Two-Stage Stochastic Program for Capacitated Disassembly Lot-Sizing Under Random Yield

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***Abstract*—This paper focuses on addressing the stochastic capacitated disassembly lot sizing problem, which aims to determine the optimal quantity and disassembly dates of used products in an uncertain environment. The objective is to satisfy the demand for components and modules while considering random yield factors. Notably, this work introduces a scenario-based two-stage stochastic integer programming model that addresses the complexities of a multi-level disassembly structure with dynamic demands for the different components at each level and the yield uncertainties. The objective of the proposed model is to minimize the expected total cost including holding, backlogging, overcapacity, and setup costs. Computational experiments are performed on several instances to evaluate the performance of the suggested model, and the benefits and implications of this research are highlighted.**

***Index Terms*—Disassembly lot-sizing, yield uncertainty, two-stage stochastic programming**

I. Introduction

The disassembly process in the handling of used products has gained significant attention due to its relevance to both environmental and economic considerations. Used and/or end-of-life products, such as vehicles and electronic devices, can be disassembled since they contain valuable resources that can be recovered and reused, reducing the demand for new raw materials and minimizing waste [1] [2]. By disassembling used returned products, constituent materials, parts, subassemblies, or other groupings can be systematically separated and sorted for recycling or refurbishment [3].

To optimize the disassembly process, various decision problems have been studied such as disassembly line balancing, disassembly sequencing, disassembly scheduling, automation and ergonomic problems [4], (see [5], [6], [7], [8], [9] for extensive literature evaluations on the aforementioned problems). Among all these issues, the focus of this paper is to study the Disassembly Lot-Sizing (DLS) problem, which is a significant planning challenge within the field of disassembly systems. The main objective is to determine the optimal schedules for disassembling the used products i.e. the quantity of products and timing of their disassembly while satisfying the demand for their individual parts and components within a given planning horizon.

In the context of industrial applications, the disassembly process is subject to diverse forms of uncertainty that can significantly impact its effectiveness. Uncertainties arise from multiple sources, including fluctuations in component demand, variability in disassembly yield rates, and unpredictable disassembly lead times [10]. These uncertainties introduce disruptions in the disassembly plan, often resulting in unfulfilled customer demands. One of the key challenges in disassembly processes is the considerable variability in the quality of returned products. This leads to the uncertainty of the number of good quality items obtained from disassembling a specific returned product. The main objective of this study is to address this challenge by devising a strategy to determine the optimal disassembly schedules under yield uncertainties.

The DLS study challenges are classified based on product structure (bi-level or multi-level), capacitated or uncapacitated problem [11], and deterministic or stochastic environment.

The focus of research has been on studying uncapacitated problems within deterministic contexts (e.g. [12],[13], [14], [15], [16]). In order to align with industrial reality, research has started considering and incorporating capacity constraints into the analysis of the deterministic DLS (e.g. [17], [18], [19], [20], [21]). Recognizing that capacity constraints alone may not capture the complexities of industrial reality in the DLS problems, attention has been directed toward addressing uncertainties in decision-making processes, as summarised in Table I. The literature has particularly explored uncertainties for used products with two-level structures. Among uncertainties, several works have considered random demand which pertains to the unknown demand for disassembled components. [22] has proposed a re-formulated reverse MRP algorithm using a fuzzy logic approach to deal with the demand uncertainty, [23] proposed a Lagrangian Heuristics (LH) for the capacitated DLS under random demand. [24] added the yield uncertainty with the random demand and proposed an Outer Approximation (OA) based algorithm to deal with the two-level capacitated DLS problem. [7] focused on the unpredictable Disassembly Lead Times (DLT) as another type of uncertainty in several works and proposed a scenario-based Stochastic Linear Programming (S-LP) model. [25] extended the work proposed by [7] by taking into account the disassembly time capacity and developed a Sample Average Approximation (SAA) approach to deal with the Two-Stage Mixed Integer Linear Programming (2S-MILP). [26] proposed an optimization methodology that combines the Monte Carlo simulation with a Genetic Algorithm (GA) to address large-scale instances as an extension of the work of [25]. [27] proposed a Scenario Aggregation (SA) approach to deal with the 2S-MILP and the random disassembly lead times scenarios. In the same disassembly structure type which is a two-level structure, [28] extended the navigation and merged the operation time uncertainty with the demand uncertainty. the authors proposed a Hybrid Genetic-based Algorithm (HGA) for the capacitated DLS MILP.

As previously stated, DLS problems under uncertainty are primarily solved for used products with a two-level echelon. However, the literature on DLS problems involving multi-level returned used products is limited. The main reason for this limitation is the presence of parental component bonds, which refer to the interdependencies among the parents and children components at each alternative level. These parental bonds significantly increase the complexity of the problem. To address this research gap with the multi-echelon returned used products, [29] proposed a stochastic demand-driven two-stage robust programming model for a three-level disassembly structure. [30] proposed a Lagrangian relaxation approach for the MILP in hybrid manufacturing and remanufacturing systems with demand uncertainty. In the same context, [31] considered an uncapacitated DLS problem within a remanufacturing system under yield and demand uncertainties. The authors suggested a Multi-Stage Mixed Integer Linear Programming (MS-MILP) approach. [32] dealt with the random Ordering Lead Times (OLT) in the multi-level DLS problem and developed a two-stage stochastic model.

In this paper, our main contributions are summarised as follows:

1) We focus on the influence of yield model selection on the quality of disassembly decisions for a single multi-level item. To the best of our knowledge, we are the first to deal with a multi-echelon capacitated DLS problem with dynamic demands and random yields. The problem is NP-hard because of the interdependence of the various sub-assemblies and components at each level and the time capacity limits [18]. Additionally, the yield uncertainties and the dynamic demands of the different components make the problem harder to solve;

2) We develop a scenario-based stochastic two-stage program that considers all the possible scenario combinations to cope with the problem's complexity.

The remainder of this work is structured as follows. Section II gives a detailed description of the problem studied. Section III presents the stochastic mathematical formulation of the problem. Section IV lays out the numerical results and finally section V concludes the paper and provides directions for future research.

II. Problem Description

We assume a multi-level disassembly system with numerous components at each level as illustrated in Fig.1.

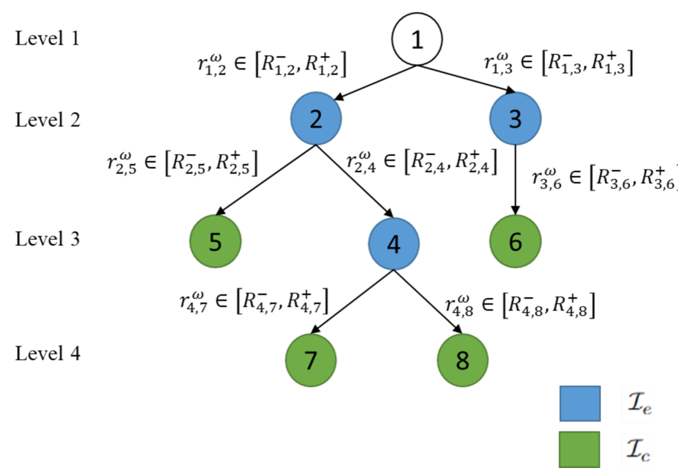

Fig. 1. A multi-level DLS system

The root item represents the product to be ordered (item 1). Sub-assemblies are intermediary modules that can be disassembled further (items 2,3 and 4), while the leaf items represent the items that cannot be further disassembled (items 5, 6, 7 and 8). Furthermore, a child item is any object that has a parent, whereas a parent item is any item that has at least one child. Each part in the disassembly product structure can have only one parent, resulting in no part commonality.

Since the returned used products differ in quality, it is unknown how many good-quality components will be obtained. The number of child item i obtained from his parent item $\phi(i)$ is random and bounded over known intervals $\left[R^-_{\phi(i),i}, R^+_{\phi(i),i}\right]$. As previously stated, demand for disassembled components is dynamic over the planning

TABLE I
RELEVENT STOCHASTIC DLS PROBLEMS

Authors	Level		Uncertainty					Capacity	Resolution approach
	2	multi	Demand	Yield	DLT	DOT	OLT		
[22]		✓	✓						F-RMRP
[23]	✓		✓					✓	MILP, LH
[29]		✓	✓						2S-MILP
[29]	✓		✓						MILP, LH
[30]	✓		✓	✓				✓	MILP, OA
[31]	✓		✓	✓				✓	MS-MILP
[33]	✓				✓				S-LP
[25]	✓				✓			✓	SAA
[26]	✓				✓			✓	GA
[27]	✓				✓			✓	SA
[32]		✓					✓	✓	2S-MILP
[28]	✓		✓			✓		✓	MILP, HGA
current paper		✓		✓				✓	2S-MILP

horizon. They are external for leaf items and sub-assembly parts and internal for root and subassemblies. Finally, the demand can only be satisfied by disassembling returned products. Furthermore, due to yield uncertainties in the disassembly process, meeting certain demands at specific levels may not be possible. Therefore, the concept of backlog is introduced to address this issue by allowing missed demands to be fulfilled at a later stage.

Without loss of generality, we make the following assumptions:

- A multi-period disassembly planning for a single type of root product is considered;
- Disassembly time capacity is limited and the added over capacity is restricted;
- The root items availability for disassembly is deterministic and constant.;
- Initial inventory and backlog levels are null;
- Disassembly yield is a random discrete variable with a known probability distribution and a bounded known interval R^+_{ji} and R^-_{ji};
- R^+_{ji} and R^-_{ji} are strictly positive;

III. MODEL FORMULATION

The objective of this research is to formulate a mathematical model specifically designed for capacitated multi-level disassembly systems under yield uncertainties. To facilitate a comprehensive understanding of the model, a list of notations used is provided in Table II.

In this paper, we present a scenario-based stochastic optimization. Specifically, we illustrate yield uncertainty by a set of scenarios. A scenario is a possible realization of the yield obtained from disassembling one unit of parent item i. Let Ω_i be the set of all possible realisations of $r^{\omega}_{\Phi(i),i}$ for each component i. Each scenario ω is a realisation of the random yield for the component i in a closed interval $\left[R^-_{\Phi(i),i}, R^+_{\Phi(i),i}\right]$, where $R^+_{\Phi(i),i}$ and $R^-_{\Phi(i),i}$ are respectively the maximum and the minimum quantities of item i obtained

TABLE II
NOTATIONS

Index

t Index of period t, $t \in \mathcal{T}$
i Index of item i, $i \in \mathcal{I}$
ω Index for scenarios of disassembly yield for each component i, $\omega \in \Omega_i$.

Parameters

$\mathcal{T}$ Set of time periods of the planning horizon
$\mathcal{I}$ Set of items
$\mathcal{I}_p$ Set of parent items
$\mathcal{I}_e$ Set of sub-assembly items
$\mathcal{I}_c$ Set of leaf items
Ω_i Set of possible scenarios of disassembly yield for each item i
d_{it} External demand for leaf or subassembly item i in time period t, $\forall i \in \mathcal{I}_{\setminus\{1\}}$
r^{ω}_{ji} Random number of units of item i obtained from disassembling one unit of j for scenario ω, $\forall i, j \in \mathcal{I}$
h_i Inventory holding cost of one unit of item i, $\forall i \in \mathcal{I}_{\setminus\{1\}}$
b_i Backlogging cost of one unit of item i at period t, $\forall i \in \mathcal{I}_c$
s_i Setup cost of parent item i, $\forall i \in \mathcal{I}_e$
ϕ_i Parent of item i, $\forall i \in \mathcal{I}_{\setminus\{1\}}$
g_i Disassembly operation time for parent item i, $\forall i \in \mathcal{I}_e$
C_t Available capacity in time-period t
F Maximum added overtime
u_t Cost of adding a unit of extra capacity in period t
M A large number

Functions

$\mathbb{E}(.)$ Expected value of (.)

First Stage Decision variables

Q_{it} Quantity of parent item i to disassemble in period t, $\forall i \in \mathcal{I}_p$
Y_{it} Binary indicator of disassembly for item i in period t, $\forall i \in \mathcal{I}_p$
O_t disassembly overtime in period t

Second Stage Decision variables

I^{ω}_{it} Inventory level of item i at the end of period t for scenarios ω, $\forall i \in \mathcal{I}_{\setminus\{1\}}, \forall \omega \in \Omega_i$
B^{ω}_{it} Backlog level of item i at the end of period t of scenarios ω, $\forall i \in \mathcal{I}_{\setminus\{1\}}, \forall \omega \in \Omega_i$

from disassembling one unit of its parent. We assume that at least one good quality item i is available at each level i.e. $R^-_{\Phi(i),i}$ is not null and it is equal to 1.
The determination of the number of scenarios for each component is determined by $|\Omega_i| = \left(R^+_{\Phi(i),i} - R^-_{\Phi(i),i} + 1\right) \forall i \in \mathcal{I}_{\setminus\{1\}}$.
Scenarios are independent and we consider that they are equally probable.

We solve the studied problem by a 2S-MILP with the first stage variables being the decisions taken prior to observing the yield scenarios and the second stage variables being decisions made after the scenarios are realized. The first stage decision variables are the disassembly quantities, the setup for item $i \in \mathcal{I}_e$, and the added overcapacity in period t while the second stage variables are the inventory and backlog levels for item $i \in \mathcal{I}_{\setminus\{1\}}$. The stochastic formulation of the capacitated multi-level disassembly lot-sizing problem considers a set of scenarios that represents all possible yield realizations for each component $i \in \mathcal{I}_{\setminus\{1\}}$. The objective is to minimize the expected objective value while determining the optimal disassembly schedule. Our model builds upon the first seminal work of [17], which focused on multi-echelon DLS with capacity constraints and deterministic yields. We include the yield uncertainties and propose the following 2S-MILP model:

$$\mathbb{E}(TC) = \ min \sum_{i\in\mathcal{I}_{\setminus\{1\}}} \sum_{t\in\mathcal{T}} \sum_{\omega\in\Omega_i} \frac{1}{|\Omega_i|} \left(h_i.I^{\omega}_{it} + b_i.B^{\omega}_{it}\right) + \sum_{t\in\mathcal{T}} \left(\sum_{i\in\mathcal{I}_p} s_i.Y_{it} + u_t.O_t \right) \tag{1}$$

s.t:

$$I^{\omega}_{it} - B^{\omega}_{it} = I_{i0} - B_{i0} + \sum_{\tau=1}^{t} r^{\omega}_{\phi(i),i}.Q_{\phi(i),\tau} - \sum_{\tau=1}^{t} Q_{i\tau} - \sum_{\tau=1}^{t} d_{i\tau} \quad \forall i \in \mathcal{I}_e, \forall t \in \mathcal{T}, \forall \omega \in \Omega_i \tag{2}$$

$$I^{\omega}_{it} - B^{\omega}_{it} = I_{i0} - B_{i0} + \sum_{\tau=1}^{t} r^{\omega}_{\phi(i),i}.Q_{\phi(i),\tau} - \sum_{\tau=1}^{t} d_{i\tau} \quad \forall i \in \mathcal{I}_c, \forall t \in \mathcal{T}, \forall \omega \in \Omega_i \tag{3}$$

$$Q_{it} \leq M.Y_{it} \qquad \forall i \in \mathcal{I}_p, \forall t \in \mathcal{T} \tag{4}$$

$$\sum_{i\in\mathcal{I}_p} g_i.Q_{it} \leq C_t + O_t \qquad \forall t \in \mathcal{T} \tag{5}$$

$$O_t \leq F \qquad \forall t \in \mathcal{T} \tag{6}$$

$$Q_{it} \geq 0 \qquad \forall i \in \mathcal{I}_p, \forall t \in \mathcal{T} \tag{7}$$

$$Y_{it} \in \{0, 1\} \qquad \forall i \in \mathcal{I}_e, \forall t \in \mathcal{T} \tag{8}$$

$$I^{\omega}_{it} \geq 0 \qquad \forall i \in \mathcal{I}_{\setminus\{1\}}, \forall t \in \mathcal{T}, \forall \omega \in \Omega_i \tag{9}$$

$$B^{\omega}_{it} \geq 0 \qquad \forall i \in \mathcal{I}_{\setminus\{1\}}, \forall t \in \mathcal{T}, \forall \omega \in \Omega_i \tag{10}$$

The objective function (1) minimizes the sum of the excepted inventory holding and backlog as well as setup and capacity exceeding costs over the planning horizon. Constraints (2) and (3) define respectively the inventory balance level for each sub-assembly item and each leaf item i at the end of each time period t for a scenario ω. Constraints (4) guarantee that a setup cost is generated in a period if any disassembly operation needs to be performed in that period. Constraints (5) give the disassembling capacity constraints in each period t. Constraints (6) present the limit of the added disassembly overtime. Finally, constraints (7)-(10) provide the domain of the decision variables.

IV. Computational experiments

In this section, we present the experimental results that were conducted to analyze and evaluate the performance of the proposed optimization approach.
The proposed model is implemented in $C++$ with Visual Studio Community 2022 17.5.3 and solved with IBM CPLEX 22.1.1 on a PC with Intel (R) Pentium Quad Core processor and 4 Go RAM under Windows 10.

A. Instance generation

The benchmark values for certain parameters used in this study are obtained from the following works [18] and [27] to accommodate the specificity of the capacitated DLS with random disassembly yields. Table III provides an overview of the generation approach for each parameter, with the notation $D \sim U(a, b)$ indicating that the parameter is randomly generated according to a discrete uniform distribution within the range $[a, b]$.

TABLE III
Characteristics of data sets

Parameters	Values
d_{it}	$D \sim U(50, 200)$
h_i	$D \sim U(5, 10)$
b_i	$D \sim U(100, 200)$
s_i	$D \sim U(500, 1000)$
g_i	$D \sim U(1, 4)$
C_t	$D \sim U(600, 720)$
u_t	$D \sim U(20, 40)$
F_t	120
$r^{\omega}_{\phi(i),i}$	$D \sim U(R^-_{\phi(i),i}, R^+_{\phi(i),i})$

A total of 135 instances were generated, consisting of 5 random instances for each combination of 3 levels of the number of periods, 3 levels of the number of components, and 3 levels of the range of yields of disassembling one unit of the parent $\phi(i)$. The level variation of these parameters is summarised in Table IV.

TABLE IV
PARAMETERS VARIATION

Parameter	Variation		
$\mathcal{T}$	10	20	30
$\mathcal{I}$	10	20	30
$R^{+}_{\phi(i),i}$	$D \sim U(2,5)$	$D \sim U(2,20)$	$D \sim U(2,50)$

B. Performance analysis

To take into account the importance of computation time in the decision-making process, a time limit of 3600 seconds was set for CPLEX to run. The performance measures that were utilized include:

- N^*: The number of optimal solutions provided by the CPLEX solver out of the 5 instances;
- CPU (s): The average computation times in seconds, which represent the amount of time required to obtain optimal solutions;
- Gap* (%): The average integrality gap obtained by CPLEX, The gap is rounded to the nearest 0.01 for approximation;

The analysis will primarily emphasize the CPU performance of the proposed approach. Specifically, the model's performance is evaluated in terms of computational efficiency and processing speed.

Table V provides insights into the impact of various factors on the performance of the proposed 2S-MILP model in capacitated disassembly problems. The factors under consideration include the number of periods, the number of items, and the disassembly yield (i.e., the number of child items obtained from disassembling a parent item). It is worth noting that these parameters directly influence the computation time, namely the number of scenarios for each component, the maximum yield achievable from the product structure, and the number of components in the product structure.

The number of scenarios for each component is important because it determines the granularity of the analysis. When the maximum yield that can be obtained from the product structure is higher, more scenarios for each component need to be considered to capture the range of possible outcomes. This increases the computational complexity and can potentially extend the computation time. Furthermore, the number of components in the product structure also plays a significant role. As the number of components increases, the total number of scenarios to be observed grows. This leads to a larger search space and subsequently increases the complexity of the problem. This increased complexity can sometimes result in the non-existence of a feasible solution in the limited time of 3600 seconds (marked with "-"), suggesting that the computational limitations of the 2S-MILP approach are encountered for larger scenario sets.

V. CONCLUSION AND PERSPECTIVES

In this study, we focused on addressing a multi-level capacitated DLS problem for a specific type of used product. The yields obtained from disassembling one unit of each parent item were treated as stochastic variables, represented using interval uncertainty. We proposed a two-stage multi-period stochastic MILP that holds significant potential for practical implementation in real-world industrial settings. Industries engaged in product recovery and remanufacturing, such as electronics or automotive face complex challenges in optimizing disassembly operations while accounting for uncertain yield outcomes. The presented model offers a promising solution to address these challenges by efficiently minimizing the expected total cost of inventory, backlogging, setup, and overcapacity. The mathematical model incorporated the representation of random yield parameters through a set of all possible scenarios. The model gives exact solutions and was tested on different size problems and performance analysis is presented.

Our ongoing work presents exciting opportunities for further research. Firstly, in real-world disassembly operations, root items (i.e., the used returned products) availability can indeed be uncertain and subject to variability. Considering this uncertainty is an important extension of the current work. Developing heuristics to address the challenges posed by large test instances would be a valuable direction to explore.

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TABLE V
PERFORMANCES OF THE 2S-MILP

2S-MILP										
Number of components		10			20			30		
$R^{+}_{\phi(i),i}$	Scenarios range	N	CPU(s)	Gap*(%)	N	CPU(s)	Gap*(%)	N	CPU(s)	Gap*(%)
(a) Number of periods is 10										
$D \sim U(2,5)$	[2, 5]	5	11.93	0.00	5	20.56	0.00	5	22.99	0.00
$D \sim U(2,20)$	[2, 20]	5	15.03	0.00	5	351.21	0.00	5	755.89	0.00
$D \sim U(2,50)$	[2, 50]	5	44.34	0.00	5	2581.69	0.00	0	-	-
(b) Number of periods is 20										
$D \sim U(2,5)$	[2, 5]	5	65.82	0.00	5	154.68	0.00	5	285.76	0.00
$D \sim U(2,20)$	[2, 20]	5	123.36	0.00	5	3613.6	0.12	5	3612.3	0.10
$D \sim U(2,50)$	[2, 50]	5	952.98	0.00	5	3612.14	0.10	0	-	-
(c) Number of periods is 30										
$D \sim U(2,5)$	[2, 5]	5	360.55	0.00	5	346.65	0.00	5	921.31	0.00
$D \sim U(2,20)$	[2, 20]	5	317.36	0.00	0	-	-	0	-	-
$D \sim U(2,50)$	[2, 50]	5	1559.55	0.00	0	-	-	0	-	-

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