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A stochastic multicriteria decision-making framework for the assessment and implementation of circular business models for the sustainable end-of-life management of wind turbine blades

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Abstract

By 2030, Europe will confront the significant challenge of recycling over 100,000 tons of wind turbine blades (WTBs) annually, which are inherently difficult to process due to their composite construction, including materials such as glass and/or carbon fibre reinforced polymers thermoplastics, wood or foams, coatings and metals. Accordingly, there is a critical need for innovative circular business models (CBMs) to facilitate reuse, repurposing, recycling and recovery strategies for the sustainable WTB end-of-life (EoL) management. This paper proposes a conceptual stochastic multi-criteria decision-making (MCDM) framework that incorporates key sources of uncertainty in both criteria weights and values to assess and compare the sustainability of six CBMs applicable to WTBs that have been identified from the literature. We argue that CBMs that consistently perform well across multiple criteria, regardless of the applied weightings, may represent the most triple-bottom-line balanced options. On the other hand, CBMs that show exceptional performance when a specific criterion is prioritized may be considered more specialized solutions, but potentially less balanced in overall sustainability. The analysis aims to guide stakeholders involved in the EoL management of WTBs in selecting strategies with Low Technological Readiness (TRL) that best align with the goals of the triple bottom line for the future deployment of sustainable value chains in the sector.

Keywords: circular economy, sustainable business model innovation, sustainable energy transition, wind energy.

1. Introduction

By 2030, Europe will confront the significant challenge of recycling 100,000 tons of WTBs annually [1] (although other forecast studies increase this figure to several million tonnes), which are inherently difficult to process due to their composition of complex thermoset matrix composites, including materials such as glass and/or carbon fibre reinforced polymers, [2, 3]. To effectively manage this issue, there is a critical need for innovative CBMs for the WTB EoL management that prioritize sustainable reuse, repurposing, recycling and recovery strategies (from higher to lower resource efficiency and environmental performance according to the circular economy solutions hierarchy), see [4]. CBMs are crucial for optimizing resource efficiency and minimizing environmental impacts, while also improving important social factors such as workforce well-being and community health, see [5]. CBMs not only can reduce the environmental impact of the wind industry but also create new opportunities for growth, cost savings, and innovation in the entire market. Thus, evaluating and ranking CBMs based on economic, environmental, and customer-related factors provides a valuable approach to understanding the mechanisms and conditions under which these models can succeed, allowing

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companies to continuously adapt to changing market conditions, see [6] . For instance, assessing the profitability and cost-effectiveness of circular initiatives includes understanding how well a CBM can generate revenue through product life extension, remanufacturing, or waste minimization [7]. Additionally, circular solutions are often ranked based on their ability to reduce carbon emissions, waste generation, and raw material consumption, e.g., [8]. It is important to note that successful CBMs are typically those that are scalable, collaborative, and responsive to both regulatory pressures and technological advancements, see [9]. However, CBMs (and the circular solutions they offer) should be properly planned, designed, deployed and managed over time to avoid the generation of rebound effects, which requires the application of system thinking.

The main goal of this paper is to evaluate and rank five potential CBMs for WTB EoL management, as identified by Mendoza et al. (2022) [10], based on their impact on key stakeholders. As the successful implementation of a CBM is determined by multiple factors, as mentioned earlier on, this becomes a MCDM problem. In order to accomplish this task, we propose to use the Analytical Hierarchy Process (AHP) to compute the weights of the criteria and then the Weighted Sum Model to provide a total score for each CBM. A key assumption in this approach is that the factors influencing the performance of CBMs, i.e., technological, market, regulatory and policy, financial, and supply chain factors, are characterized by uncertainty, particularly due to elements such as low TRL and other associated risks. Consequently, the evaluation of CBMs will involve stochastic ranking. This methodology will provide insights into the likelihood that a specific CBM can be implemented more successfully than others, while considering the inherent uncertainties associated with innovation and technological readiness. Thus, the novelty behind this paper lies in the development of a stochastic MCDM framework for CBMs related to EoL management of WTBs, incorporating environmental impacts, circularity, job opportunities and cost considerations, which at the moment is missing in the literature. La literature relevant to the present study is the one related to MCDA and CBMs under uncertainty. For instance, MCDM methods have been increasingly applied to support the implementation and optimization of CBMs in various sectors, highlighting their significance in sustainability efforts. One significant study applies a comprehensive MCDM approach to assess the environmental and economic impacts of three WTB recycling scenarios: mechanical shredding, pyrolysis, and cement co-processing [6]. These methods are evaluated using life cycle assessment (LCA) and techno-economic analysis (TEA), incorporating Shared Socio-economic Pathways (SSPs) for future projections. This research emphasizes that using MCDM allows decision-makers to navigate the complexities of emerging technologies [11] . On a different set up, Zaidan et al., (2024) [12] introduce a Neutrosophic Bipolar Fuzzy decision approach to identify the most sustainable tools among 100 circular business model innovation (CBMI) tools, helping firms improve circularity by evaluating sustainability attributes using MCDM techniques. van Hoof et al., (2023) [13] demonstrate how CBMs, such as vermicomposting, can improve waste management and economic viability for farmers, with the decision-making process being enhanced by combining MCDM with transdisciplinary methods. Along the same line of research, Krstić et al., (2023) [14] introduce a novel Axial-Distance-Based Aggregated Measurement (ADAM) method, combining it with the Best-Worst Method (BWM) to rank business models in agri-food circular economies, thus advancing sustainability through MCDM applications. Additionally, Delouyi et al., (2023) [15] explore the barriers to circular economy adoption in food supply chains using hybrid MCDM methods, identifying critical issues like technological capabilities and financial constraints. Finally, in the fashion industry, Silva & Morais, (2022) [16] evaluate outsourcing decisions for circular strategies using a MCDM, highlighting key insights for improving circularity in waste management, Another relevant area of research for this study is the incorporation of uncertainty in circularity modelling. In this context, Walzberg et al. (2023) [17] have created a framework that integrates uncertainty modelling, emphasizing the variability in costs and recycling options. This framework also highlights the significance of MCDM in prioritizing efforts for circular data collection. Moreover, Mehta et al. (2021) [18] and Hsu et al. (2022) [11] utilize quantitative uncertainties to perform material flow analysis (MFA) of plastics. Both studies employ a semi-quantitative approach that incorporates a pedigree matrix and Monte Carlo analysis. Finally, Meglin et al. (2022) [19] offer an analysis of the economic structure of a regional building material industry using an input/output approach that incorporates MFA. Their analysis employs Monte Carlo simulations and sensitivity analysis to deliver more robust policy recommendations.

The remainder of the paper is organized as follows. Section 2 provides an overview of the 6 proposed CBMs for the wind industry, along with the criteria used for their evaluation. Section 3 outlines the methodology for the stochastic ranking of the CBMs. Section 4 presents the results, including a sensitivity analysis of the criteria weights. Finally, Section 5 offers concluding remarks.

2. WTB Circular Economy Based Business Model Evaluation

2.1. WTB Circular Economy Based Business Models

CBMs for the EoL management of WTBs, as outlined by Mendoza et al. (2022), focus on strategies like extending product life cycles (e.g. through reuse and/or retrofitting), repurposing, and recycling to generate revenues and profit, while reducing environmental impacts.

$\boldsymbol{CBM_1}$: **Retrofitting (upgrading)** involves enhancing or modifying existing blades to extend their operational life. This process includes reinforcing structural components, applying advanced coatings, or incorporating new materials and technologies that improve performance and durability. By retrofitting, operators can delay decommissioning, reduce waste, and minimize the environmental impact associated with the disposal of blades, while also optimizing operational expenses (OPEX) over the extended lifespan of the asset.

$\boldsymbol{CBM_2}$: **Reuse** belongs to the next life CBMs that aim at ensuring WTs and components can have a second (or multiple) use cycles. If ageing WTs and/or components are still in relatively good condition, they can be reused either within the same wind park or in a different location.

$\boldsymbol{CBM_3}$: **Refurbishment** also belongs to the next life CBMs. If ageing WTs are not in good condition, refurbishment (i.e. advance reparation) enables partially restoring the WT operational capacity by repairing and/or replacing only worn or damaged components.

$\boldsymbol{CBM_4}$: **Repurposing** refers to reusing a product or its parts after reprocessing for functions or applications other than the original. Most of the research and industrial practice on WT repurposing concentrates on blades, as they represent a recycling challenge due to the thermoset composite construction.

$\boldsymbol{CBM_5}$: **Recycling** is understood as business contributing to extending resource value by facilitating material recovery and reprocessing into new component or products. Recycling can be divided into two main alternatives: general recycling of materials, including metals, concrete and electronics and composite recycling from WT blades and nacelle shells.

2.2. Criteria for Circular Business Models

Building upon Alamerew et al, (2020), [20], the following key criteria are essential for consideration to evaluate the performance of new CBMs. For each indicator we have defined a standard indicator to illustrate the model.

$\boldsymbol{C_1}$: **Economic Indicator.** *Cost Savings from Resource Efficiency* ***in*** *Million Euros***.** Tracks cost reductions from reduced resource use and waste

$$\text{Cost Savings \%} = \frac{\text{Cost}_{\text{circular}} - \text{Cost}_{\text{baseline}}}{\text{Cost}_{\text{baseline}}} \cdot 100 \qquad (1)$$

where:

- $\text{Cost}_{\text{baseline}}$ = Cost associated with traditional linear processes (e.g., new material extraction, manufacturing, and waste disposal).
- $\text{Cost}_{\text{circular}}$ = Cost associated with circular processes (e.g., recycling, refurbishment, reuse)

$\boldsymbol{C_2}$: **Environmental Indicator:** *Carbon Footprint Reduction Metric tons of CO_2 equivalent $\left(tCO_{2e}\right)$* . Measures reduction in GHG emissions from circular practices.

$$tCO_{2e}\ \text{Savings \%} = \frac{tCO_{2e\text{circular}} - tCO_{2e\text{baseline}}}{tCO_{2e\text{baseline}}} \cdot 100 \qquad (2)$$

where:

- $tCO_{2e\text{baseline}}$ = Carbon emissions from a traditional linear economy process (e.g., manufacturing new WTB and sending them to landfill at the EoL).
- $tCO_{2e\text{circular}}$ = Carbon emissions from the circular economy process (e.g., refurbishing or recycling WTBs).

$\boldsymbol{C_3}$: **Social Indicator.** *Job Growth Rate %.* Measures employment opportunities created by circular practices

$$\text{Job Growth Rate \%} = \frac{\text{J}_{\text{circular}} - \text{J}_{\text{baseline}}}{\text{J}_{\text{baseline}}} \cdot 100 \qquad (3)$$

where:

- $\text{J}_{\text{circular}}$ = Number of jobs created through circular economy activities (e.g., recycling, remanufacturing, refurbishment).
- $\text{J}_{\text{baseline}}$ = Number of jobs in a traditional linear economy baseline (e.g., manufacturing new products).

$\boldsymbol{C_4}$: **Technical Indicator:** *Material Recovery Rate %* Measures the percentage of mass of material recovered for reuse or recycling

$$\text{Material Recovery Rate \%} \frac{\text{M}_{\text{recovered}}}{\text{M}_{\text{Total}}} \cdot 100 \qquad (4)$$

where:

- $\text{M}_{\text{recovered}}$ = The mass of material recovered through recycling, reuse, or remanufacturing.
- M_{Total} = The total mass of the material in the end-of-life wind turbine blade or product.

3. Methodology

Step 1. The weights of the criteria are computed with Analytical Hierarchy Process (AHP) (REF) using the following equation

$$A \cdot w = \lambda_{\max} \cdot w \qquad (5)$$

where the constructed matrix A is based on pairwise comparisons of the criteria. The elements a_{ij} of this matrix indicate the relative importance of criterion i over criterion j, often using a scale from 1 to 9. The priority vector w is the normalized eigenvector associated with the largest eigenvalue $\lambda_{\max}$ of matrix A . This eigenvector provides the weights of the criteria in terms of their relative importance.

Step 2. In order to account for the uncertainty of the criteria weights and values, we stipulate the mean and standard deviation for the importance (weights) of each decision criterion

$\boldsymbol{C_1}$: *Cost Savings from Resource Efficiency* {'mean': 0.3, 'std': 0.05}

$\boldsymbol{C_2}$: *Carbon Footprint Reduction* {'mean': 0.3, 'std': 0.05}

$\boldsymbol{C_3}$: *Job Growth Rate* {'mean': 0.2, 'std': 0.03}

$\boldsymbol{C_4}$: *Material Recovery Rate* {'mean': 0.2, 'std': 0.03}

The Dirichlet distribution is used to model the random variables associated with criteria weights. It ensures that these weights conform to essential properties, such as summing to one, thereby forming a proper probability distribution**.** For a four-parameter Dirichlet distribution, the probability density function (PDF) is defined as follows:

$$f(\mathrm{x};\ \alpha_{c1},\alpha_{c2},\alpha_{c3},\alpha_{c4}) = \frac{x_{c1}^{\alpha_{c1}-1}\cdot x_{c2}^{\alpha_{c2}-1}\cdot x_{c3}^{\alpha_{c3}-1}\cdot x_{c4}^{\alpha 4-1}}{B(\alpha_{c1},\alpha_{c2},\alpha_{c3},\alpha_{c4})} \tag{6}$$

Where

$\mathrm{x}=(x_{c1},x_{c2},x_{c3},x_{c4})$ are the weights assigned to each criterion and must satisfy $x_{c1}+x_{c2}+x_{c3}+x_{c4}=1$ and each $x\geq 0$,

- $\alpha_{c1},\alpha_{c2},\alpha_{c3},\alpha_{c4}$ are the parameters of the distribution, each corresponding to one of the criteria weights in the model. These parameters are related to the mean and variance of the criteria. For instance, for C_1 we apply the following expressions

$$\mu_{c1} = \frac{\alpha_{c1}}{\alpha_{c1}+\alpha_{c2}+\alpha_{c3}+\alpha_{c4}}$$

$$\sigma_{c1}^2 = \frac{\alpha_{c1}\left((\alpha_{c1}+\alpha_{c2}+\alpha_{c3}+\alpha_{c4})-\alpha_{c1}\right)}{(\alpha_{c1}+\alpha_{c2}+\alpha_{c3}+\alpha_{c4})^2\left((\alpha_{c1}+\alpha_{c2}+\alpha_{c3}+\alpha_{c4})+1\right)}$$

- $B(\alpha_{c1}+\alpha_{c2}+\alpha_{c3}+\alpha_{c4})$ is the multivariate Beta function, which serves as normalization constant to ensure that the total probability integrates to 1. This function is defined as

$$B(\alpha_{c1}+\alpha_{c2}+\alpha_{c3}+\alpha_{c4}) = \frac{\Gamma(\alpha_{c1})\Gamma(\alpha_{c2})\Gamma(\alpha_{c3})\Gamma(\alpha_{c4})}{\Gamma(\alpha_{c1}+\alpha_{c2}+\alpha_{c3}+\alpha_{c4})} \tag{5}$$

Here, Γ denotes the Gamma function, which generalizes the factorial function with its domain extended to positive real numbers.

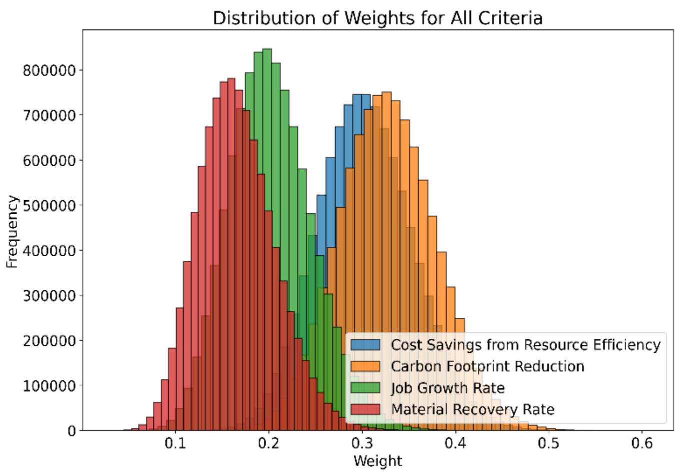

Figure 1 Dirichlet distribution of the 4 criteria: *Cost Savings from Resource Efficiency*, *Carbon Footprint Reduction,* Job *Growth Rate*, *and Material Recovery Rate*

Now, the percentages ranges (minimum and maximum) of different CBMs across each criterion are established. The percentage scores for each criterion of each CBM are assumed to be uniformly distributed

CBM_1: C1: [10, 50], C2: [10, 40], C3: [40, 80], C4: [5, 20]
CBM_2: C1: [30, 80], C2: [50, 80], C3: [80, 100], C4: [10, 30]
CBM_3: C1: [30, 60], C2: [40, 70], C3: [60, 90], C4: [20, 40]
CBM_4: C1: [20, 60], C2: [30, 60], C3: [50, 80], C4: [10, 30]
CBM_5: C1: [20, 50], C2: [20, 70], C3: [20, 80], C4: [15, 40]

It is important to note that CBM_1: *retrofitting* doesn't directly recover materials like recycling or remanufacturing does, but it can lead to indirect material recovery by extending the life of products, delaying the need for new raw materials, and reducing waste.

Step 3. A Monte Carlo Simulation is performed. In each of the 1,000 iterations, a new set of weights is sampled from the Dirichlet distribution. Additionally, for each criterion of each CBM, a score is randomly selected from its specified range using a uniform distribution. This introduces another layer of variability, simulating different potential performance outcomes within the expected range.

Step 4. Analysis For each CBM, in each simulation, the total score is computed by taking the dot product of the sampled weights and the randomly selected scores for each criterion. This results in a weighted score that reflects the importance and performance of each CBM under those specific sampled conditions. Once all simulations are completed, the total scores for each CBM across all simulations can be analysed to understand the distribution of potential outcomes. This analysis may include examining the mean score, the spread of the distribution, and other statistical measures to assess the robustness and attractiveness of each CBM under uncertainty. However, this analysis is beyond the scope of this paper. The distribution of scores for each CBM is illustrated in Figure 2, where the x-axis represents the scores, and the y-axis indicates the density of the distributions.

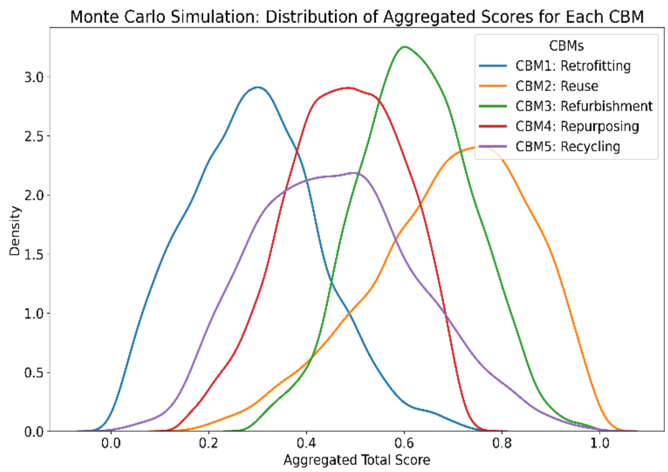

Figure 2 Score Distributions from Montecarlo Simulation for the 5 CBMs

To determine the likelihood that one CBM is better than another, we compare their score distributions by counting the number of times one CBM's score exceeds another's across all simulation runs. The process effectively provides an empirical estimate of the probability that one CBM is superior based on their score distributions. For instance, the probability that $\mathrm{CBM}_1 > \mathrm{CBM}_2$ and can be formulated as

$$\Pr(CBM_1 > CBM_2) = \frac{n^o \text{ times } CBM_1 \text{ score} > n^o \text{ times } CBM_2 \text{ score}}{\text{Total } n^o \text{ simulations}} \tag{7}$$

4. Results

By applying Eq. 4, the probability that a CBM is better than others is shown in Table 1. We observe that **CBM 2: Reuse** consistently outperforms all other CBMs considered, with a probability of being superior to any CBM exceeding 60%. Likewise, **CBM 3: Refurbishment** ranks stochastically higher than all other CBMs, except for Reuse. In contrast, **CBM 1: Retrofitting** is the poorest performer, being dominated by all other options. Similarly, **CBM 5: Recycling** ranks low, outperforming only Retrofitting. As anticipated, **CBM 3: Refurbishment** and **CBM 4: Repurposing** perform better than both Retrofitting and Recycling, but fall below Reuse, with Refurbishment demonstrating a stronger performance between the two.

Table 1. The likelihood that a CBM is better than other

	CBM_1	CBM_2	CBM_3	CBM_4	CBM_5
CBM_1	0	0.027	0.038	0.146	0.233
CBM_2	0.973	0	0.661	0.870	0.819
CBM_3	0.962	0.340	0	0.823	0.801
CBM_4	0.854	0.130	0.178	0	0.536
CBM_5	0.767	0.181	0.199	0.464	0

4.1. Sensitivity Analysis

The sensitivity analysis method used is a combination of One-at-a-Time (OAT) sensitivity analysis and Monte Carlo simulation. In this approach, we vary each criterion's weight, over the predefined intervals. While changing one criterion's weight, the others remain constant, and the sum of all weights is kept close to 1. As the sum of weights must remain equal to 1, changing one weight requires adjusting the others. We redistribute the changes proportionally across the remaining weights. For each set of weights, a Monte Carlo simulation is run, where random scores for each CBM are drawn from uniform distributions based on the previously defined ranges. The results of these simulations are used to calculate the mean score for each CBM under the corresponding weight set. This combination allows for a detailed analysis of how varying the importance of each criterion impacts the overall CBM scores, with Monte Carlo simulations introducing randomness and OAT systematically varying the criteria weights.

The results of the analyses are portrayed in Figures 3-8 where the x-axis shows the different criteria weights, and the y-axis represents the aggregated scores of each CBM alternative. The criteria *Cost Savings from Resource Efficiency* is represented by a blue curve and increases from 0.1 to 0.5, *Carbon Footprint Reduction* is denoted by an orange curve and increases from 0.1 to 0.5, the *Job Growth Rate* is denoted by a green curve and rises from 0.1 to 0.3, and finally, *Material Recovery Rate* is indicated by a red curve and grows from 0.1 to 0.3). The shadowed area above and below the curves represents the uncertainty or variability in the results. This shading is generated from the Monte Carlo simulations and reflects confidence intervals, indicating the range within which a significant portion of the simulated percentage score, such as 95%, are expected to fall. The variability shown by the shadow accounts for the randomness introduced by sampling from uniform distributions during the simulations, providing a visual representation of the potential fluctuation in performance scores for each CBM as the criteria weights change. We observe that the 5 CBMs percentage score is highly sensitive to the weight of both criteria *Job Growth Rate* and *Material Recovery Rate* because the score of the CBMs experience a sharply change when the weight of that criterion is varied. This indicates that the CBM's performance is heavily dependent on both criteria. On the contrary, the percentage score remains relatively stable for the CBMs of Retrofitting, Reuse and Repurposing across changes in the weights of criteria for *Cost savings from Resource Efficiency* and *Carbon Footprint Reduction*. This indicates that the CBM performs consistently well, regardless of which criterion is given greater emphasis. This also implies that these CBMs are more robust and reliable across changes in the aforementioned criteria.

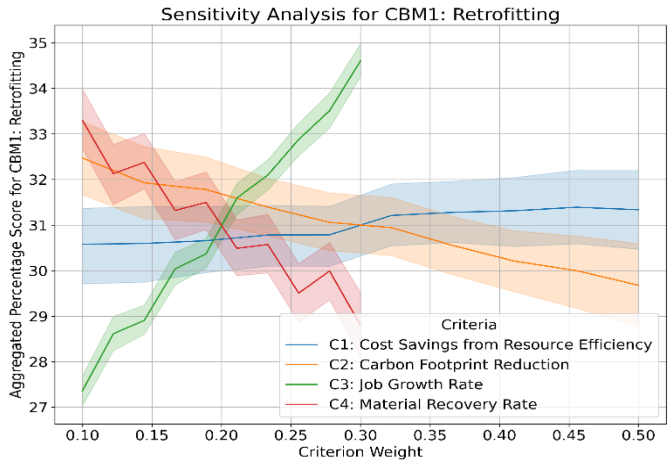

Figure 3 Sensitivity Analysis for CBM1: Retrofitting

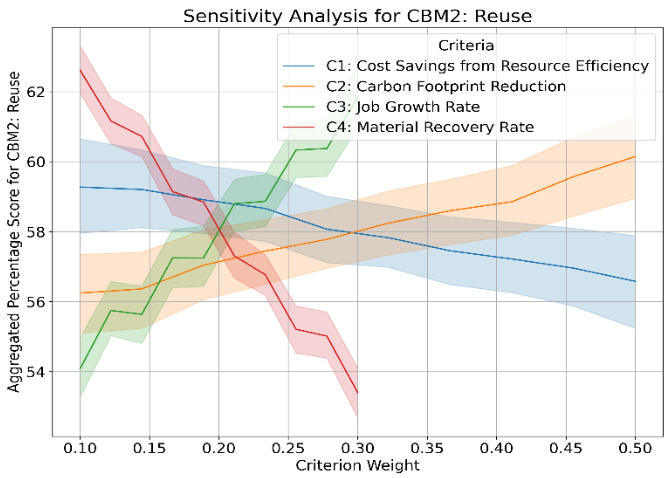

Figure 4 Sensitivity Analysis for CBM2: Reuse

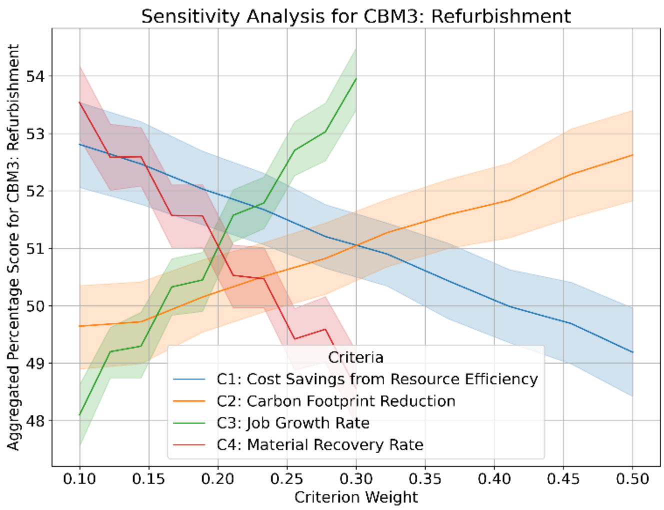

Figure 5 Sensitivity Analysis for CBM3: Refurbishment

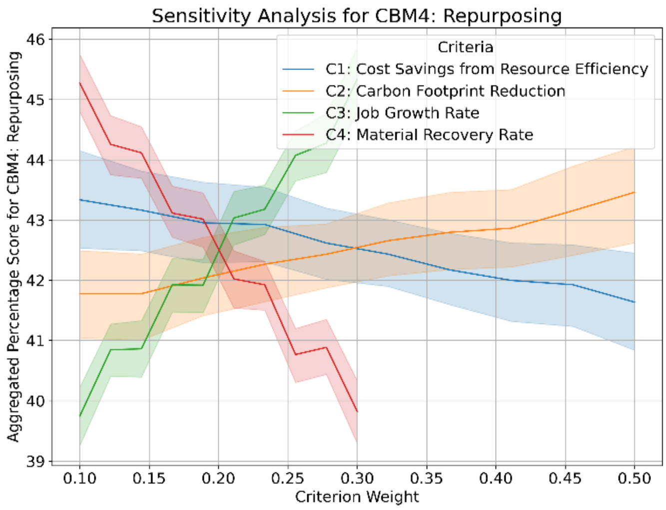

Figure 6 Sensitivity Analysis for CBM4: Repurposing

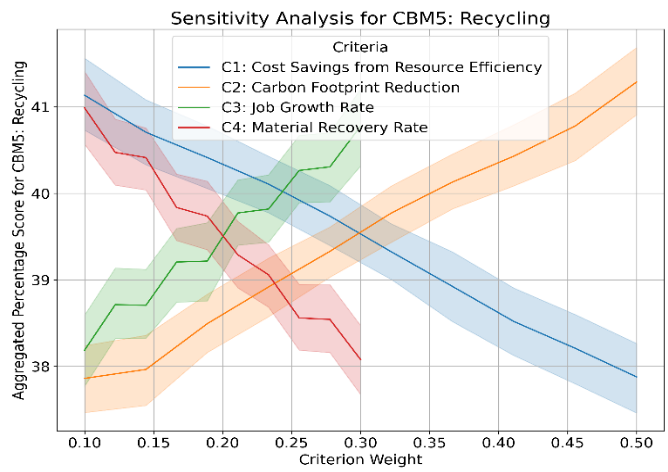

Figure 7 Sensitivity Analysis for CBM5: Recycling

A common feature is that most CBMs improve their performance as the weight of criteria for *carbon footprint reduction and job growth rate* increases but are negatively affected when other criteria are prioritized, except for CBM 1: Retrofitting where changes in cost efficiency and resource efficiency induces a slightly better performance. It is important to recall that CBM 4: Remanufacturing ranks higher than any other CBMs considered. However, the high sensitivity to variations in the weight of the 4 criteria may have significant implications. For instance, increasing the weight criteria of Cost Savings from Resource Efficiency negatively affects the aggregate percentage score leading to a shift in the CBMs ranking. On the other hand, as previously mentioned CBM 5: Recycling is one of the worst performers. Nevertheless, variations in the weight criteria for Carbon Footprint Reduction may revert this situation by levelling up its place in the ranking. In line with these arguments, it is of uppermost importance that the decision-maker consider not just the aggregate percentage score but also how robust and reliable these scores are with respect to changes in the criteria. For example, CBM2: Reuse that ranks stochastically higher than others CBMs and ranks well across multiple weight configurations (i.e., the curves for various criteria show less variation) may be considered a strong candidate for decision-making.

Conclusion

This article studied a stochastic MCDM as a tool for the sustainability assessment of CBMs for the EoL management of WTBs. It argued that sustainability assessments in this context must account for the significant sources of uncertainty introduced by the low TRL of innovative recycling and reuse technologies. Additionally, risks associated with material recovery processes, lack of standardized methods for blade dismantling, and uncertainties in the availability of infrastructure further complicate to predict the economic viability, environmental impact, and long-term sustainability of CBMs. We have also emphasized the importance of conducting a sensitivity analysis to identify an optimal model, considering both model specifications and distribution parameters. This analysis is a critical step in the development of CBMs that are resilient to uncertainties. If the sensitivity analysis reveals significant variation in certain criteria, it highlights areas of uncertainty where decision-makers may need to focus more attention. For example, if a certain criterion has a substantial influence on the aggregated scores and is subject to high uncertainty, this factor may need to be given special consideration in the final decision-making process. CBMs that demonstrate consistently high performance across multiple criteria, even when different weightings are applied, may represent the most balanced options, performing well across all dimensions, such as cost and environmental impact. In contrast, CBMs that perform exceptionally well when certain weights, e.g., *Cost savings from Resource Efficiency*, are emphasized may be viewed as more specialized solutions but potentially less balanced in their overall performance. I aim to extend this approach by incorporating and comparing other MCDM methods, such as analytical network processes (ANP), linear programming technique for multi-dimensional analysis of performance (LINMAP), performance ranking organisation method for enrichment solutions (PROMETHEE), Complex Proportional Assessment (COPRAS), interactive and multi-attribute decision-making (TODIM), order preference by similarity to the ideal solution (TOPSIS), elimination and choice expressing the reality (ELECTRE), simple additive weighting (SAW), entropy, decision-making trial and evaluation (DEMATEL), and multi-attribute utility theory (MAUT) to assess which is the most appropriate when CBMs are characterized by uncertainty. By evaluating these methods under conditions of uncertainty, I seek to identify the approach that provides the most robust and reliable support for decision-making.

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