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A Decision Support System for the Selection of Best End-of-Life Composites Route

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Abstract

The use of composite materials has increased in recent years due to their mechanical properties, low weight, and resistance to various environmental conditions. This demand corresponds with their application in sectors such as wind energy, automotive, and aerospace industries. However, managing End-of-Life (EoL) or post-service components presents challenges, as recycling composites is difficult. Information asymmetry within the composite value chain and the absence of decision support further contribute to the complexity. This study presents a multicriteria-based, two-step decision support system (DSS) aimed at enabling circular solutions within the composite industry. The first step of the DSS involves selecting a strategy for EoL management. The second step ranks recycling technologies suitable for EoL components requiring recycling. Decisions are informed by multiple criteria, including technical specifications of the recyclates, economic feasibility, and process parameters. The Best-Worst Method (BWM) is used to assign weights to the criteria, while the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) method is used to rank alternatives at each decision point. The obtained results show the potentiality of this approach in finding best secondary treatment route, also suggesting possible future research directions.

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1. Introduction

The use of composites has been steadily increasing in recent years owing to their excellent material properties. Especially the use of reinforced polymers such as carbon fiber and glass fiber reinforced polymers continues to grow in strategic sectors like wind energy, aerospace, marine and automotive due to their corrosion resistance and high strength-to-weight ratios. The market for FRPs is expected to grow between 5% and 7% CAGR in the period of 2021-2028[1]. The growth is particularly driven by an expansion in the automotive sector with an increased focus on e-mobility.

Since e-mobility demands weight reduction to extend driving range, to improve energy efficiency and to maximize vehicle range and performance, FRPs are often looked at as a solution. Other factors include an increased production of aircrafts,

increased interest in space economy, and ever-increasing wind power installations. These composites, however, do pose the problem at the end of their service life since they are predominantly made of non-recyclable polymers. As a consequence, at the end of their service life are usually treated as plastic waste in Europe and go towards either incineration or landfills that lead to loss of value and pose a threat to the environment. This along with the fact that the manufacturing of these composites is an energy-intensive process [2], the need to find an effective strategy to deal with the EoL products becomes of paramount importance.

This work discusses the idea of a DSS with the objective of enabling circular practices to EoL using a multi-criteria approach. The idea is to act on the information asymmetry that exists along the composite value chain especially between waste owners and manufacturers. To enable circular practices

the DSS uses information based on the use-phase history of the EoL component or material or composite waste such as the sector, the number of years to understand the service life served along with information from non-destructive testing (NDT) to decide the appropriate strategy for the EoL stage. This part accounts for one of the two decision making points in the DSS where the second decision point helps the user choose an appropriate recycling technology for those parts that require recycling. The choice of recycling technology considers the requirements defined by the end users using a target driven, cross sectorial approach [3]. To this end several criteria have

been defined by stakeholders involved at various levels in the value chain. The best-worst method (BWM) is used to attach relevant weights to these criteria. A TOPSIS logic is in turn used to rank the alternatives at the two points of the DSS using the weights that have been determined by the BWM method. Composite use is rising, but their difficult end-of-life creates major waste and value-loss issues. The DSS uses service-life data and NDT results to decide whether parts should be reused, repaired, or recycled. It then ranks suitable recycling options using stakeholder criteria with g-BWM and TOPSIS.

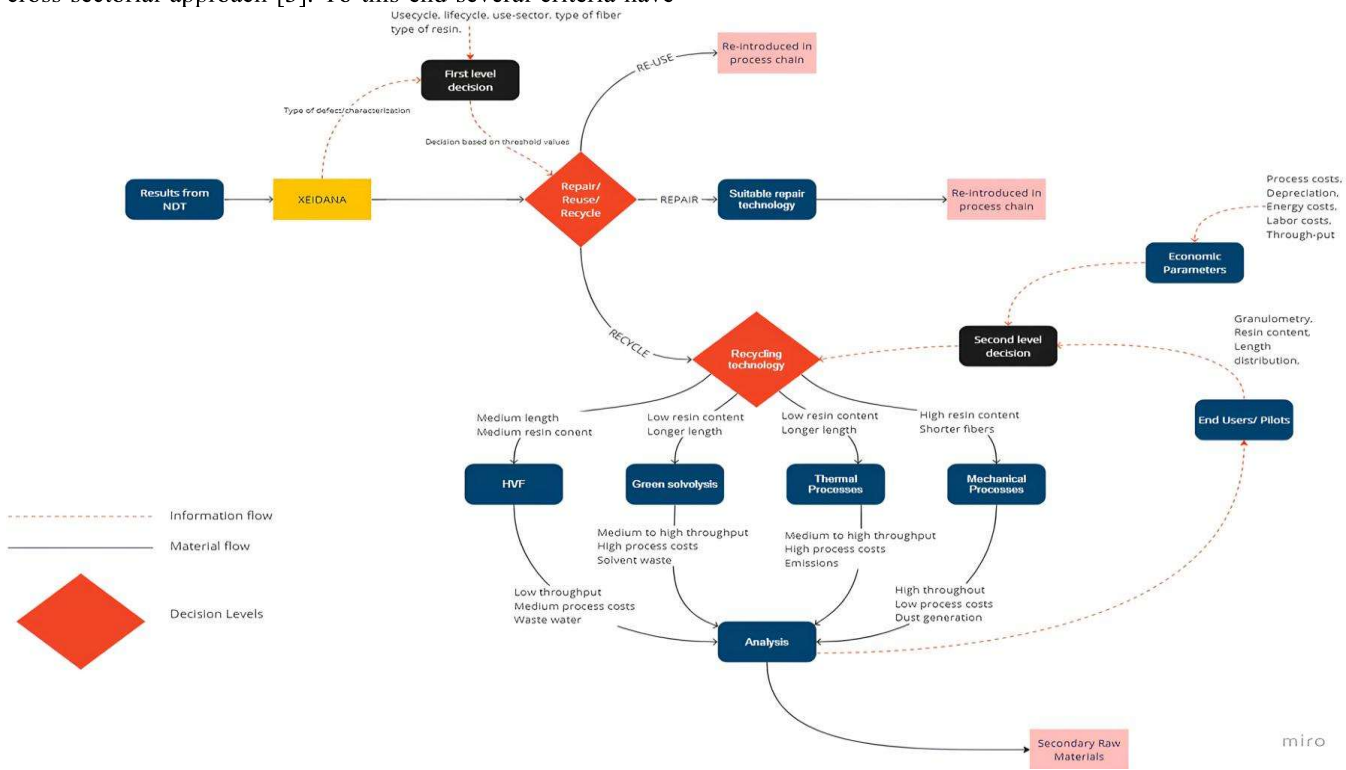


Figure 1: Architecture of the DSS.

2. Literature Review

DSS have been used for various reasons ranging from supplier selection to sustainability rating of technologies. Any decision support system has 3 fundamental parts: a knowledge base, the logic and a User Interface [4]. In the context of circular economy, while there are few examples, some interesting works can be noted.

For instance, an ontology-based decision support system (DSS) using OWL-2 has been applied to characterize post-use products based on the number of use-cycles, using numerical integers as threshold values [5]. Another interesting example involves a DSS aiding disassembly planning in the automotive industry, addressing the uncertainty surrounding the quality of end-of-life (EoL) products [6]. A specific DSS to optimize wind plants disassembly operations have been developed, suggesting the best route among several solutions [7]. Multicriteria DSSs, such as the one described in [8], leverage a Fuzzy logic-empowered Best-Worst Method (BWM) to ensure optimal supplier selection based on criteria like economic factors, performance, and sustainability. The BWM, developed by Dr. Jafar Rezaei [9], is a multi-criteria decision-making (MCDM) approach that has been frequently compared to the classical Analytical Hierarchy Process (AHP). Both BWM and

AHP use pairwise comparisons, but BWM has several advantages over AHP. It requires fewer pairwise comparisons and offers greater consistency, as it only involves comparing criteria against the "best" and "worst" options. This reduces the likelihood of inconsistency, a common issue in AHP when numerous pairwise comparisons are made.

While BWM is effective for assigning weights to criteria, the TOPSIS method excels at ranking alternatives [10]. TOPSIS achieves this by comparing alternatives to both positive and negative ideal solutions, calculating the Euclidean distance from each. Within a circular economy framework, the fuzzy TOPSIS approach has been applied to various contexts, such as analysing business models [11], selecting digital technologies for a circular supply chain, determining the location of wind farms [12] based on multiple criteria, and choosing wind blade-cutting technologies while considering economic, environmental, and social factors. To minimize uncertainty in decision-making, experts were consulted to assign weights to the criteria and clarify their definitions [13].

3. Methodology

In this section of the paper, we will discuss the methodology used for the conceptualization of the MCDM based DSS.

Beginning with the architecture of the DSS, the definition of criteria used in decision-making and logic.

3.1 The architecture of the DSS

Figure 1 depicts the architecture of the DSS including both material flows and the information flows. As aforementioned, the DSS has two distinct decision-making steps; is to first step to choose the appropriate strategy for the EoL while the second step is the choice of recycling technology.

At point one, information from the service life of the EoL along with the data provided by NDT testing is elaborated which will be explained in the next sub-section. The data from the NDT tests are quantified to understand if the defects identified presents as a structural defect using the number of defects, the depth and the volume identified by the tests. This information is further complemented by the physical appearance of the EoL. The alternatives at this point are the choice of strategy between re-use, repair, recycle and disposal.

Decision point 2 deals with the EoL parts that have been diverted towards the recycling strategy and helps the user choose the right recycling technology depending on multiple criteria that have been outlined using the demand-driven approach. The criteria also include economic considerations related to the cost of various recycling technologies as well as process parameters such the process readiness level, through put, emissions if any, energy consumption to provide a holistic picture of each recycling technology. Using the weights provided by the BWM approach the DSS will be able to rank the alternatives at this point using the TOPSIS approach to help the user identify the best possible recycling technology for their scenario. The recycling technologies are divided into 4 families: Mechanical recycling, High Voltage Fragmentation, Green Solvolysis and Thermal processes. These technologies have been chosen in accordance with the proposal of the project where Mechanical recycling and Thermal processes(pyrolysis) were back up technologies and simulate high TRL versions of HVF and Green Solvolysis respectively.

3.2 Criteria impacting the decision-making process

Table 1 enlists the various criteria that have been identified after consulting actors at various parts of the composite value chain. Since the DSS has two distinct decision-making points, the criteria identified for them are also exclusive. The dependencies of each criterion have been identified, and the objective function has been defined.

For the first decision point as mentioned before data from NDT tests has been quantified to calculate the volume of the defects which is then compared to the total volume of the EoL and using confidence intervals the appropriate strategy is chosen for the EoL. This criterion is supported by the other 3 qualitative criteria “Appearance”, “Service life rating” which is quantified in terms of the number of years for which the part was in service and “Joining elements” that refer the presence of joining elements like adhesives, rivets etc if present which hamper the recyclability of the EoL that help chose the right strategy of the EoL.

Table 1 Decision making criteria, their dependencies and objective function

S.no	Name of Criteria	Dependencies	Obj. Function
1	Defect structurality	Defect geometry, number of defects, depth of defect	Minimize based on input
2	Service life rating	Age, use cycles, sector	Minimize
3	Appearance	Physical appearance	Minimize
4	Joining Elements	Type of joining elements	Optimize
5	Material Recovery	Input mass, output mass	Maximise
6	Environmental Score	Midpoint Emissions including Co2	Minimise
7	Energy consumption	Effective energy consumed	Minimise
8	Average throughput	Processing capacity	Maximise
9	Market Value of recycle	Granulometry, percentage of clean fibres (type), resin monomers if any	Maximise
10	Technological readiness	Easy of scalability	Maximise
11	Tensile strength of rGF/CF	Tensile strength of recycled fibres	Maximise
12	Cost of recycling	Operating Costs, and Auxiliary costs	Minimise
13	Labor Effort	Throughput	Minimise

Decision point 2 has 3 major families of criteria that are either process related such as: Energy consumption, Average throughput and technological readiness, economic criteria such as: Market value and recycling cost as well as sustainability indicators such as the environment score which accounts for the emissions. The unique value is the inclusion of demand-driven or user-driven criteria which are imbedded in Market Value of the recycle that help the user chose the right technology based on the application.

3.3. BWM approach for multi-criteria decision-making

The Best Worst Method has the advantage of providing a rational approach to compare the criteria assigning them a “relative importance” and reducing the number of comparisons.

Indeed, the BWM requires only to identify the most relevant (called **Best criterion - C_B**) and less relevant (called **Worst criterion - C_W**) criteria and then assign to the other criteria a value indicating the relevance of the **Best criterion** as compared to the other criteria, and a value indicating the relevance of the other criteria as compared to the **Worst criterion**. The BWM approach suggests using the values {1, 2, ..., 9} for these “relevance values” with the following rationale.

Table 2 BWM relevance values and their meaning

Value	Meaning
1	Equal importance
2	Somewhat between Equal and Moderate
3	Moderately more important than
4	Somewhat between Moderate and Strong
5	Strongly more important than
6	Somewhat between Strong and Very strong
7	Very strongly important than
8	Somewhat between Very strong and Absolute
9	Absolutely more important than

Operationally, the BWM envisages the following steps:

1. A set of K “decision makers” convene on a set of evaluation criteria (C_i).
2. The decision makers convene on the most relevant (**Best criterion** - C_B) and less relevant (**Worst criterion** - C_W) evaluation criteria.
3. According to the indications provided above, each decision maker assigns to each remaining criterion: a relevance value of the *best criterion* as compared to the criterion i and a relevance value of the criterion i as compared to the *Worst criterion*.
4. At the end of the previous steps, there are the following vectors:
 - C_i : the set of agreed criteria.
 - $A_{Bi}^{(k)}$: the vector stating the relevance of the *best criterion* (C_B) as compared to criterion i as assigned by decision maker k . The $A_{Bi}^{(k)}$ values are selected from the set indicated above.
 - $A_{iW}^{(k)}$: the vector stating the relevance of criterion i as compared to the *Worst criterion* (C_W) as assigned by decision maker k . The $A_{iW}^{(k)}$ values are selected from the same predefined set as for the previous point.
5. The assigned relevancies are averaged to derive a common set as follows:

$$A_{Bi} = \frac{1}{K} \sum_{k=1}^K A_{Bi}^{(k)}$$

$$A_{iW} = \frac{1}{K} \sum_{k=1}^K A_{iW}^{(k)}$$

Based on the above values the BWM algorithm assigns the weights ($w_i, w_B = w_1, w_W = w_n$) to each criterion by solving the following problem:

- $\min \xi$
- $\left| \frac{w_B}{w_i} - A_{Bi} \right| \leq \xi \quad i \in \{2, \dots, n-1\}$
- $\left| \frac{w_i}{w_W} - A_{iW} \right| \leq \xi \quad i \in \{2, \dots, n-1\}$
- $w_i \geq 0 \quad i \in \{1, \dots, n\}$
- $\sum_{i=1}^n w_i = 1$

It is not difficult to show that there is a maximum value ξ_M that satisfies the following equation:

$$\xi_M^2 - (1 + 2 A_{BW}) \xi_M + A_{BW} (A_{BW} - 1) = 0$$

Where A_{BW} is the maximum value that can be assigned in the comparison. ξ_M is called the *consistency index*.

Of course, the higher the ξ the less reliable the solution is. The BWM approach defines a *consistency ratio* (CR):

- $CR = \xi / \xi_M \quad CR \in [0, 1]$

The higher the CR , the less reliable the solution.

Table 3: Thresholds for different combinations using input-based consistency measurement

Scales	Number of Criteria						
	3	4	5	6	7	8	9
3	0.1667	0.1667	0.1667	0.1667	0.1667	0.1667	0.1667
4	0.1121	0.1529	0.1898	0.2206	0.2527	0.2577	0.2683
5	0.1354	0.1994	0.2306	0.2546	0.2716	0.2844	0.2960
6	0.1330	0.1990	0.2643	0.3044	0.3144	0.3221	0.3262
7	0.1294	0.2457	0.2819	0.3029	0.3144	0.3251	0.3403
8	0.1309	0.2521	0.2958	0.3154	0.3408	0.3620	0.3657
9	0.1359	0.2681	0.3062	0.3337	0.3517	0.3620	0.3662

3.4 BWM approach when there is a disagreement between decision-makers

One of the key challenges in group decision-making, particularly when applying the Best-Worst Method, arises when decision makers fail to agree on selecting the same best and worst criteria. This divergence can lead to increased complexity in analysis and make the decision-making process more cumbersome. As the number of decision makers increases, so does the scale of the mathematical models, complicating the computational process. Furthermore, when decision makers have equal influence, the lack of a senior decision maker to resolve conflicts can make it harder to achieve a consensus.

Hafezalkotob and Hafezalkotob [14] proposed a group decision-making approach that attempts to balance both democratic and autocratic decision-making styles, allowing a senior decision maker to account for the influence of each participant based on their expertise. In contrast, Safarzadeh et al. [15] extended BWM by introducing mathematical algorithms to calculate criteria weights, thus enabling the integration of multiple decision-makers’ preferences in a more structured manner.

To address the complexities posed by disagreements, a novel Group-BWM (G-BWM) [16] approach has been proposed. In this method, decision makers are grouped based on their selection of best and worst criteria). This grouping reduces the complexity by treating each group’s preferences as a single unit of analysis. The geometric mean is then applied to the group’s evaluations, making it easier to obtain criteria weights without analyzing every individual’s input separately. [17]

The proposed G-BWM approach envisages the same initial steps as the standard BWM (Step 1 to 4) and departs from it as described in the following steps.

Step 5. Divide decision-makers into groups ($G_p, p = \{1, 2, \dots, P\}$ and P is the number of groups), ensuring that each group has the same best and worst criteria.

Step 6. Take the geometric mean of the preferences of the best criterion over other criteria ($A_{Bi}^{(k_p)}$) and the preferences of all

criteria over the worst criterion ($A_{iW}^{(k_p)}$) as expressed by each decision maker (k_p) in the group G_p (n_p is the number of decision makers in the group):

$$A_{Bi}^{G_p} = \sqrt[n_p]{\prod_{k_p=1}^{n_p} A_{Bi}^{(k_p)}}$$

$$A_{iW}^{G_p} = \sqrt[n_p]{\prod_{k_p=1}^{n_p} A_{iW}^{(k_p)}}$$

Step 7. Obtain the optimal value of criteria weights ($w_1^{G_p}, w_2^{G_p}, \dots, w_n^{G_p}$) for each group according the standard BWM non-linear or linear algorithm.

Step 8. Determine the final weights by calculating the arithmetic mean of the weights obtained for each group:

$$w_i = \frac{1}{K} \sum_{p=1}^P n_p * w_i^{G_p}$$

where

$$K = \sum_{p=1}^P n_p$$

The consistency of the assigned preferences can be verified for each group by using the values of $A_{Bi}^{(k_p)}$ and $A_{iW}^{(k_p)}$ obtained (or rather by approximating $A_{Bi}^{(k_p)}$ and $A_{iW}^{(k_p)}$ to the nearest integer in the range 1-9) as indicated in the standard BWM approach. In this way, unsatisfactory preference assignments can be easily identified. The overall consistency index can be calculated as the arithmetic average of the consistency index of each group.

3.5 TOPSIS logic for ranking alternatives

Although the BWM method is highly effective for determining the weights of identified evaluation criteria, it lacks efficiency in evaluating alternatives. Once the criteria's weights are established, the *Technique for Order of Preference by Similarity to Ideal Solution* (TOPSIS) proves to be both efficient and effective in addressing real-time problems and swiftly identifying the optimal alternative. [18] However, it falls short in deriving the weights and assessing the consistency of decision-makers' assignments.

The TOPSIS method envisages the following input elements:

- a set of evaluation criteria C_j ($j \in \{1, 2, \dots, N\}$).
- An evaluation matrix $[x_{ij}]$ ($i \in \{1, 2, \dots, M\}$, $j \in \{1, 2, \dots, N\}$) consisting of M alternatives and N criteria. Each x_{ij} reports the value assigned to criterion j in alternative i (e.g., the fiber granulometry, resin content, fiber length).
- A set of weights (w_j) ($j \in \{1, 2, \dots, N\}$) assigned to the criteria.

The N criteria can also be divided into positive and negative categories, with the goal being to maximize the positive criteria while minimizing the negative ones. The TOPSIS method envisages the following operational steps:

1. Define the Evaluation Criteria and their weights (see the previous chapter).
2. Identify Decision Alternatives: determine the set of alternatives or options available for the decision-making process
3. Construct the Decision Matrix ($[x_{ij}]$) where rows represent the alternatives and columns the criteria.
4. Assign scores or ratings to each alternative based on their performance on each criterion.
5. Normalize the Decision Matrix ($[r_{ij}]$): Normalize the values in the decision matrix to eliminate the scale differences between criteria.
6. Determine the Weighted Normalized Matrix ($[t_{ij}]$) by multiplying the normalized values with the respective weights assigned to each criterion.
7. Determine the Positive and Negative Ideal Solutions. Calculate the Positive Ideal Solution (PIS), which represents the best performance for each criterion. Calculate the Negative Ideal Solution (NIS), which represents the worst performance for each criterion.
8. Calculate the distances of each alternative from the PIS (D_i^B) and NIS (D_i^W) solutions.
9. Calculate the *similarity* (S_i) of each alternative to the NIS.
10. Rank the alternatives according to their similarities having in mind that $S_i = 0$ if and only if the alternative i has the j ; $S_i = 1$ if and only if the alternative i has the best conditions.

3. Obtained results

Final weights obtained from the g_BWM approach for both decision making points:

Table 4: Weights obtained for the criteria at each decision making point

	Criteria Name	Weights
CR1	Defect Structurality	0,5939
CR2	Service Life rating	0,1316
CR3	Appearance	0,153
CR4	Joining Elements	0,1214

	Criteria Name	Weights
CR1	Material Recovery	0,124789
CR2	Environmental score	0,088859
CR3	Energy Consumption	0,087884
CR4	Average Throughput	0,066181
CR5	Market Value of the recycle	0,154987
CR6	Technology Readiness level	0,116179
CR7	Tensile strength of rGF/rCF	0,154433
CR8	Cost of recycling	0,161993
CR9	Labor requirement	0,044695

The DSS was implemented using Microsoft Excel, creating input forms through which users could provide the required data. Dedicated Excel worksheets were created to run the TOPSIS algorithm, ensuring that the system performs all necessary calculations for decision support. In addition, all DSS configuration parameters are managed through specific Excel worksheets, allowing flexibility and customization of the

tool to adapt to different EoL management scenarios and user needs. For sake of space, only results obtained on Decision Point 1 will be presented in this paper based on the following three scenarios:

- *Scenario 1:* A EoL wind blade, with 8 defects, that has been in service for 20 years, held together by irreversible adhesives.
- *Scenario 2:* A EoL wind blade, with 4 defects, that has been in service for 10 years, held together by irreversible adhesives.
- *Scenario 3:* A EoL sport equipment, with 3 defects, that has been in service for 2 years, held together by reversible adhesives.

The three scenarios give three completely different results. In the first case the DSS suggests that the EoL wind blade should be recycled, and this in fact does follow the logical thought: the said wind blade is in the latter period of its useful life, it has many defects, it is held together by an irreversible joint, it should go towards recycling since the decision for disposing is discouraged to prevent loss of value. In the second case the DSS suggests that the EoL wind blade should be repaired since the number of defects have gone from 8 to 4 and the largest of the defects do not exist anymore: the EoL in question is now younger in this service life and the appearance has hence improved. In the last scenario, the EoL in question is a sport equipment, with a few defects at surface level, a relatively new piece of equipment and held together with reversible adhesives. The DSS in this case suggests that the part be re-used for the time being, before being subjected to any other circular treatment options.

Example of Result of Decision Point 2

- ***Scenario 1: 10kg for CFRP that is coming from pieces of sport equipment, the type of fiber is chosen to be intermediate modulus carbon fibers like T300 and the fiber to matrix ratio is 40:60.***

In this case the DSS suggests Green solvolysis given the small batch of 10 kg, high value intermediate carbon fibers recovery. The green solvolysis gets the edge over HVF and thermal processes since there is recovery of resin as oligomers as well.

4. Conclusions and future work

The developed Decision Support System for End-of-Life management demonstrates high adaptability and robustness across different application scenarios. By integrating the Best-Worst Method and the TOPSIS algorithm, the DSS enables an accessible and customizable framework for multi-criteria evaluation of EoL strategies. The three case studies confirm its ability to support context-dependent decision-making, identifying recycling, repair, or reuse as the most suitable option depending on product condition, age, and joint reversibility. Future developments will aim to incorporate advanced data analytics in DSS, potentially supported by machine learning techniques, to improve the accuracy of evaluations and recommendations. In parallel, particular attention will be devoted to enhancing user interaction and ensuring interoperability with other digital platforms for the circular economy, thereby consolidating the DSS as a scalable and reliable tool for sustainable resource management.

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