Disassembly Process Planning Under End-of-Life Product Quality

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Abstract. Quality of post-consumer products is one of the major sources of uncertainty in disassembly systems. This paper presents a decision tool for disassembly process planning under variability of the End-of-Life product quality. The objective is to maximize the profit of the disassembly process. This latter is the difference between the revenue generated by recovered parts and the cost of the disassembly tasks. The revenue of a product (subassembly, component) depends on its quality. The proposed approach helps to take decisions about the best disassembly process and the depth of disassembly, depending on the quality of the products to be disassembled. Industrial applicability and interest are shown using an industrial case focused on the remanufacturing of mechatronic parts in the automotive industry.

Keywords: Sustainable manufacturing · Product recovery · Disassembly · Quality uncertainty management · Decision support system

1 Introduction

Reverse logistics and its processes are nowadays well accepted and understood. In addition, it is well understood that ease materials recycling, reuse and remanufacturing constitute critical factors for sustainable competitiveness [12]. Remanufacturing is a key enabler technology [8,10] not only for sustainable development but as well for economic and social developments. As such, it addresses the 3 pillars of sustainability, i.e. Economic, Social, and Environmental.

The process of re-manufacturing requires to disassemble; to clean; to inspect, diagnose and sort; to re-condition and to re-assemble [4,11]. When considering "systems", with several sub-systems as cars, computers, etc., a prior step to disassembly is required in order to diagnose the defect and remaining functionalities [9]. Such prior step is a pre-require since returned products are subject to highly variable condition [3,6]. It leads to uncertainty and high variability in the disassembly step while other steps remain less impacted. Disassembly lines

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remain artisanal with versatile workstations at the expense of efficiency. In order to consider disassembly at an industrial level, one has to tackle these variability and uncertainty in returned product quality.

The present paper considers the disassembly process as an industrial process. In such a way, a single type of product is considered as input flow of the disassembly process. Such hypothesis seems realistic when considering mass products such as automobiles, cell phones, laptops, refrigerators, etc. Hence, the disassembly process cannot be considered as an artisanal-work manner as is currently. Thus, disassembly process has to be planned in advance and its financial viability has to be demonstrated. This work proposes a tool in order to define the optimal disassembly depth/level of a product regarding the profit. The originality of the proposed approach is to consider the health state of the product, its parts and sub-parts in the revenue estimation as random variables. The state of a part allows to decide its re-cycling: maintenance, re-use, regeneration or raw material recycling [7]. The re-cycling of a product impacts in a non-linear way its resale price. The recycling decision requires a quantification of the part capacity to re-enter a cycle. For such a purpose, we introduce the Remaining Usage Potential (RUP).

The economical optimization of the disassembly process considers the cost of the disassembly tasks and the revenue of the resale of the disassembled parts. The latter is highly dependent on the re-entering usage cycle whose decision is based on the RUP. The RUPs of a product and its parts are considered as distributions since we consider mass recycling.

This paper is structured as follows. A formal description of the studied problem is presented in Sect. 2. Section 3 presents the developed model along with the solution approach. Numerical experiments and optimization results are presented in Sect. 4. Section 5 concludes the paper with future research directions.

2 Problem Definition and Modeling

In this work, we consider a remanufacturing process where the revenue from retrieved parts (subassemblies and components) depends on the quality of the incoming return products. For an End-of-Life product, the problem consists on the selection of a best disassembly process alternative, among all possible ones, taking into account its RUP and precedence relationships amongst all disassembly tasks and product parts obtained during the disassembly process.

The following assumptions are used. A single type End-of-Life product has to be partially (or completely) disassembled. All received items contain all initial parts with no addition or removing of components. In the case of industrialized disassembly, as it is for remanufacturing systems, this hypothesis seems realistic when a large percentage of products arrive in these conditions. Each component or subassembly has a resale value which represents its revenue. This revenue depends on the quality of the corresponding component or subassembly. The state or quality of each subassembly is modeled using the concept of RUP which follows a probability distribution. In the optics of industrialized disassembly, i.e. a large number of products of the same category are returned, to obtain such a probability distribution, statistical studies on disassembled products can be conducted.

2.1 *And/or* Graph

All possible disassembly process alternatives of an End-of-Life product, along with the precedence relationships among tasks and product subassemblies and components, are modeled explicitly using an *and/or* graph [1] (see Fig. 1).

Each subassembly is represented by a node labeled $A_k, k \in K$. For a simplification reason of the *and/or* graph, the components generated by all disassembly tasks are not explicitly represented in the graph. Each node labeled $B_i, i \in I$, represents a disassembly task. Two types of arcs define the precedence relations between subassemblies and disassembly tasks: *and* and *or*. The first type imposes a mandatory precedence relation and the second type is employed for optional precedence dependencies. A sink node 'S' is introduced and linked with dummy arcs to all the disassembly tasks to model the case of partial disassembly (Fig. 1). For a detailed description of the *and/or* graph modeling process, see [2,5].

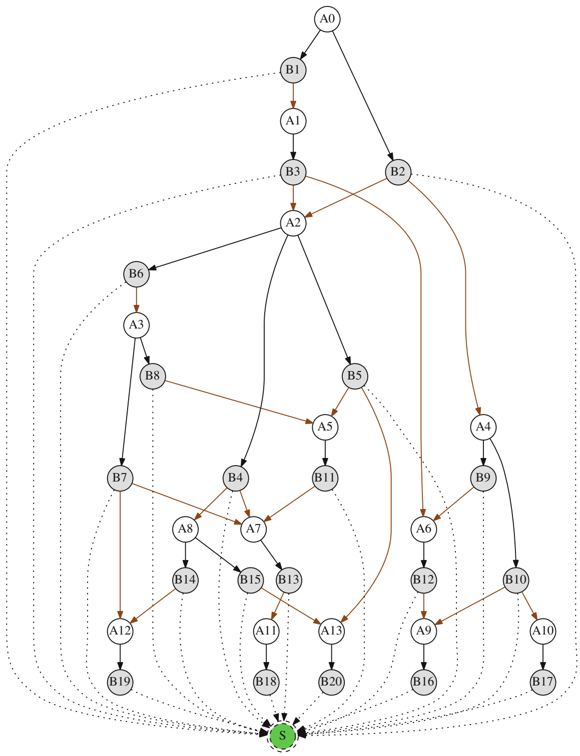

Fig. 1. *And/or* graph of the ball point pen example [1].

2.2 Remaining Usage Potential and Its Probability Density Function

In order to assess the state to be considered for disassembly, we defined the Remaining Usage Potential (RUP). The RUP stands for the “usage” quantity remaining for a product or a part. In our proposition, the RUP is evaluated *prior* to the disassembly. The RUP is evaluated on a $[0, 1]$ scale; 1 corresponds to the product state at the beginning of its exploitation (the product is at its maximal RUP); 0 means that the product/part has reached its end of life and has to be recycled as raw material.

The RUP is modeled as a probability density function since this study considers a mass disassembly process. As such, the number of products to be considered is high and the RUP shall be considered in a statistical way. We consider the RUP as a normal probability density function truncated in 0 and 1. The RUP follows a truncated normal distribution on $[0, 1]$ with μ and σ parameters: RUP $\rightsquigarrow \mathcal{N}_{[0,1]}(\mu, \sigma)$; μ and σ are respectively the mean and standard deviation of the original non truncated normal distribution. Figure 2 shows, over $[0, 1]$ interval, 3 truncated normal distribution functions with parameters: $(\mu = 0, \sigma = 0.2)$, $(\mu = 0.5, \sigma = 0.3)$ and $(\mu = 1, \sigma = 0.2)$. Curves in Fig. 2 shall stand for the RUP of either a product, a part (component) or a sub-part (subassembly):

- The yellow curve, with $\mu = 0$ and $\sigma = 0.2$, shows a heavily worm part whose RUP is statistically low.
- The blue curve, with $\mu = 1$ and $\sigma = 0.2$, shows a slightly used part whose RUP is statistically high.
- The red curve in the middle, with $\mu = 0.5$ and $\sigma = 0.3$, shows a middle term part whose RUP is statistically average.

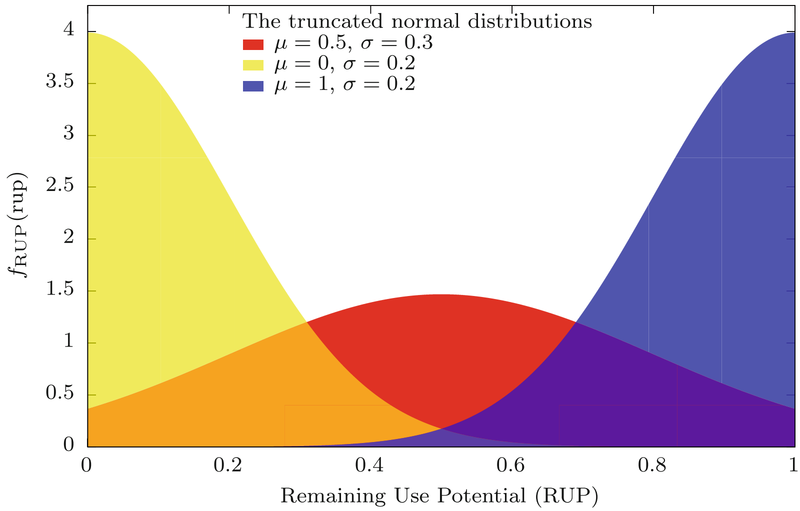

Fig. 2. RUP distribution examples as normal distributions truncated on [0, 1]. (Color figure online)

2.3 Part Revenue with Respect to Its RUP

Since the items have not the same RUP, their resale prices have to be considered as functions of their RUPs. The resale price represents the revenue (R_e) due to recycling recovery of disassembly items. Obviously, the higher the RUP, the higher the revenue. We defined the revenue R_e as a function of the RUP: $R_e(\text{RUP})$. In addition, we assume that the resale price is bounded. The upper bound corresponds to the resale price of an "almost new" used item. Indeed, it is not realistic to consider the sale price as upper bound since as soon as an item is used it depreciates. The lower bound corresponds to the resale price of the raw material of the item. The upper bound, resp. the lower one, corresponds to $R_e(\text{RUP} = 1) = b$, resp. $R_e(\text{RUP} = 0) = a$, with $b > a > 0$. We defined 3 cases for R_e according to the RUP, with the corresponding definition of $R_e(\text{RUP})$:

- The first case considers a linear RUP revenue function, i.e. R_e is proportional to the item's RUP: $R_e = (b - a) \cdot \text{RUP} + a$, affine function.
- The second case considers a rapid growth of the R_e revenue according to the item's RUP with a stabilization when the item's RUP becomes medium. Such a R_e revenue variation is modeled with a root function. Such a case means that the re-sale price of an item remains hight the long "RUP" term despite the drop of the RUP: $R_e = (b - a) \cdot \sqrt[4]{\text{RUP}} + a$, root function.
- The third one considers R_e low for low and medium RUP levels and increases rapidly for high levels of the RUP:
  $R_e = e^{\frac{1}{e-1}\left(e\ln(a)-\ln(b)\right)} e^{\frac{1}{e-1}\left(\ln(b)-\ln(a)\right)e^{\text{RUP}}}$, exponential function.

2.4 Part Revenue Probability Density Function

Combining the RUP probability density function with the part revenue function gives the part revenue probability density function. For the 3 R_e functions presented above, the corresponding probability density functions are:

$$f_{R_e}(r_e) = \frac{1}{b-a} \; \frac{\phi(\mu, \sigma, \frac{r_e-a}{b-a})}{\Phi(\mu,\sigma,1) - \Phi(\mu,\sigma,0)} \mathbb{I}_{[a,b]} \qquad \textbf{(pdf-affine)}$$

$$f_{R_e}(r_e) = \frac{4}{(b-a)^4} \; (r_e - a)^3 \; \frac{\phi(\mu, \sigma, (\frac{r_e-a}{b-a})^4)}{\Phi(\mu,\sigma,1) - \Phi(\mu,\sigma,0)} \mathbb{I}_{[a,b]} \qquad \textbf{(pdf-root)}$$

$$f_{R_e}(r_e) = \frac{1}{r_e \; (\ln(r_e) - \alpha)} \; \frac{\phi(\mu, \sigma, \ln(\frac{\ln(r_e)-\alpha}{\beta}))}{\Phi(\mu,\sigma,1) - \Phi(\mu,\sigma,0)} \mathbb{I}_{[a,b]} \qquad \textbf{(pdf-expo)}$$

$$\text{where } \alpha = \frac{1}{e-1}\;(e\ln(a) - \ln(b)) \text{ and } \beta = \frac{1}{e-1}(\ln(b) - \ln(a));$$
$$e = 2.71828\cdots \text{is the Euler's constant}$$

$\phi(\mu, \sigma, x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2\sigma^2}(x-\mu)^2}$ defines the normal probability density function of mean μ and standard deviation σ and $\Phi(\mu, \sigma, \cdot)$ defines its cumulative distribution function. We consider 3 cases for the RUP distribution, i.e. RUP $\rightsquigarrow \mathcal{N}_{[0,1]}(\mu, \sigma)$, according to the part quality (see Fig. 2): bad ($\mu = 0, \sigma = 0.2$), medium ($\mu = 0.5, \sigma = 0.3$) and good ($\mu = 1, \sigma = 0.2$).

3 Optimization Model and Solution Approach

To model the defined disassembly process planning problem, the following notations are introduced.

3.1 Adopted Notation

A_k : a subassembly: $k \in K$;
B_i : a disassembly task: $i \in I$;
c_i : cost of disassembly task B_i, $i \in I$: $c_i = c \cdot t_i, \forall i \in I$; t_i is the processing time of task B_i and c is a fixed cost per disassembly time unit, $i \in I$;
D_ℓ : set of indices of tasks disassembling subassembly $\ell, \ell \in L$;
G_ℓ : set of indices of tasks generating subassembly or component $\ell, \ell \in L$;
I : set of disassembly task indices: $I = \{1, 2, \ldots, \mathsf{N}\}$, $\mathsf{N} \in \mathbb{N}^*$;
K : set of indices for the generated subassemblies: $K = \{0, 1, \ldots, \mathsf{K}\}$, $\mathsf{K} \in \mathbb{N}$;
L : set of all product part indices (subassemblies and components): $L = \{1, 2, \ldots, \mathsf{L}\}$, $\mathsf{L} \in \mathbb{N}^*$;
L_i : set of indices of retrieved subassemblies and components by the execution of disassembly task $B_i, i \in I$;
P_k : set of indices of A_k predecessors, $k \in K$: $P_k = \{i | \ B_i$ precedes $A_k\}$;
$\widetilde{R_{e\ell}}$: revenue generated by a subassembly or component $\ell, \ell \in L$, where $\widetilde{R_{e\ell}}$ is a function of $\widetilde{\mathrm{RUP}}_\ell$: $\widetilde{R_{e\ell}}(\widetilde{\mathrm{RUP}}_\ell)$, $\ell \in L$; $\widetilde{\mathrm{RUP}}_\ell$ represents the remaining usage potential of a subassembly or component $\ell, \ell \in L$;
S_k : set of indices of A_k successors, $k \in K$: $S_k = \{i | \ A_k$ precedes $B_i\}$.

3.2 Decision Variables

$$x_i = \begin{cases} 1, & \text{if disassembly task } B_i, i \in I \text{ is selected;} \\ 0, & \text{otherwise.} \end{cases}$$

$$y_\ell = \begin{cases} 0, & \text{if } \sum_{i \in G_\ell} x_i = 1, \ell \in L \text{ and } \sum_{i \in D_\ell} x_i = 1 \, (\ell \text{ subassembly}); \\ 1, & \text{otherwise.} \end{cases}$$

Variable $y_\ell, \ell \in L$ means: for a subassembly with index $\ell \in L$, if a disassembly task with index $i, i \in G_\ell$ which generates ℓ is chosen and, next, another disassembly task $j, j \in D_\ell$, of the same disassembly process alternative, which disassembles it is also chosen, then its revenue $\widetilde{R_{e\ell}}$ is not taken into account while calculating the revenue of the whole disassembly process.

3.3 Objective Function and Constraints

The objective is to determine a disassembly process alternative with the maximum profit while considering the quality or states of the subassemblies and components generated during the disassembly process. The objective function and associated constraints are formulated as follows:

$$\max \left\{ \sum_{i \in I} \sum_{\ell \in L_i} \widetilde{R_{e\ell}} \cdot y_\ell \cdot x_i - \sum_{i \in I} c_i \cdot x_i \right\} \tag{1}$$

s.t.

$$\sum_{i \in S_0} x_i = 1 \tag{2}$$

$$\sum_{i \in S_k} x_i \leqslant \sum_{i \in P_k} x_i, \forall k \in K \backslash \{0\} \tag{3}$$

$$\text{If } \sum_{i \in D_\ell} x_i = 1 \text{ and } \sum_{i \in G_\ell} x_i = 1 \text{ then } y_\ell = 0, \forall \ell \in L \, (\ell \text{ subassembly}) \tag{4}$$

$$y_\ell = 1, \forall \ell \in L \, (\ell \text{ component}) \tag{5}$$

$$x_i, y_\ell \in \{0,1\}, \forall i \in I, \forall \ell \in L \tag{6}$$

The terms of the objective function represent, respectively, the earned profit of retrieved parts and the cost of the corresponding disassembly tasks. Precedence constraints, partial disassembly and possible values of the decision variables are defined by constraints (2)–(6).

3.4 Solution Approach

In order to solve the developed model, we consider different values of the revenue $\widetilde{R_{e\ell}}, \forall \ell \in L$, where ℓ represents a subassembly or a component. These values depend on: $\widehat{\mu}_\ell$ (mean of $\widetilde{R_{e\ell}}$) and $\widehat{\sigma}_\ell$ (standard deviation of $\widetilde{R_{e\ell}}$), $\forall \ell \in L$.

Concretely, 3 values of $\widetilde{R_{e\ell}}, \forall \ell \in L$ will be considered: $R_{e\ell} = \widehat{\mu}_\ell$ and $R_{e\ell} = \widehat{\mu}_\ell \pm \widehat{\sigma}_\ell$, $\forall \ell \in L$. The values of $\widehat{\mu}_\ell$ and $\widehat{\sigma}_\ell$ of the revenue $\widetilde{R_{e\ell}}$ of each subassembly and component $\ell, \ell \in L$, are calculated using numerical integrations. Subsequently, the obtained problems will be solved using the IBM solver CPLEX 12.6.

4 Numerical Illustration: Application to an Industrial Case

Model (1)–(6) is implemented in Linux using C++ on a PC with 8×CPU 2.80 GHz and 32 Go RAM. It is solved using ILOG CPLEX 12.6. It is applied to a case product in the automotive part remanufacturing: a Knorr-Bremse EBS 1 Channel Module. Such a product is composed of at least 45 components; see here for detailed example of End-of-Life EBS 1 Channel Module disassembly.

Figure 3 represents its *and/or* graph and gathers the obtained optimization results for different values of $R_{e\ell}, \ell \in L$. The obtained results can be summarized as follows: the profit of the disassembly process depends not only on the sequence and level of disassembly but also on the state or quality of the product. In fact, profit is the difference between revenues (R_e) of the components and/or subassemblies and costs c_i of the disassembly tasks. As disassembly costs are known and fixed, then the profit in our case depends mainly on the revenues of the components and/or subassemblies. Revenues are random and they are functions of states of the components and subassemblies. Thus, the profit of the disassembly process depends on the sequence and level of disassembly of the product. The level of disassembly is itself dependent on the states (quality) of the components and subassemblies.

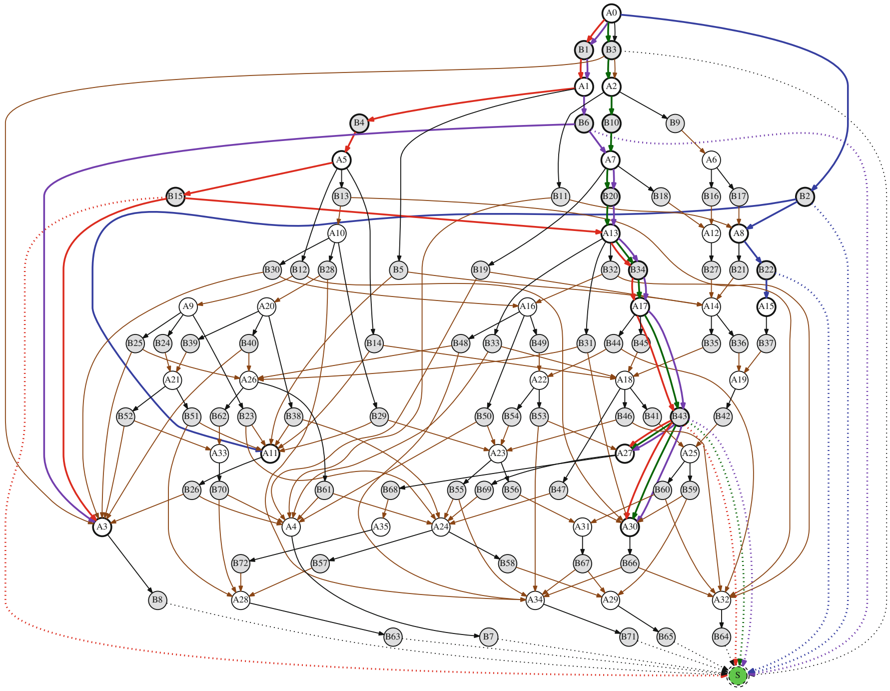

Fig. 3. Alternatives and disassembly levels returned according to the type of revenue functions: EBS 1 Module.

Figure 3 shows in detail the alternative and the level of disassembly returned for each revenue function type of components and subassemblies. In order to identify easily the disassembly alternatives in Fig. 3, a color is assigned to each alternative as shown in Table 1. Table 2 illustrates the obtained disassembly alternative and objective value for each type of revenue function and each value of this revenue ($R_{e\ell}, \forall \ell \in L$). The results, as example, show that for the same

Table 1. Colors representing all obtained disassembly alternatives.

Disassembly alternative	Alternative color	
B_2 B_{22}	(blue)	EBS 1 Module
B_1 B_4 B_{15} B_{34} B_{43}	(red)	
B_3 B_{10} B_{20} B_{34} B_{43}	(green)	
B_1 B_6 B_{20} B_{34} B_{43}	(purple)	

Table 2. Obtained disassembly alternatives and their objective values (cents €).

	$R_{e\ell} = \widehat{\mu}_\ell$	$R_{e\ell} = \widehat{\mu}_\ell - \widehat{\sigma}_\ell$	$R_{e\ell} = \widehat{\mu}_\ell + \widehat{\sigma}_\ell$	
Affine	63550.2	54146.7	72953.7	EBS 1 Module
Root	72710.7	69702.4	76084.2	
Expo	26689.4	6782.7	46828.7	

alternative and the same level of disassembly, values of the corresponding profits depend on the type of the revenue functions considered. These objective values are relatively important for functions of type root, relatively low for functions of type expo and are rather average for functions of type affine.

The results of this section show the applicability of the developed optimization model and solution approach in real disassembly context. Indeed, the computational time is short enough (maximum solution time is less than 5 s) to give to the decision maker the opportunity to generate different disassembly alternatives depending on the profit expected from the retrieved parts. The profit itself depends on the quality of the products. This model helps to make a decision on the disassembly alternative to be retained as disassembly process. Therefore, the choice between complete or partial disassembly can be made on the basis of the economic arguments.

5 Conclusion

To define effective disassembly and derive the economic benefits of the disassembly process, product quality uncertainty must be taken into account. In order to provide an answer to this expectation, we presented in this work a decision tool on the disassembly process planning taking into consideration the quality of the products to be disassembled. The quality of a product is modeled using the Remaining Usage Potential (RUP) concept. RUP models the amount of use remaining before disassembling a product (or subassembly). At the beginning of the operation phase of a product, RUP has a value of 1; a value 0 of RUP means that the product must undergo a recycling of its material. The RUP is taken as a random variable with known normal probability distribution truncated on 0 and 1. To model this problem, a stochastic program is developed. The objective is to maximize the profit of the disassembly process. The latter is the difference between revenues of subassemblies and components and costs of the disassembly tasks. Subassemblies and components revenues are defined as functions of the RUP.

The developed methodology is evaluated and applied to an industrial product, a Knorr-Bremse EBS 1 Channel Module, which represents a real case study, in the automotive part remanufacturing sector, to show the industrial applicability of the developed optimization tool. The optimization results have shown that the profit of the disassembly process depends on the alternative and level of disassembly of the product, and that the disassembly alternative and level are themselves dependent on the states or quality of the components and subassemblies. The results also showed that the level of disassembly for the same sequence or disassembly alternative depends on the type of variation of components and subassembly revenues according to RUP.

The obtained results are promising and have shown the applicability of the developed methodology to real industrial case. The modeling process and optimization tool presented can be easily adapted for more real life cases like End of Life Vehicles (ELV) or Waste Electrical and Electronic Equipment (WEEE). Undertaking such case studies is one of our next research objectives.

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