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Dealing with uncertainty in disassembly line design

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ABSTRACT

A disassembly process is usually characterized by a high level of uncertainty due to the quality of End-of-Life products. This paper presents an efficient approach for designing disassembly lines with the objective to maximize the line profit. Task times are assumed to be random variables with known probability distributions. An AND/OR graph is used to model the precedence relationships among tasks and subassemblies and the disassembly alternatives. A Monte Carlo sampling based exact solution method is developed to deal with uncertainties. Results of experiments on problem instances are presented.

1. Introduction

The main purpose of disassembly is to retrieve parts from End-of-Life (EOL) products for recycling, remanufacturing and reuse. This production process separates an EOL product into its components and subassemblies prior to the aforementioned recovery options. For higher productivity rate and automated process, disassembly lines are more suitable to carry out the disassembly operations [1]. The complex characteristics of disassembly make the design of disassembly lines more challenging than for assembly lines. A comparison of operational and technical considerations of assembly and disassembly lines is provided in [2]. Therefore, particular attentions should be paid to the design of disassembly lines and efficient tools are needed to optimize their performances by taking into account the uncertainties in the structure and quality of EOL products.

The paper deals in particular with the design of disassembly lines under uncertainty of task times. The deterministic version of this design problem is commonly known as Disassembly Line Balancing Problem (DLBP) and has been proven to be NP-complete in [2].

Disassembly planning has been an active area of research [3]. In particular, disassembly sequence generation has received quite some attention [4,5]. Practical aspects of disassembly have been also considered [6,7].

However, few papers in the literature have studied the design of disassembly lines under uncertainty. Among the existing work, the following factors of uncertainty have been partially studied:

1. *Task failures*: A heuristic method was proposed to probabilistically minimize the cost of defective parts in the presence of task failures [8]. Altekin and Akkan [9] proposed a Mixed Integer Program (MIP) for maximizing the profit generated by a disassembly line considering the possibility of the reassignment of the remaining tasks in the case of a task failure.
2. *EOL product condition*: A fuzzy colored Petri net model and a heuristic solution method were proposed by Turowski et al. [10] to deal with EOL product condition and human factors. A fuzzy optimization model was proposed in [11] with the objective to maximize the net revenue of the disassembly process under uncertainty of the quality of EOL products. A 'self-guided ants' metaheuristic was proposed as a solution method.
3. *Demand variations*: Tuncel et al. [12] used a Monte Carlo based reinforcement learning technique to solve the multi-objective DLBP under demand variations of the retrieved parts.
4. *Task time variations*: Usually in this case, the disassembly task times are assumed to be independent random variables with known normal probability distributions. A collaborative ant colony algorithm for stochastic mixed-model U-shaped DLBP was developed by Agrawal and Tiwari in [13]. The objective was to minimize the probability of line stoppage. A genetic algorithm was designed to solve a nonlinear binary bi-objective program for disassembly line design and balancing under uncertainty of the task times [14].

The literature review above shows that there are limited studies dealing with uncertainty in disassembly line design. Existing solution methods are restricted to heuristic or metaheuristic approaches without assessment of the solution quality. Many of cited papers have not assumed the case of partial disassembly and have not considered the disassembly alternatives by the means of an AND/OR graph, Koc et al. [15].

To bridge the gap, a simple mathematical model for the design of stochastic disassembly line under condition of complete disassembly has been proposed in our previous work [16]. The present paper extends this basic formulation by considering partial disassembly and calculating more precisely the recourse value, *i.e.* the penalty in the case of the cycle time overload. Task times are

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assumed to be random variables where known probability distributions can be considered and can be different from one task to another. An AND/OR graph is used to model the precedence relations among tasks. The objective is to maximize the profit of the line taking into account penalties of the cycle time overload.

The remainder of the paper is organized as follows: the Stochastic DLBP (S-DLBP) formulation of the line design problem and a solution method are presented in Section 2. Numerical experiments are presented in Section 3. Section 4 concludes the paper and discusses future research directions.

2. Problem formulation and solution method

The objective is to design a disassembly line consisting of a sequence of workstations J. The set of possible disassembly tasks I is given, but only a subset I^* of the set I is assigned to the workstations in order to maximize the line profit. The number of workstations $|J^*|$ gives the optimal number of workstations while $|J|$ represents an upper bound on the number of workstations.

The goal is the maximization of the net revenue produced by the line which is defined as the difference between the revenue generated by recovered parts and the line cost. The latter includes the operation cost of the opened stations, and the maximum penalty (recourse) cost generated by stations violating the cycle time constraint. The penalty occurs if the expectation of at least one workstation time exceeds the cycle time.

Partial disassembly is allowed and an AND/OR graph is utilized to model the precedence relationships among tasks. The AND/OR graph used represents explicitly all the possible disassembly alternatives of an EOL product and the precedence relationships among tasks and subassemblies. An example of such a graph is given in Fig. 1.

An AND/OR graph is constructed from an EOL product as follows:

1. Each subassembly is modeled by a node labeled $A_k, k \in K$, and each node labeled $B_i, i \in I$, represents a disassembly task. For simplicity, subassemblies with one component are not represented.
2. Two types of arcs define the precedence relations among subassemblies and disassembly tasks: AND and OR. If a disassembly task generates two subassemblies, or more, then, it is related to these subassemblies by AND-type arcs, in bold in Fig. 1. If several concurrent tasks may be performed on a subassembly, this latter is related to these tasks by OR-type arcs.
3. A sink node s is introduced and linked with dashed (dummy) arcs to all disassembly tasks. The use of the dummy task s allows a partial disassembly and if it is assigned to a station, then the disassembly process (partial or complete) is finished.

As mentioned above, disassembly task times $\tilde{t}_i, i \in I$, are assumed to be random variables with known probability distributions. Let $\tilde{t}_i = t_i(\tilde{\xi}), i \in I$, where $\tilde{\xi} = (\tilde{t}_1, \ldots, \tilde{t}_{|I|}) \in \Xi \subset \Re_+^{|I|}$, is a random vector of the task times and Ξ is a set of a given probability space (Ξ, F, P) introduced by $\tilde{\xi}$. Similarly, some other assumptions are defined to build a mathematical model for the S-DLBS problem: a single type discarded product is to be partially or completely disassembled on a straight paced line. The EOL products are sufficiently available. All received EOL products contain all their parts with no addition or removing of components. A disassembly task can be performed by any but only one workstation. Two types of costs are defined: a fixed cost per operating a time unit of an opened workstation and a recourse cost per operating an extra time unit of an opened station with expected processing time exceeding cycle time.

To model the S-DLBS problem, the following notations are used.

2.1. Parameters

L: set of parts' indices;
Li: set of recovered parts if task $B_i, i \in I$, is performed, $L_i \subset L, i \in I$;
r_l: revenue generated by a part $l \in L$;
F_c: fixed cost per operating a time unit of a workstation;
q: fixed recourse cost per operating an extra time unit of a workstation;
CT: cycle time;
P_k: set of indices for predecessors of $A_k, k \in K$;
S_k: set of indices for successors of $A_k, k \in K$.

2.2. Decision variables

$$x_{ij} = \begin{cases} 1 \text{ if task } B_i \text{ is assigned to station } j, \\ 0 \text{ otherwise.} \end{cases}$$

$$x_{sj} = \begin{cases} 1 & \text{if the dummy task } s \text{ is assigned to station } j, \\ 0 & \text{otherwise.} \end{cases}$$

A recourse variable $y_j, j \in J$, measures the amount of time exceeding CT if there is any.

2.3. Stochastic mixed binary program

The S-DLBS problem is formulated as follows:

$$\max\left\{\sum_{i \in I}\sum_{j \in J}\sum_{l \in L_i} r_l x_{ij} - CT \times F_c \sum_{j \in J} j x_{sj} - \max_{j \in J}(q y_j)\right\} \quad (SMIP)$$

$$s.t. \quad \sum_{i \in S_0}\sum_{j \in J} x_{ij} = 1 \quad (1)$$

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

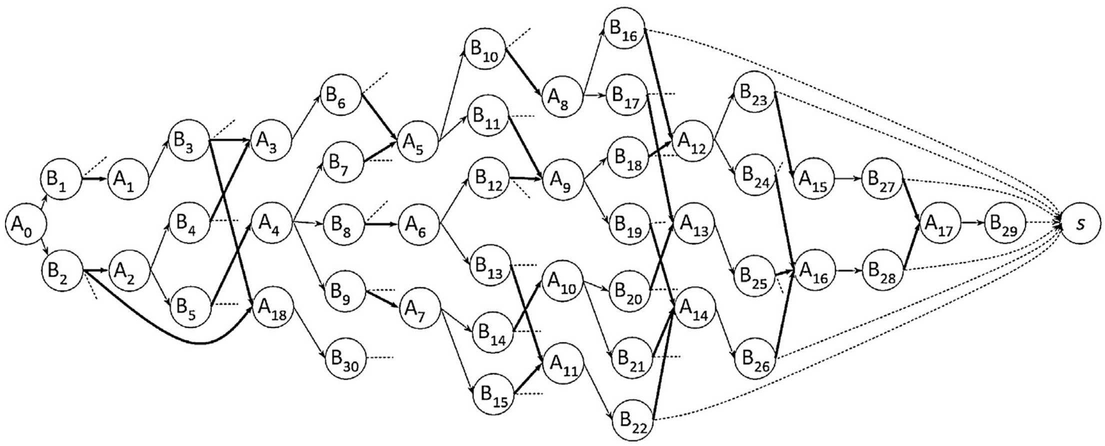

Fig. 1. AND/OR graph of a radio set adapted from [17].