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Sustainability-Driven Decision Making: A Multi-Objective Optimisation Approach to Optimise Closed-Loop Supply Chains of Electrical Drives

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ABSTRACT:

Because of growing concerns about global hike in e-waste and resource scarcity, this thesis explores how a manufacturing company can make better decisions for end-of-life (EoL) electrical drives. Electrical drives are widely used in industrial processes. They often become obsolete due to rapid technological change, creating a critical need for sustainable and cost-effective solution.

The research is based on a case study of electrical drive manufacturer who are exploring different alternatives in the principles of the circular economy and focuses on a key practical question: should a used electrical drive be repaired or disposed of when the objective is to minimize the cost and greenhouse gas (GHG) emission? A data-driven, multi-objective optimization model was developed using a Mixed Integer Linear Programming (MILP) and the Non-dominated Sorting Genetic Algorithm II (NSGA-II) to answer the question.

The model aims to minimize both total costs and GHG emissions while considering realistic constraints such as budget limits, quality of returned products, and age. As part of the case study, a batch of 50 EoL products were analyzed. The result indicated a trade-off between environmental and economic objectives - lower emissions with higher costs, and vice versa. The model was further validated by performance indicators and parameter tuning. The performance indicators confirmed the model's performance while the robustness of the model was tested through parameter tuning. Three different configuratios were selected (large, small and medium population) for parameter tuning. The configuration with large population provided the best result with cost being € 12031,60 and GHG emission being 15658,50 KgCO_2-e. The study also conducted sensitivity analysis to evaluate the influence of key variables. Product quality and transport distance were found to be the most significant factors. Improving the quality of returned products significantly reduced both costs and emissions, while longer transport distances had a measurable negative effect. Interestingly, changing the budget had little impact on decisions, confirming that technical feasibility outweighed financial flexibility in such constrained environments.

This thesis contributes a practical framework for manufacturers like the case company which are seeking to align circular economy goals with operational decision-making. The model serves as a decision-support tool that helps identify feasible and sustainable EoL decisions by offering a view of cost and environmental trade-off. The findings are also relevant for other manufacturers, policymakers, and sustainability-driven enterprises aiming to reduce e-waste and promote circular business practices.

KEYWORDS: Multi-Objective Optimization, Closed Loop Supply Chain, Circular Economy, End of Life (EoL) products, NSGA 2, MILP, Sustainability, Repair, Disposal

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Codes

Abbreviations

CBMs	Circular Business Models
CE	Circular Economy
CAGR	Compound Annual Growth Rate
CLSC	Closed-Loop Supply Chain
CRMA	Critical Raw Materials Act
CSRD	Corporate Sustainability Reporting Directive
EAs	Evolutionary Algorithms
EEA	European Environment Agency
EEE	Electrical and Electronic Equipment
EPR	Extended Producer Responsibility
EoL	End of Life
E-waste	Electronic Waste
EU	European Union

HVAC	Heating, Ventilation, and Air Conditioning
MILP	Mixed-Integer Linear Programming
MOEA/D	Multi-Objective Evolutionary Algorithm Based on Decomposition
MOO	Multi-Objective Optimization
NSGA-II	Non-dominated Sorting Genetic Algorithm II
POM	Placed on the Market
PSS	Product-Service Systems
PAES	Pareto Archived Evolution Strategy
RoHS	Restriction of Hazardous Substances
SPEA2	Strength Pareto Evolutionary Algorithm 2
WEEE	Waste Electrical and Electronic Equipment

1 Introduction

In this section, the background and motivation of the research study is explored. Besides that, the case company is introduced in this section as well. Further, the problem statement, research questions and objective of this thesis is discussed.

1.1 Background and Motivation

The rapid drive of industrialization, along with increasing global demand and technological advancement, has resulted in widespread and various type of machines and drives. Electrical drives are essential for the functioning of various machines and industrial processes. These electrical drives often face high rates of obsolescence and disposal due to rapid technological advancements and industry specific requirement. This is causing e-waste generation is increasing at an alarming rate and growing shortages of virgin materials. With 50% of global electricity consumed by motors, inefficient EoL management exacerbates resource depletion (Krishnan, 2001). According to the Global E-waste Monitor of 2024, a record 62 billion kg of e-waste was generated in 2022 globally compared to 34 billion kg in 2010 (Cornelis et al., 2024). The estimated value of the metals contained in e-waste that was lost was USD 91 billion and 60.259 billion kg CO_2 equivalent released from the discarded wastes (Cornelis et al., 2024). The report underlines the need for strategies to manage e-waste effectively, mitigate its environmental impacts, and recover valuable resources from discarded materials.

Traditional linear supply chain-where products are designed for single-use and disposal, have proven unsustainable as we are facing growing volume of wastes because of these End-of-life products. Due to their material composition and technical complexity, they contribute significantly to environmental burdens when disposed of improperly along with lost economic value (Yang, Sun, & Ni, 2021).

In response, the Circular Economy (CE) has emerged as a critical concept to address these challenges by prioritizing waste reduction and resource efficiency through reuse, remanufacturing, and recycling (Ellen MacArthur Foundation, 2015). Governments, researchers, and manufacturers are actively seeking solutions to reconcile these trade-offs. The European Union (EU) is actively promoting the transition towards a circular economy model through enacting directives and regulations. The EU's Green Deal aims to make Europe the first climate-neutral continent by 2050 (COM(2019) 640 final). one of the EU's 2030 climate targets, 55% reduction in greenhouse gas (GHG) emissions compared to 1990 levels (European Commission, 2020), highlight the urgency of adopting circular economy principles.

To be compliant with upcoming legislation and remain in competitive advantage, manufacturers are also adopting different circular business models and initiatives. A feasible business model on how these wasted products and materials can be re-utilised back in manufacturing by creating a circular supply chain, without compromising economic viability while remain in a sustainable solution is a great challenge.

For manufacturers, the adoption of CE principles often means navigating a difficult balance between economic viability and sustainability. In practice, both manufacturers and enterprises struggle with implementing End of life (EoL) strategies of the products due to various reasons. For example, repair or remanufacture may align with CE goals, but they can be expensive than disposal, especially when the quality of repair and performance is uncertain (Lieder & Rashid, 2016). These tensions highlight a growing need for systematic decision-making tools that can help manufacturers take sustainable actions without compromising economic feasibility.

At the heart of CE is the idea of closed-loop supply chain (CLSC), where end-of-life (EoL) products go through different processes to reduce waste and maximize resource efficiency. Despite global interest in circularity, closed-loop supply chain and decision-making for EoL products remain complex. Many enterprises still dispose of EoL products without assessing whether they could be repaired or remanufactured, missing opportunities for cost savings and sustainability. This challenge is intensified when decisions must consider multiple conflicting goals, such as minimizing costs while also reducing emissions (Lieder & Rashid, 2016).

Moreover, existing research and industrial efforts have often focused on supplier selection(Jahangoshai et al., 2017; Sajadiyan et al., 2022) or logistics optimization within CLSCs (Shafiee et al., 2023; Mallick et al., 2023; Lv et al., 2022), rather than the EoL product decisions themselves. Decisions around repair, or disposal are rarely supported by structured models (Govindan et al., 2015). This results in suboptimal or inconsistent actions, which do not fully align with circular economy targets.

The present study addresses this gap by focusing on optimizing end-of-life decision-making for electrical drives in CLSCs. It aims to design a data-driven, multi-objective optimization model that helps manufacturers decide when to repair or dispose of end-of-life drives balancing economic feasibility with environmental responsibility. The scope of the study being in Finland and in Nordic region, this effort supports the broader objectives of the circular economy and contribute to a more sustainable future by aligning with the EU Green Deal’s goals of reducing waste, minimizing carbon emissions, and promoting resource efficiency. By enhancing CLSC decision-making, this research directly aids in achieving the EU's target of a climate-neutral economy by 2050 and supports the 2030 objectives of reducing greenhouse gas emissions, fostering sustainable industrial practices, and improving the circularity of high-impact sectors such as electrical drives.

1.2 Problem Statement

Despite all the regulations in place and continuous technological advancement, manufacturers lack standardized tools for data-driven decision support for EoL products that take both cost and GHG emissions into account.

This research explored the complexity of decision-making for EoL electrical drives in a closed loop supply chain. The alternatives selected in this study are repair and disposal when the objective of the case company is to minimize the cost and GHG emission. This binary choice between repairing or disposing of an EoL product might seem simple at first glance but in practice, there are many factors that affect the decision making and it becomes even more complex when the objectives are conflicting with each other. For example, repairing may reduce waste, but it can be more expensive compared to disposal. On the other hand, disposal can be an easy option but may contradict with the sustainability goals of the company.

1.3 Research Questions

The purpose of this thesis is to answer the following research questions

- Is it economically beneficial and environmentally sustainable to repair or dispose of the electric drives?
- What are the factors that affect the decision making?
- What is the best suitable option (s) when the objective is to minimize the cost and GHG emission?
- How can multi-objective optimization model support cost-effective and sustainable decisions for EoL electrical drives?

1.4 Research Objectives

To answer the research questions above, the study has three core objectives:

1. To develop a model that integrates different factors that affect cost and environmental impact in the repair/disposal decision.
2. To apply the Non-dominated Sorting Genetic Algorithm II (NSGA-II) to identify a set of Pareto-optimal solutions representing the trade-offs between the objectives.
3. To conduct a sensitivity analysis to assess how robust these solutions are to changes in input data.

1.5 Document Structure

This thesis is structured as follows:

- Chapter 2 presents the introduction of concepts that are applicable in this study and literature on the subject. It also identifies the theoretical and practical gaps this study seeks to address.
- Chapter 3 discusses the methodology, including the case company detail, data sources, and modelling tools and techniques used, research limitations and the research onion philophy.
- Chapter 4 presents the details of the case study and mathematical model formulation.
- Chapter 5 presents the result and discussion, including model output, perfromance through validation and sensitivity tests. It also includes managerial implication, and future research directions.
- Chapter 6 presents the conclusion and Chapter 7 presents the acknowledgment.

2 Literature Review

In this chapter, introduction of the core concepts like electrical drives, circular economy, Closed loop supply chain, EU regulations related to sustainability and circularity, multi-objective optimization, sensitivity analysis, which are applied in this study is going to be discussed followed by the gap analysis from the current literature.

2.1 Concepts

2.1.1 Electrical Drive

An electrical drive is a system that controls and manages the speed, torque, and direction of an electric motor to control mechanical loads like pumps, fans, compressors, and industrial machines (Krishnan, 2001; Leonhard, 2001). It adjusts the power that is delivered to the motor and ensures performance with better efficiency and accuracy. Electrical drives are used in various industries, including:
Industrial Automation: Conveyors, robotics, machine tools
HVAC Systems: Fans, pumps, compressors
Transportation: Electric trains, trams, electric vehicles
Utilities: Water treatment, power generation, and distribution.

An electrical drive consists of several essential parts. The components and how they contribute to the function of the drive is described below as indicated in figure 1.

Power Source: The power source provides the electrical energy (AC or DC) to the system (Mohan, 2003). The type of electrical energy depends on the system design requirements (Krishnan, 2001).

Power Processing Unit (Modulator): The electrical power from the source is then directed to the power processing unit or modulator. The power modulator adjusts and converts electrical power to suit the motor’s requirements (Holtz, 1994) using devices like rectifiers, inverters, or choppers. It controls voltage, current, and frequency to manage motor speed and torque. It also protects the system from overload during operations.

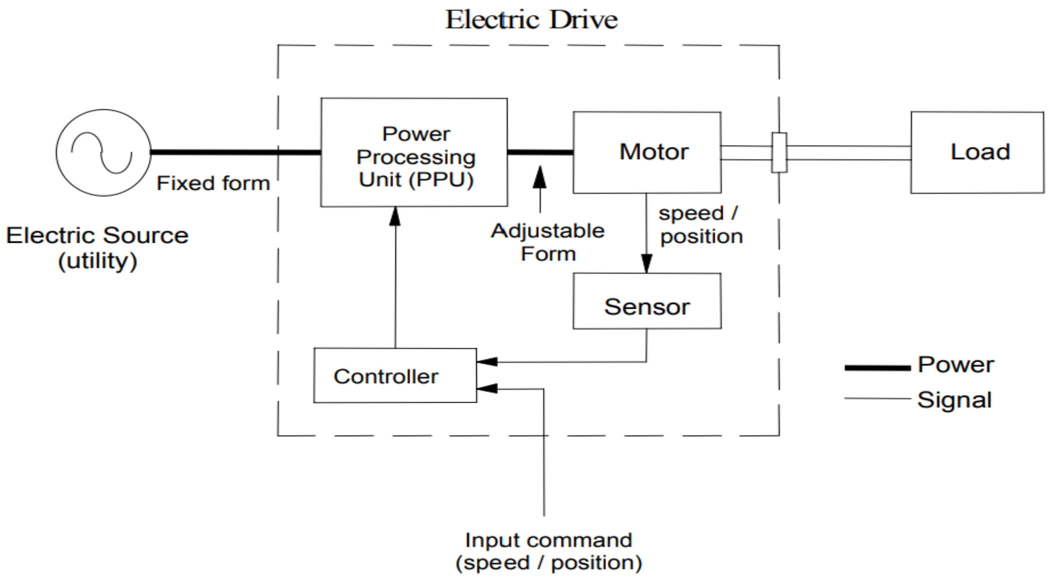

Figure 1. Block diagram of an electric drive system (Mohan, 2003)

Control Unit: A control unit oversees the power modulator's function. It processes input commands and real-time feedback from sensors and then sends signal to ensure the motor's performance matches system demands. It ensures precise control of speed, torque, and direction while protecting the system from faults (Blaschke, 1972).

Sensing Unit: Sensors track key performance indicators, including motor speed, electrical current, and sometimes position. This feedback enables instant adjustments for accuracy and protection against faults (Vas, 1998).

Motor: The motor receives the conditioned electrical energy and transforms it into mechanical motion (Pillay & Krishnan, 1989). Selection among motor types depends on application needs, such as whether constant speed, high torque, or regenerative capabilities are required.

Mechanical load: Mechanical load is the equipment (e.g., pumps, conveyors, machines) that is driven by the motor. The motor converts electrical energy into mechanical force (torque), which then drives the connected load. The electric drive ensures that the motor operates efficiently, adjusting to the load's speed and torque demands for optimal performance.

2.1.2 Circular Economy

A Circular Economy is defined as an economic system intended to eliminate waste and the continual use of resources through principles like designing for longevity, reuse, and recycling (Geissdoerfer et al., 2017). A simple model of circular economy of materials and energy is depicted by European Environment Agency (2016) as in figure 2.

Figure 2. Simplified model of circular economy (European Environment Agency, 2016)

There are three main circles in the model. The outer circle is about the energy flow. It emphasizes the need to increase energy efficiency and renewable energy use, while minimizing incineration due to its one-time energy recovery and material loss. The middle circle displays the material flows, distinguishing between technical (minerals and metals) and biological materials, noting that although biological materials are renewable, their increased use may impact ecosystems. Moreover, the mixture of technical and biological materials often make it difficults for the materials to be recovered due to the complexities. The inner circle promotes strategies like reuse, repair, and remanufacturing, which preserve the value of materials and products while reducing waste and resource consumption.

In traditional linear economy, a product is manufactured, consumed, and disposed of as waste which leads to resource depletion and environmental degradation. The Circular Economy shifts the focus from linear economy towards regenerative processes, aiming to minimize waste, maximize resource utilization, and extend product life cycles (Kirchherr et al., 2017).

Circular Economy Strategies

Many different strategies, known as R-strategies, have been developed to make the economy more circular. In this study, the 9R strategies, proposed by the PBL Netherlands Environmental Assessment Agency report has been used (Potting et al., 2017).

The 9Rs Framework describes strategies for achieving circularity, prioritizing actions from most to least desirable for resource efficiency:

R0-Refuse: Avoid the use of resource-intensive products altogether by questioning consumption habits (e.g., digital instead of paper-based products).

R1-Rethink: Change the way products are used or designed to optimize functionality

R2-Reduce: Minimize the use of resources in product manufacturing and use phases (e.g., lighter packaging materials).

R3-Reuse: Use products again for the same purpose without significant modification (e.g., second-hand clothes).
R4-Repair: Fix faulty products to extend their life (e.g., repairing electronics instead of discarding them).
R5-Refurbish: Restore old products by replacing worn-out parts and updating to newer standards (e.g., refurbished laptops).
R6-Remanufacture: Create new products using parts from old products, often involving re-engineering (e.g., remanufactured car engines).
R7-Repurpose: Use a product or its parts for a different function than originally intended (e.g., old tires used in playgrounds).
R8-Recycle: Recover raw materials from waste products to manufacture new goods (e.g., recycling plastics into new bottles).
R9- Recovery: Incineration of materials through energy recovery.

The R-numbers typically represent a range of strategies ordered from high circularity (low R-number) to low circularity (high R-number).

2.1.3 Closed-Loop Supply Chain (CLSC) for End-of-Life Management

A Closed-Loop Supply Chain integrates forward logistics (production and distribution) with reverse logistics (product take-back, remanufacturing, recycling) (Guide et al., 2003) in the whole value chain as shown in figure 2. A key aspect of the circular economy is the development of closed-loop supply chains (CLSCs) that focus on different strategies to utilise the end-of-life products to minimize waste and enhance resource efficiency. For EoL management, CLSCs are vital for collection of used products, primary sorting, quality level checking and disassembly, processing (repair, remanufacture, recycle etc.).

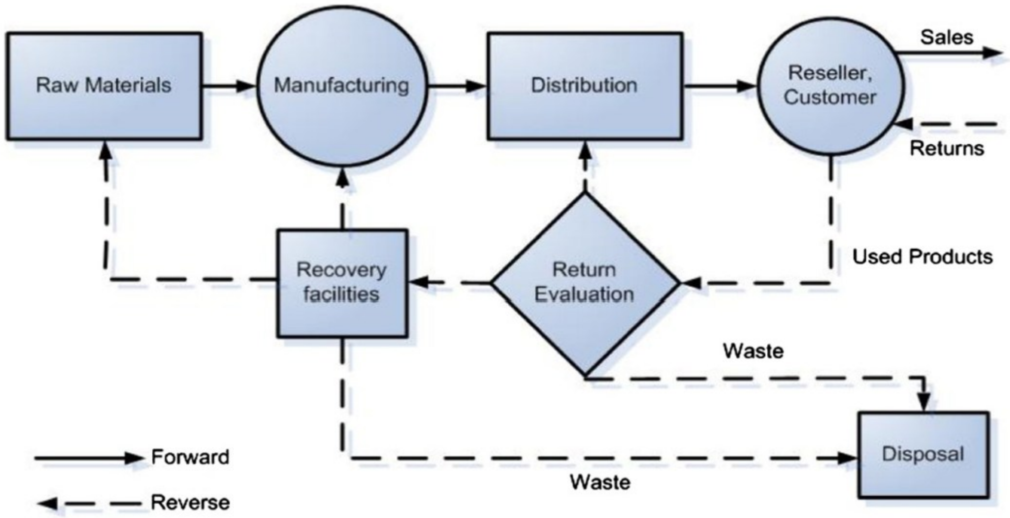

Figure 3. A generic forward/reverse logistics in a closed loop supply chain (Tonanont et al., 2008)

Studies indicate that effective CLSCs can reduce waste by up to 30% and generate substantial cost savings for industries (Govindan et al., 2015). However, some key challenges include:

Consumer participation in return programs

Economic and technical feasibility of processes

Environmental impacts of the processes

Design for disassembly and recyclability

The Circular Economy (CE) mitigates e-waste by adopting the 9R strategies within the closed loop supply chain (CLSC). While CLSCs theoretically enable circularity (Guide et al., 2003), practical challenges like feasibility of different 9R strategies for electrical drives remain unaddressed - a gap explored in Section 2.2.

2.1.4 EU Directives and Action Plans Driving Circular Economy Practices

European Union is constantly driving the sustainability agenda to integrate from the macro level to the micro level. This is why several directives and action plans are being developed and integrated into the legislation so that manufacturers can obey them and educate consumers about sustainability and their rights. Such directives are the WEEE Directive (Directive 2012/19/EU), Restriction of Hazardous Substances (RoHS) Directive (Directive 2011/65/EU), Circular Economy Action Plan (COM/2015/0614), EU Green deal (COM/2019/640 final), Corporate Sustainability Reporting Directive (CSRD) (Directive (EU) 2022/2464), The Critical Raw Materials Act (CRMA) (Regulation (EU) 2024/1252) and Right to Repair initiative (Directive 2024/1799) etc.

WEEE Directive (EU)

The Waste Electrical and Electronic Equipment (WEEE) Directive (Directive 2012/19/EU) focuses on preventing e-waste generation and improving the collection, treatment, and recycling of electronic products (Khetriwal et al., 2011). The directive (Directive 2002/96/EC) was first enacted in 2003 . Later, in 2012, some changes were made to that version, and an amendment was created. Key aspects of the 2012 version are:

- Extended Producer Responsibility (EPR) programs: Producers must finance the collection, treatment, and disposal of WEEE.
- Specific recycling and recovery targets: EU countries must meet certain collection rates (65% of EEE placed on the market (POM)or 85% of WEEE generated).
- Consumer awareness campaigns

Compliance with WEEE has led to a notable increase in collection rates, but issues remain regarding illegal exports and informal recycling sectors (Ongondo et al., 2011).

RoHS Directive (EU)

The Restriction of Hazardous Substances (RoHS) Directive (Directive 2011/65/EU) restricts the use of specific hazardous materials (e.g. lead, mercury, cadmium) in electronic equipment and prevents from entering the waste stream. The first RoHS Directive (Directive 2002/95/EC) enters into force in 2003. Then, there are some amendments made throughout these years. In 2011, the RoHS Directive was revised (Directive 2011/65/EU, often called RoHS 2), expanding its scope and strengthening compliance mechanisms. The latest amendment was made and adopted by the commission in 2023. Complying to RoHS helps to make recycling process safer and lower the environmental toxicity.

Research highlights that RoHS significantly accelerated material substitution trends in European electronics manufacturing (Widmer et al., 2005).

Circular Economy Action Plan

Circular Economy Action Plan (COM/2015/0614) was first launched in 2015. The objective of this action plan was to create the culture of sustainable products in EU and empower the consumers, ensuring less waste and leading the global effort in circularity. Products and sectors that use most resources and have a high potential to recover was given higher priority such as electronics, automobiles, batteries, packaging, textiles etc.

In 2020, the commission adopted the new Circular Economy Action Plan (COM/2020/98) under the European Green Deal. The updated action plan introduced measures for every stage of a product's lifecycle. It focuses on product design for sustainability and circularity, advancing circular economy practices, promoting responsible consumption, and emphasizes on working to minimize waste while maximizing the reuse of resources within the EU economy for as long as feasible.

European Green Deal

European Green deal (COM/2019/640 final) sets the political framework for fulfilling the goal of making Europe the first climate-neutral continent by 2050 (European Commission, 2019). This framework was launched in 2019. It covers all sectors like Clean energy, circular economy, biodiversity etc in broader perspective bringing everything under a single platform to achieve the common goal. In 2020, the new Circular Economy Action Plan (COM/2020/98) was adopted as a building block of the EU Green Deal, focusing on sustainable electronics and enforcing the "right to repair". Thus, managing WEEE became part of Europe's strategy not only for waste reduction but also for climate action and resource independence.

Corporate Sustainability Reporting Directive (CSRD)

Recognizing the need for better corporate transparency, the EU took on the Corporate Sustainability Reporting Directive (CSRD) (Directive (EU) 2022/2464) in 2022. The CSRD requires:

- Companies to report how they manage environmental issues, including waste generation, resource use, and circular economy activities.
- Disclosure of efforts to reduce e-waste, implement eco-design, or recover critical raw materials.
- Assurance that reported information is audited and digitally accessible.

For industries dealing in electronics- manufacturers, retailers, recyclers-WEEE management practices are now a key part of mandatory sustainability reporting.

Critical Raw Materials Act (CRMA)

The Critical Raw Materials Act (CRMA) (Regulation (EU) 2024/1252) is a legislative proposal by the European Commission to ensure access to a secure, diversified, and sustainable supply of critical raw materials, which is essential for green and digital transitions, defence, and aerospace industries. The objective is to boost domestic extraction, processing and recycling of the enlisted 34 critical raw materials (e.g., lithium, cobalt, rare earths), introducing strategic supply chain and promoting sustainability and circularity of the materials.

The CRMA was formally adopted and enforced by the EU in 2024 as Regulation (EU) 2024/1252 after provisional agreement in 2023. However, specific provisions will apply at different times. Companies in the EU battery, renewable energy, and defence sectors should begin compliance planning, especially for:

- Supply chain diversification (avoiding >65% reliance on a single third country).
- Recycling and sourcing benchmarks (e.g., 15% recycled content for cobalt by 2030).

The EU has visionary and stringent targets toward a sustainable and circular economy, which is not just about compliance but also about competitiveness for Manufacturers like the case company in this study. This regulatory urgency motivates the focus on cost-emission optimization for EoL decision making.

2.1.5 Repair Driven Circular Business Models (CBMs)

Repair is a key action in the Circular Economy's 9R hierarchy - positioned above refurbish, remanufacture, and recycle (Kirchherr et al., 2017). By enabling products to be fixed and returned to use without extensive energy or material input, repair strategies maximize product life and slow down resource loops (Bocken et al., 2016).

Research highlights that repair extends product service life, reduces waste streams, and cuts the need for new material extraction (Roskladka et al., 2025). Economically, it supports service-based business models and post-sales revenue streams. Considering the potential of repair in the circular business model, researchers have developed repair -driven circular business models which have been discussed below:

a) Product Life Extension Models

Businesses design products that are durable, modular, and easy to repair, often providing repair services or repair kits directly to consumers (Tukker, 2015). For example, Fairphone company design their smartphones to allow users to easily replace screens, batteries, and cameras (Fairphone, n.d.).

b) Product-Service Systems (PSS)

Under PSS, companies retain ownership of the product and sell functionality instead of the product itself (Tukker, 2004). Since firms remain responsible for product upkeep, they have strong incentives to ensure repairability and durability. Philips Lighting offers "Light-as-a-Service," where Philips maintains and repairs lighting systems for clients (Philips, n.d.).

c) Take-Back and Service Networks

Businesses offer take-back programs to customers and authorized repair centres, enabling closed-loop returns and repairs. It referes to offereing cutomers a reward or discount on their next purchase when they return the previous purchases (Forlin & Scholz, 2020). This supports reverse logistics integration into supply chains (Bressanelli et al., 2018). Fashon brand Patagonia repair and resale program encourage customers to repair garments instead of discarding them (Patagonia, n.d.).

d) Policy Drivers: Right to Repair and EU Legislation

The Right to Repair initiative (Directive 2024/1799), formalized in EU regulations starting in 2021, compels manufacturers to design products for repairability and to provide spare parts for up to 10 years (McCollough, 2009), Prolonged product lifespans, Design products that are easy to disassemble with common tools, Reduction of premature obsolescence and Empowered consumers and third-party repair markets.

Studies show that facilitating repairs could reduce electronic waste by 20% annually (Prakash et al., 2020). The current and upcoming regulations aim to normalize repair across sectors like electronics, appliances, and vehicles, and are increasingly tied to achieving the EU's Green Deal targets (Cordella et al., 2019). Despite having goals, complying with stringent laws and available business models, companies still face difficulties to operationalize repair-compliance trade-offs due to lack of comprehensive and practical tools.

2.1.6 Multi-Objective Optimization (MOO)

Multi-objective optimization: Multi-objective optimization (MOO) refers to the optimization problem where more than one objective function are optimized simultaneously (Christensen, J., & Bastien, C. , 2016). These objectives are often conflicting with each other, which leads to a set of trade-off solutions, where no single objective can be enhanced without worsening the other. The collection of these solutions forms the Pareto front. The multi objective optimization problem can be mathematically expressed as below:

$$\text{Minimize } \mathrm{F(x)} = \{f_1(x), f_2(x), \ldots, f_m(x)\} \tag{1}$$

$$\text{Subject to } \mathrm{g(x)} \leq 0 \tag{2}$$

where x_i is the vector of the variables, $f_i(x)$ is the i-th objective function, and g(x) is the constraint vector.

Types of Multi-Objective Optimization Methods

There are many methods to solve MOO problems such as:

Scalarization Methods: This method converts multiple objectives into a single objective using techniques such as weighted sums, ε-constraint, or achievement scalarizing functions (Miettinen, K., 2008). These methods allow the use of classical optimization algorithms to solve multi-objective problems by varying scalarization parameters to generate different Pareto optimal solutions.

Pareto-Based (Evolutionary) Methods: These methods directly search for a set of non-dominated solutions that approximate the Pareto front (Coello et al., 2007). Evolutionary algorithms (EAs) such as Non-(NSGA-II), Strength Pareto Evolutionary Algorithm 2 (SPEA2), and Multi-Objective Evolutionary Algorithm Based on Decomposition (MOEA/D) are widely used for this purpose.

Decomposition-Based Methods: The multi-objective problem is decomposed into several scalar optimization subproblems, and then each of the subproblem is optimized separately, often using evolutionary or metaheuristic approach (Zhang & Li, 2007; Altınöz, O. T., 2023). MOEA/D is a decomposition based method.

Goal Programming and Reference Point Methods: In this method, decision maker's preferences are incorporated by specifying goals or reference points for objectives, then the solutions that are closest to these targets, are sought after (Miettinen, K., 2008).

Interactive and Hybrid Approaches: These methods combine elements of the above, sometimes involving iterative interaction with the decision-maker to refine the search for preferred solutions (Collette & Siarry, 2004).

Although the application of different methods depends largely on the type and formulation of the problem itself (Collette & Siarry, 2004), still among all of the methods, the evolutionary algorithms are more popular due to several reasons. Evolutionary algorithms work with a population of solution, inspired by natural evolution. They are suitable for their diverse application (non-linear, discontinuous real-world problems) and better performance compared to other algorithms. They also have greater flexibility and diversity compared to other algorithms making them (Deb,K., 2001).

2.1.7 Mixed-Integer Linear Programming (MILP)

Mixed-Integer Linear Programming (MILP) is a mathematical optimization framework that extends linear programming by allowing some decision variables to take only integer values, while others can be continuous (Winston & Goldberg, 2004). The core structure of an MILP problem involves a linear objective function to be minimized or maximized, subject to a set of linear equality and inequality constraints. The distinguishing feature of MILP is the presence of integer constraints on some variables, which makes it suitable for modelling real-world scenarios where discrete decisions are required-such as yes/no choices, counts of items, or on/off states (Williams , 2013).

MILP is widely used in various industries for applications such as production planning (González et al., 2022), scheduling (Mucciarini et al., 2024), supply chain optimization (Li et al., 2023), energy management (Baader et al., 2022), and resource allocation (González-Ramírez et al., 2016).

However, Solving MILP problems is computationally challenging due to the combinatorial nature introduced by integer variables and when there are multiple objectives involved. Advanced solvers (Commercial solvers) and evolutionary algorithms can overcome this complexity.

Besides having greater flexibility and many real-world applications, MILP models can also incorporate of a wide range of constraints and objectives, allowing organizations to tailor solutions to their specific operational requirements and strategic goals (Kantor et al., 2020). The combination of optimality, flexibility, and practical solvability along with the type of the problem in the case study was why MILP modelling approach was chosen for this study.

2.1.8 Non-dominated Sorting Genetic Algorithm II (NSGA-II)

NSGA-II is a widely recognized multi-objective optimization technique, serving as a standard benchmark in the discipline (Coello et al., 2007). This is a high level meta-heuristic general purpose optimization framework.

```
Initialize Population
Generate N random solutions and insert into Population
for (i = 1 to MaxGenerations) do
    Generate ChildPopulation of size N
    Select Parents from Population
    Create Children from Parents
    Mutate Children
    Combine Population and ChildPopulations into CurrentPopulation with
size
     2N
    for each individual in CurrentPopulation do
        Assign rank based on Pareto – Fast non-dominated sort
    end for
    Generate sets of non-dominated vectors along PF_known
    Loop (inside) by adding solutions to next generation of Population
starting
    from the best front
        until N solutions found and determine crowding distance between
        points on each front
end for
Present results
```

Figure 4. Pseudo code for NSGA II (Deb,K., 2002)

The algorithm's procedures are explained in the figure 4, with additional information provided in Deb et al. (2002).

In NSGA-II algorithm, candidate solutions are selected from a pool (designated as R), including both parent and offspring population (Deb et al., 2001). The algorithm organizes these solutions using non-dominated ranking and subsequently generates the next generation by successively selecting individuals from the highest-performing Pareto fronts. The selection commences with the highest-ranked option, advances to the second-best, and continues until N solutions are selected. When the final front comprises an excess of solutions, a niching mechanism favours the most diverse (least populated) options to preserve population diversity. The residual solutions are discarded.

Algorithm parameters

NSGA-II has parameters resembling the genetics. These parameters can be adjusted to make the model more efficient and effective, so it converges to the optimum with the best solutions. It requires tuning of:

Population size: It balances diversity and computational cost (Deb et al., 2002).

Crossover probability: There are different type of crossover like uniform and half uniform crossover. Crossover is defined by probability to maintain gene flow.

Mutation probability: Small (e.g., 1/*n*, where *n* = variables) to avoid randomness.

Selection operators: selection is used for parent selection such as non-dominated sorting, crowding distance and tournament etc.

Best, worst and average solution

Best solution: The non-dominated Pareto-optimal solution with highest hypervolume (HV).

Worst solution: Dominated solutions with lowest crowding distance (poor diversity).

Average solution: This is based on mean Hypervolume or generational distance (GD) across the population.

Model validation

Model validation refers to determining if the model functions and behaves accurately for the purpose it was intended to (Aumann, 2007). The type of validation that is needed depends on the purpose of the model. Model can be validated operationally or conceptually (Sargent, 1984; Rykiel, 1996).

Performance Indicator: Performance indicator refers to the measurement metrics that evaluates the performance and quality of the solution of any algorithm (Deb, K., 2011). It is essential in testing and applying any algorithm and modelling. It is essential to know the performance of any algorithm. In case of multi objective optimization, it is even more difficult to measure the performance like distance because sometimes the optimum is not known. The model performance is measured through:

Convergence: The algorithm needs to converge to ensure that the solutions it produces are as close as possible to the true Pareto-optimal front for a given multi-objective optimization problem. Convergence in this context means that the population of solutions has evolved over generations to approach the set of non-dominated solutions where no objective can be improved without sacrificing another (Goel, T., 2010).

Diversity: Diversity in NSGA-II refers to the distribution and spread of solutions along the Pareto-optimal front (Deb, K., 2002). Maintaining diversity is critical to avoid clustering of solutions and to ensure a representative set of trade-offs for decision-makers.

Computational cost: it scales with population size and generations (Deb, K., 2002).

There are many techniques to measure the performance of multi objective optimization problems depending on the type of algorithm, modelling and the application of the algorithm (N. Riquelme, 2015). For example, Generational Distance (GD), Generational Distance Plus (GD+), Inverted Generational Distance (IGD), Inverted Generational Distance Plus (IGD+), Hypervolume (HV) and Epsilon (ε-Indicator).

Parameter tuning

Parameter tuning refers to the technique of adjusting the parameters of an algorithms to get the best possible solution out of the model for the problem it is solving and to observe the changes on the model under different configurations (Luke, 2013). It helps to validate the model further under different conditions and generalize it for future work or for real world test case.

2.1.9 Sensitivity Analysis

Running sensitivity analysis is an important step in checking how reliable a model is. This process helps figure out which parts of the model (specific settings, values, or assumptions) have the biggest effect on the results. It is repeated and used to improve the model over time.

In a sensitivity analysis, the models should be run several times while changing only one factor at a time, keeping everything else the same. This helps to indicate how much that one factor influences what the model predicts. Doing this kind of detailed check is key to making sure the model works well and justifies (Saltelli, Chan, & Scott, 2000).

Even though no model can ever be 100% “correct,” validation is about testing whether the model is trustworthy and makes reasonable predictions based on the available data (Araujo et al., 2005).

There are many different approaches for performing sensitivity analysis depending on the model, problem type, sensitivity measure and the research topic itself. Some of the methods are:

One-at-a-time (OAT) method

The One-at-a-time (OAT) method is a local sensitivity analysis technique where each input parameter is varied individually while keeping all other parameters fixed at their baseline values (Pizarroso, J., 2021). This approach allows for the direct attribution of changes in the output to the single variable being altered, increasing result comparability and minimizing the risk of model instability.

Morris method

The Morris method is a global sensitivity analysis approach designed for models with many input factors (Morris, 1991). This method is also known by also known as the method of elementary effects. It systematically varies one factor at a time at different points in the input space and calculates the elementary effects. The process is repeated a few times with different starting points, the method estimates the mean and standard deviation of the effects for each factor, and identifies the important factors that have significant influence on the model. The Morris method is computationally efficient and suitable for screening in high-dimensional models (Campolongo et al., 2007; Raj et al., 2024).

Derivative-based local methods

Derivative-based local method evaluates sensitivity by calculating the partial derivatives of the output in reference to each input variable at a fixed point in the input space (Tang, Z. 2025). These methods provide a matrix of sensitivity, but they do not capture global effects or interactions. Recent developments include derivative-based global sensitivity measures (DGSM), which average local derivatives across the input space, linking them to variance-based indices like Sobol' indices (Sobol & Kucherenko, 2009).

Regression analysis

In sensitivity analysis, regression analysis typically involves fitting a linear regression model to the outputs as a function of the inputs and interpreting the standardized regression coefficients as measures of sensitivity (Saltelli et al., 2000). This approach is straightforward and computationally not expensive, but it assumes linearity of the model. It is most appropriate when the relationship between inputs and outputs is approximately linear, as confirmed by a high coefficient of determination (Saltelli et al., 2007).

Variance-based methods

Variance-based methods, such as Sobol' indices, decompose the output variance into contributions from each input variable and their interactions (Sobol’, 1993). These methods provide an overall global sensitivity analysis by quantifying the part of output variance that is attributable to each input. Variance-based approaches are robust and widely used but can be computationally intensive, especially for models with many variables (Sobol’, 2001).

Fourier amplitude sensitivity test (FAST)

The Fourier amplitude sensitivity test (FAST) is a variance-based global sensitivity analysis method that uses Fourier series to demonstrate the output as a function of the inputs (McRae, Tilden, & Seinfeld, 1982). By transforming the multidimensional integral for variance decomposition into a one-dimensional integral using incommensurate frequencies, FAST efficiently estimates the main and, to some extent, higher-order effects of input variables. It is particularly efficient compared to Monte Carlo-based variance methods, though it is mainly limited to first-order sensitivity indices due to computational complexity (Saltelli et al., 1999).

Shapley effects

Shapley effects are a recent development in sensitivity analysis, inspired by the Shapley value concept from cooperative game theory (Benoumechiara & Elie-Dit-Cosaque, 2018). It provides an attribution of the output variance to each input variable to all possible combinations and interactions. Shapley effects are especially useful when input variables are dependent, as they offer a unique and consistent measure of variable importance. While computationally demanding, they are increasingly used in complex models for their interpretability and fairness in allocating contributions (Owen, 2014; Song et al., 2016).

2.2 Gaps in Existing Research

Waste electrical and electronic equipment (WEEE) management has evolved from a standalone waste policy to a central pillar of Europe's climate, resource, and corporate sustainability strategies. Through the WEEE and RoHS Directives, the Circular Economy Action Plans, the European Green Deal, and the CSRD, the European Union has created an integrated legal framework ensuring that electronics are safer, longer-lasting, and more circular - while holding businesses accountable for their environmental impacts. Complying with EU regulations, being in a competitive advantage from environmental sustainability point of view, while running a business case depends on so many factors. It also makes decision making complex due to conflicting objectives such as minimizing cost and GHG emission.

Among all of options of circular economy strategies mentioned in section 2.1.2, some of them received higher attention than others both in terms of research and in practical initiatives. For example, recycling and remanufacturing received much more attention than repairing. Mishra et al. (2023) analyzed in their article that most studies about end of life products are about automotive and furnitures. They also showed through their survey that recycling and remanufacturing are most dominant CE strategies, specially among e-waste and plastic. Industry. Although repair is critical for e-waste management, there are few challenges identified among which one was discussed most: quality variability of returned products. Repair feasibility depends on the condition of returned products. Due to new technology, often the cost of repair does not seem to be attractive compared to new product prices. While the paper does not specifically address electrical drives, its insights on electronics repair can be broadly applicable.

Despite multiple studies addressing elements of product lifecycle management, none comprehensively integrate product quality, component age, and repair budget constraints into end-of-life (EoL) decision-making for electrical drives. For example, Peng et al. (2017) developed a quality-dependent multi-objective optimization model but did not directly address repair versus disposal framing. Similarly, Passaporn (2019) incorporated historical quality data into machine learning classifiers for repair decisions but lacked environmental optimization and NSGA-II-based trade-offs. While age effects were considered in studies like Taleizadeh et al. (2019) and Liu et al. (2019), these analyses focused on disassembly or product return pricing rather than repair feasibility. Additionally, although budget constraints were discussed in works like Rezgui et al. (2022) and Costa (2020), they were not tightly integrated with condition-based repair decisions. As a result, no current study captures the dynamic interaction between quality degradation, aging, and budget thresholds in a unified repair versus disposal framework for industrial electrical drives. It is summarized below in table 1.

From a methodological perspective, although Mixed-Integer Linear Programming (MILP) and the Non-dominated Sorting Genetic Algorithm II (NSGA-II) have been individually applied to various optimization problems, their joint application to EoL repair/disposal decisions remains unexplored. Taleizadeh et al. (2019) utilized MILP-like approaches for product recovery and logistics optimization, yet neither targeted repairable electrical drives or incorporated emissions considerations.

Table 1. Gap analysis of EoL electrical drive decision considering different factors

Category	Paper	Focus	What's Missing
Quality	Peng et al. (2017)	Quality-dependent MOO for product recovery.	No repair vs. replace framing; lacks full decision support.
	Passaporn (2019)	Historical quality data used in repair support.	No NSGA-II, no lifecycle optimization.
	Kianpour et al. (2017)	Behavioural factors in returns; mentions quality perceptions.	No optimization model; only behaviour study.
	Jofre & Morioka (2005)	Policy-level quality insights in EEE recycling.	No technical repair or quality deterioration modelling.
Age	Taleizadeh et al. (2019)	Considers age effect on returned products' quality.	Not tied to repair vs. disposal for drives.
	Liu et al. (2019)	Age affects disassembly priority.	No EoL repair decision focus.
	Passaporn (2019)	Uses historical failure (linked to age) data for decision trees.	No GHG emission trade-offs; no NSGA-II.

Budget	Taleizadeh et al. (2019)	Indirect cost constraints in pricing models.	No explicit repair budget constraints.
	Passaporn (2019)	Repair cost vs. replacement cost comparison.	Data-driven, no NSGA-II optimization.
	Costa (2020)	Portfolio cost evaluations using NSGA-II.	No drive-level repair budgeting model.
	Rezgui et al. (2022)	LCA-based cost-emission trade-offs in buildings.	No product-specific budgeting or repair models.

On the other hand, studies such as Costa (2020), Chen et al. (2024), and Liu et al. (2019) showcased the power of NSGA-II for multi-objective problems in energy systems, circular manufacturing, and robotic disassembly, respectively. However, these applications either focused on system-level sustainability goals or manufacturing process optimization without delving into component-level repair feasibility based on technical condition and cost constraints. Therefore, there is a clear methodological gap in combining MILP-based constraint handling with NSGA-II's evolutionary search capabilities for condition-driven, budget-constrained repair versus disposal decisions in EoL electrical drives.

Table 2. Gap analysis of application of NSGA-II for EoL electrical drive decision

Category	Paper	Focus	What's Missing
MILP	Taleizadeh et al. (2019)	Mixed Integer MOO for returned products.	No repair-disposal modelling; no electrical drives.
NSGA-II	Costa (2020)	NSGA-II in portfolio evaluation.	No repair/disposal modeling.
	Chen et al. (2024)	NSGA-II in Industry 5.0 circular economy.	Generic sustainability focus; no component-level decisions.
	Liu et al. (2019)	NSGA-II, MOEA/D, SPEA2 comparison in robotic disassembly.	Disassembly focus only; no repair evaluation.
	Hu et al. (2023)	Hyper-heuristic with NSGA-II for uncertainty in disassembly.	Production lines; not repair vs. disposal.

	Qasim et al. (2023)	NSGA-II for green production planning.	No integration of condition or repairability indicators.
	Ma et al. (2023)	Survey paper; overview of NSGA-II applications.	No application to repair/disposal for electrical drives.

While individual studies understand specific EoL decision criteria such as quality, cost, and sustainability, the absence of an integrated approach highlights a need for a holistic model. This gap becomes even more when examining the optimization methods employed. Although both MILP and NSGA-II offer powerful capabilities for handling complex, multi-objective problems, their application has largely been isolated to either constraint-driven cost models or general sustainability optimization, without a focus on repair feasibility at the component level. Therefore, bridging these two dimensions - comprehensive condition-based decision criteria and advanced hybrid optimization techniques- represents a critical and novel contribution to the sustainable management of electrical drives at the end of their service life.

3 Methodology

This study is going to explore the research design for a case company who want to decide their collected End-of life (EoL) electrical drives. This is a multi-objective optimization problem to decide whether to repair or dispose of End of Life (EoL) electrical drives where the objectives are minimizing cost and minimizing GHG emission. The aim is to find practical, budget-compliant solutions while exploring the best cost-emissions trade-offs through data driven decision support model. This research is performed as a quantitative method. A case company is considered for the study. The research problem is an objective type of problem. Data is collected and analysed using mathematical modelling and sensitivity analysis to conclude.

3.1 Case Company

The case company is a key player in manufacturing electrical drives market. They specialize in energy-efficient frequency converters that optimize the motor performance which is used across various industries. With electric motors consuming approximately 50% of global electricity (Waide & Brunner, 2011), the demand for intelligent drive solutions is rising rapidly. In 2024, the global market for AC drives was valued at $17 billion (Global Market Insights, 2024). Some of the major manufacturers include ABB, Schneider Electric, Siemens, Fuji Electric, and Rockwell Automation along with the case company. The global AC drives market is expected to grow at a compound annual growth rate (CAGR) of 4.4% by 2034 with the size of $26.5 Billion (Global Market Insights, 2024), driven largely by rapid industrial automation, energy efficiency and smart city concepts. The case company is growing particularly in sectors like HVAC, water treatment, and manufacturing, where its drives can reduce energy consumption by up to 40-50% in motor applications. Newer technological trends such as smart manufacturing, IoT integration, and renewable energy systems will further boost adoption of such products.

As priority on sustainability increasing exponentially, for manufacturers like the Case Company, compliance with these laws is not just ethical but a competitive necessity. As a result, the company is focusing on circular solutions to strengthen its market share, aligning with global and European initiatives to reduce e-waste, and carbon emissions. For this reason, the company is exploring different closed loop supply chain alternatives. Currently the company only offers repair and maintenance service that is applicable for the products with the designed service life. But they do not have any initiative currently to take these products back, repurposing them for further or disposing them in a sustainable way.

3.2 Research Strategy

This research employs a case study strategy, focusing on a single case company. This is a company which manufactures different type of electrical drives applicable for different industrial processes and services. The company is exploring different circular business models to handle their EoL electrical drives which can be aligned with their strategic business goals. For this reason, they are interested to know the best solution for those returned end of life products both from economic and environmental point of view. A detailed understanding of its context (repair site capacity, product quality, budget limits, etc.) shapes the model. Since it is a case company specific problem, it is better to formulate a quantitative model based on the resource available and constraints. This is why a data driven quantitative analysis is better suited in this study to help the company with decision making. While case-specific, the model provides insights transferable to similar industrial scenarios. This enables depth rather than breadth, and contextual realism to the optimization model.

3.3 Data Collection, Preparation and Analysis

Data is collected and generated from secondary sources such as the internet, company websites (Danfoss, n.d., ABB, n.d.), benchmark database like Ecoinvent v3 (Wernet et al., 2016) EPD API (The International EPD® System, 2023a & 2023b), and publicly available dataset (Constante, 2019) due to lack of access to primary historical data. After getting ideas from discussing with case company, a pseudo dataset is generated for modelling and analysis. More detail is added in case study. After collecting and cleaning the data, the dataset is prepared in csv form. This dataset was used for further investigation, analysis and sensitivity analysis. The dataset is added in appendix 1.

3.4 Research Instruments

Modelling and Algorithm

The problem was formulated as MILP model. Then it was used to apply NSGA II algorithm. NSGA-II's unique features such as computational efficiency, elitism, and parameter less diversity preservation makes it a superior choice for multi-objective optimization compared to other algorithms (Konak, A. , 2006). This is why this algorithm was selected for this research. Deb et al. (2002) proposed an improved version of the Nondominated Sorting Genetic Algorithm (NSGA) to overcome the key limitations of the other previous Multi- objective Evolutionary Algorithms (MOEAs).

NSGA-II reduces the computation of nondominated sorting from O(MN3) for nondominated sorting, where M is the number of objectives and N is the population size) in the prior algorithm of NSGA to O(MN2) via a fast nondominated sorting approach. It incorporates elitism by combining parent and offspring populations before selection, which was impossible in previous algorithms. Traditional methods relied on a sharing parameter (σshare) to maintain diversity. NSGA-II replaced it with a different metric named as crowding-distance, which eliminated the need for user-defined parameters. Some key features of NSGA II are mentioned below:

- Fast Nondominated Sorting: Uses a better system (domination count np and dominated set Sp) to efficiently classify solutions into Pareto fronts.
- Crowding-Distance Assignment: Measures solution density in objective space to promote diversity without tuning parameters.
- Constrained Optimization: Extends NSGA-II to handle constraints by modifying the dominance principle (feasible solutions always dominate infeasible ones).

Older algorithms like PAES and SPEA either lacked such features or implemented partial forms. NSGA-III was designed for many-objective problems, incorporating reference point-based diversity maintenance (Deb & Jain, 2014). Many research showed that NSGA-II outperformed others (such as SPEA-2, and MOEA/D) in different applications (Marrero, et al., 2019; Apipie & Ioana, 2019) in different application of multi objective optimization problems. A detailed comparison is presented below in table 3 compares the key features of multi-objective optimization algorithms, highlighting the advantages of NSGA-II over older approaches (NSGA, PAES, SPEA) and newer variants (NSGA-III).

Table 3. Comparison of NSGA II and other similar algorithms

Feature	**NSGA-II (Deb et al., 2002)**	**Older NSGA / PAES / SPEA**	**NSGA-III**
Fast non-dominated sorting	Yes	No (Zitzler et al., 2001)	Yes (Chaudhari et al., 2022)
Elitism	Yes	No / Partial (Zitzler et al., 2001)	Yes
Diversity preservation	Crowding distance	Sharing parameter (Zitzler et al., 2001)	Reference points (Deb & Jain, 2014)
Parameter tuning	Minimal	Moderate (Ishibuchi et al., 2017; Knowles & Corne, 2000)	Moderate
Computational efficiency	High	Moderate/Low	Moderate (Li et al., 2015)
Solution spread	Excellent	Good/Moderate	Excellent (many obj.) (Deb & Jain, 2014)
Real-world adoption	Very high	Moderate (Coello et al., 2006); (Qingfu Zhang & Hui Li, 2007)	Growing

Sensitivity Analysis

One-at-a-time (OAT) method is applied in this study. OAT method is the most straightforward and simple method for performing sensitivity analysis (Iooss & Lemaître, 2015; Saltelli, A., et al. 2019). This method is specifically more suitable for linear system. Although it is more common to check only the increasing the parameters values in OAT sensitivity analysis (Cacuci ,2003), but it is better to test the symmetry of the model specially in model like multi objective optimization problems. In this way, the effect of both reducing and increasing the parameters can be observed and that can help with identifying the threshold of the parameters for the model to work, especially during scalarization and during testing in real world situation.

Python

Python is a widely adopted programming language in the optimization community due to its readability, extensive scientific libraries, and strong support for mathematical modelling. Python's ecosystem includes powerful optimization libraries such as Numpy, Pandas, Pytorch, Pymoo, DEAP etc. In this study, Pymoo library is used for applying NSGA 2 algorithm. Other libraries like Numpy, Pandas, Matplotlib are used for data analysis and mathematical manipulation.

Pymoo library is an open-source Python framework specifically designed for multi-objective optimization. It supports a variety of evolutionary algorithms and provides tools for problem definition, solution analysis, and visualization. While pymoo is primarily focused on multi-objective and evolutionary optimization, it exemplifies Python's versatility in supporting advanced optimization workflows, including those that may integrate or hybridize with MILP approaches for complex, real-world problems (Blank & Deb, 2020).

Excel

Microsoft Excel is used for some data analysis and visualization purpose in this study.

3.5 Research Limitations

Data Constraints: There was lack of access to primary data. Due to privacy and commercial reason, the exact price data cannot be disclosed in the report. Pseudo dataset is generated from secondary data souces, which may often differe from real life data. Transport emissions assumed a single mode (lorry), excluding rail or multimodal logistics.

Simplified Assumptions: The study treated product quality as binary (good/poor), ignoring granular quality grades or wear-and-tear effects (e.g., thermal stress, vibration). Modularity of electrical drives (e.g., separate repair of motors, bearings) was not considered.

Static Model Framework: A single-time-period analysis was used, omitting dynamic factors like seasonal demand fluctuations or inventory delays. Budget constraints were fixed, while real-world budgets may adapt to market conditions. This is a deterministic model. No uncertainty was considered forthis study except the sensitivity analysis. In real life many factors can be uncertain like quality and quantity of the end of life products.

Algorithmic Scope: NSGA-II's performance may degrade for ultra-large datasets (e.g., >10,000 products) due to computational costs. The algorithm was limited to run not more than 100 generations using current computational power.

While this study provides a foundational framework for sustainable EoL decision-making, addressing these limitations could unlock better insights for industry.

3.6 Concluding Summary: research onion model

The methodology can be summarized according to the research onion introduced by (Sauders et al., 2019). This study is grounded in positivist philosophy. The model has objective to minimize cost and GHG emissions using quantifiable variables like price, emissions (kg CO_2), transport distance, and repair cost - all measurable and independent of the researcher's interpretation. This research follows a deductive approach. It begins with established theories and then develops a mathematical model to apply those theories. It uses computational experiments to test how the theory works in a specific context. The research employs a case study strategy, focusing on a single case company. The company is exploring circular business models to handle EoL electrical drives. This study uses a mono-method quantitative approach.

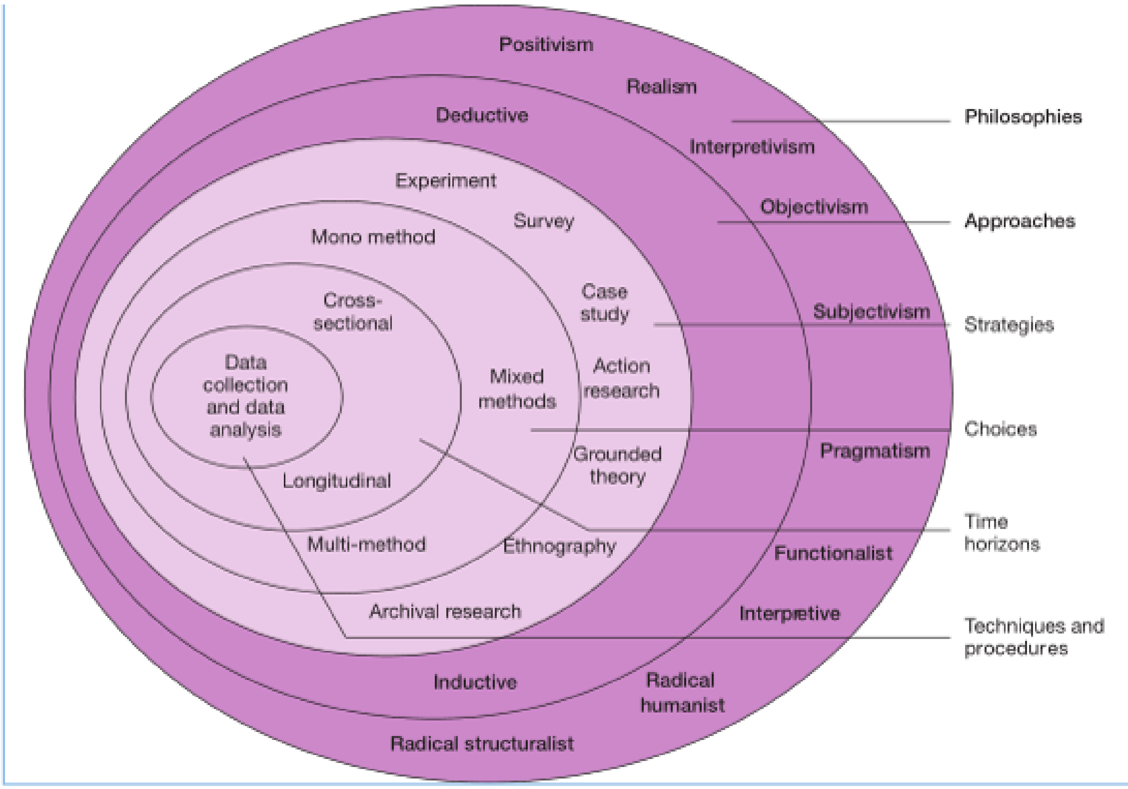

Figure 5. Research onion (Sauders et al., 2019)

The data, analysis, and model are entirely numeric and computational. Techniques include optimization algorithms, mathematical modelling and sensitivity analysis. NSGA-II generates thousands of solutions based on numerical inputs and ranks them based on objective performance.

The study takes a cross-sectional time horizon. The model represents a snapshot of operational decision-making within a defined time period, simplifying complexities like future demand or technological change. Specific tools and procedures used for data collection and analysis:

Data: Pseudo dataset based on case company context, Ecoinvent, product EPDs, and literature

Mathematical Model: A Mixed Integer Linear Programming (MILP) model

Optimization Algorithm: NSGA-II, a well-established multi-objective evolutionary algorithm.

Programming Environment: Python, using the pymoo library for implementation.

Model Validation:

Performance indicators: Application of Hypervolume (HV) score and Epsilon Indicator to measure convergence and diversity of the model

Parameter tuning: Changing the parameters of the algorithm configurations to assess model robustness.

Sensitivity Analysis: One-at-a-time (OAT) method to test how sensitive the model is to product quality, budget, and transport distance.

4 Case Study

The case company is currently looking for repairing the End-of-life products and selling them to secondary market. A batch of EoL products returned from customers to collection point. The products are of different age and quality level. They are sorted and disassembled. Then they are inspected for quality check. Once the quality grade is assigned, cut-off values are determined for repair and disposal. If the products are of good quality, they are sent for repair. If the products are poor quality and too old, they are sent for disposal. Parts required for repair are supplied by spare parts market. The repaired products are sent to warehouse and then sold to customers in the secondary market. In this study, it is assumed that there is a demand of repaired products and is fulfilled by the EoL repaired products. The capacity of the repairing site is fixed and known for the period. The demand is fulfilled while keeping the cost and GHG emission at minimum level possible, thus continuing the closed loop supply chain.

A batch of 50 EoL products are collected from different clients to the collection point for the period. Weight and dimension of the returned products are considered between 5 to 10 kilograms based on the information available from online resources, generated randomly for the batch. Emission factor for transport and other processes (repair, disposal) data is collected from Ecoinvent 3.11, cut-off database (Wernet et al., 2016). A part of emission data is also inspired from the EPD of the products (The International EPD® System, 2023a & 2023b), which are available online but unfortunately the scope and processes did not match this study completely. The GHG emission from repair is assumed between 50 and 800 KgCO_2. The GHG emission from disposal is assumed between 50 and 600 KgCO_2The distance data is taken from the dataset shared by (Constante, 2019). Transport cost is assumed as €0,5 per kilometre per kilogram of product. Age of the products are assumed to be between 3 to 14 years and generated randomly. The case study is designed for the products which have expected lifetime from 5 to 8 years. The cost of repairing the product for each quality level is calculated by multiplying the new product price by a random number chosen uniformly between 0 and 1 (Anandh & PrasannaVenkatesan, 2024), which ranges between € 100 to € 500 per product. The quality levels are at first assumed to be continuous, being from 1 is equal to good to 0 is equal to poor. Later the quality levels were decoded as binary with a threshold of 0,3. The budget for the products are estimated as 5% to 30% of the price of the new products, ranging from € 150 to € 600 per product.

4.1 Model Formulation

The model can be explained briefly from the flowchart in figure 6. The model takes the dataset as input. A population of solutions is initialized. Then the algorithm checks objective functions and constraints to evaluate the solutions. After running about the maximum generations, the model performs the trade-off analysis between the two objective functions and returns the pareto front of the best solutions.

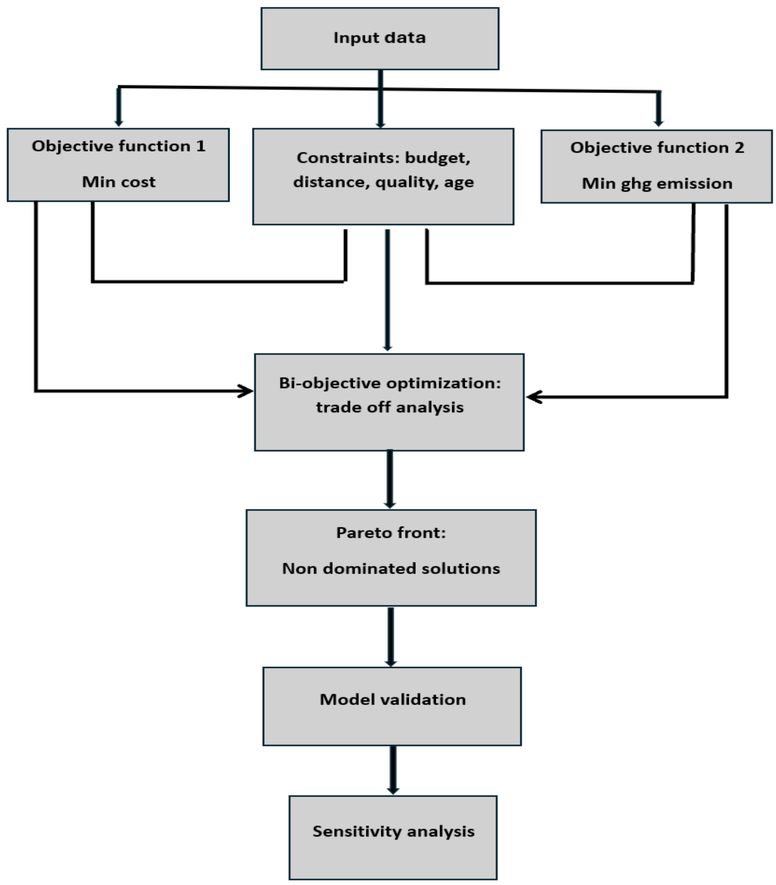

Figure 6. Flowchart of the algorithm

After that, the model was validated with techniques like performance indicators and parameters tuning. Finally, a sensitivity analysis was performed to observe the reaction or sensitivity of the model because of different changes.

4.1.1 Mathematical Model

A mixed integer linear programming model is established to formulate the problem with linear objective functions to minimize both cost and GHG emission of EoL products. The decision variable being binary, a product can only be repaired or disposed. This is why MILP method is applied to formulate the problem in this case study. At first, the assumptions of the model are mentioned below. Later all the indices, parameters, decision variables and other binary variables are explained with their notations. After that, all the equations are mentioned and explained

Assumptions:

- A single period is considered to simplify demand uncertainties.
- Returned Products have different age and quality. Quality has different grades from good to poor. Products are modular but for simplification it is not considered.
- The effort in repairing products increases as quality level decreases. It results in higher cost and emission. Likewise, the repair effort is less as quality level increases. It leads to lower cost and emission.
- Transport emissions are dependent on distance. A single mode of transport (lorry) is considered for all transportations. All transportations are aggregated into one value for each product depending on alternative decisions.
- Timeliness is negligible.
- Repair cost is calculated as a percentage of the price of new product.
- Disposal cost is calculated as per kg weight of the product.
- A budget constraint is applied reflecting real-world financial limits for repair operations.

Indices

p: Product (p=1,2,…,P)

q: Quality level (q=1,2,…,Q, where 1 = best, Q = worst)

Parameters

RC_{pq}: Repair cost for product p at quality level q

DC_{pq}: Disposal cost for product p at quality level q

RE_{pq} : Repair emissions for product p at quality level q

DE_{pq}: Disposal emissions for product p at quality level q

TC_{pq}: Transport cost of product p at quality level q

TE_{pq}: Transport emissions of product p at quality level q

a_{pq}: Age of the product p with quality level q

B_{pq}: Budget for product p with quality level q

A: Age threshold for product p with quality level q (3-14 years old)

Decision Variables

x_{pq}: Quantity of product p (quality level q) repaired

y_{pq}: Quantity of product p (quality level q) disposed

Binary Variables

zr_{pq}=1 , if product p is in the range, else 0

zd_{pq} = 1, if product p (quality level q) is disposed, else 0

q_u: Cut-off level of quality for repair (cut-off value = 0,3)

Objectives:

There are two objective functions in this model. They are described below:

Objective 1:

$$\text{Min F1}= \sum_{p=1}^{P} \sum_{q=1}^{Q} (RC_{pq} * x_{pq} + DC_{pq} * y_{pq} + TC_{pq} * (x_{pq} + y_{pq})), \quad (3)$$

Where, objective 1 is depicted as F1 is a function.

Equation 3 is the first objective function, which is about minimizing total cost. It is obtained by summation of cost of repair (RC_{pq}), cost of disposal (DC_{pq}) and cost of transportation (TC_{pq}) of the products depending on their quality level.

Equation 4 is the second function, which is about minimizing total GHG emission. It is obtained by summation of emission from repair (RE_{oq}), emission from disposal (DE_{pq}) and emission from transportation (TE_{pq}) of all products.

Objective 2:

$$\text{Min F2} = \sum_{p=1}^{P}\sum_{q=1}^{Q}(R\mathrm{E}_{pq} \ * \ x_{pq} + D\mathrm{E}_{pq} \ * \ y_{pq} + T\mathrm{E}_{pq} * \ (x_{pq} + \ y_{pq})), \quad (4)$$

Where, Objective 2 is depicted as F2 is a function.

Constraints

Constraints are important to formulate the MILP model. All constraints are explained below with their equations.

Equation (5) depicts the constraint that each product the product of x_{pq} with quality level q and the total cost (RC + TC) must not exceed its individual budget budget B_{pq}. If the cost exceeds the budget (i.e., the inequality part is true), then the left-hand side is 1, which violates the constraint g(x)=0. On the other hand, if it's false (i.e., cost is within budget), the left-hand side is 0, satisfying the constraint.

$$g(x) = [x_{pq}\left(RC_{pq} + TC_{pq}\right) > \ B_{pq}] = 0, \quad (5)$$

Where, g(x) is the function.

Equation (6) indicates the quality and age constraint for the products to be disposed. This is enforced inside the algorithm. This is enforced during evaluation by modifying the decision vector before computing cost and emissions. It means if the quality level is below the threshold and the age of the product is higher than the threshold that is considered for this model, it is best to dispose that product for several reasons like unavailability of parts, obsolete technology and high cost and emission that is not justified by the product performance after repair

For any product, $y_{pq} = 1$,

$$if\ (q_u \leq q \leq Q)\ and\ a_{pq} > A. \quad (6)$$

Equation (7) and (8) are the binary variables for quality levels. If the quality level q of a product p satisfies the constraint (Equation 7), then that product is assigned to the repair option. Otherwise, it is disposed of (Equation 8).

$$zr_{pq} = \begin{cases} 1, & if\ 1 \leq q \leq\ q_u \\ 0, & otherwise \end{cases}. \quad (7)$$

$$zd_{pq} = \begin{cases} 1, & q_{u+1} \leq q\ \leq Q \\ 0, & otherwise \end{cases}. \quad (8)$$

Equation (9) and (10) specify that the variables are non-negative and integer.

$$x_{pq}, y_{pq}\ > 0\ and\ integer, \forall_p, q. \quad (9)$$

$$zr_{pq,} zd_{pq,} > 0\ and\ integer, \forall_p, \mathrm{q}. \quad (10)$$

NSGA-II Implementation

Population Initialization: The model generates random binary vectors (0 = dispose, 1 = repair) for all products as initialization.

Evaluation: Then the algorithms compute F1 (cost) and F2 (emissions) for each solution based on the constraints (both hard and soft constraints).

Constraint Handling:

Hard constraints (e.g., budget) are enforced by discarding infeasible solutions during selection.

Soft constraints (e.g., quality thresholds) modify decisions pre-evaluation (e.g., auto-dispose if $q > q_u$).

The logics and equations of the model can be seen from the code 1 snippet below (More can be found in Appendix 2):

```
def _evaluate(self, X, out, *args, **kwargs):
    costs = np.zeros(X.shape[0])
    emissions = np.zeros(X.shape[0])
    g1 = np.zeros(X.shape[0])  # Individual budget constraints

    for i in range(X.shape[0]):
        # Initial repair decision
        repair_mask = X[i, :] == 1
        dispose_mask = ~repair_mask

        # Apply business rules:
        # 1. dispose if repair cost exceeds individual budget
        budget_violation = (cost_repair + transport_cost_repair) > individual_budget
        # 2. dispose if quality is poor AND age > 8 years
        poor_and_old = (quality == 0) & (age > 8)

        force_dispose = budget_violation | poor_and_old
        repair_mask[force_dispose] = False
        dispose_mask[force_dispose] = True

        # Calculate objectives
        total_cost = np.sum((cost_repair + transport_cost_repair)[repair_mask]) + \
                     np.sum((cost_dispose + transport_cost_dispose)[dispose_mask])

        total_emissions = np.sum((ghg_repair + transport_emission_repair)[repair_mask]) + \
                          np.sum((ghg_dispose + transport_emission_dispose)[dispose_mask])
```

Code 1. Handling constraints in evaluation phase

The constraints help the model to select the solution efficiently, provide decision maker feasible solutions and remove the infeasible ones. For example, manufacturers have an estimated budget for repairing the products for the lifetime of that product. if a product's repair cost becomes too high that exceeds the budget (repair service or warranty service), then it is not beneficial for the manufacturer to still go with the repair alternative. It is economically safe to discard the product instead. With high repair effort, usually the GHG emission of repair also increases. So, that solution is not good from environmental aspect also.

Genetic Operators:

Initial Population: initially the population is kept as 300.

Sampling: Binary random sampling is applied from the pymoo library

Crossover: Half-Uniform Crossover (HUX) preserves diversity by swapping 50% of differing bits.

Mutation: Bit-flip with probability 1/n (n=50) to explore new solutions.

Selection:

Non-dominated Sorting: Rank solutions into Pareto fronts (Front 1 = best trade-offs).

Crowding Distance: Prioritize diverse solutions within each front to avoid clustering.

Termination Criteria:

The algorithm stops running after 20 generations (empirically balances convergence and runtime).

This part of the model is shown in code 2 snippet below:

```
# Run Optimization
callback = MyCallback()
problem = ProductRepairProblem()

algorithm = NSGA2(
    pop_size=300,
    sampling=BinaryRandomSampling(),
    crossover=HalfUniformCrossover(),
    mutation=BitflipMutation(prob=1.0/n_products),
    eliminate_duplicates=True
)

termination = get_termination("n_gen", 20)

res = minimize(problem, algorithm, termination=termination, seed=42, callback=callback, verbose=True)
```

Code 2. Calling the function for optimization

Pareto Front

After evaluating the solutions, the algorithm ranks them and presents the best solutions as a pareto front.

The process is being repeated until N generations which is 20 in this case. The pareto front is generated from code 3 below:

```
# Plotting
def plot_pareto(res):
    plt.figure(figsize=(10, 6))
    feasible = np.all(res.G <= 0, axis=1) if res.G is not None else np.zeros(len(res.F), dtype=bool)


    if feasible.any():
        nds = NonDominatedSorting().do(res.F[feasible], only_non_dominated_front=True)
        plt.scatter(res.F[feasible][nds, 0], res.F[feasible][nds, 1], c='blue', s=100, label='Pareto Front')

    plt.xlabel("Total Cost (€)", fontsize=12)
    plt.ylabel("Total GHG Emissions (kg CO₂)", fontsize=12)
    plt.title("Pareto Optimal Solutions", fontsize=14)
    plt.legend()
    plt.grid(alpha=0.3)
    plt.tight_layout()
    plt.show()
```

Code 3. Plotting pareto front to visualize the trade off

4.2 Model Validation

The two conditions of NSGA II - convergence and diversity, are evaluated through performance indicators. The model in this study used two indicators to evaluate the model performance: Hypervolume (HV) score and Epsilon indicator.

Performance Indicators

Hypervolume (HV) score: Hypervolume indicator quantifies the volume of the objective space dominated by the Pareto front, relative to a reference point. In other words, it calculates the size of the region that is better (in all objectives) than a chosen reference point and is covered by the non-dominated solutions (Fonseca, 2006). The bigger the number gets with each generation, the better. Below the HV score along with each generation is provided in the table. And from the graph, it can be seen that the HV values increased with each generation (up to 20 generations). The reference number is chosen as [25000, 20000].

Epsilon (ε-Indicator): Epsilon indicator refers to the smallest distance needed to shift the Pareto front to fully dominate a reference front (or true Pareto front). It is considered as a harder metric to fulfill. It measures the precision of the model, while HV indicates the convergence of the model. The smaller the Epsilon value gets with each generation, the better the model performance gets (Liefooghe, 2018). However, in this study Epsilon indicator did not need to be called explicitly. Pymoo library of Pyhton calculated the Epsilon value in the background due to the custom Callback function and setting verbose=True in the optimization, indicated in the result. The code 4 snippet indicates that:

```
# Custom callback to track solutions and measure convergence
class MyCallback(Callback):
    def __init__(self):
        super().__init__()
        self.all_F = []
        self.all_X = []
        self.hypervolume_indicator = HV(ref_point=[25000, 20000])  # Hypervolume indicator with a reference point.

    def notify(self, algorithm):
        # Collect feasible solutions
        feasible = algorithm.pop.get("G").max(axis=1) <= 0  # all constraints satisfied
        self.all_F.extend(algorithm.pop.get("F")[feasible])
        self.all_X.extend(algorithm.pop.get("X")[feasible])

        # Track the Hypervolume indicator (for convergence)
        hv = self.hypervolume_indicator.do(np.array(self.all_F))
        print(f"Generation {algorithm.n_gen} - Hypervolume: {hv:.3f}")

        # Plot the convergence and Pareto front
        self.plot_pareto_front(algorithm)
```

Code 4. Custom callback function for measuring HV and Epsilon indicator

Parameter Tuning

The model was further tested by three different configurations (discussed in detail in next chapter). The model was re-run under these configurations to observe its performance. It returns the pareto front, the best cost, best emission and HV scores for all three configurations.

Code 5 demonstrates the process.

```
# Run all configurations and store results
all_results = []
problem = ProductRepairProblem()

for config in configurations:
    print(f"\nRunning {config['name']}...")
    print(f"Population: {config['pop_size']}, Generations: {config['n_gen']}")
    print(f"Crossover: {type(config['crossover']).__name__}, Mutation Prob: {config['mutation_prob']}")

    callback = ComparisonCallback()

    algorithm = NSGA2(
        pop_size=config['pop_size'],
        sampling=BinaryRandomSampling(),
        crossover=config['crossover'],
        mutation=BitflipMutation(prob=config['mutation_prob']/n_products),
        eliminate_duplicates=True
    )

    termination = get_termination("n_gen", config['n_gen'])
    res = minimize(problem, algorithm, termination=termination, seed=42, callback=callback, verbose=False)

    # Get Pareto front from this run
    pareto_front = callback.get_pareto_front()

    if len(pareto_front) > 0:
        # Store results
        all_results.append({
            'name': config['name'],
            'config': config,
            'pareto_front': pareto_front,
            'hypervolume': HV(ref_point=[25000, 20000]).do(pareto_front)
        })

        # Print summary
        print(f"Found {len(pareto_front)} Pareto solutions")
        print(f"Hypervolume: {all_results[-1]['hypervolume']:.2f}")
    else:
        print("Warning: No feasible solutions found for this configuration")
```

Code 5. Parameter tuning by three different configurations

This chapter discusses in detail about the case study, formulating the problem into mathematical model, how it runs and the relevant codes. The results are discussed in detail in next chapter.

5 Result and Discussion

This chapter will discuss in detail about the model output after first run, model validation results and finally sensitivity analysis.

5.1 Output

After optimization, the code plots the Pareto front showing trade-off between cost and emissions of the products. This pareto front shown in figure 6 is generated based on 20 generations. This pareto front acts like a spectrum for both cost and GHG emission aspects as these two are the objectives of this study.

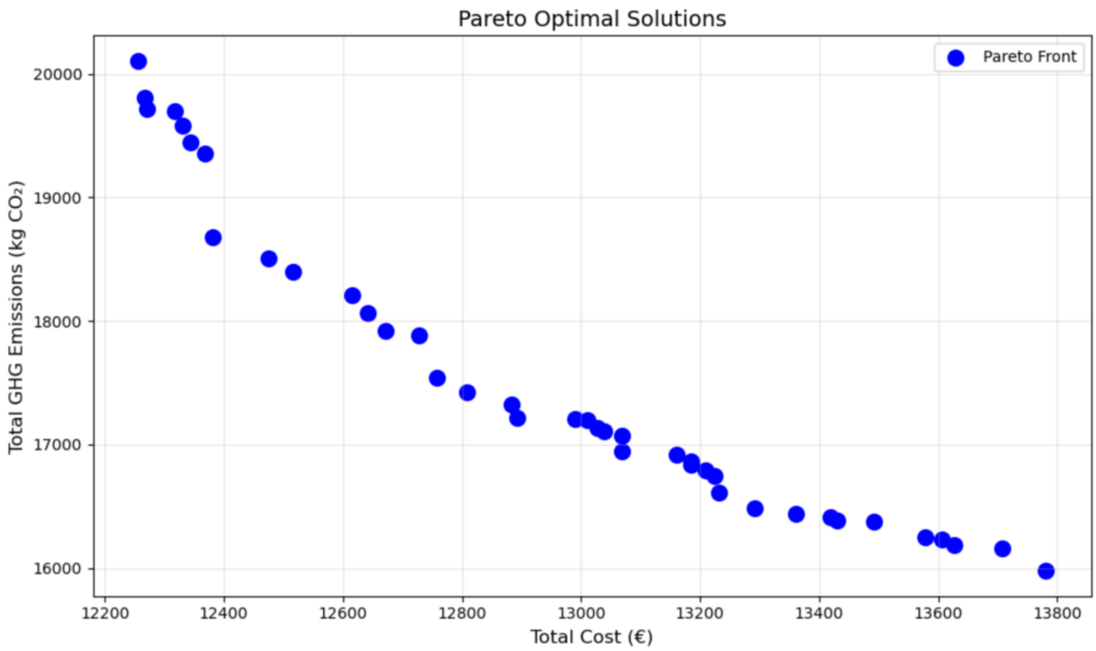

Figure 7. Pareto front after 20 generations

The Pareto Front is a prime concept in multi-objective optimization. It represents a set of solutions where one objective can not be improved without compromising another. When two or more objectives are in conflict-as is often the case in sustainability and economic planning like this case study, the Pareto front serves as a boundary between efficient and inefficient decision-making. In the figure 7, we can see that the Pareto front is visualized as a curve of blue dots that demonstrates the trade-off between total cost in euros (€) and total greenhouse gas (GHG) emissions measured in kilograms of CO_2 for the batch of 50 end of life products. Each point on this curve indicates a non-dominated solution, meaning it is not possible to improve either the cost or emissions without making the other worse.

The figure 7 above demonstrates a negative correlation between cost and GHG emission. It can be seen from the curve that as the total cost increases from €12,200 to €13,800, the GHG emission associated with the cost decreases from around 20,000 kg CO_2 to 16,000 kg CO_2. This indicates a clear trade-off between economic and environmental objectives. For example, if a solution at the lower end of the cost spectrum (e.g., €12,250) is chosen, the decision maker must account for the higher emissions (about 20,000 kg CO_2). Alternatively, achieving lower emissions (e.g., 16,100 kg CO_2) will increase the cost towards €13,800. This phenomenon reflects a classic problem in sustainable development, where economic efficiency and environmental sustainability often pull in opposite directions (Ehrgott, 2005).

Such visualizations are powerful and helpful decision-support tools in case of multi objective decision making. The Pareto front helps the case company to understand the boundaries of efficiency in their system and to choose strategies aligned with their organizational goals or regulatory constraints. It is to be kept in mind that there is not best solution in pareto optimization. The business strategy focused on climate mitigation might prefer solutions on the lower-emissions end of the curve, even at greater cost. On the other hand, if cost is the main priority, solutions closer to the left of the plot, accepting higher GHG emissions to stay within budget can be selected. IF the company aims for a balanced approach, they can go for the point in the middle (around €13,000, and 17,300 kg CO_2) that offers moderate trade-offs. The pareto front emphasizes that solutions which are not on the Pareto front are dominated, meaning there exists at least one solution that is both cheaper and more environmentally friendly. These choices can be further eliminated from consideration, thereby narrowing the decision space to only the most rational options (Deb et al., 2002).

5.1.1 Result: best, worst and average solution

The model returns the best, worst and average solution based on the configuration.

Best Solution: The best solutions of NSGA 2 are those on the Pareto front. In this case, the model returns a best solution like below:

Cost = € 13160.18, Emissions = 16912.80 kg CO_2

Worst Solution: Worst solutions in NSGA 2 are those who are in the last front or rank within the solution space. These solutions are usually excluded from the next generation during selection. Such a result is mentioned below by the current model with Cost = €16454.40 and Emissions = 23641.44 kg CO_2.

Average Solution: The average solution that was returned by the model was below:

Average Cost = € 13791.74

Average Emissions = 18813.81 kg CO_2

The model also returned a statistical values like min, max and number of feasible solution, shown in Table 4.

Table 4. Statistical result of the model after 20 generations

Item	Value
Min Cost	€ 12256,54
Max Cost	€ 16849,49
Min Emissions	15978.52 kg CO_2
Max Emissions	23641.44 kg CO_2
Number of Pareto Solutions	73
Number of Feasible Solutions	6000

The statistical summary in table 4 shows that the minimum cost was € 12256,54 and maximum cost was € 16849,49. Similarly, the minimum and maximum GHG emission was 15978.52 kg CO_2 and 23641.44 kg CO_2 respectively. The model also provided that there were 73 pareto solutions and 6000 feasible solutions. The model also can dives back to which products were repaired and which are disposed from the current population which is shown later.

5.2 Model Validation

Model validation is performed by using performance indicators and parameter tuning.

Performance indicators

There are two basic conditions in the multi-objective optimization evolutionary algorithms (MOEA) like NSGA 2 (Deb, , K. et al., 2002): (1) Convergence and (2) Diversity. Both of the performance indicators: Hypervolume indicator and Epsilon indicators are two different techniques to measure if these two conditions are fulfilled. Parameter tuning is discussed later. From the table 5, it can be seen that the HV value was increased from 9055343,297 in generation 1 to 49137817,43 after generation 20. The increment is clear in the figure 8 showing the HV value per generation also.

Table 5. HV score and epsilon indicator per generation for performance indication

Generation	HV score	Epsilon indicator
Generation 1	9055343,297	0
Generation 2	12363888,94	0,32459125
Generation 3	15526800,57	0,082666891
Generation 4	17273879,25	0,163431948
Generation 5	20305341,59	0,140468711
Generation 6	26368692,99	0,188062963
Generation 7	30777585,20	0,20299503
Generation 8	32483163,45	0,367590004
Generation 9	33512302,91	0,012126553
Generation 10	38033485,90	0,081402774
Generation 11	40529402,23	0,220334357
Generation 12	40749665,07	0,059041713
Generation 13	41026571,07	0,054706601
Generation 14	44135654,93	0,063573889
Generation 15	44500478,00	0,029698081
Generation 16	44911429,52	0,011133322
Generation 17	45771782,39	0,079833342
Generation 18	48920750,85	0,071331155
Generation 19	49060976,34	0,009748667
Generation 20	49137817,43	0,012857462

From the table 5, it can be seen that the HV value was increased from 9055343,297 in generation 1 to 49137817,43 after generation 20.

The increment is evident in the figure 8 showing the HV value per generation also.

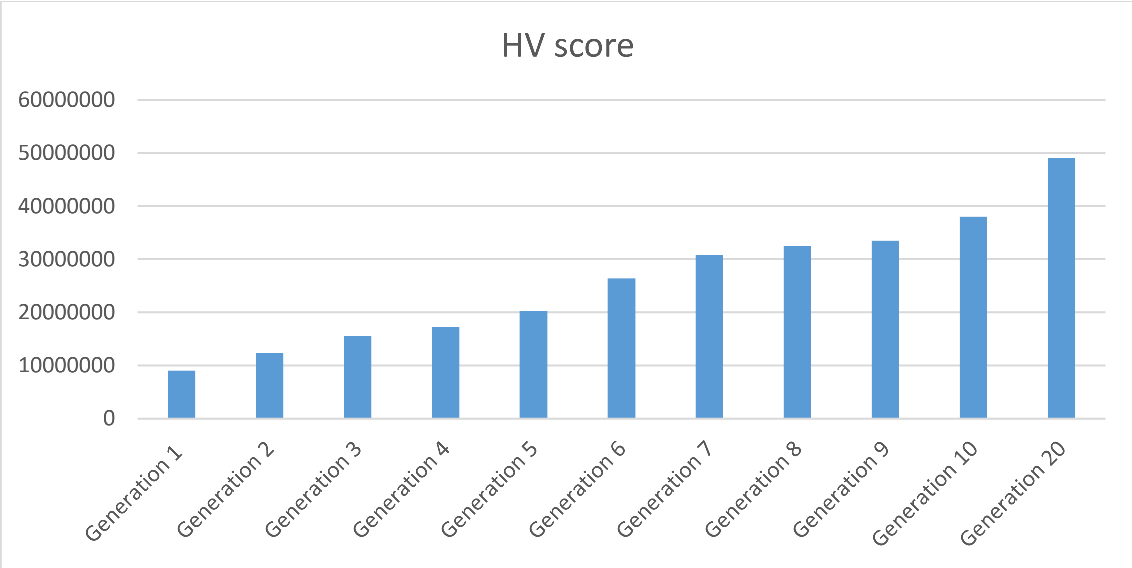

Figure 8. HV score and generations for performance indication

From the figure 9, it can be seen that the Epsilon indicator decreased with each generation despite some fluctuations in between. But gradually the model's Epsilon values decreased when the generations increased and the results were more refined.

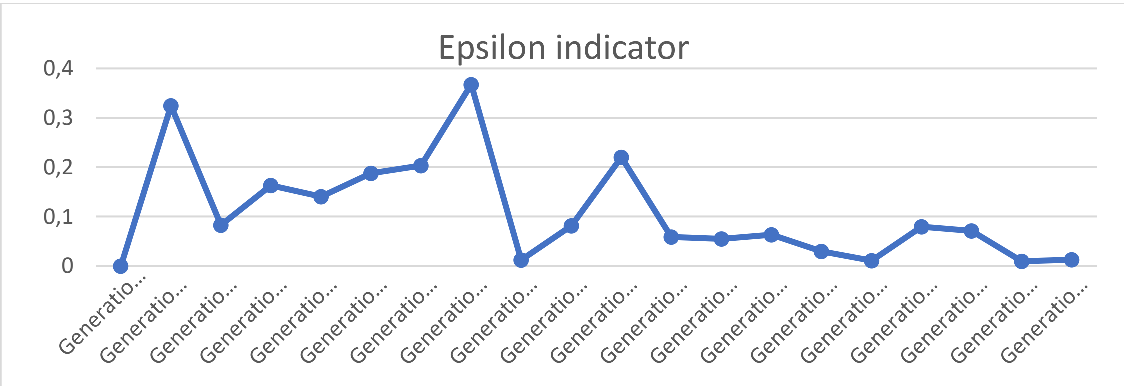

Figure 9. Epsilon indicator per generation

To explain the result with visualization , the Pareto front including the feasible solutions were generated for each generation. Visually, if solutions are clustering near the Pareto front, this shows that the algorithm is converging to optimal solutions. From the figure 10 below, it can be seen that the pareto front of generation1 and other feasible solutions are very scattered. Moreove the cost is about € 15400 and the GHG emission is just below 22000 kg CO_2.

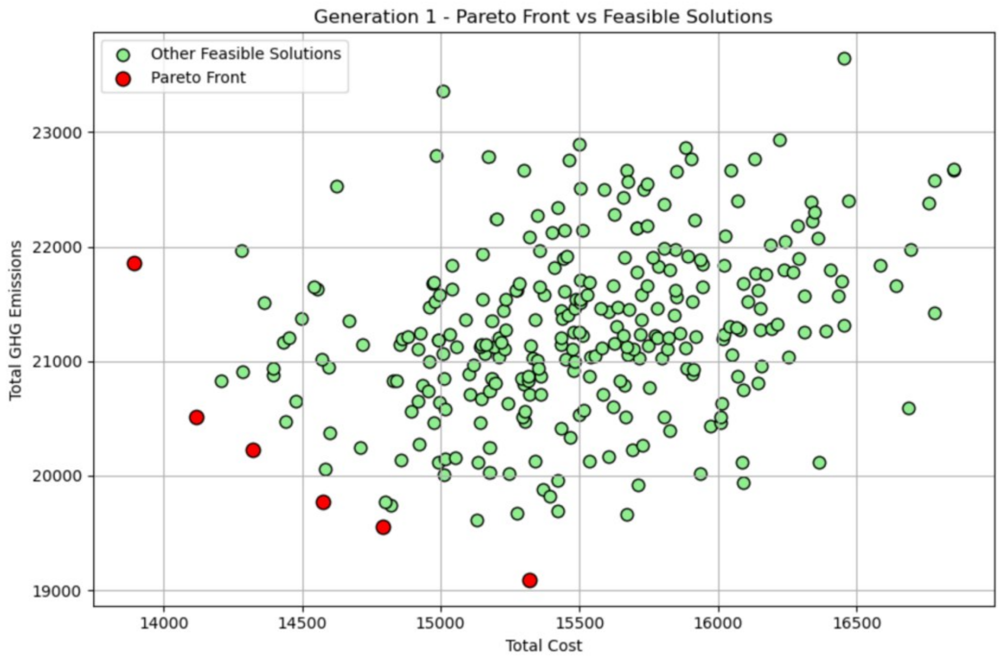

Figure 10. HV status (solution space) after Generation 1

In generation 10 shown in figure 11, both the pareto front and the feasible solutions are gathered to the optimum solution space with increasing number of pareto and feasible solutions compared to the generation 1 solution. But the pareto front is still quite scattered as compared to the ideal or best solution. However, both the cost and GHG emission is reduced compared to generation 1 values, maximum cost being just under € 15000 and maximum GHG emission being 21800 Kg CO_2.

Figure 12 shows the pareto front and other feasible solutions after generation 20. Both the pareto front has become stronger and curvy with more solutions while there are more feasible solutions are clustered in the solution space compared to generation 10 and generation 1 result. The cost point is further reduced compared to generation 10 and 1, being about € 13800. Similarly, the GHG emission value has also reduced compared to generation 10. The maximum GHG emission value is just above the 20000 Kg CO_2

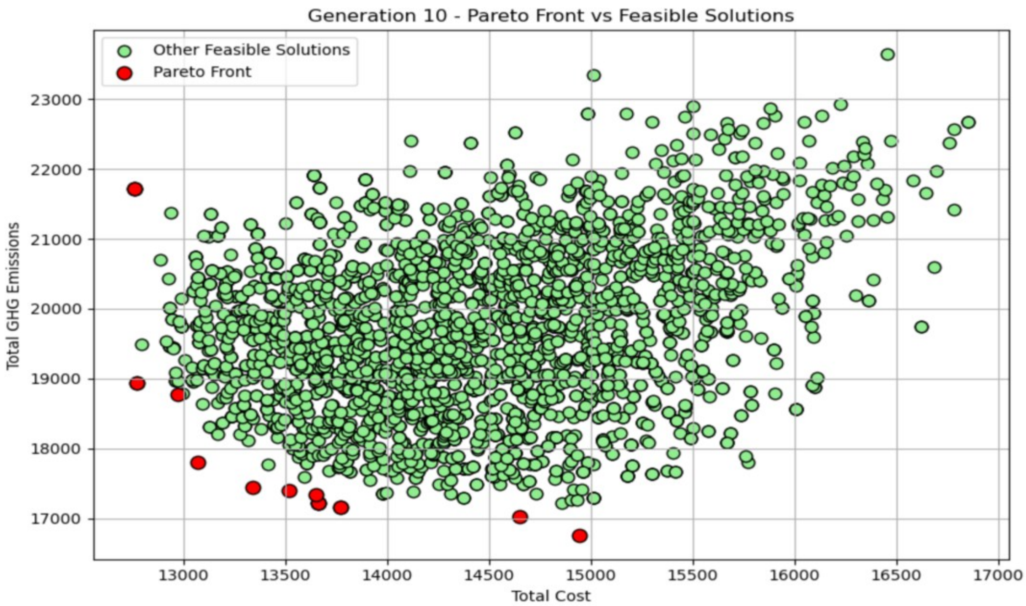

Figure 11. HV status (solution space) after Generation 10

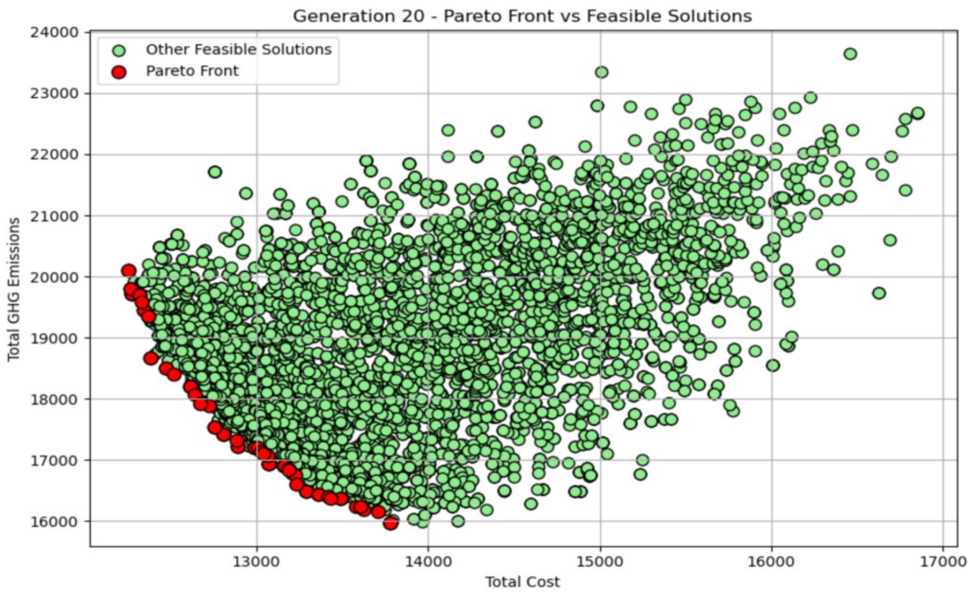

Figure 12. HV status (solution space) after generation 20

From the numerical values and the figures (10-12), it can be assured that the HV growth and reduction in Epsilon indicator confirms NSGA-II found better cost-emission trade-offs over generations meaning convergence with a higher diversity covering more trade-offs.

Parameter Tuning

The parameters of the NSGA 2 algorithms are:

Population size

Generations

Crossover

Mutation

To check the validity of the model further, two further test run were performed. One for 50 generations and another with 100 generations.

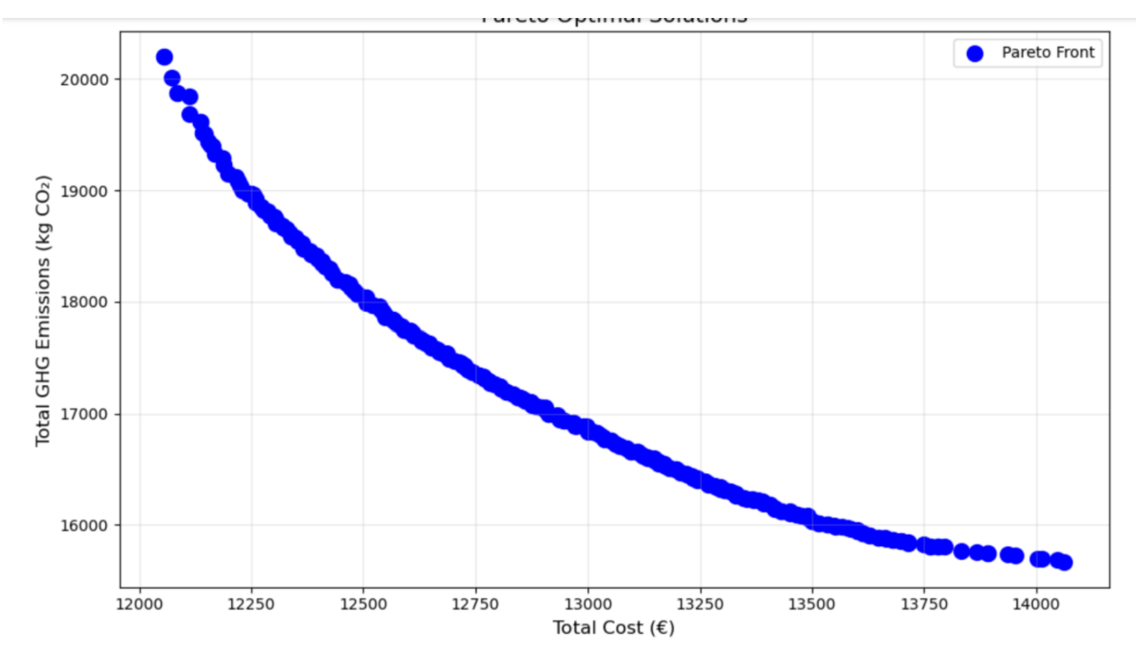

Figure 13. Pareto front after 50 generations

Figure 13 indicates the pareto front after 50 generations. The curve has become more refined with more solution point compared to generation 20. The solution space has also increased as it can be seen from the figure that there are some solution points exceeding cost value as € 14000 and similarly the GHG emission value exceeding 20000 Kg CO_2.

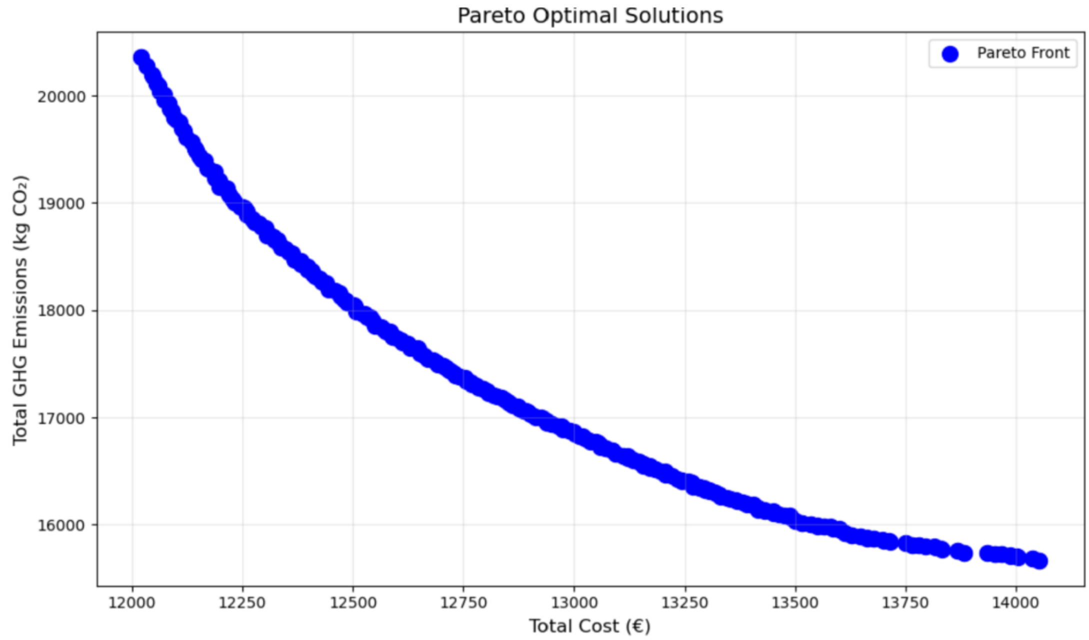

Figure 14. Pareto front after 100 generations

Figure 14 indicates the pareto front after 100 generations There is not much change in the pareto front observed compared to when it was run for 50 generations. Only change was that the pareto front was smoother and had more best solutions for 100 generations compared to 50 generations and 20 generations. But this comes at a price of longer simulation and CPU time compared to smaller generations which acts as a resource constraint in this study.

Configurations

To check the robustness of the model further, the parameters of the algorithm were changed, and the model was run under all these different configurations. The three different configurations are mentioned in table 6 below.

Te model was run under each configuration and the output was observed for all three configuration to see which configuration gives the best output and also how the model reacts under different configurations.

Table 6. Three different configurations for parameter tuning

Parameters	Configuration 1	Configuration 2	Configuration 3
Population Size	500	200	300
Generations	100	50	70
Crossover	Uniform Crossover (prob=0,3)	Uniform Crossover (prob=0,5)	Half-Uniform Crossover
Mutation probability	0,1	0,3	0,2

From the figure 15, the comparison of the Pareto front under three different configurations can be seen. The pareto fronts are close to each other even under different conditions. It indicates that the model reached it's optimum and presented the best solutions possible under different configurations. Configuration 1, which has larger populations but fewer generations compared to that, showed the longest pareto front covering a wide range of cost and GHG emission. Configuration 3 which is a balance between the large population and small population, showed somewhat similar output as the configuration 1 but with less spread. Configuration 2 which had small population and generations showed shorter span of pareto front.

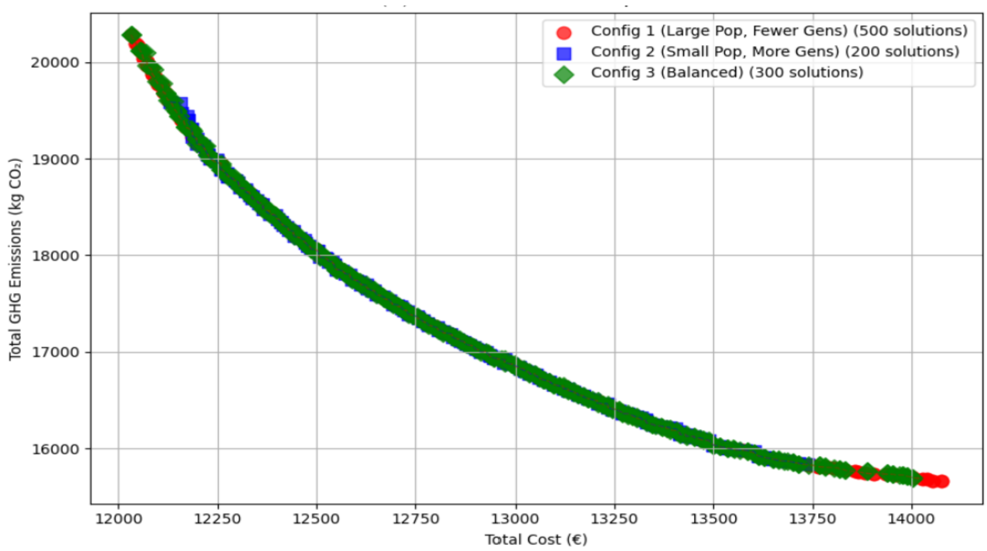

Figure 15. Pareto front comparison for three configurations

However, the comparison of three pareto fronts is not very clear from the graph due to they being very close to each other. It is not possible to come to conclusion to from this chart alone on which configuration performed better than the others. For this reason, the results are analysed further. The results were broken down into cost wise, GHG emission wise and Hypervolume wise to cross check and validate the convergence of the model and optimality of the solutions under different configurations. Breaking down the results and analyzing it separately made it easier to compare and help decision maker to help with decision making.

Best cost improvements: It can be seen from figure 16 that all models are coarse at the beginning but with increment of generation, they started to smooth out and flat. configuration 2 (blue) started from the higher price point compared to other 2 configurations. It also has more disruptions than other two configurations. But after 20th generation, it started to become smooth and flatter than before. It was flattening even more but it ran for 50 generations. It stopped after 50 generations.

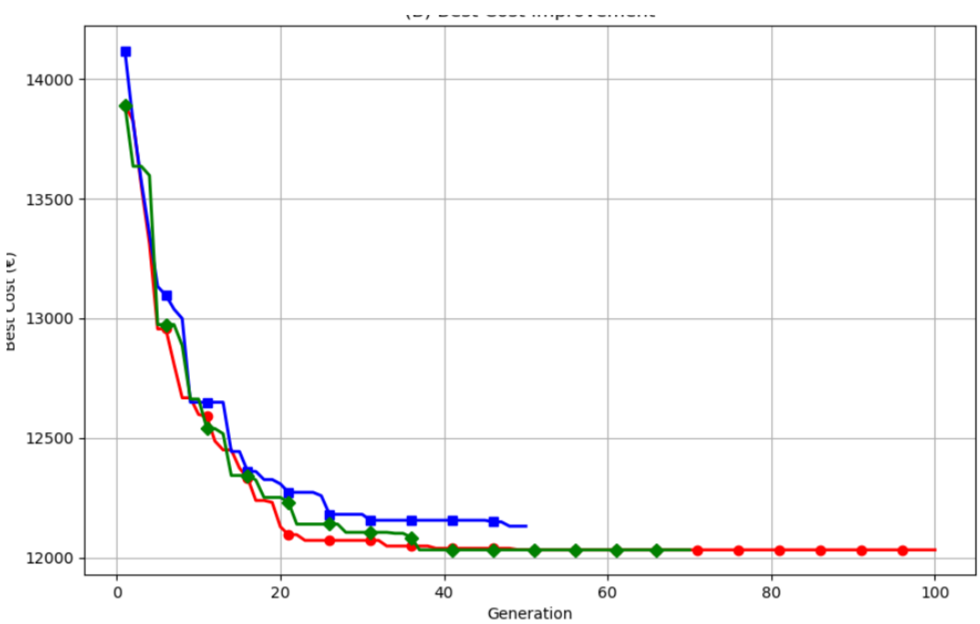

Figure 16. Best cost comparison of all 3 configurations

The Blue curve shows that the model has still room for improvement if it can be run for higher number of generations. Configuration 1 (Red) started to flatten and smoothed out after 40th generations. It became somewhat stable after that and did not change in values much. It indicates that it did not improve very significantly after 40 generations. Same for the configuration 3(Green), it became stable after 40th generations and changed in very small amount. After 60th generation, both configuration 1 and configuration 3 were on same line and returned same value. It means that the model was converged in both cases as nothing was significantly improving anymore.

Best emissions improvement: From the figure 17 below, it can be seen that configuration 2 (Blue), which has the smallest population and generation size, was fluctuating when the number of generations were small. It slowly became smoother after 30th generations. After 40 generations, it became stable and did not change in values much, meaning it was converged. Configuration 1 (Red), which was the biggest population and generation size, it also had the similar trend. But it showed a lower value of GHG emission with each generations compared to configuration 2 and 3.

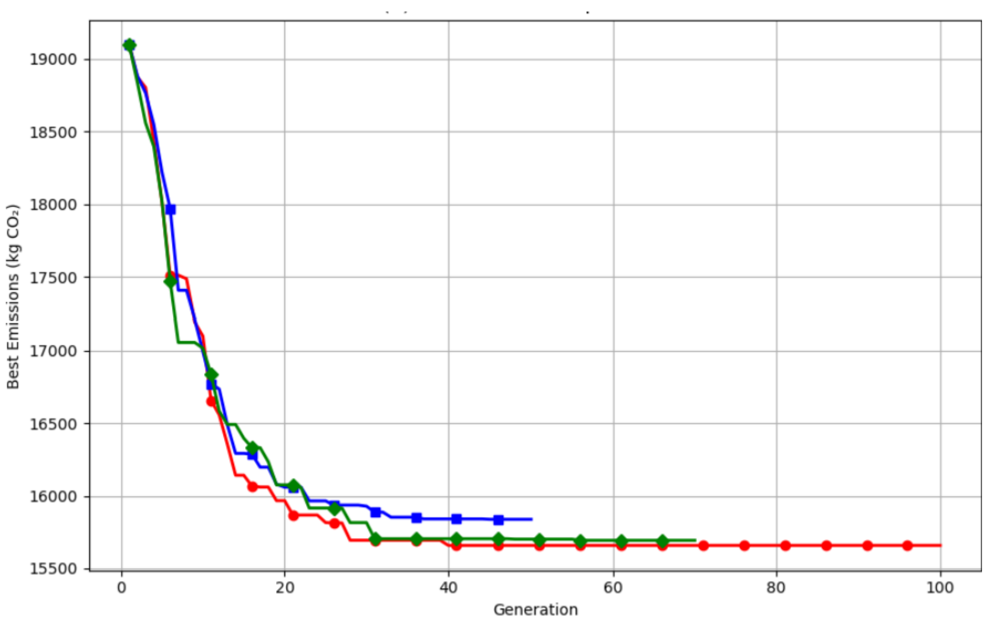

Figure 17. Best GHG emissions comparison of 3 configurations

The trend line started to smooth out and became flat after 40 generations. It has the lowest GHG emission among all 3 configurations. Finallly, Configuration 3 is was in between configuration 1 and 2. The trend line was lower than configuration 2 (Blue) but higher than configuration 1 (Red). It became flat and smooth after 30 generations. It did not change in value after that meaning the model was converging toward optimality. A common similarity was among all 3 configurations that they were rougher in the beginning but became flat after a certain number of generations when they started to converge. Configuration 3 is smoother than the other 2 configurations. Configuration1 gives slightly lower emissions than configuration 3 and significantly lower than configuration 2. If the decision maker wants to prioritize sustainability and look for lower GHG emission solutions, configuration 3 will be better choice. If the decision maker want to compromise a little but with save on computational cost and time, configuration 3 will be more suitable.

Hypervolume progress: From the figure 18, it can be seen that the configuration 2 (blue) which has smallest population size, increased the hypervolume indicator until 30 generations. But after that, it did not improve much. But it was stable in the same value. Configuration 3 (Green) which had a medium population, was coarse till generation 30 and after that it started to become smooth. It became stable and did not improve much in numerical values either. Configuration 1(Red), which had the largest populations among 3 configurations, steeply improved till generation 30. After that, the increment became less significant. But it improved compared to configuration 2 and 3. Finally, it became flat meaning it reached to convergence. IF looking closely, configuration 3 almost matched configuration 1 from generation 3. There was only a slight difference. However. Configuration1 showed better performance than the other two configurations.

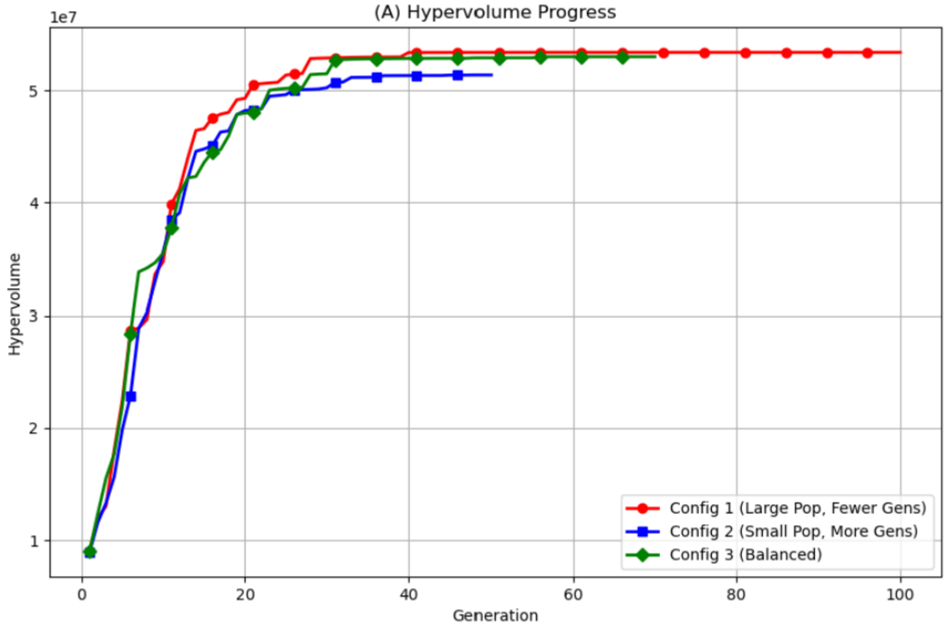

Figure 18. Hypervolume progress comparison

From the discussion, it can be concluded that in all three aspects, configuration 1 provided the best result. But configuration 1 also took much more time for generating solutions and needs higher computational resources. Configuration 2 provided the poor solutions among these 3. And configuration 3 showed same cost but slightly higher GHG emission and lower Hypervolume value compared to configuration 1. The values are mentioned in the table 7. From this table, we can conclude that if the decision maker (case company) wants to prioritize precision and GHG emission, they can select the configuration 3 result. But if they want to compromise on precision and GHG emission for the computational expenses, going for configuration is a good choice.

Table 7. Result summary comparison of 3 configuration

Metric	Config 1	Config 2	Config 3
Hypervolume	53402264,2	51389159,7	53014049,5
Best Cost (€)	12031,6	12245,9	12031,6
Best Emissions (kg CO2)	15658,5	15838, 0	15693,4

Since the objective is to minimize cost and minimize GHG emission, the best solution is provided by configurations 1. Below in table 8 indicates the number of repaired products , number of disposed and number of products whose budget were violated according to configuration 1.

Table 8. Decision Result summary

Decision result	Number of products
Number repaired	19
Number disposed	31
Budget violated	14

Table 9 shows the result returned from the model for repaired products

Table 9. Products with Repaired decision

Product	Quality	Age (yrs)	Budget (€)
1	good	3	421,25
5	good	9	573,24
7	poor	5	411, 35
13	poor	2	335,06
14	good	4	499,92

Table 10 shows the result returned from the model for disposed products. The model also mentioned which products cost exceeded the budget and that’s why disposed.

Table 10. Products with disposal decision

Product	Quality	Age (yrs)	Budget status
9	good	7	Budget exceeded
10	poor	12	-
19	poor	10	-
27	good	4	Budget exceeded
30	poor	14	-

5.3 Sensitivity Analysis

Sensitivity analysis is done based on quality, distance and budget factors. I also considered testing the symmetry of the model and that is why we considered increasing and reducing 20% of all factors, one at a time while keeping others constant (same as before). These three factors are crucial in this model as they are also contributing to the constraints and formulation of the model. All the different scenarios under each criteria is listed in table 11 below. And all the pareto fronts generated from different scenerios are displayed in figure 18. Table 12 demonstrates Hypervolume score for different scenarios compared to base score. Figure 19 is the graphical representation of the difference percentage (both positive and negative) of the HV scores of different scenerios.

Table 11. Factors and criteria for sensitivity analysis

Quality	Distance	Budget
20% More Good Products	Increase Distance 20%	Increase Budget 20%
20% More Good Products		
20% More Poor Products	Reduce Distance 20%	Reduce Budget 20%
20% Less Poor Products		

Quality:

From figure 19, when percentage of good quality products increase by 20%, the pareto front moves downward compared to the original pareto front, with lower cost and lower emission compared to original pareto front (Royal Blue), indicating more efficiency. It also had more optimal point having more trade-off options. The HV score also validates it. The HV score increased by 14% (Table 12) than the original base case indicating the better performance of the model. On the other hand, when the percentage is reduced by 20% (Orange), it moves further from the optimal solution increasing both cost and emission in the pareto front. The HV score reduced by 14% justifying the situation. It means the pareto front moved objectively further from the efficiency.

When percentage of poor products is increased by 20% (Green), it moved significantly away from the original pareto front meaning both the cost and emission became way higher compared to the original pareto front. The number of optimal points also reduced significantly compared to the original pareto front. The pareto front HV score was also reduced by 40% than the base case. The sharp drop indicates that the model is very sensitive to product quality. But when the percentage is reduced by 20% (purple), the pareto front went downward from the original front, indicating more convergence than the original pareto front and having better performance. It is also confirmed by the highest HV score among all the scenarios and having the highest increase in percentage wise (26%), shown in table 12 and figure 20. It is clear from the chart that the model is very sensitive to product quality. If the quality of the products are poor, it increases both the cost and GHG emission, which is also the case in real life. The repair effort increase when the product quality is poor compared to good quality End of life products.

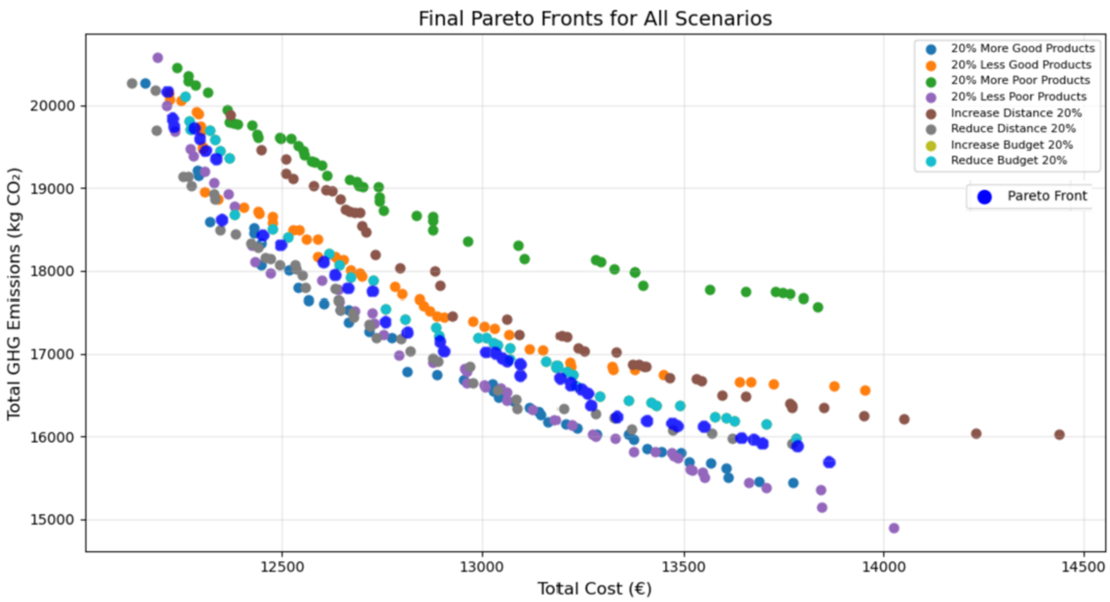

Figure 19. Sensitivity analysis for different factors and symmetry

Distance:

The increase in distance by 20% (Brown) took the pareto line further away from the original value both in terms of emission and cost in figure 19. It also spreads across the higher cost and emission. The HV score of this model was decreased by 3% compared to the base score from the original pareto front, as per table 12. But when the distance percentage is reduced by 20%, the pareto front moved downward from the original front indicating better convergence with lower cost and emission. From table 12, having a higher HV value and a positive 3% , as per figure 20, increment from the primary state also justifies that. But from the difference in HV score for both increasing and deceasing the distance, the change is very symmetric in this case, unlike the scenarios in quality.

Table 12. Hypervolume score for different scenarios compared to base score

Criteria	Hypervolume score	Difference %
Base case	49137817,43	0%
20% Less Poor Products	6,20E+07	26 %
20% More Good Products	5,60E+07	14 %
Reduce Distance 20%	5,05E+07	3%
Increase Budget 20%	4,91E+07	0%
Reduce Budget 20%	4,91E+07	0%
Increase Distance 20%	4,77E+07	-3 %
20% Less Good Products	4,22E+07	-14%
20% More Poor Products	2,94E+07	-40 %

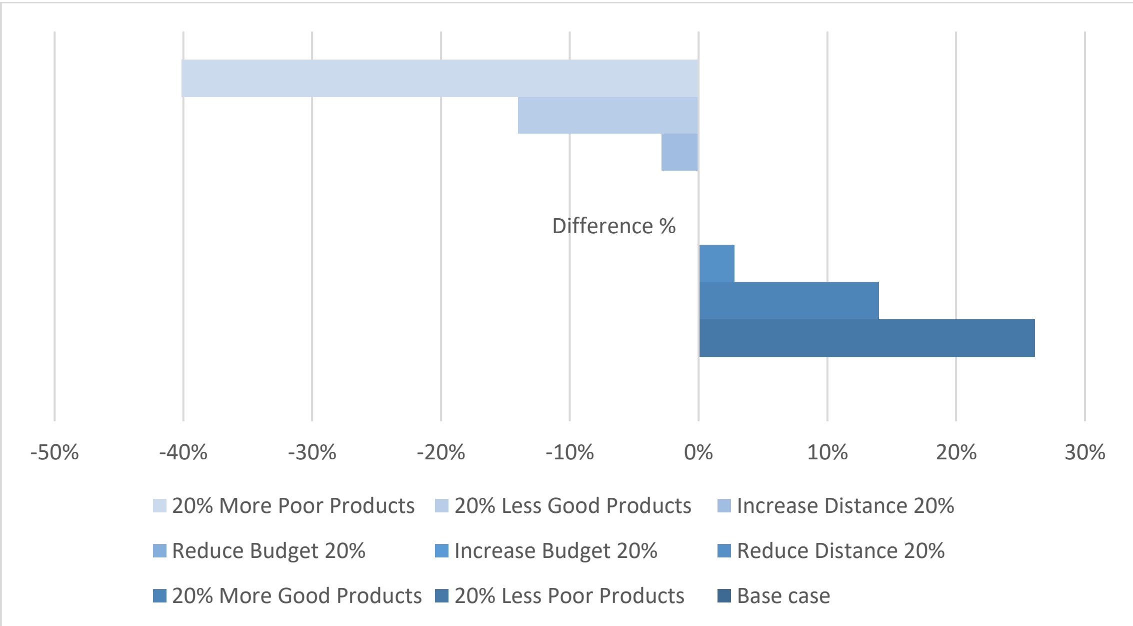

Figure 20. Hypervolume score change with sensitivity analysis

Budget:

Reducing or increasing budget by 20% did not have very significant effect in this case. They have the same pareto front not visible in figure 19, and very close to the original pareto front. It means that in both cases, products that were worth repairing could still be repaired even with a smaller budget. Products that weren’t cost-effective to repair didn't get included even with a higher budget. Further change of budget in future can have effect that can be performed in future.

From the sensitivity analysis, it is clear than the level of quality of returned products and the distance has higher impact on the model. Also, it is to be noted that the change in the model is not really symmetric under different scenarios. For example, under quality, the model was more sensitive to poor quality products (poor performance) than the change in good quality products. So it is better to crosscheck the symmetry of the model , even in linear systems.

5.4 Managerial implications

This research contributes to both practical decision-making and academic understanding. Practically, it helps manufacturing companies implement CE strategies by providing a decision-making tool that aligns economic and environmental objectives.

Managers must recognize the trade-off between minimizing costs and reducing greenhouse gas (GHG) emissions when deciding whether to repair or dispose of EoL products. The research shows that solutions with lower emissions tend to incur higher costs, and vice versa. Therefore, decision-making should be context-specific, comparing corporate sustainability goals against financial constraints.

The use of NSGA-II for multi-objective optimization can be helpful for decision makers and technical teams by integrating it into their decision-making frameworks to better navigate complex trade-offs.

The sensitivity analysis revealed that product quality is the most influential factor in improving both cost and environmental outcomes. Companies are advised to invest in better quality management system and sorting processes for returned products. The higher proportion of good quality returns can lead to more cost-effective and sustainable operations.

The model's design, which treated the budget as a hard constraint, reflects real-world operational limitations. Managers can apply this logic to filter out the economically infeasible options early, ensuring efficient decision process.

The findings also have implications for policymakers and product designers also. Product designs that are easier to repair and disassemble, investment in reverse logistics infrastructure support building circular economy initiatives.
By providing a systematic framework for data-driven decisions in EoL electrical drive management, this study offers an important step toward operationalizing circular economy goals in real-world industrial contexts.

5.5 Future Study

This research contributes significantly from academic perspective. Theoretically, the research extends current work on sustainable operations by combining MILP and evolutionary algorithms in a novel application area. However, the future study can be directed in many ways.

A future improvement of this decision model can be about condition-based maintenance and considering lifecycle emission and costing of the products. Since profits and reducing GHG emission is most important for manufacturer. Additionally, policies like carbon tax, minimum repairability standards, social lifecycle criteria can be also added into the analysis. But to perform this type of analysis, a huge amount of historical data will be required. Further, different circularity KPIs like material recovery rate could be also included.

Electrical drives are complicated products. Key components in the electrical drives are often subject to thermal wear, vibration, operating hours, failure etc. In future, a more detailed study considering breaking down the quality based on reliability and condition (physical, performance, material etc) and optimizing decisions for individual components (e.g., replacing bearings vs. rewinding motors) can be performed.

The model considered in this study was deterministic. But it can be turned into into a probabilistic model integrating uncertainty in quality, number of returned products, or even pricing. Another approach can be multi-period optimization with supply chain network integration including warranty period, inventory, different plant locations and more transport modes.

Lastly, the model can be ensembled into hybrid models. Ranking the decisions based on MCDM methods (TOPSIS, PROMETHE, VIKOR, ELECTRE etc.), combining machine learning models (e.g., random forests) to predict quality from operational data, then feed into NSGA-II.

While this study provides a foundational framework for sustainable End-of-life decision-making, future work should balance computational rigor with real-world applicability, ensuring solutions align with the triple bottom line: profit, planet, and people.

6 Conclusion

This study investigated how multi-objective optimization (MOO) can help to make decisions regarding whether to repair or dispose of End-of-Life (EoL) electrical drives, with the goal of balancing cost and environmental impact. This research bridges theory and practice, offering a replicable framework for sustainable EoL products decision making. The case study was at first formulated as Mixed Integer Linear Programming (MILP). Then NSGA-II algorithm was applied for the problem being a multi objective optimization that aims to minimize both total costs and greenhouse gas (GHG) emissions, while also considering constraints related to budget, product quality, and transport distance.

The results showed a trade-off between cost and emissions, including the lower-cost solutions were related to higher emissions, whereas reducing emissions to 16,000 kg CO_2 increased the costs to around €13,800. This highlights the importance of making context-specific decisions.

From a methodological perspective, the NSGA-II algorithm proved effective in generating a wide range of solutions, as shown by the significant improvement in hypervolume (HV) over 20 generations. The model was validated using performance indicators like Hypervolume and epsilon score. The model was further adjusted by parameter tuning and running the model with three different configurations (large, medium and small). Among these three configurations, the configuration 1 which had highest number of population and generations, provided the best result for the model with the minimum cost of €12031,60 and GHG emission of 15658,5 Kg Co2.

Then to check the robustness of the model a detailed sensitivity analysis was performed using the one-at-a-time (OAT) method including different important factors like quality, budget and distance. Product quality had a strong influence on performance of the model. Increasing the proportion of good-quality products by 20% improved efficiency, reducing both costs and emissions. On the other hand, a 20% increase in poor-quality products significantly worsened performance. Transport distance also had an impact-reducing it by 20% led to a 3% drop in emissions, while longer distances raised costs. Interestingly, changes to the budget (±20%) had little effect on decisions, suggesting that technical feasibility played a larger role than financial limits.

It was confirmed that product quality and transport distance were the most influential factors, while changes in budget had minimal effect. The reason was the budget of the products were applied as a hard constraint in this model. For this reason, the infeasible solutions were already out of the feasible solutions space because of violating the budget constraint. This way, the solution space had more feasible options making the computation and the model for efficient and suitable for real world problem solving. Because in real-world environment, it does not make any sense economically to repair a product if it costs higher than the estimated budget for the product which may result in an loss for the company.

The findings of this study indicates valuable insights for practice in real life. The case company and other similar enterprises are recommended to pay attention on collecting higher-quality returned products to reduce both costs and emissions. Policymakers can also advised to support product designs that are easier to repair and to enhance reverse logistics systems, in order to support circular economy goals.

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References

Chaudhari, P., Thakur, A. K., Kumar, R., Banerjee, N., & Kumar, A. (2022). Comparison of NSGA-III with NSGA-II for multi objective optimization of adiabatic styrene reactor. *Materials Today: Proceedings*, *57*, 1509–1514. https://doi.org/10.1016/j.matpr.2021.12.047

Coello Coello, C. A. (2006). Evolutionary multi-objective optimization: A historical view of the field. *IEEE Computational Intelligence Magazine*, *1*(1), 28–36. https://doi.org/10.1109/MCI.2006.1597059

Cornelis P. Baldé, Ruediger Kuehr, Tales Yamamoto, Rosie McDonald, Elena D'Angelo, Shahana Althaf, Garam Bel, Otmar Deubzer, Elena Fernandez-Cubillo, Vanessa Forti, Vanessa Gray, Sunil Herat, Shunichi Honda, Giulia Iattoni, Deepali S., Khetriwal, Vittoria Luda di Cortemiglia, Yuliya Lobuntsova, Innocent Nnorom, & Noémie Pralat, Michelle Wagner. (n.d.). *THE GLOBAL E-WASTE MONITOR 2024*.

Deb, K., & Jain, H. (2014). An Evolutionary Many-Objective Optimization Algorithm Using Reference-Point-Based Nondominated Sorting Approach, Part I: Solving Problems With Box Constraints. *IEEE Transactions on Evolutionary Computation*, *18*(4), 577–601. https://doi.org/10.1109/TEVC.2013.2281535

Ishibuchi, H., Setoguchi, Y., Masuda, H., & Nojima, Y. (2017). Performance of Decomposition-Based Many-Objective Algorithms Strongly Depends on Pareto Front Shapes. *IEEE Transactions on Evolutionary Computation*, *21*(2), 169–190. https://doi.org/10.1109/TEVC.2016.2587749

Lieder, M., & Rashid, A. (2016). Towards circular economy implementation: A comprehensive review in context of manufacturing industry. *Journal of Cleaner Production*, *115*, 36–51. https://doi.org/10.1016/j.jclepro.2015.12.042

Potting, J., Hekkert, M., Worrell, E., & Hanemaaijer, A. (2017). *CIRCULAR ECONOMY: MEASURING INNOVATION IN THE PRODUCT CHAIN*.

Qingfu Zhang & Hui Li. (2007). MOEA/D: A Multiobjective Evolutionary Algorithm Based on Decomposition. *IEEE Transactions on Evolutionary Computation*, *11*(6), 712–731. https://doi.org/10.1109/TEVC.2007.892759

Wernet, G., Bauer, C., Steubing, B., Reinhard, J., Moreno-Ruiz, E., & Weidema, B. (2016). The ecoinvent database version 3 (part I): Overview and methodology. *The International Journal of Life Cycle Assessment, [Online]*, *21*(9), 1218–1230.

Zitzler, E., Laumanns, M., & Thiele, L. (2001). *SPEA2: Improving the strength pareto evolutionary algorithm* (p. 21 p.) [Application/pdf]. ETH Zurich. https://doi.org/10.3929/ETHZ-A-004284029

ABB. (n.d.). Drives. https://www.abb.com/global/en/product/drives

Saunders, M.N.K., Lewis, P. and Thornhill, A. (2019). Research Methods for Business Students. 8th Edition, Pearson, New York.

Ellen MacArthur Foundation. (2015). Towards the Circular Economy: Economic and business rationale for an accelerated transition. Retrieved 24 April 2025 from https://ellenmacarthurfoundation.org/towards-the-circular-economy-vol-1

Global Market Insights. (2024). AC Drives Market Size – By Voltage, By Application, By End-Use, Analysis, Share, Growth Forecast, 2025 – 2034. Retrieved from https://www.gminsights.com/industry-analysis/ac-drives-market

Krishnan, R. (2001). Electric Motor Drives: Modeling, Analysis, and Control. Prentice Hall.

Leonhard, W. (2001). Control of Electrical Drives. (3rd ed.). *Springer.* DOI:10.1007/978-3-662-04722-9.

Mohan, N. (2003). Electric Drives: An Integrative Approach. MNPERE. ISBN 0-9715292-1-3.

J. Holtz,(1994). Pulsewidth modulation for electronic power conversion. *Proceedings of the IEEE*, vol. 82, no. 8, pp. 1194-1214. doi: 10.1109/5.301684.

Blaschke, F. (1972). The principle of field orientation as applied to the new transvector closed-loop system for rotating-field machines. *Siemens Review, 34*(3), 217–220.

Vas, P. (1998). Sensorless Vector and Direct Torque Control. Oxford University Press.

Pillay, P., & Krishnan, R. (1989). Modeling, simulation, and analysis of permanent-magnet motor drives. II. The brushless DC motor drive. *IEEE Transactions on Industry Applications, 25*(2), 274–279. https://doi.org/10.1109/28.25542

Kirchherr, J., Reike, D., & Hekkert, M. (2017). Conceptualizing the circular economy: An analysis of 114 definitions. *Resources, Conservation and Recycling, 127*, 221–232. https://doi.org/10.1016/j.resconrec.2017.09.005

Geissdoerfer, M., Savaget, P., Bocken, N. M. P., & Hultink, E. J. (2017). The Circular Economy – A new sustainability paradigm? *Journal of Cleaner Production, 143*, 757–768. https://doi.org/10.1016/j.jclepro.2016.12.048

European Environment Agency. (2016). Circular economy in Europe: Developing the knowledge base (EEA Report No 2/2016). https://www.eea.europa.eu/publications/circular-economy-in-europe

Guide, V. D. R., Jayaraman, V., & Linton, J. D. (2003). Building Contingency Planning for Closed-Loop Supply Chains with Product Recovery. *Journal of Operations Management, 21*(3), 259–279. DOI:10.1016/S0272-6963(02)00030-6

Govindan, K., Soleimani, H., & Kannan, D. (2015). Reverse Logistics and Closed-Loop Supply Chain: A Comprehensive Review to Explore the Future. *European Journal of Operational Research, 240*(3), 603–626. DOI:10.1016/j.ejor.2014.07.012

European Parliament and Council. (2012). Directive 2012/19/EU on waste electrical and electronic equipment (recast). *Official Journal of the European Union*.

European Parliament and Council. (2003). Directive 2002/96/EC on waste electrical and electronic equipment (WEEE). OJ L 37, 13.2.2003.

Khetriwal, D. S., Kraeuchi, P., & Widmer, R. (2011). Producer Responsibility for E-Waste Management: Key Issues for Consideration – Learning from the Swiss Experience. *Journal of Environmental Management, 90*(1), 153–165. DOI:10.1016/j.jenvman.2007.08.019

Ongondo, F. O., Williams, I. D., & Cherrett, T. J. (2011). How are WEEE Doing? A Global Review of the Management of Electrical and Electronic Wastes. *Waste Management, 31*(4), 714–730. DOI:10.1016/j.wasman.2010.10.023

European Parliament and Council. (2011). Directive 2011/65/EU on the restriction of hazardous substances (RoHS 2). OJ L 174, 1.7.2011.

European Parliament and Council. (2003). Directive 2002/95/EC on the restriction of hazardous substances (RoHS). OJ L 37, 13.2.2003.

European Parliament and Council. (2011). Directive 2011/65/EU on the restriction of hazardous substances (RoHS 2). OJ L 174, 1.7.2011.

Widmer, R., Oswald-Krapf, H., Sinha-Khetriwal, D., Schnellmann, M., & Boni, H. (2005). Global Perspectives on E-Waste. *Environmental Impact Assessment Review, 25*(5), 436–458. DOI:10.1016/j.eiar.2005.04.001

European Commission. (2015). *Closing the loop – An EU action plan for the circular economy* (COM(2015) 614 final). https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:52015DC0614

European Commission. (2020). *A new circular economy action plan for a cleaner and more competitive Europe* (COM(2020) 98 final). https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:52020DC0098

European Commission. (2019). *The European Green Deal* (COM(2019) 640 final). https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:52019DC0640

European Parliament and Council. (2022). Directive (EU) 2022/2464 on corporate sustainability reporting (CSRD). OJ L 322, 16.12.2022.

European Commission. (2023). Proposal for a Regulation establishing a framework for ensuring a secure and sustainable supply of critical raw materials. COM(2023) 160 final.

European Union. (2024). Regulation (EU) 2024/1252 on critical raw materials. Official Journal of the European Union. https://eur-lex.europa.eu/eli/reg/2024/1252/oj

Bocken, N. M. P., Bakker, C., & Pauw, I. D. (2016). Product design and business model strategies for a circular economy. *Journal of Industrial and Production Engineering, 33*(5), 308–320. DOI:10.1080/21681015.2016.1172124

Prendeville, S., Cherim, E., & Bocken, N. (2014). Circular Economy Design and Education: A Workshop Experience. *Procedia CIRP, 69*, 608–613. DOI:10.1016/j.procir.2017.11.060

Tukker, A. (2015). Product services for a resource-efficient and circular economy – a review. *Journal of Cleaner Production, 97*, 76–91. DOI:10.1016/j.jclepro.2013.11.049

Tukker, A. (2004). Eight types of product–service system: Eight ways to sustainability? Experiences from SusProNet. *Business Strategy and the Environment, 13*(4), 246–260. DOI:10.1002/bse.414

Bressanelli, G., Perona, M., & Saccani, N. (2018). Reshaping the washing machine industry through circular economy and product-service system business models. *Procedia CIRP, 73*, 180–185. https://doi.org/10.1016/j.procir.2017.03.065

Roskladka, N., Bressanelli, G., Saccani, N., & Miragliotta, G. (2025). Repairable electronic products for the circular economy: A review of design for repair features, practices and measures to contrast obsolescence. *Discover Sustainability, 6*, Article 53. https://doi.org/10.1007/s43621-024-00753-x

Fairphone. (n.d.). *We are Fairphone. Our journey so far*. Retrieved April 26, 2025, from https://shop.fairphone.com/about-us

Philips. (n.d.). *Breaking the vicious cycle with circular lighting*. Retrieved April 26, 2025, from https://www.mea.lighting.philips.com/support/blog/design/taking-a-circular-lighting-approach

Forlin, V., & Scholz, E.-M. (2020). Strategic take-back programs when consumers have heterogeneous environmental preferences. *Resource and Energy Economics, 60*, 101150. https://doi.org/10.1016/j.reseneeco.2020.101150

Patagonia. (n.d.). *Worn Wear*. https://wornwear.patagonia.com/

McCollough, J. (2009). Factors impacting the demand for repair services of household products: The disappearing repair trades and the throwaway society. *International Journal of Consumer Studies, 33*(6), 619-626. https://doi.org/10.1111/j.1470-6431.2009.00793.x

European Union. (2024). *Directive (EU) 2024/1799 of the European Parliament and of the Council of 13 June 2024 on common rules promoting the repair of goods and amending Regulation (EU) 2017/2394 and Directives (EU) 2019/771 and (EU) 2020/1828*. Official Journal of the European Union, L 1799. https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A32024L1799

Prakash, S., Dehoust, G., Gsell, M., Schleicher, T., & Stamminger, R. (2020). Influence of the Service Life of Products in Terms of Their Environmental Impact:

Establishment of an Information Base and Development of Strategies against "Obsolescence." Oeko-Institut. https://www.umweltbundesamt.de/publikationen/influence-of-the-service-life-of-products-in-terms

Cordella, M., Alfieri, F. and Sanfelix Forner, J. (2019). Analysis and development of a scoring system for repair and upgrade of products, EUR 29711 EN. doi:10.2760/725068, JRC114337.

Christensen, J., & Bastien, C. (2016). Introduction to general optimization principles and methods. *Nonlinear optimization of vehicle safety structures* (pp. 107–168). Butterworth-Heinemann. https://doi.org/10.1016/B978-0-12-417297-5.00003-1

Coello Coello, C. A., Lamont, G. B., & Van Veldhuizen, D. A. (2007). *Evolutionary algorithms for solving multi-objective problems* (2nd ed.). Springer. https://doi.org/10.1007/978-0-387-36797-2

Miettinen, K. (2008). Introduction to Multiobjective Optimization: Noninteractive Approaches. In: Branke, J., Deb, K., Miettinen, K., Słowiński, R. (eds) Multiobjective Optimization. Lecture Notes in Computer Science, vol 5252. Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-3-540-88908-3_1

Zhang, Q., & Li, H. (2007). MOEA/D: A multiobjective evolutionary algorithm based on decomposition. *IEEE Transactions on Evolutionary Computation, 11*(6), 712–731. https://doi.org/10.1109/TEVC.2007.892759

Altınöz, O. T. (2023). Comparing decomposition-based multiobjective optimization algorithms. In Proceedings of the 2nd International Conference on Innovative Academic Studies.

Collette, Y., & Siarry, P. (2004). *Multiobjective optimization: Principles and case studies* (1st ed.). Springer. https://doi.org/10.1007/978-3-662-08883-8

European Commission. (2020). *2030 targets*. https://commission.europa.eu/energy-climate-change-environment/overall-targets-and-reporting/2030-targets_en

Jahangoshai Rezaee, M., Yousefi, S., & Hayati, J. (2017). A multi-objective model for closed-loop supply chain optimization and efficient supplier selection in a competitive environment considering quantity discount policy. *Journal of Industrial Engineering International, 13*(2), 199–213. https://doi.org/10.1007/s40092-016-0178-2

Sajadiyan, S. M., Hosnavi, R., Karbasian, M., & others. (2022). An approach for reliable circular supplier selection and circular closed-loop supply chain network design focusing on the collaborative costs, shortage, and circular criteria. *Environment, Development and Sustainability*. https://doi.org/10.1007/s10668-022-02668-x

Shafiee Roudbari, E., Fatemi Ghomi, S. M. T., & Eicker, U. (2023). Designing a multi-objective closed-loop supply chain: A two-stage stochastic programming method applied to the garment industry in Montréal, Canada. *Environment, Development and Sustainability*, 1–32. https://doi.org/10.1007/s10668-023-02953-3

Mallick, P. K., Salling, K. B., Pigosso, D. C. A., & McAloone, T. C. (2023). Closing the loop: Establishing reverse logistics for a circular economy, a systematic review. *Journal of Environmental Management, 328*, 117017. https://doi.org/10.1016/j.jenvman.2022.117017

Lv, Y., Bi, X., Li, Q., & Zhang, H. (2022). Research on Closed-Loop Supply Chain Decision Making and Recycling Channel Selection under Carbon Allowance and Carbon Trading. *Sustainability*, *14*(18), 11473. https://doi.org/10.3390/su141811473

Winston, W. L., & Goldberg, J. B. (2004). *Operations research: Applications and algorithms* (4th ed., International student ed.). Thomson Brooks/Cole. ISBN: 0-534-52020-0

González, P. A., Martínez, J. A., & Pérez, M. (2022). Production optimization in a grain facility through mixed-integer linear programming. *Applied Sciences*, *12*(16), 8212. https://doi.org/10.3390/app12168212

Mucciarini, M., Caselli, G., De Santis, D., Iori, M., & Miranda-Bront, J. J. (2024). On incorporating variable consumption functions within energy-efficient parallel machine scheduling. *arXiv preprint arXiv:2412.17055*. https://doi.org/10.48550/arXiv.2412.17055

Saunders, M. N. K., Lewis, P., & Thornhill, A. (2019). *Research methods for business students* (8th ed.). Pearson Education Limited. ISBN: 9781292208787

Li, X., Ji, X., & Zeng, X. (2023). Optimizing supply chain networks using mixed-integer linear programming (MILP). *Theoretical and Natural Science.* 53(1):10-15. DOI: 10.54254/2753-8818/53/20240642

Baader, F. J., Bardow, A., & Dahmen, M. (2022). Simultaneous mixed-integer dynamic scheduling of processes and their energy systems. *AIChE Journal*. 68(8), e17741. https://doi.org/10.1002/aic.17741

González-Ramírez, R. G., Smith, N. R., & Askin, R. G. (2016). A mixed-integer linear programming model for harvesting, loading, and transportation operations. *Dyna*, *83*(196), 36–44. DOI: 10.15446/dyna.v83n195.49490

Kantor, I., Robineau, J.-L., Bütün, H., & Maréchal, F. (2020). A mixed-integer linear programming formulation for optimizing multi-scale material and energy integration. *Frontiers in Energy Research, 8*, 49. https://doi.org/10.3389/fenrg.2020.00049

Deb, K. (2011, February 10). *Multi-objective optimization using evolutionary algorithms: An introduction* (KanGAL Report No. 2011003). Indian Institute of Technology Kanpur. http://www.iitk.ac.in/kangal/deb.htm

Luke, S. (2013). Essentials of Metaheuristics, Lulu, second edition, available at http://cs.gmu.edu/∼sean/book/metaheuristics/

Morris, M. D. (1991). Factorial Sampling Plans for Preliminary Computational Experiments. Technometrics, 33(2), 161–174. https://doi.org/10.1080/00401706.1991.10484804

Sobol', I (1993). Sensitivity analysis for non-linear mathematical models. *Mathematical Modeling & Computational Experiment*. **1**: 407–414.

Saltelli, A., Tarantola, S., & Campolongo, F. (2000). Sensitivity analysis as an ingredient of modeling. *Statistical Science*, *15*(4), 377–395. https://doi.org/10.1214/ss/1009213004

McRae, G. J., Tilden, J. W., & Seinfeld, J. H. (1982). Global sensitivity analysis—a computational implementation of the Fourier Amplitude Sensitivity Test (FAST). *Computers & Chemical Engineering, 6*(1), 15–25. https://doi.org/10.1016/0098-1354(82)80003-3

Benoumechiara, N., & Elie-Dit-Cosaque, K. (2018). Shapley effects for sensitivity analysis with dependent inputs: Bootstrap and kriging-based algorithms. *arXiv*. https://doi.org/10.48550/arXiv.1801.03300

Campolongo, F., Cariboni, J., & Saltelli, A. (2007). An effective screening design for sensitivity analysis of large models. Environmental Modelling & Software, 22(10), 1509–1518. https://doi.org/10.1016/j.envsoft.2006.10.004

Owen, A. B. (2014). Sobol' indices and Shapley value. SIAM/ASA Journal on Uncertainty Quantification, 2(1), 245–251. https://doi.org/10.1137/130933155

Raj, R., Tismer, A., Gaisser, L., & Riedelbauch, S. (2024). A deep learning approach to calculate elementary effects of Morris sensitivity analysis. PAMM, 24(1), e202400104. https://doi.org/10.1002/pamm.202400104

Saltelli, A., Ratto, M., Andres, T., Campolongo, F., Cariboni, J., Gatelli, D., & Tarantola, S. (2008). Global sensitivity analysis: The primer. Wiley. https://doi.org/10.1002/9780470725184

Saltelli, A., Tarantola, S., & Chan, K. P.-S. (1999). A quantitative model-independent method for global sensitivity analysis of model output. Technometrics, 41(1), 39–56. https://doi.org/10.1080/00401706.1999.10485594

Benoumechiara, N., & Elie-Dit-Cosaque, K. (2018). Shapley effects for sensitivity analysis with dependent inputs: Bootstrap and kriging-based algorithms. *arXiv*. https://doi.org/10.48550/arXiv.1801.03300

Song, E., Nelson, B. L., & Staum, J. (2016). Shapley effects for global sensitivity analysis: Theory and computation. SIAM Journal on Scientific Computing, 38(6), A3673–A3693. https://doi.org/10.1137/15M1048073

Yang, W.-D., Sun, Q., & Ni, H.-G. (2021). Cost-benefit analysis of metal recovery from e-waste: Implications for international policy. *Waste Management, 123*, 42–47. https://doi.org/10.1016/j.wasman.2021.01.023

Tonanont, A., Yimsiri, S., Jitpitaklert, W., & Rogers, K.J. (2008). Performance evaluation in reverse logistics with data envelopment analysis. In: Proceedings of the 2008 Industrial Engineering Research Conference (pp. 764–769).

Deb, K. (2001). Multi-objective Optimization Using Evolutionary Algorithms. John Wiley & Sons. https://doi.org/10.1002/9780470743614.

Deb, K., Pratap, A., Agarwal, S., & Meyarivan, T. (2002). A fast and elitist multi-objective genetic algorithm: NSGA-II. IEEE Transactions on Evolutionary Computation, 6(2), 182–197. https://doi.org/10.1109/4235.996017

Aumann, Craig A. (2007). A methodology for developing simulation models of complex systems. *Ecological Modelling*, vol. 202(3), 385-396. DOI: 10.1016/j.ecolmodel.2006.11.005

Sargent, R. G. (1984). A tutorial on verification and validation of simulation models. In: S. Sheppard, U. Pooch & D. Pegde (Editors), *Proceedings of the 1984 Winter Simulation Conference*, IEEE 84CH2098-2 (pp. 115-122).

Rykiel, E. J. (1996). Testing ecological models: the meaning of validation. Ecological Modeling, 90, 229-244.

Goel, T. & Stander, Nielen. (2010). A study on the convergence of multi-objective evolutionary algorithms. Proc. Conf. Multidisciplinary Anal. Optim.. 3. 1-18.

Araujo, M. B., Pearson, R. G., Thuiller, W., & Erhard, M. (2005). Validation of species–climate impact models under climate change. *Global Change Biology*, 11(9), 1504–1513. https://doi.org/10.1111/j.1365-2486.2005.01000.x

Pizarroso, J., Portela, J., & Muñoz, A. (2021). NeuralSens: Sensitivity Analysis of Neural Networks. https://doi.org/10.18637/jss.v102.i07

Tang, Z., Chu, J., Chu, J., Zhou, Z., Zhou, T., & Yuan, K. (2025). The Sensitivity Analysis of Parameters in the 1D–2D Coupled Model for Urban Flooding. Applied Sciences, 15(4), 2157. https://doi.org/10.3390/app15042157

Sobol, I. M. (2001). Global sensitivity indices for nonlinear mathematical models and their Monte Carlo estimates. Mathematics and Computers in Simulation, 55(1–3), 271–280. https://doi.org/10.1016/S0378-4754(00)00270-6

Sobol, I. M., & Kucherenko, S. (2009). Derivative based global sensitivity measures and their link with global sensitivity indices. Mathematics and Computers in Simulation, 79(10), 3009–3017. https://doi.org/10.1016/j.matcom.2009.01.023

Mishra, A., Dutta, P., Jayasankar, S., Jain, P. and Mathiyazhagan, K. (2023), A review of reverse logistics and closed-loop supply chains in the perspective of circular economy. *Benchmarking: An International Journal*, Vol. 30 No. 3, pp. 975-1020. https://doi.org/10.1108/BIJ-11-2021-0669

Peng, C., Tan, R. R., & Klemes, J. J. (2017). Quality-dependent multi-objective optimization for sustainable product recovery. Journal of Cleaner Production, 142, 3362–3372. https://doi.org/10.1016/j.jclepro.2016.10.165

Passaporn, P. (2019). Data-driven repair decision support in remanufacturing environments. Journal of Remanufacturing, 9(1), 45–62. https://doi.org/10.1007/s13243-019-00070-x

Taleizadeh, A. A., Jolai, F., & Shekari, H. (2019). Pricing of returned products under a multi-objective mixed-integer programming approach. Computers & Industrial Engineering, 130, 595–606. https://doi.org/10.1016/j.cie.2019.02.034

Liu, C., Li, Y., Zhang, X., & Zhou, M. (2019). Multi-robot disassembly line balancing using NSGA-II, SPEA2, and MOEA/D. IEEE Transactions on Automation Science and Engineering, 16(3), 1341–1353. https://doi.org/10.1109/TASE.2018.2882881

Rezgui, Y., Mileto, C., & Alwan, Z. (2022). Multi-objective optimization for lifecycle cost and emission trade-offs in buildings. Energy and Buildings, 264, 112072. https://doi.org/10.1016/j.enbuild.2022.112072

Costa, L. A. (2020). Portfolio evaluation for energy efficiency investments using NSGA-II. Energy Reports, 6, 283–292. https://doi.org/10.1016/j.egyr.2020.11.019

Jofre, S., & Morioka, T. (2005). Comparative analysis of end-of-life strategies for electrical and electronic waste. Journal of Material Cycles and Waste Management, 7(1), 24–32. https://doi.org/10.1007/s10163-004-0117-2

Kianpour, K., Jusoh, A., Mardani, A., & Streimikiene, D. (2017). Factors influencing consumer return behavior for EoL electronic products. Sustainability, 9(9), 1657. https://doi.org/10.3390/su9091657

Chen, S.-C., Chen, H.-M., Chen, H.-K., & Li, C.-L. (2024). Multi-Objective Optimization in Industry 5.0: Human-Centric AI Integration for Sustainable and Intelligent Manufacturing. *Processes*, *12*(12), 2723. https://doi.org/10.3390/pr12122723

Hu, Y., Liu, C., Zhang, M., Jia, Y., & Xu, Y. (2023). A Novel Simulated Annealing-Based Hyper-Heuristic Algorithm for Stochastic Parallel Disassembly Line Balancing in Smart Remanufacturing. *Sensors*, *23*(3), 1652. https://doi.org/10.3390/s23031652

Qasim, M., Wong, K.Y. & Saufi, M.S.R.M. (2023). Production planning approaches: a review from green perspective. *Environ Sci Pollut Res* 30, 90024–90049. https://doi.org/10.1007/s11356-022-24995-2

Ma, Haiping & Zhang, Yajing & Sun, Shengyi & Liu, Ting & Shan, Yu. (2023). A comprehensive survey on NSGA-II for multi-objective optimization and applications. Artificial Intelligence Review. 56. 1-54. DOI: 10.1007/s10462-023-10526-z

Marrero, M., Amores, M. J., & Pacheco-Torres, R. (2019). Optimization of remanufacturing decisions in the circular economy through NSGA-II: An application in industrial motors. Sustainability, 11(13), 3648. https://doi.org/10.3390/su11133648

Waide, P., & Brunner, C. U. (2011). *Energy-efficiency policy opportunities for electric motor-driven systems*. International Energy Agency. https://iea.blob.core.windows.net/assets/d69b2a76-feb9-4a74-a921-2490a8fefcdf/EE_for_ElectricSystems.pdf

The International EPD® System**.** (2023a). *EPD for VLT® AutomationDrive FC 302 P7K5*. Environmental Product Declarations. Retrieved 9 January 2025, from https://api.environdec.com/api/v1/EPDLibrary/Files/d84f6659-5c17-4589-ef40-08db5cc782d3/Data

The International EPD® System**.** (2023b). *EPD for iC7-Automation IC7-60FA3N05*. Environmental Product Declarations. Retrieved 9 January 2025, from https://api.environdec.com/api/v1/EPDLibrary/Files/e7153c45-8de2-42f5-de0f-08dbf085b35e/Data

Konak, A., Coit, D. W., & Smith, A. E. (2006). Multi-objective optimization using genetic algorithms: A tutorial. *Reliability Engineering & System Safety*, 91(9), 992–1007. https://doi.org/10.1016/j.ress.2005.11.018

Marrero, A., Segredo, E., & León, C. (2019). On the automatic planning of healthy and balanced menus. In GECCO '19 Companion: Proceedings of the Genetic and Evolutionary Computation Conference Companion (pp. 223–224). ACM. https://doi.org/10.1145/3318043.3367876

Apipie, F. M., & Ioana, G. M. (2019). Multiobjective evolutionary algorithms: description, application and performance comparison of NSGA ii and SPEA 2. *Young Economists Journal/Revista Tinerilor Economisti*, 16(32), 82-92.

Iooss, B., Lemaître, P. (2015). A Review on Global Sensitivity Analysis Methods. In: Dellino, G., Meloni, C. (eds) Uncertainty Management in Simulation-Optimization of Complex Systems. Operations Research/Computer Science Interfaces Series, vol 59. Springer, Boston, MA. https://doi.org/10.1007/978-1-4899-7547-8_5

Cacuci, D. G. (2003). Sensitivity and Uncertainty Analysis, Volume I: Theory (1st Edition). Chapman & Hall/CRC. https://doi.org/10.1201/9780203498798

Blank, J., & Deb, K. (2020). pymoo: Multi-objective optimization in Python. IEEE Access, 8, 89497-89509. https://doi.org/10.1109/ACCESS.2020.2990567

Ehrgott, M. (2005). Multicriteria Optimization (2nd ed.). Springer. https://doi.org/10.1007/3-540-27659-9

Appendices

Appendix 1. Dataset

Product	quality	age	distance_km	cost_repair	cost_dispose	transport_cost_repair	transport_cost_dispose	ghg_repair	transport_emission_repair	transport_emission_dispose	ghg_dispose	individual_budget
0	0	14	42,53927242	406,1869167	167,8010977	21,26963621	20,73899428	673,5855078	8,507854484	5,972489525	171,772768	335,0430244
1	1	3	93,03259225	169,5516086	150,3482382	46,51629613	29,41119497	70,75296386	18,60651845	5,11694469	218,2439415	421,2518469
2	0	12	74,09083961	410,5786178	137,1029932	37,0454198	24,90747468	777,5566418	14,81816792	4,381081396	277,6375514	271,9309391
3	0	7	36,02137304	418,5393448	105,842415	18,01068652	25,78765867	777,7006389	7,204274607	2,799879097	174,5988391	209,9333064
4	0	4	59,19217757	316,1706653	191,0200164	29,59608878	43,76852563	746,8795734	11,83843551	2,427882374	260,9651895	184,2901708
5	1	9	54,4792547	120,3061225	196,0495755	27,23962735	47,20067339	56,16012752	10,89585094	9,668331975	355,7396244	573,2393222
6	0	3	96,31134231	348,4319877	92,58814621	48,15567116	12,81664523	720,3797179	19,26226846	8,777145153	452,3551007	337,487576
7	0	5	85,23071562	460,6279513	95,80457905	42,61535781	18,3567487	670,867337	17,04614312	4,839241524	467,3010663	411,5231795
8	0	3	75,99541046	394,0601269	122,842063	37,99770523	36,84574067	629,3468167	15,19908209	9,654407081	498,9905006	563,6294483
9	1	7	56,27075258	188,0467839	117,2636214	28,13537629	24,34587125	87,6290791	11,25415052	7,414159235	454,2006445	187,236789
10	0	12	60,74136074	379,7648885	199,1686194	30,37068037	20,16654596	724,4816707	12,14827215	5,860167597	418,1924734	544,4976687
11	0	9	96,69925419	463,2863746	76,3887879	48,3496271	21,81162354	728,2557903	19,33985084	5,944205262	165,3786886	398,2145426
12	0	7	62,66825353	459,669025	52,71130454	31,33412677	22,90203057	650,375868	12,53365071	2,66627529	258,1270489	224,1754175
13	0	3	31,21992229	330,1435088	124,0840573	15,60996115	43,9467918	728,1707375	6,243984458	2,733633178	302,2974878	335,0648025
14	1	4	33,14598304	121,8440437	76,82340638	16,57299152	15,46485326	58,72903933	6,629196608	6,819527407	77,24805337	499,9210277
15	0	9	20,70035921	439,1625614	104,9703177	10,35017961	38,35643988	482,673744	4,140071842	6,429624419	331,1709691	366,1665368
16	1	12	6,48545864	188,3280259	161,6255785	3,24272932	32,11279908	116,3528345	1,297091728	3,70182316	278,711424	593,3787228
17	1	14	45,22314067	132,4345021	158,1409886	22,61157033	21,86040575	85,96810387	9,044628133	9,569556343	487,2022719	319,5325365
18	1	3	42,51374423	112,2087955	96,20911878	21,25687211	26,79123426	64,08099351	8,502748845	8,250368404	587,4033812	487,310235
19	0	10	32,8813766	442,2299065	131,3810346	16,4406883	20,24827774	415,5852529	6,57627532	2,907716816	346,922872	326,845252
20	1	9	6,337583158	190,6828442	126,3221115	3,168791579	34,46054843	190,1920996	1,267516632	9,447432845	213,9312413	523,1238993
21	0	10	23,89002839	369,7331975	145,4498927	11,94501419	13,26376722	534,621686	4,778005678	9,793985668	54,73844648	406,0866611
22	1	5	72,57748551	164,7690121	87,56927279	36,28874276	10,20739451	127,5044386	14,5154971	9,967449936	557,0466982	178,5803233
23	1	6	80,06667635	100,0520377	138,4806271	40,03333818	35,1157766	148,5666993	16,01333527	2,446969237	553,8959577	166,5698404

Appendix 2. Code example (model with 20 generations)

```
# MOO
class ProductRepairProblem(Problem):
    def __init__(self):
        super().__init__(n_var=n_products, n_obj=2, n_constr=1, xl=0, xu=1)

    def _evaluate(self, X, out, *args, **kwargs):
        costs = np.zeros(X.shape[0])
        emissions = np.zeros(X.shape[0])
        g1 = np.zeros(X.shape[0])  # Individual budget constraints

        for i in range(X.shape[0]):
            repair_mask = X[i, :] == 1
            dispose_mask = ~repair_mask

            budget_violation = (cost_repair + transport_cost_repair) > individual_budget
            poor_and_old = (quality == 0) & (age > 8)
            force_dispose = budget_violation | poor_and_old
            repair_mask[force_dispose] = False
            dispose_mask[force_dispose] = True

            total_cost = np.sum((cost_repair + transport_cost_repair)[repair_mask]) + np.sum((cost_dispose + transport_cost_dispose)[dispose_mask])
            total_emissions = np.sum((ghg_repair + transport_emission_repair)[repair_mask]) + np.sum((ghg_dispose + transport_emission_dispose)[dispose_mask])

            budget_violations = np.sum((cost_repair + transport_cost_repair)[repair_mask] > individual_budget[repair_mask])

            costs[i] = total_cost
```

```
            emissions[i] = total_emissions
            g1[i] = budget_violations  # Should be zero

        out["F"] = np.column_stack([costs, emissions])
        out["G"] = g1.reshape(-1, 1)  # Only one constraint now

# Custom callback (solutions +convergence)
class MyCallback(Callback):
    def __init__(self):
        super().__init__()
        self.all_F = []
        self.all_X = []
        self.hypervolume_indicator = HV(ref_point=[25000, 20000])

    def notify(self, algorithm):
        # Collect feasible solutions
        feasible = algorithm.pop.get("G").max(axis=1) <= 0  # all constraints satisfied
        self.all_F.extend(algorithm.pop.get("F")[feasible])
        self.all_X.extend(algorithm.pop.get("X")[feasible])

        # HV indicator (for convergence)
        hv = self.hypervolume_indicator.do(np.array(self.all_F))
        print(f"Generation {algorithm.n_gen} - Hypervolume: {hv:.3f}")

        # Plotting convergence and Pareto front
        self.plot_pareto_front(algorithm)

    def plot_pareto_front(self, algorithm):
        F_all = np.array(self.all_F)
```

```
    # Identify Pareto front from feasible ones
    def is_dominated(p, others):
        return any((o[0] <= p[0] and o[1] <= p[1]) and (o[0] < p[0] or o[1] < p[1]) for o in
others)

    pareto_mask = np.array([not is_dominated(p, np.delete(F_all, i, axis=0)) for i, p in
enumerate(F_all)])
    pareto_points = F_all[pareto_mask]
    non_pareto_points = F_all[~pareto_mask]

    # Plot all feasible solutions and Pareto front
    plt.figure(figsize=(9, 6))
    plt.scatter(non_pareto_points[:, 0], non_pareto_points[:, 1], c='lightgreen', la-
bel='Other Feasible Solutions', s=60, edgecolors='k')
    plt.scatter(pareto_points[:, 0], pareto_points[:, 1], c='red', label='Pareto Front',
s=80, edgecolors='k')
    plt.title(f"Generation {algorithm.n_gen} - Pareto Front vs Feasible Solutions")
    plt.xlabel("Total Cost")
    plt.ylabel("Total GHG Emissions")
    plt.legend()
    plt.grid(True)
    plt.tight_layout()
    plt.show()

# Running Optimization
callback = MyCallback()
problem = ProductRepairProblem()

algorithm = NSGA2(
  pop_size=300,
```

```
    sampling=BinaryRandomSampling(),
    crossover=HalfUniformCrossover(),
    mutation=BitflipMutation(prob=1.0/n_products),
    eliminate_duplicates=True
)

termination = get_termination("n_gen", 20)

res = minimize(problem, algorithm, termination=termination, seed=42, callback=callback, verbose=True)

# Plotting
def plot_pareto(res):
    plt.figure(figsize=(10, 6))
    feasible = np.all(res.G <= 0, axis=1) if res.G is not None else np.zeros(len(res.F), dtype=bool)

    if feasible.any():
        nds = NonDominatedSorting().do(res.F[feasible], only_non_dominated_front=True)
        plt.scatter(res.F[feasible][nds, 0], res.F[feasible][nds, 1], c='blue', s=100, label='Pareto Front')

    plt.xlabel("Total Cost (€)", fontsize=12)
    plt.ylabel("Total GHG Emissions (kg CO₂)", fontsize=12)
    plt.title("Pareto Optimal Solutions", fontsize=14)
    plt.legend()
    plt.grid(alpha=0.3)
    plt.tight_layout()
    plt.show()
plot_pareto(res)
```