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ORIGINAL ARTICLE

Circular manufacturing 4.0: towards internet of things embedded closed-loop supply chains

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Abstract

Increased global economic competition and growing importance of environmental issues force manufacturers to consider implementation of closed-loop supply chains (CLSCs) ensuring recovery of end-of-life products (EOL) for recycling or reuse. Such CLSCs are subject to many uncertainties in their flows given the varying conditions of EOL products. In the era of Industry 4.0, developments in the field of the internet of things (IoT) allow the collection of data throughout full product life cycles to determine most optimal treatments to apply after product recovery. This study proposes a CLSC model maximizing the total profit of the manufacturing company by selecting the treatment to be applied to the collected products according to their condition as estimated by life cycle data collection enabled by IoT. A mixed integer linear programming model is considered for a modular product sharing standard components. To validate the proposed CLSC model on an actual innovative real-world application, we used a modular smartphone as case study. The developed model proposes a solution for the return loop of a CLSC to meet a refurbished product demand over multiple periods. The interest of using intelligent devices that predict the degradation of products during their life cycle is highlighted. The full implementation of such intelligent tracking technology on all products, and not only partially, would be beneficial by more than 5.3% for high remanufacturing costs. The profit would increase by more than 49% if the quantity of recoverable EOL products exceeded the demand for refurbished products.

Keywords Closed-loop supply chain · Sustainable supply chain · Internet of things · Industry 4.0 · Remanufacturing · Circular economy

Nomenclature

CE	Circular economy
CLSC	Closed-loop supply chain
CM	Circular manufacturing
EOL	End-of-life
IoT	Internet of things
MIQP	Mixed integer quadratic program
RFID	Radio frequency identification

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1 Introduction

Management and recovery of end-of-life (EOL) products have become an important issue in industry due to the growing importance of environmental issues and the exhaust of some natural resources. It also serves as a new way for industry to increase its profits in a world of ever increasing competition. Indeed, returns management, recycling, and pollution reduction are new business opportunities for many industries. Circular economy (CE) is a concept that can solve these problems [1]. It would allow the world economy to earn nearly 1000 billion US dollars per year and at the same time enable sustainable economic and environmental development [2]. The CE is not limited to the recycling of raw materials, but encourages the reuse, remanufacturing, and recycling of EOL products. Globally, the CE also aims for a more fair social economy and a better quality of life for future generations.

However, research on CE concepts generally focuses on the benefits to the economy as a whole and do not necessarily propose specifically how this can be achieved in a manufacturing reality referred to as circular manufacturing (CM). Such CM systems are specifically designed for closing the loop of products and/or components, preferably in their original form, through multiple life cycles. This is a value management approach that includes the phases of value creation, delivery, use, recovery, and reuse in a systemic perspective [3]. Awareness on the relevance of research on management and recovery of EOL products in the context of Industry 4.0 is emerging; however, only a few literature exist on the connection between Industry 4.0 and CE towards CM [4]. Launched in Germany in 2011, Industry 4.0 refers to the fourth industrial revolution emerged by new digital technologies and the intelligent interaction between physical objects without human intervention, driving manufacturing companies to move from mass production to mass customization and even mass personalization in extreme cases [5]. Industry 4.0 tools aim to increase the flexibility and productivity of manufacturing factories, especially in a world where mass customization of products has become essential to satisfy customer demand [6].

Closed-loop supply chains (CLSCs), which includes reverse logistics, are an interesting solution to adapt circular manufacturing strategies for real-world cases in industry. Reverse logistics enable the collection of EOL products from consumers to improve profitability, stability, and sustainability [7]. Deployment of CLSCs enables improved levels of recovery of used products and results in a better choice of recovery processing. Product tracking during manufacturing, use, and recovery cycles is essential to optimize the recovery process and its planning. As such, Industry 4.0 has the potential to improve considerably CLSCs performance by increasing the connectivity and data transfer across the entire supply chain using technologies such as the internet of things (IoT). The use of IoT can offer improved product tracking during its lifetime to circumvent inspection operations after recovery, which creates new opportunities for remanufacturing (i.e., complete product recovery) [8]. However, as EOL recovery technologies can greatly benefit from the technological advances of the Industry 4.0 concept, these EOL technologies tend generally to be underdeveloped compared to upstream (i.e., manufacturing) technologies [9]. It should be noted that Industry 4.0 is an evolving paradigm, including a wide variety of technologies, such as IoT, Big Data, cyber-physical systems, and many more [5, 6]. These technologies cannot control nor optimize any type of supply chain by themselves, unless they are coupled with intelligent (e.g., using artificial intelligence) decision-making processes.

This study aims to contribute in addressing this research gap on the connection between IoT and CM concepts. We propose a CLSC profit optimization approach using a mixed integer quadratic programming (MIQP) model making use of IoT enabled product status tracking and considering all possible recovery options for several EOL products. After a comprehensive literature review, we will define the problem statement resulting in the research questions for this study. Subsequently, a new CLSC model approaching real-world industrial systems, based on the deployment of IoT for product tracking, will be proposed. We will then assess a case study based on modular smartphones (e.g., Fairphone) to study the applicability and sensitivity of the developed MIQP model. Finally, an improvement of the model will be proposed allowing further optimization of both the forward and reverse supply chain.

2 Literature review

In order to propose a novel CLSC model aiming to improve CM models while optimizing the generated profit, in a first step, we need to identify the principal EOL product recovery processes and its obstacles, to understand how IoT technologies can improve the reverse logistics. In a second step, we will study and review the existing CLSC models.

2.1 Recovery processing

Different processes are possible for EOL products to avoid disposal. The simplest treatment is reuse. Reuse consists of using the EOL products as received after cleaning, i.e., without any reprocessing [10]. This is the most effective strategy for preserving natural resources [11]. Recycling is the recovery of materials and is not the most preferable option for recovering the residual value of a product or component because one loses all the added value of a product during its manufacture. The recyclability of a product depends on the materials of which it is made as well as the ability to separate them from each other (e.g., disassembly) [12].

Until recently, the recovery of raw materials by recycling and disposal was the main process for treating an EOL product. Remanufacturing is now another possible processing option for recovered products and components [8]. This is the process of restoring used products to conditions equivalent to those of a new product through disassembly, cleaning, repair, and reassembly [13]. Obstacles to remanufacturing are of various types, both at the level of the manufacturer and of the customer [14].

2.2 Industry 4.0 impact on the circular economy

The fourth industrial revolution, the revolution through intelligent digital tools, is a consequence of changing consumer demands for mass customization of products and driven by the constantly evolution of intelligent technologies. The various tools that emerged with Industry 4.0 are promising to unlock the full potential of a CE. Research studies on the impact of Industry 4.0 on the main CE strategies, recycling, repair, and reuse, are emerging, and they reveal different guidelines and recommendations [15]. For recycling, waste sorting must be done precisely in order to obtain a pure raw material at the output [16]. This sorting can be carried out with the help of artificial intelligence, which, using robots, improves this sorting stage [17]. For repair, novel – service oriented – business models arrive; for example, Philips offers an intelligent system for managing street lighting. When a lighting requires repair operations that will take a few days, there is no need to replace it. Indeed, the lights are connected by radio frequency identification (RFID) and will adapt their power if nearby equipment has been temporarily removed. In this manner, Philips gains in raw material and new equipment costs because they can afford to recondition the product [18]. For reuse, Big Data and IoT can facilitate predictive and preventive maintenance operations by providing information on the condition of a product. In this way, its lifetime is extended by delaying its decommissioning [19]. These examples show that Industry 4.0 technologies are promising to facilitate the implementation of CE strategies for manufacturing to enable CM. However, there is only a few research, which presents how Industry 4.0 could play a role as an initiator of the CE and of CM strategies. We hypothesize that this can be achieved by creating connected products that exchange product data via IoT technology between the product and the manufacturer [20]. Indeed, the analysis of this data would allow monitoring the product during its life, determine its state of degradation, and thus optimize the recovery of waste. Hence, Industry 4.0-driven strategies could control and optimize the product reverse supply chain. The CE would then be built on a sustainable supply chain. However, the impact of IoT technology's control of supply chains is still largely unknown [21]. This can be explained in particular by the fact that predicting the state of degradation of a product during its lifetime cannot be easily controlled [22]. This supply chain control, composed of a direct forward chain and a feedback loop, links the CE and CM approaches with the Industry 4.0 concept.

2.3 IoT and embedded sensors in supply chains

Product connectivity enabled by IoT technology and the use of integrated sensors to control the product life cycle are emerging strategies, which are considered promising by many research studies [23]. For example, the integration of sensors on products permitted to count the quantities of products around collection sites, which allowed to optimize the recovery in a previous study [24]. RFID systems enabling such product counting can solve the main challenges of closed-loop reverse logistics [25].

The EOL product condition is also affected by uncertainties. Sensors embedded in products reduce these uncertainties by using information collected during the life of the product [26]. This information, collected and stored on RFID tags, improves the recovery of EOL products [20], notably by improving recycling and disassembly with an exchange of information between the manufacturer and the recovery company [27]. These sensors also improve the reverse supply chain by detecting missing components before disassembly [28]. Linear programming models using IoT are available to provide an optimal solution for disassembly and remanufacturing. Meanwhile, integrated sensors provide the remaining life of the recovered product. These developed models in literature are single-objective models focusing on an economic objective [29]. Finally, the collected information on products during their life cycle using IoT has an impact on reducing transport costs in the supply chain [30]. It can be concluded that IoT and embedded sensors have the potential to improve the recovery of EOL products by focusing on specific aspects such as the remaining life of the product, its disassembly, or its location in relation to collection points. However, the link between the collection of an EOL product, its state of degradation, and its recovery treatment has not yet been studied.

2.4 Existing CLSCs models

Industry 4.0 is based on advanced intelligent tools and technologies that transform industrial plants and their processes into smarter systems. CLSCs are also evolving thanks to Industry 4.0 by digitalization to become more flexible and resilient. Supply chain management (SCM) is indeed strengthened by implementation of IoT technologies, which allows to share information from different suppliers, to connect storage locations for products and components, to trace material and product flows during transport or manufacturing, and to check the status of perishable products through temperature sensors [23]. This digitalization contributes to improved production planning [31]. The sharing of the collected data between the different actors of the supply chain is increasingly important even if its impact has not yet been quantified [32]. Nevertheless, it is recognized that this synchronization of information reduces costs at every point in the supply chain and improves its efficiency and adaptability [33, 34]. Real-time digital control of manufacturing equipment also improves supply chain performance and reduces risk [35]. Moreover, Govindan et al. [36] criticize the fact that less than 5% of scientific articles address optimization models that maximize profits to concretely assist companies in their decision-making processes. Hence, it appears necessary to propose such models to support companies in becoming more efficient and resilient. These mathematical models, which optimize profits, must firstly be based on simulations, and in a second step, researchers should attempt to obtain empirical results by implementing digital technologies [37]. Undeniably, the emergence of embedded sensor technologies and IoT is an important tool to improve supply chain performance in a

CM context. For example, intelligent reconditioning and dismantling systems that can optimally plan recovery based on customer demands are proposed. Here, IoT is used in a model to determine the remaining life of EOL products and components that have been returned [38]. Other systems have also been proposed to evaluate design variants of EOL products to facilitate disassembly and remanufacturing using the IoT. The solved model provided the total number of EOL products, which are disassembled, remanufactured, stored, recycled, and disposed for each design type [39]. Such a model has only one economic objective, specifically profit optimization. Dual-purpose models have been developed to maximize the reliability of remanufactured products and minimize processing costs by assessing the quality of returned products [40, 41]. Other CLSC production planning models aim to reduce costs and energy consumption based on collected information on recovery [36]. In fact, CLSCs can optimize the economic, energy, or quality objectives of industries. Therefore, Golinska et al. have developed a decision support tool to transition to a closed-loop system to classify the current state of remanufacturing operations and to identify and to prioritize the company's operations that require improvement actions [42].

In summary, many studies have measured the economic impact of different CLSC architectures. CLSCs can be decentralized, with a retailer collecting the products in addition to the original manufacturer. On the other hand, in a centralized model, the manufacturer manages the recovery of EOL products. The implementation of this type of CLSC can maximize profits for companies that are concerned with their social responsibility [43] and that are sensitive to environmental issues [44]. Depending on the architecture of the model and the EOL product treatment methods, the optimal choices for profit maximization will not concur. The coordination of manufacturing activities and downstream operations of the production unit by retailers is considered in the pioneering work of Xiao et al. [45]. Considering a CLSC, such as in [46], an extension of this coordination was conducted in [47], which presents for the first time a CLSC composed of a manufacturer and two retailers. In the model presented in [47], customers can return sold products in both non-defective and defective categories. The classical CLSC concept is extended to the closed-loop green supply chain (CLGSC) concept by [48] considering dual upstream and downstream channels. In the same context, [49] presents a CLGSC model over two periods with a single manufacturer and a single retailer to study the impact of green innovation, marketing effort, and used product collection rate on decision support tools.

The interactions between the different actors of the CLSC can be optimized to maximize their respective revenues [49, 50]. More complex CLSCs, including retailers and several independent collectors in addition to the manufacturer, have also been studied, providing new management insights [51, 52]. The influence of consumers on the performance of CLSCs has been studied as well. It was found that CLSCs must adapt to consumer preferences and behavior to enhance their performance and effectiveness [53, 54]. Finally, governments can encourage the establishment of CLSCs, which are more environmentally friendly, with reward systems for companies [55]. For example, the reduction of carbon emissions depending on the CLSC architecture has been highlighted by Lundmark et al. [56]. It was highlighted by Goodall et al. that depending on the selected environmental policy, the optimal parameters for generating both more profit and less pollution vary [57].

Although the different CLSC architectures and the impact of factors such as consumer behavior or ecological policies have been studied [56, 57], some aspects deserve to be further developed, in particular EOL product management using Industry 4.0 technologies such as IoT. In fact, most of the available research studies do not consider the products' components, and very few studies take into account quality assessment of the recovered EOL products and its consequences on CLSC management strategies or they only categorize EOL products without an assessment that would allow individual estimation of, e.g., remanufacturing costs. Furthermore, the potential impact of knowledge on the degradation state of EOL products and their components on supply chain control is still not well known.

Moreover, the different CLSC models discussed in literature do not simultaneously consider raw material recycling and the difference between new and remanufactured products, inventories, and management of multiple products in an Industry 4.0 context. In addition, existing literature on CLSCs does not reveal multi-period supply chain management models. To conclude, none of the reviewed CLSC models discusses case studies that incorporate data of a concrete, real-world product. This article will contribute to filling these research gaps. Table 1 presents an overview of the discussed literature on CLSC research and development, highlighting the differences between existing CLSC-related research work and the study presented in this contribution.

Throughout the presented research study, we will seek to improve a preliminary developed CLSC model [20] using IoT technology by addressing the model's limitations and to propose a CLSC model using intelligent technologies that would better reflect the industrial reality. This preliminary model established by Turan et al. [22] proposes a CLSC model, which considers the remanufacturing and disposal of a single modular product and its components. The necessary processing of the recovered products and components depends on their condition, which is evaluated by an artificial number. This number is supposed to be determined by data collected with sensors, measuring various usage parameters, and stored on a RFID tag fixed on the product. Turan et al. [22] called this conceptual intelligent product the "Device Internet of Things

Table 1 Overview of the related literature on CLSC

Authors	Product type		Period type			Objectives		Recovered product degradation evaluation		
	Single	Multi	Single	Dual	Multi (> 2)	Single	Multi	No evaluation	Classification in groups	Individual evaluation
Ondemir, O., Ilgin, M.A., Gupta, S.M. (2012) [29]	✓		✓				✓		✓	
Govindan, K., Mina, H., Esmaeili, A., Gholami-Zanjani, S.M. (2020) [36]		✓	✓				✓	✓		
Ondemir, O., Gupta, S.M. (2014) [38]		✓	✓				✓		✓	
Joshi, A.D., Gupta, S.M. (2019) [39]		✓	✓				✓		✓	
Zhang, Z., Liu, S., and Niu, B. (2020) [40]	✓		✓			✓			✓	
Panda, S., Modak, N. M., and Cardenas-Barron, L. E. (2017) [41]	✓		✓			✓		✓		
Yang, S., Ding, P., Wang, G., and Wu, X. (2020) [42]		✓	✓				✓	✓		
Xiao, L., Wang, X.-J., and Chin, K.-S. (2020) [43]	✓		✓			✓		✓		
De, M. and Giri, B. (2020) [44]		✓	✓				✓	✓		
Assarzadegan, P. and Rasti-Barzoki, M. (2020) [45]	✓		✓			✓			✓	
Mondal, C., Giri, B., and Maiti, T. (2019) [46]	✓		✓				✓	✓		
Mondal, C. and Giri, B. C. (2020) [47]	✓			✓		✓		✓		
Ma, N., Gao, R., Wang, X., and Li, P. (2020) [48]	✓		✓				✓	✓		
Ma, Z.-J., Ye, Y.-S., Dai, Y., and Yan, H. (2019) [49]	✓		✓				✓		✓	
Wei, J., Chen, W., and Liu, G. (2020) [58]	✓		✓				✓	✓		
Xu, J., Zhou, X., Zhang, J., and Long, D. Z. (2019) [50]	✓		✓				✓	✓		
Wang, N., Song, Y., He, Q., and Jia, T. (2020) [51]	✓		✓			✓		✓		
He, Q., Wang, N., Yang, Z., He, Z., and Jiang, B. (2019) [52]	✓		✓			✓		✓		
Chen, C.-K. and Akmalul'Ulya, M. (2019) [53]	✓		✓			✓		✓		
Taleizadeh, A. A., Alizadeh-Basban, N., and Niaki, S. T. A. (2019) [54]	✓		✓			✓		✓		
Giri, B. C. and Dey, S. (2019) [55]	✓		✓			✓			✓	
This presented study	✓				✓	✓				✓

Table 1 (continued)

Authors	Components degradation consideration	Raw material consideration	Recovery treatment consideration				Inventory management	Real case study
			Waste	Recycling	Remanufacturing	Reuse		
Ondemir, O., Ilgin, M.A., Gupta, S.M. (2012) [29]	✓	✓	✓	✓	✓			
Govindan, K., Mina, H., Esmaeili, A., Gholami-Zanjani, S.M. (2020) [36]			✓	✓			✓	
Ondemir, O., Gupta, S.M. (2014) [38]	✓	✓	✓	✓	✓			
Joshi, A.D., Gupta, S.M. (2019) [39]	✓	✓	✓	✓	✓		✓	
Zhang, Z., Liu, S., and Niu, B. (2020) [40]			✓		✓			
Panda, S., Modak, N. M., and Cardenas-Barron, L. E. (2017) [41]		✓			✓			
Yang, S., Ding, P., Wang, G., and Wu, X. (2020) [42]					✓			
Xiao, L., Wang, X.-J., and Chin, K.-S. (2020) [43]					✓			
De, M. and Giri, B. (2020) [44]							✓	
Assarzadegan, P. and Rasti-Barzoki, M. (2020) [45]					✓	✓		
Mondal, C., Giri, B., and Maiti, T. (2019) [46]					✓			
Mondal, C. and Giri, B. C. (2020) [47]					✓			
Ma, N., Gao, R., Wang, X., and Li, P. (2020) [48]								
Ma, Z.-J., Ye, Y.-S., Dai, Y., and Yan, H. (2019) [49]				✓	✓			
Wei, J., Chen, W., and Liu, G. (2020) [58]		✓			✓			
Xu, J., Zhou, X., Zhang, J., and Long, D. Z. (2019) [50]					✓			
Wang, N., Song, Y., He, Q., and Jia, T. (2020) [51]		✓		✓		✓		
He, Q., Wang, N., Yang, Z., He, Z., and Jiang, B. (2019) [52]				✓	✓			
Chen, C.-K. and Akmalul'Ulya, M. (2019) [53]								
Taleizadeh, A. A., Alizadeh-Basban, N., and Niaki, S. T. A. (2019) [54]				✓	✓			
Giri, B. C. and Dey, S. (2019) [55]		✓		✓				
This presented study	✓	✓	✓	✓	✓	✓	✓	✓

(DIOT)". This basic model allows decision-making on CLSC flows to maximize profit and meet the product demand. However, this DIOT-based model and other CLSC models existing in literature do not simultaneously consider the recycling of raw materials, the difference between new and remanufactured products, the materials and product inventories, and the management of multiple products in an Industry 4.0 context. In the following sections, we will develop an improved DIOT-based CLSC model by addressing the limitations of the basic DIOT model stated before and thus propose a more complete and validated CLSC model using smart technologies (here: IoT) that will better reflect its possibilities for real-world industrial uses and provide useful managerial decision-making insights.

2.5 Main contributions

The literature review, discussed in Sections 2.1, 2.2, 2.3, and 2.4, highlighted several areas for further research. It was emphasized that Industry 4.0 concepts can already facilitate the application of the CE and CM principles, for example, by allowing enhanced waste sorting. However, Industry 4.0 could reach further; its technologies, such as IoT, would allow it to be the initiator of the CE and unlock the full potential of CM approaches. Indeed, since IoT combined with intelligent decision-making processes offers a way to track products during their life cycle and to predict their state of degradation, it would be possible to control the reverse supply chain in a more optimal way. Predicting the state of EOL products using IoT technology has been discussed in literature, but it has not yet been studied on concrete, practical cases. Such intelligent CLSC control is proving to be the bridge between Industry 4.0 and the CE and CM [20]. However, the consequences of such a control of CLSCs by using IoT have not yet been studied in detail. Moreover, existing studies do not provide industrial decision-makers with concrete optimization models, illustrated by case studies that focus on the operational dimension of supply chain management. Finally, the CLSCs studied in the literature (see Table 1) almost systematically consider only one method of recovery, such as recycling, reconditioning, or reuse, and not all of these possibilities at the same time.

This research work aims to propose a MIQP model that incorporates multiple recovery technologies and solutions supported by information on the product state provided by IoT technology. Two recovery options for products will be considered: disassembly and recycling. If the product is disassembled, the components can undergo four processing options: reuse, remanufacturing, recycling, or elimination. Products, components, and raw materials are sold or stored to meet the sales and collection centre (S&C center). Finally, the developed DIOT-based CLSC model is validated in a case study using real-world product and material data by examining the modular smartphone *Fairphone 2*.

The proposed MIQP model intends to answer the following two research questions:

1) What recovery processing should be chosen for the products and components returned for each period to maximize the profit of the CLSC?
2) How many and which recoverable products should be purchased to satisfy the remanufactured product demands?

3 Problem definition and formulation

The behavior of the direct supply chain is known. This study concentrates on the return loop of a manufacturing CLSC with a range of products that aims to satisfy the demand of a sales and collection (S&C) center. The products are made from J separate components ($j = 1, \ldots, J$), manufactured with a total of K ($k = 1, \ldots, K$) raw materials. During each of the studied T periods ($t = 1, \ldots, T$), I_t EOL products ($i = 1, \ldots, It$) are recovered. The products, components, and raw materials can be sold at the S&C center. A schematic overview of the developed CLSC model for this study is presented in Fig. 1. The different direct and reverse supply chain flows for products, components, and raw materials are presented, respectively, in blue, red, and green, while the different process stages crossed by these flows are shown inside the blocks.

3.1 Assumptions

In order to define the boundaries of our developed model, we consider the following assumptions:

- A component can be used for different products.
- The production capacity is sufficient.
- All information about sales, transport, storage, and manufacturing costs is known.

3.2 Nomenclature

The different parameters and variables of the CLSC model are explained in Table 2 and 3.

3.3 Device of internet of things (DIOT)

In order to determine intelligently the recovery condition, the concept of "Device of Internet of Things" (DIOT) [22] is deployed, adding recycling as a possible recovery processing. More concretely, the DIOT is a device, such as sensors or RFID tags as shown in Fig. 2, embedded in products. This device can trace the product's life cycle, especially the

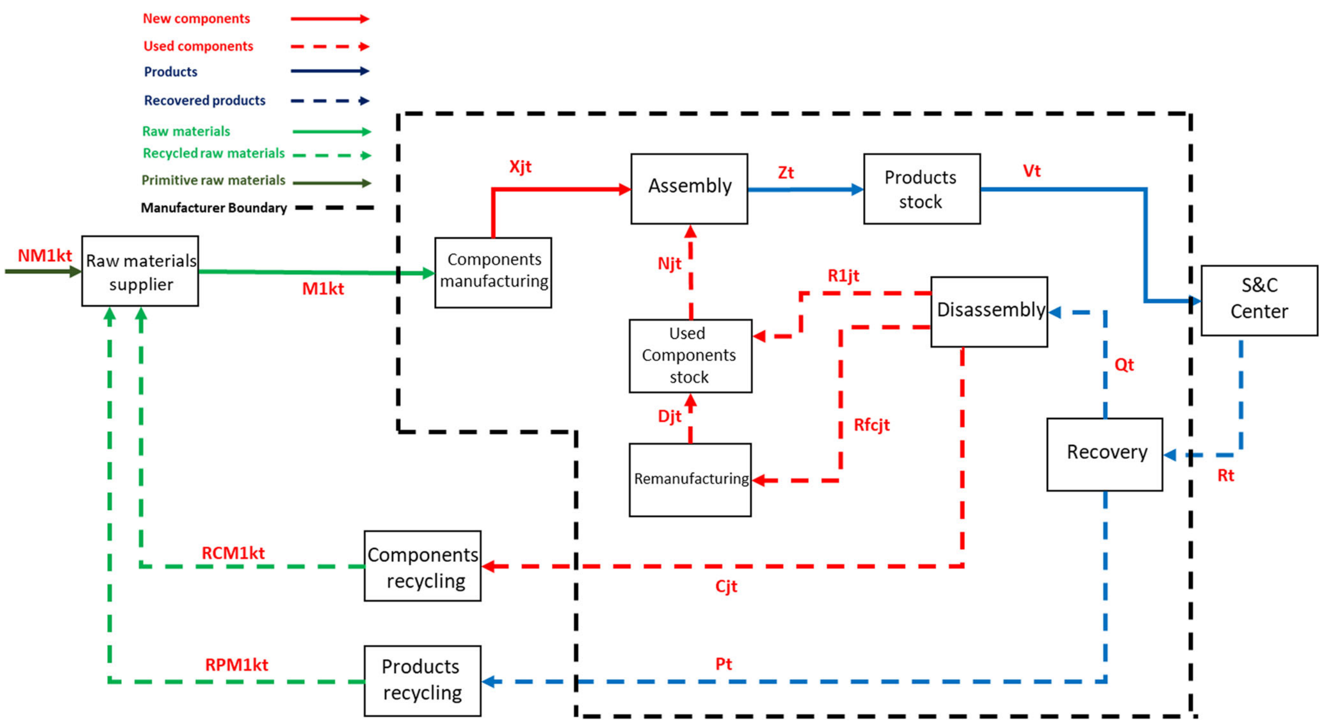


Fig. 1 CLSC model developed in the study

parameters/conditions it experienced throughout its life cycle, which could result in product/component degradation (e.g., temperature, humidity, mechanical or thermal shock, usage outside the manufacturer's specifications). All this product information can be communicated to the manufacturer via internet connections (i.e., IoT). Each recovered component is associated with a numerical value: $diot_{i,\,j,\,t}$. This number is a digital twin of the real product: the digital data allows to know the state of product degradation in the real world. This would reduce inspection operations: a recycled product or component, for example, would not require quality inspection upon receiving in a recovery facility anymore.

The $diot_{i,\,j,\,t}$ defines the condition of a recovered component by assigning a grade between 0 and 10 upon its current state. Figure 3 presents an overview of the component evaluation including the threshold values *nj1*, *nj2*, and *nj3* determining the deciding treatment (elimination, recycling, remanufacturing, reuse) for each component.

Until now, the $diot_{i,\,j,\,t}$ value was never precisely defined. In this study, a MIQP model is developed to associate the *diot* value with the remanufacturing cost for the first time. The remanufacturing cost $f_{i,\,j,\,t}$ is defined in Eq. (1) and represented in Fig. 4.

$$f_{i,j,t} = \begin{cases} rf.cn_j.\dfrac{m_j}{nj3-nj2}.\left(nj3-diot_{i,j,t}\right) \text{ if } \mathrm{nj_2} \leq \mathrm{diot_{i,j,t}} < \mathrm{nj_3} \\ 0 \text{ otherwise} \end{cases} \quad (1)$$

Each recovered product is associated with a $diot_{i,\,t}$ which, in the same way as the $diot_{i,\,j,\,t}$ for the components, defines the treatment process (disposal, recycling, dismantling) that the product will undergo according to product threshold values (*ni1*, *ni2*), as shown in Fig. 5. The $diot_{i,\,t}$ is calculated as the weighted average of the $diot_{i,\,j,\,t}$ in proportion to the weight of each component cw_j as in Eq. (2).

$$diot_{i,t} = \sum_j cw_j.diot_{i,j,t}. \quad (2)$$

The importance component weight cw_j is calculated as the average of the manufacturing cost of the product and the raw materials it contains over the total cost of the product:

$$cw_j = \frac{cn_j.\ \left(m_j + \sum_k n_{j,k}\right)}{\sum_j cn_j.\ \left(m_j + \sum_k n_{j,k}\right)}. \quad (3)$$

The $diot_{i,\,t}$ is used to determine the purchase value of the returned product. This value depends on two factors. The first factor is the manufacturing cost of the components separately (*rpa*). The second factor is the value of the raw materials present in the product after recycling (*rma*). Their expressions are given by the Eq. (4) and (5):

$$rpa = \sum_j cn_j.m_j. \quad (4)$$

$$rma = \sum_j cn_j.\sum_k h6_k.rp_k.n_{j,k}. \quad (5)$$

Table 2 Defined problem parameters of the developed CLSC model

Parameters	Description
a	Assembly cost of a product
d	Elimination cost of a product
cnj	Number of component *j* in product
cwn,j	Component *j* importance weight
h1n	Sales price of a remanufactured product
dmt	Product *n* demand of the S&C center in period *t*
sp	Product storage cost
PSM	Maximal product stock
dioti,t	DIOT of the *i* product recovered in period *t*
ni1, ni2	Threshold value of $diot_{i,t}$
rpa	Total manufacturing cost of the parts in product separately
rma	Value of the raw materials present in the product after recycling
ri,t	Purchasing cost of the product *i* in period *t* from the S&C center
mj	Manufacturing cost of a new component *j*
nj,k	Number of raw materials *k* in a component *j*
rnj,k	Number of raw materials *k* to remanufacture a component *j*
dmsj,t	New components *j* demand of the S&C center in period *t*
dmcj,t	Used components *j* demand of the S&C center in period *t*
sccj	Component *j* storage cost
UCSMj	Maximal component *j* stock
dioti,j,t	Diot of component *j* recovered in period *t*
nj1, nj2, nj3	Threshold value of *dioti,j,t*
fi,j,t	Remanufacturing cost
rpk	Recovered part of raw material *k* on products
rck	Recovered part of raw material *k* on components
cmj,k	Raw material *k* lost in the machining of component *j*
pmk	Purchasing cost of raw material *k* from the raw materials supplier
h2k	Sales price of raw material *k* from components recycling
h3k	Sales price of raw material *k* from products recycling
ic	Implementation cost of DIOTs on a product
df	Fraction of products with a DIOT

This choice was made because the cost of recovering individual parts is the critical factor that will determine if the recovery process selected for the product is more cost-effective. The recovery price for EOL products $r_{i,\ t}$ is defined as in Eq. (6), and it is represented in Fig. 6. In order to be able to plot Eq. (6), Fig. 6 outlines an example with randomly chosen values for ni_1 and ni_2 (here: $ni_1 = 1$ and $ni_2 = 3$) for illustration purposes.

$$r_{i,t} = \begin{cases} \dfrac{rpa}{10-ni2}.diot_{i,t} + rma - \dfrac{rpa.\ ni_2}{10-ni2}\ if\ ni_2 \le diot_{i,t} \\ rma\ if\ ni_1 \le diot_{i,t} < ni_2 \\ 0\ otherwise \end{cases} \quad (6)$$

4 Mathematical model

Based on the above assumptions, a CLSC mathematical model is developed to determine how returned products should be processed in order to maximize profit.

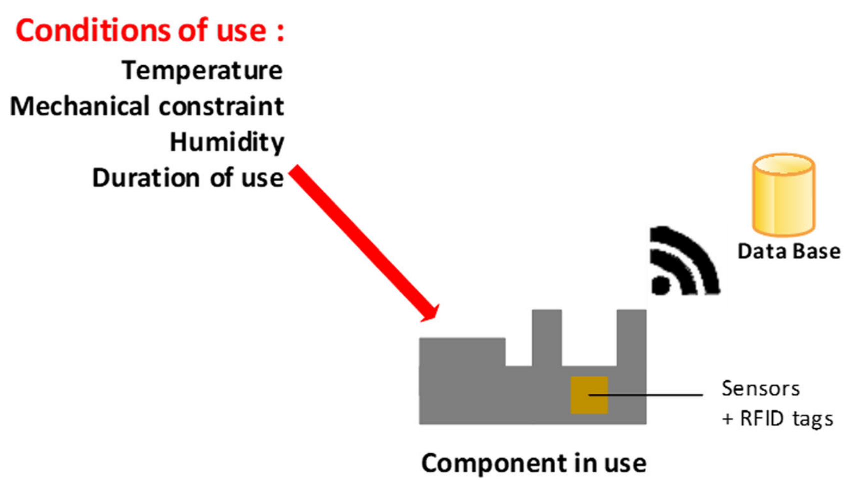
4.1 Variables and parameters

Recovered products can be eliminated, recycled, or disassembled. Binary variables are defined to indicate the recovery process when the model is solved. The variable $dis_{i,\ t}$ indicates that a product is disassembled, possible if the value of $diot_{i,\ t}$ is sufficiently large ($diot_{i,\ t} > ni2$):

Table 3 Problem decision variables of the developed CLSC model

Decision variables	Description
Zt	Number of remanufactured products sent to the stock in period *t*
Vt	Number of remanufactured products sold to the S&C center in period *t*
Rt	Number of products sent to recovery in period *t*
Qt	Number of products disassembled in period *t*
Pt	Number of products recycled in period *t*
PSt	Number of products in stock in period *t*
Xj,t	Number of new components *j* manufactured in period *t*
Wj,t	Number of new components *j* sent to the stock in period *t*
Dj,t	Number of used components *j* sent to the stock in period *t*
Nj,t	Number of used components *j* sent to assembly in period *t*
Cj,t	Number of components *j* recycled in period *t*
Rfcj,t	Number of components *j* remanufactured in period *t*
R1j,t	Number of components *j* reused in period *t*
UCSj,t	Number of used components *j* in stock in period *t*
NM1k,t	Number of primitive raw material *k* entering in the supply chain in the period *t*
M1k,t	Number of raw material *k* purchased in the period *t*
RCM1k,t	Number of raw material *k* recycled from components in period *t*
RPM1k,t	Number of raw material *k* recycled from products in period *t*
dvc1i,j,t dvc2i,j,t dvc3i,j,t	Auxiliary decision variable used to determine the value of *reui,j,t*, *reui,j,t*, and *reci,j,t* (takes the value 0 or 1)
dvp1i,t dvp2i,t	Auxiliary decision variable used to determine the value of *reci,t* and *disi,t* (takes the value 0 or 1)

Fig. 2 Device of the internet of things (DIOT)



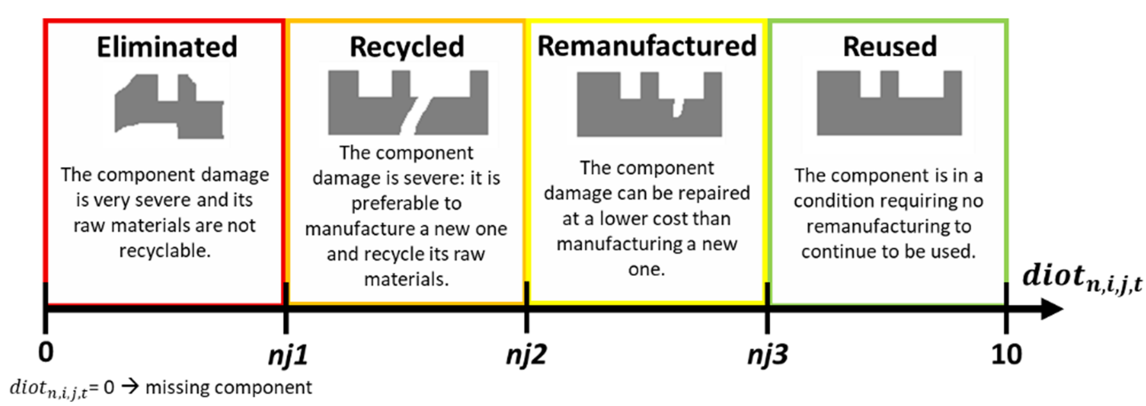


Fig. 3 Principles of choice for component recovery processing according to its $diot_{i,\,j,\,t}$ and its assessment on the threshold values *nj1*, *nj2*, and *nj3*

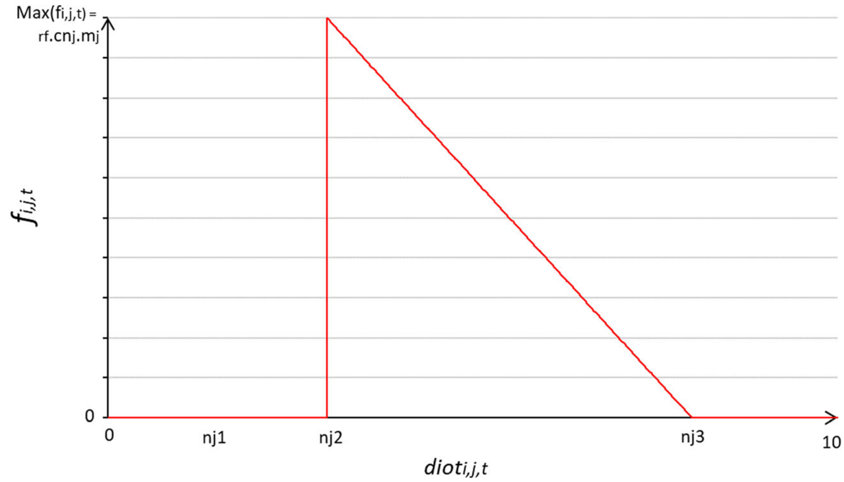


Fig. 4 Remanufacturing cost $f_{i,\,j,\,t}$ according to $diot_{i,\,j,\,t}$

$$dis_{i,t} = \begin{cases} 0 \; if \;\; diot_{i,t} < ni2 \text{ (the product is in insufficient condition to be disassembled)} \\ dvp2_{i,t} \; otherwise \text{ (1 if the product is disassembled, 0 otherwise)} \end{cases} \tag{7}$$

The variable $rec_{i,\,t}$ indicates that a product is recycled. This is possible if the value of $diot_{i,\,t}$ is sufficiently large ($diot_{i,\,t} > ni1$):

$$rec_{i,t} = \begin{cases} 0 \; if \; diot_{i,t} < ni1 \text{ (the product is in insufficient condition to be recycled)} \\ dvp1_{i,t} \; otherwise \text{ (1 if the product is recycled, 0 otherwise)} \end{cases} \tag{8}$$

The variable $was_{i,\,t}$ specifies if the product has been eliminated. A product that is not missing can only have one single recovery processing among disassembly, recycling, and disposal:

$$dis_{i,t} + rec_{i,t} + was_{i,t} = 1, \forall (t, i) \tag{9}$$

The amount of products recycled in period t is calculated as follows:

$$P_t = \sum_i rec_{i,t}. \tag{10}$$

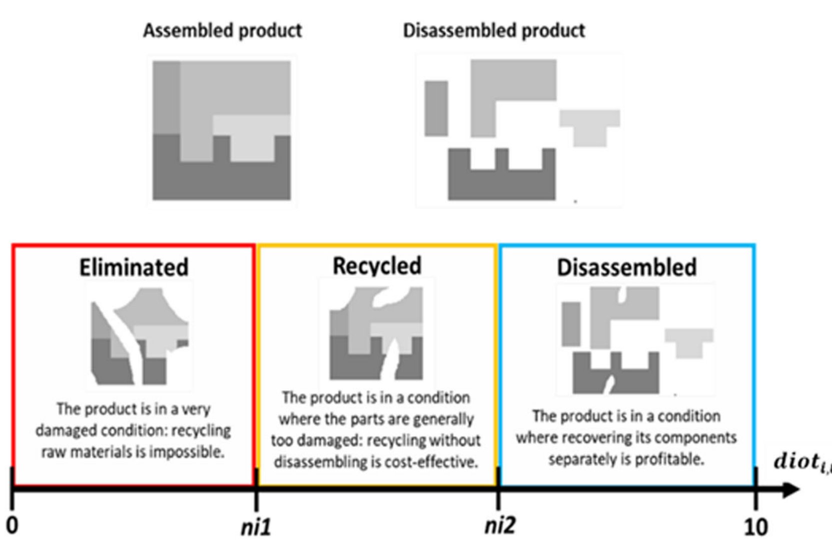
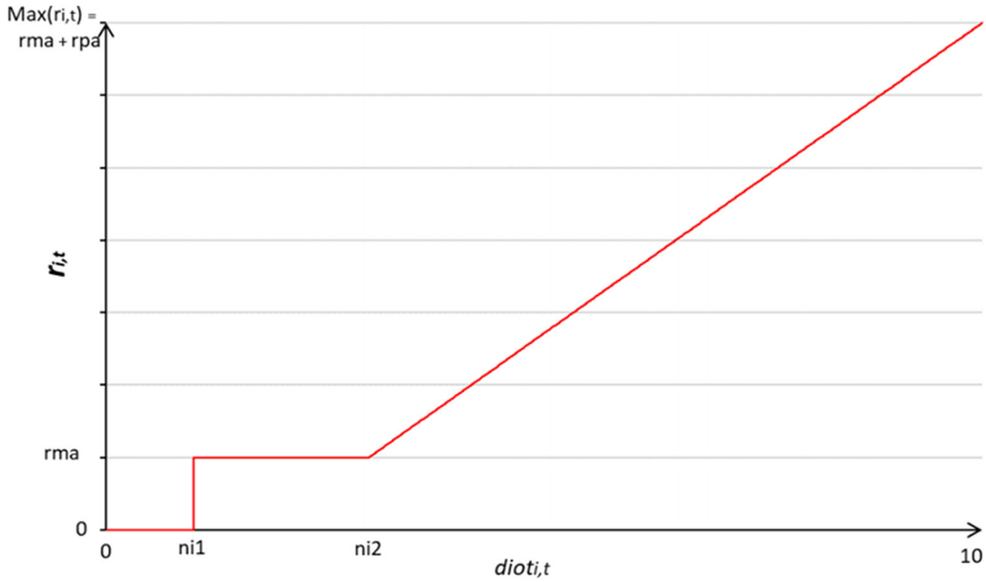


Fig. 5 Principles of choice of product recovery processing according to its $diot_{i,\,t}$ and its evaluation on the threshold values *ni1* and *ni2*

Fig. 6 Recovery cost for EOL products $r_{i,t}$ according to $diot_{i,t}$: the repurchase cost increases with a product recovered in better condition



The amount of products disassembled is:

$$Q_t = \sum_i dis_{i,t}. \tag{11}$$

The disassembled product components receive recovery processing, which is defined by the $diot_{i,j,t}$ value. The components can either be missed, eliminated, recycled, remanufactured, or reused directly. As with the products, in Eqs. (12–15), binary variables are created, which indicate the chosen processing when the model is solved:

$$mis_{i,\mathrm{j},t} = \begin{cases} 1 \; if \;\; diot_{i,\mathrm{j},t} = 0 \text{ (the component is missing)} \\ 0 \; otherwise \end{cases} \tag{12}$$

$$reu_{i,j,t} = \begin{cases} 0 \; if \;\; diot_{i,j,t} < nj3 \text{ (the component is in insufficient condition to be reused)} \\ dvc3_{i,j,t} \; otherwise \text{ (1 if component is reused, 0 otherwise)} \end{cases} \tag{13}$$

$$rem_{i,j,t} = \begin{cases} 0 \; if \;\; diot_{i,j,t} < nj2 \text{ (the component is in insufficient condition to be remanufactured)} \\ dvc2_{i,j,t} \; otherwise \text{ (1 if component is remanufactured, 0 otherwise)} \end{cases} \tag{14}$$

$$rec_{n,i,j,t} = \begin{cases} 0 \; if \;\; diot_{i,j,t} < nj1 \text{ (the component is in insufficient condition to be recycled)} \\ dvc1_{i,j,t} \; otherwise \text{ (1 if component is recycled, 0 otherwise)} \end{cases} \tag{15}$$

The variable $was2_{i,j,t}$ specifies if the component has been eliminated. A non-missing component can only undergo a single recovery treatment among reuse, remanufacturing, recycling and disposal, therefore:

$$reu_{i,j,t} + rem_{i,j,t} + rec_{i,j,t} + mis_{i,\mathrm{j},t} + was2_{i,j,t} = 1, \forall (t,i,j). \tag{16}$$

The amount of components j recycled in period t is calculated as follows:

$$C_{j,t} = cn_j.\sum_i rec_{i,j,t}.dis_{i,t}. \tag{17}$$

The amount of components j remanufactured in period t is:

$$Rfc_{j,t} = cn_j.\sum_i rem_{i,j,t}.dis_{i,t}. \tag{18}$$

The amount of components j reused in period t is:

$$R1_{j,t} = cn_j.\sum_i reu_{i,j,t}.dis_{i,t}. \tag{19}$$

4.2 Objective function

The objective of the proposed CLSC model is to maximize the profit of the company defined in Fig. 3. The total profit is calculated as the difference between the total revenue and the total cost.

4.2.1 Total revenue

The sale of products is the company's main sources of revenue. This revenue (TRS) is calculated as follows:

$$TRS = \sum_t h1.V_t. \tag{20}$$

The sale of products, components, and machining scraps containing raw materials recovered from recycling are also a source of revenue for the company. Revenue from recycling (TRR) is equal to:

$$TRR = \sum_t P_t.\sum_j cn_j.\sum_k h3_k.rp_k.n_{j,k} + \sum_t\sum_j C_{j,t}.\sum_k h2_k.rc_k.n_{j,k}. \tag{21}$$

4.2.2 Total cost

The company has two types of purchases to produce products and components. The first is the purchase of raw materials, and the second purchases are returned products. The purchase price of each product depends on the $diot_{n,\ i,\ t}$ and is given by the $r_{i,\ t}$ value. The total purchase cost (TPC) is calculated as follows:

$$TPC = \sum_t\sum_k pm_k.M1_{k,t} + \sum_t\sum_i r_{i,t}. \tag{22}$$

The company also has manufacturing costs. The company manufactures new components, assembles products, disassembles EOL products, and remanufactures recovered components. The total manufacture cost (TMC) is calculated as follows:

$$TMC = \sum_t\sum_j m_j.X_{j,t} + \sum_t a.(Z_t + F_t) + \sum_t d.Q_t + \sum_t\sum_i\sum_j cn_j.rem_{i,j,t}.f_{i,j,t}. \tag{23}$$

The products and the components are stored. The total storage cost (TSC) is calculated as follows:

$$TSC = \sum_t sp.PS_t + \sum_t\sum_j sc_j.\left(CS_{j,t} + UC_{j,t}\right). \tag{24}$$

The implementation of DIOTs has a cost between its manufacturing and data processing. This cost is proportional to the fraction of products that have a DIOT. The total cost of implementing DIOTs is:

$$TIC = \sum_t I_t.ic.df. \tag{25}$$

4.2.3 Total profit and gross profit ratio

The objective of the model is to maximize total profit (TP):

$$Max\ TP = (TRS + TRR) - (TPC + TMC + TSC + TIC). \tag{26}$$

The calculation of the total profit would allow the calculation of the gross profit ratio (GPR) by dividing it by the total revenue. This indicator is often used in the industry to measure the financial health of a company, especially in the production of a single product [59]. In our study, the GPR is a useful performance indicator because we consider the costs of raw materials and processes used to manufacture the product and we do not consider the taxes and other fixed costs. The GPR is calculated according to Eq. (27). In this study, since the total revenue is fixed by demand, the evolution of the total profit is representative for the supply chain's efficiency.

$$GPR = \frac{TP}{TR}. \tag{27}$$

4.3 Constraints

For each period t, the numbers of remanufactured products sent to the S&C center cannot exceed the S&C demand:

$$V_t \le dm_t, \forall t. \tag{28}$$

For each period t, the numbers of remanufactured products and components j (new or used) leaving the inventory are equal to the difference between the amounts arriving in stocks and the amount in stock in the previous period, and the amount in stock may not exceed the maximum stock capacity and must not be negative:

$$stock_t = stock_{t-1} + enter\,flow_t - outgoing\,flow_t, \forall t \quad (29)$$

$$0 \leq stock_t \leq maximum\ stock, \forall t. \quad (30)$$

For each period t, the amount of raw material k required to manufacture the components is calculated as follows:

$$M1_{k,t} - \sum_j X_{j,t}.n_{j,k} = 0, \forall (t,k). \quad (31)$$

The amount of raw material k recycled from products in period t is calculated as follows:

$$RPM1_{k,t} - rp_k.P_t.\sum_j cn_j.n_{j,k} = 0, \forall (t,k). \quad (32)$$

The amount of raw material k recycled from components in period t is calculated as follows:

$$RCM1_{k,t} - \sum_j C_{j,t}.rc_{j,k}.n_{j,k} = 0, \forall (t,k). \quad (33)$$

For each period t, the amount of components j arriving at the remanufacturing process is equal to the amount leaving it:

$$Rfc_{j,t} - D_{j,t} = 0, \forall (j,t). \quad (34)$$

If the number of recovered used components is not sufficient to manufacture the products with used components, new components can be added. Hence, the amount of component j to assemble the products with used components at period t is given by:

$$H_{j,t} + N_{j,t} - Z_t.rc_j = 0, \forall (t,j). \quad (35)$$

The amount of new raw material k entering the supply chain in period t to satisfy the different demands of the S&C center is:

$$M1_{k,t} - \left(NM1_{k,t} + RPM1_{k,t} + RCM1_{k,t}\right) = 0, \forall (t,k). \quad (36)$$

4.4 Integration of DIOTs in the supply chain: two use cases

DIOTs can be integrated into the supply chain in different ways. We will consider two distinct cases. In the first case, the manufacturer does not install devices on all products, which prevents the selection of products to be recovered precisely. In the second case, on the contrary, all products have a DIOT, which allows a more precise selection.

4.4.1 Partial implementation of DIOT: optimal selection is not possible

First, it is assumed that not all products have a DIOT. Therefore a certain number of EOL products will be selected randomly among the available EOL products according to the general state of degradation of the products, i.e., the probability distribution followed by the $diot_{i,j,t}$. The optimal recovery potential of EOL products is then not exploited, and an inspection step is required for products without devices. This case is illustrated in Fig. 7. In the partial implementation case, a fraction of products with a DIOT $df = 0.5$ is considered.

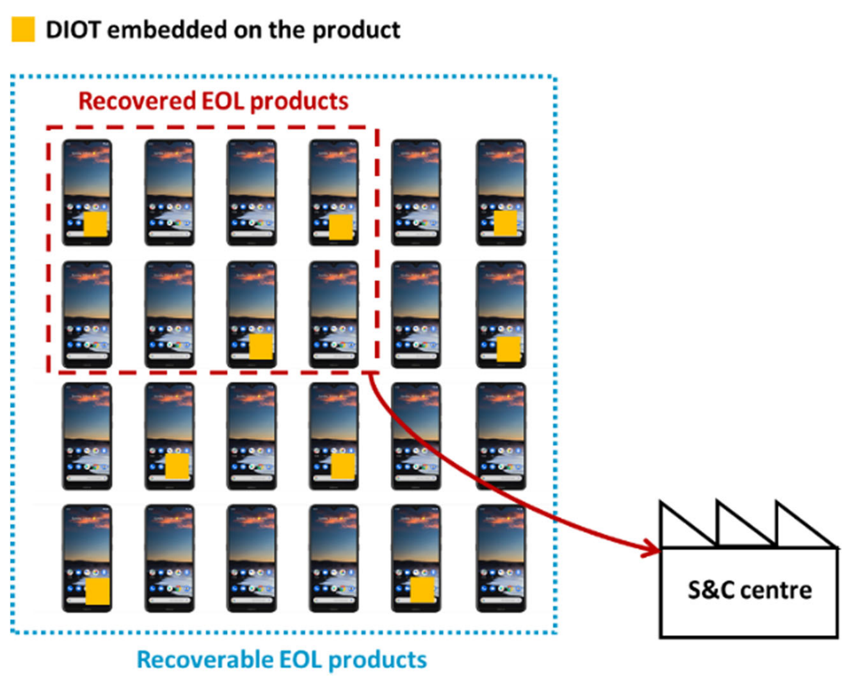


Fig. 7 Partial implementation: some of the EOL products have a DIOT

4.4.2 Full implementation of DIOT: Optimal selection is possible

The objective is to further optimize the product recovery because this is one of the main constraints of circular manufacturing. Knowing the condition of all recoverable products with an assigned DIOT, the best selection of products could be chosen to meet the demands, avoiding EOL products purchased too expensively, or those with components too expensive to remanufacture. Consequently, it is considered that not all available end-of-life products are necessarily purchased from the S&C center. This case is illustrated in Fig. 8.

The model must be adjusted to achieve this goal. Consequently, we define the binary variable $nus_{n,\ i,\ t}$, which indicates whether the product is purchased or not:

$$nus_{i,t} = \begin{cases} 1 \text{ if the EOL product is not purchased by the company} \\ 0 \ otherwise \end{cases} \tag{37}$$

Eq. (9) becomes:

$$dis_{i,t} + rec_{i,t} + was_{i,t} + nus_{i,t} = 1, \forall(t,i). \tag{38}$$

The total purchase cost TPC in Eq. (22) then becomes:

$$TPC = \sum_t \sum_k pm_k.M1_{k,t} + \sum_t \sum_i \left(1 - nus_{i,t}\right).r_{i,t}. \tag{39}$$

In the full DIOT implementation case, the fraction of products with a DIOT is $df = 1$.

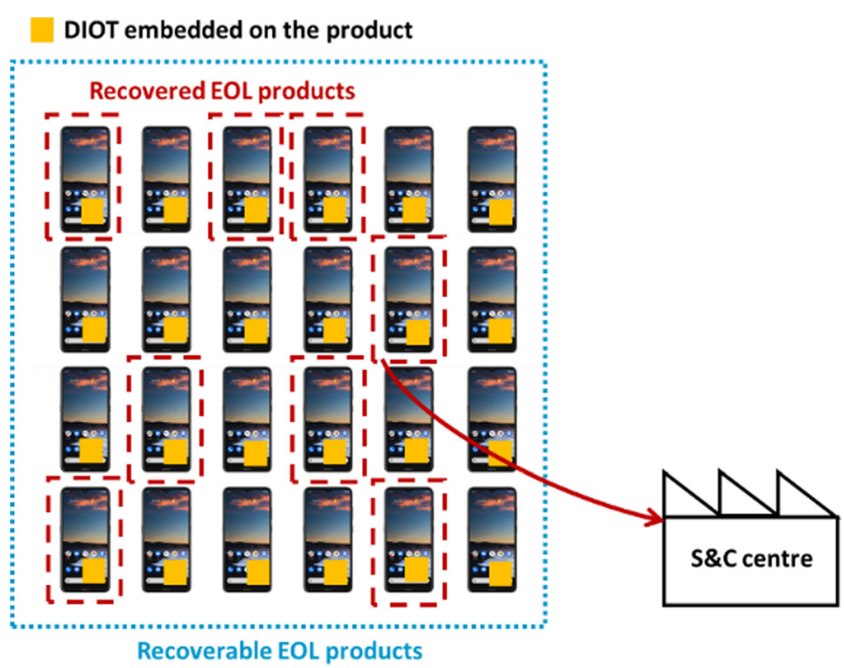


Fig. 8 Full implementation: every EOL product has a DIOT

5 Case study: Fairphone

We will now apply the developed MIQP model to a real product – a smartphone – to validate the model, to observe its behavior, and to evaluate the benefits for an industrial company. Fairphone is a Dutch company that designs and manufactures modular smartphones that are commercially fair and that are more environmentally friendly compared to other commercial smartphones [60]. Fairphone aims to further develop the circularity of its products and is already offering to buy back EOL smartphones to recycle their present raw materials. However, Fairphone buys EOL smartphones at fixed prices, regardless of their condition, and has little regard for the reuse and remanufacturing of these products. The proposed and developed case study illustrates the potential economic advantages for a company manufacturing an electronic device in large quantities and aiming to implement the proposed CLSC. In addition, this case study concerns smartphones, an electronic device whose integration into CE is currently promoted [61]. In this study, we consider the smartphone model "Fairphone 2", which can be decomposed into 10 main components (J = 10) [62]. Each component is composed of subcomponents that will not be considered individually: their manufacture and assembly will be included in the manufacturing cost of the main components. These components are outlined in Table 4, and Fig. 9 gives an overview of the components and its location at the "Fairphone 2" smartphone [63].

5.1 Numerical data

The total cost of the Fairphone 2, existing of manufacturing costs, assembly costs, taxes, sales price to dealers,

Table 4 Fairphone 2 components list

j = 1	Back cover	*j = 6*	Metal shielding plate
j = 2	Battery	*j = 7*	Top module
j = 3	Display module	*j = 8*	Core module
j = 4	Bottom module	*j = 9*	Heat dissipator
j = 5	Camera module	*j = 10*	Antenna cable

investments, and administrative operation of Fairphone, is detailed in open access literature [61]. The sales prices of the components are also known. In the data provided by Fairphone, transport and storage costs are included in the manufacturing costs. These product and component data are given in Table 5 and 6 (see Tables 2 and 3 for the formulated problem parameters and variables definitions).

The data provided by Fairphone is freely accessible and enables to estimate the numbers of raw materials in each component [60]. While the composition is not fully known, main unknowns are in the quantities of plastics that have a

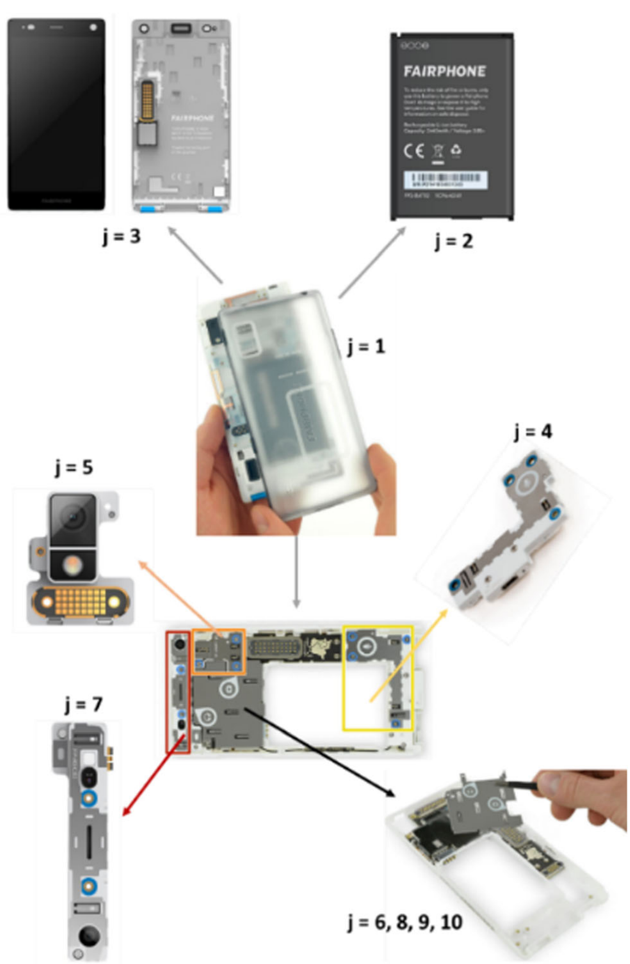


Fig. 9 Fairphone 2 disassembly components [61]

Table 5 Fairphone 2 parameters

a	*d*	*h1*	*spc*	*ic*	*ni1*	*ni2*	*nj1*	*nj2*	*nj3*
2.2	2.2	244.2	35	6	0	3	0	3	8

negligible cost compared to the costs of rare metals and will therefore not be considered in this study. We consider 27 raw materials (i.e., $K = 27$) in the Fairphone 2, which are detailed in Table 7. Detailed data for these raw materials, such as the quantity of raw material (k) in each component (j), proportion of raw material (k) recovered from the recycling of a component (rck) and a product (rpk), and purchase price (in €/g and €/mg) of raw material k (pmk), are available in the Appendix (see Supplementary Material).

5.2 DIOT modeling

In this case study, the $diot_{i,\,j,\,t}$ is randomly assigned following laws of probability for each component. There are no actual studies providing accurate data on product degradation. Therefore, we hypothesize that the degradation follows a normal distribution, since this is most commonly used in relevant literature to model product degradation [63, 64]. We denote $diot_{i,\,j,\,t\;PROB}$ as the value randomly assigned according to this law. The probability distribution is the probability that a component is at the degradation level indicated by the $diot_{i,\,j,\,t}$ at the time of recovery (see Fig. 10).

Components that are more susceptible to degradation, because they are more exposed to the external environment or because of a more fragile design and/or behavior and consequently recovered in worse conditions, have on an average $diot_{i,\,j,\,t\;PROB}$ lower values and a larger standard deviation.

$$diot_{i,j,t\;PROB} \hookrightarrow \mathcal{N}(\mu, \sigma) \tag{37}$$

The battery cannot be remanufactured or reused; therefore, it is always recycled. For this reason, we fix $diot_{i,\,j,\,t} = 2.5$ for all recovered batteries. Details of the means (μ) and standard deviations (σ) of the $diot_{i,\,j,\,t\;PROB}$ values of each component are presented in Table 8, and some key components (slim case, screen, antenna) are presented in Fig. 10.

The following convention for values of $diot_{i,\,j,\,t\;PROB}$ which are not in the interval [0,10] in the random assignment is presented by Eq. (40):

$$diot_{i,j,t} = \begin{cases} 0.1 \; if \; diot_{i,j,t\;PROB} < 0 \\ 10 \;\; if \; diot_{i,j,t\;PROB} > 10 \\ diot_{i,j,t\;PROB} \; otherwise \end{cases} \tag{40}$$

Table 6 Fairphone 2 parameters

	j=1	*j=2*	*j=3*	*j=4*	*j=5*	*j=6*	*j=7*	*j=8*	*j=9*	*j=10*
cnj	1	1	1	1	1	1	1	1	1	1
mj	17.5	14	60.9	21	31.5	2.1	17.5	63	2.1	2.1
cwj	0.075	0	0.258	0.082	0.137	0.017	0.096	0.299	0.017	0.017
sccj	1.75	1.4	6.09	2.1	3.15	0.21	1.75	6.3	0.21	0.21

Table 7 Raw materials considered in the Fairphone 2

k=1	Nickel	*k=15*	Lithium cobalt oxide
k=2	Gold	*k=16*	Graphite
k=3	Silver	*k=17*	Lithium hexafluorophosphate
k=4	Copper	*k=18*	Aluminum
k=5	Zinc	*k=19*	Glass substrate
k=6	Silicon	*k=20*	Tungsten
k=7	Phosphorus	*k=21*	Neodymium
k=8	Liquid cristal polymer	*k=22*	Palladium
k=9	Manganese	*k=23*	Praseodymium
k=10	Polycarbonate	*k=24*	Tantalum
k=11	Glass fibers	*k=25*	Tin
k=12	Polyamide 6.6	*k=26*	Steel
k=13	Brass	*k=27*	Indium
k=14	Thermoplastic polyurethane		

5.3 Product return parameters for the base case

The acceptable remanufacturing cost for components is not documented. In a first step, we will fix the coefficient *rf* with the help of the literature. For the remanufacturing cost, the cost can vary between the cost of manufacturing a new component and zero cost [64], so the average value $rf = 0.5$ is chosen. The behavior of this supply chain confronted with a typical demand profile for remanufactured products is studied. Based on the research of Guide and Van Wassenhove [65], we propose the profile of demand and recoverable EOL products over $T = 12$ periods as illustrated in Fig. 11.

6 Analysis

To obtain the average response of the model with the reference parameters, we generate sets of $diot_{i,j,t}$ and solve the model

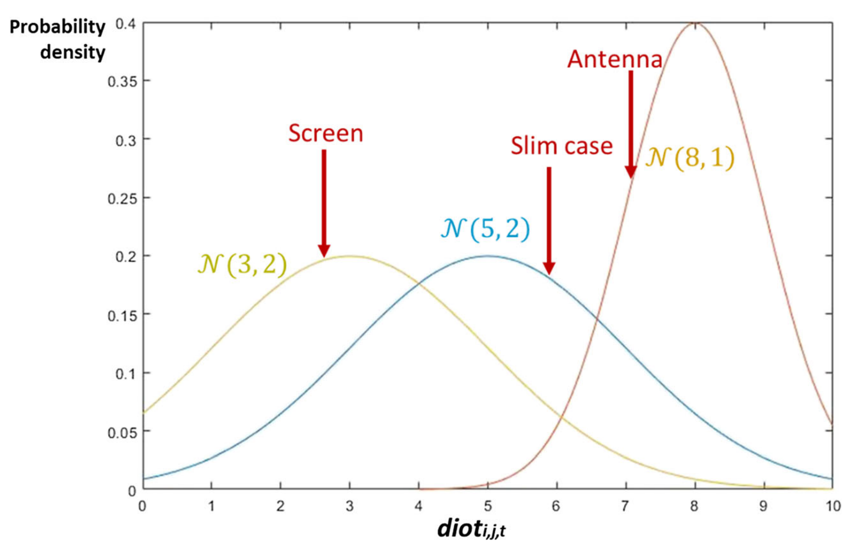


Fig. 10 Example of $diot_{i,j,t}$ distribution for the screen, the slim case, and the antenna of the modular smartphone

Table 8 Component $diot_{i,\,j,\,t\ PROB}$values

Component		$diot_{i,\,j,\,t\ PROB}$ μ	σ
Slim case	$j = 1$	5	2
Display module	$j = 3$	3	2
Bottom module	$j = 4$	5	2
Camera module	$j = 5$	4	2
Metal shielding plate	$j = 6$	8	1
Top module	$j = 7$	5	2
Motherboard	$j = 8$	5	2
Heat dissipator	$j = 9$	8	1
Antenna	$j = 10$	8	1

with LINGO 16.0. The LINGO solver was run on an Intel core 2.26 GHz processor with 16 GB of RAM.

6.1 Partial implementation

When the recovered EOL products are randomly selected, the different product flows and components for the periods $t = 1$, 2, and 3 are given in Table 9 and 10. The total number of variables is 54,245, and the total number of constraints is 5237. The optimal solution is obtained in 30.64 s. It can be seen that all available EOL products are purchased.

A solution to optimally manage our supply chain return loop is obtained. The generated profit is $TP = 68{,}435.91$ €, and the gross profit ratio is $GPR = 29.8\%$.

6.2 Full implementation

In the case where the recovered EOL products are selected according to their individual degradation states, the different product streams are given in Table 11 and 12. The total number of variables is 68,645, and the total number of constraints is 5238. The optimal solution is obtained in 198.96 s. It can be seen that not all available products are purchased. No product is recycled prior to disassembly, so the model estimates that purchasing a product whose state of degradation is so advanced that it does not need to be disassembled to recover its components is not economically viable.

A solution to optimally manage our supply chain return loop is obtained. The generated profit is $TP = 70{,}769.11$€, and the gross profit ratio is $GPR = 30.8\%$.

7 Sensitivity analysis

A sensitivity analysis has been performed to observe the model's behavior when faced with the variation of parameters that are unknown in the current Fairphone supply chain. These parameters are related to the reverse loop, and in particular, two parameters are notable: the remanufacturing cost and the remanufactured product demand.

7.1 Remanufacturing cost

The remanufacturing cost being the principal unknown among the supply chain parameters, we vary rf to observe the profit generated for these different values as well as the additional profit that DIOT implementation would generate on all products.

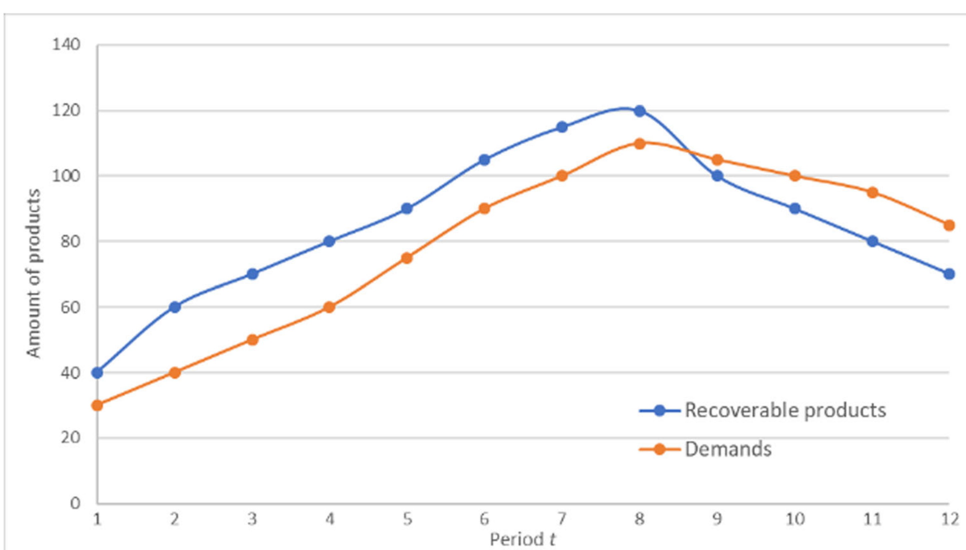


Fig. 11 Profile of the demands in the different periods

Table 9 Values of product-related decision variables for the reference case with partial implementation

t	*It*	*Rt*	*Pt*	*Qt*	*Zt*	*Vt*	*PSt*
1	40	40	3	37	30	30	0
2	60	60	8	52	40	40	0
3	70	70	5	65	50	50	0
4	80	80	8	72	60	60	0
5	90	90	7	83	75	75	0
6	105	105	13	92	90	90	0
7	115	115	10	105	100	100	0
8	120	120	6	114	110	110	0
9	100	100	8	92	105	105	0
10	90	90	7	83	100	100	0
11	80	80	6	74	95	95	0
12	70	70	2	68	85	85	0

Table 10 Values of component-related decision variables for the reference case with partial implementation

t	*Xjt*	*Njt*	*Djt*	*R1jt*	*Rfcjt*	*Cjt*	*CSjt*
t **=1**	1	29	22	7	22	8	0
	30	0	0	0	0	37	0
	16	14	10	4	10	23	0
	0	30	25	5	25	7	0
	7	23	19	4	19	14	0
	0	30	20	17	20	0	7
	1	29	29	0	29	8	0
	0	30	28	6	28	3	4
	0	30	19	17	19	1	6
	0	30	21	16	21	0	7
t **=2**	7	33	17	16	17	19	0
	40	0	0	0	0	52	0
	12	28	24	4	24	24	0
	0	40	42	4	42	6	6
	11	29	23	6	23	23	0
	0	40	23	27	23	2	17
	0	40	42	3	42	7	5
	0	40	44	2	44	6	10
	0	40	20	32	20	0	18
	0	40	18	34	18	0	19
t **=3**	0	50	38	17	38	10	5
	50	0	0	0	0	65	0
	11	39	30	9	30	26	0
	0	50	47	2	47	16	5
	7	43	38	5	38	22	0
	0	50	39	26	39	0	32
	0	50	47	5	47	13	7
	0	50	55	4	55	6	19
	0	50	29	36	29	0	33
	0	50	32	33	32	0	34

Table 11 Values of product-related decision variables for the reference case with full implementation

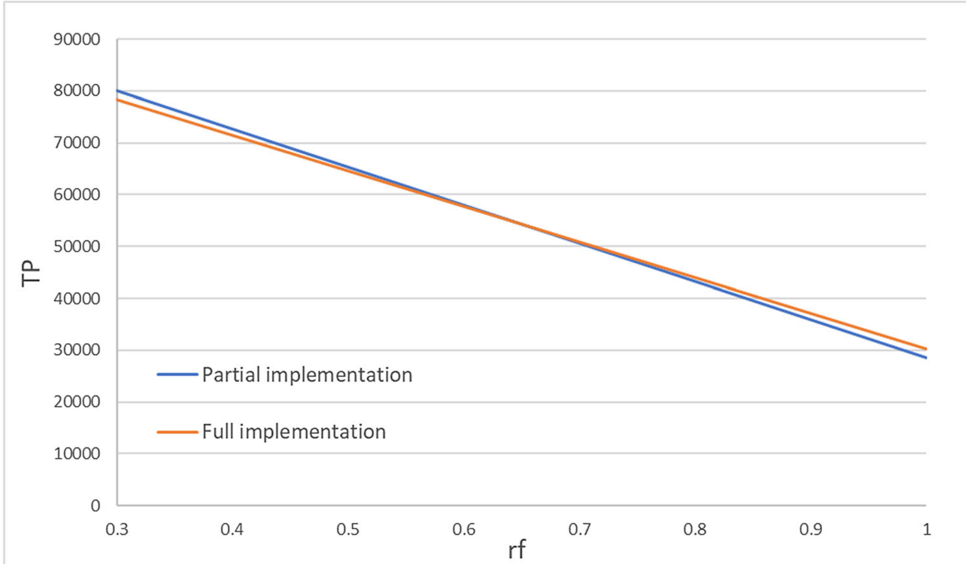
t	*It*	*Rt*	*Pt*	*Qt*	*Zt*	*Vt*	*PSt*
1	40	34	0	34	30	30	0
2	60	50	0	50	40	40	0
3	70	64	0	64	50	50	0
4	80	71	0	71	60	60	0
5	90	83	0	83	75	75	0
6	105	92	0	92	90	90	0
7	115	105	0	105	100	100	0
8	120	114	0	114	110	110	0
9	100	92	0	92	105	105	0
10	90	83	0	83	100	100	0
11	80	74	0	74	95	95	0
12	70	68	0	68	85	85	0

The generated profit increases with lower remanufacturing costs, which is an expected behavior as illustrated in Fig. 12. In Fig. 13, we observe that the integration of a DIOT system on all products would be more relevant on devices with high remanufacturing costs. Indeed, the benefit would be 5.3% higher in the case of a total selection of products at the end of their life. Conversely, when $rf \leq 0.66$, a partial

Table 12 Values of component-related decision variables for the reference case with full implementation for the periods $t = 1$ and 2

t	*Xjt*	*Njt*	*Djt*	*R1jt*	*Rfcjt*	*Cjt*	*CSjt*
t **=1**	3	27	21	6	21	7	0
	30	0	0	0	0	34	0
	17	13	10	3	10	21	0
	3	27	22	5	22	7	0
	8	22	18	4	18	12	0
	0	30	18	16	18	0	4
	2	28	28	0	28	6	0
	0	30	27	4	27	3	1
	0	30	18	15	18	1	3
	0	30	19	15	19	0	4
t **=2**	9	31	17	14	17	19	0
	40	0	0	0	0	50	0
	14	26	24	2	24	24	0
	0	40	41	3	41	6	4
	12	28	22	6	22	22	0
	0	40	23	25	23	2	12
	0	40	40	3	40	7	3
	0	40	42	2	42	6	5
	0	40	20	30	20	0	13
	0	40	17	33	17	0	14

Fig. 12 *TP* evolution according to *rf* for full and partial implementation of DIOTs on EOL products



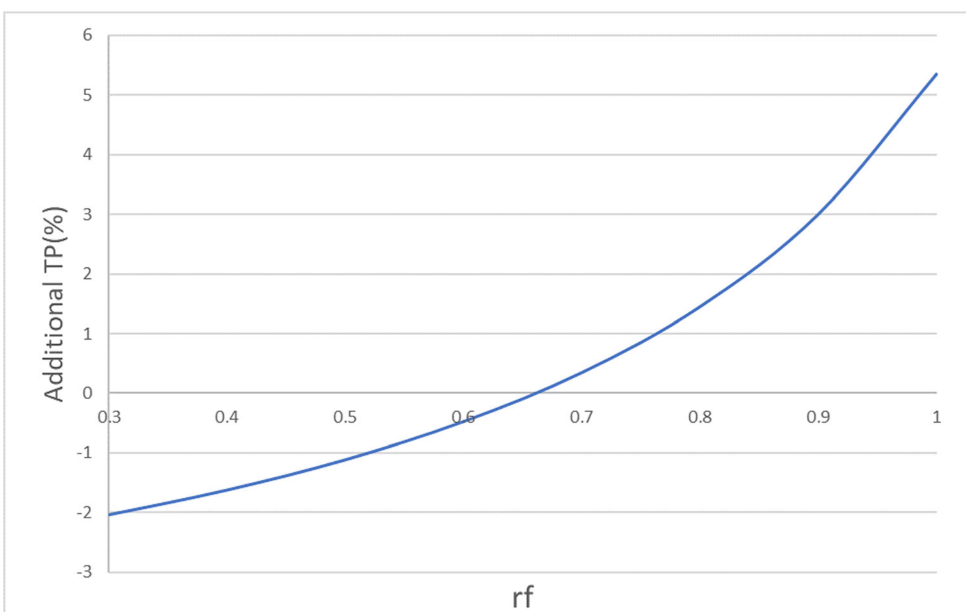
implementation of DIOTs would be more profitable than a full implementation.

7.2 Remanufactured product demand

The other parameter with significant uncertainties is the demand for remanufactured product in relation to the number of recoverable products. Demand is therefore varied to keep the same recoverable products by adding or removing the same quantity in each period compared to the base case in Table 9. The case of a demand variation of − 10 is shown in Fig. 14.

The generated profit will increase with the increase in demand. In fact, it is possible to increase profit by supplementing remanufactured products with new components. However, the greater the demand, the newer components are needed to meet it. Therefore, for a fixed quantity of recoverable products, the increase in profit tends to slow down from a certain demand because these new components are more expensive to manufacture. For lower demands, i.e., demands where the number of recoverable products is much greater than the demand for recovered product, it can be seen that a DIOT installation on all products would allow for greater profits as shown in Fig. 15, since it would be possible to optimally choose products whose components can be reused or remanufactured for remanufactured products. Therefore, the additional profit generated by selecting EOL products can be up to 49% higher

Fig. 13 Additional profit created by the full implementation of DIOTs products according to *rf*



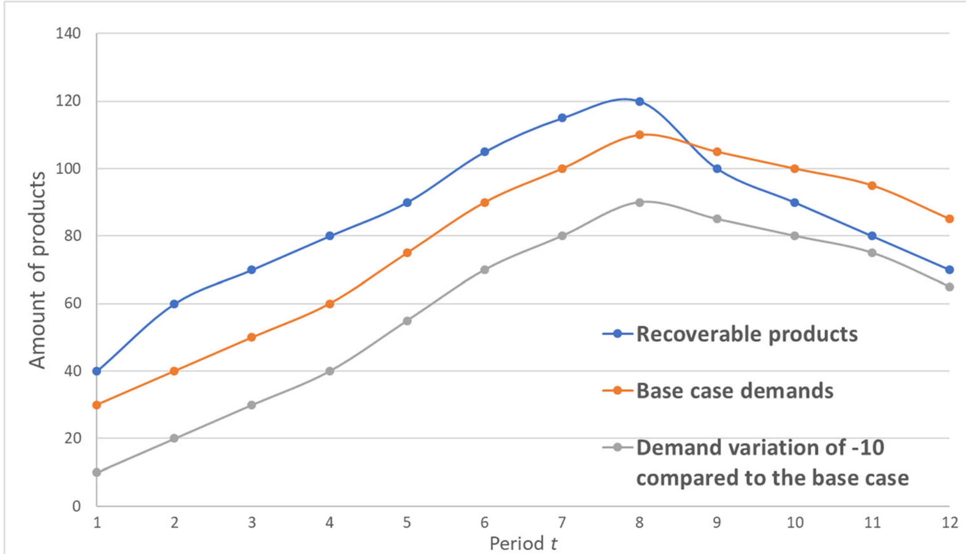


Fig. 14 Uniform demand change of −10 compared to base case (i.e., reference case) demand. The number of recoverable products remains fixed

than without selection in cases where the demand is much lower than the demand for remanufactured products as shown in Fig. 16. Otherwise, a partial implementation of DIOTs on products would be more interesting in terms of profit.

8 Managerial insights

This study presented a solution for a CLSC problem using intelligent technologies (e.g., IoT), and it calculated the difference in profit generated by a complete or partial implementation of DIOTs on products. When setting up a CLSC, an execution of this policy in the form of a decision tool is proposed to facilitate the manager's task. Figure 13 and 16 are used in the execution of our CLSC design policy. Figure 17 shows a flowchart for controlling the execution of the decisions that need to be made by the manager.

With the parameter values given in Sections 5.1 and 5.2 and for rf = 0.5, Fig. 16 shows that it is very advantageous to have a full implementation when the demand for remanufactured products is less than the number of recoverable products, specifically for demands less than the demand variation − 10 case compared to the base case. This decision-making process is illustrated in Fig. 17a.

Using the parameter values given in Sections 5.1 and 5.2 and for the base case demand, Fig. 13 shows that full implementation of DIOTs on products is more cost-effective when remanufacturing costs are high, starting at rf = 0.66. This decision-making process is illustrated in Fig. 17b.

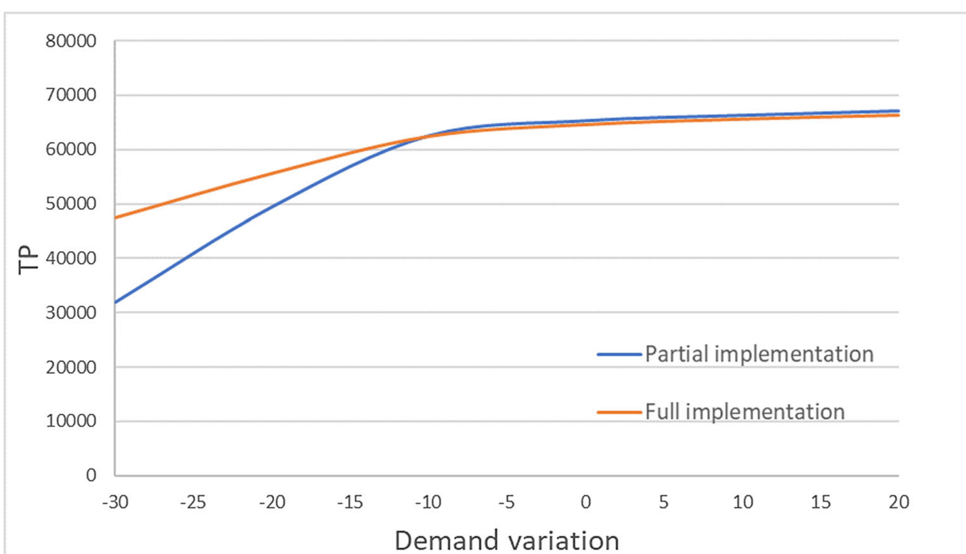


Fig. 15 *TP* evolution according to the demand variation for full and partial implementation of DIOTs on EOL products

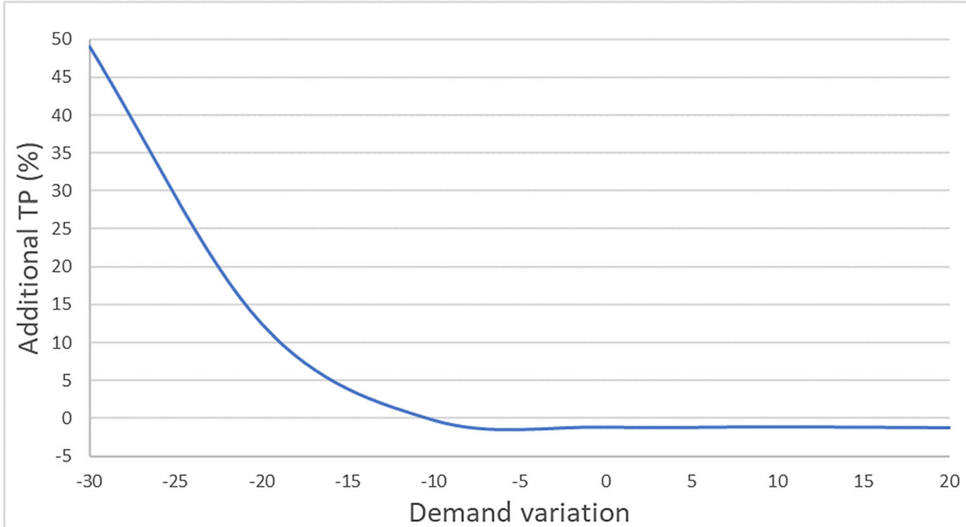


Fig. 16 Additional profit created by the full implementation of DIOTs according to the demand variation

9 Conclusion

This paper proposes a new mixed integer quadratic programming model for a closed-loop supply chain based on the prediction of the degradation state of EOL products. A review of the literature has highlighted the need for further research to propose tools for decision-making in the field of CLSCs, which are controlled using IoT and illustrated by real-world case studies. In this work, supply chain management was done in order to maximize the profit generated by the manufacturing company. A solution was developed in linear programming to solve the model, which is obtained within a reasonable time frame for a real product case. The choice of optimal recovery treatments for EOL products and components to meet a demand for remanufactured products is obtained. The implementation of an IoT device, called DIOT, to predict the state of degradation and to obtain digital twins of the products would also allow a better selection of recoverable EOL products and increase the profit.

A numerical case study was conducted using a modular smartphone (Fairphone) as an example. Different use cases were studied, considering implementation of the IoT devices (DIOT) on every product or their implementation on only a part of them. In the case of full implementation, the gains would be almost 49% higher if the quantity of recoverable EOL products is higher than the demand compared to partial implementation. These gains are also 5.3% higher in the full implementation case when remanufacturing costs are high.

An analysis of the results helps to manage the device implementation policy according to remanufacturing costs and the demand for remanufactured products. For certain threshold values, managers can decide whether it is profitable to

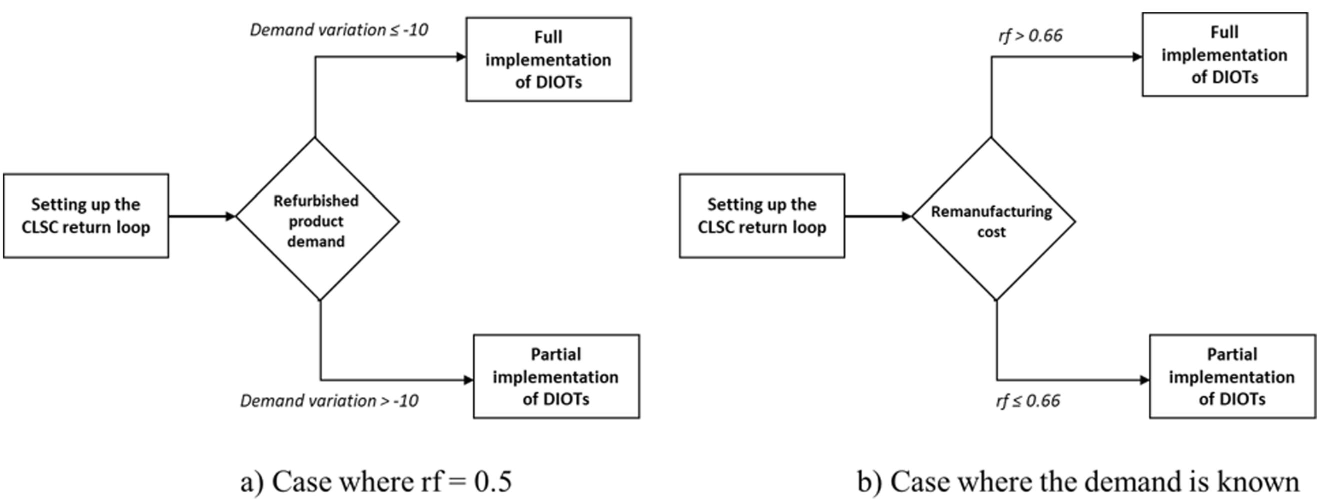


Fig. 17 Execution of the CLSC design policy: (**a**) case where the cost of remanufacturing is known; (**b**) case where the demand for reconditioned products is known

establish a partial or full implementation of DIOTs. A flowchart was presented to guide managerial decisions on execution of the optimal CLSC design policy.

Future research should focus on the method of predicting the state of degradation of EOL products and estimating more precisely the economic and environmental costs generated by IoT devices implanted in the products. In addition, the application of the model from this study for several products to complex assembly could be considered as an interesting direction for future studies.

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Code availability. Developed code related to this work will be provided upon request.

Author contributions Victor Delpla: Writing-Original Draft, Conceptualization, Methodology, Software, Investigation.

Jean-Pierre Kenné: Supervision, Writing-Review and Editing, Conceptualization, Methodology, Funding acquisition.

Lucas A. Hof: Supervision, Writing-Review and Editing, Conceptualization, Methodology, Project administration, Funding acquisition.

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Data availability Data related to this work will be provided upon request.

Declarations

Conflict of interest The authors declare no competing interests.

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