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A sustainability-based model for robotic disassembly sequence planning in remanufacturing using the Bees Algorithm

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Abstract: Remanufacturing, as a way to achieve the circular economy paradigm, can help save the environment by reducing the use of raw materials and energy, cutting greenhouse gas emissions and virtually eliminating the need for landfill. Disassembly is a critical first step in the remanufacturing process. This research uses the Bees Algorithm to optimise robotic disassembly sequence planning. Three sustainability strategies are addressed in the proposed model-based system for robotic disassembly planning: reuse, remanufacturing, and recycling. The results of two case studies based on end-of-life industrial gear pumps demonstrate that the Bees Algorithm can find the best solution for robotic disassembly sequence planning.

Keywords: Bees Algorithm, disassembly sequence, optimisation, robotics, sustainability.

1. INTRODUCTION

As part of a circular economy (CE), remanufacturing benefits the environment, society and the economy (Ellen MacArthur Foundation, 2015). Remanufacturing reduces waste generation and energy and resource consumption in manufacturing (Chiodo and Ijomah, 2014). Several researchers have pointed out that disassembly is the most critical step in remanufacturing (Lambert, 2003; Wang *et al.*, 2013, 2014; Xia *et al.*, 2014; Zhou *et al.*, 2018). Disassembly sequence planning (DSP) involves designing a detailed sequence for breaking up the product (Lambert, 2003; Zhou *et al.*, 2018).

Optimising the disassembly of a product is classified as an NP problem, which means that the number of solutions increases exponentially as the number of parts in the system increases (Elsayed *et al.*, 2012; Meng *et al.*, 2017). When calculated manually, this problem requires a significant amount of time to find the best solution. Over the last two decades, computational researchers have used metaheuristic algorithms to accelerate the solution of complex problems. The Bees Algorithm (BA), introduced by Pham *et al.* (2005), is one of the metaheuristics that is robust in finding near-optimal solutions to solve complex problems faced by industry (Yuce *et al.*, 2013).

Intelligent disassembly systems have been studied for many years (IFAC, 2004). Recent investigations have focused on the sequencing of manual disassembly (Laili *et al.*, 2022). The use of robots in place of manual labour, on the other hand, has emerged as part of a transition to flexible automation in the era of Industry 4.0. This research focuses on robotic disassembly sequence planning (RDSP), which addresses disassembly processes utilising industrial robots. As highlighted by Liu *et al.* (2018), robotic disassembly presents challenges when compared to manual disassembly due to the differences in characteristics between robots and humans, particularly the moving path of the robot's end effector to avoid collision, which also affects the total time required for disassembly. Numerous researchers have proposed optimal solutions for robotic disassembly. Laili *et al.* (2019, 2022) and Li *et al.* (2018) demonstrate that the optimal solution for robotic disassembly using the BA outperforms those found by other metaheuristic algorithms. This study proposes a sustainability model and the optimal RDSP solution using the BA.

The structure of this paper is as follows. Section 2 provides an overview of the related literature using a bibliographic analysis. Then, the methodology and the sustainability model are described in Section 3. Section 4 provides the results and discussion of the optimal solution of RDSP using the BA for the sustainability-based model. Moreover, the last section provides the conclusion and further research directions.

2. LITERATURE REVIEW

Readers are referred to the work of Zhou *et al.* (2018) for a systematic literature review of disassembly sequence planning. The steps below describe the RDSP literature review in this study. The search terms "robot*" AND "disassembly"

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AND “sequenc*” yielded 151 articles in the Scopus database. The following criteria were used to refine the articles: the full text was in English and was available. The final results were 36 articles on robotic disassembly sequence planning and 10 on human-robot collaboration in product disassembly. Articles involving human-robot collaboration were excluded as this work concerns fully robotised disassembly. The bibliographic records for RDSP were downloaded for further analysis. The first article on robotic disassembly task sequencing was published in 1996 by Suzuki *et al.*, focusing on learning control systems using Petri nets. Figure 1 shows slow progress in robotic disassembly research, and the last four years saw a rising trend, with the most articles in 2018.

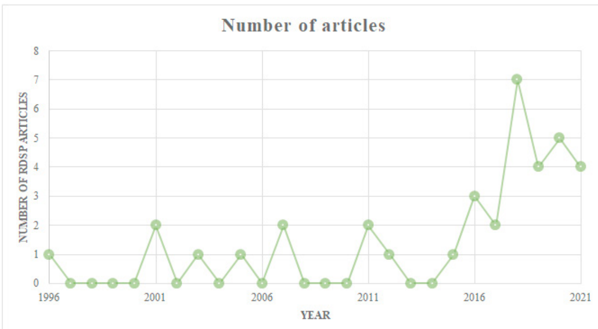

Figure 1. Robotic Disassembly Sequence Planning Trends

A co-occurrence analysis was conducted that revealed the clustering of co-authors, co-citations, and co-keywords, highlighting research trajectories, academic communities identification, and research trends (Van Eck and Waltman, 2017; Deniz and Ozcelik, 2019). Co-authorship based on authors with a threshold of a minimum of 2 documents per author shows that from 98 authors, 28 authors have worked on the same articles at least twice. The results show 7 clusters, with two closely related (Figure 2). The leading academic collaborators are Pham, Zhou, Xu and Liu. Co-authorship based on country shows that authors from seven countries have published more than two documents together. Four closely related countries were China, the UK, the USA and Spain with 11, 8, 8 and 4 documents, respectively. Germany had five documents without connection to other countries. This result reveals that the RDSP collaborators are concentrated in 4 countries.

The co-occurrence analysis also revealed the most popular keywords. 361 keywords were found, and based on a minimum of 4 occurrences, there were 19 keywords in 2 clusters. The top keywords were robotics, disassembly sequence, robot programming, disassembly sequence planning, robots, robotic disassembly, disassembly process, end-of-life products, and remanufacturing.

For a visual representation of the VOS analysis, readers can refer to https://doi.org/10.25500/edata.bham.00000778

The citation analysis in Figure 3 shows that the most cited documents were Elsayed *et al.* (2012), Gil *et al.* (2007), Vongbunyong *et al.* (2015), Liu *et al.* (2018), Ramírez *et al.* (2020) and Alshibli *et al.* (2016). The most cited authors are

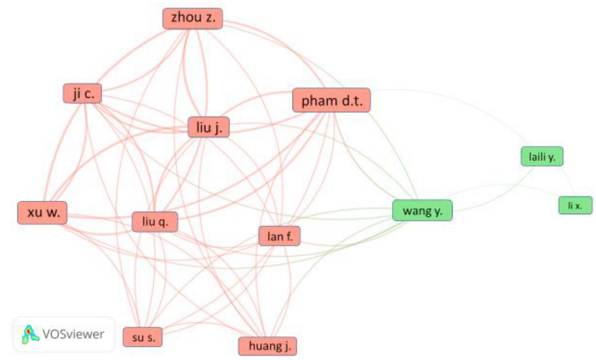

Figure 2. Top RDSP Co-authorship based on authors

Pham, Zhou, Xu, and Liu, who are also the leading academic collaborators, as previously mentioned.

The last step in the literature review was document classification, emphasising the sustainability model in RDSP. Of the 36 RDSP articles, only 3 used sustainability objectives.

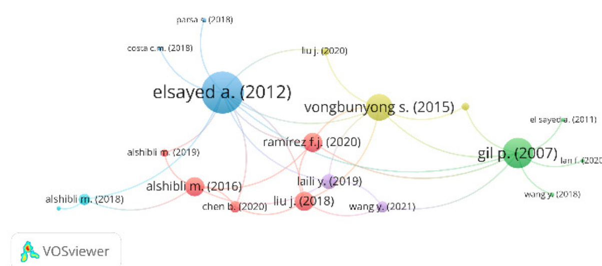

Figure 3. Top RDSP Citation based on documents

Another article, Alshibli *et al.* (2018), considered environmental, economic and social criteria and adopted the analytical hierarchy process (AHP) to decide the end-of-life option focusing on minimising disassembly time. The main contribution of this research is the sustainability-based model as shown in Table 1.

Table 1. Research Position

Authors	Recovery Options	Objectives	Disassembly Output
Alshibli *et al.* (2018)	Recycling, Reuse, Disposal	Min time. Using AHP for environmental, economic, social criteria	Sequence and Recovery
Gao *et al.* (2018)	-	Min energy	Sequence, Direction, Tool
Wang *et al.* (2021)	-	Min makespan and energy	Sequence
This paper	Recycling, Remanufacturing, Reuse, Disposal	Max profit, energy savings, environmental impact	Sequence, Recovery, Direction, Tool

3. METHODOLOGY AND MODEL

The research steps are shown in Figure 4. To eliminate infeasible sequences, the first step was to prepare the input data and evaluate part interference and precedence relationships, as suggested by Zhou *et al.* (2018). Initially, extensive information was acquired on the product, its components, its properties, and the viability of its recovery. Data from CAD files were used as the input for the model. Additionally, unlike manual disassembly, the model must include the disassembly direction to establish the proper paths for robot movement. Finally, the proposed model was evaluated on two industrial gear pumps (Figures 5 and 6) to demonstrate its feasibility.

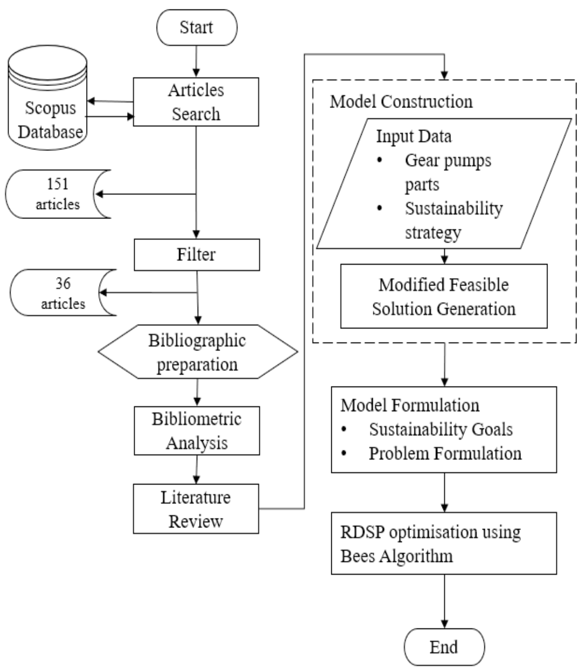

Figure 4. Research Steps

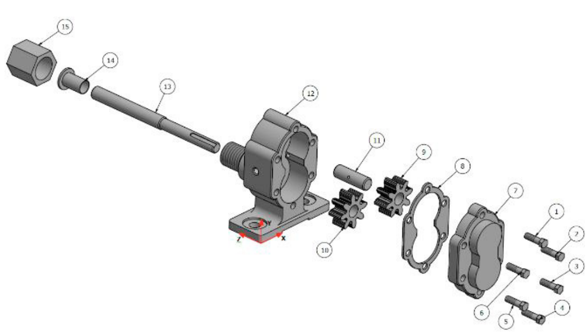

Figure 5. Gear Pump A (Exploded view).
Source: Liu *et al.* (2018)

This study utilises three sustainable recovery strategies to address the RDSP: reuse (REU), remanufacturing (REM), and recycling (REC). Due to the nature of the components, not all of them may have the same recovery mode. For instance, the gasket will be unsuitable for reuse, remanufacturing or recycling and therefore will be discarded. Consequently, three strategies were developed for each component. Table 2 shows the strategies in detail.

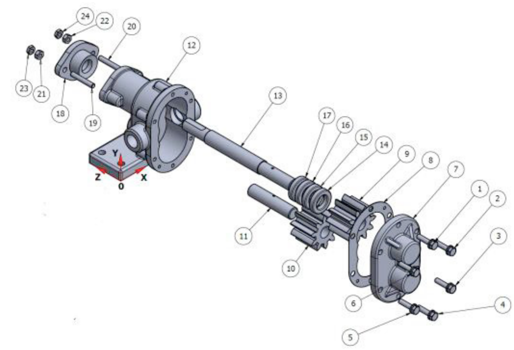

Figure 6. Gear Pump B (Exploded view).
Source: Grabcad Community (2020) and Ramírez *et al.* (2020)

Table 2. Sustainability Strategy for each part

Gear pump A strategy				Gear pump B strategy			
Part	REU	REM	REC	Part	REU	REM	REC
1	3	3	3	1	3	3	3
2	3	3	3	2	3	3	3
3	3	3	3	3	3	3	3
4	3	3	3	4	3	3	3
5	3	3	3	5	3	3	3
6	3	3	3	6	3	3	3
7	1	2	3	7	1	2	3
8	4	4	4	8	4	4	4
9	1	2	3	9	1	2	3
10	1	2	3	10	1	2	3
11	1	2	3	11	1	2	3
12	1	2	3	12	1	2	3
13	1	2	3	13	1	2	3
14	1	2	3	14	4	4	4
15	1	2	3	15	4	4	4
				16	4	4	4
				17	4	4	4
				18	1	2	3
				19	1	2	3
				20	1	2	3
				21	3	3	3
				22	3	3	3
				23	3	3	3
				24	3	3	3
Recovery mode: 1=reuse, 2 = remanufacturing, 3 = recycling,4 = disposal							

The disassembly precedence in six disassembly directions (X+, X-, Y+, Y-, Z+, Z-) is described using the space interference matrix, as proposed by Jin *et al.* (2013). However, when the products to be disassembled contain fasteners, the previous approach is inadequate. Liu *et al.* (2018) proposed a solution to this problem, called modified feasible solution generation (MFSG), to analyse each matrix independently.

The second step is the model formulation for the RDSP, which includes objective definition and problem formulation. The optimisation goal of this robotic disassembly operation is to maximise the objective, as shown in Eq. (1):

$$Objective = max(f1, f2, f3) \tag{1}$$

The variable descriptions for the equations are listed in Table 3. The objectives are profit (f1), energy savings (f2) and environmental impact reduction (f3), as presented in Eqs. (2)-(4), respectively. In addition, Eq. (5) ensures that each part only has one recovery mode, Eq. (6) guarantees that all parts are disassembled, Eq. (7) ensures that the precedence disassembly sequence is followed, and Eq. (8) guarantees that the total number of dismantled parts is not exceeded. Of course, different sustainability strategies produce different outcomes, and the purpose of this model is to identify the most suitable strategies for each objective.

$$f_1 = \sum_{i=1}^{N}\sum_{j=1}^{2} RP_i r_{i,j}\alpha_i + \sum_{i=1}^{N} RC_i r_{i,3}\alpha_i - \sum_{i=1}^{N} CD_i r_{i,4}(1-\alpha_i) - \Bigg[\sum_{i=1}^{N-1} t_b(x_i)\alpha_i c_T + \sum_{i=1}^{N-1}\left(\frac{PD(x_i,M)}{v_e} + t_c(x_i,x_{i+1}) + \frac{PD(M,x_{i+1})}{v_e} + t_u(x_i,M) + t_w(M,x_{i+1})\right)\gamma_i\alpha_i c_T + \sum_{i=1}^{N-1}\left(\frac{PD(x_i,x_{i+1})}{v_e} + t_z(x_i,x_{i+1})\right)(1-\gamma_i)\alpha_i c_T\Bigg] - \sum_{i=1}^{N}\sum_{j=1}^{2} rc_{i,j} r_{i,j}\alpha_i - \sum_{i=1}^{N}\sum_{j=1}^{4} oh_{i,j} r_{i,j}\alpha_i - \sum_{i=1}^{N}\sum_{j=1}^{4} dp_{i,j} r_{i,j}\alpha_i \quad (2)$$

$$f_2 = \sum_{i=1}^{N}\sum_{j=1}^{2} r_{i,j} gr_{i,j} f_w \alpha_i - \sum_{i=1}^{N-1}\Bigg[t_b(x_i)PR_1\gamma_i + \frac{PD(M,x_i)PR_2\gamma_i}{v_e} + t_c(x_i,x_{i+1})PR_2\gamma_i + \frac{PD(M,x_{i+1})PR_2\gamma_i}{v_e} + \frac{PD(x_i,x_{i+1})PR_2(1-\gamma_i)}{v_e}\Bigg]\frac{f_w\alpha_i}{3600} - \sum_{i=1}^{N}\sum_{j=1}^{3} r_{i,j} gc_{i,j} f_w \alpha_i - \sum_{i=1}^{N} r_{i,4} gc_{i,4} f_w (1-\alpha_i) \quad (3)$$

$$f_3 = \sum_{i=1}^{N}\sum_{j=1}^{2} r_{i,j} er_{i,j}\alpha_i - \sum_{i=1}^{N}\sum_{j=1}^{3} r_{i,j} ec_{i,j}\alpha_i - \sum_{i=1}^{N} r_{i,4} ec_{i,4}(1-\alpha_i) - \sum_{i=1}^{N-1} ed(x_i)\alpha_i - \sum_{i=1}^{N-1} ed(x_{i,}, x_{i+1})\alpha_i \quad (4)$$

$$\sum_{j=1}^{4} r_{i,j} = 1 \qquad \forall i \quad (5)$$

$$r_{i,1} + r_{i,2} + r_{i,3} \le \alpha_i \quad (6)$$

$$\alpha_i \ge \alpha_{i+1} \quad (7)$$

$$\sum_{i=1}^{N} \alpha_i \le N-1 \quad (8)$$

4. RESULTS AND DISCUSSION

The algorithm used in this study to find the best solution for RDSP was the Bees Algorithm proposed by Pham *et al.* (2005). In this research, the version called the Enhanced Discrete Bees Algorithm (EDBA) presented by Liu *et al.* (2018) was adopted. The algorithm starts from initialisation with parameter settings as follows: number of elite sites (*e*) = 1, number of selected sites (*m*) = 5, number of elite site bees (*nep*) = 10, number of selected site bees (*nsp*) = 5, population sizes (*n*) = 50, 60, 70, 80. The maximum number of iterations, which was chosen as the stopping criterion, was set at 100, 200, 300, 400, and 500. MFSG was used to generate (*n*) scout bees that represented feasible disassembly sequences. Subsequently, the *n* scout bees were sorted by fitness value. The elite site bees (*nep*) used a neighbourhood strategy to search the elite sites (*e*). The *nsp* bees adopted the same neighbourhood strategy to search the selected sites (*m*). The remaining bees (*n-m*) performed a random search exploring the solution space. The best RDSP data were retained, and the procedure repeated until the maximum number of iterations was reached.

Table 3. Variable Description

Variable	Description
α_i	indicator that takes the value of 1 if component *i* is to be disassembled and 0 otherwise.
CD_i	disposal cost of component *i* being disposed of
c_T	cost per unit of time
$dp_{i,j}$	depreciation cost assigned to component *i* to be disassembled
$ec_{i,j}$	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
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*
$gd_{2,i}(x_i,\mathrm{M})$	energy consumption of the robot in the movement between the position x_i and M
$gd_{3,i}(\mathrm{M})$	energy consumption of the robot in the tool change
$gd_{4,i}(\mathrm{M},x_{i+1})$	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}
γ_i	indicator taking the value 1 if operation x_{i+1} requires changing the tool used in previous operation x_i
$gr_{i,j}$	energy reclaimed from component *i* being reused or remanufactured
i	index for each component and varies from 0 to *N*
j	indicator of the recovery mode and equal to 1 if component *i* is assigned to be reused, 2 if it is to be remanufactured, 3 if it is to be recycled or 4 if it is to be 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}
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
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* to be 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

Variable	Description
$t_u(x_i,M)$	penalty time for process direction changes along the path between x_i and the tool magazine (M) and formulated as follows: 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}, and is formulated as t_u
$t_z(x_i,x_{i+1})$	penalty time for process direction changes along the path between x_i and x_{i+1}, and formulated as t_u
v_e	line velocity of the industrial robot's end effector

The input data used in this study and the results obtained can be found at https://doi.org/10.25500/edata.bham.00000778. As discussed earlier, a single-objective experiment for each objective was conducted to find the near optimal solution for the three sustainability strategies. The experimental results for each objective show that the BA under different population sizes and iteration sizes yielded similar optimal solutions for the reuse, recycling, and remanufacturing strategies. Figure 7 presents the experimental results, showing the maximum fitness value for each goal.

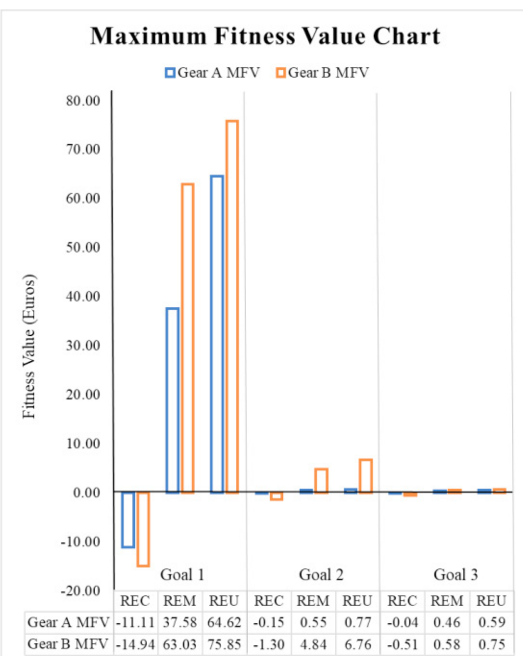

Figure 7. Maximum Fitness Value Result

The REU strategy yielded the highest fitness value, followed by remanufacturing and recycling strategies for both gear pumps. This is understandable due to the additional processing for REM and REC compared to the REU Strategy. The findings show that the best sustainability strategies for each goal were REU and REM. The first objective, profit, yields the highest value for the REU strategy as well as the lowest solution for the REC strategy among the objectives. The environmental impact reduction (Goal 3) show the lowest recovery value (in Euros).

Table 4 illustrates the RDSP output by displaying the disassembly output for gear pump A in the REM strategy. The sequence, direction, recovery mode, and tools are all presented. The previous link provides the results for the REC and REU strategies and for gear pump B.

Table 4. Gear Pump A (REM strategy)

Goal	Disassembly	
1	Sequence	15-1-2-3-4-5-6-7-10-11-9-14-13-8-12
	Direction	1-2-2-2-2-2-2-2-2-2-2-1-1-2-1
	Mode	2-3-3-3-3-3-3-2-2-2-2-2-2-4-2
	Tool	2-1-1-1-1-1-1-4-3-3-3-3-3-3-4
	MFV	37.58 Euro
2	Sequence	2-1-6-5-4-3-7-9-11-10-8-15-12-13-14
	Direction	2-2-2-2-2-2-2-2-2-2-2-1-2-2-2
	Mode	3-3-3-3-3-3-2-2-2-2-4-2-2-2-2
	Tool	1-1-1-1-1-1-4-3-3-3-3-2-4-3-3
	MFV	0.55 Euro
3	Sequence	3-5-4-1-6-2-7-8-10-9-13-11-15-12-14
	Direction	2-2-2-2-2-2-2-2-2-2-2-2-1-2-1
	Mode	3-3-3-3-3-3-2-4-2-2-2-2-2-2-2
	Tool	1-1-1-1-1-1-4-3-3-3-3-3-2-4-3
	MFV	0.46 Euro
Disassembly Direction: 1 = Y+ direction, 2 = Y- direction		
Disassembly Mode: 1=reuse, 2=remanufacturing, 3=recycling, 4=disposal		
Disassembly Tool: 1=Spanner-I, 2 = Spanner-II, 3 = Gripper-I, 4 = Gripper-II		
MFV = Max Fitness Value		

5. CONCLUSION

This research has contributed a sustainability-based method using the Bees Algorithm to solve the RDSP problem. Three recovery strategies, REC, REM and REU, have been investigated. The REU and REM strategies both yielded positive values for profit, energy savings and environmental impact reduction. In comparison, REC gave negative values for all three objectives. This study has determined the highest possible value for each goal when considered independently of the others. Further research will be conducted using a multiobjective, nondominated approach to examine the interaction between the goals. In addition, the Bees Algorithm will be benchmarked against other optimisation techniques to establish its strong performance.

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