



Modeling a remanufacturing reverse logistics planning problem: some insights into disruptive technology adoption

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Abstract

Remanufacturing is the process to restore the functionality of high-value end-of-life (EOL) products, which is considered a substantial link in reverse logistics systems for value recovery. However, due to the uncertainty of the reverse material flow, the planning of a remanufacturing reverse logistics system is complex. Furthermore, the increasing adoption of disruptive technologies in Industry 4.0/5.0, e.g., the Internet of things (IoT), smart robots, cloud-based digital twins, and additive manufacturing, has shown great potential for a smart paradigm transition of remanufacturing reverse logistics operations. In this paper, a new mixed-integer program is modeled for supporting several tactical decisions in remanufacturing reverse logistics, i.e., remanufacturing setups, production planning and inventory levels, core acquisition and transportation, and remanufacturing line balancing and utilization. The model is further extended by incorporating utilization-dependent nonlinear idle time cost constraints and stochastic takt time to accommodate different real-world scenarios. Through a set of numerical experiments, the influences of different demand patterns and idle time constraints are revealed. The potential impacts of disruptive technology adoption in remanufacturing reverse logistics are also discussed from managerial perspectives, which may help remanufacturing companies with a smart and smooth transition in the Industry 4.0/5.0 era.

Keywords Reverse logistics · Remanufacturing · Decision-support system · Mathematical programming · Technology adoption · Industry 4.0/5.0

1 Introduction

Remanufacturing is the process of restoring the functionality of end-of-life (EOL) products to “like-new” conditions [59]. As a substantial link to the circular economy and sustainable development [42], the value recovery of EOL products through remanufacturing is becoming increasingly important in reverse logistics. With a focus on the recovery of high-value EOL products, remanufacturing enhances all three pillars of sustainable development. From the economic perspective, remanufacturing may help to achieve a 50% cost reduction [57], while at the same time, saving up to 40% energy for the traditional heavy manufacturing industries, where the energy efficiency is usually less than 30% [9]. Due to the cost efficiency, the price of a remanufactured product

may, in some cases, be 40% lower than a new product [37]. For some EOL products, remanufacturing has become a highly economically viable and profitable way for value recovery. For instance, Xiong et al. [86] have revealed that, through the remanufacturing of lithium-ion batteries from electric vehicles, the potential cost saving could be up to 1.87 USD/kg cell produced. From the environmental perspective, remanufacturing has been proved to be eco-efficient over the entire product life cycle through a significant reduction of waste generation and resource consumption [44], which further leads to a reduction of carbon footprints [39]. In comparison with the manufacturing of new cylinder head blocks, the average environmental impact of remanufacturing with laser cladding technology can be reduced by 63.8% [58]. In addition, compared with other reverse logistics options for EOL product recovery, e.g., material recycling and energy recovery, remanufacturing is a more environmentally preferable choice [77]. From the social perspective, remanufacturing provides more business opportunities and creates more employment [70]. Furthermore, many tasks in remanufacturing, e.g., sorting and cleaning, are entry-level and have a

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low requirement of professional skills, which consequently minimizes the social exclusion due to the lack of skills [59] and promotes equity in the job market.

Reverse logistics aims at effectively and efficiently managing the flows for value recovery from EOL products through various options, in which remanufacturing is one of the most important links. Recently, the policy drivers and the establishment of a standardized remanufacturing reverse logistics system have been widely focused on [93]. The planning of a remanufacturing reverse logistics system is a complex problem that involves several important decisions at strategic, tactical, and operational levels. The quality variation of the EOL products in remanufacturing reverse logistics yields uncertainty [19], which may lead to significant challenges to several decision-making problems, e.g., inventory control, production planning, and disassembly line balancing [4]. For instance, due to the uncertain quality of EOL products, the unit processing time, procedures, and routing on the shop floor may be highly unpredictable in the remanufacturing process compared with that in the manufacturing process, which drastically compromises the benefits of scheduling [29].

The recent industrial revolution provides new opportunities and solutions to minimize the impact of uncertainty and improve the smart planning and sustainable operations of various reverse logistics activities [75]. While Industry 4.0 primarily focuses on improving connectivity and smartness through the Internet of things (IoT), artificial intelligence (AI), and smart robots, Industry 5.0, on the other hand, puts the human, environment, and sustainability in the center of the industrial and social transition led by disruptive technologies [38]. One of the most important success factors for remanufacturing in the age of Industry 4.0/5.0 is to better link manufacturers, end-users, EOL product collectors, and remanufacturers through digitalization and the increasing use of new technologies [43]. Besides, a cloud-based digital twin provides information throughout the entire product life cycle [84], which helps to minimize the uncertainty of reverse logistics and to better plan the remanufacturing operations. Furthermore, the increasing use of smart robots and additive manufacturing may also help to improve the flexibility, reconfigurability, and efficiency of the remanufacturing process [1, 53].

Even though decision-support models have been developed for different decisions in remanufacturing and reverse logistics considering new technology integration, e.g., additive manufacturing [100] and human–robot collaboration [87], they are mainly focused on a single problem in either a remanufacturing process, e.g., process planning, inventory management, production planning, and disassembly scheduling, or on the entire reverse logistics network at strategic level [15]. However, there is still a lack of modeling efforts that can simultaneously support several interrelated tactical decisions for managing a remanufacturing reverse

logistics system. Furthermore, even though Industry 4.0/5.0 technologies have been analyzed from the operational planning level, the managerial implications in remanufacturing reverse logistics have not been thoroughly investigated, especially from the strategic and tactical planning perspectives, with quantitative methods [76]. Therefore, this paper aims at making the following contributions:

1. A new mixed-integer program is developed to simultaneously support several tactical decisions in remanufacturing reverse logistics.
2. The uncertain EOL quality and different remanufacturing line balancing constraints are modeled and analyzed.
3. Some managerial insights into disruptive technology adoption in Industry 4.0/5.0 are discussed based on the analytical results.

The rest of the paper is organized as follows. Section 2 reviews the relevant research. Section 3 formulates the mathematical model. Section 4 extends the model by considering two practical conditions. Section 5 validates the proposed models with a set of numerical experiments. Section 6 concludes the paper.

2 Literature review

In this section, the relevant studies are reviewed from two perspectives concerning: (1) remanufacturing reverse logistics and (2) decision-support models and methods. Based on these, the literature gaps are identified.

2.1 Remanufacturing reverse logistics

The definition of remanufacturing was first given in the 1980s, but the conceptual development was inconsistent in the 1990s [59]. For example, Amezcua et al. [2] defined remanufacturing as a process to restore the functionality of a product by reusing, reconditioning, and replacing key elements, while, on the other hand, Haynsworth and Lyons [33] emphasized the functionality of an EOL product could be restored to the “like-new” condition by replacing and rebuilding key elements. During the last two decades, it has been widely accepted that reuse and reconditioning are different value recovery options for EOL products due to their different quality requirements. While reuse and reconditioning aim to restore the functionality of EOL products at lower quality levels compared with the new product counterpart [47], remanufacturing, on the other hand, restores the functionality at an equivalent or a higher quality [36]. Because of the high-quality requirement, not all types of EOL products are suitable for remanufacturing. As argued by several researchers, e.g., Matsumoto and Ijomah [59], Östlin et al. [66], and Paterson et al. [68], some fundamental

characteristics of a remanufacturable EOL product include the cores that can be disassembled and remanufactured, sufficient supplies and demands, high product recovery value, product design, and stable technology. For instance, some consumer electronics, e.g., smartphones, are not suitable for remanufacturing, because, with technological superiority, the new products may have much better functions. Besides, the remanufactured products may also lead to cannibalization with new products [28].

Reverse logistics aims at effectively and efficiently managing the material, information, and capital flows for maximum value recovery from EOL products through different options [72]. Remanufacturing is an important value recovery alternative in a reverse logistics system or in a closed-loop supply chain where the manufacturing process is combined [3]. Even though the term has been used in several studies [96, 97], remanufacturing reverse logistics has not been well defined. Compared with a general reverse logistics system, where an overall optimal solution may not be easily achieved in reality due to the involvement of multiple stakeholders, the remanufacturing reverse logistics system focuses on a certain part of activities from the remanufacturer’s perspective concerning the acquisition of cores, remanufacturing planning, and demand fulfillment. Figure 1 identifies the system boundary

of a remanufacturing reverse logistics system. As can be seen, the remanufacturing reverse logistics focuses on effective collaboration with core suppliers, recyclers, and customers so that the remanufacturing process can be optimized. In remanufacturing reverse logistics, the tasks are usually taken by three types of companies, namely, original equipment manufacturers (OEMs), contracted remanufacturers, and non-contracted remanufacturers [59]. Besides, the remanufacturing reverse logistics can be driven either by market demands or by waste flows, where the remanufacturer has a more strong control of core acquisition in the former case [30].

2.2 Decision-support models and methods

Mathematical programming is the most important decision-support method for remanufacturing and reverse logistics, and it has also been used to evaluate different technological or legislative drivers. For example, Heydari et al. [34] investigated the incentive given by the retailer to promote the proper return of EOL products from customers. Considering the decisions at strategic, tactical, and operational levels in remanufacturing and reverse logistics, significant modeling efforts have been spent [71].

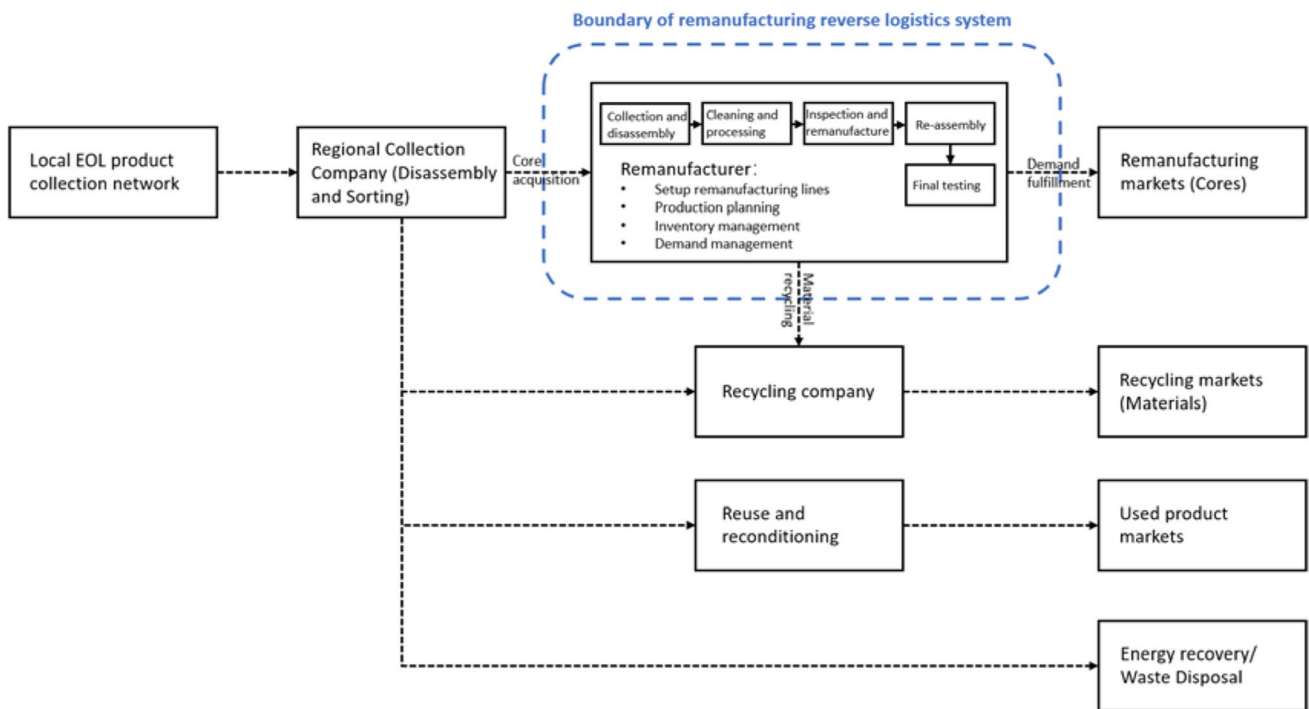


Fig. 1 The remanufacturing reverse logistics system

2.2.1 Strategic decision-support models

At the strategic level, network design, product design, and marketing management are the most important decisions. Significant efforts have been given to the development of decision-support models and computational algorithms for both open-loop and closed-loop reverse logistics network design [27, 97]. For example, Demirel and Gökçen [14] proposed a mixed-integer program to minimize the total cost related to the establishment and operations of a remanufacturing reverse logistics network. Due to the complexity and the conflict between different stakeholders, multi-objective optimization has been extensively used to simultaneously manage economic benefits, environmental footprints, and social impacts [25, 81, 90, 94]. Product design is another critical issue for the success of remanufacturing reverse logistics [26]. Boorsma et al. [8] identified both opportunities and barriers for implementing design for remanufacturing in OEMs, and Lindkvist Haziri and Sundin [52] proposed a remanufacturing-to-OME information framework to allow a collaborative and better design management in the initial stage. Using both vector space model and case-based reasoning, Ke et al. [41] developed an intelligent decision-support framework to help OMEs with the implementation of design for remanufacturing.

Marketing management is another success factor, which is the process of formulating strategies and implementing decisions to fulfill customer demands in a profitable way [49]. Pricing, warranty, and sales channels are the most important decisions for marketing management in remanufacturing reverse logistics [10, 71]. In this regard, Li et al. [50] proposed a game theoretic model for the joint design of remanufacturing channels and post-sales service pricing, which optimized both economic gains and sustainability. Tang et al. [78] and Yazdian et al. [89] investigated joint pricing and warranty decisions for remanufacturing supply chains. Gong and Zhang [24] developed a robust optimization model for both core acquisition and pricing decisions in a remanufacturing network. Zhang and Zhang [98] investigated the influence on channel selection and logistics design from the cannibalization between new and remanufactured products.

2.2.2 Tactical decision-support models

Core acquisition, production planning, and inventory control are tactical decisions in remanufacturing reverse logistics management. The time, quality, and quantity of the returned EOL cores determine the profit potential of the remanufacturing process [30]. Several analytical models have been developed for EOL return prediction, return channels and

strategy, core classification and acquisition control [85]. One of the most significant challenges for core acquisition in remanufacturing reverse logistics is uncertainty, where the uncertainty related to quality has attracted more attention [71]. For instance, Teunter and Flapper [79] developed a mathematical model for determining the optimal remanufacturing policies and core acquisition with quality variations. Besides, the core acquisition strategy can be used to manage the demand fluctuation in remanufacturing reverse logistics [61].

Production planning and inventory control have been extensively focused on, and they determine the amount of disassembled, remanufactured, and stocked cores in each planning period. In this regard, Erol and Nakiboglu [16] formulated an optimization model for the material requirement planning (MRP) problem in a multi-product remanufacturing reverse logistics system. Chen and Abrishami [11] proposed a mixed-integer program to minimize the total cost in a hybrid manufacturing-remanufacturing plant by determining the optimal levels of material acquisition, production, remanufacturing, and inventory. Giglio and Paolucci [22] modeled a multi-period remanufacturing planning problem that optimizes the production quantity, purchasing quantity, and storage level in each period. Pradenas et al. [69] investigated a real-life sawmill remanufacturing problem to determine the system setup and the remanufacturing quantity and time.

Uncertainty is one of the most significant factors that affects remanufacturing planning. As a result of the heterogeneous quality of EOL cores, the production planning and inventory control in remanufacturing reverse logistics is much more complex [32, 37, 82]. Taking into account the uncertain working time and possible delay of order delivery, Subulan et al. [74] formulated a fuzzy mixed-integer program to solve the remanufacturing planning problem in a closed-loop supply chain. Naeem et al. [62] investigated a stochastic and dynamic single-product lot sizing problem to optimize the production planning and inventory control of a hybrid manufacturing-remanufacturing system. Recently, Liu et al. [56] studied the production planning problem of a hybrid manufacturing-remanufacturing supply chain under stochastic demand and supply, while, on the other hand, Assid et al. [5] investigated the remanufacturing production planning problem under quality stochasticity. Considering service level and sustainability, Sarkar and Bhuniya [73] optimized the remanufacturing material flows under demand variation.

2.2.3 Operational decision-support models

At the operational planning level, disassembling planning, process planning, and scheduling have attracted great attention in remanufacturing reverse logistics. Disassembly is

the initial stage of a remanufacturing process, which drastically affects the reuse rate and the quality of remanufactured products [35]. Compared with other operations, disassembly is less predictable due to the impact of the heterogeneous quality of EOL cores [12]. To solve this challenge, significant research efforts have been given to developing decision-support models for disassembly sequence and line balancing. For instance, the modeling of the disassembly sequence planning problem has been focused on since the 1990s [31, 65]. Recently, considering the increasing adoption of Industry 4.0/5.0 technologies, some research, e.g., Liu et al. [54], investigated disassembly sequence optimization problems for robot-assisted remanufacturing systems, particularly in a human-machine collaborative environment [88]. Disassembly line balancing is another highly focused topic. Early research focused on the modeling and solution algorithms for disassembly line balancing problems in remanufacturing and reverse supply chains [67]. However, the recent research efforts have been predominantly given to the disassembly line balancing problem for human-robot collaborative remanufacturing systems [55, 87].

Process planning determines a set of operations and routing in the remanufacturing process [46] while scheduling links the operations with limited resources. As a result of the high computational complexity to solve the remanufacturing

algorithms have been the most effective methods [20, 23, 60]. For example, Gao et al. [21] solved a flexible shop floor scheduling problem with an improved artificial bee colony algorithm. Zhang et al. [95] developed an improved artificial bee colony algorithm for the decision-support of both remanufacturing process planning and scheduling. In addition, the impact of disruptive technology has also been discussed. For instance, Zheng et al. [100] investigated the remanufacturing process planning problem considering both subtractive and additive manufacturing processes. Li et al. [51] solved remanufacturing process planning problem by integrating blockchain with case-based reasoning.

2.3 Summary and literature gaps

This paper investigates the tactical planning problem of remanufacturing reverse logistics systems, and Table 1 compares the most relevant research. Even though significant efforts have been given to the model development, there are still several research gaps related to multiple decisions and impacts from the increasing adoption of disruptive technologies in Industry 4.0/5.0:

1. There is a lack of modeling efforts that simultaneously support several tactical decisions, i.e., remanufacturing setup, production, inventory, acquisition, transportation,

Table 1 Comparison of the relevant literature related to tactical planning of remanufacturing reverse logistics

Paper	Period	Product	Uncertainty	Industry 4.0/5.0	Tactical planning decisions					
					SU	ACQ	M/R	TR	INV	LB
Teunter and Flapper [79]	Single	Multiple	Probability		✓					
Subulan et al. [74]	Multiple	Multiple	Fuzzy		✓	✓	✓	✓		
Naeem et al. [62]	Multiple	Single	Stochastic			✓		✓		
Chen and Abrishami [11]	Multiple	Multiple			✓	✓		✓		
Giglio and Paolucci [22]	Multiple	Multiple			✓	✓		✓		
[61]	Multiple	Single	Probability		✓	✓				
Erol and Nakiboglu [16]	Multiple	Multiple			✓	✓		✓		
Liu et al. [56]	Multiple	Multiple	Stochastic			✓	✓		✓	
Pradenas et al. [69]	Multiple	Multiple			✓		✓			
Assid et al. [5]	Multiple	Single	Stochastic		✓		✓		✓	
Sarkar and Bhuniya [73]	Multiple	Single	Scenarios		✓		✓	✓	✓	
This paper	Multiple	Multiple	Stochastic	✓	✓	✓	✓	✓	✓	✓

SU, setup of remanufacturing systems; ACQ, acquisition of cores; M/R, manufacturing/remanufacturing quantity; TR, transportation planning; INV, inventory control; LB, line balancing of the remanufacturing system

operational planning problems, heuristic and meta-heuristic

and line balancing.

2. Several real-world conditions, i.e., different line balancing requirements, demand patterns, and uncertainty, have not been holistically analyzed in remanufacturing reverse logistics planning.
3. Finally, disruptive technology adoption in Industry 4.0/5.0 will lead to the paradigm shift of remanufacturing reverse logistics. However, there is a lack of quantitative analysis and managerial insights from the tactical planning perspective.

Therefore, this paper aims at filling these gaps.

3 Mathematical model

In this paper, we investigate a market-driven contracted remanufacturing reverse logistics system, as shown in Fig. 1. A mixed-integer programming model is developed for the key tactical decisions, i.e., remanufacturing system setups, production and inventory levels, core acquisition and transportation, and remanufacturing line utilization and balancing over several consecutive periods within the planning horizon. The model's assumptions and notations are first given.

Model assumptions:

- The remanufacturing reverse logistics system deals with multiple EOL cores.
- The remanufacturing line is flexible.
- The cost related to internal logistics operations is not considered.
- The relevant parameters of the remanufacturing reverse logistics system are known.

Notations:

Sets

- E Set of EOL cores for remanufacturing, indexed by e
- C Set of collection companies, indexed by c
- F Set of recycling/waste management companies, indexed by f
- D Set of customers for remanufactured products/cores, indexed by d
- L Set of remanufacturing line, indexed by l
- P Set of periods, indexed by p

Parameters

- $STLC_l$ Setup cost of remanufacturing line l
- PUC_{ec} Purchasing cost of EOL core e from collection company c
- FLC_{ef} Treatment cost of non-remanufacturable parts by waste management company f
- RMC_{el} Remanufacturing cost of EOL core e at line l
- TAC_{ec} Unit transportation cost of EOL core e from collection company c
- TBC_{ef} Unit transportation cost of non-remanufacturable parts to waste management company f
- TCC_{ed} Unit transportation cost of remanufactured product/core e to customer d
- IPC_e Unit inventory holding cost of remanufactured product/core e
- IDC_l^p Unit Idle time cost of line l in each period
- PNC_e Unit penalty cost of unfulfilled demand of remanufactured product/core e
- DMD_{ed}^p Demand for remanufactured product/core e at customer d in each period
- γ_e Conversion rate to non-remanufacturable parts from EOL product/core e
- θ_e Conversion rate to remanufacturable product/core e
- $PDSM_l^p$ Remanufacturing line capacity for EOL product e
- $taDT_e$ Takt time of EOL product/core e at remanufacturing line l
- WTD_l^p Available working time of remanufacturing line l in each period
- RCD_l Resource requirement for setting up remanufacturing line l for EOL product e
- TRL^p Total resource availability in each period

Decision variables

- q_l^p Binary variable. If $q_l^p = 1$, the remanufacturing line l is setup in period p . If $q_l^p = 0$, otherwise.
- XTA_{ecl}^p Amount of EOL product e acquired and transported from collection company c in period p
- XTB_{elf}^p Amount of unusable parts transported to waste management company f in period p
- XTC_{eld}^p Amount of remanufactured product transported to customer d in period p
- $XDSM_{el}^p$ Amount of EOL product e processed at remanufacturing line l in period p
- $InvenP_{el}^p$ Inventory level of remanufactured product e at line l in period p

Auxiliary variables

- TTD_l^p Total working time of remanufacturing line l in period p
- YD_l^p Idle time of remanufacturing line l in period p

The objective function Eq. (1) minimizes the total operating cost of the remanufacturing system, which consists of the setup cost, purchasing cost of EOL products, transportation cost, remanufacturing cost, inventory holding cost, recycling and disposal cost, line balancing cost, and penalty cost of unmatched customer demands. It is noteworthy that, different from some other studies that employ two binary decision variables to set up the lines and then assign the flow to them [40], we, however, assign and link the material flows directly to each remanufacturing line with XTA_{ecl}^p , XTB_{elf}^p , XTC_{eld}^p , $XDSM_{el}^p$, and $InvenP_{el}^p$ due to the fact that the remanufacturing lines are flexible to treat different EOL cores. By minimizing the use of binary variables, the model becomes more computationally effective. Besides, the impact of internal logistics within the remanufacturing plant is not taken into account, so the unit transportation costs from different remanufacturing lines to the same location are identical, for example, TCC_{ed} is the unit transportation cost of remanufactured product e to customer d , which is the same for all $l \in L$. At the remanufacturing plant, the total amount of each type of EOL product received, remanufactured, and held in inventory

in each period can be calculated by $\sum_{c \in C} \sum_{l \in L} XTA_{ecl}^p$, $\sum_{l \in L} XDSM_{el}^p$, and $\sum_{l \in L} InvenP_{el}^p$, respectively.

$$\begin{aligned} \text{Min } Z = & \sum_{l \in L} \sum_{p \in P} STLC_l q_l^p + \sum_{e \in E} \sum_{c \in C} \sum_{p \in P} (PUC_{ec} + TAC_{ec}) XTA_{ecl}^p \\ & + \sum_{e \in E} \sum_{l \in L} \sum_{p \in P} RMC_{el} XDSM_{el}^p + \sum_{e \in E} \sum_{l \in L} \sum_{p \in P} IPC_e InvenP_{el}^p \\ & + \sum_{e \in E} \sum_{f \in F} \sum_{p \in P} (FLC_{ef} + TBC_{ef}) XTB_{elf}^p + \sum_{e \in E} \sum_{d \in D} \sum_{p \in P} TCC_{ed} XTC_{eld}^p \\ & + \sum_{l \in L} \sum_{p \in P} IDC_l^p YD_l^p + \sum_{e \in E} \sum_{d \in D} \sum_{p \in P} PNC_e UMC_{ed}^p \end{aligned} \tag{1}$$

The model is restricted by 13 sets of constraints. Constraint (2) is the demand fulfillment requirement for each period, and the unmatched demand will lead to a penalty in the objective function. The penalty cost can help to reduce the hardware redundancy of a system and to yield reasonable decisions [91].

$$\sum_{l \in L} XTC_{eld}^p + UMC_{ed}^p \geq DMD_{ed}^p, \forall e \in E, d \in D, p \in P \tag{2}$$

Constraint (3) ensures that, in each period, the acquisition of EOL cores from the collection companies cannot exceed their upper limits.

$$\sum_{l \in L} XTA_{ecl}^p \leq COW_{ec}^p, \forall e \in E, c \in C, p \in P \tag{3}$$

Equations (4) and (5) are flow balance and conversion at the remanufacturing plant. Equation (4) specifies the number of different types of EOL cores processed at each remanufacturing line in each period. Equation (5) calculates the un-remanufacturable parts that need to be sent for material recycling or disposal.

$$XDSM_{el}^p = \sum_{c \in C} XTA_{ecl}^p, \forall e \in E, l \in L, p \in P \tag{4}$$

$$XDSM_{el}^p \gamma_e = \sum_{f \in F} XTB_{elf}^p, \forall e \in E, l \in L, p \in P \tag{5}$$

Constraint (6) guarantees that the selling amount of each type of remanufactured product cannot exceed the available amount in each period. Equation (7) is the inventory balance constraint.

$$XDSM_{el}^p \theta_e + InvenP_{el}^p \geq \sum_{d \in D} XTC_{eld}^p, \forall e \in E, l \in L, p \in P \tag{6}$$

$$InvenP_{el}^p = InvenP_{el}^{p-1} + XDSM_{el}^p \theta_e - \sum_{d \in D} XTC_{eld}^p, \forall e \in E, l \in L, p \in P \tag{7}$$

Equation (8) is the capacity constraint of the remanufacturing lines, for example, due to equipment limits. It is noteworthy that the inbound flow at each remanufacturing line is also restricted by the working hours, which usually sets a stricter requirement for the upper bound. However, at the lower bound, Eq. (8) ensures

that the EOL products cannot be processed at a remanufacturing line, which is not in operation during that period.

$$\sum_{e \in E} XDSM_{el}^p \leq PDSM_l^p q_l^p, \forall l \in L, p \in P \tag{8}$$

Constraints (9–11) are related to the remanufacturing line balance. Equation (9) calculates the total working time at each remanufacturing line in each period. Equation (10) sets the upper bound of the maximum working time. Equation (11) calculates the idle time of each remanufacturing line.

$$\sum_{e \in E} XDSM_{el}^p taDT_e = TTD_l^p, \forall l \in L, p \in P \tag{9}$$

$$TTD_l^p \leq WTD_l^p, \forall l \in L, p \in P \tag{10}$$

$$YD_l^p = WTD_l^p - TTD_l^p, \forall l \in L, p \in P \tag{11}$$

Constraint (12) is the resource requirement constraint, which limits the number of remanufacturing lines that can be opened in each period.

$$\sum_{l \in L} RCD_l q_l^p \leq TRL^p, \forall p \in P \tag{12}$$

Finally, constraints (13) and (14) are binary and non-negative requirements for the decision variables.

$$q_l^p \in \{0, 1\}, \forall l \in L, p \in P \tag{13}$$

$$XTA_{ec}^p, XTB_{ef}^p, XTC_{ed}^p, XDSM_{el}^p, Inven_{el}^p \geq 0, \forall e \in E, c \in C, l \in L, f \in F, d \in D, p \in P \tag{14}$$

4 Model extensions

In this section, we extend the mathematical model by taking into account two different conditions.

4.1 Utilization-dependent remanufacturing line balancing constraint

In real-life manufacturing and logistics systems, resources may not be utilized at 100% in most cases. Therefore, a threshold value can be set up for an acceptable range of the utilization rate, e.g., 90%, and a larger idle time cost is incurred only when the threshold value is not met. To model this, $UTLD_l^p$ and $UDRE^p$ are first defined for the utilization rate of each remanufacturing line and the threshold value set by the decision-maker. Furthermore, PID^p and QID^p are introduced to determine the corresponding unit idle time cost for each period. Two sets of constraints (15) and (16) are then formulated and incorporated with the original model. Equation (15) calculates the utilization rate

of each opened remanufacturing line, and Eq. (16) determines the value of the unit idle time cost for each opened remanufacturing line at each period. Due to the non-linearity of the two added constraints, the model becomes a mixed-integer non-linear program.

$$UTLD_l^p = TTD_l^p / WTD_l^p \times 100\%, \forall l \in L, p \in P \tag{15}$$

$$IDC_l^p = \begin{cases} PID^p, & \text{if } UTLD_l^p \geq UDRE^p \\ QID^p, & \text{otherwise} \end{cases}, \forall l \in L, p \in P \tag{16}$$

4.2 Stochastic takt time of uncertain quality

One of the most significant challenges related to effective remanufacturing reverse logistics planning and management is the heterogeneous quality in the reverse flows [12], which leads to a high variation in the processing time for the remanufacturing of different EOL products [34, 99]. This uncertainty may yield a great impact on the planning decisions and system performance, so it needs to be properly dealt with in the mathematical model and thoroughly analyzed in the decision-making. In this paper, considering the uncertain quality of EOL products, we extend the original model into a two-stage stochastic programming model, where the takt time of each type of EOL product is a stochastic parameter. The first-stage variables determine the configuration of the remanufacturing lines in each period, and the second-stage variables are scenario-dependent recourse decisions that determine the optimal operation of the remanufacturing system under different scenarios. To formulate the stochastic programming model, s and S are first defined as the index and the set of scenarios, and $Prob_{(s)}$ is the probability of realization of each scenario. Based on these, the scenario-dependent stochastic parameters and variables are given as follows:

Stochastic parameters

$taDT_e^{(s)}$
Takt time of EOL core e in scenario s

Stochastic variables

$XTA_{ec}^{p(s)}$ Amount of EOL core e transported from collection company c in period p and scenario s

$XTB_{ef}^{p(s)}$ Amount of unusable parts transported to waste management company f in period p and scenario s

$XTC_{ed}^{p(s)}$ Amount of remanufactured product/core transported to customer d in period p and scenario s

$XDSM_{el}^{p(s)}$ Amount of EOL core e processed at remanufacturing line l in period p and scenario s

$InvenP_{el}^{p(s)}$ Inventory level of remanufactured product/core e at line l in period p and scenario s

$TTD_l^{p(s)}$ Total working time of remanufacturing line l in period p and scenario s

$YD_l^{p(s)}$ Idle time of remanufacturing line l in period p and scenario s

The original model is then reformulated into a two-stage stochastic program, where Eq. (17) is the objective function that seeks the overall optimal solution considering all possible scenarios. Constraints (18–28) are converted from the respective constraints in the deterministic counterpart. In addition, constraints (12) and (13) are also held in the stochastic model.

$$\begin{aligned} \text{Min } Z^{(s)} = & \sum_{l \in L} \sum_{p \in P} STLC_l q_l^p + \sum_{s \in S} Prob_{(s)} \left(\sum_{e \in E} \sum_{c \in C} \sum_{p \in P} (PUC_{ec} + TAC_{ec}) XTA_{ecl}^{p(s)} \right. \\ & + \sum_{e \in E} \sum_{l \in L} \sum_{p \in P} RMC_{el} XDSM_{el}^{p(s)} + \sum_{e \in E} \sum_{l \in L} \sum_{p \in P} IPC_e InvenP_{el}^{p(s)} \\ & + \sum_{e \in E} \sum_{f \in F} \sum_{p \in P} (FLC_{ef} + TBC_{ef}) XTB_{elf}^{p(s)} \\ & + \sum_{e \in E} \sum_{d \in D} \sum_{p \in P} TCC_{ed} XTC_{eld}^{p(s)} + \sum_{l \in L} \sum_{p \in P} IDC_l^p YD_l^{p(s)} \\ & \left. + \sum_{e \in E} \sum_{d \in D} \sum_{p \in P} PNC_e UMC_{ed}^{p(s)} \right) \end{aligned} \tag{17}$$

S.t.

$$\sum_{l \in L} XTC_{eld}^{p(s)} + UMC_{ed}^{p(s)} \geq DMD_{ed}^p, \forall e \in E, d \in D, p \in P, s \in S \tag{18}$$

$$\sum_{l \in L} XTA_{ecl}^{p(s)} \leq COW_{ec}^p, \forall e \in E, c \in C, p \in P, s \in S \tag{19}$$

$$XDSM_{el}^{p(s)} = \sum_{c \in C} XTA_{ecl}^{p(s)}, \forall e \in E, l \in L, p \in P, s \in S \tag{20}$$

$$XDSM_{el}^{p(s)} \gamma_e = \sum_{f \in F} XTB_{elf}^{p(s)}, \forall e \in E, l \in L, p \in P, s \in S \tag{21}$$

$$XDSM_{el}^{p(s)} \theta_e + InvenP_{el}^{p(s)} \geq \sum_{d \in D} XTC_{eld}^{p(s)}, \forall e \in E, l \in L, p \in P, s \in S \tag{22}$$

$$\begin{aligned} InvenP_{el}^{p(s)} = & InvenP_{el}^{p-1(s)} + XDSM_{el}^{p(s)} \theta_e \\ & - \sum_{d \in D} XTC_{eld}^{p(s)}, \forall e \in E, l \in L, p \in P, s \in S \end{aligned} \tag{23}$$

$$\sum_{e \in E} XDSM_{el}^{p(s)} \leq PDSM_l^p q_l^p, \forall l \in L, p \in P, s \in S \tag{24}$$

$$\sum_{e \in E} XDSM_{el}^{p(s)} taDT_e^{(s)} = TTD_l^{p(s)}, \forall l \in L, p \in P, s \in S \tag{25}$$

$$TTD_l^{p(s)} \leq WTD_l^p, \forall l \in L, p \in P, s \in S \tag{26}$$

$$YD_l^{p(s)} = WTD_l^p - TTD_l^{p(s)}, \forall l \in L, p \in P \tag{27}$$

$$\begin{aligned} XTA_{ecl}^{p(s)}, XTB_{elf}^{p(s)}, XTC_{eld}^{p(s)}, XDSM_{el}^{p(s)}, InvenP_{el}^{p(s)} \\ \geq 0, \forall e \in E, c \in C, l \in L, f \in F, d \in D, p \in P, s \in S \end{aligned} \tag{28}$$

The proposed two-stage stochastic optimization model is solved with the sample average approximation (SAA). The SAA is a simulation-based optimization method [18], which can be used to approximate the optimal value of a large stochastic optimization problem [48]. A real-world stochastic optimization problem usually possesses a large number of scenarios, which makes the problem computationally expensive. Thus, the SAA aims at solving a set of smaller problems, whose results are stable and good enough to approximate the original stochastic optimization problem. With the embedded Monte-Carlo simulation procedures, the SAA minimizes the influence of the scenario generation procedures and helps to ensure a high level of confidence in the approximated results [92]. In the planning of reverse logistics systems, the SAA method has been used to evaluate the impact of uncertainty on facility location decisions [6, 80]. The introduction and algorithm procedures of the SAA method are provided in Appendix and Table 8. For more details on the SAA method and implementations, see Verweij et al. [83] and Kim et al. [45].

5 Numerical experiments and discussions

This section presents the design of the numerical experiments and computational results, based on which several implications are discussed.

5.1 Experimental design

In the numerical experiments, a remanufacturing reverse logistics planning problem for the EOL refrigeration equipment in Southern Norway was investigated, where real-world location, distance, and transportation data were used.

Fig. 2 The remanufacturing reverse logistics network

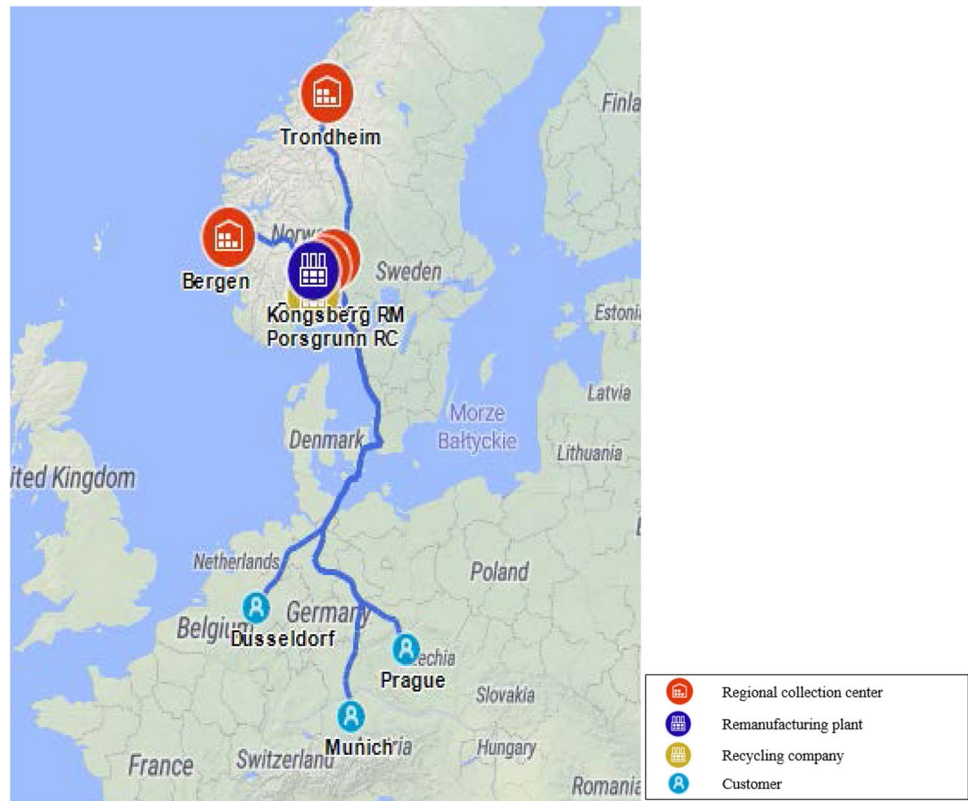


Table 2 The collection areas and total population of each regional collection center

Collection centers	Collection areas	Total population ¹
Oslo	Oslo, Viken, Innland	2,306,044
Bergen	Vestland, Møre og Romsdal	901,769
Trondheim	Trøndelag, Nordland, Troms og Finnmark	953,248
Drammen	Rogaland, Agder, Vestfold og Telemark	1,206,519

¹Source: <https://www.ssb.no/en/befolkning/befolkningsframskrivinger/statistikk/regionale-befolkningsframskrivinger>

The remanufacturer is located in Kongsberg, Norway, whose business focus is related to the remanufacturing of the core components from refrigeration equipment. The EOL refrigeration equipment is mainly collected at the municipality level and is then sent to and disassembled at four large regional collection centers in Oslo, Bergen, Trondheim, and Drammen. The remanufactured cores will be sold to three manufacturing plants of refrigeration equipment in Dusseldorf, Munich, and Prague, and the waste will be sent to the recycling center in Porsgrunn for material recovery. Figure 2 illustrates the structure of the remanufacturing reverse logistics system under investigation.

Table 2 shows the collection areas that are served by each regional collection center as well as their total populations. The number of EOL products collected by each regional collection center is assumed to be positively related to the size of the population. Based on Eurostat [17], the annual generation of

large waste electrical equipment per capita in Norway is 8.45 kg, among which 30% is assumed to be refrigeration equipment. The average weight of the refrigeration equipment is 80 kg, and the weight of the refrigeration core that can be remanufactured is approximately 9.47%. Thus, the maximum supply of EOL refrigeration cores at each regional collection center can be estimated. Two types of EOL refrigeration cores (P1 and P2) will be remanufactured, each type constitutes 50% of the total amount.

The planning horizon is set to 1 year, which is divided into 6 consecutive periods with 2 months each. Based on this, the upper bound of the EOL core supply at each regional collection center per period can be calculated. Besides, two different demand patterns are taken into account in the experiment. The first one is without seasonality, and the periodic demands for both P1 and P2 at the three demand points are randomly generated from the intervals [3500, 4500] units, [4000, 5000] units, and [2000, 3000] units. The second one considers the impact

Table 3 Demand for remanufactured products in both non-seasonality and seasonality scenarios (units)

Period	Non-seasonality						Seasonality					
	Dusseldorf		Munich		Prague		Dusseldorf		Munich		Prague	
	P1	P2	P1	P1	P2	P1	P1	P2	P1	P2	P1	P2
1	3,910	4,140	4,361	4,688	2,793	2,474	2,452	2,461	3,359	2,875	1,687	1,448
2	3,855	4,167	4,361	4,045	2,217	2,928	3,760	3,617	3,787	4,270	2,442	2,325
3	4,433	4,434	4,140	4,367	2,884	2,746	5,081	5,015	5,230	5,033	2,546	2,677
4	4,259	4,440	4,876	4,064	2,625	2,142	5,342	5,239	6,236	5,638	3,359	3,569
5	3,598	4,335	4,778	4,054	2,801	2,516	4,198	3,656	4,189	4,457	2,891	2,904
6	4,494	3,746	4,725	4,496	2,071	2,386	3,312	4,049	4,172	4,395	2,354	2,424

of seasonal demand patterns, and the demand is adjusted by the seasonality of 0.7, 0.9, 1.2, 1.3, 1, and 0.9 for each period. Table 3 shows the demand for both remanufactured products in each demand point under the two demand patterns.

The remanufacturer may set up at most 4 remanufacturing lines in each period, and the fixed setup cost for each line and the remanufacturing cost for each unit are randomly generated from the intervals [200000, 300000] NOK and [200, 350] NOK, respectively. The unit inventory costs for P1 and P2 are set to 18 NOK and 20 NOK. The unit penalty costs are identical for all the customers, which are 600 NOK for P1 and 650 NOK for P2. The distances from the regional collection centers in Oslo, Bergen, Trondheim, and Drammen to the remanufacturing plant are 84.1 km, 403 km, 566 km, and 40.4 km. The distances to the recycling center at Porsgrunn and to the customers in Dusseldorf, Munich, and Prague are 90.8 km, 1162 km, 1573 km, and 1391 km. According to Delgado et al. [13], the unit transportation cost is set to 0.00875 NOK/kg/km, based on which the transportation cost per unit of EOL/remanufactured refrigeration core can be calculated for each route.

Considering the remanufacturing line utilization and balancing, the normal working hours of 8 h/day and 5 days/week are used in the experiment, so the total working time for each remanufacturing line is 19,200 min in each period. Both linear and non-linear remanufacturing line balancing problems are taken into account. A unit cost of 25 NOK/min is used for the linear remanufacturing line balancing problem. For calculating the unit idle time cost in the non-linear line balancing problem, the threshold value is set to 80%. A unit cost of 35 NOK/min is incurred if the remanufacturing line utilization is less than 80%. Otherwise, the unit line balancing cost is 10 NOK/min. The remanufacturing line is flexible to process both types of EOL refrigeration cores, and the takt times for P1 and P2 are set to 2.13 min and 2.56 min, respectively.

Finally, the impact of uncertainty related to the quality of the EOL refrigeration cores on the tactical planning of the remanufacturing reverse logistics system is evaluated with the stochastic model. Based on the simulation

experiments given by Okorie et al. [63], the takt times for P1 and P2 are assumed to follow the uniform distribution with a parameter interval of $\pm 15\%$, based on which the required number of test scenarios can be generated accordingly with the Latin Hypercube sampling approach. To perform the SAA experiments, the sample size and the number of repetitions are set to 20 and 20, respectively. The size of the reference sample is set to 500.

5.2 Computational results

All the optimization problems are solved with Lingo 19.0 professional version on a PC with Intel(R) Core(TM) i5-6200U 2.30 GHz CPU and 8 GB RAM under Windows 10 operating system. First, we solved the deterministic model considering four problems with different combinations of demand patterns and remanufacturing line balancing constraints, shown as follows:

1. Linear line balancing problem with non-seasonality in demands (MILP)
2. Linear line balancing problem with seasonality in demands (MILP)
3. Non-linear line balancing problem with non-seasonality in demands (MINLP)
4. Non-linear line balancing problem with seasonality in demands (MINLP)

Table 4 shows the optimal objective values and first-stage decisions of the four problems, and the respective cost components are given in Table 5. As can be seen, the remanufacturing lines 1 and 4 are set up in all the periods, but the use of remanufacturing line 2 is by no means identical under different combinations of demand patterns and remanufacturing line balancing constraints. Besides, it is also observed that the total operating costs of the remanufacturing reverse logistics system are, in general, higher by using the given linear line balancing constraint. When the remanufacturing reverse logistics system is operated under non-seasonal demands, all remanufacturing lines 1, 2, and 4 are set up for all the periods with both line

Table 4 Optimal objective values and configurations of the four problems

Idle time	Seasonality	Total cost (NOK)	System setup
Linear (MILP)	Non-seasonality	53,139,406	Line 1 (1, 2, 3, 4, 5, 6) Line 2 (1, 2, 3, 4, 5, 6) Line 4 (1, 2, 3, 4, 5, 6)
	Seasonality	52,819,553	Line 1 (1, 2, 3, 4, 5, 6) Line 2 (2, 3, 4, 5) Line 4 (1, 2, 3, 4, 5, 6)
Non-linear (MINLP)	Non-seasonality	52,152,692	Line 1 (1, 2, 3, 4, 5, 6) Line 2 (1, 2, 3, 4, 5, 6) Line 4 (1, 2, 3, 4, 5, 6)
	Seasonality	52,450,250	Line 1 (1, 2, 3, 4, 5, 6) Line 2 (2, 3, 4, 5, 6) Line 3 (4) Line 4 (1, 2, 3, 4, 5, 6)

Table 5 Cost components in the optimal solutions of the four problems

Penalty	Seasonality	Cost components (%)					
		Setup	Transportation	Remanufacturing	Inventory	Penalty	Idle time
Linear (MILP)	Non-seasonality	9.45%	20.99%	66.47%	0	0	3.09%
	Seasonality	8.40%	20.56%	65.52%	0.86%	4.66%	0
Non-linear (MINLP)	Non-seasonality	9.62%	21.39%	67.73%	0	0	1.26%
	Seasonality	9.58%	21.37%	67.42%	0.32%	0	1.31%

balancing constraints. All the demands can be satisfied, and the inventory levels are minimized with the leveled remanufacturing. However, the shares of the idle time costs with both line balancing constraints are 3.09% and 1.26%, respectively. This is the main driver that leads to a cost reduction of 1.85% when the given non-linear idle time costs are used.

Next, under the seasonal demand pattern, different line balancing requirements result in different first-stage decisions. For the linear line balancing problem, remanufacturing line 2 is opened for 4 periods with a 100% utilization rate. In this scenario, the shares of inventory holding cost and penalty cost are 0.86% and 4.66%, respectively. The demands for remanufactured refrigeration cores can be fully satisfied at the manufacturing plants in Dusseldorf and Prague during all periods. However, at the manufacturing plant in Munich, 15.1% demand for P1 and 19.7% demand for P2 cannot be met in period 4, and 7.6% demand for P1 and 34.4% demand for P2 cannot be fulfilled in period 6. On the other hand, with the non-linear line balancing constraint, remanufacturing line 2 is used for 5 periods and remanufacturing line 3 is also opened in the high-demand period in order to provide enough capacity to fulfill all the customer demands for the remanufactured refrigeration cores. In this scenario, the inventory is also maintained at a much lower level. Therefore, when the demand pattern follows the seasonality in the experiment, implementing the given utilization-based non-linear line balancing constraint may help to improve the fulfillment

rate and service level while, at the same time, reducing the total operating cost of the remanufacturing reverse logistics system by 369,283 NOK.

Figure 3 shows the average utilization rates of remanufacturing lines 1, 2, and 4 in the four problems. Under non-seasonal demands, the utilization rates of both remanufacturing lines 1 and 4 reach 100% with the linear line balancing constraint, while the average utilization of line 2 is 71%. With the non-linear line balancing constraint, except for remanufacturing line 4 which is utilized at 100%, the workload is more evenly allocated to remanufacturing lines 1 and 2 with average utilization rates of 87% and 85%, respectively. Under the seasonal demand pattern, the optimal solution with the linear line balancing constraint leads to a 100% utilization of all the remanufacturing lines opened. However, when the non-linear line balancing constraint is implemented, the average utilization rates of remanufacturing lines become 88%, 84%, and 99%, respectively. It is noteworthy that, under the same demand pattern, there is a tradeoff between utilization, demand fulfillment, and cost when different remanufacturing line balancing constraints are used. Figure 4 illustrates the allocation of the EOL refrigeration cores and the utilization of remanufacturing lines in each period. In all the problems, remanufacturing line 2 is dedicatedly used for P1, and remanufacturing line 4 is dedicatedly used for P2. Remanufacturing line 1 provides flexibility to receive both

Fig. 3 The average utilization rates of remanufacturing lines 1, 2, and 4 in the four problems

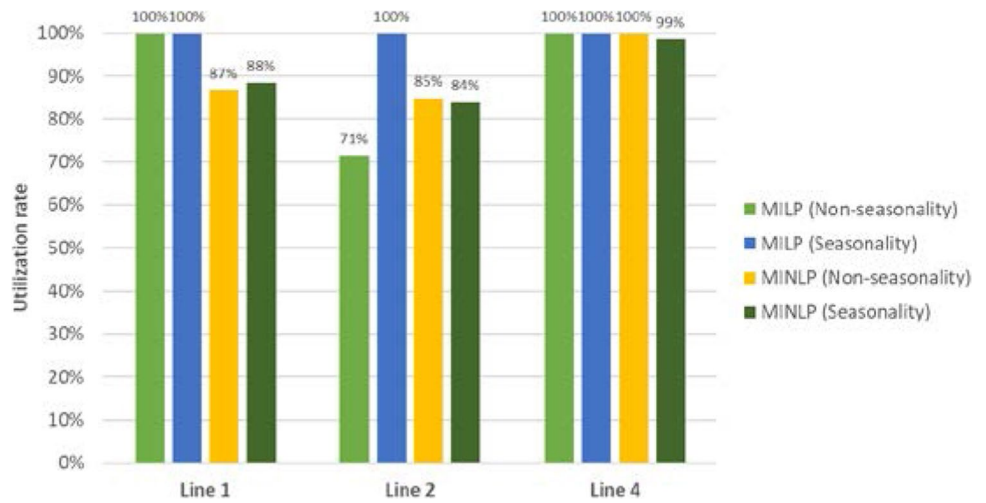


Fig. 4 Product allocation and remanufacturing line utilization in each period

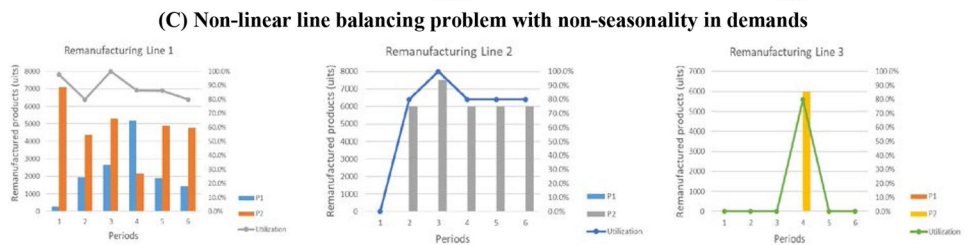
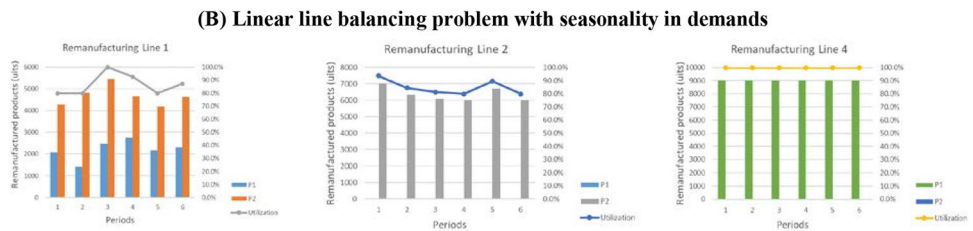
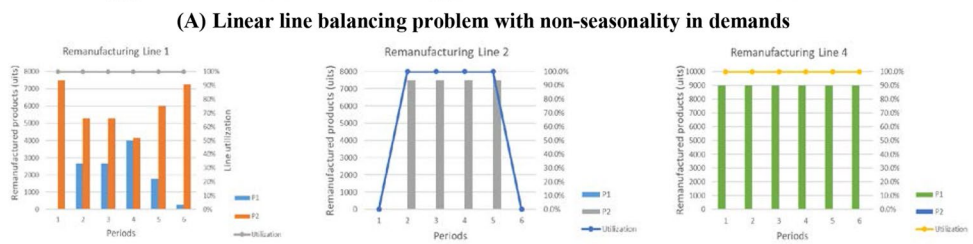


Table 6 Statistical bounds, gap estimators, and the best solution to the SAA problems with $Q=20$, $P=20$, and $Q'=500$

Computational results		Non-seasonality	Seasonality
Lower bound	Average (NOK)	53,596,694	53,563,750
	σ (LB) (NOK)	16,677	38,111
Upper bound	Average (NOK)	52,675,734	53,281,693
	σ (UB) (NOK)	543,473	1,335,152
Optimality gaps	Gap (NOK)	- 920,959	- 282,057
	%	- 1.75%	- 0.53%
	σ (NOK)	24,589	60,315
Best solution	First-stage decisions	Line 1 (1, 2, 3, 4, 5, 6)	Line 1 (1, 2, 3, 4, 5, 6)
		Line 2 (1, 2, 3, 4, 5, 6)	Line 2 (2, 3, 4, 5)
		Line 4 (1, 2, 3, 4, 5, 6)	Line 4 (1, 2, 3, 4, 5, 6)
	Optimal value (NOK)	53,583,647	53,409,195

Table 7 The results of the EVPI and the VSS under both demand patterns

	EVPI (NOK)	% (EVPI)	VSS (NOK)	% (VSS)
Non-seasonality	1,183,414	2.21%	0	0
Seasonality	1,309,056	2.44%	13,252	0.02%

P1 and P2. When the non-linear line balancing constraint is implemented under seasonal demands, remanufacturing line 3 is opened and used for P2 in period 4.

To investigate the impact of uncertainty, the stochastic models were then solved with $Q=20$, $P=20$, and $Q'=500$. Table 6 presents the statistical bounds, gap estimators, and the best solution to the SAA problems, which indicate the confidence levels of the respective stochastic optimization problems with the given sample size and repetitions. It can be seen that the gap between the upper bound and the lower bound under seasonal demand is approximately three times lower compared with the value under non-seasonal demand. However, on the other hand, the deviation of the SAA results under seasonal demand is much larger. Besides, evaluating the quality of the first-stage decisions in the remanufacturing reverse logistics system under a stochastic environment is also of importance. For the SAA problems under non-seasonal demands, all the first-stage decisions are identical for the given case. However, different first-stage decisions may be obtained for the SAA problems under seasonal demand patterns.

To further evaluate the effectiveness of the stochastic program, we calculated the expected value of perfect information (EVPI) and the value of the stochastic solution (VSS) with a sample size of 20 scenarios. The EVPI is measured by the absolute value of the difference between the wait-and-see solution (WS) and the optimal solution of the recourse

problem (RP), which shows the value of perfect information in an optimization problem with uncertainty. The VSS is measured by the absolute value of the difference between the RP and the expected result of using the expected value solution (EEV), which reveals the improvement of using a stochastic program. The EVPI and the VSS can be calculated with the following equations. For more details, Birge and Louveaux [7] can be referred to.

$$EVPI = |RP - WS|$$

$$VSS = |EEV - RP|$$

Table 7 shows the results of the EVPI and the VSS under both non-seasonal demands and seasonal demands. As can be seen, the EVPIs under the two demand patterns are 1,183,414 NOK and 1,309,056 NOK, which lead to 2.21% and 2.44% cost reductions, respectively. This result reveals that, if perfect information can be obtained to minimize the impact of the uncertain quality of the EOL refrigeration cores, the total operating cost of the remanufacturing reverse logistics system within the planning period can be drastically reduced. On the other hand, the VSS under non-seasonal demand is 0 due to the same first-stage decisions obtained. The VSS is 13,252 NOK under seasonal demands, which shows a slight improvement of 0.02%. The results of the VSS indicate that, for the given stochastic optimization problem, good first-stage decisions can be made with the EEV.

5.3 Discussions

Based on the computational results of the numerical experiments, discussions are given from two perspectives. First, from the management perspective, the remanufacturing reverse logistics planning is significantly affected by the

demand patterns. When the system is operated under non-seasonal demands, leveled remanufacturing is observed. However, when seasonality appears, the first-stage decisions and the inventory holding show a close-to-chasing strategy. Besides, implementing different remanufacturing line balancing constraints may lead to different decisions and system performance. In our numerical experiments, under the two demand patterns, the use of non-linear idle time cost results in cost reductions of 1.85% and 0.7%, respectively. Besides, the EOL cores are more evenly allocated to different remanufacturing lines. In all the problems solved, only remanufacturing line 1 is used as a flexible unit, and the other remanufacturing lines opened are used as dedicated lines for one type of EOL product. Furthermore, the results also illustrate the trade-off between the utilization of remanufacturing lines opened and the demand fulfillment rate. For instance, under the seasonal demand pattern, the optimal result with the linear idle time cost constraint achieves a 100% utilization rate for all the opened remanufacturing lines throughout the planning horizon, but, due to the capacity limitation, the customer demands for remanufactured cores cannot be fully met. On the other hand, the optimal result with the non-linear idle time cost constraint employs more resources with a lower utilization rate, but all the customer demands can be fulfilled, and both the inventory level and the total operating cost can be minimized. Finally, the uncertainty related to the quality of EOL products has an impact on the remanufacturing reverse logistics planning. However, for the given case, using the EEV may yield good first-stage decisions with much lower computational efforts.

From the disruptive technology adoption perspective, one observation is that, under seasonal demands, the remanufacturing plant needs to be more flexible to adjust its capacity to achieve a close-to-chasing strategy. However, remanufacturing is a complex process, and the capacity adjustment requires high reconfigurability. In this regard, the adoption of some disruptive technologies in Industry 4.0/5.0, e.g., IoT, smart collaborative robots (cobots), and additive manufacturing, may help to improve the flexibility and reconfigurability of a remanufacturing system. Another observation is that several remanufacturing lines opened are utilized at 100%, so the disruption of one remanufacturing line caused by an equipment failure may drastically affect the demand fulfillment and service level when little or no redundancy is available in other remanufacturing lines. In this regard, adopting AI-enabled predictive maintenance in the highly utilized remanufacturing lines helps to minimize the risk of disruptions. Last but not least, uncertainty has a significant impact. To solve this challenge, Industry 4.0/5.0 provides new opportunities to improve the availability and quality of

data. Through a cloud-based digital twin, the quality condition of the product can be retrieved in the EOL stage, which provides valuable information for accurate remanufacturing reverse logistics planning. The computational results show that, for the given case, the information provided by the digital twin may help to reduce the total operating costs under the two demand patterns by up to 2.21% and 2.44%, respectively.

6 Conclusions

Due to its significant impact on sustainable development and circular economy, remanufacturing, which is a substantial link in reverse logistics systems, has been extensively focused on by both academia and industrial practitioners for the past three decades. This paper first proposes a new mixed-integer linear program for a remanufacturing reverse logistics planning problem, which is then extended by incorporating non-linear idle time cost constraints and stochastic takt time for different real-world scenarios. A set of numerical experiments are given to show the applicability of the proposed models. The computational results show the impacts of different demand patterns, different remanufacturing line balancing constraints, and the quality uncertainty on remanufacturing reverse logistics planning, based on which discussions are given from both management and disruptive technology adoption perspectives. The generic managerial implications and research implications are given as follows:

Managerial implications This paper provides a decision-support model for companies and practitioners, which can be used for effective remanufacturing reverse logistics planning under uncertainty and for a comprehensive analysis of different line balancing constraints. Moreover, the results may also help decision-makers with selecting and adopting the most appropriate technologies in Industry 4.0/5.0. For example, the adoption of smart cobots may be more effective for a highly flexible and reconfigurable remanufacturing reverse logistics system under seasonal demands. However, on the other hand, a cloud-based digital twin may help to achieve a significant cost reduction under different demand patterns.

Research implications Disruptive technologies in Industry 4.0/5.0 have provided new opportunities to improve the remanufacturing reverse logistics. In this regard, this research shows how the potential impact of new technologies, e.g., digital twins, on a remanufacturing reverse logistics system can be studied by using a mathematical modeling approach. Future research is thus invited to use operations research methods and analytical models to provide comprehensive

quantitative analyses and insights into adopting Industry 4.0/5.0 technologies in a smart way [64].

Limitations and future works The research has two limitations. First, the discussions are given based only on one case, which may lack generality that can be adapted to other regions. Second, the comparison between the flexible and rigid remanufacturing reverse logistics systems is not considered in this paper. Thus, future research is suggested to tackle these two limitations.

Appendix

Equation (29) gives a general form of a two-stage stochastic program, where i is the first-stage variables and j is the scenario-dependent recourse decisions. Due to a large number of future scenarios (potentially unlimited), the expected objective value of the recourse function $\mathbb{E}_{\mathcal{P}}[\Phi(i, \xi(j))]$ cannot be determined exactly. Equation (30) is the SAA of the original stochastic program, which approximates the optimal value of Eq. (29) by a simplified problem with a sample size Q .

Table 8 The algorithm procedures of the SAA method

- Step 1 Determine the sample size Q and repetition P in the SAA experiment
 Step 2 Generate the SAA problems with Latin Hypercube sampling based on the given distribution
 Step 3 Solve the SAA problems and calculate the mean $\bar{f}_{Q,P}$ and variance $\sigma_{\bar{f}_{Q,P}}^2$ with Eqs. (31) and (32)

$$\bar{f}_{Q,P} = \frac{1}{P} \sum_{p=1}^P \tilde{f}_Q^p \tag{31}$$

$$\sigma_{\bar{f}_{Q,P}}^2 = \frac{1}{(P-1)P} \sum_{p=1}^P \left(\tilde{f}_Q^p - \bar{f}_{Q,P} \right)^2 \tag{32}$$

- Step 4 Estimate the lower bound of the problem with $\bar{f}_{Q,P}$
 Step 5 Solve the original problem and calculate the upper bound estimators with Eqs. (33) and (34). A much large problem Q' is given as the original problem, and a vector of first-stage decisions \hat{i} is selected from the SAA solutions

$$\hat{f}_{Q'}(\hat{x}) := C^T \hat{i} + \frac{1}{Q'} \sum_{q=1}^{Q'} \Phi(\hat{i}, \xi(y^q)) \tag{33}$$

$$\sigma_{\hat{f}_{Q'}(\hat{x})}^2 = \frac{1}{(Q'-1)Q'} \sum_{q=1}^{Q'} \left(C^T \hat{i} + \Phi(\hat{i}, \xi(y^q)) - \hat{f}_{Q'}(\hat{x}) \right)^2 \tag{34}$$

- Step 6 Calculate the gaps between the lower bound estimators and the upper bound estimators. If the quality requirement is not met, the procedures need to be repeated with increased Q and P

$$\min_{i,j \in V} \{f(i,j) := C^T i + \mathbb{E}_p[\Phi(i, \xi(j))]\} \quad (29)$$

$$\min_{i,j \in V} \left\{ \tilde{f}_Q(i,j) := C^T i + \frac{1}{Q} \sum_{q=1}^Q \Phi(i, \xi(j^q)) \right\} \quad (30)$$

The algorithm procedures of the SAA method are given in Table 8.

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Code availability Code is available on request from the author.

Declarations

Ethics approval and consent to participate Not applicable.

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