SCIENTIFIC OASIS

Spectrum of Mechanical Engineering and Operational Research

Journal homepage: www.smeor-journal.org
ISSN: 3042-0288

Comparative Sensitivity Analysis in Composite Material Selection: Evaluating OAT and COMSAM Methods in Multi-criteria Decision-making

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ARTICLE INFO

Article history:
Received 13 June 2024
Received in revised form 6 October 2024
Accepted 30 October 2024
Available online 2 November 2024

Keywords:
Sensitivity analysis; COMSAM; Decision-making; Results robustness; OAT; COMET

ABSTRACT

The decision-making process is critical across various fields, influencing essential aspects like performance, safety, and sustainability. In engineering and materials science, selecting suitable materials is a complex process involving multiple interdependent criteria, which impact the reliability and lifecycle of a design. Traditional sensitivity analysis methods, such as the one-at-a-time (OAT) approach, assess the effects of individual parameter changes but often fail to capture the cumulative impact of simultaneous modifications. It can limit the effectiveness of decision tools in real-world scenarios where multiple factors vary concurrently. This study utilizes the Comprehensive Sensitivity Analysis Method (COMSAM) to address limitations in traditional sensitivity analysis by modeling simultaneous parameter adjustments across multiple criteria. Specifically, the study aims to validate COMSAM's effectiveness in the practical problem of composite material selection, comparing it with the traditional OAT approach within a multi-criteria decision-making (MCDM) framework. By integrating both sensitivity analysis techniques with the Characteristic Objects Method (COMET), this research ensures robust evaluation and mitigates vulnerabilities like the rank reversal paradox. The findings demonstrate that COMSAM provides enhanced insights into the impact of parameter interdependencies, offering a more resilient foundation for decision-making in high-stakes environments where material properties and performance are paramount.

1. Introduction

Effective decision-making is essential across diverse fields, as it directly influences the reliability and outcomes of the selection process [1]. Decision-support tools play a critical role in enhancing

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https://doi.org/10.31181/smeor21202524

understanding of the potential of available options, significantly impacting key aspects such as performance, safety, and sustainability of systems and products [2]. In engineering and materials science, the selection of suitable materials is a critical decision, influencing the success of a design and its cost-efficiency, durability, and overall lifecycle [3]. This process often involves balancing a complex set of criteria, such as strength, durability, weight, and cost. Multiple factors included in the evaluation have the potential to significantly affect the final product's performance [4]. However, obtaining accurate, reliable data for these criteria is challenging, as measurements of specific material properties can be affected by equipment limitations, leading to variability and potential errors. Such uncertainties can impact multiple parameters simultaneously, introducing risks to the decision-making process if not adequately accounted for. In high-stakes applications, a robust approach to material selection is therefore crucial to minimize these risks and ensure that chosen materials meet the required standards.

In addition to measurement errors, there are scenarios where simultaneous adjustments across multiple parameters are made intentionally. Within the Multi-Criteria Decision Analysis (MCDA) process [5], the specifications of each considered alternative across various criteria are stored in the decision matrix, which captures the characteristics of the alternatives and serves as the input data for evaluating decision options [6]. For example, manufacturers often aim to improve material quality by refining specifications and must predict which adjustments will deliver the most favorable outcomes [7]. Modeling multiple changes simultaneously within the decision matrix is therefore essential to evaluate how these modifications influence overall material selection. This need for a comprehensive approach is even more critical when multiple criteria are interdependent or display non-linear responses to variations in input data [8].

To manage these complexities, sensitivity analysis is an essential tool for assessing how variations in input parameters impact the robustness of decisions [9]. Sensitivity analysis is a flexible approach that can model changes across different aspects of the input data, from adjustments in the decision matrix to variations in criteria weights or even the exclusion of specific criteria to evaluate their influence on outcomes [10]. Traditional methods, particularly the one-at-a-time (OAT) approach, evaluate the effects of modifying individual parameters in isolation [11]. Although this method can be useful, it often overlooks the cumulative impact of simultaneous changes. As a result, OAT may fall short in real-world scenarios, where multiple variables frequently fluctuate together. Recognizing these limitations, recent research work has proposed the Comprehensive Sensitivity Analysis Method (COMSAM), which extends the traditional OAT approach [12]. COMSAM builds upon the assumptions and strengths of OAT while broadening its scope to accommodate simultaneous variations across multiple criteria. This method allows for a more comprehensive understanding of how interconnected input parameters influence decision outcomes, enabling decision-makers to better anticipate and manage the complexities inherent in real-world problems. The motivation for undertaking this study arises from the fact that, while COMSAM has been presented in a theoretical context, it has yet to be applied to practical problems to validate its effectiveness.

To achieve this goal, this study concentrates on comparative sensitivity analysis in composite material selection, specifically highlighting the differences between the traditional OAT approach and the COMSAM method within a multi-criteria decision-making (MCDM) framework. Through a detailed comparison, we illustrate how COMSAM offers deeper insights into the decision-making process. This method aims to enhance the assessment of how variations across multiple parameters impact final selection outcomes, where changes can arise from measurement uncertainties or intentional adjustments. By modeling realistic scenarios that incorporate simultaneous changes, the application of the COMSAM seeks to empower decision-makers to make choices that are robust against both anticipated and unexpected variations in material properties. Both examined approaches of OAT and COMSAM are integrated with the Characteristic Objects Method (COMET), which effectively handles multi-criteria decision analysis evaluations while being resistant to the rank reversal paradox [13]. The main contributions of the study are:

- This study presents a comparative analysis of the traditional OAT approach and the COMSAM method in conducting sensitivity analysis for multi-criteria decision-making processes
- The practical problem of composite material selection is examined using the COMSAM method, along with comprehensive sensitivity analysis, to verify the robustness of the recommendations
- The research provides validation for COMSAM, demonstrating its effectiveness in enhancing multi-criteria assessments in a real-world scenario

The rest of the paper is organized as follows. Section 2 presents the preliminaries of the COMET and COMSAM methods. Section 3 describes the study case directed toward the evaluation of composite material selection and sensitivity analysis to examine the robustness of the recommendations. Finally, Section 4 presents the conclusions drawn from the research and further directions of the study.

2. Preliminaries

2.1 *The COMET method*

The Characteristic Objects Method (COMET) is a multi-criteria decision-making approach that employs a fuzzy inference model to assess various decision variants. It is resistant to the rank reversal phenomenon, as each alternative is evaluated independently [13]. The effectiveness of the COMET method has been demonstrated across various fields and validated in numerous multi-criteria decision-making scenarios [14, 15]. In this research, we used the *pymcdm* library to perform calculations with the COMET method [16, 17]. The main steps of this method were listed below.

Step 1. Define the Space of the Problem – the expert determines the problem's dimensionality by selecting the number r of criteria, $C_1, C_2, ..., C_r$. Then, the set of fuzzy numbers for each criterion C_i is selected (1):

$$C_r = \{\tilde{C}_{r1}, \tilde{C}_{r2}, ..., \tilde{C}_{rc_r}\} \tag{1}$$

where $c_1, c_2, ..., c_r$ are numbers of the fuzzy numbers for all criteria.

Step 2. Generate Characteristic Objects – The characteristic objects (CO) are obtained by using the Cartesian Product of fuzzy numbers cores for each criterion as follows (2):

$$CO = C(C_1) \times C(C_2) \times ... \times C(C_r) \tag{2}$$

Step 3. Evaluate the Characteristic Objects – The expert creates the Matrix of Expert Judgment (MEJ) by comparing characteristic objects (COs) pairwise. In the MEJ matrix, α_{ij} represents the comparison result between CO_i and CO_j, based on the expert's mental function f_{exp} which relies solely on their knowledge (3). The Summed Judgments (SJ) vertical vector is then calculated using Equation (4).

$$\alpha_{ij} = \begin{cases} 0.0, & f_{exp}(CO_i) < f_{exp}(CO_j) \\ 0.5, & f_{exp}(CO_i) = f_{exp}(CO_j) \\ 1.0, & f_{exp}(CO_i) > f_{exp}(CO_j) \end{cases} \tag{3}$$

$$SJ_i = \sum_{j=1}^{t} \alpha_{ij} \tag{4}$$

Finally, preference values are estimated for each Characteristic Object, resulting in the vertical vector P , where the $i-th$ element represents the estimated preference value for CO_i.

Step 4. The Rule Base – each Characteristic Object and value of preference is converted to a fuzzy rule as follows (5):

$$IF\ C(\tilde{C}_{1i})\ AND\ C(\tilde{C}_{2i})\ AND\ ...\ THEN\ P_i \tag{5}$$

In this way, the complete fuzzy rule base is obtained.

Step 5. Inference and Final Ranking – Each alternative is represented by a set of crisp numbers corresponding to criteria $C_1, C_2, ..., C_r$. Mamdani's fuzzy inference method is used to compute the preference of each alternative, ensuring unambiguous results. The bijection ensures the COMET method is free from the rank reversal phenomenon.

2.2 *The COMSAM method*

The Comprehensive Sensitivity Analysis Method (COMSAM) is a newly introduced approach for performing sensitivity analysis [12]. It offers a structured approach that systematically incorporates simultaneous modifications across multiple values within the decision matrix. The COMSAM method allows for a detailed exploration of decision scenarios under changing evaluation conditions. The method introduces modification bounds that specify the permissible range of changes for each criterion, leading to the generation of diverse combinations of criteria indexes. It enables researchers and practitioners to conduct sensitivity studies effectively while providing clarity through formal notation and mathematical representations.

Furthermore, the COMSAM method goes beyond traditional one-at-a-time analyses by deepening the understanding of interdependencies within the decision matrix, enriching the evaluation of complex decision-making scenarios. It allows for the modeling of potential uncertainties in measured values, offering insights into how results may vary due to inaccuracies in the calculation process or intentional adjustments. This capability extends the reach of sensitivity analysis, providing valuable perspectives for decision-makers navigating intricate and dynamic environments. The simplified flow of the proposed COMSAM method is presented in Figure 1. The detailed descriptions of the subsequent steps of the method are defined below.

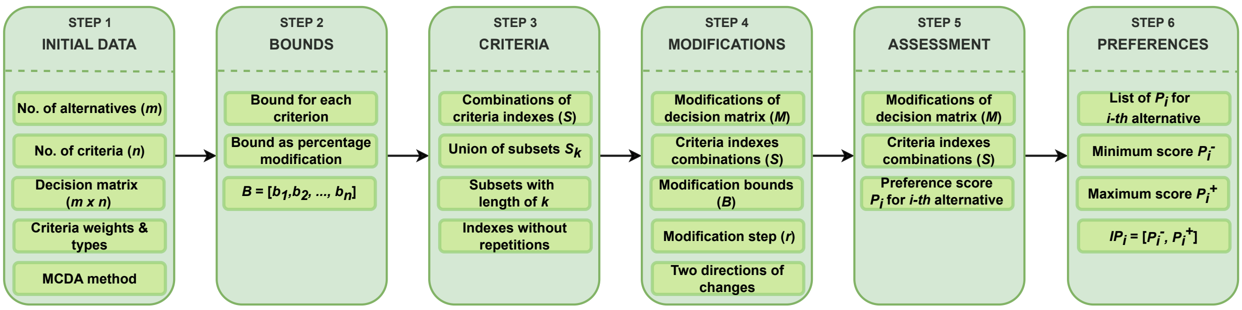

Fig. 1. Subsequent steps of the COMSAM method.

Step 1. Define the number of alternatives (m), number of criteria (n), decision matrix $(X_{m\times n})$, criteria weights and types, select the MCDA method for the multi-criteria assessment. The iterator i represents the number of $i-th$ alternative, while j indicates the $j-th$ criterion. Moreover, $i \in \{1, \ldots, m\}$

and $j \in \{1, \ldots, n\}$.

Step 2. Define the modification bounds (B) for the criteria in the problem as the percentage modifications applied to the initial values of each column in the decision matrix, where each element (b_j) represents a specified range of percentage modifications for the $j-th$ criterion. Each b_j signifies the maximum allowable modification size for the values associated with the $j-th$ criterion in the decision matrix. The modification process involves increasing and decreasing the initial values, and the resulting B can be formally defined as (6).

$$B = [b_1, b_2, \ldots, b_j, \ldots, b_n] \tag{6}$$

Step 3. Generate possible combinations of criteria indexes (S). The set S is formed as the union of subsets S_k where k represents different lengths of indexes within each subset. The union is taken over all possible lengths from the minimum criteria (mc) to the total number of criteria (n). When $mc = 1$, part of the sensitivity analysis evaluations is performed as the one-at-a-time analysis since certain subsets of criteria indexes include only one criterion index. The length of indexes could be defined as $mc \leq k \leq n$. The formula for defining the criteria indexes combinations (S) is given by (7):

$$S = \bigcup_{k=mc}^{n} S_k \tag{7}$$

Each subset S_k consists of sets L_{kp} representing combinations of criteria indexes of length k without repetitions of the indexes. The number of combinations of criteria indexes generated for a given length k can be expressed by formula $q = \frac{n!}{k!(n-k)!}$. The formal representation of S_k is defined as (8):

$$S_k = \{L_{k1}, L_{k2}, \ldots, L_{kp}, \ldots, L_{kq}\}, \quad p \in \{1, 2, \ldots, q\} \tag{8}$$

Each set L_{kp} within S_k is defined as combinations of individual criteria indexes of length k, ensuring that there are no repetitions. The criteria indexes are represented as l_x, l_y, for the $x-th$ and $y-th$ criteria, respectively. The criteria indexes should be distinct within the set, ensuring that the index appears only once in a single combination. The definition of L_{kp} is as follows (9):

$$L_{kp} = (l_1, l_2, \ldots, l_x, l_y \ldots, l_k) \quad l_x, l_y \in \{1, \ldots, n\}, \quad l_x \neq l_y \text{ and } l_x < l_y \tag{9}$$

Step 4. Generate possible modifications (M) of decision matrix values using (10). For this purpose, previously defined subsets of criteria indexes (S_k) are used. Each subset (S_k) of the criteria indexes combinations set (S) should be iterated over its constituent subsets of length q, denoted as L_{kp}, ensuring coverage of all possible combinations of criteria indexes. Then, for each L_{kp} the modifications set (md_{l_y}) for l_y-th criterion should be created by employing the Cartesian Product, incorporating a step size (r) for modification size generation. Based on the generated modifications, the initial values of $i-th$ alternative and l_y-th criterion represented as $x^*_{il_y}$ should be changed. The increase of the initial value from the decision matrix is represented as $x^{*+}_{il_y}$, while its decrease is represented as $x^{*-}_{il_y}$. This step-by-step process results in a comprehensive set of modifications (M), capturing the details of simultaneous changes across multiple criteria index subsets.

$$\forall(S_k) \in S\, \forall(L_{kp}) \in S_k, \exists M : M = \{md_{l_1} \times md_{l_2} \times \ldots md_{l_y} \times \ldots \times md_{l_k}\}$$
$$md_{l_y} = \{0, r, 2r, \ldots, b_{l_y}\} \tag{10}$$
$$x^{*+}_{il_y} = x_{l_y} + (x_{l_y} \cdot md_{l_y}), \quad x^{*-}_{il_y} = x_{l_y} - (x_{l_y} \cdot md_{l_y})$$

Step 5. Assess alternatives with generated criteria index combinations (S) and on modification sizes (M). For each alternative, the evaluation should be performed separately. The preference scores (P_i) of $i-th$ alternative obtained within the multi-criteria evaluation should be stored for further analysis.

Step 6. Determine the interval preference values for alternatives. Based on the stored results, the interval preference (IP_i) of $i-th$ alternative could be calculated by indicating minimum (P_i^-) and maximum (P_i^+) preference value from the P_i vector, as follows (11):

$$IP_i = [(P_i^-), (P_i^+)] \tag{11}$$

3. Study case

In this study, the problem of composite material selection is addressed to demonstrate and compare the effectiveness of the OAT approach and the recently developed COMSAM method in assessing the robustness of decision outcomes. Composite materials are valued for their adjustable mechanical properties and high strength-to-weight ratios. However, selecting the most suitable variant involves a complex, multi-criteria decision process that is sensitive to varying input parameters. To assess considered materials, we used the COMET method. It served as a decision-making tool that ranks alternatives across multiple criteria, to create a baseline ranking for further comparison. The OAT approach and COMSAM method were then applied to systematically introduce variations in input data and observe how these changes modeled in the decision matrix influence the final rankings. By comparing the results of OAT, which considers changes in one parameter at a time, with COMSAM, which allows for simultaneous variations across multiple criteria, this study aims to provide insights into the robustness and reliability of the composite material selection process. The findings aim to reveal differences in sensitivity between the two approaches.

The dataset used in this evaluation includes eight composite materials, each assessed based on a set of key criteria to support effective material selection. The problem was already addressed in the literature in [18], where authors assessed the considered alternatives with the Analytical Hierarchy Process (AHP) method combined with the Multi-Objective Optimization on the basis of Ratio Analysis (MOORA). The criteria included in the evaluation encompassed a range of physical, mechanical, and wear-related properties essential for evaluating composite materials. Specifically, density (C_1), measured in gm/cc, represents the material's mass per unit volume and is crucial for applications requiring lightweight solutions. Two slurry abrasion wear properties ($Ws(n)$ marked as (C_2) and $Ws(v)$ labeled as (C_3)) capture the specific wear rate (in cm^3/N-m) under varying conditions, with $Ws(n)$ reflecting wear at different normal loads and $Ws(v)$ measuring wear under different sliding velocities; lower values indicate better wear resistance. The mechanical properties include micro-hardness (C_4), measured in Hv, which indicates the material's resistance to localized deformation, tensile strength (C_5) in MPa, the maximum stress the material can endure when stretched, flexural strength (C_6), in MPa, its resistance to bending forces, inter-laminar shear strength (ILSS) (C_7), in MPa, critical for layered composites to prevent delamination, and impact strength (C_8), in J, which measures the material's ability to absorb energy upon impact. These criteria offer a comprehensive view of the materials' properties, from durability and strength to resistance against wear, enabling a robust evaluation of composite suitability. Detailed descriptions of the eight materials considered are available in the initial study [18]. Table 1 presents the decision matrix with criteria weights and their types, forming the foundation for applying the COMET method to rank alternatives and subsequently applying the OAT and COMSAM approaches to test the robustness of the results.

Table 1
Decision matrix used MCDA evaluation for composite material selection

A_i	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
A_1	1.2060	0.02958	0.02982	23.90	30.27	41.85	49.34	1.351
A_2	1.2078	0.02673	0.02140	28.70	38.46	47.13	53.92	1.505
A_3	1.2127	0.02588	0.01877	33.30	42.23	53.42	59.43	1.796
A_4	1.2221	0.02404	0.01635	35.20	38.65	50.26	51.04	1.933
A_5	1.2130	0.03497	0.02213	24.27	36.19	51.71	55.59	1.556
A_6	1.2180	0.02982	0.01648	29.58	40.06	54.36	57.13	1.924
A_7	1.2260	0.02566	0.01376	35.12	44.53	58.67	60.87	2.036
A_8	1.2330	0.02398	0.01228	37.43	39.87	57.09	56.19	2.192
Weights	0.0201	0.2218	0.2694	0.0394	0.1815	0.0853	0.0735	0.1090
Types	Cost	Cost	Cost	Profit	Profit	Profit	Profit	Profit

The comparison of rankings between the COMET method and MULTIMOORA (MOORA$_{rs}$ (ratio system), MULTIMOORA, and MOORA$_{rp}$ (reference point)) presented in Table 2 showed strong consistency, particularly at the highest and lowest ranks. The COMET, MOORA$_{rs}$, and MULTIMOORA methods consistently identify A_8 as the top alternative. Moreover, the order of all considered decision variants remained the same while utilizing those MCDA methods. On the other hand, minor ranking differences were observed within the MOORA$_{rp}$ method. The differences could be seen particularly between A_7 and A_8, where the order of these alternatives was reversed, promoting A_7 to 1st place. It highlighted subtle differences in the performance across methods, with COMET offering a stable ranking that matched recommendations from the MOORA$_{rs}$ and MULTIMOORA methods.

Table 2
Comparison of the results obtained with the COMET method
with the ones presented in the reference research [18].

	COMET		MOORA$_{rs}$	MULTIMOORA	MOORA$_{rp}$
A_i	Preference	Ranking	Ranking	Ranking	Ranking
A_1	0.032	8	8	8	8
A_2	0.574	6	6	6	6
A_3	0.843	4	4	4	5
A_4	0.875	3	3	3	3
A_5	0.177	7	7	7	7
A_6	0.755	5	5	5	4
A_7	0.969	2	2	2	1
A_8	0.985	1	1	1	2

The comparison between the OAT approach and COMSAM method was conducted using the initial decision matrix from Table 1 to evaluate the differences in findings generated by each technique. Initially, the sensitivity of the results was assessed by modifying values in the decision matrix for the three most influential criteria (C_2, C_3, and C_5) with a maximum change of 10%, representing potential measurement errors or intentional changes in the characteristics of composite material properties. As the COMSAM method applies adjustments in the decision matrix incrementally for specified combinations, a step size of 5 was used to balance the precision of changes with computational efficiency, ensuring a practical compromise between accuracy and the time required to model these variations.

The detailed analysis focused on alternative A_7, which was initially ranked 2nd, with a small preference score difference of 0.017 compared to the top-ranked alternative A_8. Table 3 presents the results obtained from the performed sensitivity analysis. It was observed that the OAT approach, which models changes in the decision matrix for one parameter at a time, resulted in smaller variations in A_7's preference scores than those produced by the COMSAM method, which allows for simultaneous adjustments across multiple parameters.

Table 3
The preference scores obtained with the COMET method for alternative A_7 using the OAT approach and the COMSAM method.

OAT (single)												COMSAM (multiple)			
S	M	P_7^-	P_7^+	S	M	P_7^-	P_7^+	S	M	P_7^-	P_7^+	S	M	P_7^-	P_7^+
2	0	0.969	0.969	3	0	0.969	0.969	5	0	0.969	0.969	(2, 3, 5)	(0, 0, 0)	0.969	0.969
2	0	0.969	0.969	3	0	0.969	0.969	5	5	0.969	0.969	(2, 3, 5)	(0, 0, 5)	0.969	0.969
2	0	0.969	0.969	3	0	0.969	0.969	5	10	0.953	0.969	(2, 3, 5)	(0, 0, 10)	0.969	0.953
2	0	0.969	0.969	3	5	0.960	0.977	5	0	0.969	0.969	(2, 3, 5)	(0, 5, 0)	0.960	0.977
2	0	0.969	0.969	3	5	0.960	0.977	5	5	0.969	0.969	(2, 3, 5)	(0, 5, 5)	0.960	0.977
2	0	0.969	0.969	3	5	0.960	0.977	5	10	0.953	0.969	(2, 3, 5)	(0, 5, 10)	0.960	0.964
2	0	0.969	0.969	3	10	0.952	0.985	5	0	0.969	0.969	(2, 3, 5)	(0, 10, 0)	0.952	0.985
2	0	0.969	0.969	3	10	0.952	0.985	5	5	0.969	0.969	(2, 3, 5)	(0, 10, 5)	0.952	0.985
2	0	0.969	0.969	3	10	0.952	0.985	5	10	0.953	0.969	(2, 3, 5)	(0, 10, 10)	0.952	0.974
2	5	0.956	0.981	3	0	0.969	0.969	5	0	0.969	0.969	(2, 3, 5)	(5, 0, 0)	0.956	0.981
2	5	0.956	0.981	3	0	0.969	0.969	5	5	0.969	0.969	(2, 3, 5)	(5, 0, 5)	0.956	0.981
2	5	0.956	0.981	3	0	0.969	0.969	5	10	0.953	0.969	(2, 3, 5)	(5, 0, 10)	0.956	0.970
2	5	0.956	0.981	3	5	0.960	0.977	5	0	0.969	0.969	(2, 3, 5)	(5, 5, 0)	0.946	0.988
2	5	0.956	0.981	3	5	0.960	0.977	5	5	0.969	0.969	(2, 3, 5)	(5, 5, 5)	0.946	0.988
2	5	0.956	0.981	3	5	0.960	0.977	5	10	0.953	0.969	(2, 3, 5)	(5, 5, 10)	0.946	0.978
2	5	0.956	0.981	3	10	0.952	0.985	5	0	0.969	0.969	(2, 3, 5)	(5, 10, 0)	0.936	0.994
2	5	0.956	0.981	3	10	0.952	0.985	5	5	0.969	0.969	(2, 3, 5)	(5, 10, 5)	0.936	0.994
2	5	0.956	0.981	3	10	0.952	0.985	5	10	0.953	0.969	(2, 3, 5)	(5, 10, 10)	0.936	0.986
2	10	0.943	0.985	3	0	0.969	0.969	5	0	0.969	0.969	(2, 3, 5)	(10, 0, 0)	0.943	0.985
2	10	0.943	0.985	3	0	0.969	0.969	5	5	0.969	0.969	(2, 3, 5)	(10, 0, 5)	0.943	0.985
2	10	0.943	0.985	3	0	0.969	0.969	5	10	0.953	0.969	(2, 3, 5)	(10, 0, 10)	0.943	0.975
2	10	0.943	0.985	3	5	0.960	0.977	5	0	0.969	0.969	(2, 3, 5)	(10, 5, 0)	0.931	0.991
2	10	0.943	0.985	3	5	0.960	0.977	5	5	0.969	0.969	(2, 3, 5)	(10, 5, 5)	0.931	0.991
2	10	0.943	0.985	3	5	0.960	0.977	5	10	0.953	0.969	(2, 3, 5)	(10, 5, 10)	0.931	0.982
2	10	0.943	0.985	3	10	0.952	0.985	5	0	0.969	0.969	(2, 3, 5)	(10, 10, 0)	0.920	0.997
2	10	0.943	0.985	3	10	0.952	0.985	5	5	0.969	0.969	(2, 3, 5)	(10, 10, 5)	0.920	0.997
2	10	0.943	0.985	3	10	0.952	0.985	5	10	0.953	0.969	(2, 3, 5)	(10, 10, 10)	0.920	0.990

In the OAT results, the most visible changes for A_7 occurred in C_2 (where preference scores varied from 0.943 to 0.985) and C_3 (preferences scores between 0.952 and 0.985), while C_5 yielded stable scores, ranging between 0.953 and 0.969. When applying the COMSAM method, preference score fluctuations for A_7 were observed from 0.920 to 0.997, showing that modifying parameters C_2, C_3, and C_5 by a certain percentage change simultaneously could potentially allow A_7 to surpass A_8, the initial top-ranked alternative. In contrast, with OAT, even the highest changes could only yield preference scores equivalent to, but not surpassing, A_8, indicating that the COMSAM method provides a broader and more flexible analysis of sensitivity in this multi-criteria problem.

Furthermore, the general findings and outcomes obtained from the comparison of applying the OAT approach and COMSAM method were presented in Table 4, where potential preference scores for all considered alternatives were shown. The results indicated that, for most alternatives analyzed, modifications in C_2 by 10% yielded the most significant changes in preference scores when using the OAT approach, affecting both increases and decreases in the initial preference scores. Notably, alternative A_4 showed the largest improvement with a 10% modification in C_3, while for A_5, changes in C_3 by 10% produced both the minimum and maximum preference scores for that alternative. For A_7, modifying C_3 by 10% also resulted in the highest preference score within the OAT approach.

Table 4
Comparison of the potential preference scores under modifications made in the decision matrix with the OAT approach and the COMSAM method for the considered alternatives.

	OAT (single)						COMSAM (multiple)					
A_i	S	M^-	P_i^-	S	M^+	P_i^+	S	M^-	P_i^-	S	M^+	P_i^+
A_1	2	10	0.015	2	10	0.128	(2, 3, 5)	(10, 0, 0)	0.015	(2, 3, 5)	(10, 0, 0)	0.128
A_2	2	10	0.445	2	10	0.702	(2, 3, 5)	(10, 10, 0)	0.369	(2, 3, 5)	(10, 10, 0)	0.757
A_3	2	10	0.770	2	10	0.896	(2, 3, 5)	(10, 10 0)	0.723	(2, 3, 5)	(10, 10, 0)	0.922
A_4	2	10	0.803	3	10	0.906	(2, 3, 5)	(10, 10, 0)	0.759	(2, 3, 5)	(5, 10, 0)	0.908
A_5	3	10	0.137	3	10	0.243	(2, 3, 5)	(0, 10, 0)	0.137	(2, 3, 5)	(0, 10, 0)	0.243
A_6	2	10	0.620	2	10	0.838	(2, 3, 5)	(10, 10, 0)	0.563	(2, 3, 5)	(10, 10, 0)	0.877
A_7	2	10	0.943	3	10	0.985	(2, 3, 5)	(10, 10, 0)	0.920	(2, 3, 5)	(10, 10, 0)	0.997
A_8	2	10	0.958	2	0	0.985	(2, 3, 5)	(10, 0, 0)	0.958	(2, 3, 5)	(0, 0, 0)	0.985

Conversely, with the COMSAM method. where multiple simultaneous changes were modeled, the majority of the lowest and highest preference scores were observed when C_2 and C_3 were adjusted by 10%, while C_5 remained constant as per the initial decision matrix. Additionally, it was observed that for alternative A_8, no improvement occurred when C_2, C_3, and C_5 were modified, suggesting stability in its initial ranking and no potential benefits from changing parameters within the examined ranges of modifications. For A_1, despite the potential for multiple value adjustments, both the lowest and highest preference scores were achieved when only C_2 was modified by 10%, showing consistent outcomes with the OAT approach.

Further analysis revealed that adjustments to the initial values in the decision matrix for A_3 and A_4 could significantly enhance their preference scores, with A_3 increasing from 0.843 to 0.922 and A_4 from 0.875 to 0.908. These findings suggest that with specific modifications in characteristics related to $Ws(n)$, $Ws(v)$, and tensile strength, A_3 could potentially be ranked higher, advancing to 3rd place in the ranking and positioning itself as a more attractive solution.

An additional sensitivity analysis was conducted using the COMET and COMSAM methods, focusing on the four most significant criteria, each exceeding a weight value of 0.10. From these criteria, four distinct combinations were generated and analyzed within the COMSAM framework, with modifications applied in a range of 5% of the initial values from the decision matrix for all considered criteria.

This analysis aimed to assess how variations in the four key criteria could impact preference scores, simulating potential measurement errors or intentional alterations in the parameters of composite materials. Table 5 presents the interval preference scores obtained within the performed analysis and examined pairs of criteria.

Table 5
Interval preferences derived from the integration of the COMET and COMSAM methods, showcasing pairs of criteria (S) that include combinations of the four most significant criteria in the composite material selection problem.

S	$(2,3,5)$		$(2,3,8)$		$(2,5,8)$		$(3,5,8)$	
A_i	P_i^-	P_i^+	P_i^-	P_i^+	P_i^-	P_i^+	P_i^-	P_i^+
A_1	0.024	0.079	0.024	0.079	0.024	0.079	0.032	0.032
A_2	0.470	0.671	0.470	0.671	0.509	0.638	0.534	0.609
A_3	0.786	0.893	0.786	0.893	0.806	0.879	0.825	0.860
A_4	0.820	0.892	0.820	0.892	0.839	0.876	0.859	0.891
A_5	0.157	0.198	0.157	0.198	0.177	0.177	0.157	0.198
A_6	0.661	0.823	0.661	0.823	0.688	0.800	0.729	0.781
A_7	0.946	0.988	0.946	0.988	0.956	0.981	0.960	0.977
A_8	0.972	0.985	0.972	0.985	0.972	0.985	0.985	0.985

The results indicated that the most visible changes in preference scores occurred for the criteria pairs (2, 3, 5) and (2, 3, 8), highlighting that the two most critical criteria, C_2 and C_3, which represent $Ws(n)$ and $Ws(v)$, significantly influence the attractiveness of the composite materials. Notably, within a 5% variation of the initial characteristics, alternative A_7 could achieve higher preference scores than A_8, which was initially ranked first. Similarly, alternative A_3 demonstrated the potential to surpass A_4 in preference scores, with a difference of 0.001, positioning A_3 as a viable third-choice option. Conversely, the combination of criteria (3, 5, 8) exhibited the most concise spread of preferences among all alternatives analyzed in the COMSAM method, suggesting that for these combinations of criteria, significant improvement cannot be achieved.

The findings from this study underscored the effectiveness of the COMSAM method in enhancing the sensitivity analysis of composite material selection compared to the traditional OAT approach. By examining simultaneous changes across key criteria—specifically C_2, C_3, and C_5, it was evident that COMSAM provided a more nuanced understanding of how interdependencies among parameters affect preference scores. In addition, it should be highlighted that the COMSAM method extends the OAT approach, and in certain scenarios, findings from both techniques could be identical, as in the case of alternative A_1 and results presented in Table 4. Moreover, the analysis revealed that modifying C_2 and C_3 by 10% consistently resulted in significant fluctuations in preference scores across multiple alternatives, particularly for A_7, which could outperform the initially preferred A_8 under certain conditions. Additionally, the potential for A_3 to rise in ranking further highlights the importance of these criteria in shaping decision outcomes.

Moreover, the sensitivity analysis using distinct combinations of the four most significant criteria demonstrated that small alterations introduced simultaneously could lead to substantial changes in the attractiveness of the composite materials. Notably, pairs including C_2 and C_3 yielded the most considerable shifts in preference scores, reinforcing their critical roles in the evaluation process. The study illustrates that employing the COMSAM method improves the robustness of decision-making and enables decision-makers to better anticipate the impacts of measurement uncertainties or intentional modifications in material properties, ultimately guiding them toward more informed and reliable choices in high-stakes environments.

4. Conclusions

In conclusion, this study successfully demonstrated the advantages of the Comprehensive Sensitivity Analysis Method over the traditional one-at-a-time approach in the context of composite material selection. The research highlighted that the COMSAM method can effectively extend the findings obtained through the OAT approach in sensitivity analysis for MCDA problems. By incorporating simultaneous modifications of critical parameters, COMSAM provided a deeper understanding of the interdependencies among decision criteria, allowing for a more accurate assessment of how variations can impact material preferences. The results revealed that certain criteria, particularly C_2 and C_3, significantly influenced the attractiveness of the alternatives, indicating that even small adjustments in these parameters could lead to substantial shifts in material rankings.

Furthermore, this study emphasized the practical implications of these findings for composite material selection, where factors such as strength, weight, and cost are crucial for optimizing performance and reliability. The integration of the COMET method further enhanced the evaluation process by mitigating vulnerabilities like the rank reversal paradox, ensuring that decision-makers have a robust framework for analyzing potential materials. This research underscores the necessity of adopting comprehensive sensitivity analysis techniques in multi-criteria decision-making frameworks, offering valuable insights for industry practitioners facing complex material selection challenges.

For future research directions, it is worth considering the application of the COMSAM in various industries beyond composite material selection, such as aerospace, automotive, and construction, where material performance and reliability are critical. Furthermore, expanding the scope of sensitivity analysis to include more criteria or exploring the effects of inter-criteria dependencies could provide deeper insights into complex decision-making scenarios. Lastly, it would be beneficial to conduct case studies that validate the findings of this research in practical applications, ensuring that the methodologies developed can be effectively implemented in real-world settings.

Acknowledgement

The work was supported by the National Science Centre, Poland, Decision number UMO-2021/41/B/HS4/01296.

Conflicts of Interest

The authors declare no conflicts of interest.

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