Available online at www.sciencedirect.com

ScienceDirect

Procedia CIRP 140 (2026) 641–646

www.elsevier.com/locate/procedia

33rd CIRP Conference on Life Cycle Engineering (LCE 2026)

# Development of a Decision Tool for Assessing the Circularity of Electric Traction Motors

Nicolaus Klein[a,*], Markus Heim[a], Hans Philipp Zorn[a], Florian Kößler[a], Jürgen Fleischer[a]

[a] Karlsruhe Institute of Technology (KIT), wbk Institute of Production Science, Kaiserstraße 12, 76131 Karlsruhe, Germany

* Corresponding author. Tel.: +49 1523 9502582. *E-mail address:* nicolaus.klein@kit.edu

**Abstract**

The end-of-life treatment of complex electromechanical products, such as electric traction motors, requires balancing technical, economic, and environmental considerations. Individual components may retain substantial residual value if recovered, cleaned, and inspected, but the costs of disassembly, preparation, and diagnostics can outweigh the benefits of reuse. Disassembly is further constrained by mechanical dependencies, meaning that operations must follow a feasible sequence. The final decision to execute direct reuse, remanufacturing, or recycling must account for both recovered value and the extent of part recovery. To address these challenges, a structured decision framework is needed that represents the disassembly process as a precedence-constrained network of operations, each tied to a potentially recoverable part. The framework consists of three interconnected phases. First, disassembly planning determines a technically feasible execution order and selects operations expected to yield economically meaningful parts. Second, the cleaning and diagnostics phase assigns each recovered part a cleaning outcome and a fault profile, producing estimates of value loss and diagnostic cost, including partial decontamination, handling of delicate components, and probabilistic repair efforts. Third, rule-based decision logic identifies the appropriate end-of-life strategy. The resulting approach supports systematic exploration of disassembly options, transparent cost-benefit evaluation, and alignment of technical feasibility with economic goals.



*Keywords:* Electric traction motor; permanent magnet synchronous machine; R-strategy; Remanufacturing; Decision Tool; End-of-Life; EoL

## 1. Introduction

Effective management of end-of-life (EoL) processes for complex electromechanical products is a critical challenge in the transition toward a circular economy. Electric traction motors, which are key components of modern electric vehicles, contain valuable materials and components whose recovery can reduce raw-material consumption, lower environmental impacts, and support regulatory compliance [1]. However, the technical and economic complexity of disassembling, cleaning, diagnosing, and reconditioning these motors poses significant challenges to decision makers, who must balance residual value against processing costs and sequencing constraints. Existing research on EoL treatment follows two complementary paths: (i) qualitative frameworks that classify recovery strategies and outline technical or economic criteria, and (ii) quantitative decision-support models that formalize specific trade-offs, often using life-cycle assessment or rule-based approaches. While these contributions provide valuable insights, they typically address only subsets of the problem, such as environmental evaluation, disassembly sequencing, or cost accounting [2]. What is still missing is an integrative approach that simultaneously captures component-level value maximization, probabilistic uncertainty, and interactive

2212-8271 © 2026 The Authors. Published by Elsevier B.V.

10.1016/j.procir.2026.05.108

parameter exploration within a single tool. To address this gap, this study develops a decision-support tool that combines a mixed-integer nonlinear programming model with an interactive Streamlit dashboard. The optimization model enforces disassembly order, incorporates cleaning-related value losses and diagnostic costs, and applies a profitability threshold to maximize net residual value. The dashboard allows users to adjust key parameters in real time and instantly see how the optimal strategy (reuse, remanufacturing, recycling) changes, as demonstrated with real motor data in the case study.

## 2. Literature Review

Research on EoL strategies for complex electromechanical products spans qualitative classifications, environmental assessments, and technical studies on disassembly. Several contributions also differ in how broadly they address R-strategies, how explicitly they model EoL processes, and whether they employ quantitative methods or practical decision tools. Early works provide foundational recovery categories and later structured tools combine technical, economic, and environmental criteria [3,4]. Environmental aspects are often examined through LCA approaches, including spreadsheet-based comparisons of repair and replacement and reuse evaluations based on combined inventory and economic data [5,6]. Broader circularity indicators extend these evaluations to sector or organizational level [7,8]. Disassembly-focused research provides more explicit modeling of EoL processes. Estimations of disassembly effort use liaison matrices and cost factors. Algorithmic planning methods rely on level and liaison matrices to structure feasible sequences [9,10]. Time-based studies apply MOST analyses [11]. More advanced contributions integrate digital models and simulation to support adaptive robotic disassembly, and design-oriented works introduce metrics such as disassembly efficiency indices and CAD-based remanufacturability indicators [12-14]. A third set of studies links product condition with strategy selection. Rule-based connections relate disassembly outcomes, cleaning levels, and fault profiles, while qualitative work highlights remanufacturing-relevant design features and terminology for reuse [15-17]. Furthermore, uncertainty analyses consider product, process and organizational levels. In addition, control focused models propose policies for remanufacturing under uncertain return quality and quantity [18,19]. Overall, prior work shows progress but clear gaps. Early classifications establish recovery categories; LCA approaches highlight environmental trade-offs at product level; and circularity indicators extend the view to sectors, but without addressing component-level decisions. Technical studies advance understanding of disassembly complexity but remain separate from economic evaluation. Rule-based frameworks provide guidance but lack integration with optimization or interactive tools. Missing is a comprehensive approach that jointly considers systematic R-strategies, explicit process modeling, mathematical optimization, and transparent implementation, a gap this study aims to address. Table 1 summarizes selected contributions across four dimensions: R-strategy treatment, EoL process modelling, mathematical optimization, and implementation as simulation or decision tool. The limited overlap highlights the methodological gap addressed in this paper.

Table 1. Comparison of studies along key dimensions for EoL decision-making (○ low coverage ●strong coverage).

| Study | Treatment of R-strategies | EoL Process Modeling | Mathematical Optimization | Simulation/ Tool |
|---|---|---|---|---|
| Thierry (1995) | ● | ◔ | ○ | ○ |
| Fang (2016) | ◕ | ◕ | ◔ | ◔ |
| Germani (2014) | ◑ | ● | ◔ | ◑ |
| Priyono (2015) | ◕ | ◑ | ○ | ○ |
| Gharfalkar (2016) | ◕ | ◔ | ○ | ○ |
| Jiang (2018) | ◑ | ◕ | ○ | ○ |
| Mandolini (2018) | ◑ | ● | ◔ | ◔ |
| Pini (2019) | ◕ | ◔ | ○ | ◔ |
| Bovea (2020) | ◕ | ◔ | ○ | ◔ |
| Neidhardt (2022) | ◑ | ◔ | ○ | ◔ |
| Bobba (2023) | ◑ | ◔ | ○ | ◔ |
| Ahlstedt (2023) | ◕ | ◑ | ○ | ◔ |
| Grosse Erdmann (2023) | ◑ | ● | ◑ | ◑ |
| Hansjosten (2023) | ◕ | ● | ◑ | ● |
| Lachnit (2025) | ● | ◕ | ◔ | ◕ |
| Taheri (2024) | ● | ● | ◑ | ◑ |
| Magnanini (2025) | ◑ | ● | ● | ◑ |

## 3. Problem Definition & Decision Framework

This section introduces the formal decision model for assessing EoL options of electric traction motors. The goal is to determine, based on technical feasibility and economic criteria, whether a motor should undergo reuse, remanufacturing, or recycling. The analysis focuses on component level, where value retention, accessibility, and defect risks must be systematically evaluated. From a linear to a circular perspective, a broad spectrum of R-strategies exists. In this study, emphasis is placed on reuse, remanufacturing, and recycling, while broader discussions can be found in reviews [20]. Figure 1 visualizes the different R-strategies. Disassembly is the central enabling process of remanufacturing, as it defines which components can be recovered and assessed for viability. The disassembly process is modeled as a directed acyclic graph, with nodes as steps and edges as dependencies. Binary variables indicate whether parts are recovered, restricted to accessible components with potential residual value. Recovered parts then undergo cleaning and diagnostics. Cleanability is captured by discrete categories linked to value loss coefficients, while diagnostics use fault probabilities and repair costs, adjusted by a penalty reflecting cleaning quality. These are integrated into a residual value function, which serves as the model's objective. The residual value is compared to a profitability threshold, defined as a fraction of the initial value. Based on this and the recovery ratio, the model assigns a strategy: reuse if all recoverable parts retain sufficient value, remanufacturing if recovery is partial but profitable, and recycling otherwise. By integrating sequencing, value degradation, probabilistic diagnostics, and threshold-based rules, the model enables consistent and transparent strategy recommendations. This framework forms the basis for the simulations and interactive analyses presented in subsequent sections.

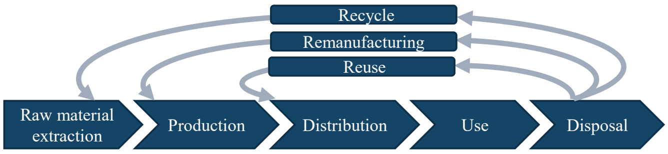


Fig. 1. Circular Economy strategies.

## 4. Mathematical Model

The mathematical formulation is derived directly from the rule-based strategy. Since the strategy outcome depends on the final residual value after all recovery steps as well as on the number of successfully retrieved parts, the strategy rule forms the conceptual starting point of the derivation. The three possible outcomes are given by

$$\text{Strategy} = \begin{cases} \text{Reuse: } Z_{final} \geq \alpha Z_0 \cap \mathcal{P}_{rec} = |\mathcal{P}| \\ \text{Remanufacturing: } Z_{final} \geq \alpha Z_0 \cap \mathcal{P}_{rec} < |\mathcal{P}| \\ \text{Recycling: otherwise.} \end{cases} \quad (1)$$

$Z_{final}$ final residual value after all recovery steps
$Z_0$ initial total value of all parts
$\alpha$ Profitability threshold applied to $Z_0$
$\mathcal{P}$ set of recoverable parts
$\mathcal{P}_{\mathrm{rec}}$ set of recovered parts, $\{i \mid x_i = 1\}$

To evaluate these conditions, the process shown in Fig. 2 is formalized step by step. The workflow consists of disassembly, cleaning, diagnostics, and profitability checks, each contributing a specific component to the final residual value. The mathematical expressions governing these contributions are introduced alongside the corresponding process steps. The workflow begins with the disassembly of the product. Each disassembly operation potentially yields a recoverable part and its outcome is represented by a binary decision variable. Let $x_i = 1$ if part $i$ is successfully recovered and $x_i = 0$ otherwise. This step introduces the retained-value term $c_i x_i$, where $c_i$ denotes the value of part $i$. Precedence relations among disassembly operations are implemented through

$$x_i \leq x_j \ \forall (i,j) \in E, \quad (2)$$

ensuring that a step can only be executed if all of its predecessors have been completed. After disassembly, each recovered part enters the cleaning phase. Cleaning affects the residual value through outcome dependent losses represented by the coefficient $\lambda_i$. A part with cleaning outcome $\delta_i \in \{V, M, N\}$ retains only a fraction $(1 - \lambda_i)$ of its original value. This yields the cleaning-loss contribution

$$-\sum_{i \in \mathcal{P}} c_i \lambda_i x_i, \quad (3)$$

$x_i$ recovery decision for part $i, x_i \in \{0, 1\}$
$c_i$ initial total value of all parts
$\lambda_i$ value-loss coefficient determined by cleaning outcome $\delta_i$
$\delta_i$ cleaning outcome $(V, M, N)$
$\mathcal{P}$ set of recoverable parts

which appears as the second component of the residual value expression. At this stage of the workflow, profitability is checked against the intermediate residual value $Z_{clean}$, mirroring the decision points in Fig. 2.

If the cleaning stage passes the profitability threshold, the parts are inspected for potential fault modes. Diagnostics introduce expected repair costs that depend on the probability of each fault mode $F_j$, its associated cost $\kappa(F_j)$ and the diagnostic accuracy, which itself depends on the cleaning outcome through the function $f(\delta_i)$. The penalty parameter $\gamma$ adjusts the cost upward in cases of reduced accuracy. The resulting diagnostic cost contribution is

$$-\sum_{i \in \mathcal{P}} \sum_{j=1}^{n} Pr(F_j \mid i)\, \kappa(F_j) \left(1 + \gamma(1 - f(\delta_i))\right) x_i \quad (4)$$

$Pr(F_j \mid i)$ Probability of fault mode $F_j$ occurring in part $i$
$\kappa(F_j)$ repair cost associated with fault mode $F_j$
$f(\delta_i)$ value-loss coefficient determined by cleaning outcome $\delta_i$
$\gamma$ penalty factor for reduced diagnostic accuracy
$x_i$ recovery decision for part $i, x_i \in \{0, 1\}$
$\mathcal{P}$ Set of recoverable parts

which completes the definition of the final residual value $Z_{final}$ obtained at the end of the workflow in Fig. 2. At this point, the second profitability check determines whether the process proceeds toward reuse or remanufacturing or whether it is terminated in recycling. The preceding derivation shows how each process step contributes directly to the structure of the residualvalue objective. Collecting the retained value, cleaning losses, and diagnostic costs yields

$$\max Z_{final} = \sum_{i \in \mathcal{P}} c_i x_i - \sum_{i \in \mathcal{P}} c_i \lambda_i x_i - \sum_{i \in \mathcal{P}} \sum_{j=1}^{n} Pr(F_j \mid i) \kappa(F_j) \left(1 + \gamma(1 - f(\delta_i))\right) x_i \quad (5)$$

To ensure feasibility and consistency with the workflow logic, several additional constraints are required.

$$Z_{final} \geq \alpha Z_0 + \epsilon \quad (6)$$

$$\sum_{i \in \mathcal{P}} x_i \geq 1 \quad (7)$$

$$\sum_{i \in \mathcal{P}} x_i \leq K \quad (8)$$

$$x_i \in \{0, 1\}, \forall i \in P \quad (9)$$

$\alpha$ Profitability threshold applied to $Z_0$
$\epsilon$ small positive margin enforcing strict profitability
K maximum allowable number of recovered parts

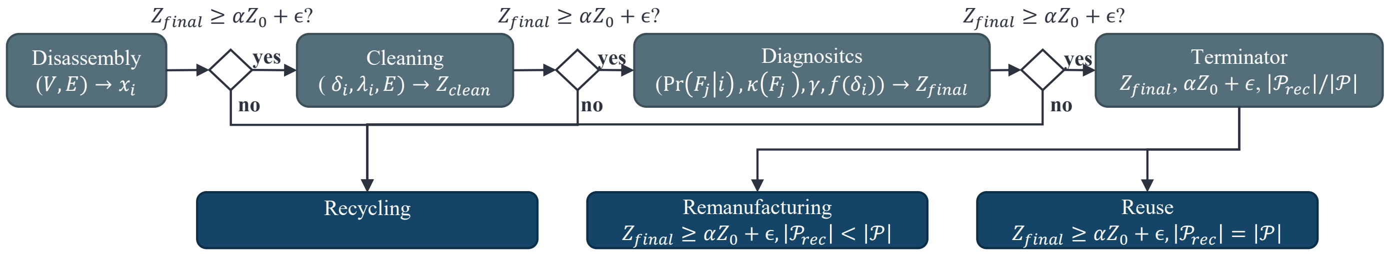


Fig. 2. Sequential decision workflow with profitability checks at each stage.

The model's objective is to maximize the final residual value $Z_{final}$, obtained from the retained value of recovered parts minus cleaning losses and expected diagnostic costs (4). Structural feasibility is enforced through the precedence relations (2), which allow recovery only if all predecessors are selected. Economic viability follows from the profitability condition (6), requiring $Z_{final} \geq \alpha Z_0 + \varepsilon$. The minimum recovery level (7) and the optional cardinality bound (8) restrict the scope of feasible solutions, while binary constraints (9) preserve the combinatorial decision structure.

Together, these constraints complete the mathematical representation of the workflow in Fig. 2 and guide the final strategy choice. From the optimized solution, the recovered set $\mathcal{P}_{rec} = \{i \in \mathcal{P} \mid x_i = 1\}$ and the resulting residual value determine the end-of-life option via (1): full and profitable recovery yields Reuse, profitable partial recovery leads to, and all other outcomes result in Recycling.

## 5. Methodology

In what follows, the motor's progression through the three core phases of the workflow disassembly planning, cleaning evaluation, and diagnostics is first described in a general methodological manner. Each step is highlighted to show how intermediate decisions drive toward a final strategy of reuse, remanufacturing, or recycling. In the disassembly planning phase, the parts that can be removed without violating any precedence relation $(i, j) \in E$ are first determined, as illustrated in Fig. 3.

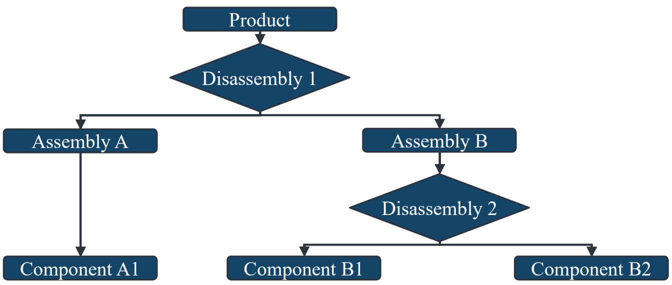


Fig. 3. Disassembly tree structure.

For each candidate part $i$, the recovery decision is represented by a binary decision variable $x_i$. As parts are selected, their values $c_i$ are accumulated into a running total. If at any point the sum of recovered values falls below the threshold $\alpha Z_0$, the workflow is halted and the motor is directed to recycling. By this early termination, wasted effort on unprofitable recovery sequences is minimized, and only economically viable disassemblies are allowed to proceed further. Parts that pass the initial check enter the cleaning evaluation phase. Each selected part receives a cleaning outcome $\delta_i \in \{V, M, N\}$ ("fully cleanable," "moderately dirty," "non-cleanable"), with an associated value-loss coefficient $\lambda_i$ reflecting reduced worth. After adjusting the residual value by all $\lambda_i$ the result is compared to $\alpha Z_0$. If the cleaned-value falls below this threshold, the process stops and recycling is recommended to avoid costly diagnostics on low-value parts. In the final diagnostics phase, each cleaned part is tested across all fault modes $F_j$. For each mode, the probability $Pr(F_j \mid i)$ repair cost $\kappa(F_j)$, and the cleaning - quality penalty define the expected diagnostic expenses deducted from the residual value. The resulting $Z_{\text{final}}$ is then compared to $\alpha Z_0$. If it falls short, the motor is recycled; otherwise, the "Terminator'' block computes the recovery rate $|\mathcal{P}|/|\mathcal{P}_{\text{rec}}|$. Full recovery yields reuse, partial recovery leads to remanufacturing, and unprofitable outcomes result in recycling. The phase uses decision variables $x_i$, $\delta_i$, parameters $(\alpha, \lambda_i)$ and fault distributions $(Pr(F_j \mid i), \kappa(F_j))$ to guide continuation or termination.

## 6. Data Structure & Implementation with Streamlit

The framework is implemented in Streamlit, which links a Python backend with a reaction-based frontend. A single script runs as the server, re-rendering only changed widgets and managing interactivity via *st.session_state*. At startup, dictionaries track completed steps, recovered parts, cleaning status, and diagnostic results; a reset clears all values and reruns the script.

It consists of three modules disassembly, cleaning/diagnostics, and strategy selection which unlock sequentially once tasks and profitability thresholds are met. The decision process is based on a directed acyclic graph $G = (V, E)$, where each node represents a disassembly step and edges encode precedence. In the code, the graph is stored as a list of dictionaries with *id*, *name*, and *depends_on*, from which internal mappings (*steps_dict*, *children_map*) are derived. Steps labeled with *"Part"* correspond to recoverable parts and to the decision variables $x_i \in \{0, 1\}$. User interaction follows this structure: non-part steps appear as buttons

(*“Complete”*/*”Fail”*), while parts are selected via checkboxes. Once a part is confirmed, additional inputs for cleaning status and fault type appear, influencing residual value, cleaning losses ( $\lambda_i$ ), and diagnostic costs. Session state stores all decisions (*completed_steps*, *found_parts*, *cleaning_status*, *analysis*, *analysis_cost*) and updates metrics such as $Z$, $Z_{clean}$ and $Z_{final}$ in real time. Based on profitability $Z_{final} \geq \alpha Z_0$ and recovery ratio $|\mathcal{P}|/|\mathcal{P}_{\text{rec}}|$, the strategy is automatically assigned to reuse, remanufacturing, or recycling. By merging graph logic with session-state tracking, the tool ensures that disassembly order is respected and decisions remain transparent. The modular design allows extensions such as additional part attributes or real-time sensor data.

he three scenarios were constructed by varying recovery feasibility, cleaning behavior, and diagnostic parameters within the OEM-based baseline dataset.

## 7. Case Study: Scenario-Based Validation and Strategy

The practical utility of the decision workflow (Fig. 2) is demonstrated by considering a permanent-magnet synchronous traction motor (PSM) supplied by a leading German OEM. The unit represents a typical 150 kW main drive used in mid-size battery-electric vehicles and includes the standard components of modern traction motors including stator, rotor with embedded magnets and housing. The motor consists of 33 individual components, indexed by $i \in \mathcal{P}$ , each with a nominal market value $c_i$. Based on current market prices and target cost-recovery ratios, the total initial value $Z_0$ and the profitability threshold $\alpha$ are defined.

Each reflects different combinations of recovery feasibility, cleaning, and fault behavior. In the first scenario, representing a low-recovery case, only 9 of 33 parts (27 %) were recovered, giving $Z = 272.7$ €, below the profitability threshold $\alpha Z_0 = 500$ €. Constraint (6) was violated and the process ended with recycling, showing the model’s ability to exclude unprofitable plans early. In the second scenario, designed as a medium-recovery and moderate-cleaning-loss case, 20 parts were recovered with $Z = 606$ €. Cleaning losses reduced this to $Z_{clean} = 454.5$ €. Diagnostics then applied probabilities, costs $\kappa(F_j)$ , and the penalty term $\left(1 + \gamma\left(1 - f(\delta_i)\right)\right)$ , yielding $Z_{final} \approx 304.5$– $354.5$ €. Since profitability held but not all parts were recovered, remanufacturing was selected, illustrating how the framework balances partial recovery with economic viability. In the third scenario, representing a full-recovery and full-cleanability case, all 33 parts were recovered and fully cleanable, giving $Z_{clean} = Z = Z_0 = 1000$ € with negligible diagnostic costs. Both criteria were satisfied, and reuse was chosen. These cases confirm that the dual rule-profitability $Z_{final} \geq \alpha Z_0$ and recovery ratio $|\mathcal{P}|/|\mathcal{P}_{\text{rec}}|$-yields robust and interpretable outcomes. The framework halts unprofitable plans, manages trade-offs in borderline cases, and recommends reuse under favorable conditions. Because it was implemented in an interactive dashboard with OEM data, it can also support training and industrial workflows, with potential extensions toward real-time fault models and sensor input.

Compared with existing work, the model unifies technical, economic, and diagnostic parameters in one structure. It incorporates cleaning losses, fault probabilities, and graph-based precedence logic, while the simulation interface adds practical relevance. For industry, it supports disassembly simulation, trade-off evaluation, and early strategy identification. For research, it offers a basis for extensions such as linearizing non-linear terms or reusing its hierarchical data model.

Regarding limitations, the framework adopts simplifying assumptions. The disassembly graph and recovery parameters are treated as known, although recent studies show that inspection uncertainty can strongly influence remanufacturing policies [19]. The strategy rule applies a fixed threshold and binary recovery classification, which may miss borderline cases. Dynamic updates (e.g., re-routing after unexpected faults) are not yet included. Non-linear expressions (e.g., probabilistic cost estimations) may affect solver performance, suggesting future work on linearization or robust optimization as in ILP and Markov-based remanufacturing models [21].

## 8. Conclusion and Future Work

This paper presented a decision framework for evaluating the circularity potential of electric traction motors at end-of-life. By combining a graph-based disassembly structure with a mixed-integer optimization model, the framework enables consistent strategy selection based on residual value, cleaning effort, and diagnostic costs. The integration into an interactive Streamlit dashboard enhances transparency and usability, making the tool applicable in both industrial and educational settings. Scenario-based validation confirmed that the model behaves robustly across a range of technical and economic conditions, and outperforms existing approaches in terms of decision granularity and practical applicability.

From a practical perspective, the model helps decision-makers avoid unprofitable recovery paths and prioritize reuse or remanufacturing when economically justified. The modular structure also allows for the integration of real-world product data and user-defined thresholds, supporting customized evaluation routines in remanufacturing environments. Engineers can explore disassembly options, quantify trade-offs, and generate recommendations without requiring advanced programming or mathematical skills. Future research should aim to improve the model’s scalability and precision. One direction is the linearization of non-linear diagnostic cost functions to improve solver performance on larger systems. Another is the integration of uncertainty through robust or stochastic optimization to better reflect variability in fault probabilities and cleaning outcomes. Further extensions may also include dynamic process re-evaluation, where the strategy is updated as new condition data become available during disassembly. Additionally, linking the tool with sensor-based inspection systems or digital twins could enable real-time decision-making in industrial applications. Overall, the proposed framework offers a foundation for intelligent EoL decision support and provides a starting point for further advances in circular product evaluation and optimization.

## CRediT authorship contribution statement

**Nicolaus Klein**: Writing – review & editing, Writing – original draft, Visualization, Supervision, Project administration, Conceptualization. **Markus Heim**: Writing – original draft. **Hans Philipp Zorn**: Writing – review & editing, Writing – original draft, Visualization, Conceptualization. **Florian Kößler**: Writing – review & editing, Supervision. **Jürgen Fleischer**: Writing – review & editing, Supervision, Conceptualization.

## Acknowledgements

The authors of this paper would like to thank the German Federal Ministry for Economic Affairs and Climate Action for sponsoring the research project REASSERT (19S23004E). Further, we would like to thank the TÜV Rheinland Consulting GmbH for their project management.

## References

[1] Y. Xiao, G. K. Goyal, J. Su, H. Abbasi, H. Yan, X. Yao, K. Tantratian, Z. Yan, A. Alksninis, M. Phipps, P. Hernley, Q. Wang, L. Zuo, L. Chen, A comprehensive review of electric vehicle recycling: Processes in selective collection, element extraction, and component regeneration, Resources, Conservation and Recycling 219 (2025) 108309. doi:10.1016/j.resconrec.2025.108309.

[2] S. Kara, M. Hauschild, J. Sutherland, T. McAloone, Closed-loop systems to circular economy: A pathway to environmental sustainability?, CIRP Annals - Manufacturing Technology 71 (1) (2022) 505–528. doi:10.1016/j.cirp.2022.05.008.

[3] M. Thierry, M. Salomon, J. A. E. E. Van Nunen, L. N. Van Wassenhove, Strategic issues in product recovery management, California Management Review 37 (2) (1995) 114–135.

[4] T. Lachnit, et al., Comprehensive assessment of remanufacturing suitability and enhancement, in: H. Kohl, G. Seliger, F. Dietrich, H. Vien (Eds.), Decarbonizing Value Chains. GCSM 2024, Lecture Notes in Mechanical Engineering, Springer, Cham, 2025. doi:10.1007/978-3-031-93891-7_63.

[5] M. D. Bovea, V. Ibáñez-Forés, V. Pérez-Belis, Repair vs. replacement: Selection of the best end-of-life scenario for small household electric and electronic equipment based on life cycle assessment, Journal of Environmental Management 254 (2020) 109679. doi:10.1016/j.jenvman.2019.109679.

[6] M. Pini, F. Lolli, E. Balugani, R. Gamberini, P. Neri, B. Rimini, A. M. Ferrari, Preparation for reuse activity of waste electrical and electronic equipment: Environmental performance, cost externality and job creation, Journal of Cleaner Production 222 (2019) 77–89. doi:10.1016/j.jclepro.2019.03.004.

[7] S. Bobba, U. Eynard, T. Maury, F. Ardente, G. A. Blengini, F. Mathieux, Circular input rate: Novel indicator to assess circularity performances of materials in a sector – application to rare earth elements in electric vehicle motors, Resources, Conservation and Recycling 197 (2023) 107037. doi:10.1016/j.resconrec.2023.107037.

[8] M. Neidhardt, J. Mas-Peiro, M. Schulz-Mönninghoff, J. Pou, R. Gonzalez-Olmos, A. Kwade, B. Schmuelling, Forecasting the global battery material flow: Analyzing the break-even points at which secondary battery raw materials can substitute primary materials in battery production, Applied Sciences 12 (9) (2022) 4790. doi:10.3390/app12094790.

[9] M. Germani, M. Mandolini, M. Marconi, M. Rossi, An Approach to Analytically Evaluate the Product Disassemblability during the Design Process, Procedia CIRP 21 (2014) 336–341. doi:10.1016/j.procir.2014.03.153.

[10] M. Mandolini, C. Favi, M. Germani, M. Marconi, Time-based disassembly method: how to assess the best disassembly sequence and time of target components in complex products, The International Journal of Advanced Manufacturing Technology 95 (1-4) (2018) 409–430. doi:10.1007/s00170-017-1201-5.

[11] J. G. Erdmann, J. Koller, J. Brimaire, F. Döpper, Assessment of the disassemblability of electric bicycle motors for remanufacturing, Journal of Remanufacturing 13 (2) (2023) 137–159. doi:10.1007/s13243-023-00124-1.

[12] M. Hansjosten, J. Fleischer, Towards autonomous adaptive disassembly of permanent-magnet synchronous motors with industrial robots, Manufacturing Letters 35 (2023) 1336–1346. doi:10.1016/j.mfglet.2023.08.084.

[13] H. Jiang, J. Yi, X. Zhu, Z. Li, Generating disassembly tasks for selective disassembly using ontology-based disassembly knowledge representation, Assembly Automation 38 (2) (2018) 113–124. doi:10.1108/AA-04-2016-034.

[14] H. Fang, S. Ong, A. Nee, An integrated approach for product remanufacturing assessment and planning, Procedia CIRP 40 (2016) 262–267. doi:10.1016/j.procir.2016.01.118.

[15] F. Taheri, G. Sauvé, K. Van Acker, Development of a decision tool for assessing the circularity of electric traction motors, in: Procedia CIRP, Vol. 122, 2024, pp. 265–270. doi:10.1016/j.procir.2024.01.038.

[16] E. Ahlstedt, E. Sundin, Assessing product suitability for remanufacturing – a case study of a handheld battery-driven assembly tool, Procedia CIRP Vol. 116 (2023) 582–587. doi:10.1016/j.procir.2023.02.098.

[17] M. Gharfalkar, Z. Ali, G. Hillier, Clarifying the disagreements on various reuse options: Repair, recondition, refurbish and remanufacture, Waste Management & Research: The Journal for a Sustainable Circular Economy 34 (10) (2016) 995–1005. doi:10.1177/0734242X16628981.

[18] A. Priyono, W. L. Ijomah, U. S. Bititci, Strategic operations framework for disassembly in remanufacturing, Vol. 5, 2015, p. 11. doi:10.1186/s13243-015-0018-3.

[19] M. C. Magnanini, T. Tolio, Optimal control of remanufacturing systems with uncertainty in quality identification, CIRP Annals – Manufacturing Technology 74 (1) (2025) 591–595. doi:10.1016/j.cirp.2025.04.055.

[20] D. Reike, W. Vermeulen, S. Witjes, The circular economy: New or refurbished as ce 3.0? — exploring controversies in the conceptualization of the circular economy through a focus on the 9r framework, Resources, Conservation and Recycling 135 (2018) 246–264. doi:10.1016/j.resconrec.2017.08.027.

[21] F. Stamer, J. Sauer, Optimizing quality and cost in remanufacturing under uncertainty: A novel optimization framework utilizing quality and process modelling, Production Engineering 19 (3-4) (2025) 369–390. doi:10.1007/s11740-024-01314-x.