A Disassembly Line Design Approach for Management of End-of-Life Product Quality

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Abstract. The purpose of this work is to efficiently design a disassembly line, as disassembly system, handling variability of End-of-Life (EoL) product quality as well as uncertainty of disassembly process operations and provides an optimal revenue of such a system. The main finding of this work is the development of a decision tool that allows decision-makers to choose the best disassembly process and disassembly depth, while assigning the corresponding tasks to the line workstations under precedence and cycle time constraints. Task times are assumed to be random variables with known normal probability distributions. Presence of hazardous material is considered and line cycle time constraints are to be jointly satisfied with at least a certain service (probability) level set by the decision-maker. The revenue of a product part depends explicitly on its EoL state or quality. Industrial applicability is shown using an industrial case focused on remanufacturing of mechatronic parts in the automotive industry.

Keywords: Sustainable manufacturing · Product recovery · Disassembly · Line design · EoL product quality · Uncertainty · Decision aiding

1 Introduction

This work develops a decision tool to optimize line design by minimizing the number of needed workstations and selecting optimal disassembly process and depth regarding line revenue. A line consists of an ordered sequence of workstations connected by a material handling system. At each workstation, an EoL product or one or more of its subassemblies are separated into their components and parts. The line revenue is defined as the difference between the revenue generated by recovered parts and the line operation cost. The latter includes the workstations operation cost and additional cost of workstations handling hazardous parts. In fact, certain parts or subassemblies may contain hazardous material and require a particular treatment incurring a supplementary cost.

The originality of the proposed approach is to consider the health state of the EoL product, its parts and sub-parts in the revenue estimation as random variables. The recycling decision requires a quantification of the part capacity to re-enter a cycle. For such a purpose, we use the Remaining Usage Potential

(RUP) concept introduced in [8]. An extended literature review on disassembly lines can be found in [1,10].

The economical optimization of the disassembly line takes into account revenue gained from disassembled parts resale. 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 taken as distributions since we consider mass recycling. The novelty of the proposed decision tool as well is task processing times uncertainty management in the optimization approach. This is done by designing a line where cycle time constraints are jointly satisfied with at least a certain service level, $1-\alpha$, fixed by the decision-maker. In industrial terms, the probability level $(1-\alpha)$ reflects the level of the EoL product demand satisfaction; hence, it defines the level of customers satisfaction or the capability of the designed disassembly system to meet the demand.

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

2 Problem Formal Definition

In this work, we study a disassembly process where the revenue from retrieved parts depends on the quality of the incoming return products. For an EoL 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. At the same time, selected disssembly tasks are optimally assigned to an ordered sequence of workstations, while satisfying cycle time constraints under uncertainty of the task processing times.

The goal is to design a line, as a disassembly system, providing the maximal revenue and resulting in a minimized number of stations. Cycle time (C_T) constraints for all workstations have to be jointly respected with at least a probability level $(1-\alpha)$ fixed by the decision maker; C_T is the amount of time allocated to each station to complete its assigned tasks. Line revenue is the difference between the profit generated by recovered parts and the line operation cost. Line cost includes the workstations operation cost and additional cost of workstations handling hazardous parts. Disassembly task processing times $t_i, i \in I$, are assumed to be random variables with known normal probability distributions; I represents the set of all possible disassembly tasks. In the case of task times assumed to be random variables following a different probability distribution, the resulted time of each workstation is not guaranteed to be normally distributed for any number of tasks assigned to it.

Each task time is noted as: $\widetilde{t}_i, i \in I$. A disassembly task $i \in H \subset I$ is called hazardous if its execution generates a hazardous subassembly or component; H is the set of hazardous tasks. The maximum disassembly level is the compo-

nents level. A task can be performed at any workstation but cannot be split between two workstations. A fixed cost per operating a time unit of an opened workstation and an additional fixed cost per operating a time unit for treating a hazardous part are given. 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. This distribution models the variability of RUP of the input return products. 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. The RUP concept is explained in detail in [2,8] and is summarized here in subsections 2.2 and 2.3.

2.1 Modeling of Disassembly Process and Precedence Relations

And/or graph models explicitly all possible disassembly process alternatives of an EoL product, as well as the precedence relationships among tasks and product subassemblies and components [5,2] (see Figure 1).

Each subassembly is represented by a node labeled $A_k, k \in K$; K is the set of all generated subassemblies (only subassemblies). Each node labeled $B_i, i \in I$,

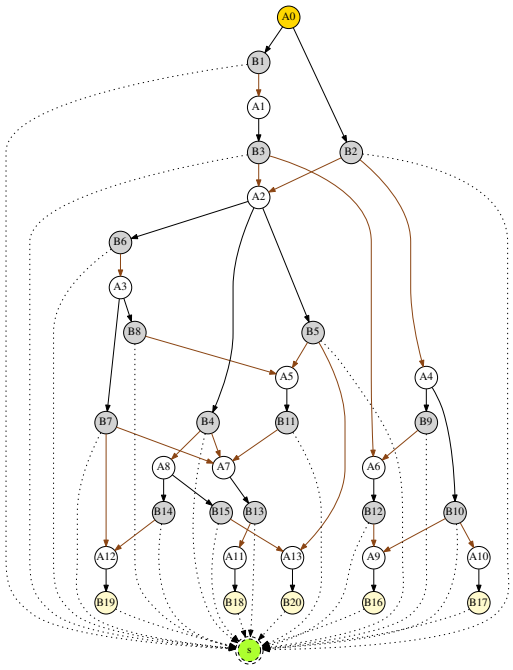

Fig. 1: *And/or* graph of a ballpoint pen example [3].

represents a disassembly task. For a more detailed description of the *and/or* graph modeling process, see our precedent work [4,7,8].

2.2 Idea of RUP Concept and its PDF

The RUP is evaluated on a $[0,1]$ scale; 1 corresponds to the product state at the beginning of its life or 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. It is modeled as a normal Probability Density Function (PDF) 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: $\mu=0,\sigma=0.3$; $\mu=0.5,\sigma=0.2$; $\mu=1,\sigma=0.3$.

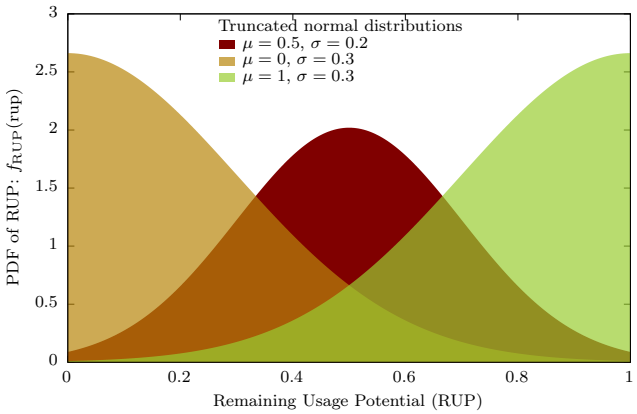

Fig. 2: RUP PDF examples as normal distributions truncated on [0,1].

2.3 Part Revenue with Respect to its RUP and Part Revenue PDF

All product items have not the same RUP, so 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. The revenue R_e is defined as a function of the RUP: $R_e(\mathrm{RUP})$. Three cases of $R_e(\mathrm{RUP})$ are studied: (a) $R_e=(b-a)\cdot\mathrm{RUP}+a$, affine function; (b) $R_e=(b-a)\cdot\sqrt[4]{\mathrm{RUP}}+a$, root function; (c) $R_e=e^{\frac{1}{e-1}\left(e\ln(a)-\ln(b)\right)}e^{\frac{1}{e-1}\left(\ln(b)-\ln(a)\right)e^{\mathrm{RUP}}}$, exponential function.
Here, $R_e(\mathrm{RUP}=1)=b$ and $R_e(\mathrm{RUP}=0)=a$, with $b>a>0$; b and a are upper and lower bounds on resale prices, respectively.

Combining RUP probability density function with part revenue function gives part revenue probability density function. For the 3 R_e functions presented

above, the corresponding probability density functions are defined in [2]. Again, three cases for the RUP distribution, i.e. RUP $\rightsquigarrow \mathcal{N}_{[0,1]}(\mu, \sigma)$, according to the part quality are studied: 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

The objective is profit maximization of the disassembly system to be designed. To model the defined problem, the following notations are introduced.

3.1 Parameters and Sets

I: set of disassembly task indices: $I = \{1, 2, \ldots, \mathsf{n}\}$, $\mathsf{n} \in \mathbb{N}^*$;
J: set of workstation indices: $J = \{1, 2, \ldots, \mathsf{m}\}$, $\mathsf{m} \in \mathbb{N}^*$, $\mathsf{m} \leqslant \mathsf{n}$;
H: set of hazardous disassembly task indices;
L: set of all product part indices (subassemblies and components): $L = \{1, 2, \ldots, \mathsf{l}\}$, $\mathsf{l} \in \mathbb{N}^*$;
K: set of indices for the generated subassemblies: $K = \{0, 1, \ldots, \mathsf{k}\}$, $\mathsf{k} \in \mathbb{N}$, $K \subseteq L$;
L_i: set of indices of retrieved subassemblies and components by the execution of disassembly task $B_i, i \in I$;
G_ℓ: set of indices of tasks generating subassembly or component $\ell, \ell \in L$;
D_ℓ: set of indices of tasks disassembling subassembly $\ell, \ell \in L$;
P_k: set of indices of A_k predecessors, $k \in K$: $P_k = \{i |\ B_i$ precedes $A_k\}$;
S_k: set of indices of A_k successors, $k \in K$: $S_k = \{i |\ A_k$ precedes $B_i\}$;
A_k: a subassembly, $k \in K$;
B_i: a disassembly task, $i \in I$;
$\mathtt{F_c}$: fixed cost per operating a time unit of a workstation, $\mathtt{F_c} > 0$;
$\mathtt{H_c}$: additional cost per time unit for stations handling hazardous parts, $\mathtt{H_c} > 0$;
$\mathrm{C_T}$: cycle time, $\mathrm{C_T} > 0$;
$\widetilde{t_i}$: processing time of task $B_i, i \in I$, where $\widetilde{t_i} \rightsquigarrow \mathcal{N}(\mu_i, \sigma_i), i \in I$;
$\widetilde{R_{e\ell}}$: revenue generated by a subassembly or component $\ell, \ell \in L$ (see subsection 2.3), 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 use potential of a subassembly or component $\ell, \ell \in L$, as defined in subsection 2.2;
$1 - \alpha$: probability or line service level fixed by the decision-maker: cycle time constraints are jointly satisfied with at least this level value; α represents a risk and in general $\alpha \leqslant 10\%$.

3.2 Decision Variables

$$x_{ij} = \begin{cases} 1, & \text{if task } B_i \text{ is assigned} \\ & \text{to workstation } j; \\ 0, & \text{otherwise.} \end{cases} \qquad x_{\mathtt{s}j} = \begin{cases} 1, & \text{if disassembly is finished at} \\ & \text{station } j, \text{ complete or partial;} \\ 0, & \text{otherwise.} \end{cases}$$

$$h_j = \begin{cases} 1, & \text{if a hazardous task is} \\ & \text{assigned to station } j; \\ 0, & \text{otherwise.} \end{cases} \qquad y_\ell = \begin{cases} 0, & \text{if } \sum_{i \in G_\ell} x_i = 1 \text{ and} \\ & \sum_{i \in D_\ell} x_i = 1, \ \ell \text{ subassembly;} \\ 1, & \text{otherwise.} \end{cases}$$

Variable $y_\ell, \ell \in L$ prevents to compute a subassembly revenue, in the objective function, when this latter is itself disassembled. Only revenues of its components or subassemblies (not disassembled) are used afterwards.

3.3 Set of Constraints and Objective Function

The decision tool proposed in this paper uses the optimization model defined below. This model allows to determine a disassembly process alternative with the maximum profit and assign its tasks to minimal number of workstations, while considering the quality or states of the subassemblies and components (generated during the disassembly process) and task processing times uncertainty. As mentioned in subsection 2.2, the state of a product (subassembly or component) is modeled using RUP. Thus, by taking the RUP of each subassembly and component, the optimization model allows to choose which components and subassemblies to retrieve in order to maximize the disassembly process profit. As explained in subsection 2.3, revenue R_e of each component or subassembly depends on its RUP, i.e. $R_e(\text{RUP})$. The objective function and associated constraints are formulated as follows.

$$\max \left\{ \sum_{i \in I} \sum_{j \in J} \sum_{\ell \in L_i} \widetilde{R_{e\ell}} \cdot y_\ell \cdot x_{ij} - \mathrm{C_T} \left(\mathtt{F_c} \cdot \sum_{j \in J} j \cdot x_{sj} + \mathtt{H_c} \cdot \sum_{j \in J} h_j \right) \right\} \qquad (\mathbf{I})$$

s.t.

$$\sum_{i \in S_0} \sum_{j \in J} x_{ij} = 1 \qquad (1)$$

$$\sum_{j \in J} x_{ij} \leqslant 1, \forall i \in I \qquad (2)$$

$$\sum_{i \in S_k} \sum_{j \in J} x_{ij} \leqslant \sum_{i \in P_k} \sum_{j \in J} x_{ij}, \forall k \in K \backslash \{0\} \qquad (3)$$

$$\sum_{i \in S_k} x_{iv} \leqslant \sum_{i \in P_k} \sum_{j=1}^{v} x_{ij}, \forall k \in K \backslash \{0\}, \forall v \in J \qquad (4)$$

$$\sum_{j \in J} x_{\mathtt{s}j} = 1 \qquad (5)$$

$$\sum_{j \in J} j \cdot x_{ij} \leqslant \sum_{j \in J} j \cdot x_{\mathtt{s}j}, \forall i \in I \qquad (6)$$

$$h_j \geqslant x_{ij}, \forall j \in J, \forall i \in H \tag{7}$$

$$\text{If } \sum_{i \in D_\ell} x_i = 1 \text{ and } \sum_{i \in G_\ell} x_i = 1 \text{ then } y_\ell = 0, \forall \ell \in L \ (\ell \text{ subassembly}) \tag{8}$$

$$y_\ell = 1, \forall \ell \in L \ (\ell \text{ component}) \tag{9}$$

$$P\Big(\sum_{i \in I} \widetilde{t_i} \cdot x_{ij} \leqslant \mathrm{C_T}, \forall j \in J\Big) \geqslant 1 - \alpha \tag{10}$$

$$x_{\mathtt{s}j}, x_{ij}, h_j, y_\ell \in \{0,1\}, \forall i \in I, \forall j \in J, \forall \ell \in L \tag{11}$$

Terms of the objective function represent, respectively, the earned profit of retrieved parts, the cost of operating workstations and the additional cost for handling hazardous parts. Constraint (1) models the fact that exactly one disassembly task, among all possible ones, must be chosen to start disassembling the EoL product, symbolized by A_0. Constraint set (2) indicates that a task is to be assigned to at most one workstation. Constraints (3) ensure that only one or-successor is selected. Constraint set (4) defines the precedence relationships among tasks and subassemblies. Constraint (5) imposes the assignment of the dummy task $\mathtt{s}$ to one workstation. Constraints (6) ensure that all disassembly tasks are assigned to lower or equal- indexed workstations than the one to which $\mathtt{s}$ is assigned. Constraints (7) ensure the value of h_j to be 1 if at least one hazardous task is assigned to a workstation j. Constraints (8), as previously mentioned, model an exclusion between the revenue of a subassembly (which is disassembled) and the revenue of its subassemblies and components. Constraints (9) are introduced in order to include in the retained disassembly process revenues that are generated by selected components. Constraints (10) enforce the workstation operating time to remain within the cycle time $\mathrm{C_T}$, for all opened workstations, jointly with at least a predefined probability $1 - \alpha$. Finally, set (11) represents the possible values of the decision variables.

In the next section, lower and upper bounding schemes will be defined in order to transform conraints (8) and (10) and optimally solve problem (**I**) with quadratically constrained program solvers, such as CPLEX.

3.4 Solution of the Problem

Upper Bounding Scheme for Program (I)

The optimal value of program (**UMinI**) below defines an upper bound of (**I**) [9,6].

$$\min \left\{ \mathrm{C_T}\left(\mathtt{F_c} \cdot \sum_{j \in J} j \cdot x_{sj} + \mathtt{H_c} \cdot \sum_{j \in J} h_j \right) - \sum_{i \in I} \sum_{j \in J} \sum_{\ell \in L_i} \widetilde{R_{e\ell}} \cdot z_{ij\ell} \right\} \quad \textbf{(UMinI)}$$

s.t.

$$v_j \leqslant \mathrm{C_T} - \mu^{\mathsf{T}} \cdot x_j, \forall j \in J \tag{12}$$

$$w_{ij} \geqslant \sigma_i \cdot z_{ij}, \forall i \in I, \forall j \in J \tag{13}$$

$$v_j \geqslant \|w_j\|, \forall j \in J \tag{14}$$

$$z_{ij} \geqslant a_k \cdot x_{ij} + b_k \cdot y_{ij}, \forall i \in I, \forall j \in J, k = 1, \ldots, m \tag{15}$$

$$\sum_{j\in J} y_{ij} = \sum_{j\in J} o_{ij}, \forall i \in I \tag{16}$$

$$o_{ij} \leqslant x_{ij}, \forall i \in I, \forall j \in J \tag{17}$$

$$o_{ij} \leqslant q_j, \forall i \in I, \forall j \in J \tag{18}$$

$$q_j + x_{ij} \leqslant 1 + o_{ij}, \forall i \in I, \forall j \in J \tag{19}$$

$$\sum_{j\in J} q_j = 1 \tag{20}$$

$$x \in X, v_j, q_j, y_{ij}, w_{ij}, o_{ij}, z_{ij} \geqslant 0, \forall i \in I, \forall j \in J \tag{21}$$

Where x is a vector of decision variables $x_{ij}, x_{sj}, h_j, y_\ell, \forall i \in I, \forall j \in J, \forall \ell \in L$, and $X = \{x|$ constraints (1)-(9), and (11) are satisfied$\}$; $z_{ij\ell} \leqslant y_\ell$, $z_{ij\ell} \leqslant x_{ij}$ and $z_{ij\ell} \geqslant y_\ell + x_{ij} - 1$, $\forall i \in I, \forall j \in J, \forall \ell \in L$.

Lower Bounding Scheme for Program (I)

Program (**LMinI**) here after defines a lower bound for (**I**); $\alpha_j, j \in J$ are parameters verifying $\sum_{j\in J} \alpha_j = \alpha$ [11,9].

$$\min \left\{ \mathrm{C_T}\left(\mathtt{F_c} \cdot \sum_{j\in J} j \cdot x_{sj} + \mathtt{H_c} \cdot \sum_{j\in J} h_j \right) - \sum_{i\in I} \sum_{j\in J} \sum_{\ell\in L_i} \widetilde{R}_{e\ell} \cdot z_{ij\ell} \right\} \quad \textbf{(LMinI)}$$

s.t.

$$v_j \leqslant \frac{1}{\Phi^{-1}(1-\alpha_j)} \cdot \left(\mathrm{C_T} - \mu^{\mathsf{T}} \cdot x_j \right), \forall j \in J \tag{22}$$

$$w_{ij} \geqslant \sigma_i \cdot x_{ij}, \forall i \in I, \forall j \in J \tag{13}$$

$$v_j \geqslant \|w_j\|, \forall j \in J \tag{14}$$

$$x \in X, v_j, w_{ij} \geqslant 0, \forall i \in I, \forall j \in J \tag{23}$$

In order to solve the defined problem, formulated as (**I**), using developed lower and upper bound models, (**LMinI**) and (**UMinI**), 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 $\widetilde{R}_{e\ell}$). Three values of $\widetilde{R}_{e\ell}, \forall \ell \in L$ will be studied: $R_{e\ell} = \widehat{\mu}_\ell$ and $R_{e\ell} = \widehat{\mu}_\ell \pm \widehat{\sigma}_\ell$, $\forall \ell \in L$.

4 Numerical Illustration

Models (**LMinI**) and (**UMinI**) as well as the nonlinear optimizations and numerical integrations are implemented in Linux using C++ on a PC with 8×CPU 2.80 GHz and 32 Go RAM. Nonlinear optimizations are done with ALGLIB, numerical integatons with Gauss-Legendre quadrature while models (**LMinI**) and (**UMinI**) are solved using CPLEX 12.6. All are applied to a remanufacturing industrial case product: a Knorr-Bremse EBS 1 Channel Module. It represents a

Table 1: Lower bound of problem (**I**): obtained disassembly alternative, opened workstations and corresponding line profit for each revenue function type

	$R_{e\ell} = \widehat{\mu}_\ell$	(stat,hstat)	time(s)	$R_{e\ell} = \widehat{\mu}_\ell - \widehat{\sigma}_\ell$	(stat,hstat)	time(s)	$R_{e\ell} = \widehat{\mu}_\ell + \widehat{\sigma}_\ell$	(stat,hstat)	time(s)	
Affine	63478.0	(2, 1)	2.6	54074.5	(2, 1)	3	72881.5	(2, 1)	2.5	EBS 1
Root	72638.5	(2, 1)	2.4	69630.2	(2, 1)	2.4	76040.2	(1, 1)	2.4	
Expo	26617.2	(2, 1)	2.7	6710.6	(2, 1)	3	46756.5	(2, 1)	2.8	
Mixture	71298.5	(2, 1)	2.5	68495.2	(2, 1)	3	75823.6	(1, 1)	2.4	

Table 2: Upper bound of problem (**I**): obtained disassembly alternative, opened workstations and corresponding line profit for each revenue function type

	$R_{e\ell} = \widehat{\mu}_\ell$	(stat,hstat)	time(s)	$R_{e\ell} = \widehat{\mu}_\ell - \widehat{\sigma}_\ell$	(stat,hstat)	time(s)	$R_{e\ell} = \widehat{\mu}_\ell + \widehat{\sigma}_\ell$	(stat,hstat)	time(s)	
Affine	63478.0	(2, 1)	45.9	54074.5	(2, 1)	101.5	72881.5	(2, 1)	104.9	EBS 1
Root	72638.5	(2, 1)	79.0	69630.2	(2, 1)	84.4	76040.2	(1, 1)	2.5	
Expo	26617.2	(2, 1)	3.15	6710.6	(2, 1)	3.0	46756.5	(2, 1)	2.8	
Mixture	71298.5	(2, 1)	48	68495.2	(2, 1)	3.3	75823.6	(1, 1)	2.5	

real case study in the automotive part remanufacturing sector. Such a product is composed of at least 45 components [8].

Tables 1 and 2 and Figure 3 summarize the obtained optimization results for different values of $\widetilde{R}_{e\ell}, \ell \in L$. Columns '(stat,hstat)' and 'time(s)' in Tables 1 and 2 indicate, respectively, the number of opened workstations of the disassembly system, the number of hazardous workstations, if there is any, and the resolution time in seconds. Table 1 presents the obtained optimization results for the lower bound of problem (**I**) and Table 2 presents those of the upper bound. Results of Tables 1 and 2 with Figure 3 are analysed according to three main points: optimality of solved instances, obtained disassembly process alternatives and task assignment to defined workstations. They can be summarized as follows: the profit of the disassembly process, so task assignement to line workstations, depends not only on the sequence and level of disassembly but also on the state or quality of the product, subassemblies and components.

From optimality aspect of solved instances, as it can be seen in Tables 1 and 2, all instances of the EBS module are solved to optimality. In fact, for each instance the objective function value (that is line revenue) for both lower and upper bounds are equal.

From obtained disassembly process alternatives aspect, Figure 3 illustrates in detail the sequence and the level of disassembly returned for each revenue function type of components and subassemblies. In order to identify easily disassembly alternatives in Figure 3 one different color is assigned to each alternative.

We can see that the disassembly sequence corresponding to the maximum profit depends on the revenue functions. It can be observed that the level of disassembly for the same alternative depends on the type of revenue functions. For example, tasks B_1 B_6 B_{20} B_{34} B_{43} and B_1 B_6 B_8 B_{20} B_{34} B_{43} represent two different disassembly levels of the same disassembly alternative, see Figure 3. The results show also that for the same alternative and the same level of disassembly, values of the corresponding profits depend on the type of the revenue functions considered. As example, for upper bound values and $R_{e\ell} = \widehat{\mu}_\ell - \widehat{\sigma}_\ell, \forall \ell \in L$, functions Affine, Root and Mixture define the same alternative B_1 B_4 B_{15} B_{34} B_{43}, but values of the objective functions are all different, see Table 2.

From task assignment to defined workstations aspect, we can deduce two main behaviours. The first one is the fact that for a same disassembly alternative and same number of workstations, task assignement is different. This is the case of alternative B_1 B_4 B_{15} B_{34} B_{43} (a: B_1 B_4 assigned to wrkstation 1 then B_{15} B_{34} B_{43} to 2, b: same but B_{15} assigned to workstation 1). The second one concerns solution with the same workstations number and same revenue but different disassembly alternatives are retained as optimal. Alternatives B_1 B_6 B_8 B_{20} B_{34} B_{43} and B_3 B_8 B_{10} B_{20} B_{34} B_{43} with objective value of 71298.5 present

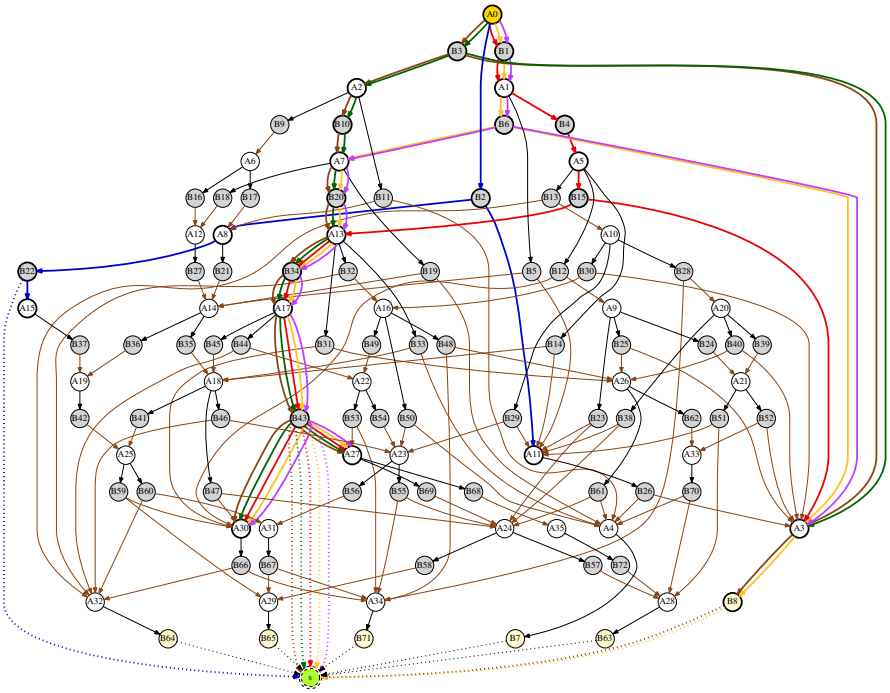

Fig. 3: Alternatives and disassembly levels returned according to the type of revenue functions: a Knorr-Bremse EBS 1 Channel Module

such an example. Furthermore, hazardous tasks are assigned to workstations in a manner to be, as possible, grouped in the same workstation and as possible such a workstation is located at the begening of the designed line to minimize risk of hazardous material accidents and avoid accident risk propagation.

5 Discussion and Conclusion

The disassembly process plays a key role in the recovery of End-of-Life products. It allows, effectively, obtaining components and/or materials that can be reused or recycled with much more interesting recovery rates. To define effective disassembly and derive the economic benefits of the disassembly process, product quality and task processing times uncertainties 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 and line design handling the quality of the products to be disassembled and uncertainty of task times. 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. 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. Task processing times are also modeled as random variables with known normal distributions.

To model this problem, a stochastic program along with lower and upper bounding schemes are developed. The objective is to maximize the profit of the disassembly line to be designed. This is done by designing a line where cycle time constraints are jointly satisfied with at least a certain service level, $1 - \alpha$, fixed by the decision-maker. Line revenue is calculated as the difference between the revenue generated by recovered parts (subassemblies, components) and the line operation cost. The latter includes the workstations operation cost and additional cost of workstations handling hazardous parts. Subassemblies and components revenues are defined as functions of the RUP. All the possible disassembly alternatives of a product and the precedence relationships among tasks and subassemblies/components are modeled using an *and/or* graph.

The developed apprach is evaluated and applied to an industrial instance: Knorr-Bremse EBS 1 Channel Module which represents a real case study, in the automotive part remanufacturing sector. The results show the applicability of the developed decision aiding tool in real disassembly context. In fact, the sensibility of results to the RUP, i.e. product quality, highlights 2 main points. First, the assessment of the product quality is mandatory for industrial issues, periodically not just ones, in order to re-optimize the disassembly level if it changes and, then, re-organize the disassembly line if required. Second, such assessment must be reliable and accurate. This requirement ensures the confidence in the results and thus in the industrial decision to be made.

Sensitivity of the results to the revenue leads, for industrial decision maker, to follow the resale price of the parts and raw materials. Disassembly level op-

timization should be redone when resale price evolves. The evolution of resale price is mainly market driven. Indeed, some market intelligence would allow anticipating resale price.

Finally, the computational time is short enough to give to the decision maker the opportunity to generate different disassembly alternatives and line configurations 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 economic arguments.

The modeling process and decision aiding tool presented can be easily adapted for more real life cases like End of Life Vehicles or Waste Electrical and Electronic Equipment. Undertaking such case studies is one of our future research objectives.

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