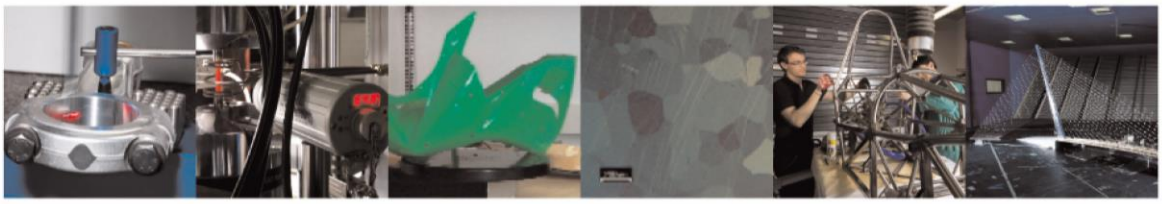

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A Decision Support System to Manage the Quality of End-of-Life Products in Disassembly Systems

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The quality of post-consumer products is one of the major sources of uncertainty in disassembly systems. This paper develops a methodology to design disassembly lines under variability of the End-of-Life product quality, with the objective to maximize the profit. This decision support system helps to take decisions about the depth of disassembly and the organization of the disassembly system, depending on the pre-process measurement of the key quality characteristics of the product to be disassembled. The industrial benefits are demonstrated in a real industrial case focused on the remanufacturing of mechatronic parts in the automotive industry.

Disassembly; Part quality; Decision support system.

1. Introduction, motivation and objectives

Circular Economy has been recently proposed as a new paradigm for sustainable development, showing potentials to generate new business opportunities in worldwide economies and to significantly increase resource efficiency in manufacturing [1]. However, a sustainable transition to Circular Economy businesses will need to be supported by substantial technological improvements. Remanufacturing is one of the key enabling technologies for an efficient implementation of Circular Economy, in several high-tech industries, such as the automotive, aeronautics, and electronics. Remanufacturing includes the set of technologies, tools, and knowledge-based methods to recover and re-use functions and materials from post-consumer high-value products. Advantages of remanufacturing include, on average, 80%-90% savings in raw materials and energy, avoiding the disposal costs that manufacturers by law have to support. Moreover, remanufacturing can allow a general price reduction of 35% - 40% with an average margin of 20% in the aftermarket, which nowadays represents about 50% of the automotive entire business [2]. Due to these features, remanufacturing is achieving increasing importance in the worldwide political and research agendas, as reported in the 2015 G7 Summit Declaration [3].

A remanufacturing process-chain typically includes disassembly, cleaning, re-conditioning and re-assembly stages. The performance of remanufacturing systems is strongly bounded by the negative impact of variability and uncertainty due to the high variability of return product conditions, mainly caused by different age of the return products, variable use modes by the customers, and environmental conditions. The effect is high variability in disassembly processing times and risk of encountering technical process feasibility issues in disassembly [4]. To overcome this problem, remanufacturers usually carry out pre-process visual and functional inspections and assess the conditions of the input return products to identify remanufacturable and damaged units. This decision is extremely critical as it entails a risk to either process a part that shows to be damaged only after expensive disassembly tasks have been already performed, or to discard potentially re-usable return products. However, quality information about return products is rarely used in industry to adapt the disassembly strategy.

In the scientific literature, the benefit of sorting the return products has been shown and grading them for quality to improve the disassembly has been recommended [5]. For example, the experimental study reported in [6] shows that increasing the pre-process inspection effort may be beneficial in decreasing the disassembly time. In spite of the relevance of this correlation in the remanufacturing industry, the development of specific methodologies to plan the disassembly process in presence of quality uncertainty of return products has received relatively low attention in the literature. The problems of defining the best level of disassembly [7] and balancing disassembly lines have been traditionally approached under a deterministic point of view [8]. Recently, attempts to include variability in the task time duration, due to the effect of manual operations, have been made [9]. A method to solve the line-balancing problem considering complete product disassembly and multiple quality classes was proposed [10]. The problem of finding an optimized re-assembly strategy under uncertainty in the quality of return products have been considered in [11]. As a matter of fact, a method to jointly define the best disassembly level and line balancing when disassembly task times depend on the input product quality classification outcomes has never been proposed. Important questions like “what is the economic impact of adapting the disassembly strategy based on the quality of the specific return product under processing?” remain unsolved, thus undermining the efficiency of remanufacturing systems.

This paper proposes for the first time a decision support system based on a methodology to optimize the specific disassembly strategy and process, considering variable quality conditions of the input return products, in the remanufacturing planning phase. The decision support system can be used at shop floor level to support the operators in adjusting the disassembly sequence on the basis of the measured key quality characteristics of the input return products. The proposed methodology is applied to a real case study in the automotive part remanufacturing sector, to show its industrial benefits.

2. Disassembly problem formulation

In this paper, we consider a remanufacturing process where the disassembly task time duration and distribution depends on the quality of the incoming return products. It is assumed that a set of critical product characteristics, defined for the return product, can be observed at the beginning of the disassembly process by pre-process inspection. For example, characteristics such as the corrosion on the part, corrosion on the screws, or the weight of the part can be considered. According to the outcome of inspection, the return products can be classified into quality classes. A quality class represents a proper combination of critical product characteristic values that is useful to aggregate return products with similar disassembly challenges. The parts in each quality class are characterized by the same task time distributions. However, different quality classes may possess different time distributions for identical disassembly tasks.

The joint disassembly level and line balancing problems, under definition of the tasks for different quality classes of the product, can be formulated as follows. The objective is to design a disassembly line consisting of a sequence of workstations J. The set of possible disassembly tasks I_p is given for each product $p \in P$, but it is possible to assign only a subset I_p^* of the set I_p if complete disassembly is not economically profitable. The set I represents the whole set of all possible disassembly tasks for all products $I=\cup_{p\in P} I_p$. Note that each quality class is modeled as a different product p. The objective is to maximize the profit of the disassembly line, which is defined as the difference between the net revenue of the recovered parts of the End-of-life (EOL) products and the line operation cost. The latter comprises two types of costs defined as follows:

- F_c, a fixed cost for operating a time unit of a station,
- C_h, an additional fixed cost for operating a time unit of a station handling hazardous parts.

The precedence relations are modelled by a precedence graph which is created for each product to be disassembled. For each task i for product p, P_{pi} is defined as the set of direct predecessors of task $i \in I_p$, with $p \in P$. All predecessors of task i should be assigned before task i in the sequence of tasks.

Disassembly task times $\tilde{t}_{pi}, p\in P, i\in I_p$, are assumed to be random variables with known probability distributions. A disassembly task is not preemptive and can be performed by any, but only one, workstation. A task $i \in H \subset I$ is called hazardous if it generates a hazardous part; H is the set of all hazardous tasks.

It should be also noted that the setup time between different disassembly tasks should be taken into account. This setup time is sequence-dependent. For this reason, the tasks should not only be assigned to stations but also sequenced at each station.

3. Description of the disassembly planning procedure

3.1. Adopted Notation

To model the disassembly line design problem, the following notations are introduced.

Parameters:

- P: set of products to be disassembled;
- Q_p: the quantity of products of type p to be disassembled during the planning period;
- M: set of parts' indices;
- M_{pi}: set of recovered parts if task $i \in I_p$ is performed on product p, $M_{pi} \subset M, i \in I_p$;
- r_m: revenue generated by a part $m, m \in M$;
- d_{iq}: setup time necessary to switch from task i to q;
- T: length of planning horizon;
- TT: takt time;
- h_i=1, if task i is hazardous, h_i=0, otherwise, $i \in I$
- P_{pi}: set of direct predecessors of task $i \in I_p$ $p \in P$;
- q_0: maximum number of tasks authorized to be assigned to a station. Each station cannot contain more than q_0 tasks;
- j_0: upper bound on the number of stations;
- $l_0 = q_0 * j_0$: maximal length of the sequence of tasks (longer than the number of tasks since some positions for some stations can be empty);
- $S(j)$: set of possible positions for tasks at station j. This set is given by an interval of indexes and the maximum possible interval is $S(j) = \{q_0 (j-1)+1, q_0 (j-1)+2, \ldots, q_0 * j\}, j=1, 2, \ldots, j_0$;
- $J(i)$: set of stations where task i can be processed, $J(i) \subseteq \{1, 2, \ldots, j_0\}$, calculated on the basis of the precedence constraints and the takt time;
- $L_p(i)$: set of possible positions for task i for product p in the sequence of all tasks, $L_p(i) \subseteq \{1, 2, \ldots, q_0 j_0\}$;
- $N_p(j)$: set of tasks for product p which can be processed at station j;
- $A_p(l)$: set of tasks for product p which can be assigned to position l.

Binary Decision variables

$$y_j = \begin{cases} 1 & \text{if station } j \text{ is open,} \\ 0 & \text{otherwise.} \end{cases}$$

$$x_{pil} = \begin{cases} 1 & \text{if task } i \text{ for product } p \text{ is assigned at position } l, \\ 0 & \text{otherwise.} \end{cases}$$

$$z_j = \begin{cases} 1 & \text{if a hazardous task is assigned to station } j, \\ 0 & \text{otherwise.} \end{cases}$$

Auxiliary real decision variables

- τ_{pl} setup time required between tasks assigned to the same station at position l and $l+1$ for product p;
- Pr_j minimal probability (among all products p) to respect takt time at station j; $Pr_j \in [0,1]$, i.e. the probability that the value of the sum of task times at station j is inferior or equal to a given value of takt time TT.

3.2. Objective Function and Constraints

The objective function aims at maximizing the disassembly profit taking into account the revenue from retrieved parts and the cost of all opened stations, including supplementary cost for treating hazardous tasks. The objective function is formulated as follows:

$$\max\left\{\sum_{p\in P}\sum_{i\in I_p}\sum_{l\in L_p(i)}\sum_{m\in M_{pi}} Q_p r_m x_{pil} - T\left(F_C \sum_{j\in J} y_j + C_h \sum_{j\in J} z_j\right)\right\} \qquad (1)$$

The introduced constraints are described in the following. Each disassembly task is assigned at most once (at one position l) and for each product p, a disassembly task can be not assigned if the disassembly is partial.

$$\sum_{l\in L_p(i)} x_{pil} \le 1, \quad \forall p \in P, \forall i \in I_p \qquad (2)$$

Each position is occupied by at most one task:

$$\sum_{l\in A_p(l)} x_{pil} \le 1, \quad \forall p \in P, l = 1,2,\ldots l_0 \qquad (3)$$

The equation (4) assures that a task is assigned to station j to a position l+1 only if another task is already assigned to the preceding place (l) of the sequence to the same station (there is no empty place in the sequence of assigned operations inside a station).

$$\sum_{i\in A_p(l)} x_{pil} \ge \sum_{i\in A_p(l+1)} x_{pi(l+1)}, \forall l\in S(j) \setminus \max\{S(j)\}, \mathrm{j}=1,2,\ldots, j_0 \forall p\in P \qquad (4)$$

The equation (5) assures that stations are opened in an increasing order, without empty stations:

$$\sum_{i\in A(l')} x_{pil'} \geq \sum_{i\in A_p(l'')} x_{pil'}, l' = q_0(j-1)+1, l'' = q_0 j+1, j = 1,2,\ldots, j_0 - 1, \forall p\in P \quad (5)$$

The equation (6) assures that a station is opened if at least one operation is assigned to it:

$$y_j \geq \sum_{i\in A_p(l')} x_{pil'}, l' = q_0(j-1)+1,\ \forall p\in P, j=1,2,\ldots, j_0 \quad (6)$$

Moreover, the precedence constraints for tasks is formulated:

$$1 + \sum_{l\in L_p(q)} l\cdot x_{pql} \leq \sum_{l\in L_p(i)} l\cdot x_{pil}, \forall p\in P, \forall i\in I_p, \forall q\in P_{ip} \quad (7)$$

A station is considered “hazardous” if at least one hazardous task is assigned to it. Therefore, this constraint follows:

$$z_j \geq \sum_{l\in L(j)} h_i \cdot x_{pil}, \forall p\in P, j=1,2,\ldots, j_0, \forall i\in I_p \cap N(j) \quad (8)$$

Equation (9) calculates the additional time between task *i* and task *q* when task *q* is processed directly after task *i* for product *p* at the same station:

$$\begin{aligned}\tau_{pl} \geq & \sum_{q\in A_p(l+1)\setminus\{i\}} d_{iq}\cdot(x_{pil} + x_{pq(l+1)} - 1), \\ & \forall p\in P, \forall i\in A_p(l), j\in J, \forall l\in S(j)\setminus \max\{S(j)\}\end{aligned} \quad (9)$$

The probability to respect the assigned takt time at each workstation is calculated for the worst case among all products:

$$Pr_j \leq Pr\Big(\sum_{l\in S(j)\setminus\max\{S(j)\}} \tau_{pl} + \sum_{i\in N_p(j)} \sum_{l\in S(j)} t_{pi}\left(\tilde{\xi}\right)\cdot x_{pil} \leq TT\Big), \forall p\in P, j\in J \quad (10)$$

Finally, the cycle time constraint has to be jointly satisfied with at least a probability (1-α), where α is fixed by the decision maker:

$$Pr(Pr_j \leq TT\ \forall j=1,2,\ \ldots, j_0) \geq 1-\alpha \quad (11)$$

This problem is solved using stochastic programming techniques (for more details on the method see [12]). It should be noted that in order to speed up the optimization process the task assignment to workstations for different products can be parallelized with joint verification of the takt time constraints.

4. Application to a real remanufacturing industrial case

The proposed approach has been applied to the remanufacturing of automotive mechatronic products at Knorr-Bremse, a leading global provider of braking systems for rail and commercial vehicles. Remanufacturing is an established and profitable business for the company [13]. One of the most successfully remanufactured products is the Electronic Breaking System (EBS-2). Recently, the next generation EBS-5 breaking system has started to be collected by the aftermarket logistics network. The company is therefore interested in the definition of a profitable disassembly strategy for this product. In particular, the analysis is focused on one critical mechatronic component of the EBS-5, which is the Trailer Control Module (TCM). A view of a TCM and its sub-components is reported in Fig. 1.

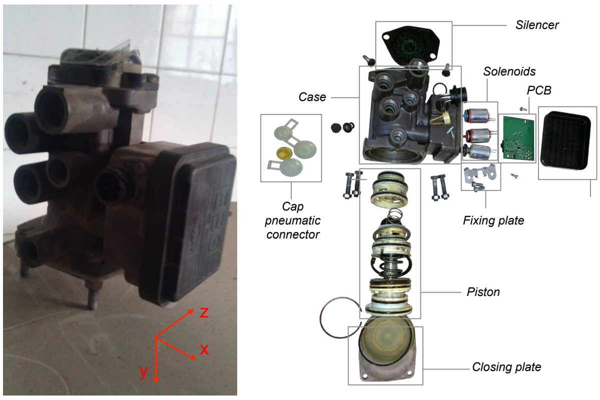

Fig. 1. EBS-5, TCM (left) and its sub-components (right).

To design an efficient disassembly process for this product, the case study was conducted following two main phases. The first phase aimed at analysing the real return products in order to determine the number of different quality classes and the discriminating factors to be inspected in order to classify a return product in one of the classes. In the second phase, the information about the quality classes was provided in input to the model (1)-(11) in order to determine the number of stations and the tasks to be performed at each station for each quality class, with the objective to maximize the overall system profit. The performance of the optimal configuration solution was compared with the one of a system configuration obtained without differentiating quality classes. The two main phases are described in the following.

Definition of quality classes. A sample of 60 post-consumer TCMs has been processed in the Mechatronics Demanufacturing Pilot Plant at ITIA-CNR, Milan [14]. The parts in the sample were analysed and classified in terms of quality, according to a set of qualitative and quantitative classification criteria, designed in cooperation with the company and reported in Fig. 2. These classification criteria could be either observed on the external surface of the return product or measured in-line by the operator.

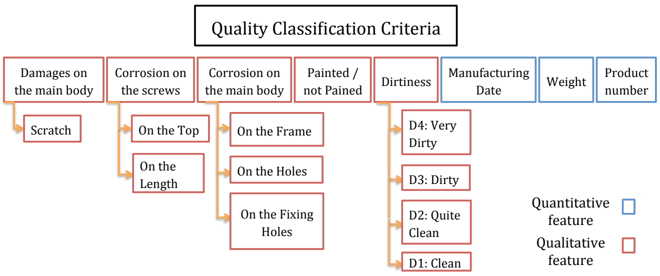

Fig. 2. Quality classification criteria.

In order to analyse the impact of each classification criterion on the disassembly process, complete disassembly has been performed for each part in the sample. The information on the feasibility of disassembly tasks, the quality of the obtained components in terms of corrosion levels, and the disassembly times has been collected. The ANOVA analysis of the collected data showed that only three out of the eight considered quality features proved to be significantly affecting the disassembly process, among which the return product age, its level of dirtiness and the level of corrosion on screws. By analysing also the interactions among these quality features, six quality classes that, according to the analysed sample, significantly affect the disassembly process have been determined.

Disassembly Line Design. In the second phase of the activity, the method proposed in this paper has been used to jointly optimize the disassembly level and to balance the line, considering the characterized quality classes. The list of tasks and the estimated task times, for each quality class, *Q1, Q2,...,Q6,* are reported in Table 1. In this table, the time unit (TU) duration is omitted for confidentiality reasons. The probability of a part being associated to a specific quality class was estimated by the experimental results described above and was respectively equal to 0.15, 0.1, 0.25, 0.15, 0.2, 0.15. Any task could be assigned to any workstation under the respect of the precedence constraints. Setup times exist between tasks and vary between 0.5 and 1TU.

The optimal designs of the disassembly line, considering a target takt time of 60 TU are reported in Table 2. In particular, two configurations are compared. Configuration 1 is obtained by solving the disassembly line design problem by considering a single aggregated quality class with task times obtained by averaging the value of the 6 quality classes. Configuration 2 is obtained by adopting the approach proposed in this paper, which considers the different quality classes in the problem.

Table. 1. Task description for the study case.

ID	Disassembled part	Mean task time						Var	P_{1i}
		Q1	Q2	Q3	Q4	Q5	Q6		
1	PCB case	19	18	21	22	13	14	4	-
2	PCB	22	21	35	32	20	20	11	1
3	Pressure sensor	2	2	2	2	2	2	1	2
4	Fixing plate	5	5	5	5	5	5	0.2	2
5	3 solenoids	5	5	5	5	5	5	0.2	4
6	Connector case	3	2	3	3	3	3	1	-
7	Connector	2	1	2	2	2	2	0.3	2
8	Air filter	1	1	1	1	1	1	0.5	-
9	Pneumatic connectors	4	4	4	4	4	4	2	-
10	Cap	2	2	4	3	1	2	0.5	-
11	Silencer	2	2	2	2	2	2	1	10
12	Main Body	2	2	2	2	2	2	1	-
13	Cover	14	13	16	15	12	13	3	12
14	Lower piston part	2	2	2	2	2	2	1	13
15	Sealing	2	2	2	2	2	2	1	14
16	Upper piston part	2	2	2	2	2	2	1	15

Table. 2. Optimal Line Designs.

Conf.	Quality class	Station	Task sequence	Mean total station time	Var
1	/	WS1	T1, T10 to T16.	50	-
		WS2	T2 to T9	50	-
2	Q1, Q2, Q5, Q6	WS1	T1, T10 to T16.	51, 49, 42,45	15
		WS2	T2 to T9	47,46,45,45	16.2
	Q3	WS1	T1, T12 to T16.	49	12.5
		WS2	T2 to T5, T7	52	12.7
	Q4	WS1	T1, T12 to T16.	49	12.5
		WS2	T2 to T5, T7, T8.	50.5	13.2

As it can be noticed, if the quality classes are neglected (configuration 1) all tasks are assigned to the 2 workstations. If the quality classes are considered (configuration 2), the optimal solution is the same for four classes while it differs for quality classes 3 and 4. In particular, task T6 becomes uneconomical and it is not allocated. The related performance, in terms of probability of not exceeding the target takt time, is reported in Table 3. As it can be observed, by applying a design method that neglects the quality classes, workstation 2 will fail to respect the takt time in 50% of cases where return products of quality class 3 are treated, and in 22.8% of cases where return products of quality class 4 are treated. On the contrary, the developed model provides a different partial disassembly plan for different part quality classes giving the priority to the disassembly tasks with a higher recovering value, thus providing a higher probability of meeting the target takt time, for each quality class.

Table. 3. Line performance comparison.

Configuration	Station	Quality classes					
		Q1	Q2	Q3	Q4	Q5	Q6
1 (average values)	WS1	99	99.8	78	85	100	99.99
	WS2	99.9	99.9	50	77.2	99.99	99.99
2 (quality classes)	WS1	99	99.8	99.9	99.9	100	99.99
	WS2	99.9	99.9	98.7	99.5	99.99	99.99

Decision Support System. The obtained results confirmed the importance of classifying return products in quality classes. A Decision Support System was developed to enable the operator to (i) characterize and sort the parts in quality classes by using automatic data gathering systems, and (ii) to visualize to the operators in the workstation the specific strategy depending on the classified quality class of the return product. To this purpose, specific inspection technologies and methods including an optical character recognition approach and a hyperspectral imaging system have been developed for automatic bar code reading and for making inference on the level of the corrosion on the external surface of the screws. All in all, the developed solution provided the company with a new methodology and new enabling technologies for adapting the disassembly process depending on the quality class of the return product.

5. Conclusions and discussions

In this paper, a new method to support robust disassembly planning under uncertainty of the input product quality has been proposed. The developed method has been successfully applied on a real case study in the auto-part remanufacturing industry. Numerical results show that the proposed methodology can improve the efficiency and robustness of the disassembly process, thus supporting remanufacturing and the transition to new circular economy oriented business. Future research will concern the integration of disassembly strategy definition, line balancing and buffer design in order to reduce the inventory in the system, while keeping the same advantages of the proposed approach. Moreover, the possibility of integrating distributed, in line inspection stations to refine product information along the process-chain will be considered, under a zero defect remanufacturing viewpoint. Furthermore, the method will be extended to integrate manual, and semi-automatic tasks within the planning problem, following the recent innovations in cognitive robotics for future disassembly systems [15].

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