

Article

Optimisation of Product Recovery Options in End-of-Life Product Disassembly by Robots

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Abstract: In a circular economy, strategies for product recovery, such as reuse, recycling, and remanufacturing, play an important role at the end of a product's life. A sustainability model was developed to solve the problem of sequence-dependent robotic disassembly line balancing. This research aimed to assess the viability of the model, which was optimised using the Multi-Objective Bees Algorithm in a robotic disassembly setting. Two industrial gear pumps were used as case studies. Four objectives (maximising profit, energy savings, emissions reductions and minimising line imbalance) were set. Several product recovery scenarios were developed to find the best recovery plans for each component. An efficient metaheuristic, the Bees Algorithm, was used to find the best solution. The robotic disassembly plans were generated and assigned to robotic workstations simultaneously. Using the proposed sustainability model on end-of-life industrial gear pumps shows the applicability of the model to real-world problems. The Multi-Objective Bees Algorithm was able to find the best scenario for product recovery by assigning each component to recycling, reuse, remanufacturing, or disposal. The performance of the algorithm is consistent, producing a similar performance for all sustainable strategies. This study addresses issues that arise with product recovery options for end-of-life products and provides optimal solutions through case studies.



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1. Introduction

The United Nations' Sustainable Development Goal 12 states that unsustainable production and consumption are the root causes of climate change, biodiversity loss, and pollution [1]. The circular economy is a way to address these problems by keeping products and materials in use for longer [2]. This is different from the linear economy, in which products are made from raw materials, then used, and finally thrown away. There are four main options in a circular economy: recycling, remanufacturing, repair and reuse. Recycling is the outermost loop in the circular economy technical cycle [2]. Recycling should be considered the last option at the end of a product's life [2] because it consumes more energy, generates waste, and causes pollution [3–5] when compared to other options, the aim of which is to extend the product's life span. Remanufacturing is expected to become an increasingly significant component of the future manufacturing sector, as it has the potential to generate an EU market of €90 billion by 2030 [6] and is considered the backbone of a circular economy [7–9]. Remanufacturing is a process of transforming an end-of-life (EoL) product to its original performance with a warranty that it is the same or

better than a new product [10–16]. Remanufacturing benefits the environment as it reduces waste, raw material usage, CO₂ emissions, energy consumption and the need for landfill space [17–27].

Disassembly is the first activity in remanufacturing [28–37], and due to complexities in EoL products, disassembly has generally to be kept a manual activity [38–40]. However, technological developments in the current era of Industry 4.0 have facilitated the shift from human labour to automated processes. To ensure future success and be competitive, remanufacturing companies have to embrace automation [41]. Research interest in disassembly automation is reflected in the number of publications on that subject since 2014. Disassembly sequence planning and line balancing are two important research lines that promise to improve remanufacturing plant efficiency and productivity. Previous research in robotic disassembly has shown that it is important to consider the interconnection of sequence planning and line balancing, which are intertwined problems [39,42–44]. To reflect this, the term “sequence-dependent line balancing” is used in the majority of previous publications in this area, as it will be throughout the remainder of this article. Disassembly problems are NP-complete, meaning that the solution time grows exponentially as the number of components increases [45,46]. Previous research reports that a metaheuristic can find the optimal solution efficiently using a multi-objective approach when there are conflicting objectives [43,47–55]. The Bees Algorithm (BA) is a robust metaheuristic that can find the optimal solution to a complex problem, such as those involved in robotic disassembly [39,42,56,57]. Hence, a Multi-Objective Bees Algorithm (MOBA) was used as an optimisation tool for this study.

Most previous research on disassembly line balancing has been oriented toward maximising profit [58–63], the same with robotic disassembly line balancing. However, recent developments in robotic disassembly line balancing have incorporated sustainability as one of the objectives. This research was motivated by the need to expand the focus beyond profitability and address sustainability concerns. Sustainability was defined by the United Nations in 1987 as meeting the current needs without undermining the needs of future generations [64]. Sustainability is also described as the intersection of economic, social, and environmental factors — the-so-called triple bottom line [65]. A total of 35 articles on robotic disassembly line balancing published between 2014 and 2023 were found using the Scopus search engine. However, only 17 of those articles had sustainability as one of their objectives. Of those 17 articles, 10 focus on reduction of energy consumption [43,47–50,52,54,55,66,67], while two articles target the reduction of carbon emissions [51,53]. The present study contributes to the development of a sustainability model to fill a gap in robotic disassembly line balancing research, whereas prior studies have only focused on environmental aspects of sustainability. The model considers four objectives, namely, maximising profit, energy savings and environmental benefits and minimising line imbalance. In addition, this study provides a recovery path for each part such as recycling, reusing, or remanufacturing, and the last option of disposal if the parts cannot be recovered, which previous research did not address. This article considers optimal recovery options overlooked in previous research to propose a model for end-of-life products, taking real industrial products as examples. Four sustainability scenarios were developed, and the optimal solutions are presented. The scenarios are based on the characteristics of each component and developed after discussion with remanufacturers in England and Spain. In the REC (recycling) scenario, most of the components are recycled. In the REU (reuse) and REM (remanufacturing) scenarios, most of the components are reused or remanufactured, respectively. Unlike in previous work, the product recovery was optimised for each component by the algorithm in the OPT (optimal) scenario. The proposed model was applied to two industrial gear pumps under these four sustainability scenarios. Industrial gear pumps were chosen for their low wear, making them excellent subjects for studying complete disassembly sequence planning (DSP) without destruction. A hypervolume indicator was used to evaluate the optimal results found by the MOBA and to assess the performance of the algorithm.

The paper is structured as follows. The next section describes relevant previous work, the research steps, the proposed sustainability model, the case studies and the MOBA. The results obtained are then presented and analysed. The final section discusses the significance of the findings, summarises the main conclusions, outlines the study's strengths and limitations, and suggests future research directions.

2. Relevant Work

As previously highlighted, the impact of disassembly sequences on line balancing is beginning to emerge. Existing research has shown that sequence-dependent manual disassembly line balancing [68–76] is an increasingly significant phenomenon. Recent scholarly work, outlined in Table 1, further underscores the central role of sequence dependency in the field of robotic disassembly line balancing. Table 1 presents relevant publications in robotic disassembly line balancing.

Table 1. Overview of Robotic Disassembly Line Balancing Research.

References	Metaheuristic	Sustainability Related Objective(s)	MO-ND	Sequence-Dependent
[77]				
[78]				
[79]				
[80]				
[42]	✓		✓	✓
[43]	✓	✓	✓	
[81]	✓			
[82]				
[47]	✓	✓	✓	✓
[48]	✓	✓	✓	✓
[66]				
[51]	✓		✓	✓
[83]	✓			
[50]	✓		✓	✓
[84]	✓		✓	✓
[39]	✓			✓
[49]	✓	✓	✓	✓
[85]	✓	✓	✓	✓
[44]	✓		✓	✓
[52]	✓	✓	✓	
[53]	✓	✓	✓	
[86]	✓		✓	
[28]	✓	✓	✓	
[67]		✓	✓	
[87]	✓			
[88]	✓	✓	✓	
[54]	✓	✓	✓	
[55]	✓	✓	✓	
[89]	✓	✓	✓	
[90]	✓			
[91]	✓	✓	✓	
[92]	✓	✓	✓	
[93]	✓	✓	✓	
[94]	✓	✓	✓	
[95]	✓			✓
This work	✓	energy savings, environmental benefits	✓	✓

3. Methods

The first step in this research was to create a sustainability model for the sequence-dependent robotic disassembly line balancing (RDLBSD) problem. In the second step, input data for experiments and product recovery scenarios are prepared. In the final step, the optimisation algorithm used to find the optimal solution is described.

3.1. Sustainability Model for RDLBSD

The approach used in this research was to aggregate the first three objectives (profit, energy savings, and environmental benefits) and treat them as one goal and then use the non-dominated approach for the aggregated goal and the fourth objective (unbalanced line) using MOBA. This approach was used because the first three objectives have the same unit of measure, Euros (or dollars, or another currency), and the aim is maximisation. In contrast, the fourth objective measures imbalance in the disassembly line and aims to minimise it. The objective is expressed in Equation (1).

$$\text{Objective} = \max(O_1), \min(O_2) \quad (1)$$

For these three objectives, a scalar approach was adopted using an aggregation method by adding the objective function in a linear way [96]. This is expressed in Equation (2). The objectives are to maximise profit, save energy and reduce environmental impact (see Equations (3)–(5)). The fourth objective is to minimise the unbalanced lines, as presented in Equation (6). This equation will result in zero if the disassembly line is in the perfect balance state [97]. Tables 2–5 describe the variables for each objective.

$$O_1 = \text{Profit} + \text{Energy Savings} + \text{Environmental Benefits} \quad (2)$$

Equation (3) assesses the economic profit of the whole disassembly process, obtained as the disassembly gains minus the disassembly costs. Disassembly gains include the revenues obtained from the components to be reused or remanufactured, and the revenues from the components to be recycled. Disassembly costs consist of the disposal costs of the components to be thrown away, the costs involved in the disassembly operations, the costs involved in the moving path of the robot, the recovery costs of the components to be reused or remanufactured, the overhead costs of the company, and the depreciation costs of the machinery (robotic cells).

$$\begin{aligned} \text{Profit} = & \sum_{i=1}^N \sum_{j=1}^2 RP_i r_{i,j} \alpha_i + \sum_{i=1}^N RC_i r_{i,3} \alpha_i - \sum_{i=1}^N CD_i r_{i,4} (1 - \alpha_i) - \\ & \left[\sum_{i=1}^{N-1} t_b(x_i) \alpha_i c_T + \sum_{i=1}^{N-1} \left(\frac{PD(x_i, M)}{v_e} + t_c(x_i, x_{i+1}) + \frac{PD(M, x_{i+1})}{v_e} + t_u(x_i, M) + \right. \right. \\ & \left. \left. t_w(M, x_{i+1}) \right) \gamma_i \alpha_i c_T + \sum_{i=1}^{N-1} \left(\frac{PD(x_i, x_{i+1})}{v_e} + t_z(x_i, x_{i+1}) \right) (1 - \gamma_i) \alpha_i c_T \right] - \\ & \sum_{i=1}^N \sum_{j=1}^2 rc_{i,j} r_{i,j} \alpha_i - \sum_{i=1}^N \sum_{j=1}^4 oh_{i,j} r_{i,j} \alpha_i - \sum_{i=1}^N \sum_{j=1}^4 dp_{i,j} r_{i,j} \alpha_i \end{aligned} \quad (3)$$

Equation (4) defines the energy savings obtained in the whole disassembly process, obtained as the reclaimed energy from the components to be reused or remanufactured less the energy consumption in the disassembly process. Energy consumption includes the energy consumption of the robot in the disassembly of the components, the energy consumption of the robot in the movement between the position of disassembly and the magazine tools, the energy consumption of the robot in the tool change, the energy consumption of the robot in the movement between the magazine tools and the disassembly position, the energy consumption of the robot in the movement between disassembly

points, the energy consumption involved in recovering the components to be reused, remanufactured, recycled or disposed of.

$$\begin{aligned}
 Energy\ savings &= \sum_{i=1}^N \sum_{j=1}^2 r_{i,j} gr_{i,j} f_W \alpha_i - \sum_{i=1}^{N-1} \left[gd_{1,i}(x_i) + gd_{2,i}(x_i, M) \gamma_i + gd_{3,i}(M) \gamma_i + \right. \\
 &\quad \left. gd_{4,i}(M, x_{i+1}) \gamma_i + gd_{5,i}(x_i, x_{i+1}) (1 - \gamma_i) \right] f_W \alpha_i - \\
 &\quad \sum_{i=1}^N \sum_{j=1}^3 r_{i,j} gc_{i,j} f_W \alpha_i - \sum_{i=1}^N r_{i,4} gc_{i,4} f_W (1 - \alpha_i) \\
 &= \sum_{i=1}^N \sum_{j=1}^2 r_{i,j} gr_{i,j} f_W \alpha_i - \sum_{i=1}^{N-1} \left[t_b(x_i) PR_1 \gamma_i + \frac{PD(M, x_i) PR_2 \gamma_i}{v_e} + t_c(x_i, x_{i+1}) PR_2 \gamma_i + \right. \\
 &\quad \left. \frac{PD(M, x_{i+1}) PR_2 \gamma_i}{v_e} + \frac{PD(x_i, x_{i+1}) PR_2 (1 - \gamma_i)}{v_e} \right] \frac{f_W \alpha_i}{3600} - \\
 &\quad \sum_{i=1}^N \sum_{j=1}^3 r_{i,j} gc_{i,j} f_W \alpha_i - \sum_{i=1}^N r_{i,4} gc_{i,4} f_W (1 - \alpha_i)
 \end{aligned} \tag{4}$$

Table 2. Description of variables for economic profit.

Variable	Description
α_i	an indicator that takes the value of 1 if component i is to be disassembled and 0 otherwise
CD_i	disposal cost of component i
c_T	cost per unit of time
$dp_{i,j}$	depreciation cost assigned to component i to be disassembled
γ_i	indicator taking the value 1 if operation x_{i+1} requires changing the tool used in previous operation x_i
i	index for each component and varies from 0 to N
j	indicator for part recovery. It is 1 if the component is reused, 2 if remanufactured, 3 if recycled, and 4 if it is disposed of
$oh_{i,j}$	overhead cost assigned to component i to be disassembled
$PD(M, x_{i+1})$	length between the position of the tool magazine (M) and the point of the disassembly operation x_{i+1}
$PD(x_i, M)$	distance between the point of the disassembly operation x_i and the position of the tool magazine (M)
$PD(x_i, x_{i+1})$	distance between the point of the disassembly operation x_i and the point of disassembly operation x_{i+1}
RC_i	revenue obtained from component i being recycled
$rc_{i,j}$	recovery cost of component i being reused or remanufactured
$r_{i,j}$	indicator of the recovery mode: 1 if mode j is assigned to component i
RP_i	the revenue obtained due to the component i being reused or remanufactured not having been manufactured again for a new product
$t_b(x_i)$	basic time to perform disassembly operation x_i
$t_c(x_i, x_{i+1})$	tool change time and depends on the tool type
$t_u(x_i, M)$	penalty time for process direction changes along the path between x_i and the tool magazine (M), given 0 if the direction is not changed, p_1 if the direction is changed by 90° , p_2 if the direction is changed by 180°
$t_w(M, x_{i+1})$	penalty time for process direction changes along the path between the tool magazine (M) and x_{i+1} , which is formulated as t_w
$t_z(x_i, x_{i+1})$	penalty time for process direction changes along the path between x_i and x_{i+1} , which is formulated as t_z
v_e	line velocity of the industrial robot's end effector

Equation (5) assesses the environmental benefit obtained in the whole disassembly process, expressed as the reclaimed environmental impact from components being reused or

remanufactured, less the environmental impact caused by the disassembly operations and the recovery of the components, which includes the environmental impact in the recovering process, the environmental impact in the disassembly operations, and the environmental impact produced by the movement of the robot between disassembly operations.

$$\text{Environmental Benefits} = \sum_{i=1}^N \sum_{j=1}^2 r_{i,j} er_{i,j} \alpha_i - \sum_{i=1}^N \sum_{j=1}^3 r_{i,j} ec_{i,j} \alpha_i - \sum_{i=1}^N r_{i,4} ec_{i,4} (1 - \alpha_i) - \sum_{i=1}^{N-1} ed(x_i) \alpha_i - \sum_{i=1}^{N-1} ed(x_i, x_{i+1}) \alpha_i \quad (5)$$

$$O_2 = \sum_{i=1}^{NWS} (CyT - ST_i)^2 \quad (6)$$

Table 3. Description of variable for energy savings.

Variable	Description
f_W	conversion factor from kWh to monetary units
$gc_{i,j}$	energy consumption involved in recovering component i with mode j
$gd_{1,i}(x_i)$	energy consumption of the robot in the disassembly operation of component i
$gd_{2,i}(x_i, M)$	energy consumption of the robot in the movement between the position x_i and M
$gd_{3,i}(M)$	energy consumption of the robot in the tool change
$gd_{4,i}(M, x_{i+1})$	energy consumption of the robot in the movement between M and x_{i+1}
$gd_{5,i}(x_i, x_{i+1})$	energy consumption of the robot in the movement between x_i and x_{i+1}
$gr_{i,j}$	energy reclaimed from component i being reused or remanufactured
PR_1	power of the robot used in the disassembly operation
PR_2	power of the robot used in the movements between the disassembly points

Table 4. Description of variables for environmental benefits.

Variable	Description
$ec_{i,j}$	environmental impact in the recovering process of component i with mode j
$ed(x_i)$	environmental impact in disassembly operation x_i
$ed(x_i, x_{i+1})$	environmental impact produced by the movement of the robot between disassembly operations x_i and x_{i+1} , considering that the robot must change the tool in M if operation x_{i+1} requires using a tool different from the one used in the previous operation x_i
$er_{i,j}$	reclaimed environmental impact from component i being reused or remanufactured

Table 5. Description of variables for unbalanced line.

Variable	Description
Cy_T	cycle time
NWS	number of workstations
S_T	station time

The constraints are expressed in Equations (7)–(10). Equation (7) ensures that there is only one doable way to retrieve each component, either recycle, remanufacture, reuse, or dispose. Equation (8) ensures that each part has been completely taken apart. Equation (9) is needed to ensure that the precedence sequence is adhered to. Equation (10) ensures that the total number of removed components is lower than the product's total number of components.

$$\sum_{j=1}^4 r_{i,j} = 1 \quad \forall i \quad (7)$$

$$r_{i,1} + r_{i,2} + r_{i,3} \leq \alpha_i \quad (8)$$

$$\alpha_i \geq \alpha_{i+1} \quad (9)$$

$$\sum_{i=1}^N \alpha_i \leq N - 1 \quad (10)$$

The model is based on several underlying assumptions. First, it presupposes that complete disassembly of all components is feasible. Second, it relies on the assumption that task times are both known and deterministic. Third, the model is founded on the premise that the remanufacturing company operates for 220 days annually, with 8-h shifts each day. Additionally, it takes into account an initial investment cost of 150,000 euros for the robotic cell and an hourly operating cost of 120 euros. Furthermore, the model considers the expected lifetime of the robotic cell.

3.2. Case Study

Two industrial gear pumps were chosen as case studies (see Figures 1 and 2). The Bill of Materials (BOM) is provided in Tables 6 and 7. The input data were prepared as follows. Data on the CAD model, component materials, gear pump properties, and disassembly tools were gathered. The space interference matrix was designed to represent the disassembly precedence in directions Y+ and Y-, as the gear pumps could only be dismantled in these two directions. These matrices considered the fastener and the so-called modified feasible solution generation (MFSG). The interested reader is referred to the article by Liu et al. [42] on the development of MFSGs.

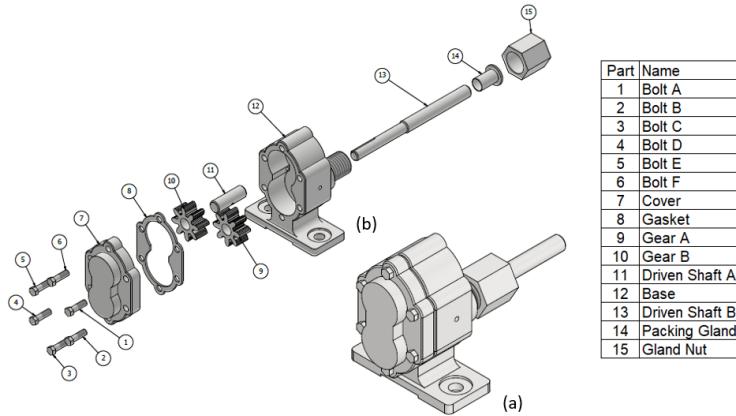


Figure 1. Gear pump A: (a) assembled view; (b) exploded view. Source: Liu et al. [42].

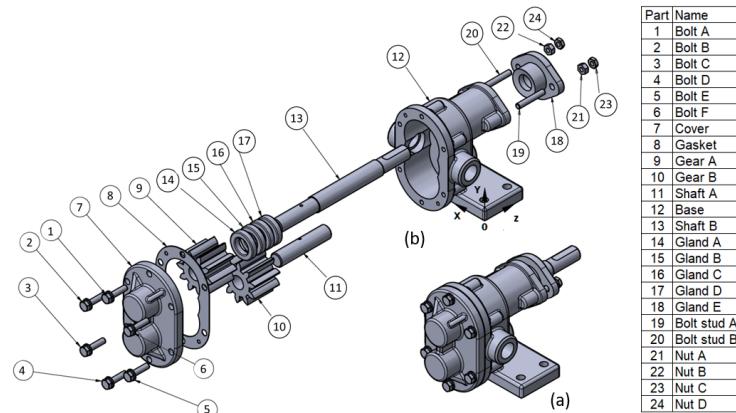


Figure 2. Gear pump B: (a) assembled view; (b) exploded view. Source: Ramírez et al. [98].

Table 6. BOM for Gear Pump A.

Part Number	Part Name	Weight (g)	Material
1	Bolt A	7.90	Steel
2	Bolt B	7.90	Steel
3	Bolt C	7.90	Steel
4	Bolt D	7.90	Steel
5	Bolt E	7.90	Steel
6	Bolt F	7.90	Steel
7	Cover	538.14	Steel
8	Gasket	4.23	Rubber
9	Gear A	119.44	Steel
10	Gear B	119.44	Steel
11	Driven Shaft A	40.88	Steel
12	Base	1534.98	Steel
13	Driven Shaft B	143.40	Steel
14	Packing Gland	21.27	Steel
15	Gland Nut	94.57	Steel

Table 7. BOM for Gear Pump B.

Part Number	Part Name	Weight (g)	Material
1	Bolt A	9.76	Steel
2	Bolt B	9.76	Steel
3	Bolt C	9.76	Steel
4	Bolt D	9.76	Steel
5	Bolt E	9.76	Steel
6	Bolt F	9.76	Steel
7	Cover	753.39	Steel
8	Gasket	5.22	Rubber
9	Gear A	167.22	Steel
10	Gear B	167.22	Steel
11	Shaft A	50.48	Steel
12	Base	2148.98	Steel
13	Shaft B	177.10	Steel
14	Gland A	7.14	PTFE
15	Gland B	7.14	PTFE
16	Gland C	7.14	PTFE
17	Gland D	7.14	PTFE
18	Gland E	113.48	Steel
19	Bolt stud A	7.83	Steel
20	Bolt stud B	7.83	Steel
21	Nut A	2.27	Steel
22	Nut B	2.27	Steel
23	Nut C	2.27	Steel
24	Nut D	2.27	Steel

The KUKA LBR-iiwa 14 R820 robot was chosen for this study. Information about the robot was obtained from the manufacturer's technical data sheet. Information and other data were collected from recycling and remanufacturing companies in the United Kingdom and Spain. As described earlier, the product recovery scenarios REC, REM, REU, and OPT for gear pumps were developed and are shown in Tables 8 and 9. Figure 3 depicts a robotic disassembly line using two KUKA robots to disassemble a gear pump.

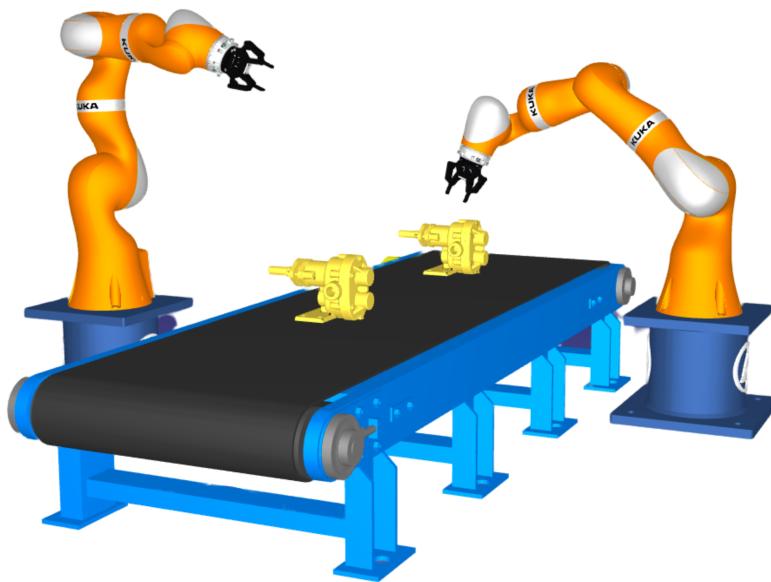


Figure 3. Robotic disassembly line.

Table 8. The product recovery options for the case study gear pump A.

Component No	REC Scenario	REM Scenario	REU Scenario	OPT Scenario
1	Recycle	Recycle	Recycle	Recycle/Remanufacture/Reuse *
2	Recycle	Recycle	Recycle	Recycle/Remanufacture/Reuse *
3	Recycle	Recycle	Recycle	Recycle/Remanufacture/Reuse *
4	Recycle	Recycle	Recycle	Recycle/Remanufacture/Reuse *
5	Recycle	Recycle	Recycle	Recycle/Remanufacture/Reuse *
6	Recycle	Recycle	Recycle	Recycle/Remanufacture/Reuse *
7	Recycle	Remanufacture	Reuse	Recycle/Remanufacture/Reuse *
8	Disposal	Disposal	Disposal	Disposal
9	Recycle	Remanufacture	Reuse	Recycle/Remanufacture/Reuse *
10	Recycle	Remanufacture	Reuse	Recycle/Remanufacture/Reuse *
11	Recycle	Remanufacture	Reuse	Recycle/Remanufacture/Reuse *
12	Recycle	Remanufacture	Reuse	Recycle/Remanufacture/Reuse *
13	Recycle	Remanufacture	Reuse	Recycle/Remanufacture/Reuse *
14	Recycle	Remanufacture	Reuse	Recycle/Remanufacture/Reuse *
15	Recycle	Remanufacture	Reuse	Recycle/Remanufacture/Reuse *

* MOBA assigned the best product recovery options.

3.3. Multiobjective Bees Algorithm

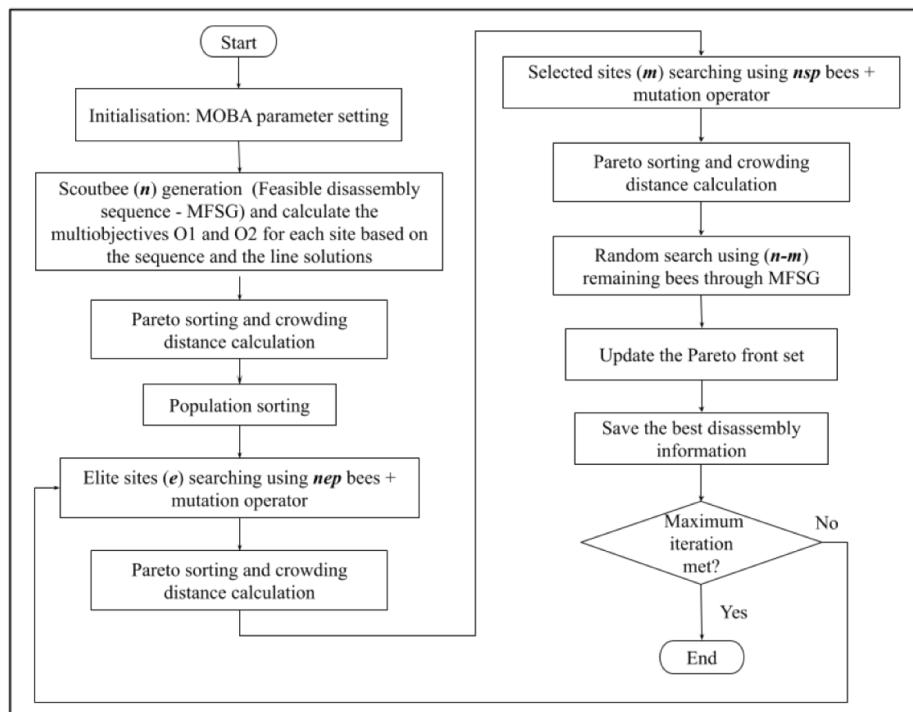
As mentioned in the introduction, the disassembly problem is an NP-complete problem [45,46]. This designation indicates that it would take a significant amount of time to find the optimal solutions, making it inappropriate for real-world problems that require prompt solutions. In the past two decades, metaheuristic algorithms have been utilised by the majority of researchers as a method for acquiring optimal solutions more quickly, with this strategy being suitable for complex problems such as disassembly.

The Bees Algorithm is a population-based metaheuristic inspired by the foraging behaviour of bees, which can find sources of nectar by exploring the solution space and exploiting abundant nectar sources therin [99]. Recent research in remanufacturing applications that used the Bees Algorithm (BA) shows that it is a robust algorithm [42,57,100]. In addition, it has been demonstrated that the BA outperforms other algorithms in the robotic disassembly line balancing problem [39,44]. A hybrid MOBA combining the aggregate and non-dominated approaches, as previously mentioned, was developed for this RDLBSD problem. Figure 4 depicts a flowchart of the hybrid MOBA.

Table 9. The product recovery options for the case study gear pump B.

Component No	REC Scenario	REM Scenario	REU Scenario	OPT Scenario
1	Recycle	Recycle	Recycle	Recycle/Remanufacture/Reuse *
2	Recycle	Recycle	Recycle	Recycle/Remanufacture/Reuse *
3	Recycle	Recycle	Recycle	Recycle/Remanufacture/Reuse *
4	Recycle	Recycle	Recycle	Recycle/Remanufacture/Reuse *
5	Recycle	Recycle	Recycle	Recycle/Remanufacture/Reuse *
6	Recycle	Recycle	Recycle	Recycle/Remanufacture/Reuse *
7	Recycle	Remanufacture	Reuse	Recycle/Remanufacture/Reuse *
8	Disposal	Disposal	Disposal	Disposal
9	Recycle	Remanufacture	Reuse	Recycle/Remanufacture/Reuse *
10	Recycle	Remanufacture	Reuse	Recycle/Remanufacture/Reuse *
11	Recycle	Remanufacture	Reuse	Recycle/Remanufacture/Reuse *
12	Recycle	Remanufacture	Reuse	Recycle/Remanufacture/Reuse *
13	Recycle	Remanufacture	Reuse	Recycle/Remanufacture/Reuse *
14	Disposal	Disposal	Disposal	Disposal
15	Disposal	Disposal	Disposal	Disposal
16	Disposal	Disposal	Disposal	Disposal
17	Disposal	Disposal	Disposal	Disposal
18	Recycle	Remanufacture	Reuse	Recycle/Remanufacture/Reuse *
19	Recycle	Remanufacture	Reuse	Recycle/Remanufacture/Reuse *
20	Recycle	Remanufacture	Reuse	Recycle/Remanufacture/Reuse *
21	Recycle	Recycle	Recycle	Recycle/Remanufacture/Reuse *
22	Recycle	Recycle	Recycle	Recycle/Remanufacture/Reuse *
23	Recycle	Recycle	Recycle	Recycle/Remanufacture/Reuse *
24	Recycle	Recycle	Recycle	Recycle/Remanufacture/Reuse *

* MOBA assigned the best product recovery options.

**Figure 4.** Hybrid MOBA flowchart.

The setting parameters for MOBA are as follows: number of elite sites (e) = 1, number of selected sites (m) = 5, number of recruited bees around elite sites (nep) = 10, and number of recruited bees around selected sites (nsp) = 5 [57]. The maximum number of iterations and population size are varied to evaluate the algorithm's performance under different

parameter settings. The iteration was set to 100 and increased by 100 until 500, whereas the bees population was set to 50 and increased by 10 until 80. The experiments were run 50 times in MATLAB 2020a on the University of Birmingham's BEAR Cloud Service.

4. Results

The hypervolume indicator (HI), which has become a standard, was the most widely used method for evaluating the performance of multiobjective algorithms [101]. Higher HI values are better because they show that the set of Pareto optimal solutions (POSs) is more diverse [102]. The indicator measures convergence and diversity [96,103]. The HI for both gear pumps is presented in Figure 5. The diagram demonstrates that for gear pump A, the HI in each scenario is reasonably similar. This indicates that the MOBA performs consistently. On the other hand, the HI for gear pump B is lower when a lower number of iterations and a smaller bee population are utilised. It becomes more consistent after 300 iterations. This is logical considering that gear pump A has fewer components than gear pump B.

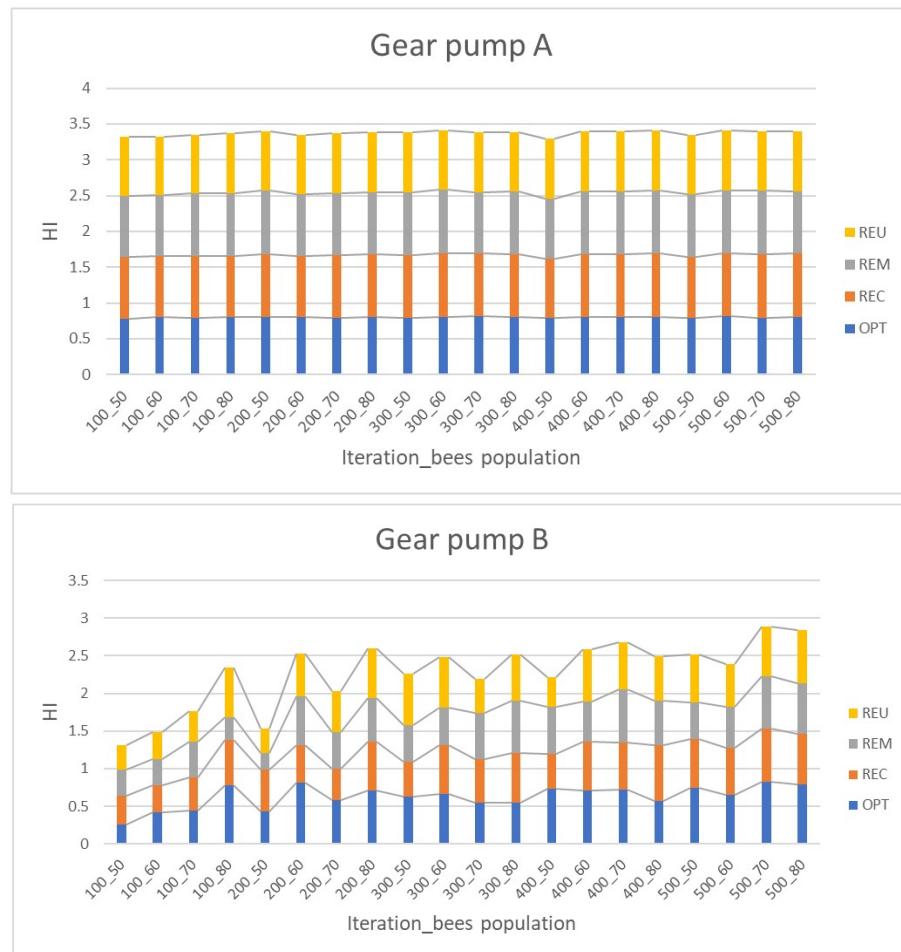


Figure 5. Hypervolume Indicator.

The following figures and tables show the output of the highest HI for each scenario. The Pareto optimal solutions are depicted in Figures 6 and 7. The four scenarios show similar results; the difference can be seen in the x-axis, which measures the monetary goals.

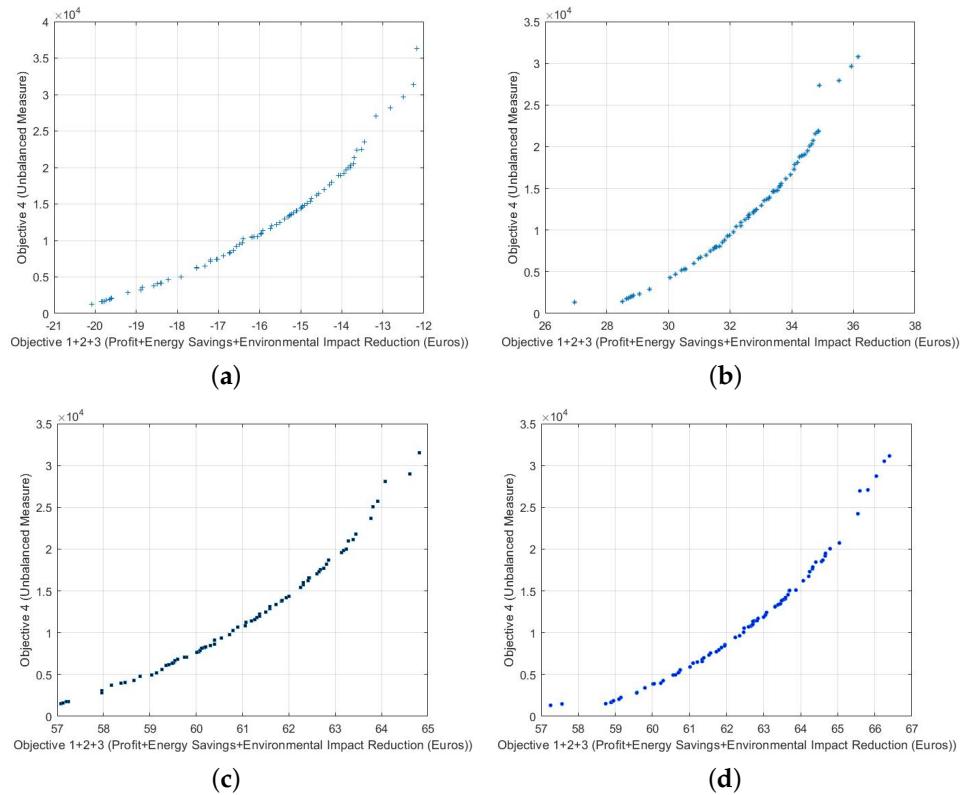


Figure 6. Plot of gear pump A best solutions under four sustainability scenarios **(a)** REC scenario; **(b)** REM scenario; **(c)** REU scenario; **(d)** OPT scenario.

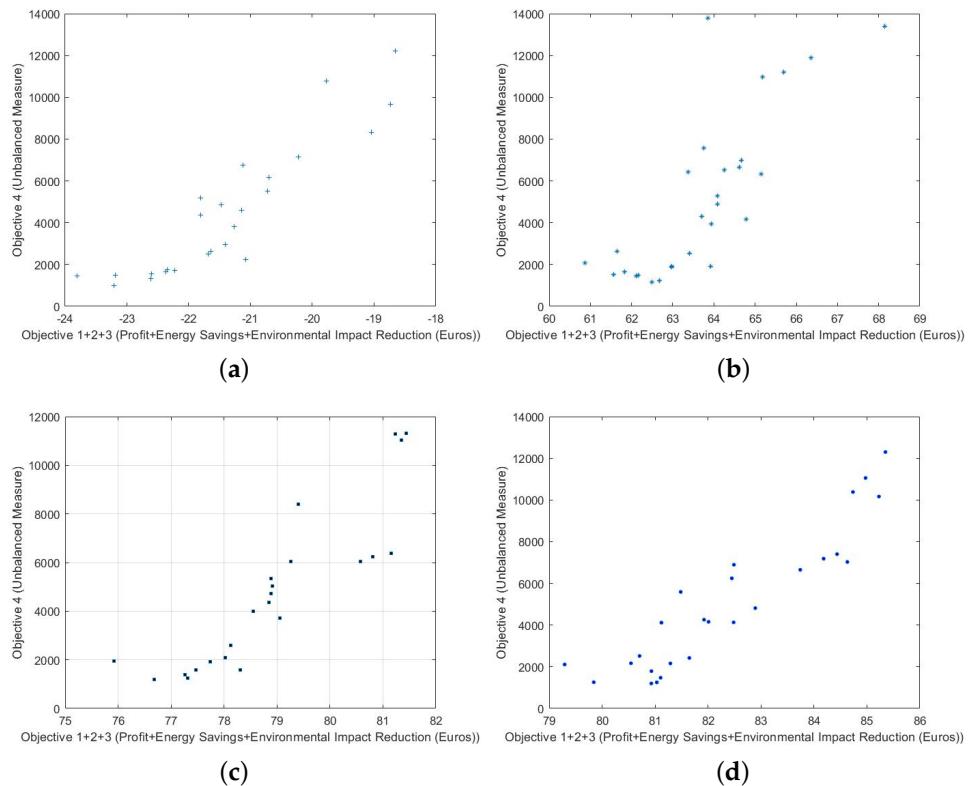


Figure 7. Plot of gear pump B best solutions under four sustainability scenarios **(a)** REC scenario; **(b)** REM scenario; **(c)** REU scenario; **(d)** OPT scenario.

The best outputs of the experiments are presented in Tables 10 and 11, showing the disassembly sequence, the disassembly direction, the product recovery for each component, the disassembly tool, the robotic workstation, and the value of the objectives for the case study.

Table 10. Example output of Gear Pump A under four scenarios.

Output	REC Scenario	REM scenario
Disassembly sequence	15-6-2-1-3-4-5-7-11-9-13-8-10-14-12	15-3-1-2-5-4-6-7-9-11-10-14-13-8-12
Disassembly direction	1-2-2-2-2-2-2-2-2-2-2-1-1	1-2-2-2-2-2-2-2-2-2-1-2-2-2
Component recovery	3-3-3-3-3-3-3-3-3-3-4-3-3-3	2-3-3-3-3-3-2-2-2-2-2-4-2
Disassembly tools	2-1-1-1-1-1-4-3-3-3-3-3-4	2-1-1-1-1-1-4-3-3-3-3-3-4
Robotic workstation	1-1-1-1-1-2-2-2-2-2-3-3-3	1-1-1-1-1-2-2-2-2-2-3-3-3
O ₁ (Euros)	-13.52	36.15
O ₂	31,140.35	22,514.56
Output	REU scenario	OPT scenario
Disassembly sequence	3-4-5-2-1-6-15-7-10-11-9-14-13-8-12	3-2-5-6-1-4-15-7-10-9-11-14-13-8-12
Disassembly direction	2-2-2-2-2-2-1-2-2-2-1-2-2-1	2-2-2-2-2-2-1-2-2-2-1-2-2-2
Component recovery	3-3-3-3-3-3-1-1-1-1-1-1-4-1	1-1-1-1-1-1-1-1-1-1-1-4-1
Disassembly tools	1-1-1-1-1-2-4-3-3-3-3-3-4	1-1-1-1-1-2-4-3-3-3-3-3-4
Robotic workstations	1-1-1-1-1-2-2-2-2-3-3-3-3	1-1-1-1-1-2-2-2-2-3-3-3-3
O ₁ (Euros)	64.82	66.40
O ₂	30,795.94	31,530.36

Direction 1 = Y+, 2 = Y-; recovery options 1 = reuse, 2 = remanufacturing, 3 = recycling, 4 = disposal;
Tools 1 = Spanner-I, 2 = Spanner-II, 3 = Gripper-I, 4 = Gripper-II

Table 11. Example output of Gear Pump B under four scenarios.

Output	REC Scenario
Disassembly sequence	2-3-5-4-1-24-23-22-21-19-20-6-18-7-13-11-17-16-9-10-8-12-14-15
Disassembly direction	2-2-2-2-2-1-1-1-1-1-2-1-2-1-1-2-2-2-2-2
Component recovery	3-3-3-3-3-3-3-3-3-3-3-3-3-4-4-3-3-4-4
Disassembly tools	1-1-1-1-3-3-3-3-2-2-1-4-5-4-4-4-4-4-5-4-4
Robotic workstation	1-1-1-1-1-1-1-1-2-2-2-2-3-3-3-3-3-3-3-3
O ₁ (Euros)	-22.6
O ₂	1310.7
Output	REM scenario
Disassembly sequence	4-5-6-3-2-1-24-23-21-22-20-7-8-19-9-18-11-13-10-17-12-14-15-16
Disassembly direction	2-2-2-2-2-2-1-1-1-1-2-2-1-2-1-2-1-2-2-2-2
Component recovery	3-3-3-3-3-3-3-3-3-2-2-4-2-2-2-2-4-2-4-4-4
Disassembly tools	1-1-1-1-1-3-3-3-3-2-5-4-2-4-4-4-4-4-5-4-4
Robotic workstation	1-1-1-1-1-1-1-1-2-2-2-2-3-3-3-3-3-3-3-3
O ₁ (Euros)	63.94
O ₂	3946
Output	REU scenario
Disassembly sequence	3-5-4-1-2-6-7-8-10-9-11-23-24-22-21-19-20-18-17-13-12-16-15-14
Disassembly direction	2-2-2-2-2-2-2-2-2-1-1-1-1-1-1-1-2-1-1-2
Component recovery	3-3-3-3-3-3-1-4-1-1-1-3-3-3-1-1-1-4-1-1-4-4
Disassembly tools	1-1-1-1-1-5-4-4-4-3-3-3-2-2-4-4-4-5-4-4
Robotic workstations	1-1-1-1-1-1-2-2-2-2-2-2-3-3-3-3-3-3-3
O ₁ (Euros)	78.88
O ₂	4712.87

Table 11. Cont.

Output	OPT scenario
Disassembly sequence	4-1-3-2-5-6-7-24-9-10-11-8-22-23-21-20-19-18-13-12-14-17-16-15
Disassembly direction	2-2-2-2-2-2-1-2-2-2-1-1-1-1-1-2-2-1-1-2
Component recovery	1-1-1-1-1-1-1-1-1-4-1-1-1-1-1-4-4-4-4
Disassembly tools	1-1-1-1-1-5-3-4-4-4-4-3-3-3-2-2-4-4-5-4-4-4-4
Robotic workstations	1-1-1-1-1-1-2-2-2-2-2-2-3-3-3-3-3-3-3-3
O ₁ (Euros)	82
O ₂	4155

Direction 1 = Y+, 2 = Y-; recovery options 1 = reuse, 2 = remanufacturing, 3 = recycling, 4 = disposal; Tools 1 = Spanner-I, 2 = Spanner-II, 3 = Spanner-III, 4 = Gripper-I, 5 = Gripper-II

5. Discussion

The proposed sustainable product recovery model was implemented using the Bees Algorithm to optimise the integration of robotic disassembly sequence planning and disassembly line balancing, with two industrial gear pumps as case studies. The MOBA was able to find the best solutions for the proposed four strategies of REC (recycling), REM (remanufacturing), REU (reuse), and OPT (optimal). Comparing the four strategies, the REU and OPT show similar results, which is logical given that if the parts are retained and reused in remanufacturing, they will yield higher profit, energy savings and environmental benefits. The difference is that OPT, which is the strategy generated by the MOBA, outperforms the REC, REM and REU strategies, producing higher Euro values.

The maximum value was generated by the OPT scenario for both gear pumps A and B. This scenario is the best recovery option for each part and yields the maximum value for the first three objectives, which use Euros as the unit of measurement. As has been seen, the REC scenario results in negative monetary values as the activities involving recycling demand a greater amount of energy and other resources. Recycling presents greater challenges than the other product recovery options, including the separation of EoL product materials to achieve a higher quality of material, energy consumption, and environmental impact. This finding supports the notion that recycling should be the last product recovery option. The proposed model could be adopted by industries to extend the life of resources and environmental benefits, allowing them to make the best product recovery decisions.

Although the sustainability model and product recovery options presented in this study show good results, a limitation is that it assumes that the EoL product can be completely disassembled and is in good condition. However, it is known that the condition of an incoming EoL product is uncertain. It might be worn out or corroded or have missing parts and other problems. This should be investigated in the future.

Nonetheless, the encouraging results obtained should motivate academic researchers and companies to investigate the possibility of incorporating the proposed model, given that doing so would increase productivity, efficiency, and monetary value while simultaneously making a positive contribution to the environment.

6. Conclusions

The viability of the sustainability model was demonstrated on real EoL products by optimising it using the Multi-Objective Bees Algorithm. This demonstrated that the model could be applied to a robotic disassembly cell. The recovery strategies show that recycling should be the final option, which is consistent with the circular economy's goals. Since robotic disassembly is emerging research while manual disassembly has matured, future work should consider tools in manual disassembly research, such as machine learning (including deep learning), that could also be used to investigate robotic disassembly. Additionally, other metaheuristic optimisation algorithms could be added as benchmarks. Furthermore, future studies will involve other more complex EoL products to

demonstrate the versatility of this method. Finally, further studies could be conducted on the impact of incoming product uncertainty on disassembly.

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Abbreviations

The following abbreviations are used in this manuscript:

BA	Bees Algorithm
CAD	Computer-Aided Design
EoL	End-of-Life
HI	Hypervolume Indicator
MFSG	Modified Feasible Solution Generation
MO	Multi-objective
MOBA	Multi-Objective Bees Algorithm
MCDM	Multiple-criteria Decision-making
NP	Non-Deterministic Polynomial
OPT	Optimal
POSs	Pareto Optimal Solutions
REC	Recycling
REM	Remanufacturing
REU	Reuse
RDLBSD	Sequence-Dependent Robotic Disassembly Line Balancing

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