Optimizing Electric Traction Motor Design: Analyzing the Benefits of a Circular Economy

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Note: This is the authors' final version of the paper (pre-print) that is published as:

Jesús R. Pérez-Cardona, Neha Shakelly, Matthew J. Triebe, and John W. Sutherland, Optimizing electric traction motor design: Analyzing the benefits of a circular economy. *Journal of Cleaner Production* 486 (2024): 144522

DOI: https://doi.org/10.1016/j.jclepro.2024.144522

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Abstract

The circular economy (CE) shifts from a linear economy (LE) to prioritize preserving value improving resource efficiency through closed loops. This shift demands product designs that facilitate repurposing and recycling, reducing waste and new material use. Achieving this requires changes in industry practices, consumer behavior, and supportive policies / incentives. Yet, the absence of standardized metrics poses evaluation challenges. This study introduces a combined life cycle and techno-economic assessment within a parametric design model to optimize CE strategies, including a disassembly planning algorithm linking end of life (EoL) outcomes (reuse, remanufacturing, recycling, landfill) to the life cycle inventories. Applied to a permanent magnet synchronous motor in an electric vehicle, the model evaluates supply risk, environmental benefits, and economic gains compared to LE methods. A one-way sensitivity analysis on motor collection rates explored three scenarios: baseline, 100% disassembly and recycling, and 100% reuse. Results showed significant improvements in economic and supply risks aspects under CE though environmental impact was less pronounced due to the high energy use during the use stage. Furthermore, EoL motor upper-level subassemblies had a greater effect than lower-level ones, with no interaction effects found. This paper proposes a formal method for measuring CE performance based on these findings.

Keywords: Multi-objective optimization, Supply risk, Sustainable design, Sustainable manufacturing, Circular economy, Electric traction motors

1. Introduction

In the prevailing linear economy (LE) model, products follow a direct path from inception to disposal. Companies conceptualize designs, procure raw materials, engage in production processes to transform these materials into finished goods, conduct quality inspections, products are distributed to consumers, consumers use the goods, and finally the used product is disposed (Vimala, 2024; Pacheco et al., 2024). However, this linear consumption pattern generates significant waste and environmental harm, leading to resource depletion and negative environmental impacts. To counteract this, designers must prioritize solutions enabling continuous resource reuse, especially during the initial design phase. This proactive approach emphasizes extended product lifespans, easy disassembly for recycling, and the use of recycled or renewable materials (van Dam et al., 2020).

The emergence of the circular economy (CE) challenges the conventional linear approach, both in terms of production and consumption patterns (Lewandowski, 2016; Lüdeke-Freund et al., 2019). At its core, CE seeks to transform our current linear system into one that operates with minimal waste. In this envisioned waste-free life cycle paradigm, the very concept of waste as we traditionally understand it becomes obsolete. The CE rests on two key principles. Firstly, it reimagines how materials circulate within the economy, emphasizing a closed-loop system where resources are continually repurposed, reused, or recycled (Negrei & Istudor, 2018). Consequently, it minimizes waste and reduces the need for new raw materials. Secondly, the CE calls for a reevaluation of the necessary conditions to support such a resource-efficient material flows, which may include incentives for recycling, sustainable design and manufacturing, and responsible consumption.

Transitioning from a linear to a circular economy is undoubtedly challenging and multifaceted on multiple fronts (Afteni et al., 2021; Kayikci et al., 2021). It necessitates a fundamental shift in mindset across industries and society as a whole. This transformation demands alterations in production methods, business models, and consumer behavior. Businesses must adopt circular strategies like leasing products, designing for longevity, and creating systems for recycling and refurbishment (Lewandowski, 2016). Policymakers also play a crucial role in facilitating this transition by implementing regulations and incentives that promote sustainable practices (Kirchherr et al., 2018; Milios, 2018; Schröder et al., 2020).

The CE has also been subjected to some criticism. As discussed by Millar et al. (2019), because of the second law of thermodynamics there will always be waste and by-products due to increasing entropy. Therefore, closed material loops are theoretically impossible. In addition, Allwood (2014) noted that currently it is impossible to break down certain types of waste or purify certain liquids. To recycle this waste would require far more energy than to produce virgin material and would not be worth doing so. Allwood (2014) also argued that there is currently no evidence that primary production can be completely displaced by secondary production. Korhonen et al. (2018) further argued that if the global economy continues to grow at an unsustainable rate, resource depletion will occur regardless of whether a LE or CE is adopted due to an increased demand for material resources.

Despite the criticisms of CE and the complexities involved in this transition, CE holds the promise of significantly reducing waste, preserving our finite natural resources, and mitigating the environmental impact of our economic activities. Beyond these environmental and ecological benefits, it also offers economic opportunities, such as job creation and innovative business models (Sulich and Sołoducho-Pelc, 2022). As a result, the concept of the CE has gained increasing attention and interest from a wide range of stakeholders, including scholars, practitioners, and policymakers (Geissdoerfer et al., 2017). Researchers are actively studying its principles and implications, businesses are exploring innovative circular practices, and governments are considering policy measures to accelerate the shift towards a sustainable circular economic model (Berry et al., 2022; Centobelli et al., 2021; Haas et al., 2020; Morseletto, 2023).

The work of Pearce & Turner (1989) has been widely acknowledged by numerous researchers (Andersen, 2007; Ghisellini et al., 2016; Greyson, 2007) as the pioneering effort that first introduced the concepts of “circularity” and the interdependence between economic systems and the environmental consequences. Although Olson and Sutherland (1993) did not explicitly mention the word “circularity,” they did highlight the need to close material loops and its economic benefits through the concept called “demanufacturing.” De Pascale et al. (2021) provided a systematic review of 61 indicators used to measure CE strategies at the micro (company/product), meso (eco-industrial parks), and macro (city/region/country) levels.

CE indicators are assessed based on various criteria, including their methodology (quantitative or qualitative), alignment with the core CE principles (often referred to as the 6Rs: reduce, reuse, recycle, recover, remanufacture, redesign), and the consideration of different sustainability dimensions (typically environmental and economic, with fewer incorporating social aspects) (Geissdoerfer et al., 2017; Velenturf et al., 2021). It is worth noting that a significant emphasis is often placed on recycling metrics, mainly within the environmental and economic realms. However, the current landscape reveals a lack of standardized methodologies for measuring CE performance (Muradin and Foltynowicz, 2019). This absence of uniformity makes it challenging to evaluate changes across different initiatives (Flynn and Hacking, 2019). Indicators can range from single, specific metrics to more comprehensive composite indicators that encompass multiple dimensions of CE performance. At the micro level, common indicators focus on aspects like recyclability, material circularity, and the ease of product disassembly

(Kristensen et al., 2020). On the macro scale, circularity is typically assessed at the overall system level, where material flow analysis is commonly employed (Barreiro-Gen, et al., 2020). Lightweighting products by substituting materials can lower their environmental footprint, but it necessitates the creation of new recycling systems. Process enhancements, such as redesigning machine tools and implementing smart manufacturing techniques, can substantially enhance energy and resource efficiency (Sutherland et al., 2020).

To advance the effectiveness of CE initiatives and provide clearer guidance for policy and business decisions aimed at embracing circular models, there is a pressing need for the standardization of CE measurement methods. An emerging field, green manufacturing planning, integrates environmental goals with conventional process planning and scheduling metrics. Nonetheless, there are persistent obstacles in the path to a CE centered on increased recycling and reuse. These challenges encompass rising product complexity and the disconnect between waste streams and market demands for recycled materials. The way forward toward industrial sustainability involves focusing on sustainable product and process design, developing green planning tools, and effectively closing material loops. Establishing a common framework for measuring CE performance will facilitate more accurate assessments, comparisons, and ultimately, the advancement of CE practices (De Pascale et al., 2021; Sutherland et al., 2020; Triebe et al., 2023).

To address some of the present challenges to implement a CE, the engineering design method should be transformed towards a broader life cycle thinking to holistically measure the CE performance. Taking this as the main motivation, the first objective of this paper is to propose a CE design approach that can be part of a parametric design model that integrates life cycle assessment (LCA) and techno-economic assessment (TEA); the design model may then be optimized. The approach of this design method builds upon previous studies (Pérez-Cardona et al., 2023, 2024a-b). The proposed model applies a new disassembly planning algorithm that quantifies outcomes (reusing, remanufacturing, recycling, disposing) for each subassembly/part of a discrete product collected at the end-of-life (EoL). Specifically, this model is used as part of the life cycle inventory (LCI) to include post-consumer processing steps and discount the materials and components reused. Figure 1 shows the life cycle stages of a general product for linear and circular economies. For the purposes of illustration, a case study was chosen: a permanent magnet synchronous motor (PMSM) (for Sm-Co and sintered Nd-Fe-B magnets scenarios) applied to an electric vehicle (EV). This case study may be suitable due to the complexity involved in designing a PMSM and, the presence of critical materials in the permanent magnets which have high supply risk and environmental impact. The parametric design model used for this motor are based on a previous study (Pérez-Cardona et al., 2023).

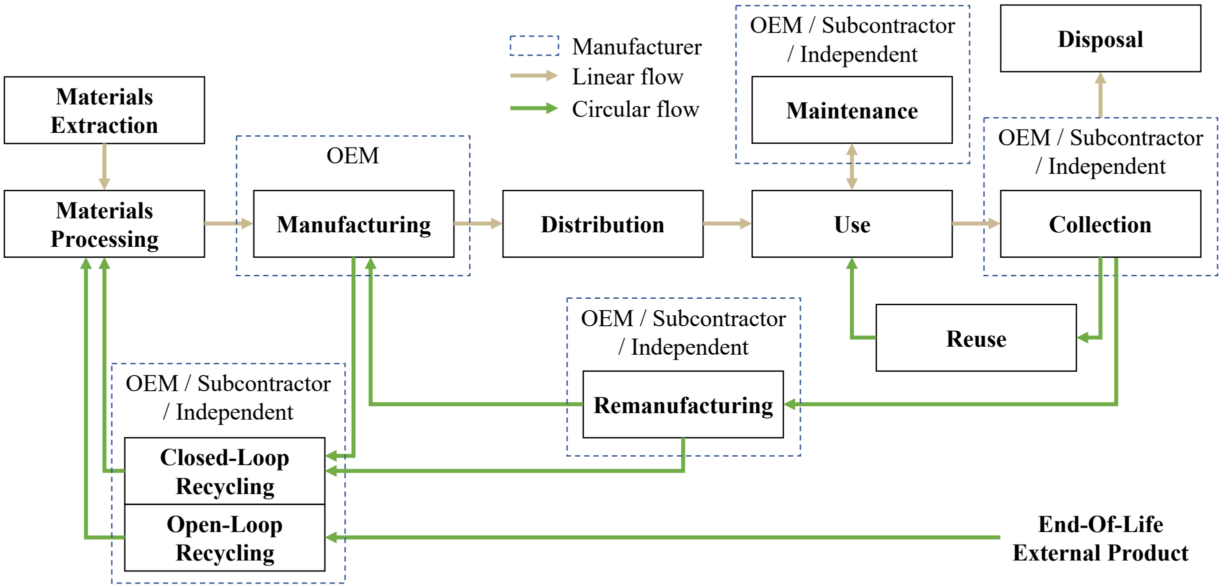

Figure 1. Product life cycle stages for linear and circular economies (adapted from Sutherland et al., 2020)

The completion of the first objective may help to contribute to the standardization of CE measurement methods by incorporating broad performance metrics and comparing them against LE performance. Hence, the second goal of this paper is to compare the benefits of considering the CE against the LE as part of a product design stage analysis. The performance metrics used for this comparison are the motor mass, energy consumption per unit of distance driven, supply risk-equivalent (SR-eq.), environmental impact single-score (*I*), the levelized cost of motor production (LCOP), and the levelized cost of EV driving (LCOD). The benefits of CE, if any, relative to LE are quantified by comparing the differences in optimized performance metrics.

Based on the outcomes of this study, unique contributions and novelty can be stated as follows:

- Methods / Models:
  - Presenting an innovative approach for incorporating CE principles into the parametric design and optimization of electric traction motors
  - Integrating LCA and TEA within a comprehensive design model, enabling the quantification of supply risk, environmental benefits, and economic gains compared to LE methods
  - Proposing a disassembly planning algorithm to effectively link EoL outcomes to the LCI
- Results:
  - Demonstrating the tradeoffs among multiple objectives and the significant benefits of applying CE strategies – through a well-structured case study of a PMSM in an EV
  - Providing valuable insights into the effects of motor collection rates and disassembly levels

The remainder of the paper is organized as follows. First, the method to model the CE as part of the design stage is proposed. Then, the CE is integrated as part of the parametric design model for optimization. Then, the results of the non-dominated optimal solutions and CE benefits are analyzed. Finally, a summary and conclusions for this study are provided.

2. Method to model the CE for electric traction motors

This section outlines the methodology employed to model the Circular Economy (CE) for electric traction motors. In addition to considering a parametric model for the design of a motor that considers the manufacturing and use of the motor, it also encompasses a disassembly planning process that spans from the collection of an EoL motor to the recovery and reuse of valuable subassemblies and parts. The objective of the recovery portion of the method is to quantify the percentage of recovered subassemblies and parts for collected EoL motors. Table 1 illustrates the model using a hypothetical example based on assumptions.

In Table 1, the ‘Id’ column, in conjunction with the ‘Level of Subassembly’ column (denoted as ‘Lvl’), embodies a reverse logistics approach to disassembling a discrete product, in this case, a motor associated with an EoL EV. Each index i corresponds to a specific subassembly or part of the product. The Lvl column represents the hierarchical tree of disassembly operations defined by the discrete function $l(i)$, where an “upper-level subassembly” refers to a parent subassembly that contains “lower-level subassemblies” children. In the provided example, the sequence $(l(1), l(2), ..., l(39))$ is represented as $(1, 2, ..., 3)$. Within each subassembly/part, there are four potential outcomes: “to inventory” (indicating it possesses minimal wear for reuse), “to disassembly”,“to recycling”, and “to landfill” (for disposal). These outcomes are subject to the constraint:

$$\sum_{j} a_{i,j} = a_{i,1} + a_{i,2} + a_{i,3} + a_{i,4} = 1 \tag{1}$$

where j represents the four possible outcomes. The variables $a_{i,j}$ represent the fraction of the ith subassembly/part that end up in the jth outcome. A noteworthy advancement in practice involves proposed non-destructive evaluation (NDE) techniques, as suggested by Cui et al. (2022). These techniques measure the condition of each subassembly/part, informing decisions on whether it should be reused, disassembled for valuable component recovery, recycled, or disposed. Consequently, empirical data $a_{i,j}$ may become accessible in the future.

Table 1. Hierarchical tree structure for disassembling a motor

Id ***i***	**Lvl** ***l(i)***	**Subassembly / Part**	**To inventory (%)** ***j*** **= 1**	**To disassembly (%)** ***j*** **= 2**	**To recycling (%)** ***j*** **= 3**	**To landfill (%)** ***j*** **= 4**
1	1	Electric motor, for distribution	1%	97%	0%	2%
2	2	Electric motor, for painting	1%	99%	0%	0%
3	3	Stator package, complete, for assembly	5%	95%	0%	0%
4	4	Stator package, impregnated	5%	95%	0%	0%
5	5	Stator package, bandaged	0%	100%	0%	0%
6	6	Stator package, with winding	0%	100%	0%	0%
7	7	Stator core, with slot insulation	0%	100%	0%	0%
8	8	Stator core, coated	5%	95%	0%	0%
9	9	Stator laminations	0%	100%	0%	0%
10	10	Electrical steel sheet	0%	0%	100%	0%
11	8	Slot liner and separator foil	0%	0%	0%	100%
12	7	Magnet wire	0%	0%	100%	0%
13	7	Silicone, cable isolation	0%	0%	0%	100%
14	7	Mica tape	0%	0%	0%	100%
15	6	Nylon lacing cord	0%	0%	0%	100%
16	5	Epoxy resin, slot insulation	0%	0%	0%	100%
17	4	Copper lugs, tin plated	80%	0%	20%	0%
18	3	Rotor package, on shaft, for assembly	5%	95%	0%	0%
19	4	Rotor package, on shaft, unbalanced	60%	40%	0%	0%
20	5	Stacked rotor with magnets	0%	100%	0%	0%
21	6	Rotor laminations	0%	100%	0%	0%
22	7	Electrical steel sheet	0%	0%	100%	0%
23	6	Permanent magnets	0%	0%	100%	0%
24	6	Magnet fixation resin	0%	0%	0%	100%
25	5	Shaft	0%	100%	0%	0%
26	6	Steel rod	0%	0%	100%	0%
27	5	SS, rotor endplates	5%	95%	0%	0%
28	6	SS, sheet	0%	0%	100%	0%
29	3	Housing and PBT terminal block	5%	95%	0%	0%
30	4	Housing body, for assembly	0%	100%	0%	0%
31	5	Housing body, to cleaning	10%	90%	0%	0%

32	6	Die cast, unfinished housing body	0%	0%	100%	0%
33	4	Endbells, for assembly	0%	100%	0%	0%
34	5	Endbells, to cleaning	20%	80%	0%	0%
35	6	Die cast, unfinished endbells	0%	0%	100%	0%
36	4	PBT part, terminal block	50%	0%	0%	50%
37	3	Resolver	50%	0%	0%	50%
38	3	Bearings	0%	0%	100%	0%
39	3	Galvanized fasteners and plates	0%	0%	100%	0%

The structure presented in Table 1 reveals a nested dependency in disassembly processes: The percentage outcome for each subassembly/part is contingent on the percentage of disassembly from the upper-level subassembly. For instance, if only 50% of the motors are collected when their EoL is reached (a upper-level assembly), and if only 50% of the permanent magnets (inside the motors) are recovered from the collected motors, then only 25% of the permanent magnets in all the EoL motors will be secured. To adjust the outcomes based on the percentage of disassembly from a upper-level subassembly, an multiplier $b_{i,j}$ is calculated:

$$b_{i,j} = \begin{cases} a_{i,j}, & i = 1 \\ b_{s,2}a_{i,j}, & i > 1 \end{cases} \tag{2}$$

where s denotes the upper-level subassembly that undergoes disassembly ($j = 2$) to yield one or more subassemblies/parts. The ith subassembly/part is one of those components originating from the sth subassembly, and is determined by:

$$s = \max(\{u | x_u = 1\}) \tag{3}$$

where the sequence is defined as:

$$(x_u)_{u=1}^{i-1}, \qquad \mathrm{x_u} = l(i) - l(u) \tag{4}$$

For instance, to identify the corresponding upper-level subassembly for “Housing body, for assembly” ($i = 30$ and $l(i) = 4$), the index is calculated as $s = max(\{3, 18, 29\}) = 29$ which corresponds to“Housing and PBT terminal block” From Equations 1 and 2, it follows that the sum of the outcomes for each subassembly/part ($i > 1$) adheres to:

$$\sum_j b_{i,j} = b_{i,1} + b_{i,2} + b_{i,3} + b_{i,4} = b_{s,2} \quad (5)$$

Due to this nested dependency, the subassemblies being reused and disposed must be allocated to the lower-level subassemblies/parts. The final correction, to establish the outcomes for each subassembly/part as a function of one collected EoL motor, is calculated as:

$$c_{i,j} = \begin{cases} b_{i,j}, & i = 1 \; or \; j = 2 \\ c_{s,j} + b_{i,j}, & i > 1 \end{cases} \quad (6)$$

Consequently, the sum of $c_{i,j}$ for each ith subassembly/part is expected to equal 1.

If all the motors reaching the EoL are not collected, the outcomes for each subassembly/part may be calculated as:

$$d_{i,j} = r_{collected} c_{i,j} \quad (7)$$

where $r_{collected}$ represents the product collection rate at the EoL. These outcomes then inform the subsequent manufacturing, remanufacturing, and recycling operations as:

Reusing: $r_{i,reuse} = d_{i,1}$ (8)

Manufacturing: $r_{i,manufacturing} = d_{i,3} + d_{i,4} + (1 - r_{collected})$ (9)

Remanufacturing: $r_{i,remanufacturing} = d_{i,2}$ (10)

Recycling: $r_{i,recycling} = d_{i,3}$ (11)

These demand breakdowns are linked to the Life Cycle Inventory (LCI), providing insights into the necessary operations for each component reaching the EoL. For example, if 50% (i.e., $1-r_{collected}$) of the unprocessed material (steel) of the motor shafts reaching the EoL is not collected, and 18.25% (i.e., $d_{26,3}$) and 1% (i.e., $d_{26,4}$) are collected but recycled and disposed, then 69.25% (i.e., $r_{26,manufacturing}$) of them must be manufactured via primary production. The remaining 30.75% (i.e., $d_{26,1}$) is designated for reuse. Please see the Supplementary Information (SI) to illustrate further with all calculations using the hypothetical example.

3. **Integrating the CE as part of the parametric design model**

In this section we describe how LCA and TEA of PMSMs were performed. In addition, a discussion of the parametric design model with optimization is provided.

3.1. Life cycle assessment (LCA) framework

The primary goal of an LCA model is to quantify the environmental impact associated with a system, be it a process, product, or service. Previous studies and datasets provide comprehensive details on conducting an LCA for producing and operating a one PMSM in the United States for a LE (Pérez-Cardona, 2023; Pérez-Cardona et al., 2024a). To compare LE and CE in the production and operation of one PMSM, it may be needed to consider two use cycles. For an LE, it would mean two new motors, whereas for a CE, it would mean one new and one remanufactured motor. Since the first use cycle for both scenarios is the same, the same functional unit can be defined as in previous studies, with the exception that the CE scenario produces the PMSM starting from the collection of one PMSM reaching the EoL (i.e., at the end of its first use cycle). The PMSM to be designed in this case study is for the 2019 Nissan Leaf S EV (see Table S9 in the SI for EV specifications).

Furthermore, an extended system boundary (SB) is proposed to encompass unit processes associated with circularizing the product, as depicted in Figure 2. In this representation, gold arrows illustrate material and energy flows through various life cycle stages, including extraction and processing of materials, manufacturing, distribution, EV use, and pre-consumer recycling. Green arrows signify circular flows through unit processes like EV collection, motor collection, inventory management, non-destructive evaluation/testing, disassembly operations, post-consumer recycling, and landfill.

Certain processes, such as EV collection, NDE, disassembly operations, and landfill waste treatment, are not included in the SB due to lack of data. Please note that the inclusion of these processes in a future might have a slight effect on the results of this study. It is assumed that there exists a 1:1 ratio between the number of EVs and motors. Note that other ratios could be considered to account for other scenarios in extended models, to observe the effect of having more quantity of smaller motors per EV. Motor collection incorporates the transportation of one motor from the EV collection facility to the motor collection facility (assuming a 100 km distance). The inventory process involves storing products, subassemblies, and parts for further processing and/or assembly in the manufacturing factory. Post-consumer recycling involves an energy intensity of 66 kWh/ton of recyclable material for shredding and separation steps (Hernandez et al., 2017), with scrap materials being co-products (listed in Figure 2).

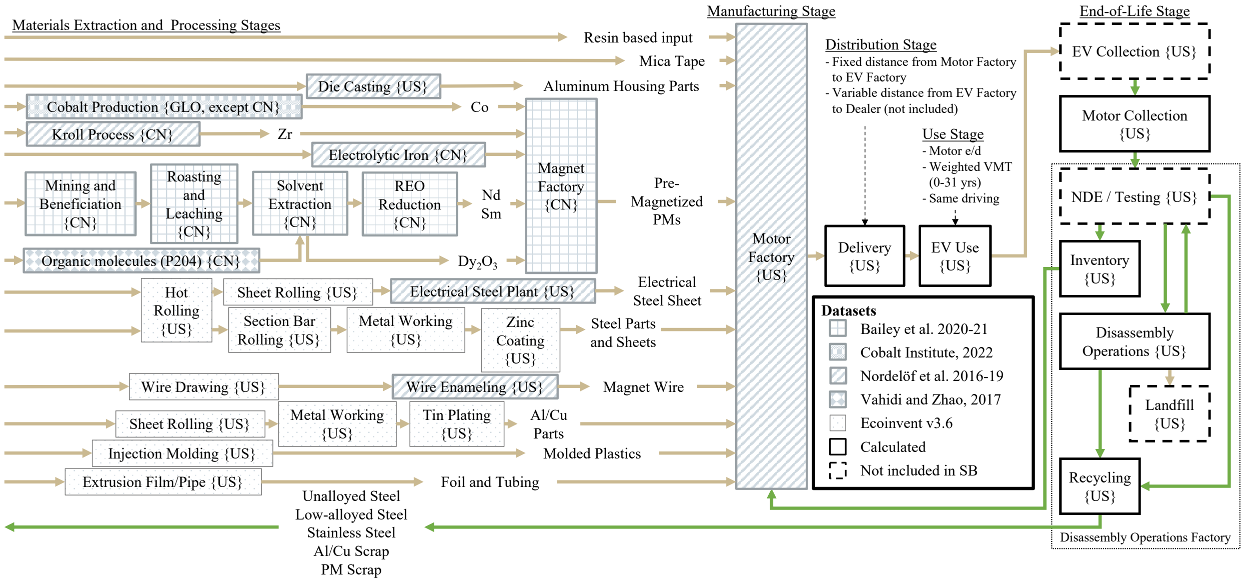

Figure 2. Extended system boundary for conducting LCA (adapted from Pérez-Cardona, et al., 2024a) (gold arrows = linear flows, green arrows = circular flows; CN = China, US = United States)

Regarding LCI, both foreground (Bailey et al., 2020, 2021; Cobalt Institute, 2022; Nordelöf et al., 2016, 2019; Nordelöf and Tillman, 2018; Vahidi and Zhao, 2017) and background (Wernet et al., 2016) datasets remain consistent with those utilized in the previous LCA study (Pérez-Cardona et al., 2024a). The new additions encompass unit processes linked with post-consumer recycling and the integration of the CE model to estimate the environmental impacts of remanufacturing and motor operation.

For Life Cycle Impact Assessment (LCIA), the ten mid-point impact categories that were used are associated with the Tool for Reduction and Assessment of Chemicals and Other Environmental Impacts (TRACI) 2.1, developed by the EPA (Bare, 2011). Given that the objective of this LCA is the integration into the design process, U.S. & Canadian normalization (Ryberg et al., 2014) and weighting factors (Gloria et al., 2007) are incorporated, followed by aggregation within the LCA framework. While this approach introduces potential uncertainties, it is capable of addressing multiple objectives; in the absence of such an approach, the interpretation and decision-making associated with results may be challenging.

3.2. Life cycle costing (LCC) framework

3.2.1. Techno-economic assessment (TEA)

A TEA endeavors to quantify the economic and technical performance of a system (Pérez-Cardona et al., 2024b). In this study, a comparative TEA is conducted to evaluate the economic and technical performance of manufacturing versus remanufacturing a motor in the United States. Specifically, it compares the costs associated with producing a motor from scratch in a manufacturing facility with the costs of remanufacturing from recovered components (involving multiple facilities). It is important to note that all facilities, including the manufacturing factory, collection facility, and disassembly operations factory, are assumed to belong to the same original equipment manufacturer (OEM). For such a situation, the revenue and costs associated with all activities are owned by the OEM.

In the context of this study, and due to the lack of a detailed process plan for disassembling these motors, capital expenses only include those associated with the manufacturing factory. Operating expenses encompass costs for the manufacturing factory, transportation to the motor collection facility, and recycling costs. It is assumed that the collection facility and disassembly operations factory are in close proximity to the manufacturing facility, making transportation costs between facilities negligible. Although the study currently does not factor in labor costs associated with disassembly, recycling, and testing of collected EoL motors, this could be a future area of refinement. Additionally, it is worth noting that the EoL product acquisition (collection + purchase) cost was not considered in this study.

Pérez-Cardona et al. (2024a-b) have furnished all technical and economic inputs for manufacturing a traction motor. The facility is assumed to produce 50,000 motors per year, operate 330 days a year, 24 hours a day, and has a lifespan of 20 years. All relevant cost information is included in Tables S1–S5 from the SI. Revenue sources for motor remanufacturing include motor sales and pre- and post-consumer recyclable scrap materials. The selling prices of scrap materials are based on market prices, and the motor price is calculated from the LCOP. From the LCOP, this cost can be obtained by breakeven in terms of net present value (NPV) to be equal to zero.

3.2.2. Total cost of ownership (TCO)

To calculate the LCOD, the total cost of ownership (TCO) equation is essential. TCO is the net present value (NPV) from the consumer's perspective such that it takes into account the initial purchase (or down payment) cost, operating and maintenance expenses, debt financing, and salvage value. Similar to LCOP, LCOD represents the cost of driving when the NPV is equal to zero.

3.3. Optimization of parametric design model parameters

Implementation details for the parametric design and optimization process have been extensively described in various studies (Pérez-Cardona et al., 2023, 2024a-b). In this study, as explained in subsection 3.1 and 3.2, additional datasets and enhancements have been incorporated to account for the scenario involving circular economy principles. The fixed parameters **D** and variable parameters **θ** are provided in Tables S6–S8 in the SI.

This study considers six objective functions: 1) designed motor mass, m_d, 2) energy consumption per unit of distance, e/d, 3) supply risk-equivalent (SR-eq.), SR_{eq}, 4) environmental impact single-score, I, 5) levelized cost of production (LCOP), c_{LCOP}, and 6) levelized cost of driving (LCOD), c_{LCOD}. Each of these objectives reflects different aspects of the motor's performance, from its physical characteristics to its environmental and economic impacts. It is important to note that while mass and energy consumption are typically minimized, tradeoffs may exist among these objectives.

The Supply Risk-Equivalent (SR-eq) undergoes a slight refinement from Pérez-Cardona et al. (2023). The updated definition is:

$$SR_{eq} = \frac{\sum_{i=1}^{n} m_{mfg,i} SR_i}{\sum_{i=1}^{n} m_{mfg,i}} = \frac{\sum_{i=1}^{n} s_i m_i SR_i}{\sum_{i=1}^{n} s_i m_i} \tag{12}$$

where all materials must have a SR-eq. greater than zero (i.e., $m_{mfg,i} > 0$ and $SR_i > 0$). Originally, the definition counted all materials contained in a product, even if the material had a SR-eq. equal to zero. This adjustment ensures that only materials with a non-zero SR-eq. value are included, thus avoiding deflation of SR-eq. values due to an increase in the mass of materials with zero SR-eq. values. In addition, this study now considers manufacturing data to account for material efficiency (or buy-to-fly ratio) (i.e., $s_i > 1$). m_i is the mass of *i*th material subject to SR_i supply risk in the product. Note that $m_{mfg,i}$ is the mass required of the *i*th material to manufacture the motor. The environmental impact single-score *I*, LCOP, and LCOD are calculated as described in subsections 3.1 and 3.2.

In this study, a Genetic Algorithm (GA), specifically the Genetic Optimization Systems Engineering Tool (GOSET) – version 2.6, is applied to the optimization model. A GA is a heuristic search algorithm inspired by the process of natural selection. It is used to find approximate solutions to optimization and search problems. A GA operates by evolving a population of potential solutions over multiple generations, utilizing processes such as selection, crossover, and mutation to generate increasingly better solutions. Table S7 shows the 30 genes and ranges considered. The fitness function contains six objective functions to evaluate the performance of the designed motor:

$$\mathbf{f} = \begin{bmatrix} m_d & e/d & SR_{eq} & I & c_{LCOP} & c_{LCOD} \end{bmatrix}^T \tag{13}$$

This fitness function is used to find feasible and non-dominated optimal solutions. The GA is run for a population size of 3,000 and for 3,000 generations. The GA is run twice, once for each type of magnet: Sm-Co and sintered Nd-Fe-B magnets. To analyze the results of a multi-objective optimization problem generated by the GA model, previous works used a number of graphs placed in a matrix structure (Pérez-Cardona et al., 2023, 2024a-b). In this matrix, graphs in the *i*th row correspond to the *i*th objective, and these objective values are displayed on the vertical axis of the graph. Similarly, graphs in the *j*th column correspond to the *j*th objective, and these objective values are displayed on the horizontal axis of the graph. The graphs lying on the diagonal (i.e., where $i = j$) display a frequency histogram of the distribution of non-dominated solutions related to the *i*th objective function. For graphs that do not lie on the diagonal ($i \neq j$), the results show the non-dominated optimal solution of four-objectives projected in two-dimensions (*i*th objective versus *j*th objective). Each axis is normalized from 0 (best-performing solution for each objective function) to 1 (worst-performing solution). Since a six-dimensional Pareto front cannot be easily visualized in a static image, the six-dimension front is projected into two-dimensions. The data points representing the non-dominated solutions are colored from blue-to-green-to-red, where blue represents the motor with the best energy performance and red represents the worst.

To have a fair comparison of the benefits of applying the CE model, the optimization is only run without applying the CE model. Then, the best motor solution for each objective function is selected; then the CE approach is applied and the corresponding fitness function is calculated. A contribution analysis is performed to study the benefits of the CE model. In addition, sensitivity analyses are conducted to study the effect of disassembly planning.

4. **Results and discussion**

4.1. Non-dominated optimal solutions

Figure 3 displays the projections of the Pareto fronts and non-dominated optimal solutions for each pair of objective functions, along with histograms illustrating the values of the objective function across all non-dominated solutions. A "matrix of plots" is presented for each magnet type: Sm-Co and Nd-Fe-B. The best solution for each objective function is largely consistent, except for LCOP and LCOD, where PMSM with Nd-Fe-B magnets outperform (LCOP: \$608.69 / motor for Sm-Co vs \$411.17 / motor for Nd-Fe-B; LCOD: \$30.13 / 100km vs \$30.03 / 100km).

There are 15 combinations of the six objectives (taken two at a time) that may be examined to explore the tradeoffs among objectives. Starting with the graph that displays mass versus energy (row 1, column 2), we see such a tradeoff; as mass is reduced through the use of a smaller motor, there is an increase in stator resistivity losses and increased energy consumption. The tradeoff between mass and SR-eq. (1, 3) is primarily due to the manner in which SR-eq. is defined (as a weighted average of mass). Since environmental impact relates mostly to energy consumption, the tradeoff between mass and environmental impact (1, 4) resembles the tradeoff between mass and energy. Looking at the energy vs environmental impact (vs LCOD) plots (2, 4) (2, 6), it is observed that there is a direct relationship between them, owing to the high significance of energy consumption on the overall environmental impact (LCOD). Hence, the tradeoff between mass and I (and LCOD) (1, 4) (1, 6) looks similar to mass and energy. The tradeoff between mass and LCOP (1, 5) is somewhat present in terms of energy performance. The best LCOP performing solution is among the worst energy performing solutions and the heaviest motors. Even though a heavier motor may incur higher LCOP, the combination of material masses results in lower manufacturing costs (i.e., smaller permanent magnets than similar heavy motors). A similar analysis can be performed for the lightest motor with better energy performance (i.e., having bigger permanent magnets than similar light motors).

The tradeoff between energy and SR-eq. (2, 3) is mainly present for heavier motors (smaller permanent magnets). Smaller permanent magnets reduce the SR-eq. while increasing energy consumption. Again, the observed tradeoff between SR-eq. and environmental impact (and LCOD) (3, 4) (3, 6) is related to the linear relationship between energy and environmental impact and permanent magnet mass. The observed tradeoff between SR-eq. and LCOP (3, 5) is more difficult to discern (perhaps, it is related to the interaction between permanent magnets, electrical winding, and housing body masses). Finally, the tradeoffs between environmental impact and LCOP (4, 5) and LCOD (4, 6) are related to energy performance. Improved energy performance decreases environmental impact and LCOD but increases LCOP (5, 6). In other words, improving the environmental performance and consumer cost leads to increased manufacturing costs (indirectly related to increased permanent magnets mass).

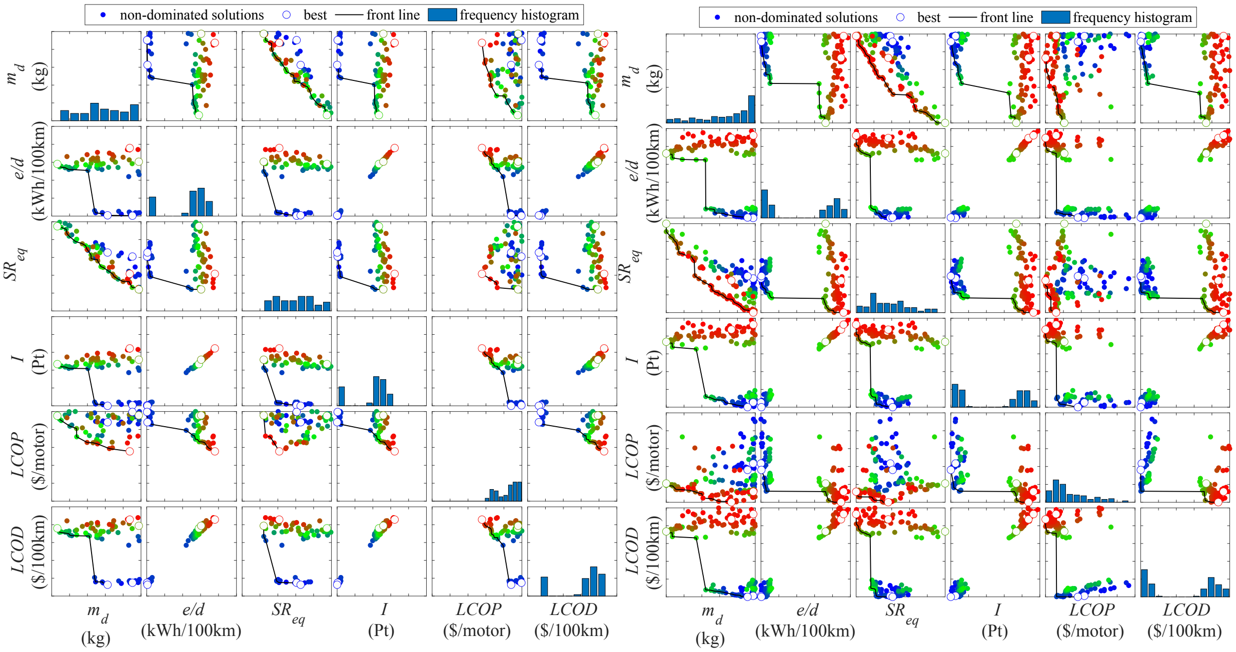

Figure 3. Non-dominated solutions and Pareto fronts for all objective function pairs and density histograms for each objective function (left: Sm-Co, right: Nd-Fe-B; blue-green-red data points, where blue represents the best energy performing solution; all axes are normalized from 0 to 1)

To observe the corresponding genes (i.e., decision variables) that map the resulting non-dominated solutions, please refer to Figure S1 in the SI. Additionally, to test whether this optimization has converged to optimal solutions, see Figures S2 and S3. Figure S2 shows the evolution of the GA population of the best, mean, and median fitness values for each objective. Figure S3 shows how the ferromagnetic constraints reached their limit for the final generation. The figures provide confidence that the GA model produced optimal solutions.

4.2. Contribution analysis

Figure 4 illustrates the benefits of applying the CE model (assuming a 100% collection rate) and the effects of optimizing for different objective functions on the best motor solutions for each objective function (see parameters of best solutions in Table S10). Based on these results, motor manufacturers and EV designers may benefit to prioritize CE strategies and balancing multiple objectives to decide which is the best motor design for them. Figure 4a showcases the mass required, $m_{mfg,i}$, across the life cycle of the product for selected materials (Co, Nd, Dy, Al, Sm, Ni, Cu). It is evident that there is a significant effect from applying the CE model, surpassing the impact of choosing a specific optimization strategy (e.g., SR-eq. over mass).

In Figure 4b, environmental impact single-scores are presented, including a breakdown of the impact into life cycle stages. Here, when applying the CE model and selecting an optimization strategy, both exhibit substantial effects on the environmental impact. Due to the high significance of energy consumption and its linear relationship with the resulting environmental impact and LCOD, minimizing energy consumption, environmental impact single-score, or LCOD yield similar environmental performance. Figure S4 in the SI demonstrates that minimizing the environmental impact single-score aligns with minimizing any of the TRACI environmental impact categories. Electricity consumption also dominates most of the impact across all categories. Additionally, it is observed that the cradle-to-gate impacts (from material extraction to motor transportation) are reduced when the CE model is applied.

Figure 4c provides insight into the processing costs of manufacturing a motor, offering a detailed breakdown into processing and assembly operations. Notably,“Stacking and mounting magnets” (AO_{11}) emerges as the operation with the highest cost contribution across all scenarios, primarily due to the expense of the permanent magnets (refer to the list of manufacturing operations in Table S11). When the CE model is applied, significant savings are realized, particularly when the subassemblies containing the magnets are reused (e.g., rotor package – refer to Table 1. Hierarchical tree structure for disassembling a motor). It is also observed that choosing an optimization strategy has a notable impact on manufacturing costs. Minimizing LCOP demonstrates the most favorable effect, as anticipated. However, it is noted that achieving motor solutions that minimize energy consumption, environmental impact, or LCOD may require a higher manufacturing cost.

Finally, Figure 4d presents the LCOD values, including a breakdown into different consumer costs. Applying the CE model does not yield a significant effect, as the majority of the LCOD is attributed to EV purchase. While a less expensive motor may contribute to a less expensive EV, its impact is limited. Choosing among the best energy, environmental impact, or LCOD motor solutions may enhance consumer cost over other objectives. The observed effect on consumer cost highlights that improving the EV's energy performance carries greater significance than minimizing motor manufacturing cost.

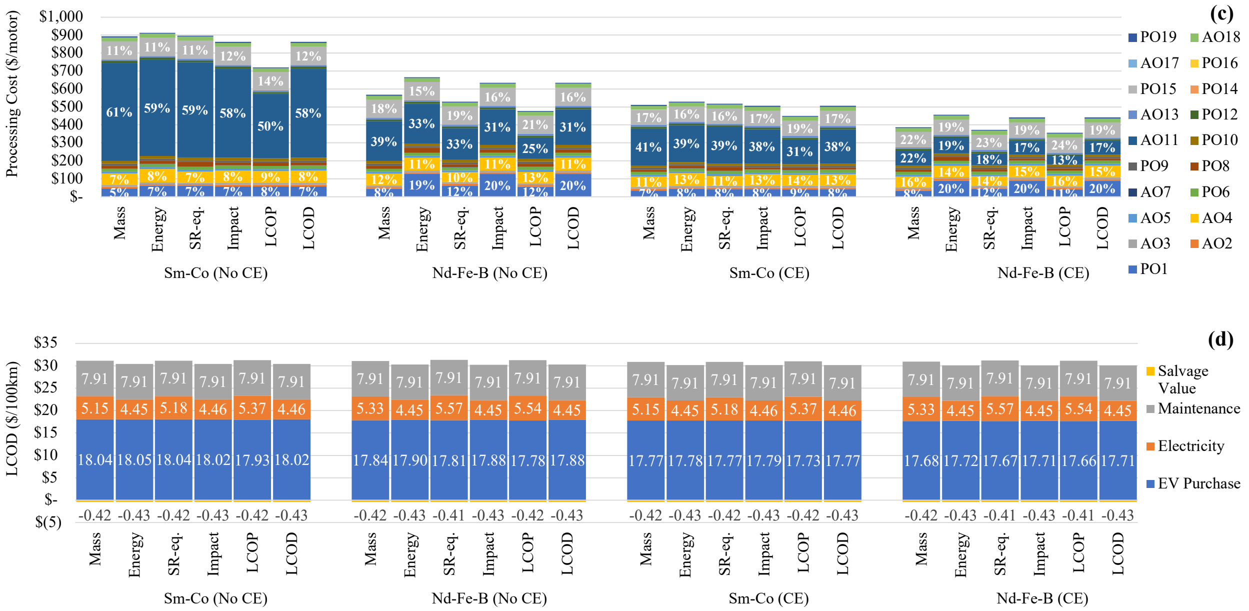

Figure 4. Effect of applying the CE model at 100% collection rate and minimizing for different objectives on (a) the amount of mass needed for each selected material, (b) the environmental impact single-score, (c) the producer motor minimum selling price to breakeven at NPV = 0 (PO = processing operation, AO = assembly operation), and (d) the consumer cost of driving to breakeven at NPV = 0

4.3. Sensitivity analysis

The study of the tradeoffs among objective functions and the effect of applying the CE were analyzed in subsections 4.1 and 4.2. However, these tradeoffs are based on nominal settings of variables, which in practice may deviate from those values. Figure 5 shows the results of a sensitivity analysis by varying the EoL motor collection rate from 0% to 100% on the best motor solutions for each objective function and three scenarios: a) baseline scenario (refer to Table 1), b) 100% disassembly of each component and 100% recycling (if recyclable), and c) 100% EoL motor reuse. Scenario b) may involve disassembly planning in the absence of NDE techniques, rendering measurement of subassembly/part condition impossible; consequently, everything is disassembled and recycled whenever feasible. Scenario c) is an optimistic scenario where all EoL motors are assumed to have ‘as new’ condition and no disassembly is needed. The latter scenario is considered purely for calculating the ‘best’ values of each objective function. Unfortunately, this scenario is not achievable in practice since all products will undergo some degree of degradation. For scenarios a) and b), since labor cost has not been included, LCOP may be higher, resulting in slightly flatter slopes for LCOP curves.

Examining the effects of applying the CE on the three scenarios, scenario a) falls between scenarios b) and c). Scenarios b) and c) can be seen as two endpoints with various levels of disassembly (or levels of reuse) in between. When comparing these scenarios, LCOP appears to be the most affected when applying the CE, followed by SR-eq. and LCOD, respectively. The environmental impact seems to be the least affected when compared to both scenarios. This doesn’t imply that applying the CE model is ineffective in terms of the environmental impact, but rather that energy consumption during the use stage has the highest contribution to the environmental impact. One final observation is that, regardless of the optimal motor solution and magnet type, the LCOP values are very close to each other as the collection rate approaches 100% and reuse reaches 100%.

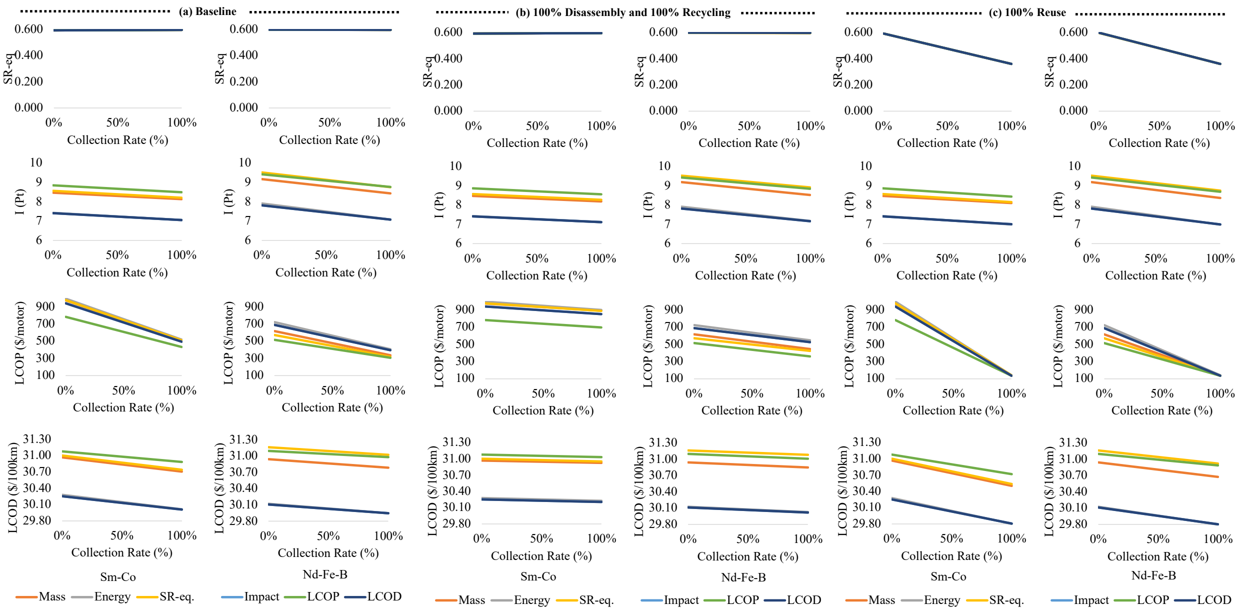

Figure 5. Sensitivity analysis varying collection rate from 0% (no CE) to 100% on the best motor solutions of each objective function and the following scenarios: (a) baseline scenario – Table 1, (b) 100% disassembly and 100% recycling, (c) 100% disassembly and 0% recycling (left: Sm-Co, right: Nd-Fe-B)

In addition to the sensitivity analysis on the collection rate and the three chosen scenarios, another sensitivity analysis is pertinent to study the effect of choosing a different level of disassembly (or reuse) in the disassembly planning outlined in Table 1. Figure S5 presents tornado plots that offer a view of the effects of varying the disassembly/reusing/recycling levels, one-variable-at-a-time, for SR-eq., *I*, LCOP, and LCOD objectives for both magnet type scenarios. It is to be noted that each disassembly/part level has four outcomes, two are fixed, one is controlled, and one is balanced to 100% based on the input chosen for the controlled variable. The figure indicates which variable is controlled and which is balanced at each level. High and low values are set at ±5% of the base values (see Table S12). It is notable that the effect of varying one-variable-at-a-time is most pronounced on LCOP (up to a 3% change compared to up to 0.07%

change on the rest of the objective functions and scenarios). Generally, the subassemblies/parts at the higher levels (e.g., stator package, complete, for assembly) exert a greater influence on the values of all objective functions. Based on the most sensitive subassembly/part to multiple objectives, these insights could inform the development of more targeted CE strategies and policies for electric traction motors. To confirm that there are no interaction effects affecting the variation of two or more variables at a time, Figures S6 and S7 depict the absolute effects for each main and interaction effects. The results affirm that there are no significant interaction effects on any optimization strategy and objective function for either magnet type. This further substantiates that the results and analysis from the tornado plots are crucial in understanding the effects of varying the levels of disassembly, reuse, or recycling.

The results presented demonstrate that applying the CE to a broader scope, such as designing an optimal EV, does not automatically imply that the 'best' motor is needed to produce the 'best' EV. Future work could encompass exploring other motor topologies that may obviate the need for permanent magnets, evaluating how supply risk-equivalent, environmental, and economic performance are impacted. Moreover, considering a different set of objectives in relation to the social pillar of sustainability would be an interesting avenue for investigation. Regarding the feasibility and challenges of achieving high collection rates and disassembly levels in practice, it would be interesting to identify new strategies to facilitate these in a future work. As a final thought, in line with the observations by Pérez-Cardona et al. (2024a) and given the new insights gleaned from applying CE principles, this study underscores the imperative to decarbonize the electric grid system to minimize the environmental impact associated with EV electricity consumption during the use stage.

4.4. Method applicability to other products

This study makes a strong case for the application of the proposed approach to electric traction motors in EVs. It is noteworthy that the applicability of the presented methodology can be adapted to other products. To achieve this, it would be necessary to integrate a custom parametric design model as well as appropriate environmental and economic data (e.g., LCI and cost information) for the product.

5. Summary and conclusions

The circular economy represents an emerging paradigm aimed at enhancing resource efficiency, while also achieving the goals of environmental and economic sustainability. In this study, we applied a novel design and optimization framework to address, at the early design stage, the life cycle environmental and economic issues associated with producing and using a product. An electric traction motor for an electric vehicle (EV) was chosen as a case study, considering six objective functions: motor mass, energy consumption per unit of distance, supply risk-equivalent (SR-eq.), environmental impact single-score (I), levelized cost of production (LCOP), and levelized cost of driving (LCOD). The study delved into potential tradeoffs among non-dominated optimal solutions across these multiple objectives, emphasizing the importance of selecting the appropriate objective functions.

We proposed a circular economy (CE) model/algorithm to establish a disassembly plan linked to the life cycle inventory (LCI). This approach enabled the evaluation of the benefits of applying CE to the best optimal solutions for each objective function. To assess the effects of applying CE, we conducted a one-way sensitivity analysis on the motor collection rate and considered three scenarios: baseline, 100% disassembly and recycling, and 100% reuse. Notably, LCOP, SR-eq., and LCOD objectives demonstrated a significant improvement due to the application of CE. The environmental impact, however, seemed to be influenced at a lesser level due to the substantial impact of energy consumption during the use stage.

Additionally, a sensitivity analysis was performed to examine the effects of varying the levels of disassembly, reusing, or recycling in the circular economy strategy. Tornado plots revealed that outcomes of upper-level subassemblies had a more pronounced effect compared to lower-level ones. Further analysis confirmed that no interaction effects were observed, validating the findings from the tornado plots.

In summary, this paper analyzed the tradeoffs involved in optimizing for six objective functions and applying CE to electric traction motors for EVs. It is worth noting that the environmental impact of some processes such as EV collection, NDE, disassembly operations, and landfill waste treatment were not included due to lack of data, which might have a sort of significance when analyzing the tradeoffs involved among the six objective functions. Another limitation of this study is that the ratio between the number of motors in an EV is in the order of 1:1. Considering other configurations may change the results as well. Furthermore, applying CE to a broader scope, such as designing an optimal EV, may not necessarily lead to the selection of the 'best' motor for constructing the 'best' EV (i.e., isolated optimal parts of a system do not necessarily lead to optimal system due to interactions and interconnectedness). Future research directions could explore alternative motor topologies and consider a different set of objectives, particularly in relation to the social dimension of sustainability. This study reinforces the critical need to decarbonize the electric system, thereby minimizing the environmental impacts associated with EV electricity consumption during use. Broadly, the optimization strategies and methods outlined in this paper may provide valuable insights for advancing the standardization of CE performance metrics.

Acknowledgements

Author Pérez-Cardona acknowledges funding from DARPA's EMBER (Environmental Microbes as a BioEngineering Resource) program through the Lawrence Livermore National Laboratory under Contract DE-AC52-07NA27344; and Neha Shakelly gratefully acknowledges funding from the Critical Materials Institute (CMI) under Contract DE-AC02-07CH11358.

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