Modelling and multi-objective optimization of closed loop supply chains: a case study

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Abstract: This study investigates the issue of optimizing the asset management process in a real closed-loop supply chain (CLSC), consisting of a pallet provider, a manufacturer and 7 retailers. A detailed simulation model, based on an adapted economic order quantity (EOQ) policy is developed under Microsoft ExcelTM to reproduce the reorder process of assets by the manufacturer and the corresponding flow of returnable transport items (RTIs) in the CLSC. A multi-objective optimization, including both economic and strategic key performance indicators of the system, is then carried out exploiting the commercial software ModeFRONTIERTM. The optimization investigates three scenarios, which refer to as many operating conditions of the manufacturer. Scenario 1 basically reproduces the current operating conditions of the manufacturer, while scenarios 2 and 3 are both hypothetical, and describe situations where the manufacturer would like to minimize the purchase of new assets and the pick-up of assets from its customers, respectively. For each scenario, the optimal configuration (i.e., the setting of the asset management process that performs best in the multi-objective optimization) is identified. Scenarios 1 and 3 are found to generate the most interesting performance of the assets management process, from both the economic and strategic perspectives. Because the present paper is grounded on a real CLSC, the results are expected to be useful to logistics and supply chain managers, to support the evaluation of the performance of CLSCs.

***Cover Letter**

The Editor of Computer and Industrial Engineering

Prof. Mohamed Dessouky
Department of Industrial and Systems Engineering, University of Southern California, 3715 McClintock Avenue, Los Angeles, CA 90089-0193, California, USA

Parma, Wednesday, 29 April 2015

Dear Editor,

please find enclosed an electronic copy of our revised manuscript:

Paper title: Modelling and multi-objective optimization of closed loop supply chains: a case study

Authors: Eleonora Bottani, Roberto Montanari, Marta Rinaldi, Giuseppe Vignali

which we send You for possible consideration on *Computers & Industrial Engineering*.

The paper has been amended according to the reviewer's requests and we hope that it will now be suitable for publication.
We confirm that this paper:

- is your own original work, and does not duplicate any other previously published work, including our own previously published work;
- is not currently under consideration or peer review or accepted for publication or in press or published elsewhere;
- does not contain anything abusive, defamatory, libellous, obscene, fraudulent, or illegal.

We wish to take this opportunity to send to You our best regards and we look forward to hearing from You soon.

Yours sincerely,
The authors

*Title Page including Author Details

Modelling and multi-objective optimization of closed loop supply chains: a case study

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Highlights

- The optimization of the asset management process in a closed-loop supply chain is investigated
- A simulation model, based on an adapted EOQ policy, is developed to reproduce the assets flow
- A multi-objective optimization, including both cost and strategic KPIs, is carried out on the CLSC
- The optimal configuration of the asset management process is identified for each scenario simulated

***Detailed Response to Reviewers**

Paper title: Modelling and multi-objective optimization of closed loop supply chains: a case study

Submitted for publication to: *Computers & Industrial Engineering*

Note to the reviewer

Dear reviewer,
many thanks for your time and care in reviewing our manuscript. We have considered your comments in amending the paper. Parts of the paper that have been modified (either in response to your comments or as our corrections) are blue highlighted. A note on how we have addressed your comments is provided below.

<u>Reviewer's #1 comments:</u>

1. This paper considers the efficient treatment of returnable transport items (RTIs) and shows how to optimize the RTIs management in CLSC. In section 1 Introduction, the background and necessities of this study are well introduced. Especially, the related-conventional studies are well analyzed. In section 2 "The context", the pallet management process and criticalities of the current process are carefully explained. In section 3 "Modelling framework", decision process and key performance indicators (KPIs) by using real company A are systematically explained in detail. These decision processes and KPIs are used in simulation model in section 4. In simulation, three scenarios are considered and their simulation results in multi-objective optimization are carefully analyzed. In the whole contents, this paper is well established and shows a contribution to the researchers who study the CLSC. Although some data used in simulation are randomly generated, this paper considers a real CLSC, and as mentioned in conclusion, this paper can be applied to different CLSCs. Finally, reviewer thinks that this paper can be published in this journal without any revision.

   <u>Our reply</u>: Many thanks for your positive comments about our paper.

2. However, the author may consider justifying why only 3 scenarios were simulated and the use of the data generated.

   <u>Our reply</u>: thank you for this remark. It is obvious that the multi-objective optimization could be carried out with a variety of scenarios. We have decided to analyze three scenarios that could be of greatest interest for Company A, because of their likelihood of being applied in the near future. In the revised paper we have added some more explanations about the scenarios simulated, see paragraph "*The analysis was focused on those scenarios [...] against returning operation*" (section 4.2). With respect to the number of scenarios considered, you can see from the correlation analysis that almost all outcomes of the model correlate to each other. This means their trends are related, as well. Indeed, our initial idea was to analyze 5 scenarios, three of which reflect those presented in the paper, while the remaining two had different setting of the KPIs to optimize. However, because of the correlation among KPIs, we found that the results of scenario 2 and 4 were almost the same, and that the same happened for scenarios 3 and 5. Therefore, we limited the analysis to three scenarios. Nonetheless, we think that this argument could be valid in general: because the performance parameters and the input variables are strictly correlated, it is likely that, even if we analyze more scenarios, results partially overlap with those presented in the paper. We added a note to this point in the paper.
   We also acknowledge that numerous results are generated by the simulations; therefore, we have tried to discuss in greater detail the usefulness of those results. To this extent, we have added a paragraph in section 5 ("*The results provided aim at identifying the existence of relationships between the reorder policy parameters and the model outputs. Because those relationships cannot be immediately evident from the model description in section 3, outcomes are substantiated by a correlation analysis, whose detailed results are reported in Appendix*"). A mention to those points has also been added in the Conclusions.
   We hope that this satisfies your request.

Modelling and multi-objective optimization of closed loop supply chains: a case study

Abstract

This study investigates the issue of optimizing the asset management process in a real closed-loop supply chain (CLSC), consisting of a pallet provider, a manufacturer and 7 retailers. A detailed simulation model, based on an adapted economic order quantity (EOQ) policy is developed under Microsoft Excel™ to reproduce the reorder process of assets by the manufacturer and the corresponding flow of returnable transport items (RTIs) in the CLSC. A multi-objective optimization, including both economic and strategic key performance indicators of the system, is then carried out exploiting the commercial software ModeFRONTIER™. The optimization investigates three scenarios, which refer to as many operating conditions of the manufacturer. Scenario 1 basically reproduces the current operating conditions of the manufacturer, while scenarios 2 and 3 are both hypothetical, and describe situations where the manufacturer would like to minimize the purchase of new assets and the pick-up of assets from its customers, respectively. For each scenario, the optimal configuration (i.e., the setting of the asset management process that performs best in the multi-objective optimization) is identified. Scenarios 1 and 3 are found to generate the most interesting performance of the assets management process, from both the economic and strategic perspectives. Because the present paper is grounded on a real CLSC, the results are expected to be useful to logistics and supply chain managers, to support the evaluation of the performance of CLSCs.

Keywords: closed-loop supply chain (CLSC); returnable transport items (RTIs); simulation model; multi-objective optimization; case study.

1 Introduction

Closed-loop supply chains (CLSCs) focus on managing the returns of items (i.e., product and assets) from customers and recovering added value by reusing them entirely and/or in some of their modules, components and parts (Guide and Van Wassenhove, 2009). Returns of items in a supply chain can occur for a number of reasons. Following a product life-cycle perspective, Dekker et al. (2004) and Flapper et al. (2005) suggest the returns to be classified into production-, distribution-, use- and end-of-life-related. Looking at the production and distribution perspectives, commercial returns involve products that are returned by consumers to the vendor, within some days after the purchase (Tibben-Lembke, 2004). End-of-use returns occur when a functional product is replaced by a technological upgrade; hence, they are particularly frequent when the product becomes technically obsolete or no longer contains any utility for the current user (Guide and Van Wassenhove, 2009). Additionally, in production- and distribution-related returns, returnable transport items (RTIs) are used for internal transport of materials, components, semi-finished products and for the distribution of finished products. According to the European Commission (2007), RTIs are ‘means to assemble goods for transportation, storage, handling and product protection in the supply chain which are returned for further usage’. Among RTIs, pallets as well as all forms of reusable crates, totes, trays, boxes, roll pallets, roll cages, barrels, trolleys, pallet collars, racks, lids and refillable liquid or gas containers can be mentioned (ISO/IEC, 2007).

CLSCs have received increased attention in supply chain and operations management literature. The main reasons for the increased interest include the tightening of environmental regulations and the business opportunities related to the residual value of end-of-life products (Guide et al., 2003a). Indeed, with the awareness of the environmental protection increasing, reducing the use of materials, by reusing RTIs and remanufacturing the used products, is currently a critical issue for enterprises (Wang and Hsu, 2010). Moreover, besides the operational and ecological benefits, RTIs are recognised as means to help comply with waste regulation (Karkkainen et al., 2004). To achieve these benefits, however, there is the need for procedures that ensure efficient and loss-free flows of RTIs in the CLSC (Martìnez-Sala et al., 2009).

To this latter extent, there are basically two procedures to handle the flow of RTIs within a CLSC, namely: (i) direct or deferred exchange between supply chain partners and (ii) asset pooling. In (i), supply chain players own some RTIs, which are exchanged between all the actors of the chain. The exchange can be 'direct', meaning that assets are returned immediately and in the same quantity of those shipped, or 'deferred', if the return is completed at later time. Conversely, in (ii), a pool operator owns the RTIs and manages assets' deliveries and returns (Johansson and Hellstrom, 2007). The direct/deferred exchange is widely adopted by many companies, owing to its simplicity and ease of implementation; however, such procedure often suffers from several weaknesses, namely the difficulty of checking the quality of the assets exchanged or the need for numerous paper documents to keep track of the inbound/outbound flow of RTIs. On the other hand, one of the main advantages of pooling systems is the possibility to outsource the RTI management, thus allowing producers to focus on their core activities, e.g. production processes (Bottani et al., in press). Moreover, pooled RTIs can be reused and do not add to the amount of items to be recycled or destroyed. Nonetheless, to work correctly, pooling systems require fast and synchronised communications between partners (European Commission, 2007).

Many cost components are associated with the use of RTIs in a CLSC. Rosenau et al. (1996) provide a comprehensive list of those costs, which include, among others, packaging material, damages, inbound and outbound transportation, sorting, solid waste, tracking, labour, maintenance, ergonomics and safety. Moreover, a RTI fleet often represents a significant capital investment for a company. Estimates by Aberdeen Group (2004) indicate that companies can lose more than 10% of their RTIs fleet annually; this can generate a significant cost, considering the unitary cost of RTI (approx. 10 € for pallets up to thousands of € for containers). The considerations above suggest that RTIs are often of high value, vulnerable to thefts or misplacements, critical to production and distribution activities, and have a relevant impact on the environmental performance of a company; therefore, their management is particularly crucial (McKerrow, 1996; Twede, 1999; Witt, 2000).

There is a large body of literature related to the design of CLSC, either by means of simulation or by other optimization techniques. However, most of those studies focus on optimally balancing manufacturing and remanufacturing activities of items (see, e.g., Zhang et al. 2014, Georgiadis and Athanasiou, 2013, Alinovi et al. 2012, among recent works), including end-of-life considerations (Özkır and Baslıgil, 2013; Tanimizu and Shimizu, 2014; Kim et al. 2010). The focus of this paper, conversely, is on the optimal management of RTIs in CLSC. Literature related to this topic covers two main areas of interest. A first group of paper proposes the use of advanced ICT tools to track the flows of RTIs in the CLSC. For instance, Thoroe et al. (2009), Bottani and Bertolini (2009) and Martìnez-Sala et al. (2009) discussed the use of radio-frequency identification (RFID) technology to track different kinds of RTIs, such as pallets or containers. A second group of studies proposes decision support models for the cost-effective and efficient design of RTIs system. Since the present study focuses on optimizing the cost of assets management in a CLSC, we have paid particular attention to this second group of works. Among them, Mollenkopf et al. (2005) proposed a model to compare the relative cost of an expendable container system to the cost of a reusable one, with the purpose of assessing the viability of implementing a reusable container system in a reference scenario. Kroon and Vrijens (1995) presented a model for the placement and set-up of a logistics depot system. Kelle and Silver (1989) considered the forecasting of returns of reusable containers and formulated a model for purchasing quantities of new containers in a returnable network. Choong et al. (2002) and Di Francesco et al. (2009) proposed models for repositioning of empty containers. Hellström and Johansson (2010) proposed a simulation model to analyse the impact of the control strategy on the investment and operating cost of RTIs.

Given the limited number of studies related to the optimization of RTIs flows in the supply chain, and in real contexts in particular, this study tries to contribute to the literature by proposing a model to optimize the cost of RTIs management in a real CLSC. A detailed model is developed to reproduce the CLSC, which consists of a pallet provider, a manufacturer and 7 retailers, and to evaluate the flows of RTIs in the system. The model is then reproduced on a Microsoft Excel™ simulator and exploited for multi-objective optimization purpose, supported by the commercial software ModeFRONTIER™, to identify the optimal setting of the system under different operating conditions of the manufacturer.

The remainder of the paper is organised as follows. Section 2 describes the context where the present study was developed. In section 3, we detail the simulation model developed to reproduce the flow of RTIs in the targeted CLSC. The multi-objective optimization procedure and the scenarios examined are illustrated in section 4. The main results from the simulation runs are discussed in sections 5 and 6. Section 7 summarises the main findings of the study, discusses implications and limitations and outlines future research directions.

2 The context

2.1 The CLSC analysed

The core company of the CLSC examined in this study is a manufacturer of fast moving consumer goods operating in the North of Italy; it will be referred to as *Company A* for confidentiality. Company A owns a stock of proprietary pallets, used for its shipments to 7 customers (delivery points), i.e. distribution centres of fast moving consumer goods. Moreover, the CLSC includes a pallet provider that supplies new pallets to Company A when necessary. Shipments from/to the customers can be made either by Company A or exploiting third party logistics (3PL) service providers. A scheme of the CLSC is proposed in FIGURE 1.

INSERT HERE FIGURE 1

2.2 The pallet management process

The analysis carried out in this paper focuses expressively on Company A, because of its key role in the asset management process in the CLSC examined. The way pallets are currently managed in the CLSC examined is as follows. Company A receives orders (of finished products) from its final customers. Fulfilling those orders requires a certain amount of pallets, which are used by Company A to prepare the stock keeping units (SKUs) for shipment. More precisely, pallets are used after picking operations, when products are placed on the asset and packed. Once the order preparation is complete, pallets are loaded on trucks to be transported to the different delivery points and shipped to the company's customers. Here, the packaged SKUs (including pallets) will be unloaded and stored in the customer's warehouse.

In the current scenario, Company A adopts the deferred exchange of pallets with its customers. Specifically, customers are not able to return the amount of pallets received to Company A immediately after receiving. More often, the pallets received will be used by the customers for a given time, to store products in their warehouse. At the same time, customers will return some empty pallets, currently available in their warehouse, but not corresponding to the whole amount of pallets shipped. Hence, Company A will have to collect the remaining pallets from the customers at a later date. To this purpose, the manufacturer should keep track of its pallet flows, meaning that it should know the exact inbound/outbound flows of assets and the corresponding debit of each customer. Moreover, to retrieve the remaining pallets, Company A needs to organize dedicated trips, since it is not always possible to exploit the return flows of subsequent shipments to pick pallets from the customers. Retrieving pallets from the delivery points, however, is a very critical process. First of all, some pallets are inevitably lost during this process. The company has low control on the flow of assets damaged or lost during the shipment; nonetheless, by assessing the difference between the assets shipped and those returned, Company A estimates to lose approx. 2.5% of pallets per cycle. This means that, for each shipment to a customer, this percentage of pallets will not be returned by that customer, neither during the interchange, neither in subsequent retrieving. Moreover, additional losses are generated by damages of the pallet: according to the company's estimates, this accounts for an additional 1% of the total amount of pallets handled per year. Overall, the flows of returned pallets are somehow affected by stochasticity, both in time and quantity, meaning that Company A does not exactly know how many pallets will be returned and when the pallets will be back to the company.

At the same time, because assets are used to ship products to its customers, Company A should avoid out-of-stock situations. Indeed, lack of pallets in stock means that Company A will not be able to ship products to its customers, resulting in a loss of sales. Hence, in the case the amount of assets currently in stock is not sufficient to fulfil the orders of those customers, Company A will either (in order of priority):

1. try to retrieve pallets from the customers (retrieving process). On the basis of the flow of pallets shipped and got back during the exchange, Company A can estimate the amount of assets available at each customer's site. The customer that owns the highest amount of assets could be selected by Company A to retrieve the pallets;
2. purchase new pallets from the pallet provider (regular order). This alternative solution will be exploited whenever the amount of assets available at the customers' sites is found to be too low to justify the retrieving. The order lot size for new assets is fixed and corresponds, approximately, to a full truck load shipment of empty pallets;
3. purchase new pallets with urgency (urgent order). Such solution is exploited by Company A when an out-of-stock situation is observed. In this case, the amount of pallets purchased covers the exact need of the company and the purchasing cost is higher, because of the urgent delivery.

Obviously, both the retrieving operations and the purchase of new assets have a fixed lead time, meaning that the pallets will be available at Company A after some days. The lead time of urgent orders, instead, is significantly lower. Overall, the pallet management process generates the following flows at Company A:

- outbound flow of pallets used for shipments to the customers;
- outbound flow of pallets lost or damaged during the shipment;
- inbound flow of new pallets, purchased from the pallet provider (either as regular or urgent orders);

- inbound flow of returned pallets, i.e. pallets got back from customers as a result of the deferred interchange or retrieving operations.

2.3 Criticalities of the current process

The current assets management process of Company A, as described above, is characterised by some inefficiencies and could be improved in several ways. The main inefficiencies are listed below.

- Despite the fact that Company A should properly balance its inbound and outbound flows of assets, to avoid out-of-stock situations, the current inventory management process of the company appears as non-optimized. Indeed, because the flow of returned pallets is unknown and difficult to predict, the company is unable to apply any specific inventory management policy, which prevents the optimization of the asset inventory. Moreover, because of the presence of return flows, traditional inventory management policies (e.g., EOQ or EOI) could not even be directly applied; rather, those policies would need to be adapted to the case of a CLSC;
- we have mentioned that Company A should keep track of the exact inbound/outbound flows of assets of each customer, but that the company has low control on the flow of assets damaged or lost during the shipment and, therefore, cannot precisely know the exact amount of assets available at each customer. The logical consequence of this considerations is that Company A is unable to optimise the process of retrieving assets from its final customers;
- as a final point, the Company would like to limit the use of urgent orders, because of the higher purchasing cost they generate.

Moving from the criticalities listed above, the analysis carried out in this paper is intended to optimize the current asset management process of Company A, from the economic and strategic perspectives.

3 Modelling framework

3.1 Decision process of Company A

To model the reorder process of assets at Company A, we started from the traditional EOQ policy (Harris, 1913), which was modified and adapted to the presence of return flows. A scheme of the decision process of Company A resulting with the adapted EOQ policy is shown in Figure 2. The notation in TABLE 1 is used to describe the process.

INSERT HERE TABLE 1 AND FIGURE 2

Because of the presence of several inbound/outbound flows, the decision process is quite articulated, consisting, overall, of 6 branches and including several circumstances where the stock of assets of both Company A and its customers should be updated. The decision process is characterised by two operating leverages, namely *OP* and *MPQ*. *OP* is the traditional order point of the EOQ policy and is used to decide whether the stock of assets should be replenished. *MPQ*, instead, denotes a minimum amount of pallets that should be available for retrieving and is used to drive the retrieving operations at the delivery points. The decision process is detailed below with respect to the branches of the decision tree.

Start of the process. At time *t*, Company A receives orders from its delivery points. The company checks whether the whole amount of orders received can be fulfilled exploiting its 'physical' stock of assets. The initial (*t*=0) stock of assets is generated as a random number ranging from 0 to O_A. If

$I_A^P(t-1) \geq \sum_{i=1}^{7} O_{DP,i}(t)$, Company A will follow the order fulfilment process (*branch 1*); otherwise, it will incur in an out-of-stock situation (*branch 2*).

Branch 1 (order fulfilment). Whenever $I_A^P(t-1) \geq \sum_{i=1}^{7} O_{DP,i}(t)$, Company A will prepare the order and ship the pallets to its customers. The stock of pallets available at Company A will be subject to a first update, as follows:

$$I_{A,I}^P(t) = I_A^P(t-1) - \sum_{i=1}^{7} S_{A,i}(t) \quad (1)$$

where $S_{A,i}(t) = O_{DP,i}(t)$. At the beginning of the process (*t=0*), the 'theoretical' inventory position of Company A does not differ from the physical one, i.e. $I_{A,I}^P(t) = I_{A,I}^T(t)$. Once pallets are shipped, the inventory of each delivery point will be checked, to assess whether some assets can be returned through the deferred interchange. A specific decision process, called 'pallet exchange logic' (cf. section 3.1.1) is applied to this extent. The deferred interchange requires LT_r days and leads to $DI_{DP,i}(t)$ assets returned to Company A. The inventory of the delivery point is thus updated as follows (first update):

$$I_{DP,i,I}^P(t) = I_{DP,i}^P(t-1) + S_{A,i}(t-LT_d) - DI_{DP,i}(t-LT_r)$$

$$I_{DP,i,I}^T(t) = I_{DP,i}^T(t-1) + S_{A,i}(t) - DI_{DP,i}(t) \quad (2)$$

At the same time, pallets exchanged will be received at company A, causing a second update of the company's assets inventory, as follows:

$$I_{A,II}^P(t) = I_{A,I}^P(t) + DI_{DP,i}(t-LT_r)$$

$$I_{A,II}^T(t) = I_{A,I}^T(t) + DI_{DP,i}(t) \quad (3)$$

Once the inventory is updated, Company A will check whether the stock of assets is lower than *OP*. In line with the EOQ policy, the check is made on the theoretical inventory position (i.e., $I_{A,II}^T(t) \leq OP$), to take into account also those assets that have been ordered, or exchanged, but are 'in transit' and have not yet been received by Company A. If $I_{A,II}^T(t) > OP$, Company A will not need to replenish its stock of assets (*branch 1.1*), otherwise it will follow the replenishment procedure *(branch 1.2)*.

Branch 1.1 (no replenishment). If replenishment is not required, the process ends. The 'theoretical' and 'physical' inventory positions of Company A and its customers are updated as follows:

$$I_A^P(t) = I_{A,II}^P(t)$$

$$I_A^T(t) = I_{A,II}^T(t) \quad (4)$$

$$I_{DP,i}^P(t) = I_{DP,i,I}^P(t)$$

$$I_{DP,i}^T(t) = I_{DP,i,I}^T(t) \quad (5)$$

Branch 1.2 (asset replenishment). In line with the decision process described in section 2.2, the company will first check whether assets can be retrieved from the delivery points, so as to avoid purchasing new assets. In general, delivery points always have assets than can be retrieved; therefore, the check reduces to identify one delivery point whose inventory exceeds the *MPQ*, i.e. $\{\exists i | I_{DP,i}(t) \geq MPQ, i = 1,...7\}$. The rationale behind the introduction of *MPQ*, which does not formally exist in the current decision process of Company A, is essentially economic. Indeed, to retrieve pallets from the delivery points, it is likely that Company A should organise a dedicated trip, with related cost; this will be done only if that trip allows retrieving at least a minimum amount of pallets. For a similar reason, the possibility of organising a trip to visit more than one delivery point to retrieve pallets is not considered, since, because of the distance between the delivery points, the resulting cost would be excessively high. This means that *MPQ* assets should be available at one single delivery point. In the case one (or more) customers own more than *MPQ* assets, the Company will start the retrieving process (*branch 1.2.1*); otherwise, it will follow the reorder process (*branch 1.2.2*).

Branch 1.2.1 (retrieving). Company A will apply the 'retrieving logic' to choose the i^*-th customer from which pallets should be retrieved (cf. section 3.1.2). We recall that retrieving pallets from the delivery points requires LT_r days and the amount of pallets retrieved is $R_{DP,i*}(t)$. The retrieving process causes a second update of the inventory of the delivery points, as follows:

$$I^P_{DP,i,II}(t) = I^P_{DP,i,I}(t) - R_{DP,i*}(t - LT_r)$$

$$I^P_{DP,i,II}(t) = I^P_{DP,i,I}(t) - R_{DP,i*}(t - LT_r) \quad \text{if } i = i^*$$

$$I^P_{DP,i,II}(t) = I^P_{DP,i,I}(t)$$

$$I^P_{DP,i,II}(t) = I^P_{DP,i,I}(t) \quad otherwise \tag{6}$$

The pallets retrieved from the i^*-th customer will cause a third update of the inventory of Company A, as follows:

$$I^P_{A,III}(t) = I^P_{A,II}(t) + R_{DP,i*}(t - LT_r)$$

$$I^P_{A,III}(t) = I^P_{A,II}(t) + R_{DP,i*}(t) \tag{7}$$

The update ends *branch 1.2.1* of the decision process. The inventory positions of Company A and its customers are finally set at:

$$I^P_A(t) = I^P_{A,III}(t)$$

$$I^T_A(t) = I^T_{A,III}(t) \tag{8}$$

$$I^P_{DP,i}(t) = I^P_{DP,i,II}(t)$$

$$I^T_{DP,i}(t) = I^T_{DP,i,II}(t) \quad (9)$$

Branch 1.2.2 (reorder process). If none of the delivery points owns a sufficient stock of assets (i.e. $\{\neg\exists i | I_{DP,i}(t) \geq MPQ, i = 1,...7\}$, Company A will place a regular order for new assets to a pallet provider. In line with the EOQ policy, the amount of pallets purchased through regular orders is fixed (i.e., $O_A(t) = O_A = \text{cost}, \forall t$) and the lot size should be preliminary determined by Company A. The pallet provider is assumed to have infinite availability of assets, meaning that out-of-stock situations cannot occur for this player (this also applies to urgent orders). Regular orders are available after LT_o days and generate a physical flow of new pallets from the pallet provider to Company A. Hence, the inventory position of Company A should be, once again, updated, according to the following formula (fourth update):

$$I^P_{A,IV}(t) = I^P_{A,II}(t) + O_A(t - LT_o)$$

$$I^T_{A,IV}(t) = I^T_{A,II}(t) + O_A(t) \quad (10)$$

This ends *branch 1.2.2* of the decision process. Therefore, the inventory positions of Company A are finally set at:

$$I^P_A(t) = I^P_{A,IV}(t)$$

$$I^T_A(t) = I^T_{A,IV}(t) \quad (11)$$

The inventory of the delivery points was not subject to updates in this branch; therefore it is the same as described in eq.5.

Branch 2 (out-of-stock). In the case the physical inventory of assets at the company's site does not allows fulfilling the orders received from its customers, i.e. $I^P_A(t-1) < \sum_{i=1}^{7} O_{DP,i}(t)$, Company A will incur in an out-of-stock situation. Under that circumstance, the company will place an urgent order to the pallet provider. Urgent orders are characterised by $LT_u < LT_o$, so that the new assets are available in a shorter time compared to regular orders. On the other hand, the cost of urgent orders is significantly higher than that of regular orders. Because of this higher cost, the amount of assets purchased urgently is limited to those strictly required to fulfil the order, i.e.

$$UO_A(t) = \sum_{i=1}^{7} O_{DP,i}(t) - I^P_A(t-1) \quad (12)$$

$UO_A(t)$ also denotes the amount of out-of-stock experienced. The urgent order generates a physical flow of pallets, from the pallet provider to Company A, and therefore will cause the (fifth) update of the inventory position, as follows:

$$I^P_{A,V}(t) = I^P_A(t-1) + UO_A(t - LT_u)$$

$$I^T_{A,V}(t) = I^T_A(t-1) + UO_A(t) \quad (13)$$

Therefore, following this branch of the decision process, the inventory positions of Company A account for:

$$I_A^P(t) = I_{A,V}^P(t)$$

$$I_A^T(t) = I_{A,V}^T(t) \quad (14)$$

3.1.1 The 'pallet exchange logic'

As mentioned, anytime Company A ships pallets to a delivery point, this latter can return some assets. However, the amount of assets returned does not reflect the original shipment, because of the pallets lost and damaged, as well as because the delivery point may not have the empty pallets available for being returned immediately. The amounts of pallets of Company A that are lost or damaged at the *i*-th delivery point are estimated as follows:

$$L_{DP,i}(t) = S_{A,i}(t - LT_s) * \%_L \quad (15)$$

$$D_{DP,i}(t) = S_{A,i}(t - LT_s) * \%_D \quad (16)$$

The amount of pallets the *i*-th delivery point can, theoretically, return by deferred exchange at time *t* accounts for:

$$DI_{DP,i}^*(t) = I_{DP,i}^P(t) - D_{DP,i}(t) - L_{DP,i}(t) \quad (17)$$

However, to take into account the fact that some pallets can be unavailable, the real amount of assets returned at time *t* is obtained as a random number, ranging from 0 and $DI_{DP,i}^*(t)$, i.e.:

$$DI_{DP,i}(t) = rnd\left[0; DI_{DP,i}^*(t)\right] \quad (18)$$

3.1.2 The 'retrieving logic'

The 'retrieving logic' is as follows. Whenever only one delivery point owns more than *MPQ* assets, Company A will retrieve pallets from that customer. Conversely, in the case more than one delivery point owns a stock of assets higher than *MPQ*, Company A will have to choose the customer from which pallets should be retrieved. The choice grounds mainly on economic considerations; specifically, the logic is expected to identify the delivery point which will generate the lowest retrieving cost, thus minimizing the total cost of the CLSC.

To this extent, it is first necessary to estimate the unitary retrieving cost $c_{r,i}$ [€/pallet] for each delivery point whose stock of assets is higher than *MPQ*. The computation is as follows:

$$c_{r,i} = d_{A,i} * c_{km} * n_{trucks} * \frac{1}{I_{DP,i}^P(t)} \quad \forall i | I_{DP,i}^P(t) \geq MPQ \quad (19)$$

In turn, n_{trucks} [trucks] is computed by rounding to the next whole number the following expression:

$$n_{trucks} = \frac{I_{DP,i}^P(t)}{n_{pallets/truck}} \quad (20)$$

where $n_{pallets/truck}$ is a fixed quantity describing the amount of pallets that can be loaded on a truck of a given capacity. Once $c_{r,i}$ has been computed for all the relevant delivery points, Company A will select the i^*-th delivery point that minimizes the retrieving cost, i.e. $\left\{ i^* \middle| c_{r,i^*} = \min c_{r,i} \text{ and } I^P_{DP,i}(t) \geq MPQ \right\}$. The amount of assets retrieved from the i^*-th delivery point will account for the entire stock of pallets available at that customer, i.e.:

$$R_{DP,i^*}(t) = I^P_{DP,i^*}(t) \tag{21}$$

Combining the above formula with eq.6., it is easy to deduce that, after retrieving, the inventory of the i^**-th* delivery point scores 0.

3.2 Key performance indicators

The key performance indicators (KPIs) used to assess the performance of Company A against the pallet management process cover both economic aspects and strategic ones.

3.2.1 Economic KPIs

Given the characteristics of the CLSC analysed and the decision process described above, the following economic KPIs are computed:

1. Cost of retrieving (C_r), which reflects the cost for picking up pallets from the delivery points, according to the ‘pallet retrieving logic’. We compute its daily value as follows:

$$C_r = \frac{\sum_{t=1}^{N_{days}} \left(c_{r,i} * I^P_{DP,i}(t) \right)}{N_{days}} \quad [€/day] \tag{22}$$

2. Cost of purchasing – regular order ($C_{p,r}$), which is the cost for purchasing new pallets from the pallets provider, in the case of a regular order. It is computed starting from the amount of pallets purchased and the unitary cost of assets and averaged over the time horizon considered, as follows:

$$C_{p,r} = \frac{\sum_{t=1}^{N_{days}} \left(c_{asset,r} * O_A(t) \right)}{N_{days}} \quad [€/day] \tag{23}$$

3. Cost of purchasing – urgent order ($C_{p,u}$), which is the cost to purchase new pallets from the pallets provider, in the case of urgent orders. It is computed starting from the amount of pallets purchased urgently and the unitary cost of urgent assets and averaged over the time horizon considered, as follows:

$$C_{p,u} = \frac{\sum_{t=1}^{N_{days}} \left(c_{asset,u} * UO_A(t) \right)}{N_{days}} \quad [€/day] \tag{24}$$

4. Inventory cost (C_I), which reflects the cost of storing pallets in the warehouse of Company A. It is computed starting from the physical inventory of assets at Company A and the unitary cost of holding the stock of assets and averaged over the time horizon considered, i.e.:

$$C_I = \frac{\sum_{t=1}^{N_{days}} \left(c_I * I_A^P(t) \right)}{N_{days}} \qquad [€/day] \qquad (25)$$

5. Opportunity cost (C_{opp}), which reflects the immobilization of capital, used to purchase pallets, with the sacrifice of alternative investments. It is quantified starting from the economic value of the assets Company A owns at a given time and the weighted average capital cost (WACC). The result is averaged over the time horizon considered. The economic value of assets $CP_A(t)$ is computed as follows:

$$CP_A(0) = I_A^P(0) * c_{asset,r}$$

$$CP_A(t) = CP_A(t-1) + UO_A(t) * c_{asset,u} + O_A(t) * c_{asset,r} \qquad [€] \qquad (26)$$

C_{opp} thus results from the following formula:

$$C_{opp} = \frac{\sum_{t=1}^{N_{days}} CP_A(t) * WACC}{N_{days}} \qquad [€/day] \qquad (27)$$

6. Total cost (C_{tot}), which reflects the total cost Company A incurs in. It is obtained adding up all the contributions above, according to the following formula:

$$C_{tot} = C_{opp} + C_I + C_{p,u} + C_{p,r} + C_r \qquad [€/day] \qquad (28)$$

3.2.2 Strategic KPIs

With respect to the strategic aspects of the pallet management process, the following KPIs are considered in this study:

1. Amount of proprietary assets (P_A), which reflects the average number of pallets owned by Company A and is expressed in [pallets]. As mentioned, P_A is computed starting from the physical inventory of Company and adding the amount of pallets the company has shipped to its customers, as follows:

$$P_A = \frac{\sum_{t=1}^{N_{days}} \left(I_A^P(t) + \sum_{i=1}^{7} S_{A,i}(t) \right)}{N_{days}} \qquad [pallets] \qquad (29)$$

2. Asset rotation (*AR*): the asset rotation measures the number of times per year where the pallets rotates and is, therefore, expressed in [year^{-1}]. This KPI is a measure of the efficiency with which a company is deploying its own assets: the higher the number of rotations, the higher the capacity of Company A to exploit its proprietary assets. *AR* can be computed as the inverse of the cycle time *CT* [days], which measures the time required for an asset to complete a cycle in the CLSC considered. A complete 'cycle' consists of the following processes: storage at the warehouse of Company A; shipment to the customer; storage at the customer's warehouse; shipment back to Company A. The same asset cannot be shipped from one customer to another, so that the cycle time can include the contribution of only one customer. Given the description above, the *CT* can be computed starting from the following formula:

$$CT = T_{stock,A} + T_{stock,DP} + LT_r + LT_d \qquad [days] \qquad (30)$$

$T_{stock,A}$ can be estimated starting from the average stock of assets at Company A and the average amount of pallets shipped daily by the company, as follows:

$$T_{stock,A} = \frac{\sum_{t=1}^{N_{days}} I_A^P(t) / N_{days}}{\sum_{t=1}^{N_{days}} \sum_{i=1}^{7} S_{A,i}(t) / N_{days}} \quad \text{[days]} \tag{31}$$

Similarly, $T_{stock,DP}$ can be estimated as the ratio between the average stock of assets available at the delivery points and the average amount of assets shipped or retrieved from the same point, i.e.:

$$T_{stock,DP} = \frac{\sum_{t=1}^{N_{days}} \sum_{i=1}^{7} I_{DP,i}^P(t) / N_{days}}{\sum_{t=1}^{N_{days}} \left(\sum_{i=1}^{7} S_{A,i}(t) + \sum_{i=i^*} R_{DP,i}(t) \right) / N_{days}} \quad \text{[days]} \tag{32}$$

Once *CT* has been determined, *AR* can be computed according to the following formula:

$$AR = \frac{1}{CT} * 260 \quad \text{[year}^{-1}\text{]} \tag{33}$$

3. Pallet utilization rate ($U_{\%}$): this KPIs is computed as the ratio between the time [days] in which the asset is used in the CLSC, meaning that it is either at the delivery point or in transit (but not in the warehouse of Company A to store goods), and the *CT* [days] of the asset. It is, therefore, expressed in [%], according to the following formula:

$$U_{\%} = \frac{T_{stock,DP} + LT_r + LT_s}{CT} \quad [\%] \tag{34}$$

4. Out-of-stock (*OOS*): this KPI is intended to provide a quantitative measure of those critical situations where Company A does not have pallets available to ship products to the final customer. We measure the number of days per year where the OOS situation is observed, i.e.:

$$OOS = \frac{\text{number of out-of-stock situations}}{N_{days}} * 260 \quad \text{[days/year]} \tag{35}$$

3.3 Input data

To apply the model described in the previous sub-sections to the targeted CLSC, several input data were collected from Company A. They are summarised in TABLE 2.

INSERT HERE TABLE 2

3.4 Software implementation

The set of equations described in section 3.1 (and related sub-sections) was embodied in a Microsoft Excel™ simulation model. The simulation model consists of two spreadsheets. The first one is the complete database of the inbound/outbound flows Company A handled in 2013, i.e. the shipments to the delivery points and the pallets returned by them. The second spreadsheet reproduces the decision process of Company A. The demand from the delivery points is modelled as a random number and ranges, for each customer, from 0 to the maximum demand value recorded in 2013 and available in the first spreadsheet. As an example, for customer 1, the demand ranges from 0 to 78 pallets/day. The aggregated demands from the final customers compose the $O_{DP,i}(t)$ and are used as the input for the whole model (eq.1-21).

The data related to the inbound flows of Company A in 2013 are used to assess the correctness of the deferred exchange logic used in the model. More precisely, as can be seen from eq.18, the amount of assets a customer can return to Company A is estimated as a random number, ranging from 0 to the theoretical availability of assets of the customer. The same computation is implemented in Microsoft Excel™, meaning that $DI_{DP,i}(t)$ is generated as a random number. This latter is compared to the real inbound flow of Company A, to ensure that the randomly generated data are in line with the real scenario.

The input data listed in Table 1 were also set in the simulation. As far as the *OP* and *MPQ* are concerned, none of those parameters is used by Company A in its current decision process. Therefore, they were varied in a range of possible values, to identify the optimal (i.e., minimum cost) configuration of the asset management process. Specifically, *OP* and *MPQ* were varied from 50 to 1200 (pallets). For each combination of *OP* and *MPQ*, the spreadsheet computes the economic and strategic KPIs, according to eq.22-31. The simulation duration was set at N_{days}=3,000 days. When computing the KPIs, outputs were collected starting from day 150, to limit warm-up effects of the simulation.

4 Simulation and optimization

The simulation model described above was used to evaluate three different scenarios of the CLSC, which were considered of particular interest for Company A. The scenarios differ with respect to the KPIs that are chosen for optimization and reflect the situation where the company is interested in optimising some specific aspects of the pallet management process. The multi-objective optimization procedure was supported by the commercial software ModeFRONTIER™ release 4.5.4 (Esteco S.p.A.).

4.1 Optimization procedure

ModeFRONTIER™ is a multi-objective optimization and process integration tool based on the Pareto-optimal frontier of the objectives space. The logic of the optimization loop can be set up in a graphical way, building up a workflow structure by means of interconnected nodes. The optimization starts from the interaction of ModeFRONTIER™ with the Microsoft Excel™ simulation model, with some fixed input data (cf. Table 1) and two variable parameters, i.e. *OP* and *MPQ*. The first variation of *OP* and *MPQ* in their range was made by setting a Design of Experiments (DoE) procedure, with a 3^2 full factorial design, which takes the boundary values and the intermediate one for each parameter (i.e., 50, 625 and 1200). The DoE provides a preliminary investigation of the design space and is useful to guide the subsequent non-dominated sorting genetic algorithm (NSGA-II) towards the optimal solution. Overall, the NSGA-II carries out 270 simulations. This number is significantly lower than that required if the simulation model was simply run under Microsoft Excel™ by varying the *OP* and *MPQ* in their range, with the purpose of identifying the optimal configuration. For instance, varying *OP* and *MPQ* from 50 to 1200 (step 50) would lead to 24*24=576 simulation runs. Indeed, NSGA-II is a fast and elitist multi-objective genetic algorithm that allows solving high complexity multi-objective optimization problems with a relatively limited number of iterations, preserving elitist solutions (Deb et al. 2002).

4.2 Simulation scenarios

The multi-objective optimization procedure was used to examine three different scenarios of the asset management process of Company A; these scenarios are briefly described below.

- *Scenario 1*: in this scenario, the performance parameters set for the multi-objective optimization are C_{tot} (minimum), $U_{\%}$ (maximum), *AR* (maximum) and *OOS* (minimum);

- *Scenario 2*: this scenario is the same as the first one for the strategic KPIs, while the cost component considered in the optimization is the total cost of purchasing new assets, i.e. $C_{p,r} + C_{p,u}$ (minimum);

- *Scenario 3*: this scenario is the same as the previous ones for the strategic KPIs, while the cost component considered in the optimization is the cost of retrieving assets from the customers, i.e. C_r (minimum).

The analysis was focused on those scenarios because of the following reasons. Scenario 1 basically reflects the current operating conditions of Company A: the primary goal of the company is to minimise the total cost of its asset management process, but, at the same time, the company tries to optimize the assets usage and rotations and to avoid out-of-stock situations. Therefore, results of the multi-objective optimization for scenario 1 are expected to provide Company A with guidelines for the optimization of its current asset management process. Scenario 2 reflects a possible situation where Company A would like to avoid (or limit) the purchase of new assets, with the purpose of enhancing the use of its proprietary pallets. The solutions resulting from the multi-objective optimization under this scenario are expected to improve the utilization of the proprietary assets of Company A, at the same time identifying potential benefits resulting with a strategy of asset management different from the current one. The last scenario reflects a possible situation where Company A is no longer able to manage the reverse flows of its assets. Because managing the reverse flows of assets is, currently, a critical process, it is likely that, in the near future, Company A will leave the management of this process. Hence, it is useful to Company A to have an estimate of the total cost of assets management in the case the Company will privilege the purchasing of new pallets against returning operation[1].

For all scenarios, a constraint related to the amount of proprietary pallets was added in ModeFRONTIER™, so as to consider the finished storage capacity of Company A. Accordingly, we forced P_A <3000 pallets and limited the analysis to those solutions that meet this constraint. Also, only integer values were allowed for this parameter, as well as for *OP* and *MPQ*.

5 Multi-objective optimization results

In this section, we report the main results of the simulation runs, in terms of the trend of the KPIs optimized as a function of the operating leverages of the decision process, i.e. *OP* and *MPQ*. The results provided aim at identifying the existence of relationships between the reorder policy parameters and the model outputs. Because those relationships cannot be immediately evident from the model description in section 3, outcomes are substantiated by a correlation analysis, whose detailed results are reported in Appendix. Because the trends observed, as well as the results of the correlation analysis, are similar across the scenarios, we provide the detailed outcomes for scenario 1, while, for the remaining scenarios, we discuss some selected outcomes.

[1] With respect to the number of scenarios analysed, the discussion in section 5 and the correlation analysis in Appendix show that the trends of almost all model outputs correlate to each other. Because of this correlation, it is likely that, even if we analyse more than three scenarios with some modifications in the KPIs to optimize, the results will partially overlap with those presented in section 5. We have therefore limited the analysis to three scenarios with the purpose of avoiding repetitions.

5.1 Scenario 1

FIGURE 3 shows the trend of C_{tot} as a function of *OP* (a) and *MPQ* (b). From Figure 3(a) it is easy to see that the design space includes solutions with low C_{tot} (approx. 200 €/day) obtained setting very different *OP* (from 100 to 1100 pallets). At the same time, however, some configurations with *OP*≈600-700 pallets experience very high C_{tot}. This would suggest that those variables do not have a direct relationship. Indeed, *OP* has a different impact on the cost components included in C_{tot}. Specifically, increasing *OP* means that Company A will place orders for new pallets when a higher stock of assets is available; consequently, the average inventory level increases, thus increasing C_I. At the same time, orders will be placed more frequently, increasing $C_{p,r}$. Moreover, because of the higher number of regular orders placed, Company A would (probably) have lower need for placing urgent orders, generating a lower $C_{p,r}$. The reduced number of urgent orders generates a decreased C_{opp}, since, despite the fact that regular orders are characterised by a high number of assets, those assets have a lower value. Those relationships are confirmed by the correlation analysis in Appendix (TABLE A-1). The same analysis highlights that the correlation between *OP* and C_{tot}, although significant, is very weak (-0.330), thus confirming that these variables do not exhibit a direct relationship (Taylor, 1990). With respect to the trend of C_{tot} as a function of *MPQ*, outcomes in Figure 3(b) show a more evident relationship between those variables. Specifically, very high C_{tot} are observed with *MPQ*<300 pallets, while, for higher values of *MPQ*, C_{tot} is stable and accounts for less than 200 €/year. Correlation analysis confirms that the negative relationships between *OP* and C_{tot} is strong (-0.735). This result is the combination of the different effects *MPQ* has on the cost components. Specifically, the increase in *MPQ* generates a higher C_{opp}, because of the presence of more assets at Company A, which, in turn, increases C_I too. Similarly, if more pallets are picked from the customers in a single shipment, the frequency of picks from the customers would be lowered, thus decreasing C_r. Under that circumstance, Company A would purchase new pallets through regular orders, thus justifying the positive correlations with $C_{p,r}$.

FIGURE 4 shows the trend of *AR* as a function of *OP* (a) and *MPQ* (b). FIGURE 4(a) shows a trend which is similar to that of FIGURE 3(a), in that *OP* and *AR* do not seem to be directly related. Indeed, the design space shows that the highest *AR* (approx. 40 rotations/year) is obtained with *OP*<100 pallets, but there are also configurations with *OP*<100 pallets which generate a significantly lower *AR*. The correlation coefficient (TABLE A-1) shows a modest negative relationship between *OP* and *AR* (-0.453). This could be motivated considering that increasing *OP* involves a corresponding increase in the number of proprietary assets of Company A, and thus an increase in the *CT* of assets (corresponding to a decrease in *AR*). The relationship between *AR* and *MPQ* is stronger (-0.799) and evident from FIGURE 4(b). When the *MPQ* is higher, Company A will decrease retrieving operations, but, at the same time, will increase the number of regular orders, resulting in an increased number of proprietary assets. As per the previous variables, with more assets available at Company A, the average cycle time of assets will be higher, resulting in a lower *AR*.

The trend of *OOS* as a function of *OP* and *MPQ* is proposed in FIGURE 5(a-b). The relationship between *OP* and *OOS* is obvious: higher *OP* generates higher inventory available when orders are placed, so that out-of-stock situations are less likely to occur. This is also confirmed by the good correlation coefficient between those variables (-0.714). From FIGURE 5(a) it can be seen that configurations with *OP*>300 pallets always generate null *OOS*, while for *OP*<200 pallets *OOS* situations are more likely to occur. The relationship between *OOS* and *MPQ* is less evident and also weaker, as shown by the lower correlation coefficient (-370). In general, lower *MPQ* seems to generate higher *OOS*; this is probably due to the fact that increasing *MPQ* increases the amount of proprietary assets of Company A, thus making *OOS* situations less likely to occur. Nonetheless, some configurations with *MPQ*<100 pallets generate null *OOS* and, at the same time, some configurations with higher *MPQ* (from 300 to 400) generate quite high *OOS*.

As far as the relationship between $U_{\%}$ and *OP* is concerned, FIGURE 6(a) shows that $U_{\%}$ tends to decrease with the increase in *OP*. As already mentioned, increasing *OP* involves a corresponding increase in the number of proprietary assets of Company A, and, consequently, a high *CT* of assets. Since $U_{\%}$ is computed starting from the inverse of *CT*, is decreases accordingly. This is also confirmed by a high correlation coefficient between those variables (-0.903). The relationship between $U_{\%}$ and *MPQ* seems to be opposite (FIGURE 6b), although the correlation between those variables is very weak (0.159).

INSERT HERE FIGURES 3-6

5.2 Scenario 2

The trends of $U_{\%}$, *AR* and *OOS* as a function of *OP* and *MPQ* obtained under scenario 2 reflect those described for the previous scenario, indicating that the relationships between those variables is almost the same under the two scenarios. This is also confirmed by the correlation analysis in TABLE A-2, which shows that the correlation coefficients of scenario 2 are similar to those of scenario 1, thus suggesting the same trends. Therefore, for brevity, we limit the discussion of the outcomes to the trend of the economic KPI (i.e., the total purchasing cost) as a function of *OP* and *MPQ* (FIGURE 7). From FIGURE 7(a) one can appreciate that low *OP* generates a high purchasing cost, while for *OP*>300 the purchasing cost is almost constant and accounts for approx. 40 €/day; overall, this trend suggests a negative correlation between these variables. However, looking at the correlation coefficients (TABLE A-2), it can be seen that *OP* has a different effect on $C_{p,r}$ and $C_{p,u}$; in particular, $C_{p,r}$ increases with the increase in *OP*, while $C_{p,u}$ decreases. This outcome was partly expected: indeed, increasing the *OP* forces Company A to place more orders (regular), which increases the corresponding cost. Moreover, the similarity between the correlation coefficients (0.581 vs. -0.580) suggests that $C_{p,r}$ and $C_{p,u}$ are almost perfectly negatively correlated. This means that whenever Company A makes use regular orders, urgent orders will be correspondingly less required (and *vice versa*).

The trend of $C_{p,r} + C_{p,u}$ as a function of *MPQ* (FIGURE 7b) is again negative, although less evident. Low *MPQ* seems to generate the highest purchasing cost; however, there is not a strict correspondence between the *MPQ* and the resulting purchasing cost. The correlation analysis confirms this consideration, since both correlation coefficients are quite low (0.324 and -0.323). As per the previous case, the effect of *MPQ* against $C_{p,r}$ and $C_{p,u}$ is opposite. It should also be noted that *MPQ*>600 always generates unfeasible solutions.

INSERT HERE FIGURE 7

5.3 Scenario 3

As per the previous scenario, the trends of $U_{\%}$, *AR* and *OOS* as a function of *OP* and *MPQ* obtained under scenario 3 reflect those described for the scenario 1. The similar trends are also confirmed by the correlation analysis in TABLE A-3. The related description is omitted, for brevity. We focus, instead, on the trend of the economic KPI (i.e., the retrieving cost) as a function of *OP* and *MPQ* (FIGURE 8). From FIGURE 8(a) it is immediate to see that the C_r does not have any specific relationship with the *OP* set in the simulation, meaning that this latter does not affect the retrieving cost to an appreciable extent. Indeed, the correlation between those variables is very weak (-0.174). Conversely, *MPQ* and C_r show a more evident negative relationship, which is also confirmed by the good correlation coefficient (-0.755). Such outcome was expected, because, as already remarked, *MPQ* has a direct role in driving retrieving operations of Company A.

INSERT HERE FIGURE 8

6 Multi-criteria decision making

The multi-criteria decision making (MCDM) tool of ModeFRONTIER™ was exploited to rank the 270 configurations of each scenario in a rational order and to identify the best dyad *MPQ-OP* of each scenario. This tool works exactly as the traditional multi-criteria decision analysis of operational research. Specifically, the different objectives set in the optimization model are treated as (conflicting) criteria, and the simulation runs are ranked on the basis of their score against those criteria, to identify the optimal configuration. A linear MCMD model was selected, with the following weights:

- 0.40 for the cost criterion. Such a weight reflects the relevance of the economic considerations in the asset management process;
- 0.30 for *OOS*. This choice is motivated by the fact that, as already mentioned, *OOS* should be possibly avoided for Company A;
- 0.15 for the remaining KPIs, i.e. *AR* and $U_{\%}$.

The application of the MCDM tool was limited to the feasible configurations of each scenario.

6.1 Scenario 1

TABLE 3 provides an extract of the top 5 simulation runs of scenario 1, as they were ranked after the application of the MCDM tool. Grey highlighting indicates the KPIs that were optimized in this scenario. From Table 4 it can be seen that the top 5 configurations are quite similar in terms of $U_{\%}$ and *AR*, which are always close to 83% and 13 rotations/year, respectively. All configurations generate null *OOS* and do not require urgent orders ($C_{p,u}$=0). The amount of proprietary assets is quite high, always exceeding 2,170 pallets. The first ranked configuration provides the lowest total cost (182.39 €/day), a significant part of which is due to retrieving operations (126.67 €/day). Such configuration is obtained setting *OP*=310 pallets and *MPQ*=372 pallets. Nonetheless, *OP* and *MPQ* of all configurations vary in a very limited range (from 306 to 312 and from 372 to 386 respectively).

INSERT HERE TABLE 3

6.2 Scenario 2

TABLE 4 shows the top 5 simulation runs of scenario 2, after ranking. We recall that, in this scenario, Company A is interested in minimising $C_{p,r} + C_{p,u}$, while the strategic KPIs are the same as in the previous scenario. The top 5 configurations of TABLE 4 are similar in terms of $U_{\%}$ (from 83.04% to 85.03%), while significant differences can be found against the remaining KPIs. Indeed, the top 2 configurations shows the minimum cost of purchasing (less than 39 €/day and entirely due to regular orders) as well as a null *OOS*; *AR* ranges from 11 to 12 rotations/year. Those configurations are obtained setting quite high *OP* and *MPQ*, accounting for more than 300 and more than 400 pallets, respectively. The remaining 3 configurations, instead, are obtained setting significantly lower *OP* and *MPQ* (less than 200 and less than 80, respectively) and generate a higher *AR* (more than 30 rotations/year). However, the cost of purchasing is always higher than 40 €/day, due to the presence of urgent orders, and thus of *OOS* situations. Because of the low *MPQ*, under those configurations Company A will be forced to perform very frequent retrieving operations at the delivery points, resulting in a high C_r. In turn, this leads to a poor performance in terms of C_{tot}, which is approx. double compared to the top 2 configurations.

The first ranked configuration is obtained setting *OP*=329 pallets and *MPQ*=434 pallets and, overall, appears as the most interesting for a practical implementation, because of the good $U_{\%}$, the null *OOS* and the low cost of purchasing.

INSERT HERE TABLE 4

6.3 Scenario 3

TABLE 5 lists the top 5 simulation runs of scenario 3, after ranking. In this scenario, Company A is interested in minimising C_r, as well as the same strategic KPIs as in the previous scenarios. A first consideration from TABLE 5 is that the $U_{\%}$ is quite similar in all the configurations proposed, ranging from 86.77% to 89.06%, and is significantly higher compared to the previous scenarios. All configurations generate a low *OOS*, with configuration 1 generating null *OOS*, which could be particularly interesting for a practical implementation. The top 3 configurations are similar in terms of the *MPQ* (from 338 to 340 pallets) and *AR* (approx. 15 rotations/year), while different values are observed in the remaining configurations.

The first ranked configuration is obtained setting *OP*=177 pallets and *MPQ*=340 pallets. This setting generate the minimum cost of retrieving (127.75 €/day), but, overall, this cost does not vary significantly from configuration 1 to configuration 5, suggesting that Company A could also select an alternative setting and would get similar performance. By comparing these outcomes with those of scenario 1 (cf. TABLE 3), it is immediate to see that results, in terms of C_r and C_{tot} are very similar, meaning that, when minimising, e.g., the cost of retrieving, the total cost of asset management will be minimised as well. In turn, this is due to the fact that the cost of retrieving is the most significant part of the total cost of assets management for Company A, so that C_{tot} has almost the same trend of C_r.

INSERT HERE TABLE 5

7 Discussion and conclusions

This study has proposed a comprehensive analysis of the performance of the asset management process in a real CLSC, consisting of a pallet provider, a manufacturer (Company A) and seven retailers. The analysis was supported by a Microsoft Excel™ simulation model, which reproduces, through an adapted EOQ policy, the asset management process of Company A and computes the corresponding cost and performance. The model was subsequently used in a multi-objective optimization procedure, supported by ModeFRONTIER™, which examined three different operating conditions of Company A and generated, for each scenario, the optimal configuration of the manufacturer's reorder process. The scenarios investigated describe either the current operating conditions of Company A or reflect potential operating conditions that could be implemented by the company in the near future.

In particular, under the first scenario of the multi-objective optimization, which reproduces the current situation of Company A, we found that the best performance are achieved setting *OP*=310 pallets and *MPQ*=372 pallets in the decision process of Company A. Under this configuration, the total cost of asset management is approx. 182 €/day. Scenario 2 reflects a potential situation where Company A would like to enhance the use of its proprietary pallets, thus minimising the purchase of new assets. The optimal setting of the decision process is *OP*=329 pallets and *MPQ*=434 pallets: such setting generates null OOS, low purchasing cost and good $U_{\%}$, while *AR* is limited. An alternative setting could be *OP*=185 pallets and *MPQ*=66 pallets. In this case, Company A would improve the asset rotation and would experience very limited out-of-stock situations; however, because of the low *MPQ*, this setting generates a relevant total cost of assets management (approx. 421 €/day), since Company A will be forced to increase retrieving operations. Scenario 3 reflects a situation, which is once again hypothetical, where Company A is no longer able to retrieve assets from its customers; therefore, the retrieving cost should be minimised. The optimal setting for this scenario is *OP*=177 pallets and *MPQ*=340 pallets; this setting generates a retrieving cost of approx. 128 €/day, resulting in a total cost of approx. 180 €/day, which is in line with the optimal values obtained in scenario 1. In fact, scenarios 1 and 3 are quite similar in terms to the cost they generate, as the cost of retrieving is the most significant part of the total cost of assets management for Company A.

From a practical perspective, the results summarised above provide Company A with an overview of the performance of its asset management process and can be useful in the case the company is interested in changing its current asset management policy, by defining a different strategy (e.g., minimising the purchase of new assets or retrieving operations). In this regard, results obtained in scenario 2 indicate that a strategy aimed at reducing the purchase of new assets, by enhancing the use of proprietary pallets, would be sustainable from the economic perspective only if Company A sets adequate values of *OP* and *MPQ*. Conversely, a strategy aimed at reducing (or avoiding) retrieving operations at the customer's sites turns out to be suitable for implementation by Company A, since such strategy would also optimise the total cost of assets management for the company. Therefore, it would not be problematic, for Company A, to embrace this new strategy.

From the theoretical perspective, the model developed in this paper is quite detailed, including an articulated decision process and two optimization logics. Such a model could be used also to reproduce different settings or operating conditions of Company A or, at the same time, it could be adapted to analyse other companies or CLSCs, characterised, for instance, by a different number of customers. Similarly, the multi-objective optimization procedure could be applied with different settings of the performance parameters, so as to explore additional assets management strategies. Therefore, the model itself represents an interesting addition to the literature about CLSC.

Starting from this study, several future research directions could be undertaken. As mentioned, the model developed could be applied for the analysis of a different CLSC, in terms of input data or supply chain structure, with the purpose of analysing the performance of systems different to that investigated. As a further research direction, the model developed in this paper could be exploited to investigate how the performance of the CLSC changes as a function of some of the input data. In this study, we used input data from a real company; those data were not altered to preserve the correspondence with the company investigated. Therefore, the trend of the KPIs as a function of the input data could be investigated in future studies.

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Appendix: detailed results of correlation analysis

The following tables (Table A-1-Table A-3) report the results of the correlation analysis between the operating leverages of the decision process, i.e. *OP* and *MPQ*, and the KPIs measured. The Pearson's correlation coefficient (Stigler, 1989) is used to evaluate the relationship between the variables. The correlation analysis was supported by Statistical package for the social science (SPSS), release 21 for Windows (IBM), and was carried out separately for each simulation scenario, exploiting the simulation outcomes (N=270) as input data.

Pearson's correlation coefficient	C_{tot}	C_I	C_{opp}	$C_{p,r}$	$C_{p,u}$	C_r	*AR*	*OOS*	*CT*	$U_{\%}$	P_A
OP	-.330**	.906**	-.421**	.709**	-.711**	-.061	-.453**	-.714**	.241**	-.903**	.303**
MPQ	-.735**	.495**	.680**	.354**	-.353**	-.749**	-.799**	-.370**	.984**	.159**	.972**

** significant correlation at p<0.01
* significant correlation at p<0.05

Table A-1: correlation between *OP* and *MPQ* with strategic and economic KPIs under scenario 1 (N=270).

Pearson's correlation coefficient	C_{tot}	C_I	C_{opp}	$C_{p,r}$	$C_{p,u}$	C_r	*AR*	*OOS*	*CT*	$U_{\%}$	P_A
OP	-.154*	.876**	-.328**	.581**	-.580**	.078	-.306**	-.580**	.202**	-.872**	.258**
MPQ	-.762**	.530**	.706**	.324**	-.323**	-.764**	-.841**	-.337**	.987**	.206**	.978**

** significant correlation at p<0.01
* significant correlation at p<0.05

Table A-2: correlation between *OP* and *MPQ* with strategic and economic KPIs under scenario 2 (N=270).

Pearson's correlation coefficient	C_{tot}	C_I	C_{opp}	$C_{p,r}$	$C_{p,u}$	C_r	*AR*	*OOS*	*CT*	$U_{\%}$	P_A
OP	-.174**	.930**	-.266**	.604**	-.606**	-.017	-.436**	-.621**	.191**	-.906**	.265**
MPQ	-.755**	.321**	.796**	.312**	-.306**	-.779**	-.763**	-.324**	.970**	.289**	.949**

** significant correlation at p<0.01
* significant correlation at p<0.05

Table A-3: correlation between *OP* and *MPQ* with strategic and economic KPIs under scenario 3 (N=270).

Table(s)

Symbol	Description	Unit of measure
Subscripts		
i	delivery point number (i=1,...7)	-
DP	delivery point	-
A	Company A	-
I, II, III, IV, V	step of inventory update	
Superscripts		
P	'physical'	-
T	'theoretical'	-
Simulation parameters		
t	simulation day (t=0,...N_{days})	-
N_{days} N_{days}	simulation duration	[days]
Delivery point parameters		
$O_{DP,i}(t)$	order issued	[pallets]
$I^P_{DP,i}(t)$, $I^T_{DP,i}(t)$	physical and theoretical stock of assets	[pallets]
$DI^*_{DP,i}(t)$, $DI_{DP,i}(t)$	theoretical and real amount of assets returned by deferred interchange	[pallets]
$R_{DP,i*}(t)$	amount of assets retrieved	[pallets]
$L_{DP,i}(t)$, $D_{DP,i}(t)$	amounts of assets lost or damaged	[pallets]
$\%_L$, $\%_D$	percentage of assets lost or damaged	[%]
$c_{r,i}$	unitary retrieving cost	[€/pallet]
$d_{A,i}$	distance to Company A	[km]
$T_{stock,DP}$	time assets are in stock at the delivery point warehouse	
Company A parameters		
$S_{A,i}(t)$	shipment to the i-th delivery point	[pallets]
$I^P_A(t)$, $I^T_A(t)$	physical and theoretical stock of assets	[pallets]
$UO_A(t)$, $O_A(t)$	amount of assets purchased through a urgent order or regular order	[pallets]
$P_A(t)$	amount of proprietary assets	
$T_{stock,A}$	time assets are in stock at company's warehouse	
OP	order point	[pallets]
MPQ	minimum picked quantity, i.e. minimum amount of assets to be collected through retrieving operations	[pallets]
Economic parameters		
c_{km}	unitary cost of transport of a truck	[€/km/truck]
$c_{asset,r}$, $c_{asset,u}$	cost of assets for regular or urgent orders	[€/pallet]
c_I	unitary cost of holding stocks	[€/pallet/day]
Other parameters		
$n_{pallets/truck}$	amount of pallets that can be loaded on a truck	[pallets/truck]
n_{trucks}	number of trucks required for retrieving	[trucks]
LT_r	retrieving lead time	[days]
LT_d	delivery lead time	[days]
LT_o	lead time for regular orders	[days]

LT_u	lead time for urgent orders	[days]

Table 1: notation used for the model.

Parameter	Numerical value	Measurement unit
LT_d	2	days
LT_r	2	days
LT_o	2	days
LT_u	1	days
O_A	500	pallets
$\%_L$	2.5%	-
$\%_D$	1%	-
$d_{A,i}$	362 (*i*=1); 358 (*i*=2); 606 (*i*=3); 352 (*i*=4); 232 (*i*=5); 934 (*i*=6); 632 (*i*=7)	km
c_{km}	1.86	€/km/truck
$n_{pallets/truck}$	500	pallets/truck
$c_{asset,r}$	9	€/pallet
$c_{asset,u}$	45	€/pallet
c_I	0.025	€/pallet/day
WACC	5%	-

Table 2: fixed input data for the CLSC examined.

Simulation run	*OP*	*MPQ*	C_{tot}	C_I	C_{opp}	$C_{p,r}$	$C_{p,u}$	C_r	*AR*	*OOS*	$U_{\%}$	P_A
120	310	372	182.39	12.71	3.81	39.20	0.00	126.67	13.76	0	83.21%	2172
121	306	371	182.91	12.71	3.88	39.20	0.00	127.13	13.49	0	83.46%	2254
199	311	372	182.96	12.88	3.86	39.20	0.00	127.04	13.58	0	83.42%	2205
261	310	386	183.28	12.98	3.98	39.20	0.00	127.13	13.34	0	83.36%	2310
188	312	372	183.29	12.85	3.87	39.20	0.00	127.37	13.60	0	83.31%	2205

Table 3: optimal configurations for scenario 1 (*Note*: grey highlighting = KPIs optimized).

Simulation run	*OP*	*MPQ*	C_{tot}	C_I	C_{opp}	$C_{p,r}$	$C_{p,u}$	C_r	*AR*	*OOS*	$U_{\%}$	P_A
101	329	434	189.79	14.11	4.37	38.94	0.00	132.37	12.23	0.00	83.37%	2513
171	369	467	196.10	15.61	4.73	38.74	0.00	137.02	11.30	0.00	83.04%	2807
209	185	66	421.06	5.16	1.35	38.71	2.02	373.82	34.23	0.59	83.25%	741
34	176	54	476.31	4.61	1.40	37.57	9.15	423.58	36.71	1.49	83.67%	679
172	157	78	382.31	4.72	1.44	38.48	3.69	333.98	33.01	1.19	85.03%	768

Table 4: optimal configurations for scenario 2 (*Note*: grey highlighting = KPIs optimized).

Simulation run	*OP*	*MPQ*	C_{tot}	C_I	C_{opp}	$C_{p,r}$	$C_{p,u}$	C_r	*AR*	*OOS*	$U_{\%}$	P_A
78	177	340	180.34	8.99	3.44	39.00	1.17	127.75	15.25	0.00	86.77%	1916
135	173	338	181.63	8.83	3.44	39.23	1.65	128.48	15.37	0.45	87.11%	1884
155	109	338	195.44	7.33	4.47	36.21	18.06	129.38	15.47	3.27	89.06%	1876

203	146	594	187.69	11.63	5.67	39.20	3.31	127.88	9.96	0.67	88.95%	2997
55	112	242	210.20	6.08	3.56	35.72	19.81	145.03	19.37	3.94	89.00%	1392

Table 5: optimal configurations for scenario 3 (*Note*: grey highlighting = KPIs optimized).

Figure(s)

Figure captions

Figure 1: the CLSC considered.

Figure 2: the decision process of Company A.

Figure 3: trend of C_{tot} as a function of *OP* (a) and *MPQ* (b) - scenario 1.

Figure 4: trend of *AR* as a function of *OP* (a) and *MPQ* (b) - scenario 1.

Figure 5: trend of *OOS* as a function of *OP* (a) and *MPQ* (b) - scenario 1.

Figure 6: trend of $U_{\%}$ as a function of *OP* (a) and *MPQ* (b) - scenario 1.

Figure 7: trend of $C_{p,r} + C_{p,u}$ as a function of *OP* (a) and *MPQ* (b) - scenario 2.

Figure 8: trend of C_r as a function of *OP* (a) and *MPQ* (b) - scenario 3.

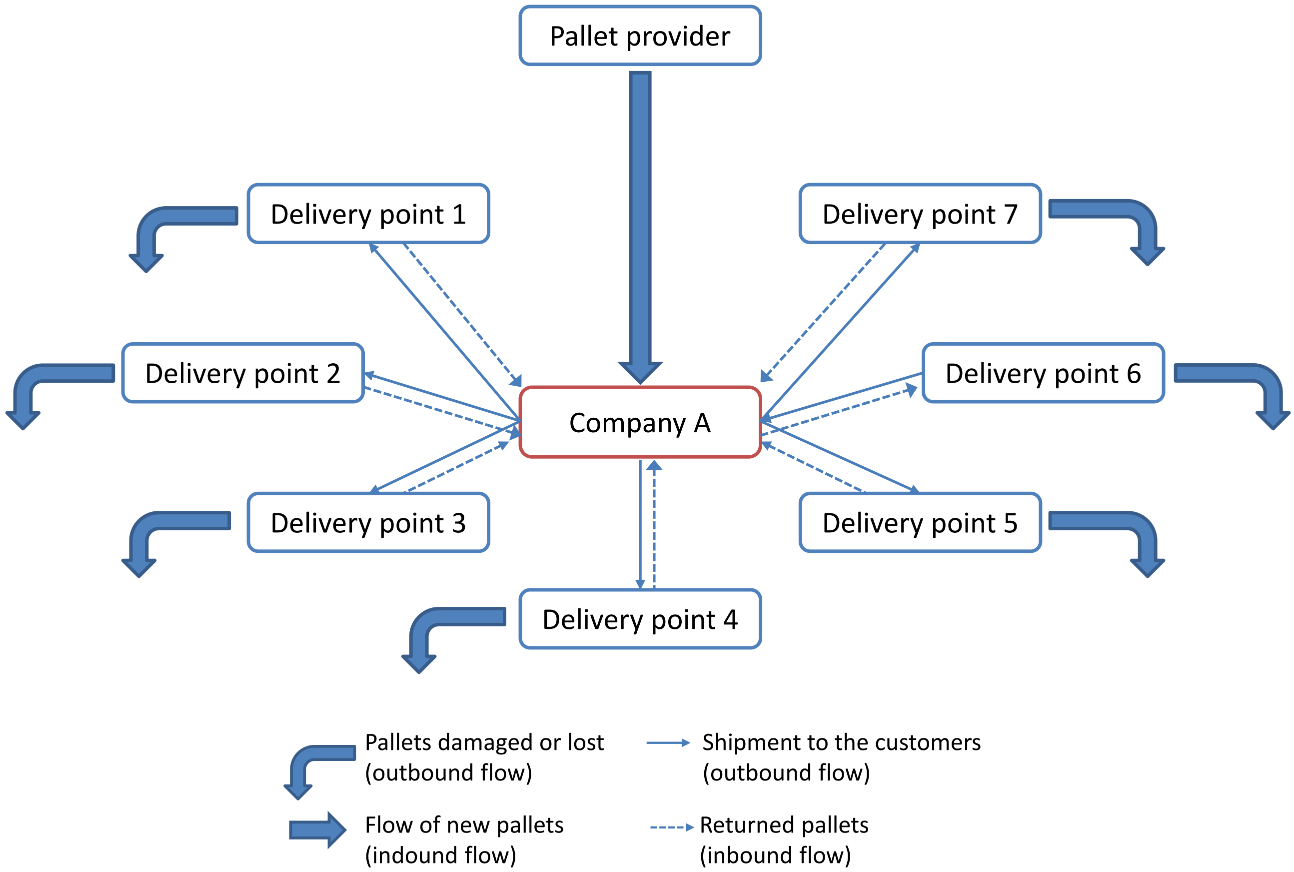

Figure 1: the CLSC considered.

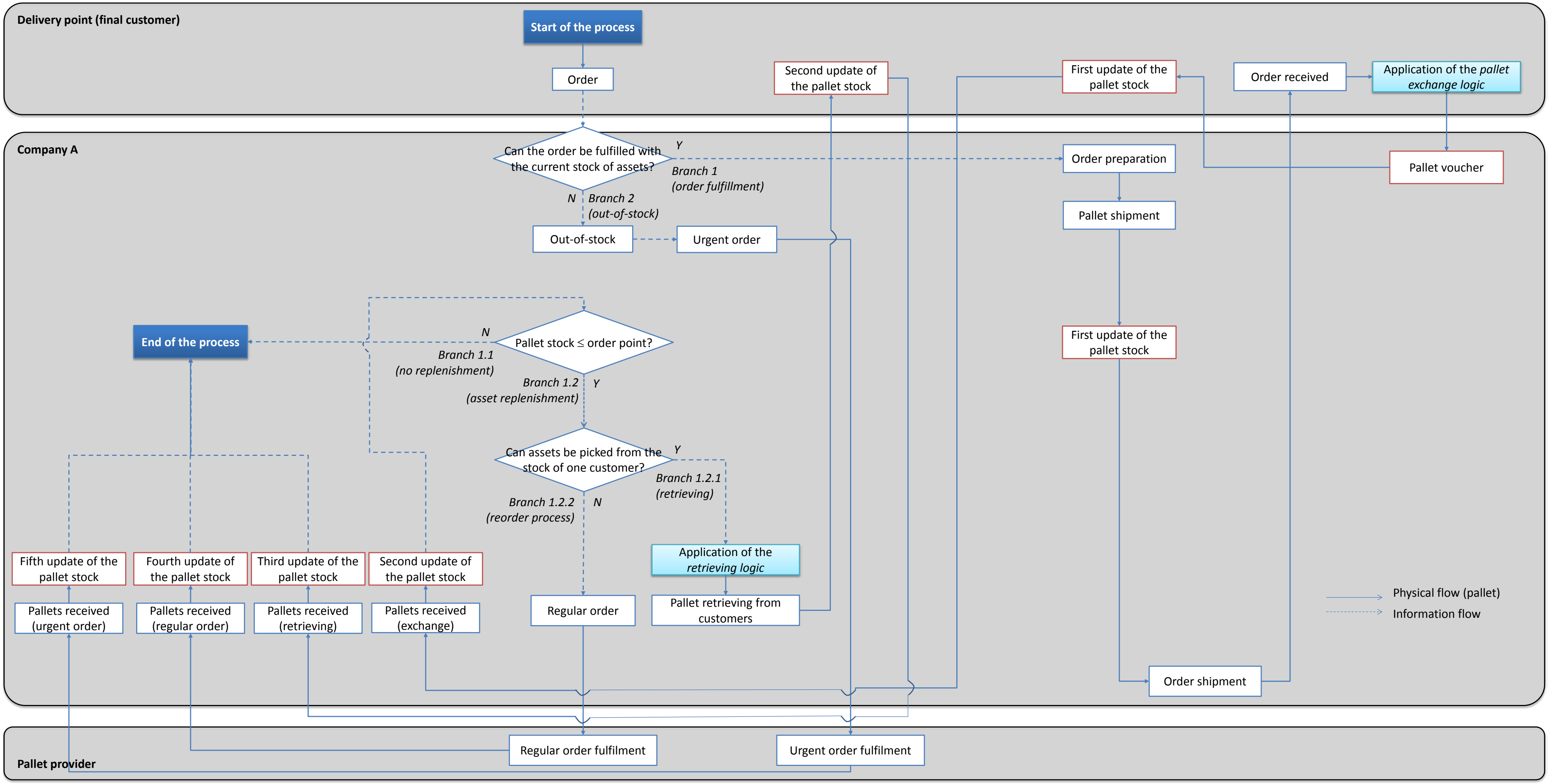

Figure 2: the decision process of Company A.

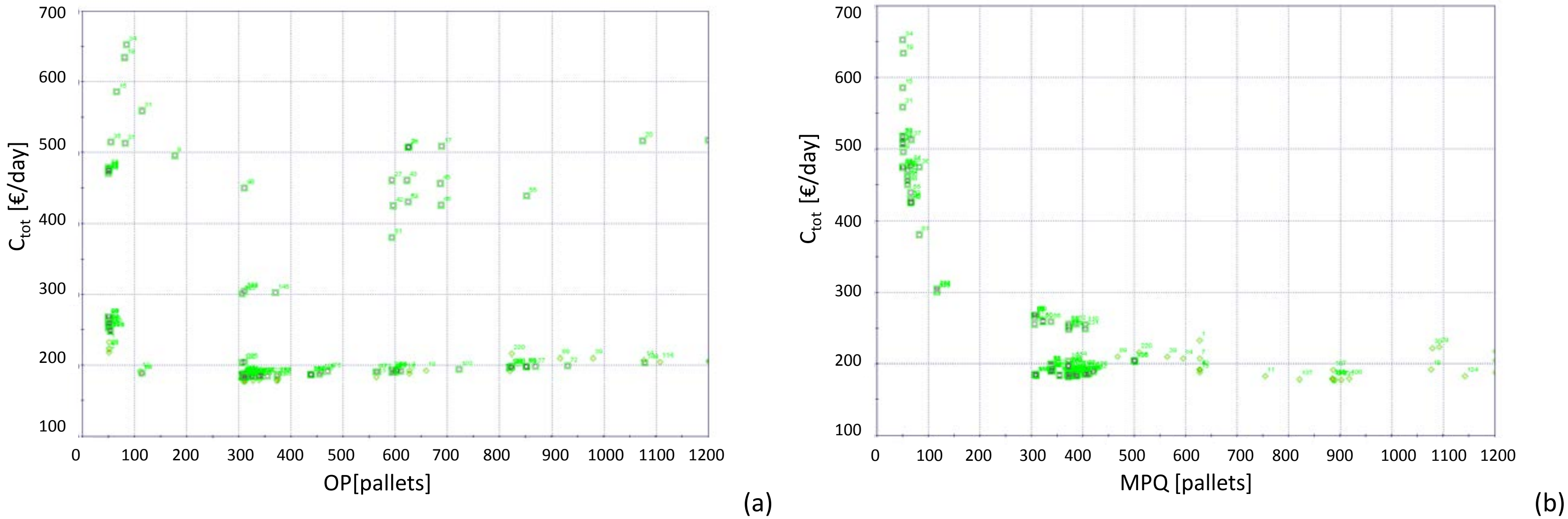

Figure 3: trend of C_{tot} as a function of *OP* (a) and *MPQ* (b) - scenario 1.

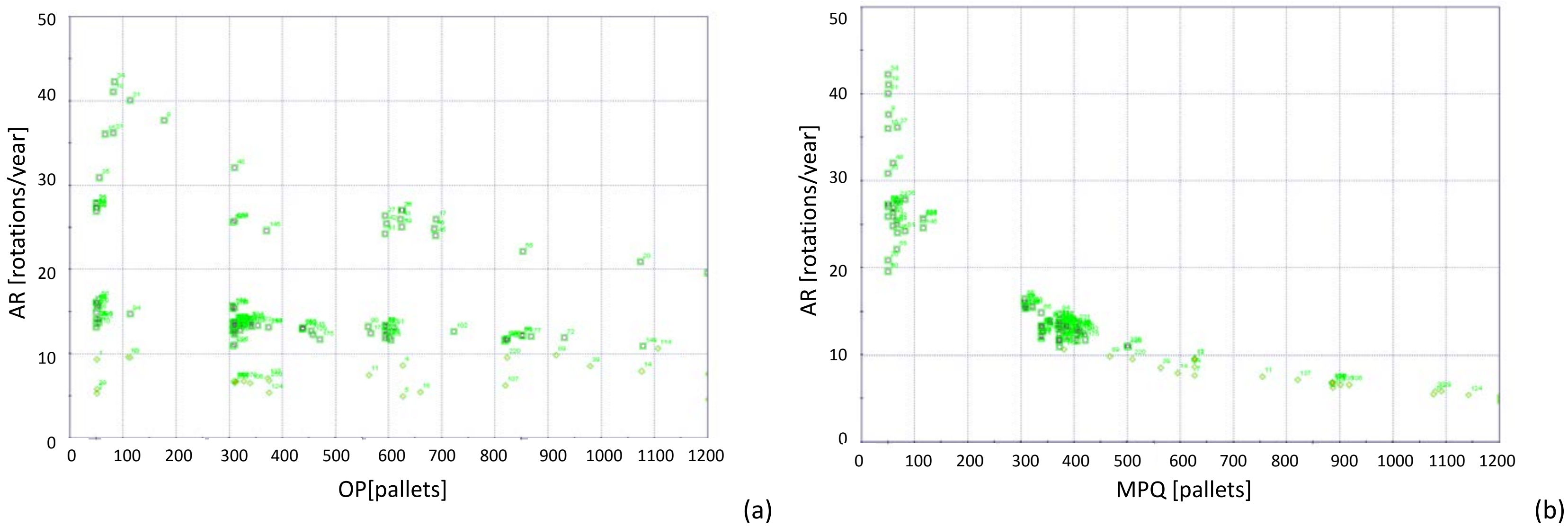

Figure 4: trend of *AR* as a function of *OP* (a) and *MPQ* (b) - scenario 1.

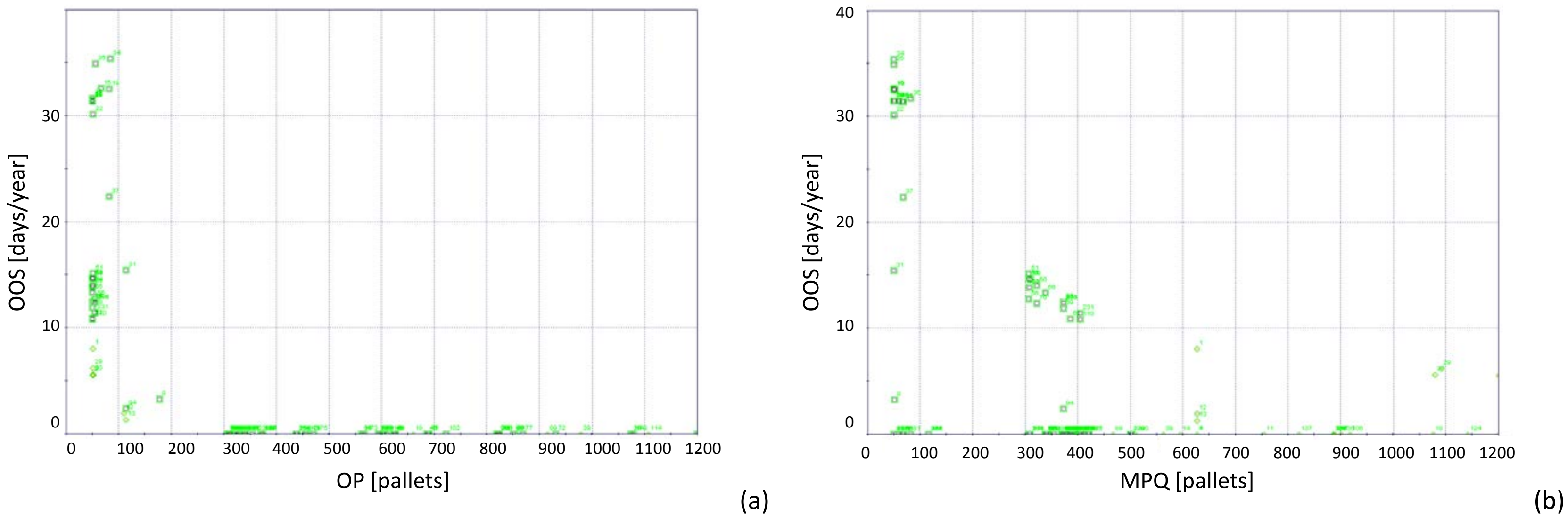

Figure 5: trend of *OOS* as a function of *OP* (a) and *MPQ* (b)- scenario 1.

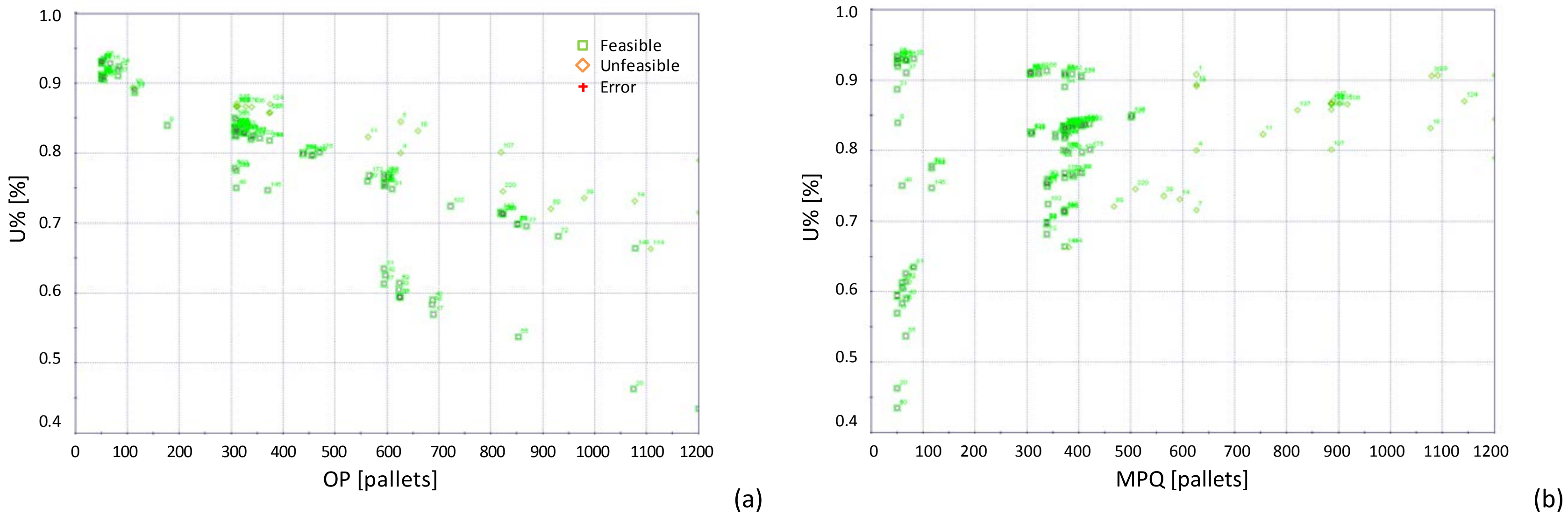

Figure 6: trend of $U_{\%}$ as a function of *OP* (a) and *MPQ* (b) - scenario 1.

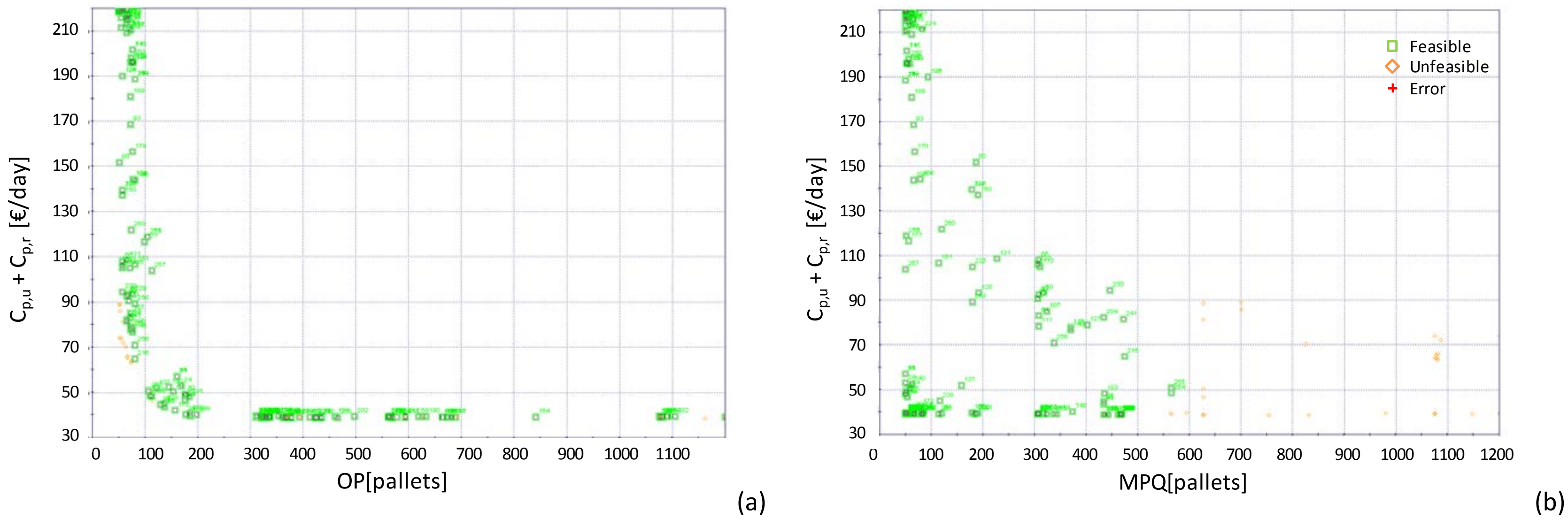

Figure 7: trend of $C_{p,r} + C_{p,u}$ as a function of *OP* (a) and *MPQ* (b) - scenario 2.

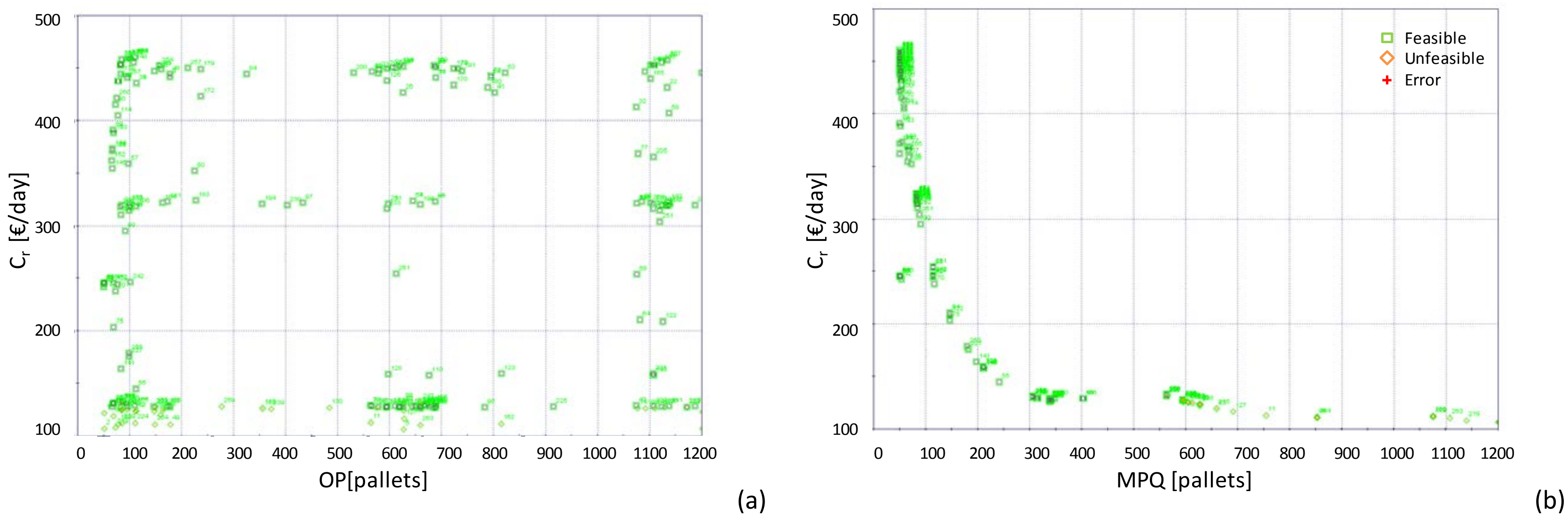

Figure 8: trend of C_r as a function of *OP* (a) and *MPQ* (b) - scenario 3.