Journal of Remanufacturing (2021) 11:243–261
https://doi.org/10.1007/s13243-021-00104-3

RESEARCH

A capacitated disassembly scheduling problem considering processing technology selection and parts commonality

M. N. Darghouth[1] · M. Abdel-Aal[1]

Received: 18 February 2021 / Accepted: 27 July 2021 / Published online: 16 August 2021

Abstract
In this paper, a multi-product multi-period capacitated disassembly scheduling problem with parts commonality, along with start-up and setup costs, and processing technology selection is formulated as a mixed-integer linear programming (MILP) model. Energy consumption cost is associated with each disassembly processing technique. We assume that unsatisfied demand for leaf items is backlogged. The model aims at quantifying energy costs by considering the expense incurred during the disassembly process to illustrate realistic remanufacturing concerns under several restrictions. The objective is to determine the optimal decisions on the quantity, the timing, and the processing technology of disassembling root items to satisfy leaf item demand over the planning horizon. The periodic capacity of disassembling root items is considered to be limited. Different numerical investigations based on data from the literature are considered and solved using CPLEX solver. A comprehensive sensitivity analysis is conducted to demonstrate the significance of the proposed mathematical model. Thus, the impact of the major key parameters of the developed model has been analyzed. Important managerial insights are drawn to demonstrate the practical application of the suggested methodology. Lastly, conclusions and future research perspectives are presented.

Keywords Sustainable remanufacturing · Capacitated disassembly scheduling · Mixed-integer linear programming · Energy processing technology selection · Parts commonality

Introduction

The scarcity of natural and economic resources coupled with the emergence of a variety of environmental legislation aimed at protecting the environment from damaging practices

✉ M. N. Darghouth
darghouth@kfupm.edu.sa

M. Abdel-Aal
mabdelaal@kfupm.edu.sa

[1] Systems Engineering Department, King Fahd University of Petroleum and Minerals, Dhahran, 31261, Saudi Arabia

have forced manufacturers to pay special attention to the efficient management and operation of reverse supply chains. The main objective of such practices is to ensure a certain level of sustainability of end-of-life (EOL) manufactured items through the collection and the reuse of different parts and materials. Disassembly scheduling and sequencing remain the two major phases of a successful recovery process [42]. Disassembly scheduling can be defined as an organized process for separating an item with a specific structure into subassemblies, components, or any other form of groupings according to a given order with respect to the relationships between different parts. Usually, the objective is to define the quantity and timing of the EOL products known as root items to be disassembled to satisfy time-varying demands for their parts known as leaf items obtained from the disassembly process over a planning horizon under different restrictions. For general reviews on disassembly problems considering different modeling aspects for single and multiple items refer to the work of [14, 20, 29, 33, 37, 41, 45]. In addition to the degradation state of the collected EOL products, the choice of the disassembly processing technology represents a contributing factor to achieve consistently high performance with the lowest cost. Thus, the development of disassembly scheduling procedures with energy efficiency consideration plays an important role in optimizing the reverse supply chain under various limitations.
It has been pointed out in the literature that several disassembly techniques can be utilized in real-life applications [1, 4], and [5]. These disassembly techniques can be characterized according to the energy consumption and the yield ratio associated with them. The selection of the disassembly technique is a critical decision that affects the financial and quality aspects of the disassembly process [23]. Several real-life practical and industrial applications have been presented in the literature that shows the application of the disassembly lot-sizing problem including: the disassembly of industrial valves in [13, 24], and [25], the disassembly of inkjet printers in [22], and [15], the disassembly of automobile engines in [12], the disassembly of Kodak single-use cameras and Xerox photocopiers in [8], and meat cut industry in [35], it also includes complicated cases like the disassembly of jet turbine engines discussed in [9], and [8], to name a few.

In the present research, the main goal is to investigate the disassembly scheduling problem with energy efficiency consideration. Several research studies were dedicated to the investigation of the energy-efficient production scheduling problems. However, no prior research work on disassembly scheduling problems with energy efficiency consideration was reported in the literature. In this paper, we propose a disassembly scheduling model with capacity constraint and parts commonality under energy efficiency consideration as a mixed-integer linear programming (MILP) model. Our contributions are two-fold:

1. Firstly, the multi-product, multi-period, capacitated disassembly scheduling problem with parts commonality, setup and start-up costs, and processing technology selection under different energy consumption and dependent yield ratios is formulated and investigated as a comprehensive MILP model. To our knowledge, the developed model is the first that integrates energy efficiency with dependent yield ratios into the capacitated disassembly scheduling problem. The value of the objective function varies according to the selected disassembly technique, making the proposed model an efficient asset to reduce the energy consumption related costs.
2. Secondly, we propose useful managerial insights to managers through an extensive sensitivity analysis conducted on the model key parameters. The performed computational experiments on problem instances with different sizes and input parameters showed that increasing the number of disassembly techniques helps to dramatically reduce the

total cost by offering the best disassembly schedule considering the tradeoff between the energy cost and the disassembly yield ratio.

The structure of the paper is as follows. A literature review of related research is presented in "Literature review". Section "Problem statement and model formulation" introduces the tackled problem and formulates the model. In "Numerical analysis", numerical experimentations are provided. Section "Managerial insights" discusses managerial insights based on a sensitivity analysis of the model key parameters. Conclusions and promising research extensions are presented in "Conclusions and possible extensions".

Literature review

Several researchers have demonstrated interest in investigating the uncapacitated disassembly scheduling problem and its industrial application under different constraints (e.g., demand, sequence, cost, etc.). The problem was initially introduced by [10]. The authors developed a complex algorithm for scheduling the uncapacitated disassembly of the discrete parts of products based on the reverse of the materials requirement planning (MRP) structure. Kim et al. [15] considered the disassembly scheduling problem for multiple product types with parts commonality. Parts commonality implies that different root items share the same disassembly components/parts, which creates additional dependencies. Kongar and Gupta [17] addressed the disassembly-to-order problem under uncertainty. The objective was to find the quantity and the type of each product to be collected under various constraints. Lambert and Gupta [18] focused in determining the optimal lot-sizes of used products to be disassembled with the aim of satisfying the leaf item time-variant demand subject to parts commonality constraint. Lee and Xirouchakis [21] determined the disassembly schedules and the quantity of root items to satisfy varying leaf item demand using a two-stage solving algorithm. Neuendorf et al. [32] proposed the application of Petri nets to solve the disassembly scheduling problem under a parts commonality assumption. The same problem has been addressed by [43] considering multiple structures of used products. Recently, [50] presented a mixed disassembly line balancing model for multiple products in a random working environment with part structure similarities.

Unlike the uncapacitated disassembly scheduling problem which has been extensively investigated in the literature, studies on the capacitated problem are limited. This is mainly due to the complexity of the problem, especially when parts commonality is considered. The capacitated disassembly scheduling problem involves resource capacity restrictions such as financial and human resources, equipment, and machines, etc. The work of [22] represents the earliest study on disassembly scheduling problems under capacity restrictions. The authors proposed a MILP model based on the reversed multi-level capacitated lot-sizing problem subject to capacity restrictions. Kim and Xirouchakis [16] considered a variant of the capacitated multi-product disassembly scheduling problem with stochastic demand for leaf items for a two-level product structure. Ji et al. [13] introduced the start-up cost component to the total cost function for a more pragmatic representation of an industrial setting. Tian and Zhang [45] examined the capacitated disassembly scheduling problem considering multi-item and multi-period pricing of returned products with price-dependent yields. Liu et al. [24] proposed a mixed-integer nonlinear program (MINLP) to model the capacitated scheduling problem with uncertainty in demand. Wang and Huang [48] proposed a methodology with a two-stage robust programming model for multiple products with a hierarchical product structure to be disassembled to satisfy uncertain demand. Ullerich and

Buscher [47] presented a MILP model to formulate the capacitated disassembly scheduling problem for flexible disassembly systems by integrating the task sequencing in disassembly planning. Hyong-Bae et al. [11] suggested a two-stage heuristic based on construction and improvement algorithms to solve a cost-based disassembly scheduling model under resource capacity constraints. Ehm [6] proposed a systematic methodology to generate feasible AND/OR graphs based on product design assumptions. The approach is used to jointly analyze the operations sequence planning and machine scheduling disassembly problems. More recently, [40] developed a new mixed-integer programming (MIP) model to maximize the disassembly process revenue considering capacity constraints and defective items.

Due to the climbing cost of energy and the paucity of natural resources, many researchers have focused their efforts on considering energy-saving measures in production scheduling. Originally, the cost of energy in production was introduced as a fixed parameter. However, due to the necessity to increase the economic benefits in order to survive a highly competitive global market, energy-saving rapidly becomes a fundamental ingredient for a successful business. It has been proven that the adoption of energy-efficient production-based schedules helps to achieve robust performance in terms of energy efficiency without the need to acquire new operating equipment generating considerable investment cost. Mouzon et al. [31] developed energy-efficient production methods based on a multi-objective optimization model to minimize the power consumption of production equipment. Mouzon and Yildirim [30] suggested a framework to jointly optimize the total energy consumption and the total tardiness. Yildirim and Mouzon [51] presented a multi-objective production scheduling optimization model which simultaneously considers the energy consumption level and the total completion time. Moon et al. [28] used reliability models to integrate the energy cost aspect in the production scheduling problem. Shrouf et al. [39] developed a mathematical model able to determine the optimal schedule for an operations manager that provides the least expensive production cost during a working shift. In subsequent work, [27] considered a flexible job-shop scheduling problem to find a balanced solution between total production and energy costs considering energy resources and storage. Rager et al. [38] considered a parallel machine configuration with specific orders and processing times for energy-efficient operations scheduling. Mikhaylidi et al. [26] presented a production scheduling model for a single machine that incorporates energy-saving aspects capable of finding an optimal electricity consumption plan. Tan et al. [44] established a multi-objective production scheduling optimization model for the economic dispatch problem considering time-varying electricity costs for hot rolling processing. Willeke et al. [49] developed a simulation model to highlight the effect of fluctuations in energy prices in production via manufacturing control. Patterson et al. [34] presented a MILP model that schedules haulage activity to minimize the truck and shovel energy consumption subject to satisfy time-varying production goals. Aghelinejad et al. [2] investigated a generalized model for a single machine production system by jointly considering the scheduling of the production at both the machine and job levels. Cao et al. [3] proposed a disassembly method for a disassembly line balancing problem considering a destructive disassembly mode for both non-detachable and detachable parts with a low value by considering energy consumption and disassembly times using an artificial bee colony algorithm. Liang et al. [23] extended the research on the production scheduling by integrating the energy efficiency concern. An extensive literature review synthesizing existing energy-related production scheduling problems for intelligent manufacturing systems along with promising future research avenues has been recently provided by [7].

All of the above-mentioned research studies investigated production scheduling problems considering energy-efficiency. In practice, production and disassembly processes are characterized as two distinct scheduling problems. The main difference lies in the function, the processing methodology, and the dependency of the process efficiency on the input quality. Production can be defined as the action of using material elements (raw material, parts, components, etc.) to make a new product exists according to a specific manufacturing sequence. Disassembly is the reverse process of production. Disassembly is the action of unbuilding EOL products according to a set of processing activities aiming to extract the subassemblies, components, raw materials, and/or other forms of obtained output. The throughput of the disassembly process is highly affected by the quality of EOL returned items. The cost of the disassembly process depends on the nature and the complexity of the product to be disassembled. Despite the recent technological advances in manufacturing, the disassembly process remains expensive and fastidious. Special attention should be devoted to optimizing the disassembly process by establishing an optimal operational schedule leading to a minimum disassembly cost. This paper complement existing studies in disassembly scheduling especially the work performed by [13] where the authors formulated the problem as a MILP considering simultaneously capacity restrictions, parts commonality and start-up cost by introducing the following two ideas:

- The cost of energy characterized by the selection of the disassembly technique to be used to satisfy the time-varying demand initially investigated by [23] to study the capacitated production planning and scheduling problem (CPPS) with sequence-dependent setups is considered. Thus, each disassembly technique is associated with a specific yield ratio of leaf items and charge different energy costs. The value of the objective function varies according to the selected disassembly technique, making the proposed model an efficient asset to reduce the energy consumption related costs. Therefore, the multi-product, multi-period, capacitated disassembly scheduling problem with parts commonality, setup and start-up costs, and processing technology selection under different energy consumption and dependent yield ratios is formulated and investigated as a comprehensive MILP model.
- Extending existing works in disassembly scheduling under capacity constraint by considering the opportunity to backlogging unsatisfied demand of leaf items.

Problem statement and model formulation

The problem under consideration is a representation of the multi-product, multi-period disassembly scheduling problem under capacity constraints considering parts commonality, start-up and setup costs, and disassembly processing technology selection. According to the parts commonality principle, a single root item (parent) may give rise to all available leaf items (child) with different yield ratios as shown in Fig. 1. A yield ratio is defined by the parameter a_{oji} and it is associated with the disassembly technique o of the root item i to the leaf item j. A time-varying cost e_{ot} is associated with each disassembly processing technique. We consider that the demand for leaf items (d_{jt}) is deterministic and varies from one period to another. If the quantity of leaf items at the end of a period exceeds the demand, an inventory occurs with a cost h_j. Otherwise, all unsatisfied demand for the leaf items is backlogged with a cost b_j per unit. Setup and start-up costs are reflected in the objective function to fit the most common disassembly setting problems. A start-up cost s_{io} is

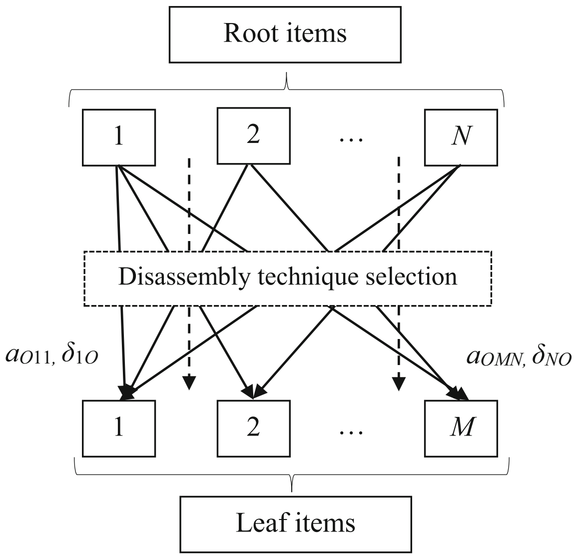


Fig. 1 Disassembly with parts commonality and technology selection technique

incurred each time root item i is disassembled using the disassembly technique o. Figure 2 represents the structure of the addressed problem. The resultant objective function consists of the start-up cost, the setup cost, the energy consumption cost, the procurement cost, and the inventory and backlogging costs.

Recall that the proposed MILP model is jointly inspired by the work [13] where capacity restrictions, parts commonality, and start-up cost are considered and formulated as a MILP model, and the work of [23] where an energy-efficient production planning and scheduling problem with processing technology selection is developed and solved. In this paper, the proposed model aims at cutting down energy consumption costs by considering expenditures incurred during the disassembly process and fitting them to real concerns. Thus, a MILP model is then proposed to illustrate the considered framework.

It is essential to elucidate the sense of the term ”disassembly technique” here. In practice, the disassembly technique parameter might carry several meanings. In general, any disassembly technique is identified by a sequence of technical actions organized according to a specific precedence schedule with the aim of decomposing an item into different sets of subassemblies or components with minimum damage to the leaf items. Thus, each disassembly technique is based on specific disassembly actions to be performed under a specific processing policy including different input parameters such as disassembly type (e.g. destructive disassembly, non-destructive disassembly, reverse disassembly, etc), a set of operations, specialized tools, etc. Special attention is devoted to the choice of the disassembly technique since it determines the major trend in terms of cost improvement through an energy centred disassembly process. A sensitive trade-off between a high disassembly yield ratio and the associated energy cost is then established. Alternative definitions of operational disassembly can be found in [10] and [43].

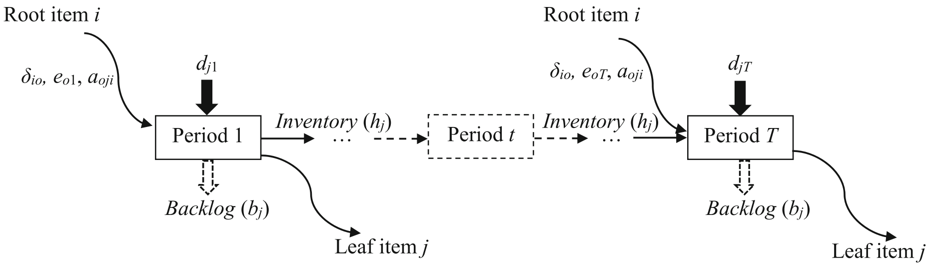


Fig. 2 Illustration of the considered problem.

The following assumptions are considered:

- Root items are available when required (no shortage).
- All root items are exploitable (no defective root items).
- All disassembly techniques are available when needed.
- No disassembly delay. The disassembly operation is performed immediately.
- Only one disassembly level is considered. Moreover, each single root item can share all available leaf items (parts commonality).
- All unsatisfied demand for leaf items is backlogged. Backlogging cost is independent of the time period.
- At most one disassembly technique is selected every period.
- A single disassembly technique can be selected to disassemble multiple products.

The following notation are utilized throughout the paper:

Indices

i root item index, $i = 1, 2, \ldots, N$
j leaf item index, $j = 1, 2, \ldots, M$
t planning horizon index, $t = 1, 2, \ldots, T$
o disassembly techniques index, $o = 1, 2, \ldots, O$

Parameters

s_{io} : start-up cost of disassembling root item i using disassembly technique o
p_{it} : procurement cost of root item i in period t
sc_{io} : setup cost of disassembling root item i using disassembly technique o
e_{ot} : energy cost of using technique o to disassemble the root item i in period t
a_{oji} : yield ratio of leaf item j to root item i using the disassembly technique o
d_{jt} : demand of leaf item j in period t
δ_{io} : has a value of 1 if the root item i can be disassembled using disassembly technique o and 0 otherwise
h_j : holding cost of leaf item j
b_j : backlog cost per unit of leaf item j per period
l_i : lower level of scheduled quantity of root item i to be disassembled
u_i : upper level of scheduled quantity of root item i to be disassembled
C : disassembly capacity limitation

Decision variables

Z_{iot} : a binary variable that has a value of 1 if there is a start-up for root item i using disassembly technique o in period t and 0 otherwise

Y_{iot} : a binary variable that has a value of 1 when scheduling root item i to be disassembled using technique o in period t and 0 otherwise

X_{iot} : disassembly quantity of root item i using disassembly technique o in period t

The proposed mathematical model is as follows:

$$\min \quad \sum_{i=1}^{N}\sum_{o=1}^{O}\sum_{t=1}^{T} s_{io} \times Z_{iot} + \sum_{i=1}^{N}\sum_{o=1}^{O}\sum_{t=1}^{T} sc_{io} \times Y_{iot} + \sum_{o=1}^{O}\sum_{t=1}^{T}\sum_{i=1}^{N} e_{ot} \times X_{iot} + \sum_{o=1}^{O}\sum_{t=1}^{T}\sum_{i=1}^{N} p_{it} \times X_{iot} + \sum_{j=1}^{M}\sum_{t=1}^{T} h_j \times \left(I_{jt} + \left(b_j \times B_{jt}\right)\right), \tag{1}$$

subject to

$$I_{jt} = I_{j,t-1} + \sum_{i=1}^{N}\sum_{o=1}^{O}\left(a_{oji} \times X_{iot}\right) - d_{jt} + B_{jt} \quad \text{for}\, j = 1, 2, ..., M; t = 1, ..., T, \text{ and}\, I_{j,0} = 0 \tag{2}$$

$$\sum_{i=1}^{N} X_{iot} \le C \quad \text{for} \quad t = 1, 2, ..., T \quad \text{and} \quad o = 1, ..., O, \tag{3}$$

$$\sum_{o=1}^{O}\sum_{i=1}^{N} e_{ot} \times X_{iot} \le W \quad \text{for} \quad t = 1, 2, ..., T, \tag{4}$$

$$Y_{iot} \le \delta_{io} \quad \text{for} \quad i = 1, 2, ..., N; \quad o = 1, ..., O \quad \text{and} \quad t = 1, ..., T, \tag{5}$$

$$\sum_{o=1}^{O} Y_{iot} \le 1 \quad \text{for} \quad i = 1, 2, ..., N \quad \text{and} \quad t = 1, ..., T, \tag{6}$$

$$l_i \times Y_{iot} \le X_{iot} \le u_i \times Y_{iot} \quad \text{for } i = 1, 2, ..., N; \ o = 1, ..., O \text{ and } t = 1, ..., T, \tag{7}$$

$$Y_{iot} - Y_{io,t-1} \le Z_{iot} \quad \text{for } i = 1, 2, ..., N; \ o = 1, ..., O \text{ and } t = 2, ..., T, \tag{8}$$

$$Y_{io,1} \le Z_{io,1} \quad \text{for} \quad i = 1, 2, ..., N; \quad \text{and} \quad o = 1, ..., O, \tag{9}$$

$$X_{iot} \ge 0, \quad \text{for } i = 1, 2, ..., N; \ o = 1, ..., O \text{ and } t = 1, ..., T, \tag{10}$$

$$B_{jt} \ge 0, \quad \text{for} \quad j = 1, 2, ..., M; \quad \text{and} \quad t = 1, ..., T, \tag{11}$$

$$Y_{iot}, Z_{iot} \in \{0, 1\} \quad \text{for } i = 1, 2, ..., N; \ o = 1, ..., O \text{ and } t = 1, ..., T, \tag{12}$$

Equation 1 represents the total disassembly cost as the objective function to be minimized. The total disassembly cost includes the setup costs, the start-up costs, the energy costs in disassembly, the procurement costs of the root items, and the inventory and backlogs costs. The energy cost is characterized by the selection of the disassembly technique to be used to satisfy the time-varying demand. Each disassembly technique is associated with a specific yield ratio of leaf items and charge different energy costs.

Constraint (2) denotes the inventory balance constraint. The second term indicates the generated quantity of leaf item j using the disassembly technique o to disassemble the root item i in period t. We assume that a_{oji} is independent of the time period t. Terms three and four present the demand and the backlogged amount of leaf item j at period t, respectively. The restriction that in any period the summation of the disassembly quantity of root item i using disassembly technique o in period t does not exceed the maximum available capacity is illustrated by constraint (3). The total energy consumption restriction cost for each time period is enforced in equation (4). The admissibility constraints indicating that in any period, a root item can only be disassembled with no more than one disassembly technique are expressed by constraints (5) and (6). Equation 7 specifies the semi-continuous property of disassembly quantity with the disassembly technique selection. Jointly constraints (8) and (9) define the start-up relationships. The last set of equations (10), (11), and (12) are the non-negativity and binary decision variables constraints.

The problem has $N \times O \times T + M \times T$ continuous vaiables, $2\,(N \times O \times T)$ binary variables, and $N \times O + 3\,(N \times O \times T) + (M + O + N + 1) \times T$ constraints. [46] proved that the capacitated lot-sizing problem with start-up cost, which represents a particular instance of the proposed model, is NP-complete. It is worth to mention that using exact methods to solve such problems, particularly with a large number of root items, a long planning horizon, and a high number of disassembly techniques, is ill-advised as the problem complexity and the required computational time increase exponentially [10], [19], and [36].

Numerical analysis

This section demonstrates the performance of the state-of-the-art MILP CPLEX solver for solving the proposed mathematical model in terms of the computational time and the gap between the obtained solution of the solver and the best available lower bound. Several computational experiments focusing on the impact of the number of disassembly techniques with different characteristics on the objective function components, including the costs of inventory, energy, procurement, setup, start-up, and backlogging were conducted on various test instances including different problem sizes and different inputs parameters. In our experiments, we adopted the values of the input parameters from the literature; i.e. [13] and [23], which are based on real-life production scenarios. The input parameters are shown in Table 1.

Ten instances for each problem size were generated and solved. The experiments were implemented in GAMS programming language version 24.7.4 and the models were solved using CPLEX solver version 12.6.3 and run on a computer with an Intel Core i7 2.8 GHz processor and 8GB of RAM. The calculation time limits of the CPLEX solver were set to 1000 seconds.

Performance analysis of the CPLEX MILP solver for the proposed model based on 1000 seconds runtime

Table 2 summarizes the results on the gap between the best available lower bound and the obtained solutions using the CPLEX solver. The gap has been illustrated by the minimum,

Table 1 Values of input parameters

Input parameter	Value
s_{io}	$U\,[400, 500]$
p_{it}	$U\,[6, 8]$
sc_{io}	$U\,[100, 200]$
e_{ot}	$U\,[1, 2]$
a_{oij}	$U\,[1, 4]$
d_{jt}	$U\,[15, 35]$
δ_{io}	1
h_j	$U\,[20, 40]$
b_j	$U\,[100, 200]$
l_i	$U\,[30, 50]$
u_i	$U\,[60, 80]$
C	250
W	200

the average, and the maximum value of the deviation from the optimal solution or the lower bound and calculated using the following equation:

$$Relative\ Gap = \frac{\left|z_{lp}^{*} - z_{milp}\right|}{\max\left\{\left|z_{lp}^{*}\right|, \left|z_{milp}\right|\right\}} \tag{13}$$

where z_{lp}^{*} is the optimal objective value of the relaxed linear program of the proposed model, which is the best lower bound on the objective value of the proposed model, while z_{milp} is the obtained objective value of the proposed MILP.

Test instances with different values of the total number of root items (N), the total number of leaf items (M), and the sizes of the available disassembly techniques set (O) have been investigated for different time periods varying from 5 to 15. In Table 2, when the maximum value of the gap is zero, this means that the solver was able to solve all of the ten instances of that problem size to optimality. However, when the minimum value of the gap is positive, this means that the solver was unable to obtain the optimal solution to any of the ten instances of that problem size to optimality. Additionally, when the maximum value of the gap is positive and the minimum value is zero, this means that the solver was able to solve some of the ten instances of that problem size to optimality; the problems highlighted in the color grey in Table 2 are related to this category.

The obtained results show clearly that for a planning horizon which consists of 5 time periods, the CPLEX solver can provide the optimal solution without any observable deviation. The gap starts from a time horizon of 10 periods, especially for instances with large disassembly technique sets (O). This is mainly due to the difficulty of solving the proposed MILP problem which involves a large number of binary variables in a short span of time. It is worth noticing that the maximum recorded deviation is about 51% obtained with a planning horizon of 15 periods for the largest test instance.

In contrast, the CPLEX solver was able to reach the optimal solution for some of the generated instances for 15 different problem sizes as highlighted in grey in Table 2. For instance, CPLEX succeed in obtaining the optimal solutions for six instances of the ten generated test instances of problem size (N, M, O, T) = (5,15,5,15) and (15,15,5,10), while it obtained the optimal solutions for nine instances of the ten generated test instances of

Table 2 GAP (%) of the obtained solutions for different problem sizes

Number of time periods (T)									
	5			10			15		
	Gap			Gap			Gap		
(N,M,O)	Min	Avg	Max	Min	Avg	Max	Min	Avg	Max
(5,5,5)	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
(5,5,10)	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	2.70%	11.00%
(5,5,15)	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	11.70%	20.00%
(5,10,5)	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	%0.00%	1.40%	14.00%
(5,10,10)	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	10.00%	19.50%	28.00%
(5,10,15)	0.00%	0.00%	0.00%	0.00%	1.70%	9.00%	18.00%	26.30%	30.00%
(5,15,5)	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	3.80%	15.00%
(5,15,10)	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	15.00%	24.70%	33.00%
(5,15,15)	0.00%	0.00%	0.00%	0.00%	7.90%	22.00%	22.00%	30.30%	34.00%
(10,5,5)	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	4.70%	20.00%
(10,5,10)	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	12.00%	20.20%	24.00%
(10,5,15)	0.00%	0.00%	0.00%	0.00%	2.50%	17.00%	15.00%	27.90%	35.00%
(10,10,5)	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	3.00%	16.70%	24.00%
(10,10,10)	0.00%	0.00%	0.00%	0.00%	4.30%	17.00%	25.00%	29.50%	34.00%
(10,10,15)	0.00%	0.00%	0.00%	0.00%	19.90%	31.00%	31.00%	33.50%	37.00%
(10,15,5)	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	15.00%	21.00%	29.00%
(10,15,10)	0.00%	0.00%	0.00%	0.00%	10.30%	26.00%	27.00%	31.70%	38.00%
(10,15,15)	0.00%	0.00%	0.00%	22.00%	26.90%	32.00%	34.00%	36.60%	42.00%
(15,5,5)	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	7.00%	20.10%	30.00%
(15,5,10)	0.00%	0.00%	0.00%	0.00%	0.60%	6.00%	19.00%	26.20%	29.00%
(15,5,15)	0.00%	0.00%	0.00%	0.00%	11.80%	25.00%	27.00%	31.70%	40.00%
(15,10,5)	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	21.00%	25.20%	30.00%
(15,10,10)	0.00%	0.00%	0.00%	0.00%	22.30%	32.00%	26.00%	36.10%	41.00%
(15,10,15)	0.00%	0.00%	0.00%	4.00%	25.50%	41.00%	33.00%	37.10%	41.00%
(15,15,5)	0.00%	0.00%	0.00%	0.00%	4.60%	23.00%	27.00%	29.90%	33.00%
(15,15,10)	0.00%	0.00%	0.00%	20.00%	28.90%	37.00%	29.00%	36.10%	45.00%
(15,15,15)	0.00%	0.00%	0.00%	29.00%	33.50%	39.00%	39.00%	44.40%	51.00%

problem size (5,10,5,15) and was able to obtain the optimal solutions for only one instance of the ten generated test instances of the problem size (15,10,10,10).

The minimum, the average, and the maximum CPU times in seconds (s) needed to achieve the optimal or nearly optimal solution are presented in Table 3. We can see that the CPLEX solver can reach the optimal solution within a reasonable computing time, especially for low and medium-size problem test instances up to a planning horizon consisting of 10 time periods, except for some test instances with large-sized disassembly techniques. Also, we can notice that for a planning horizon of 15 time periods and for problem instances starting from the indices N, M, and O respectively equal to 5, 10, and 10, the CPU time (s) hits the maximum predefined running time frame of 1000 (s). The obtained results once

Table 3 CPU solving time (s) for different problem sizes

Number of time periods (T)									
	5 CPU (s)			10 CPU (s)			15 CPU (s)		
(N,M,O)	Min	Avg	Max	Min	Avg	Max	Min	Avg	Max
(5,5,5)	1.33	1.80	3.50	4.10	10.39	17.10	39.60	146.38	329.06
(5,5,10)	1.86	2.60	4.07	19.65	71.29	122.98	88.28	709.363	1000.00
(5,5,15)	2.16	3.98	7.69	67.60	194.43	550.13	848.69	984.66	1000.00
(5,10,5)	2.13	3.78	9.48	14.89	62.45	165.59	99.78	397.15	1000.00
(5,10,10)	2.08	5.84	15.88	52.79	136.32	233.97	1000.00	1000.00	1000.00
(5,10,15)	3.31	11.88	19.50	112.84	518.65	1000.00	1000.00	1000.00	1000.00
(5,15,5)	3.45	5.95	7.88	32.54	59.14	85.14	286.89	768.77	1000.00
(5,15,10)	5.44	8.68	15.56	107.14	300.29	634.80	1000.00	1000.00	1000.00
(5,15,15)	4.44	17.21	26.91	431.49	762.85	1000.00	1000.00	1000.00	1000.00
(10,5,5)	2.47	3.57	5.64	20.78	74.88	185.21	196.08	685.37	1000.00
(10,5,10)	4.66	5.98	9.81	30.63	220.39	592.03	1000.00	1000.00	1000.00
(10,5,15)	5.16	12.84	19.74	197.35	575.72	1000.00	1000.00	1000.00	1000.00
(10,10,5)	3.87	6.04	10.02	88.32	157.90	244.10	1000.00	1000.00	1000.00
(10,10,10)	5.51	11.48	31.65	162.75	755.49	1000.00	1000.00	1000.00	1000.00
(10,10,15)	7.38	14.11	29.75	761.60	981.35	1000.00	1000.00	1000.00	1000.00
(10,15,5)	4.58	7.80	13.37	123.58	323.51	564.40	1000.00	1000.00	1000.00
(10,15,10)	13.53	23.473	43.75	632.10	908.36	1000.00	1000.00	1000.00	1000.00
(10,15,15)	12.23	35.59	70.25	1000.00	1000.00	1000.00	1000.00	1000.00	1000.00
(15,5,5)	2.74	3.98	5.89	18.17	152.22	580.56	1000.00	1000.000	1000.00
(15,5,10)	8.42	14.33	21.39	39.11	601.66	1000.00	1000.00	1000.00	1000.00
(15,5,15)	10.89	23.51	38.80	710.36	964.27	1000.00	1000.00	1000.00	1000.00
(15,10,5)	3.67	5.85	9.29	121.41	319.63	596.89	1000.00	1000.00	1000.00
(15,10,10)	7.49	20.756	28.82	601.17	962.21	1000.00	1000.00	1000.00	1000.00
(15,10,15)	21.81	42.87	64.94	1000.00	1000.00	1000.00	1000.00	1000.00	1000.00
(15,15,5)	7.20	12.74	22.41	273.63	832.68	1000.00	1000.00	1000.00	1000.00
(15,15,10)	19.97	37.30	47.48	1000.00	1000.00	1000.00	1000.00	1000.00	1000.00
(15,15,15)	34.20	45.66	57.67	1000.00	1000.00	1000.00	1000.00	1000.00	1000.00

again show the difficulty of solving the proposed MILP problem where the number of binary variables increases significantly.

Sensitivity analysis on the model key parameters

In this subsection, we investigate the effect of some key parameters of the model on the value of the objective function and its cost components. Our main focus is to study the effect of providing several alternative disassembly techniques on the model and its constituting costs. Thus, a sensitivity analysis is conducted on the total cost, the backlog cost, and all of the cost components involved in the objective function, namely the inventory cost, the energy cost, the procurement cost, the setup cost, and the start-up cost. The tests are performed under the parameter values provided in Table 4. The energy capacity constraint, as well as the energy selection constraint, are relaxed to allow for the possibility of using a multitude of disassembly techniques. Note that the root item procurement cost, the energy cost, the start-up cost, and the setup cost are set to be fixed values for all of the disassembly techniques to eliminate their effect on the selection of the technique.

The backlogging cost is set to be equal to the value of α (root item procurement cost + the energy cost) to be meaningful in terms of operational cost. We examine the effect of varying the multiplier α (from 1 to 5) on the model components.

Figure 3 exemplifies the performance of the total cost as a function of the number of disassembly techniques for different values of α. As shown, the total cost decreases as the number of disassembly techniques increases. This result is valid for all values of α. Also, we can notice that the total cost slightly converges to a finite value starting from a number of disassembly techniques equal to 6. This decrease in the total cost is mainly due to a negative correlation between the backlogging cost and the number of disassembly techniques for all considered values of α as presented in Fig. 4. A relatively high number of disassembly techniques and the corresponding yield ratios offer the possibility to achieve better disassembly performance and help to fulfill the time-varying demand and reduce the need to backlog portions of the demand.

Figure 3 exemplifies the performance of the total cost as a function of the number of disassembly techniques for different values of α. As shown, the total cost decreases as the number of disassembly techniques increases. This result is valid for all values of α. Also, we can notice that the total cost slightly converges to a finite value starting from a number of disassembly techniques equal to 6. This decrease in the total cost is mainly due to a negative correlation between the backlogging cost and the number of disassembly techniques for all considered values of α as presented in Fig. 4. A relatively high number of disassembly techniques and the corresponding yield ratios offer the possibility to achieve better disassembly performance and help to fulfill the time-varying demand and reduce the need to backlog portions of the demand.

As shown in Fig. 5, all the cost components constituting the model increase as the number of disassembly techniques increases and converge at a certain value starting from a number of disassembly techniques equal to 6. This result is true for all values of the multiplier α. It is worth noticing that all of the cost components almost reach a fixed level of their increase at a number of disassembly techniques equal to 6, except for the inventory cost component which has a higher level of cost increase as the multiplier α increases. This happens because the increase in the value of the multiplier α increases the backlog cost per unit. Therefore, the effect of this increased cost is mainly mitigated by keeping more units as inventory for future demand and hence increasing the inventory cost component, although at a significantly slower rate than the increasing rate of the backlogging cost. Eventually, this leads to a reduction in the total cost.

Table 4 Sensitivity analysis model parameter values

Parameter	Value
Root item procurement cost, p_{it}	1
Energy cost, e_{ot}	1
Setup cost, s_{iot}	100
Start-up cost, sc_{io}	500

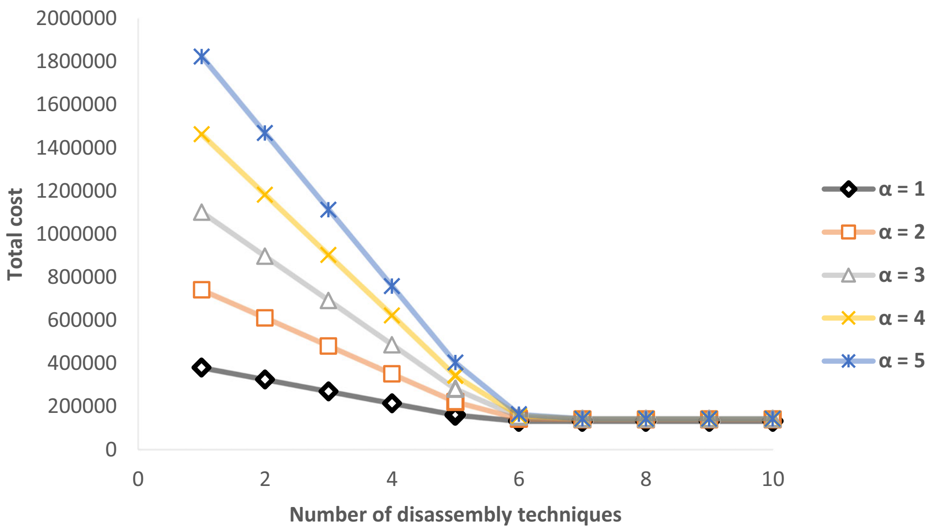


Fig. 3 The total cost versus the number of disassembly techniques for different values of α

Managerial insights

In this part, we propose some useful managerial insights based on the results obtained from the conducted experiments on the model parameters. The derived observations may be used as guidelines to lighten the efforts required to reduce the energy costs during the disassembly process. The performed sensitivity analysis revealed useful managerial recommendations for a more cost-efficient disassembly process. Increasing both the number of disassembly techniques and the capacity restriction has a beneficial impact on the total disassembly cost.

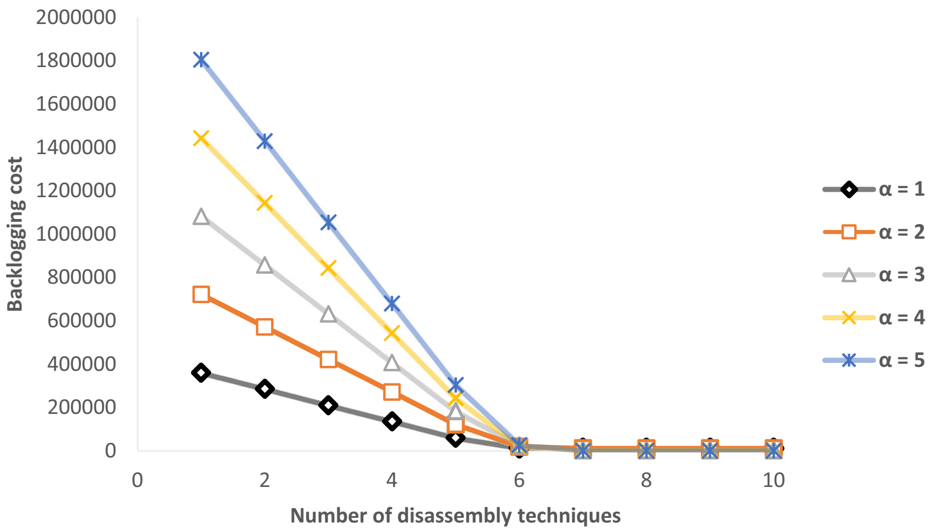
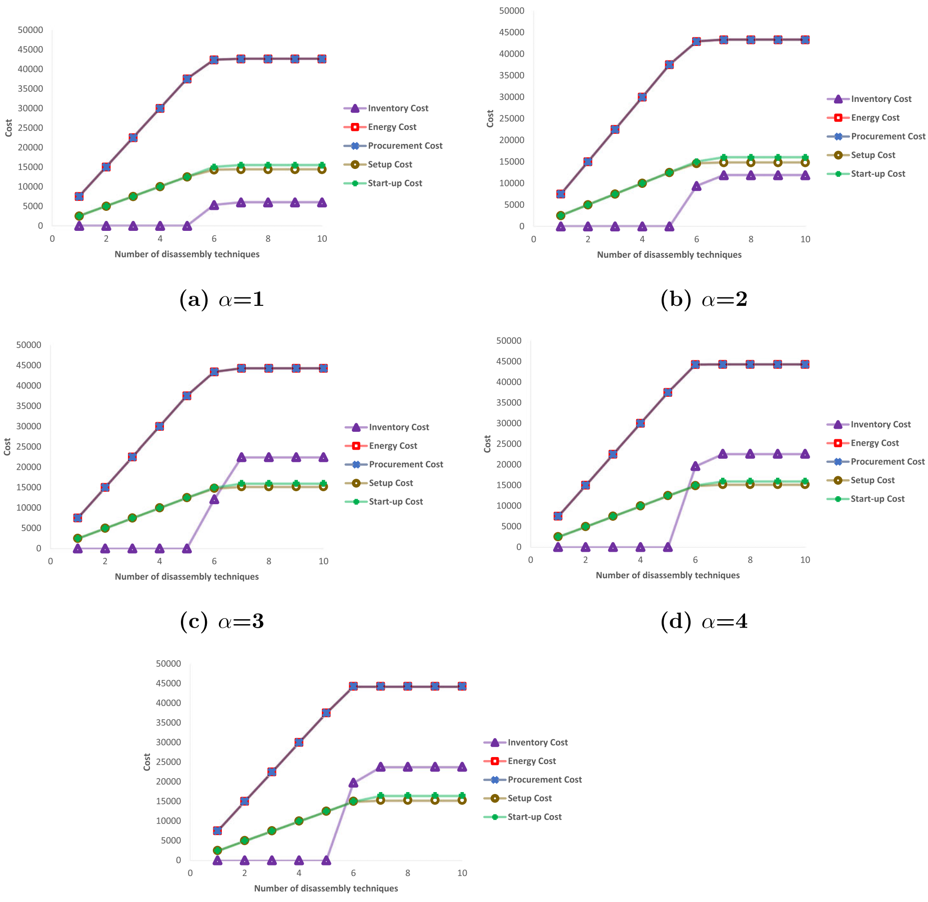


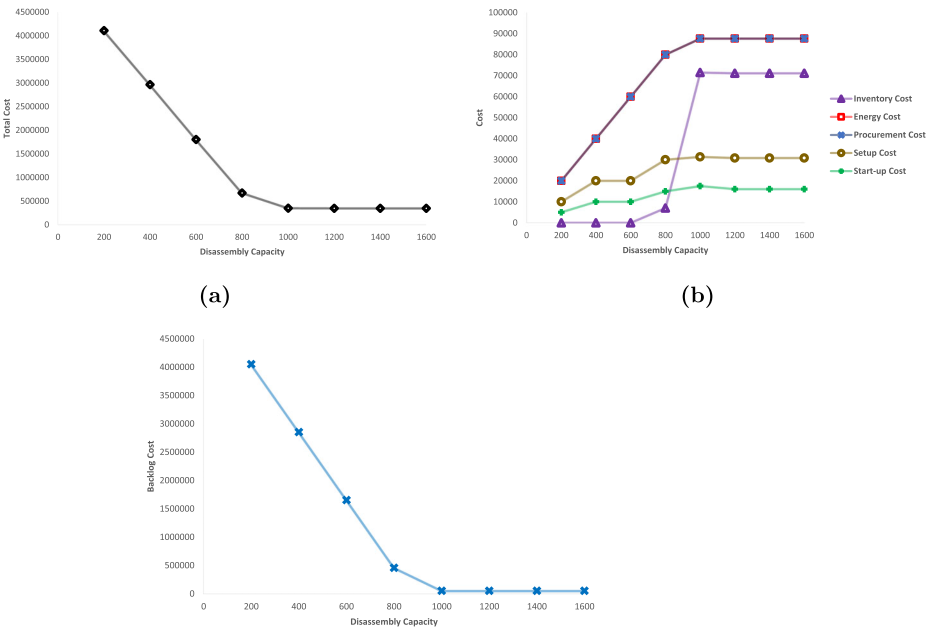
Fig. 4 The backlogging cost versus the number of disassembly techniques for different values of α



(a) $\alpha=1$ (b) $\alpha=2$ (c) $\alpha=3$ (d) $\alpha=4$ (e) $\alpha=5$

Fig. 5 The inventory cost, the energy cost, the procurement cost, the setup cost, and the start-up cost versus the number of disassembly techniques for different values of α

In fact, increasing the number of disassembly techniques that can be used each period of time provides more alternatives to fulfill the demand for leaf items, leading to the appropriate use of the plant capacity. However, the cost improvement stops at a certain threshold of the number of disassembly techniques, as demonstrated in Figs. 3–5. As stated in Table 3, the difficulty of solving the proposed problem for large size instances with a high number of disassembly techniques within a reasonable computational time urges the managers to consider strategic planning decisions based on a limited number of disassembly techniques to prevent any delay. Thus, the joined computational and economic side represents a crucial aspect for the decision-makers. It is worth pointing out the negative correlation between the total cost, relative Gap, and CPU time with the available disassembly capacity. Hence, expanding capacity is preferred in terms of both computation times and operational costs. Therefore, managers should weigh and analyze the trade-off between larger disassembly capacity investment and lower operational disassembly costs, and improved relative Gap and CPU time. [13] and [40] have demonstrated similar results.



(a) (b) (c)

Fig. 6 **(a)** The total cost versus the disassembly capacity for α=3. **(b)** The inventory cost, the energy cost, the procurement cost, the setup cost, and the start-up cost versus the disassembly capacity for α=3. **(c)** The backlog cost versus the disassembly capacity for α=3

In terms of capacity constraint, the performed analysis illustrated in Fig. 6 shows that increasing the capacity offers more flexibility to the production planner so that the periodic demand for leaf items can be satisfied appropriately, avoiding backlog penalties. However, like the number of disassembly techniques, increasing the capacity constraint has a limited beneficial impact on the total disassembly cost. We can notice that beyond a capacity threshold of 1000 there is no tangible improvement in the total disassembly cost and its components. The manager is called to carefully investigate these two parameters to reduce the total disassembly cost and avoid oversizing the required resources.

Also, it is essential to mention that considering a high number of root items may have a negative effect on the total disassembly cost. This conclusion indicates the difficulty of cutting down the energy cost with a more significant number of root items, especially when disassembly techniques are limited. In a case in point, managers are advised to consider more disassembly techniques to improve cost reduction performance. Finally, we mention that the length of the planning horizon has no critical effect on the energy-saving performance. Thus, managers have a certain degree of flexibility in defining the planning horizon.

Conclusions and possible extensions

Businesses are continuously looking for a level of operational efficiency that enables them to be competitive and ideally positioned in the global market. Unfortunately, they are confronted with the various constraints associated with the working environment such as capacity and budget limitations. Only through stringent demands, in terms of rationing energy use and wise resources management, will it be possible to survive the actual challenges. To address these challenging issues in the context of the operational disassembly of EOL products, we establish a multi-product, multi-period capacitated disassembly scheduling problem with parts commonality, along with start-up and setup costs, considering disassembly technology selection as a MILP model. Each energy disassembly technique is characterized by its incurred cost and a specific yield ratio. Our objective is to determine the optimal decisions on the quantity, the timing, and the processing technology for disassembling root items to satisfy leaf item demand over the planning horizon under capacity constraints.

Numerical experiments for different problem sizes, along with sensitivity analyses of the model key parameters, are performed using data selected from the literature. The obtained results demonstrate the consistency and robustness of the proposed model. Interesting managerial insights have been drawn to demonstrate the practical application of the suggested methodology. The present study highlighted that increasing the number of disassembly techniques and loosening the capacity restrictions has a significant impact on the total disassembly cost. Increasing the number of disassembly techniques and the capacity constraint beyond a certain level has a limited beneficial impact on the total disassembly cost. In addition, cutting down the energy cost with a greater number of root items, especially when the number of disassembly techniques is limited, is difficult to achieve. Managers are advised to consider more disassembly techniques to achieve an improved cost reduction performance.

The key findings of this study are helpful for both investors and managers in devising a strategy based on both engineering factors and market parameters. In addition, it is hoped that they will help to enrich the literature dealing with the capacitated disassembly scheduling problem by introducing several cost determinant aspects. Nevertheless, there are additional issues related to the proposed analysis that could be investigated further. In our study, we considered a time-varying deterministic demand and backlogs. A more ambitious framework considering stochastic demand with a service level and the opportunity to procure unfulfilled demand for leaf items from external suppliers will help to achieve better results. We based our resolution on the CPLEX solver performance. Developing solving algorithms able to achieve better performance in terms of computational time, especially for large-size instances, represents an exciting approach to solve the problem. Another possible extension of the proposed research is introducing energy conservation emission reduction and carbon mitigation in alignment with the current conservative industrial development trends. Finally, one of promising avenues for future research is to investigate a more realistic framework in which the quality of returned items and its impact on the disassembly techniques and the corresponding incurred cost is considered with a certain level of uncertainty. The main objective is to enhance energy-saving awareness in the disassembly scheduling field.

References

1. Abuzied H, Senbel H, Awad M, Abbas A (2020) A review of advances in design for disassembly with active disassembly applications. Engineering Science and Technology, an International Journal 23(3):618–624
2. Aghelinejad MM, Ouazene Y, Yalaoui A (2018) Production scheduling optimisation with machine state and time-dependent energy costs. Int J Prod Res 56(16):5558–5575

3. Cao J, Xia X, Wang L, Zhang Z, Liu X (2019) A novel multi-efficiency optimization method for disassembly line balancing problem. Sustainability 11(24)
4. Duflou J, Seliger G, Kara S, Umeda Y, Ometto A, Willems B (2008) Efficiency and feasibility of product disassembly: A case-based study. CIRP Ann 57(2):583–600
5. Duflou J, Willems B, Dewulf W (2006) Towards self-disassembling products design solutions for economically feasible large-scale disassembly. In: Brissaud D, Tichkiewitch S, Zwolinski P (eds) Innovation in life cycle engineering and sustainable development. Springer Netherlands, Dordrecht, pp 87–110
6. Ehm F (2019) A data-driven modeling approach for integrated disassembly planning and scheduling. J Remanufacturing 9(2):89–107
7. Gao K, Huang Y, Sadollah A, Wang L (2020) A review of energy-efficient scheduling in intelligent production systems. Complex & Intelligent Systems 6(2):237–249
8. Guide VR, Jayaraman V, Linton JD (2003) Building contingency planning for closed-loop supply chains with product recovery. J Oper Manag 21(3):259–279
9. Guide VR, Srivastava R (1998) Inventory buffers in recoverable manufacturing. J Oper Manag 16(5):551–568
10. Gupta SM, Taleb KN (1994) Scheduling disassembly. Int J Prod Res 32(8):1857–1866
11. Hyong-Bae J, Jun-Gyu K, Hwa-Joong K, Dong-Ho L (2006) A two-stage heuristic for disassembly scheduling with capacity constraints. Management Science and Financial Engineering 12:95–112
12. Inderfurth K, Vogelgesang S, Langella IM (2015) How yield process misspecification affects the solution of disassemble-to-order problems. Int J Prod Econ 169:56–67
13. Ji X, Zhang Z, Huang S, Li L (2016) Capacitated disassembly scheduling with parts commonality and start-up cost and its industrial application. Int J Prod Res 54(4):1225–1243
14. Kim H-J, Lee D-H, Xirouchakis P (2007) Disassembly scheduling: literature review and future research directions. Int J Prod Res 45(18-19):4465–4484
15. Kim H.-J., Lee D.-H., Xirouchakis P, Züst R. (2003) Disassembly scheduling with multiple product types. CIRP Ann 52(1):403–406
16. Kim H.-J., Xirouchakis P (2010) Capacitated disassembly scheduling with random demand. Int J Prod Res 48(23):7177–7194
17. Kongar E, Gupta SM (2006) Disassembly to order system under uncertainty. Omega 34(6):550–561. Reverse production systems
18. Lambert AJD, Gupta SM (2002) Demand-driven disassembly optimization for electronic products package reliability. J Electron Manuf 11(02):121–135
19. Langella IM (2007) Heuristics for demand-driven disassembly planning. Comput Oper Res 34(2):552–577. Reverse Logistics
20. Lee D-H, Kang J-G, Xirouchakis P (2001) Disassembly planning and scheduling: Review and further research. Proc Inst Mech Eng B J Eng Manuf 215(5):695–709
21. Lee D.-H., Xirouchakis P (2004) A two-stage heuristic for disassembly scheduling with assembly product structure. J Oper Res Soc 55(3):287–297
22. Lee D.-H., Xirouchakis P, Zust R (2002) Disassembly scheduling with capacity constraints. CIRP Ann 51(1):387–390
23. Liang J, Wang Y, Zhang Z.-H., Sun Y (2019) Energy efficient production planning and scheduling problem with processing technology selection. Comput Ind Eng 132:260–270
24. Liu K, Wang M, Zhang Z.-H. (2019) An outer approximation algorithm for capacitated disassembly scheduling problem with parts commonality and random demand. Springer International Publishing, Cham, pp 153–181
25. Liu K, Zhang Z-H (2018) Capacitated disassembly scheduling under stochastic yield and demand. Eur J Oper Res 269(1):244–257
26. Mikhaylidi Y, Naseraldin H, Yedidsion L (2015) Operations scheduling under electricity time-varying prices. Int J Prod Res 53(23):7136–7157
27. Moon J.-Y., Park J (2014) Smart production scheduling with time-dependent and machine-dependent electricity cost by considering distributed energy resources and energy storage. Int J Prod Res 52(13):3922–3939
28. Moon J.-Y., Shin K, Park J (2013) Optimization of production scheduling with time-dependent and machine-dependent electricity cost for industrial energy efficiency. Int J Adv Manuf Technol 68:523–535
29. Morgan SD, Gagnon RJ (2013) A systematic literature review of remanufacturing scheduling. Int J Prod Res 51(16):4853–4879
30. Mouzon G, Yildirim MB (2008) A framework to minimise total energy consumption and total tardiness on a single machine. Int J Sustain Eng 1(2):105–116
31. Mouzon G, Yildirim MB, Twomey J (2007) Operational methods for minimization of energy consumption of manufacturing equipment. Int J Prod Res 45(18-19):4247–4271

32. Neuendorf K-P, Lee D-H, Kiritsis D, Xirouchakis P (2001) Disassembly scheduling with parts commonality using petri nets with timestamps. Fundam Inf 47(3–4):295–306
33. Ong SK, Chang MML, Nee AYC (2021) Product disassembly sequence planning: state-of-the-art, challenges, opportunities and future directions. Int J Prod Res 0(0):1–16
34. Patterson S, Kozan E, Hyland P (2017) Energy efficient scheduling of open-pit coal mine trucks. Eur J Oper Res 262(2):759–770
35. Piewthongngam K, Chatavithee P, Apichottanakul A (2019) Disassembly scheduling for the meat processing industry with product perishability. J Adv Manuf Syst 18:447–467
36. Pour-Massahian-Tafti M, Godichaud M, Amodeo L (2020) New models and efficient methods for single-product disassembly lot-sizing problem with surplus inventory decisions. Int J Prod Res 0(0):1–21
37. Priyono A, Ijomah WL, Bititci US (2015) Strategic operations framework for disassembly in remanufacturing. J Remanufacturing 5(1):11
38. Rager M, Gahm C, Denz F (2015) Energy-oriented scheduling based on evolutionary algorithms. Comput Oper Res 54:218–231
39. Shrouf F, Ordieres-Meré J, García-Sánchez A, Ortega-Mier M (2014) Optimizing the production scheduling of a single machine to minimize total energy consumption costs. J Clean Prod 67:197–207
40. Slama I, Ben-Ammar O, Dolgui A, Masmoudi F (2020) New mixed integer approach to solve a multi-level capacitated disassembly lot-sizing problem with defective items and backlogging. J Manuf Syst 56:50–57
41. Slama I, Ben-Ammar O, Masmoudi F, Dolgui A (2019) Disassembly scheduling problem: literature review and future research directions. IFAC-PapersOnLine 52(13):601–606. 9th IFAC Conference on Manufacturing Modelling, Management and Control MIM 2019
42. Srivastava SK (2008) Network design for reverse logistics. Omega 36(4):535–548. Special issue on logistics: new perspectives and challenges
43. Taleb KN, Gupta SM (1997) Disassembly of multiple product structures. Comput Ind Eng 32(4):949–961. New advances in analysis of manufacturing systems
44. Tan M, Duan B, Su Y, He F (2015) Optimal hot rolling production scheduling for economic load dispatch under time-of-use electricity pricing. arXiv:1501.05502
45. Tian X, Zhang Z.-H. (2019) Capacitated disassembly scheduling and pricing of returned products with price-dependent yield. Omega 84:160–174
46. Trigeiro WW, Thomas LJ, McClain JO (1989) Capacitated lot sizing with setup times. Manag Sci 35(3):353–366
47. Ullerich C, Buscher U (2013) Flexible disassembly planning considering product conditions. Int J Prod Res 51(20):6209–6228
48. Wang H-F, Huang Y-S (2013) A two-stage robust programming approach to demand-driven disassembly planning for a closed-loop supply chain system. Int J Prod Res 51(8):2414–2432
49. Willeke S, Ullmann G, Nyhuis P (2016) Method for an energy-cost-oriented manufacturing control to reduce energy costs: Energy cost reduction by using a new sequencing method. In: 2016 International Conference on Industrial Engineering, Management Science and Application (ICIMSA), pp 1–5
50. Xia X, Liu W, Zhang Z, Wang L, Cao J, Liu X (2019) A balancing method of mixed-model disassembly line in random working environment. Sustainability 11(8)
51. Yildirim MB, Mouzon G (2012) Single-machine sustainable production planning to minimize total energy consumption and total completion time using a multiple objective genetic algorithm. IEEE Trans Eng Manag 59(4):585–597