RRP in the TOPSIS method by modifying Algorithm 1 from Step 3. Although they reduced the effects of the RRP by adding alternatives to or removing them from the problem, according to the results that were presented, the modifications were not sufficient to solve the RRP.

Senouci et al. [51] considered four normalization procedures in order to analyze the effect of the RR cases in the TOPSIS. In general, based on the values of the new alternatives, the authors explain the situations in which RR can occur, despite not presenting a definitive solution to eliminate the problem.

Cables et al. [52] proposed the Reference Ideal Mode (RIM), which considers the "reference ideal" to doing the normalization procedure and does not present RR. Different from TOPSIS, the ideal solutions of the method can be a set of values or a simple value, which facilitates its operationalization.

Mousavi-Nasab and Sotoudeh-Anvari [12] proposed a method that was based on the Simple Additive Weighting (SAW), TOPSIS, and COPRAS methods in order to help the decision-maker select sustainable materials considering the RRP. The model uses COPRAS and TOPSIS to compare the rankings that are obtained and selects the best alternative based on the Spearman Correlation Index (SCI). If a new alternative is added to the analysis, SAW is also used along with COPRAS and TOPSIS to define the best alternative when comparing ranking with SCI. The authors found that the TOPSIS method exhibited the worst performance of all the methods that were analyzed.

Sałabun [53] proposed the characteristic objects method (COMET), in which preferences of each alternative are obtained on the basis of the distance from the nearest characteristic objects and their values. The COMET method proved to be completely free of RR, a fact that was reinforced by other studies (see Sałabun and Piegat [59] and Jankowski et al. [60])

Dezert et al. [54] proposed the Stable Preference Ordering Towards Ideal Solution (SPOTIS) method. In this method, the preference ordering is established from the score matrix of the MCDM problem under consideration, not requiring relative comparisons between alternatives, but only comparisons with respect to the ideal solution that is chosen by the MCDM system designer. Besides being free of RR, the authors also point out that the method requires much less information with respect to the COMET approach and fits easily into the framework of classical problematic MCDM.

Munier [55] proposed the Sequential Interactive Method for Urban Systems (SIMUS), a method that is based on linear programming which, although not guaranteeing an optimal solution, gives a compromise solution, that is, a balance or equilibrium of compliance, in a lesser or greater degree of what the set of criteria demand, the same as other heuristic methods (Munier [61]). According to the author, SIMUS is free of RR because it is based on the Simplex algorithm, which does not allow RR to happen.

Wątróbski et al. [56] proposed the Data Variability Assessment Technique for Order of Preference by Similarity to Ideal Solution (DARIA-TOPSIS), which provides aggregate efficiency results of evaluated alternatives' performance considering the dynamics of changes over the time range being investigated. As in the case of João, this method is also free of RR.

Yang et al. [57] proposed the Improved TOPSIS to overcome the RRP. The proposed method is based on linear max-min normalization with absolute maximum and mini-mum values by modifying the normalization formula and ideal solutions. According to the authors, the proposed TOPSIS overcomes the RRP perfectly.

Also noteworthy is the study by Kizielewicz et al. [58], who proposed a hybrid method. The proposal is to use the COMET and combining it with the TOPSIS and PROMETHEE II methods. As COMET requires a very large number of pair comparisons, this task will be performed using the PROMETHEE II and TOPSIS methods.

Finally, Aires and Ferreira [24] proposed a new method, called RTOPSIS, in order to solve the RRP in the classic TOPSIS method. The authors demonstrated its robustness using 4800 simulated decision problems and a real case. This method is described in detail in Section 3.2.

2.3. TOPSIS for Material Selection

Since the MCDM methods have the potential to significantly improve the material selection process [62], a number of studies on the subject have used this approach, in particular, the TOPSIS method. Kaushik et al. [63] used TOPSIS to analyze material selection in a paper coating pigment composition. The authors reported that TOPSIS was an efficient tool for selecting and ranking the composition that was best suited to different coated paper properties.

Bhosale et al. [64] used TOPSIS to select the material composition for the powder metallurgy process. Kumar and Singal [65] applied AHP, TOPSIS, and Modified TOPSIS to solve the material selection problem for penstock in small hydropower installations. Based on two case studies, they found that the TOPSIS and Modified TOPSIS methods are best suited to penstock material selection and that mild steel is more suitable than other materials. Hybrid models and extensions have also been used.

Yazdani and Payam [66] applied an Ashby approach, TOPSIS, and VIKOR to select the most appropriate microelectromechanical systems. The results showed good agreement between these material selection methods. Tewari et al. [35] applied the Entropy-TOPSIS method to determine the ranking of sintered material for the automobile sector. The weight was calculated by entropy and the TOPSIS method was used to select the best alternative based on cost and mechanical properties.

Ma et al. [31] combined TOPSIS and IEM to select sustainable materials considering the life cycle assessment (LCA) method. Yadav et al. [38] proposed a new hybrid methodology called TOPSIS-PSI to help select the best material for marine applications.

As capabilities in handling impreciseness are inherent in measuring material properties, Liao [67] presented two interval Type 2 fuzzy multi-attribute decision-making methods for material selection, extended from two existing TOPSIS methods based on a Type 1 fuzzy set.

Bhattacharjee et al. [68] also applied TOPSIS in a fuzzy environment. In this case, it was used considering multiple qualitative and quantitative criterion values to find the best aluminum alloy for industrial applications.

Loganathan and Mani [69] proposed a model that was aimed at evaluating a suitable phase change material for thermal management systems. They suggested the Fuzzy AHP (FAHP)—integrated with TOPSIS, VIKOR, and Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE). In general, FAHP was used to compute the weights of the evaluation criteria and then as the input for TOPSIS, VIKOR, and PROMETHEE for ranking alternative materials.

Tian et al. [70] proposed a hybrid multi-criteria decision-making approach integrating AHP and Grey Correlation TOPSIS (GC-TOPSIS) to qualitatively select the optimal green decoration materials. Similar to Loganathan and Mani [60], the weights were determined by AHP and the GC-TOPSIS was applied to obtain the final ranking and select the optimal green decoration materials.

The studies that are presented in Sections 2.1–2.3 demonstrate the need for a new approach to SMS using the MCDM and TOPSIS concepts, in particular, a new robust strategy, immune to rank reversal, which considers the different RR cases that are presented in the literature.

3. Materials and Methods

3.1. TOPSIS

The TOPSIS method is one of the most widely used multi-criteria decision analysis methods (see Behzadian et al. [23] and Ferreira et al. [71]). It was proposed by Hwang and Yoon [16] and extended by Yoon (1987). With this method, the best alternative is the one that is nearest to the positive ideal solution (PIS) and farthest from the negative ideal solution (NIS). PIS is a hypothetical alternative that maximizes the benefit criteria (B) while simultaneously minimizing the cost criteria (C). By contrast, NIS maximizes the cost criteria and simultaneously minimizes the benefit criteria. The alternative with the shortest Euclidean distance from PIS and farthest from NIS is the best of all [50]. In the last step, a closeness coefficient (CC_i) is calculated for each alternative, which is ranked in descending order using the CC_i that is obtained.

Algorithm 1 describes the steps of the TOPSIS method as proposed by Hwang and Yoon [16], where: $A = [a_i | i = 1, \ldots, m]$ is a set of alternatives; $C = [c_j | j = 1, \ldots, n]$ a set of criteria; $W = [w_j | j = 1, \ldots, n]$ $w_j > 0$. and $\sum_{j=1}^{n} w_j = 1$. the importance level of the criteria; $X = [x_{ij} | i = 1, \ldots, m; j = 1, \ldots, n]$ the decision matrix; and x_{ij} the performance rating of the alternative a_i with respect to the criterion c_j.

Algorithm 1 TOPSIS Method

Step 1: Calculate the normalized decision matrix $\left(n_{ij}\right)$ as:

$$n_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}{}^{2}}, i = 1, \ldots m; j = 1, \ldots, n \tag{1}$$

Step 2: Calculate the weighted normalized decision matrix (r_{ij}) as:

$$r_{ij} = w_j \times n_{ij}, i = 1, \ldots,\ m; j = 1, \ldots, n. \tag{2}$$

Step 3: Obtain the positive (PIS) and negative (NIS) ideal solutions as:

$$PIS = \left[r_1^+, \ldots, r_j^+, \ldots, r_n^+\right], where\ v_j^+ = \begin{cases} \max\left(r_{ij}\middle| i = 1, \ldots, m\right), if\ j \in B \\ \min\left(r_{ij}\middle| i = 1, \ldots, m\right), if\ j \in C \end{cases} \tag{3}$$

$$NIS = \left[r_1^-, \ldots, r_j^-, \ldots, r_n^-\right], where\ v_j^- = \begin{cases} \min\left(r_{ij}\middle| i = 1, \ldots, m\right), if\ j \in B \\ \max\left(r_{ij}\middle| i = 1, \ldots, m\right), if\ j \in C \end{cases} \tag{4}$$

Step 4: Calculate the distances of each alternative *i* in relation to the ideal solutions as:

$$S_i^+ = \sqrt{\sum_{j=1}^{n}\left(r_{ij} - r_j^+\right)^2}, i = 1, \ldots, m. \tag{5}$$

$$S_i^- = \sqrt{\sum_{j=1}^{n}\left(r_{ij} - r_j^-\right)^2}, i = 1, \ldots, m. \tag{6}$$

Step 5: Calculate the closeness coefficient of the alternatives (CC_i) as:

$$CC_i = \frac{S_i^-}{S_i^+ + S_i^-} \tag{7}$$

Step 6: Sort the alternatives in descending order. The highest CC_i value indicates the best performance in relation to the evaluation criteria

3.2. R-TOPSIS Method

The R-TOPSIS method was proposed by Aires and Ferreira [24] to solve the rank reversal problem in the TOPSIS method. As their primary premise, the authors considered that changes in the original method should be minimal to make the new method easier for users of the TOPSIS method and maintain compatibility and rationality between them. Thus, the authors proposed two changes to the original TOPSIS method, as follows:

- The use of an additional input parameter called the domain, i.e., a numerical value (integer or real) that represents the range of possible values that each criterion could take;
- A change in the normalization procedure. R-TOPSIS uses Max-Min normalization or Max normalization to fix the ideal solutions and ensure there is no change in the values of the normalized and weighted decision matrices after modifications are introduced to the initial decision problem.

Based on the changes that are proposed, the method proved to be robust and immune to the different RR cases that were presented in the literature when it was submitted to numerous simulated decision problems and a real student selection case—see Aires et al. [72]. Algorithm 2 shows the different steps of the R-TOPSIS method.

Algorithm 2 R-TOPSIS Method

Step 1: Define a set of alternatives $(A = [a_i]_m)$;
Step 2: Define a set of criteria $\left(C = \left[c_j\right]_n\right)$, as well as a subdomain of real numbers $D = \left[d_j\right]_{2\ x\ n}$, where $d_j \in \mathbb{R}$, to evaluate the rating of the alternatives, where d_{1j} is the minimum value D_j and d_{2j} the maximum value of D_j;
Step 3: Estimate the performance rating of the alternatives as $X = \left[x_{ij}\right]_{m\ x\ n}$;
Step 4: Elicit the criteria weights as $W = \left[w_j\right]_n$, where $w_j > 0$ and $\sum_{j=1}^{n} w_j = 1$;
Step 5: Calculate the normalized decision matrix $\left(n_{ij}\right)$ using *Max* or *Max-Min* as:
Step 5.1: Max

$$n_{ij} = \frac{x_{ij}}{d_{2j}},\ i = 1, 2 \ldots m; j = 1, \ldots, n. \tag{8}$$

Step 5.2: Max-Min

$$n_{ij} = \frac{x_{ij} - d_{1j}}{d_{2j} - d_{1j}},\ i = 1, 2 \ldots m; j = 1, \ldots, n. \tag{9}$$

Step 6: Calculate the weighted normalized decision matrix (r_{ij}) as:

$$r_{ij} = w_j \times n_{ij}, i = 1, 2, \ldots,\ m; j = 1,\ \ldots,\ n. \tag{10}$$

Step 7: Set positive (PIS) and negative (NIS) ideal solutions as:

$$PIS = \left[r_1^+, \ldots, r_n^+\right], where\ r_j^+ = w_j\ if\ j \in B\ and\ r_j^+ = \frac{d_{1j}}{d_{2j}} w_j\ if\ j \in C \tag{11}$$

$$NIS = \left[r_1^-, \ldots, r_n^-\right],\ where\ r_j^- = \frac{d_{1j}}{d_{2j}} w_j\ if\ j \in B\ and\ r_1^- = w_j\ if\ j \in C \tag{12}$$

Step 8: Calculate the distances of each alternative i in relation to the ideal solutions as:

$$S_i^+ = \sqrt{\sum_{j=1}^{n} \left(r_{ij} - r_j^+\right)^2}, i = 1, \ldots, m. \tag{13}$$

$$S_i^- = \sqrt{\sum_{j=1}^{n} \left(r_{ij} - r_j^-\right)^2}, i = 1, \ldots, m. \tag{14}$$

Step 9: Calculate the closeness coefficient of the alternatives (CC_i) as:

$$CC_i = \frac{S_i^-}{S_i^+ + S_i^-} \tag{15}$$

Step 10: Arrange the alternatives in descending order. The highest (CC_i) value indicates the best performance in relation to the evaluation criteria.

3.3. Design of the Experiments

This section presents the methodological procedures that were used to (i) demonstrate the RR causes in the TOPSIS method, (ii) demonstrate how R-TOPSIS overcomes the RRP, and (iii) show that R-TOPSIS is an alternative approach for sustainable material selection.

Thus, we initially implemented the TOPSIS and R-TOPSIS methods in Java programming language to facilitate the execution and analysis of the experiments. After implementation, two basic procedures were used to validate the computational implementation of the models: internal and external validation [73]. For internal validation, we used the data of García-Cascales and Lamata [74] to verify the results that were produced by the step-by-step methods and correct all the inconsistencies that were observed. Next, the TOPSIS method underwent external validation, comparing the results that were produced by the present algorithm with those that were described in the following studies: García-Cascales and Lamata [74], Iç [75], Senouci et al. [51], Ostad-Ahmad-Ghorabi and Attari [76], and Phaneendra Kiran et al. [77]. Internal/external validation of the R-TOPSIS method was also conducted. In this case, any differences in the ranking that were produced by the changes introduced into the method must be weighted.

In this step, in addition to comparing the rankings that were produced, Spearman's correlation for ranks (SCR)—SCR = $1 - \left[\left(\sum_{i=1}^{n} \left(r_i^1 - r_i^2\right)^2\right) / \left(n\left(n^2 - 1\right)\right]\right.$—mean absolute error of ranks (MAER)—MAER = $\left(\sum_{i=1}^{n} \left|r_i^1 - r_i^2\right|\right)$—weighted rank measure of correlation (R_w) [78]—$R_w = 1 - 6\sum_{i=1}^{n} \left(R_{xi} - R_{yi}\right)^2 \left(\left(n - R_{xi} + 1\right) + \left(n - R_{yi} + 1\right)\right) /\ n^4 + n^3 - n^2 - n$—and WS coefficient of rankings similarity (WS) [79]—WS = $1 - \sum_{i=1}^{n} (2^{-R_{xi}} \cdot \left| R_{xi} - R_{yi} \right| / \max\{|1 - R_{xi}|, |N - R_{xi}|\}$ were used to assess the degree of similarity between the rankings that were produced by the TOPSIS and R-TOPSIS methods for all the alternatives of the problem $(i = 1, \ldots, n)$.

After the computational implementation was validated, Algorithm 3 was also implemented to assess these methods in relation to different RR cases that were presented by Aires and Ferreira [18]. This algorithm uses a sample of different decision problems as input (**P**). Each problem p is represented by a decision matrix **A**, where the lines (i) correspond to the alternatives and columns (j) the criteria; by the weight and domain of each criterion, represented by vector **W** and matrix **D**, respectively; in addition to the type of each criterion, cost (**C**) or benefit (**B**). Parameter **D** is applied only when the R-TOPSIS method is used.

After the input parameters are defined for each decision problem, the algorithm calculates the ranking of the initial problem (R_o) using a previously defined MCDM method. R_o is used as a reference throughout the algorithm to determine whether or not RR occurred as a result of the changes that were made to the initial decision matrix of the problem (**A**). Next, a first new matrix ($A_1 = A + a'$) is generated with the addition of an irrelevant alternative a' to the initial decision matrix (**A**), as well as a new ranking (R_1).

Step 2.5 of the algorithm can be repeated one or more times, depending on the purpose of the analysis. In this case, for each iteration, two new matrices are created: (i) A_2^i obtained from excluding alternative i of the original decision matrix (**A**), and (ii) A_3^i obtained by substituting alternative i for another with inferior performance in all the criteria. These matrices are used to obtain two new rankings (R_2^i and R_3^i).

The aim of steps 2.6 to 2.10 is to divide the initial decision problem (**A**) into two new sub-problems (A_4) and (A_5).

After the new rankings are calculated (R_1, R_2^i, R_3^i, R_4, and R_5), the final steps of Algorithm 3 are used to determine the following types of ranking reversal cases: (i) change in the recommended best alternative by adding an irrelevant alternative (T_{11}), (ii) change in the recommended best alternative by excluding an irrelevant alternative (T_{12}), (iii) change in the recommended best alternative by substituting an irrelevant alternative (T_2^i), (iv) change in the transitivity relations by adding an irrelevant alternative (T_{31}^i), (v) change in the transitivity relations by excluding an irrelevant alternative (T_{32}^i), and (vi) assessment of the transitivity relations (T_4) between R_o, R_4 and R_5 by decomposing the initial problem.

Algorithm 3 Rank Reversal Analysis

Step 1: Define a sample of multicriteria decision-making problems (**P**);
Step 2: For each problem p in **P**, do:
[Step 2.1] Set $S_a = \varnothing;\ A,\ W,\ D,\ T,\ C\ and\ B\ from\ p;$
[Step 2.2] $R_o = getRanking(A,\ W,\ D,\ C,\ B);$
[Step 2.3] $A_1 = A + a'$
[Step 2.4] $R_1 = getRanking(A_1,\ W,\ D,\ C,\ B);$
[Step 2.5] For a subset of non-optimal alternatives i in **A**, obtain:
[Step 2.5.1] $S_a \leftarrow S_a \cup i;$
[Step 2.5.2] $A_2^i \leftarrow A - i;$
[Step 2.5.3] $A_3^i \leftarrow Replace(A_i);$
[Step 2.5.4] $R_2^i = getRanking\left(A_2^i, W, D, C, B\right);$
[Step 2.5.5] $R_3^i = getRanking\left(A_3^i, W, D, C, B\right);$
[Step 2.6] $mid \leftarrow n/2$
[Step 2.7] $A_4 \leftarrow A[1 : mid];$
[Step 2.8] $A_5 \leftarrow A[mid + 1 : n];$
[Step 2.9] $R_4 = getRanking(A_4, W, D, C, B);$
[Step 2.10] $R_5 = getRanking(A_5, W, D, C, B);$
[Step 2.11] $T_{11} = checkRRType1(R_o, R_1);$
[Step 2.12] For each non-optimal alternative i in S_a, do:
[Step 2.12.1] $T_{12} = checkRRType\#1\left(R_o,\ R_2^i\right);$
[Step 2.12.2] $T_2^i = checkRRType\#2\left(R_o,\ R_3^i\right);$
[Step 2.12.3] $T_{31}^i = checkRRType\#3(R_o,\ R_1);$
[Step 2.12.4] $T_{32}^i = checkRRType\#3\left(R_o,\ R_2^i\right);$
[Step 2.13] $T_4 = checkRRType\#4(R_o,\ R_4,\ R_5);$
Step 3: Print results;
Step 4: End.

4. Results

This section initially presents the RR causes of the TOPSIS method from the two decision problems that were used here. First, we will present the decision problem of Jee and Kang [80] and the results that were obtained with the TOPSIS method for this case, as illustrated in Table 1. A Type #32 reverse ranking problem can be generated for this case by removing alternative A10, according to the new results that were obtained with the TOPSIS method that are depicted in Table 2.

Table 1. TOPSIS results—Case #2—Jee and Kang [80].

Alt	Fatigue Limit (+)	Fracture Toughness (+)	Fragmentability (+)	Price (−)	CC_i	Ordering
A_1	0.0411	0.0372	0.0312	0.0013	0.2872	9
A_2	0.0204	0.0582	0.0312	0.0007	0.2807	10
A_3	0.0321	0.0543	0.0312	0.0007	0.2878	8
A_4	0.0448	0.1124	0.0312	0.0033	0.3597	6
A_5	0.0288	0.0432	0.0936	0.0009	0.3199	7
A_6	0.0679	0.1081	0.0936	0.0013	0.4309	5
A_7	0.1811	0.0951	0.0728	0.0111	0.6795	2
A_8	0.0999	0.1235	0.0728	0.0035	0.4997	4
A_9	0.2536	0.1480	0.0728	0.0079	0.9264	1
A_{10}	0.2057	0.0994	0.0520	0.0989	0.6081	3
w_j	0.4	0.3	0.2	0.1	-	-
PIS	0.2536	0.1480	0.0936	0.0007	-	-
NIS	0.0204	0.0372	0.0312	0.0989	-	-

Table 2. TOPSIS results: Transitivity rule by excluding the irrelevant alternative A_{10}.

Alt	Fatigue Limit (+)	Fracture Toughness (+)	Fragmentability (+)	Price (−)	CC_i	Ordering
A_1	0.0480	0.0395	0.0323	0.0090	0.2022	9
A_2	0.0238	0.0617	0.0323	0.0045	0.2028	8
A_3	0.0374	0.0575	0.0323	0.0045	0.2092	7
A_4	0.0522	0.1191	0.0323	0.0226	0.2818	5
A_5	0.0336	0.0458	0.0969	0.0059	0.2526	6
A_6	0.0791	0.1145	0.0969	0.0088	0.3742	4
A_7	0.2112	0.1008	0.0754	0.0762	0.6155	2
A_8	0.1165	0.1309	0.0754	0.0236	0.4448	3
A_9	0.2957	0.1569	0.0754	0.0537	0.8482	1
w_j	0.4	0.3	0.2	0.1	-	-
PIS	0.2957	0.1569	0.0969	0.0045	-	-
NIS	0.0238	0.0395	0.0323	0.0762	-	-

In this case, the transitivity rule was violated because a comparison of the results that were obtained in Tables 1 and 2 showed changes in the positions of alternatives A_1 and A_2. The causes of this problem in TOPSIS are as follows:

- The normalization procedure. In this case, in Step 1 of Algorithm 1, the denominator of the normalization procedure for each criterion involves the square root of the sum of the score of all the alternatives that are raised to a power of 2. Thus, any change in the initial decision matrix, whether by adding, removing, or altering the ratings of the alternatives, may affect all the findings of the resulting normalized decision matrix. For example, after A_{10} was excluded, all the values of the new normalized and weighted decision matrix (Table 2) differed from those of the initial problem (Table 1);
- The change in the value of the ideal solutions. Given that the new normalized and weighted decision matrix may be totally different from the initial matrix as a function of the normalization procedure of the method, changes could occur in the PIS and NIS, according to Step 3 of Algorithm 1. For example, the results that are presented in Tables 1 and 2 show a change in all the NIS and PIS for this case.

To underscore that these situations are recurring and represent the primary causes of RR in the TOPSIS method, we conducted another experiment using the decision problem of Khorshidi et al. [81]. Table 3 presents the results that were obtained by applying the TOPSIS method. In this case, we added a new irrelevant alternative (A_{11}) to the initial decision problem. The new results that were obtained by applying the TOPSIS method are exhibited in Table 4.

Table 3. TOPSIS results—Case #9—Khorshidi et al. [81].

Alt	Ultimate Tensile (+)	Elongation (+)	Cost (−)	CC_i	Ordering
A_1	0.1971	0.0460	0.0233	0.2973	7
A_2	0.2032	0.0531	0.0307	0.2949	8
A_3	0.2087	0.0655	0.0307	0.3695	5
A_4	0.2063	0.0637	0.0458	0.2869	9
A_5	0.2048	0.0620	0.0608	0.2277	10
A_6	0.2087	0.0850	0.0233	0.3577	6
A_7	0.2048	0.1275	0.0233	0.3718	4
A_8	0.2009	0.1381	0.0233	0.5117	3
A_9	0.1932	0.2583	0.0233	0.8275	1
A_{10}	0.1855	0.1381	0.0233	0.8109	2
w_j	0.6370	0.2583	0.1046	-	-
PIS	0.2087	0.1381	0.0233	-	-
NIS	0.1855	0.0460	0.0608	-	-

Table 4. TOPSIS results: Transitivity rule by adding the irrelevant alternative A_{11}.

Alt	Ultimate Tensile (+)	Elongation (+)	Cost (−)	CC_i	Ordering
A_1	0.1876	0.0448	0.0202	0.2752	9
A_2	0.1935	0.0516	0.0265	0.2733	8
A_3	0.1986	0.0637	0.0265	0.3554	4
A_4	0.1964	0.0620	0.0395	0.2815	7
A_5	0.1950	0.0603	0.0526	0.2291	10
A_6	0.1986	0.0551	0.0202	0.3587	6
A_7	0.1950	0.0603	0.0202	0.3526	5
A_8	0.1913	0.0826	0.0202	0.4991	3
A_9	0.1839	0.1240	0.0202	0.8269	1
A_{10}	0.1766	0.1343	0.0202	0.8118	2
A_{11}	0.1950	0.0603	0.0526	0.2291	-
w_j	0.6370	0.2583	0.1046	-	-
PIS	0.1986	0.1343	0.0202	-	-
NIS	0.1766	0.0448	0.0526	-	-

In this case, the rule of transitivity was also violated, since there were changes in the positions of alternatives A_1, A_3, A_4, and A_7. The same causes that were described in the first problem are evident again, especially the effect of the vector normalization procedure in modifying the entire new normalized and weighted decision matrix that is derived from the initial decision problem, a side effect being changes in the NIS and PIS of the initial decision problem (Table 4).

After this series of initial experiments, Algorithm 3 was applied to assess the behavior of the TOPSIS method using the decision problems that are presented in Mousavi-Nasab and Sotoudeh-Anvari [12] as sample (**P**). The input data that make up sample **P** are summarized in Table 5, while the results that are obtained are presented in Table 6.

Table 5. Sample of decision problems (**P**).

Case	Author(s)	Problem Analyzed
#1	Findik and Turan [82]	Material selection for load wagon walls
#2	Jee and Kang [80]	Material selection for flywheel
#3	Dehghan-Manshadi et al. [83]	Material selection for a cryogenic tank
#4	Rao [84]	Material selection in high temperature oxygen-rich environment
#5	Çaliskan et al. [85]	Material selection for tool holder
#6	Milani et al. [86]	Material selection for gear
#7	Sarfaraz Khabbaz et al. [87]	Material selection for sailing-boat mast
#8	Fayazbakhsh et al. [88]	Material selection for high-speed naval craft
#9	Khorshidi et al. [81]	Condition selection for tensile properties of Al-15%Mg2Si composite
#10	Yazdani and Payam [66]	Material selection for microelectromechanical systems
#11	Khorshidi and Hassani [89]	Material selection Al/SiC composite
#12	Zhou et al. [90]	Sustainable material selection for drinks container
#13	Jeya Girubha and Vinodh [91]	Sustainable material selection for automotive components

Table 6. Summary of rank reversal cases: TOPSIS.

Type	#1	#2	#3	#4	#5	#6	#7	#8	#9	#10	#11	#12	#13	Sum
#1	No	No	No	No	No	No	No	No	No	No	No	No	No	0
#2	No	No	No	No	No	No	No	No	No	No	No	No	No	0
#3	No	No	No	No	No	No	No	No	No	No	No	No	No	0
#4	No	No	No	No	Yes	Yes	No	Yes	Yes	No	No	No	No	4
#5	No	Yes	Yes	Yes	Yes	Yes	No	Yes	No	Yes	Yes	No	No	7
#6	No	No	Yes	No	No	No	No	No	Yes	Yes	Yes	No	Yes	4

As in Mousavi-Nasab and Sotoudeh- Anvari [12], the RR cases were found for the TOPSIS method in the vast majority of decision problems that were analyzed, especially for situations involving the transitivity property, according to the following examples:

- In Case #5, we obtained RR Type#3.1, since the initial R_o changed to R_1 with the addition of an irrelevant alternative A_{10} to the problem, as the following: $R_o = \{A_3, A_6, A_5, A_4, A_7, A_1, A_2\}$ $R_1 = \{A_9, A_8, A_1, A_5, A_3, A_6, A_2, A_1, A_4, A_7\}$ $A_{10} = \{593, 4405, 14.05, 0.00135, 1250, 79.6\}$
- In Case #3, we obtained RR Type#3.2 with the exclusion of alternatives A_1, A_3, and A_7 to the problem, as the following: $R_o = \{A_9, A_8, A_5, A_2, A_3, A_1, A_6, A_4, A_7\}$ $R_2^1 = \{A_3, A_5, A_6, A_4, A_7, A_1\}$ $R_2^3 = \{A_5, A_6, A_4, A_7, A_1, A_2\}$ $R_2^7 = \{A_3, A_5, A_6, A_4, A_1, A_2\}$
- In Case #9, we also obtained RR Type#4 by decomposing the original problem into two sub-problems, as the following: $R_o = \{A_7, A_8, A_5, A_9, A_{10}, A_6, A_4, A_3, A_1, A_2\}$ $R_4 = \{A_4, A_3, A_1, A_2, A_5\}$ $R_5 = \{A_9, A_{10}, A_8, A_6, A_7\}$

However, no cases of RR Type #1.1, #1.2, and #2 were found during the experiments. Earlier studies also demonstrated that the most severe cases of RR in the TOPSIS and other MCDM methods, such as AHP and ELECTRE, are related to the transitivity property (see Aires and Ferreira [24], Ferreira et al. [92], Chamodrakas et al. [93], and Wang and Triantaphyllou [94]).

Since RR is a classic problem in the area of MCDM, some solutions have been proposed in the literature to solve or minimize this problem. The R-TOPSIS method proved to be immune to RR for 4800 simulated decision problems and one real case. In the present study, the R-TOPSIS method was assessed for sustainable material selection using the decision problems that were presented in Table 5. In this step, our method was submitted to Algorithm 3 and no rank reversal cases were found, confirming the results that were obtained by Aires and Ferreira [24].

To illustrate that R-TOPSIS does not undergo RR and that the causes of RR in the TOPSIS method were corrected in Algorithm 2, the same cases as those in the experiments that were carried out with the TOPSIS method were used. Tables 7–10 present the results that were obtained with the R-TOPSIS method. In the new normalization procedure that is proposed, the weighted decision matrices, PIS and NIS of the modified decision problems are modified and remain unchanged when compared with the initial decision problem.

Table 7. R-TOPSIS results—Case #2—Jee and Kang [80].

Alt	Fatigue Limit (+)	Fracture Toughness (+)	Fragmentability (+)	Price (−)	CC_i	Ordering
A_1	0.0400	0.0517	0.0600	0.0008	0.2080	9
A_2	0.0199	0.0809	0.0600	0.0004	0.2219	10
A_3	0.0312	0.0753	0.0600	0.0004	0.2224	8
A_4	0.0436	0.1560	0.0600	0.0021	0.3136	6
A_5	0.0280	0.0600	0.1800	0.0005	0.3077	7
A_6	0.0660	0.1500	0.1800	0.0005	0.3996	5
A_7	0.1761	0.1321	0.1400	0.0071	0.4751	2
A_8	0.0971	0.1714	0.1400	0.0022	0.4213	4
A_9	0.2466	0.2055	0.1400	0.0050	0.6459	1
A_{10}	0.2000	0.1380	0.1000	0.0630	0.4680	3
D_j	20–1000	1–50	1–10	1000–500,000	-	-
w_j	0.4	0.3	0.2	0.1	-	-
PIS	0.400	0.300	0.200	0.0002	-	-
NIS	0.0080	0.0060	0.0200	0.1000	-	-

Table 8. R-TOPSIS results: Transitivity rule by excluding the irrelevant alternative A_{10}.

Alt	Fatigue Limit (+)	Fracture Toughness (+)	Fragmentability (+)	Price (−)	CC_i	Ordering
A_1	0.0400	0.0517	0.0600	0.0008	0.2080	9
A_2	0.0199	0.0809	0.0600	0.0004	0.2219	10
A_3	0.0312	0.0753	0.0600	0.0004	0.2224	8
A_4	0.0436	0.1560	0.0600	0.0021	0.3136	6
A_5	0.0280	0.0600	0.1800	0.0005	0.3077	7
A_6	0.0660	0.1500	0.1800	0.0005	0.3996	5
A_7	0.1761	0.1321	0.1400	0.0071	0.4751	2
A_8	0.0971	0.1714	0.1400	0.0022	0.4213	4
A_9	0.2466	0.2055	0.1400	0.0050	0.6459	1
D_j	20–1000	1–50	1–10	1000–500,000	-	-
w_j	0.4	0.3	0.2	0.1	-	-
PIS	0.400	0.300	0.200	0.0002	-	-
NIS	0.0080	0.0060	0.0200	0.1000	-	-

Table 9. R-TOPSIS results–Case #9–Khorshidi et al. [81].

Alt	Ultimate Tensile (+)	Elongation (+)	Cost (−)	CC_i	Ordering
A_1	0.5415	0.0672	0.0267	0.4058	10
A_2	0.5584	0.0775	0.0350	0.4451	9
A_3	0.5733	0.0956	0.0350	0.5026	4
A_4	0.5669	0.0930	0.0523	0.4735	7
A_5	0.5627	0.0904	0.0696	0.4477	8
A_6	0.5733	0.0827	0.0267	0.4858	5
A_7	0.5627	0.0904	0.0267	0.4815	6
A_8	0.5521	0.1240	0.0267	0.5280	3
A_9	0.5308	0.1860	0.0267	0.6156	1
A_{10}	0.5096	0.2015	0.0267	0.5994	2
D_j	200–300	1–10	0.1–1	-	-
w_j	0.6370	0.2583	0.1046	-	-
PIS	0.6370	0.2583	0.0105	-	-
NIS	0.4247	0.0258	0.1046	-	-

Table 10. R-TOPSIS results: Transitivity rule by adding the irrelevant alternative A_{11}.

Alt	Ultimate Tensile (+)	Elongation (+)	Cost (−)	CC_i	Ordering
A_1	0.5415	0.0672	0.0267	0.4058	10
A_2	0.5584	0.0775	0.0350	0.4451	9
A_3	0.5733	0.0956	0.0350	0.5026	4
A_4	0.5669	0.0930	0.0523	0.4735	7
A_5	0.5627	0.0904	0.0696	0.4477	8
A_6	0.5733	0.0827	0.0267	0.4858	5
A_7	0.5627	0.0904	0.0267	0.4815	6
A_8	0.5521	0.1240	0.0267	0.5280	3
A_9	0.5308	0.1860	0.0267	0.6156	1
A_{10}	0.5096	0.2015	0.0267	0.5994	2
A_{11}	0.5627	0.0904	0.0696	0.4477	-
D_j	200–300	1–10	0.1–1	-	-
w_j	0.6370	0.2583	0.1046	-	-
PIS	0.6370	0.2583	0.0105	-	-
NIS	0.4247	0.0258	0.1046	-	-

Finally, the rankings that were produced by the TOPSIS and R-TOPSIS methods were compared with the decision problems of our sample. The results that are contained in Table 11 reveal a high degree of correspondence between the rankings that were generated by the four methods (except Case #12), demonstrating that the changes that were implemented in the R-TOPSIS method, particularly establishing a domain for each criterion and the change in calculating NIS and PIS, did not compromise the philosophy of the classic method.

Table 11. Similarity statistics: TOPSIS and R-TOPSIS.

Alt	SRC	MAER	R_w	WS
Case #1	0.964	0.857	0.866	0.919
Case #2	0.989	0.800	0.958	0.845
Case #3	0.994	0.285	0.951	0.989
Case #4	0.980	0.666	0.918	0.771
Case #5	0.977	0.888	0.868	0.813
Case #6	1.000	0.000	1.000	1.000
Case #7	1.000	0.000	1.000	1.000
Case #8	0.983	0.400	0.917	0.917
Case #9	0.991	0.600	0.939	0.969
Case #10	1.000	0.000	1.000	1.000
Case #11	0.968	1.250	0.780	0.619
Case #12	0.797	2.571	−0.857	0.233
Case #13	1.000	0.000	1.000	1.000
Average	0.973	0.640	0.795	0.852

Rank Reversal, Sustainability, and Management Implications

The previous sections presented a new approach to select sustainable materials based on the concepts supporting multiple criteria and rank reversal decisions. The idea was to design and validate a robust selection method that was immune to rank reversal problems.

After this initial stage, we selected one of the literature cases to demonstrate some of the managerial implications caused by the rank reversal problem in sustainable material selection. For example, Agrawal [34] presents a case study that is aimed at selecting sustainable materials using selective laser sintering (SLS) based on seven criteria: accuracy (C_1), surface finish (C_2), sintered part density (C_3), tensile strength (C_4), Young's modulus (C_5), elongation (C_6), and hardness (C_7). The alternatives that were assessed were Castform Polystyrene (A_1), Duraform Thermoplastic Elastomer (A_2), Duraform Thermoplastic Polyurethane (A_3), Duraform Flame Retardent (A_4), Duraform Polypropylene (A_5), and Duraform Glass Filled (A_6). The weights used were w_{c1} = 0.091, w_{c2} = 0.189, w_{c3} = 0.098,

$w_{c4} = 0.173$, $w_{c5} = 0.147$, $w_{c6} = 0.163$, and $w_{c7} = 0.139$, respectively. The following ranking was obtained from these data using the TOPSIS method: A_5, A_6, A_3, A_4, A_2, and A_1.

The choice of alternative A_5 as the best option is acceptable from the sustainable and managerial standpoint, since it performs the best in the most important criteria. A_6 can also be considered a good alternative in relation to the others, since it performs the best in three criteria and similarly in the other two. Finally, A_2 and A_1 can be considered the least recommended alternatives for this decision context, since they perform very poorly in the most important criteria, thereby compromising their global assessment. Thus, given that the set of alternatives is immutable, the TOPSIS model is considered suitable and acceptable for problem resolution.

However, we are currently involved in a globalized context, where new technologies and products emerge increasingly faster and with different properties, making them competitive, especially in the context of sustainability where the weighting of different factors is normally considered. Thus, the most appropriate decision context to model the sustainable material selection problem is that presented by Campanella and Ribeiro [47], where decision problems are dynamic, and alternatives can be added and removed from the decision problem at any time. In this case, adopting a multicriteria decision support method that is immune to the rank reversal problem may avoid undesired situations, as described below.

For example, consider the following situations: (1) adding a new alternative (A_7) that is irrelevant to the problem, that is, an inferior alternative when compared to the best in initial ranking (A_5 and A_6); (2) applying the TOPSIS method to the new decision problem, and (3) generating a new ranking: A_3, A_5, A_6, A_4, A_7, A_2, A_1. Since this results in an undesirable managerial situation, how can it be justified that inserting a new alternative that is irrelevant to the problem affects the indication of the best alternative? In addition, how can the selection be justified given that the new best alternative is inferior to five of the seven decision criteria?

In addition to indicating the best alternative, transitivity is another problem that may occur with the TOPSIS method in dynamic decision-making environments in the sustainable material selection context. For example, consider the following situations: (1) adding a new alternative (A_8) irrelevant to the problem, (2) applying the TOPSIS method to the new decision problem, and (3) generating a new ranking: A_5, A_6, A_4, A_3, A_2, A_8, A_1. In this case, the ranking of the two best alternatives remained unchanged, but from the standpoint of the decision-maker, an important change occurred with the rank reversal of alternatives A_3 and A_4. This is also a serious managerial and methodological problem, since it is related to the preferences of the decision-maker and transitivity.

These problems are not limited to isolated cases, and we simulated different experiments, observing at least eight extremely undesirable cases of rank reversal: two cases that were related to the indication of the best alternative for including irrelevant alternatives, one case of changing the best alternative for excluding an irrelevant alternative, two cases of affecting transitivity by adding irrelevant alternatives, two cases that affected transitivity by excluding irrelevant alternatives, and one case where transitivity was affected by decomposing the initial problem. Thus, from a managerial standpoint, in dynamic decision-making environments and the sustainable material selection context, the object of this study, the TOPSIS method can create numerous inconsistencies as a decision-making support tool.

It is, therefore, recommended to avoid the use of TOPSIS in the sustainable material selection context, using R-TOPSIS instead. The recommendation extends to all other methods that allow reverse rank.

This advice will have a large effect on procurement practice since material selection is one of the critical factors for managers to take advantage of sustainability and plays a significant role in the entire design manufacturing process [34].

In addition, although sustainable materials are considered one of the main options for environmentally correct constructions, they are scarce in supply and have high costs. Thus, decision-makers in the construction industry face the dilemma of designing sustainable projects within budget limitations, a problematic characteristic of MCDM methods.

Therefore, the present study has clear practical implications on the importance of developing an adequate decision-making structure for the selection of sustainable materials.

5. Conclusions

Over the course of this study, it became evident that the use of MCDM-based approaches for the sustainable material selection problem has increased steadily. In particular, the TOPSIS method stands out as one of the most widely used methods in the literature and one of the most suitable for the material selection problem, as reported by Mousavi-Nasab and Sotoudeh-Anvari [13]. The RRP is one of the limitations of these methods. A number of authors, such as Salem and Awasthi [95] and Anbaroglu et al. [96], consider that this problem may be a barrier to the use of these methods in decision-making support processes.

In the present study, R-TOPSIS is presented as a new approach for SMS. This method was immune to the RRP, first for simulated decision problems, as described by Aires and Ferreira [24], and in this study for the sample of decision problems that were described by Mousavi-Nasab and Sotoudeh-Anvari [12]. During the experiments, the R-TOPSIS method was submitted to Algorithm 3 and no cases of RR were found. The results differ when the TOPSIS method is considered, since in this case, various RR cases were obtained, but we were able to demonstrate the causes of this problem in the TOPSIS method.

The primary contributions of this study are as follows: (i) proposing an algorithm that can be used to assess MCDM methods in relation to the different types of RR that are presented in the literature; (ii) analyzing the TOPSIS method in terms of the RRP, using a real decision problem in the area of SMS; (iii) demonstrating the causes of RRP in the TOPSIS method; and (iv) proposing a new approach for SMS, demonstrating ranking that is similar to that of the TOPSIS method and immune to the RRP.

The limitations of the study are linked to the sample, which was limited to the 13 decision problems of the Mousavi-Nasab study and Sotoudeh-Anvari [12]. The article also did not present a case study of its own, given its experimental bias. These points are considered opportunities for future research.

Furthermore, future research also could use and improve Algorithm 3 to assess other MCDM methods for sustainable material selection. For example, evaluating fuzzy extensions of classical methods is a promising research opportunity.

The computational experiments that were performed can also be enhanced by using other combinations of cases of RR, for example, to evaluate the effect of the non-discriminating criterion.

Finally, it would be useful to study to what extent different sustainable material selection methods are used in different countries and the efficiency of the proposed approach in other sustainability decision problems.

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