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Closed-loop supply chains: How do production capacity and production control policies impact the performance?

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ABSTRACT

The paper addresses the impact of manufacturing and remanufacturing capacity in a multi-product closed-loop supply chain. In the problem under investigation, the manufacturing system of the factory node is characterized by a failure-prone production line that is not able to manufacture both types of product simultaneously. Therefore, changeover operations are needed to switch from one product type to another. Since failure events and changeover times may involve unforeseen problems, the production control policy of the factory assumes a key role to enhance both the internal and external performance of the closed-loop supply chain. For that reason, this research compares four production control policies in terms of bullwhip effect, fill rate, and average inventory levels. We consider the well-established Hedging Corridor Policy and Improved Modified Hedging Corridor Policy, and two different versions, named Closed-Loop Hedging Corridor Policy and Closed-Loop Improved Modified Hedging Corridor Policy, which adapt the original policies to the features of the closed-loop supply chain. Through an extensive experimental analysis, the results can guide managers in assessing the effects of multi-product manufacturing and remanufacturing operations on the performance of closed-loop supply chains and in comparing the effectiveness of the production control policies.

1. Introduction

1.1. Context

The Circular Economy is an economic system that is based on business models which replace the end-of-life concept with reducing, alternatively reusing, recycling, and recovering materials in production/distribution and consumption processes (Mhatre, Panchal, Singh, & Bibyan, 2021). The final work program for Horizon 2020 highlights "Connecting economic and environmental gains – the Circular Economy" as one of the four strategic priorities for Europe (Völker, Kovacic, & Strand, 2020). The overall budget for this topic (€941 million) illustrates that the transition from linear to circular economy models has become a fundamental need for modern societies (see *e.g.* European Commission, 2021); while the name of this pillar underlines that uncovering the economic opportunities of such circular models is a key catalyst for accelerating the transition. As a result, remanufacturing has become one of the key ones, as it retains the whole value of the product (in contrast to repairing or reusing) by delivering a product whose performance is at least to its original specifications (Reimann, Xiong, & Zhou, 2019). Analogously, novel sustainable business structures are converting into essential strategies towards the circular economy, such as the closed-loop supply chain (CLSCs), by incorporating the processes of collecting used products (cores) from customers and restoring them up to an operational state (Genovese, Acquaye, Figueroa, & Koh, 2017). Also, CLSCs were recently recognized as a valuable SC configuration to reduce carbon emissions due to their recycling and remanufacturing practices (Yang, Goodarzi, Bozorgi, & Fahimnia, 2021). For this reason, research on CLSCs is gaining momentum in a bid to encourage organizations to move towards this sustainable business model (*e.g.* Shekarian, 2020). As an example, Ellen MacArthur Foundation and McKinsey Center for Business and Environment estimate that pursuing profitable CLSC opportunities would reduce annual net European resource spending by up to 32 % by 2030 (Aguilar-Hernandez, Rodrigues, & Tukker, 2021; Schulze, 2016). The same report highlighted that such resource reduction along with other economic benefits (*e.g.* a decrease in externality costs) would yield annual savings of €1.8 trillion by that year.

Thus, in the last decade, CLSCs have increasingly attracted the interest of many researchers, who explore their environmental and

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economic opportunities and challenges from different perspectives (Bhatia, Jakhar, Mangla, & Gangwani, 2020; Govindan, Soleimani, & Kannan, 2015). However, a consolidated area of research in traditional production and distribution systems, often labelled as supply chain dynamics (Framinan, 2021; Yu & Yan, 2021), has still received relatively little attention in closed-loop settings (Braz, De Mello, de Vasconcelos Gomes, & de Souza Nascimento, 2018; Goltsos et al., 2019; Ponte, Naim, & Syntetos, 2019; Wang & Disney, 2016). This discipline analyses the time-varying behaviours that emerge from the interactions between the nodes of the supply chain, and their impact on internal (*i.e.*, production efficiency) and external (*i.e.*, customer service level) performance. Interestingly, supply chain dynamics studies capture simultaneously different perspectives that are often explored separately but are strongly interrelated, such as customer demand satisfaction, the transportation problem, and the bullwhip effect (BWE)—*i.e.*, the operational dynamics of supply chains that amplify the variability of orders in the upstream direction (Chatfield & Pritchard, 2013; Fu, Ionescu, Aghezzaf, & De Keyser, 2014; Tai, Duc, & Buddhakulsomsiri, 2019; Framinan, 2021; Huang, Potter, & Eyers, 2021). As such, the BWE has strong economic consequences on production, transportation, and inventory costs (Braz et al., 2018; Ponte, Dominguez, Cannella, & Framinan, 2022).

1.2. Background and motivation

In supply chain dynamics, the paper of Tang and Naim (2004) is usually considered the seminal work that explores the dynamics of CLSCs. They observed that such systems can benefit from improved dynamics as compared to traditional, or open-loop, supply chains, especially if the information on the reverse flow of materials is used to manage the forward flow. They concluded that increasing the return rate generally reduces order variability, which was also noticed by later works in this area; *e.g.* Zhou and Disney (2006), Adenso-Díaz, Moreno, Gutiérrez, and Lozano (2012), Dev, Shankar, and Choudhary (2017), Zhou, Naim, and Disney (2017) and Dominguez, Cannella, Ponte, and Framinan (2020). However, Hosoda, Disney, and Gavirneni (2015) revealed that in certain scenarios CLSCs experience a higher order variability than traditional systems. The impact of closing the loop on inventories has also been investigated in prior works, leading to what may be interpreted as contradicting conclusions. For example, Zhou and Disney (2006) observed that increasing the return rate has a positive impact on inventory variability (thus helping to better manage the trade-off between service level and stock required). The impact of the return volume on inventory performance thus seems to be very sensitive to the modelling assumptions. On the other hand, Tombido, Louw, van Eeden, and Zailani (2022) recently highlighted the relevant impact of remanufacturing capacity limitations on the BWE of CLSCs.

Previous works have also focused on other endogenous and exogenous key features of a CLSC. *i.e.*, (1) the effect of manufacturing and remanufacturing lead times (Dominguez, Ponte, Cannella, & Framinan, 2019; Hosoda & Disney, 2018), (2) the performance of complex CLSCs in terms of structures (Dominguez et al., 2020; Tombido, Louw, & van Eeden, 2020), (3) the impact of order batching (Ponte et al., 2022), (4) the benefit provided by the visibility of the information on remanufacturing processes (Hosoda et al., 2015; Papanagnou, 2021; Tang & Naim, 2004), (5) the dynamics of CLSCs with return flows at different stages of the multi-echelon system (Dominguez, Cannella, & Framinan, 2021) and multiple returns (Zhou et al., 2017), (6) the effect of substitution policy between new and remanufactured products (Tombido & Baihaqi, 2020), (7) the impact of pricing (Giri & Glock, 2021), among others.

These prior works arguably shed light on the CLSC dynamics under a variety of operational and market conditions. However, exploring and understanding the dynamic of CLSCs continue to be an important challenge for both researchers and practitioners, particularly by considering the need of investigating unexplored real-life conditions of the production and distribution system, such as the effect of (1) Production Control Policies (PCPs) and (2) capacity constraints on the performance of CLSCs. In the following, we detail these two aspects:

(1) We recognize that a common assumption in CLSC dynamics is to consider that all echelons adopt the same order policy, which is usually represented by periodic-review replenishment rules, such as the Proportional or Smoothing Order-Up-To (SOUT) policy (see *e.g.* Cannella, Ponte, Dominguez, & Framinan, 2021; Disney, Ponte, & Wang, 2021). In CLSC dynamics literature, some works have focused on the impact of adopting classical or ad-hoc replenishment policies at the factory stage. In their seminal work, Tang and Naim (2004) explore the effect of different SOUT policies, characterized by an increasing level of information transparency. Similar problems, under different operational and structural conditions of CLSCs, have been also investigated by Adenso-Díaz et al. (2012), Hosoda et al. (2015), Hosoda and Disney (2018), Framinan (2021) and Lin, Zhou, Spiegler, Naim, and Syntetos (2021). All mentioned works have been considerably contributing to the understanding of the dynamics of a CLSC under different replenishment rules. However, even if assuming the OUT replenishment rules and their variants, such as the SOUT can well capture the dynamics of most echelons of the supply chain (*e.g.* Distributors, Wholesalers, Retailers), it can be argued that, at the factory level, it would be more appropriated to emulate operations by considering PCPs (*e.g.* the Hedging Corridor Policy) and better capture the dynamics of real-life SCs (Corsini, Costa, & Fichera, 2021; Corsini, Costa, Cannella, & Framinan, 2022; Costa, Cannella, Corsini, Framinan, & Fichera, 2020). To the best of the authors' knowledge, all works dealing with the dynamics of CLSCs always adopted a replenishment policy at the factory level, thus without focusing on how the key variables of manufacturing systems (*e.g.* the adoption and parametrization of specific PCPs, the changeover times, stochastic failures in the production system) can influence the performance of the whole CLSC.

(2) A further common assumption in CLSC dynamics concerns the structure of the system. Usually, works have adopted the uncapacitated mono-product single production–distribution system. Even if this type of structure can easily and suitably emulate the dynamics of whole SCs (Dominguez et al., 2019), recent works have shown that by adopting novel assumptions, that better reflect real-life conditions of the supply chain, original and insightful findings may emerge, which are not always easily observable under simplified assumptions. Particularly, as the capacity constraints in supply chains can negatively impact the performance by producing high and variable production and distribution lead-times (Shukla & Naim, 2017) and stock-out phenomenon (Costa et al., 2020), this real-life condition of the production systems should be considered to enrich our knowledge on the dynamics of CLSCs. However, most of the works assume a CLSC with unlimited capacity. Only two studies consider the effect of capacity constraints, *i.e.*, Dominguez et al. (2019) and Tombido et al. (2020). Both works observe that in some scenarios capacity limitations can reduce the BWE in the fabrication of both new and remanufactured products while maintaining a good inventory performance. Nonetheless, in both studies, the capacity constraint is implemented by a limitation on orders placed to suppliers or orders' acceptance channels. This modelling approach is known in supply chain dynamics literature as Limiting Orders (Costa et al., 2020). Under this assumption, it has been shown that capacitated SCs may benefit from an improved dynamic performance in comparison to unconstrained systems, as a limitation in the order can smooth the amplification of the demand and thus overestimate the performance of a supply chain (Framinan, 2021). However, Costa et al. (2020) demonstrated that the production capacity constraint can be generated

by a compendium of realistic endogenous characteristics of manufacturing systems, such as failures, multi-product environments, changeover times, etc. However, they merely focus on the dynamics of a forward SC, and thus, to the best of the authors' knowledge, the dynamics of a CLSC operating in a multi-echelon, multi-product capacitated production control system has not been still explored

1.3. Objective

Motivated by the relevance of CLSCs for sustainable development and the lack of studies addressing how different PCPs influence CLSC dynamics under real-life operational conditions, such as the production capacity constraints, this work thoroughly investigates the performance of a multi-product, multi-echelon, capacitated CLSC. This paper focuses on a CLSC implementing the remanufacturing process on the used products collected from the market. This practice has been implemented in several industries, *e.g.* computers, cameras, medical equipment, automobile engines and aircrafts, among others (Maleki, Pasandideh, Niaki, & Cárdenas-Barrón, 2017). To do so, we model and emulate the dynamics of a CLSC composed of three nodes, *i.e.*, factory, retailer, and remanufacturer. Specifically, we include a remanufacturer who collects and remanufacture two products coming from the customer. To emulate real-life CLSC behaviour and investigate unexplored effects, we consider (i) at the customer stage, a common real-life demand model (*i.e.*, the independent and identical distribution), (ii) at the retailer stage, the order-up-to as an industrially popular replenishment policy, i.e, the SOUT policy (Disney et al., 2021), and, (iii) at the factory stage, four different PCPs. The PCPs considered in our paper are the Hedging Corridor Policy (HCP), the Improved Modified Hedging Corridor Policy (IMHCP), the Closed-Loop Hedging Corridor Policy (CLSC-HCP) and the Closed-Loop Improved Modified Hedging Corridor Policy (CLSC-IMHCP). HCP, introduced by Elhafsi and Bai (1996), was widely adopted by the literature to cope with the production control problem of two-product manufacturing systems with no-negligible changeover times. Inspired by HCP, IMHCP was proposed by Assid, Gharbi, and Hajji (2014) to reduce the total cost incurred by manufacturing systems. In this paper, we also consider two variants of these policies, namely CLSC-HCP and CLSC-IMHCP, with the aim of adapting them to the features of the CLSC dynamics. To rigorously explore the dynamics of the modelled CLSC, we adopt a full-factorial Design Of Experiments, composed of 8 experimental factors: 3 factors related to the remanufacturer stage (*i.e.*, mean of returns of products, the variance of returns of products, and the coefficient of remanufacturing capacity) and the other 5 related to the production system of the factory (*i.e.*, the adopted PCPs, the ratio between the nominal production capacity and the mean customer demand, the changeover time, the failure rate of the production system and the inventory threshold factor). To assess the dynamics of the CLSC, in line with the supply chain dynamics discipline, we adopt a non-financial performance metric system based on two criteria, *i.e.*, internal performance efficiency and customer satisfaction. To assess the internal process efficiency we adopt the order rate variance ratio (Chen, Drezner, Ryan, & Simchi-Levi, 2000) and the average inventory levels (Disney et al., 2021), while customer satisfaction is assessed with the well-recognized fill rate metric (Kleijnen & Smits, 2003). In brief, the results show relevant and novel insights into the field of CLSC dynamics. We note that PCPs and changeover time have a significant impact on the CLSC performance and managers need to adopt an adequate PCP in CLSCs to operate efficiently, *i.e.*, achieving a high fill rate while keeping low inventory levels at the factory.

The rest of the paper is organized as follows. Section 2 details the model of the CLSC, by presenting the mathematical formalization, the related modelling assumptions, the sequence of events and the adopted key performance indicators. Section 3 presents the four PCPs adopted for testing the dynamics of the CLSC. Section 4 reports the design of the simulation experiments and the statistical analysis of results. Section 5 summarises the findings and managerial implications of our work. Finally, Section 6 concludes and reflects on the next directions for research.

2. Problem statement

The supply chain problem under study refers to the multi-product EXPO model developed by Costa et al. (2020). We extend the structure since the reverse flow of the two product types joins the forward flow of the SC. To do this, we include a remanufacturer that collects and restores the two product types coming from the customer. The reverse structure considered in this work refers to the model of Dominguez et al. (2019). It is assumed that these product types achieve the condition of as-good-as-new standard (Zhou, Naim, Tang, & Towill, 2006). After the remanufacturing operations, the units of products are delivered to the factory inventory with a remanufacturing delivery lead-time. The factory consists of a failure-prone manufacturing system with a production line that is not able to manufacture both types of product simultaneously. For that reason, the production line requires changeover operations to switch from one product type to another. Based on the factory inventory level, a PCP is adopted to decide when a changeover operation is needed (Corsini et al., 2021; Corsini, Fichera, & Costa, 2022). The units of products stored in the inventory level are used to satisfy the orders arising from the retailer, which are delivered with a no-negligible delivery lead-time. The retailer adopts the SOUT to decide the order quantity for each product type (Corsini, Fichera, & Costa, 2022; Costantino, Di Gravio, Shaban, & Tronci, 2015; Disney & Lambrecht, 2008; Framinan, 2021; Lin, Naim, Purvis, & Gosling, 2017). The order quantity is subject to the non-negative condition, *i.e.*, in case of overstock, returns of finished products to the factory are not allowed (Chatfield & Pritchard, 2013). The units of products stored in the retailer inventory are used to fulfill the customer demand. The delivery lead-time from the retailer to the customer is neglected. Fig. 1 depicts the forward and reverse flows of the units of products and the information flows that characterized the CLSC model at hand.

The simulation model is based on discrete-time difference equations, which is a technique widely used by the relevant literature in supply chain dynamics (Framinan, 2021; Ponte, Wang, de la Fuente, & Disney, 2017; Warburton & Disney, 2007). Considering the complexity, dynamics and interactions that permeate a SC, computational modeling and simulation can support managers in the decision-making process. Furthermore, the SC simulation can assist decision-makers in the analysis of various scenarios and the selection of appropriate solutions and can also be a useful tool for understanding interactions and improving SC performance (Oliveira, Lima, & Montevechi, 2016). To model the non-linear conditions of the CLSC (*i.e.*, constrained capacities, lost sales, non-negative condition of the order quantity, etc.), we think that simulation can be considered as one of the most proper methodologies to address such non-linearities, which are often present in real-life supply chains.

The related nomenclature is presented in Table 1. Each product type is represented by an index p. The position of each node in the CLSC is denoted by the index i (*i.e.*, $i = 1$ factory; $i = 2$ retailer; $i = 3$ remanufacturer). The next sub-sections describe the dynamics equations used for the operations of each node of the CLSC and the key performance indicators considered in this research.

2.1. Factory

The factory is characterized by a manufacturing system with a production line subject to failure and changeover operations to switch from one product type to another. The factory is composed of the inventory of raw materials, which are used as input for the production stage, and the inventory of finished products, which is filled by the output of the production stage. It is assumed that the factory always has raw materials available and, thus, it does not issue orders to any supplier. The time

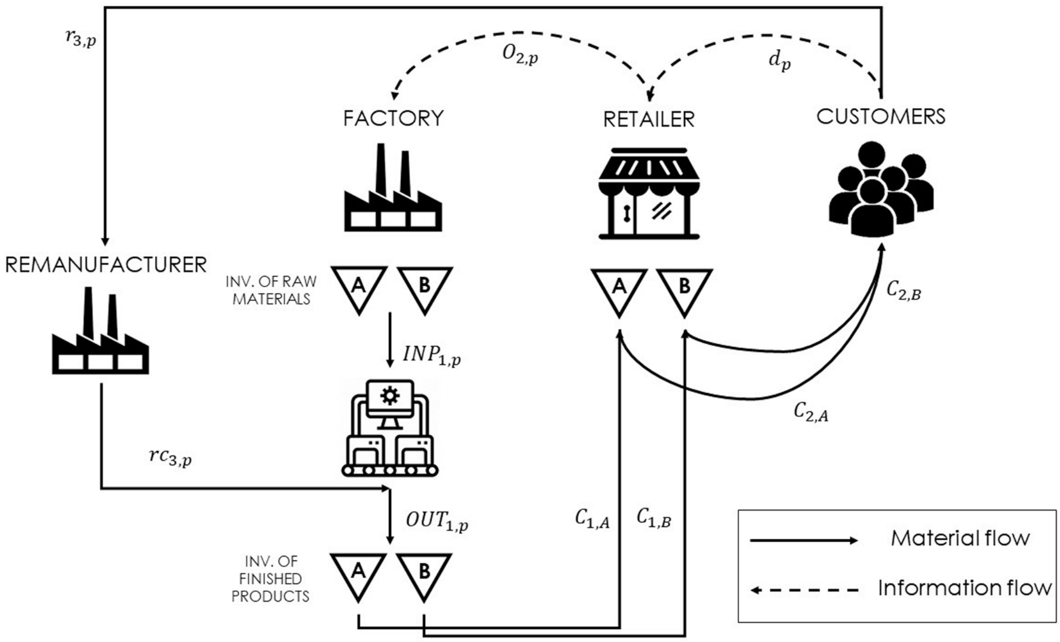


Fig. 1. The scheme of the CLSC model.

needed by the manufacturing system to complete the production operations of the input quantity, $INP_{INP}(t)$, is represented by the flow time, F (Lee, Lee, Yang, & Ignisio, 2008; Scholl, 1999). $INP_{INP}(t)$ depends on the nominal production capacity, χ_p, of the manufacturing system. In fact, since the production line produces at the maximum production rate, $INP_{1,p}(t)$ equals χ_p. However, the input quantity can be reduced by changeovers or failure events. The changeover operations involve non-negligible setup or changeover time, $CO_{1,p'p}(t)$ to switch from a product type p' to p, which depends on the maximum changeover time, δ. The failures involve a time to repair, $tr_1(t)$, that depends on the failure rate, λ (Patriarca, Costantino, & Di Gravio, 2016). $CO_{1,p'p}(t)$ and $tr_1(t)$ are calculated as follows:

$$CO_{1,p'p}(t) = \begin{cases} \delta & \textit{if a decision on changeover is made} \\ \max\{CO_{1,p'p}(t);\ \} & \textit{otherwise} \end{cases} \quad (1)$$

$$tr_1(t) = \begin{cases} U \in (0,1) & \textit{if rand } \leq \lambda \textit{ and no changeover event} \\ 0 & \textit{otherwise} \end{cases} \quad (2)$$

The input quantity, $INP_{INP}(t)$, is higher than 0 if the manufacturing system is producing the product type p and there is no changeover. Precisely, the conditions are the following:

1. The production line processed product type p at the previous time t-1 and no decision on product changeover is taken at time t ($INP_{1,p}(t-1) > 0$ *and* $CO_{1,pp'}(t) = 0$);
2. The product changeover to switch from p' to p is nearly completed ($CO_{1,p'p}(t) \in]0,1[$);
3. The product changeover to switch from p' to p is definitively completed ($CO_{1,p'p}(t-1) \geqslant 1$ *and* $CO_{1,p'p}(t) = 0$).

Therefore, $INP_{INP}(t)$ is calculated as follows:

$$INP_{1,p}(t) = \begin{cases} \chi_p \cdot \left(1CO_{1,p'p}(t)\right) \cdot (1tr_1(t)) & \textit{if the system is producing p} \\ 0 & \textit{otherwise} \end{cases} \quad (3)$$

As stated above, the input quantity, $INP_{INP}(t)$, becomes output quantity, $OUT_{INP}(t)$, after the production flow time, F:

$$OUT_{1,p}(t) = INP_{1,p}(t-F) \quad (4)$$

The output quantity, $OUT_{INP}(t)$, is stored in the inventory of the finished products, $I_{INP}(t)$, that is used to satisfy the retailer's orders, $O_{2,p}(t$-$1)$, issued in the previous time t-1. The inventory level is also increased by the units of products coming from the remanufacturer, represented by $rc_{3,p}(t)$ (see Eq. (16)). The inventory of finished products can assume negative values so as to represent a backlog scenario in which the inventory level is not enough to fulfill the retailer's orders. However, the backlogs are limited by a threshold of lost sales (Sajadi, Esfahani, & Sörensen, 2011), which is computed as $-k \cdot \mu_{d_p}$. The inventory level, $I_{INP}(t)$, at time t is calculated as:

$$I_{1,p}(t) = max\left\{I_{1,p}(t-1) + OUT_{1,p}(t) - O_{2,p}(t-1) + rc_{3,p}(t);\ -k \bullet \mu_{d_p}\right\} \quad (5)$$

Finally, the units of products delivered by the factory to the retailer, $C_{INP}(t)$, are calculated as follows:

$$C_{1,p}(t) = max\left\{min\left\{I_{1,p}(t-1) + OUT_{1,p}(t) + rc_{3,p}(t); O_{2,p}(t-1)\right\}, 0\right\} \quad (6)$$

2.2. Retailer

The retailer has to satisfy the customer demand, which is assumed to be normally distributed with mean μ_{d_p} and variance $\sigma^2_{d_p}$. The capacity of the retailer to fulfill the customer demand depends on the inventory level, $I_{2,p}(t)$, which is increased by the units of products delivered by the factory after the delivery lead time, $C_{INP}(t$ - $LT)$, as follows:

$$I_{2,p}(t) = max\left\{I_{2,p}(t-1) + C_{1,p}(t-LT) - d_{2,p}(t);\ -k \bullet \mu_{d_p}\right\} \quad (7)$$

As for the factory, the retailer's inventory level is limited by the threshold of lost sales. The delivery work-in-progress, $W_{2,p}(t)$, is used to record the units of product coming from the factory:

$$W_{2,p}(t) = W_{2,p}(t-1) + C_{1,p}(t) - C_{1,p}(t-LT) \quad (8)$$

Based on the current inventory level and the customer demand at time t, the units of products delivered by the retailer, $C_{2,p}(t)$, are calculated as follows:

$$C_{2,p}(t) = max\left\{min\left\{I_{2,p}(t-1) + C_{1,p}(t-LT); d_{2,p}(t)\right\}, 0\right\} \quad (9)$$

Finally, the retailer adopts the SOUT policy to define the order

Table 1
The nomenclature of the model.

Symbol	Description	Domain
Indices		
I	Set of echelons	$I \in \mathbb{N}$
i	Echelon	$i = 1, \ldots, I; I \in \mathbb{N}$
P	Set of product types	$P \in \mathbb{N}$
p	Product type in-process	$p = 1, \ldots, P; P \in \mathbb{N}$
p'	Product type in-waiting	$p' = 1, \ldots, P; P \in \mathbb{N}$
T	Time horizon	$T \in \mathbb{N}$
t	Time unit	$t = 1, \ldots, T; T \in \mathbb{N}$
Parameters		
α	Forecasting smoothing factor	$\alpha \in [0, 1] \cap\mathbb{R}$
β	Proportional controller	$\beta \in [0, 1] \cap\mathbb{R}$
ε	Safety stock factor	$\varepsilon \in \mathbb{R}^+$
z	Threshold of inventory factor	$z \in \mathbb{R}^+$
$\mathrm{Z_p}$	Maximum inventory threshold of product type p	$\mathrm{Z_p} \in \mathbb{R}^+$
$\mathrm{a_p}$	Minimum inventory threshold of product type p	$\mathrm{a_p} \in [0, \mathrm{Z_p}] \cap\mathbb{R}$
$\mathrm{b_p}$	Safety inventory threshold of product type p	$\mathrm{b_p} \in \mathbb{R}^+$
φ	Factor of minimum inventory threshold	$\varphi \in [0, 1] \cap\mathbb{R}$
CoCr	Coefficient of remanufacturing capacity of product type p	$\mathrm{CoCr} \in \mathbb{R}^+$
δ	Changeover time	$\delta \in \mathbb{R}^+$
F	Flow time	$F \in \mathbb{N}$
k	Threshold of lost sales factor	$k \in \mathbb{R}^+$
λ	Failure rate	$\lambda \in [0, 1] \cap\mathbb{R}$
LT	Delivery lead-time	$LT \in \mathbb{N}$
LTc	Consumption lead-time	$\mathrm{LTc} \in \mathbb{N}$
LTr	Remanufacturing lead-time	$\mathrm{LTr} \in \mathbb{N}$
$\mathrm{T_{warm}}$	Warm-up period	$\mathrm{T_{warm}} \in [0, \mathrm{T}\ ] \cap\mathbb{N}$
ψ_p	Remanufacturing capacity of product type p	$\psi_p \in \mathbb{N}$
χ_p	Nominal production capacity of product type p	$\chi_p \in \mathbb{N}$
$\mu_{a\%}$	Mean of return rate	Î¼$_{\mathrm{a\%}}$ $\in [0, 1] \cap\mathbb{R}$
μ_{d_p}	Mean of customer demand of product type p	$\mu_{d_p} \in \mathbb{N}$
$\sigma_{a\%}$	Standard deviation of return rate	$\sigma^2_{a\%} \in [0, 1] \cap\mathbb{R}$
σ_{d_p}	Standard deviation of customer demand of product type p	$\sigma_{d_p} \in \mathbb{R}^+$
Variables		
$\mathrm{C_{i,p}(t)}$	Units of product type p delivered to echelon i at time t	$\mathrm{C_{i,p}(t)} \in \mathbb{N}$
$CO_{1,p'p}(t)$	Residual changeover time to switch from product type p' to p in the factory at time t	$CO_{1,p'p}(t) \in [0, \delta] \cap\mathbb{R}$
$\mathrm{d_{i,p}(t)}$	Demand of product type p in echelon i at time t	$\mathrm{d_{i,p}(t)} \in \mathbb{N}$
$\widehat{d}_{ip}(t)$	Demand of product type p forecasted by echelon i at time t	$\widehat{d}_{ip}(\mathrm{t}) \in \mathbb{N}$
$\mathrm{I_{i,p}(t)}$	Inventory level of product type p in echelon i at time t	$\mathrm{I_{i,p}(t)} \in \mathbb{N}$
$\widehat{I}_{1,p}(t)$	Forecasted inventory level of product type p in the factory at time t	$\widehat{I}_{1,p}(t) \in \mathbb{N}$
$\mathrm{INP_{1,p}(t)}$	Input quantity of product type p in the factory at time t	$\mathrm{INP_{1,p}(t)} \in [0, \chi_p] \cap\mathbb{N}$
$\mathrm{O_{2,p}(t)}$	Order quantity of product type p issued by the retailer at time t	$\mathrm{O_{2,p}(t)} \in \mathbb{N}$
$\mathrm{OUT_{1,p}(t)}$	Output quantity of product type p in the factory at time t	$\mathrm{OUT_{1,p}(t)} \in [0, \chi_p] \cap\mathbb{N}$
$\mathrm{r_{3,p}(t)}$	Return of product type p at time unit t	$\mathrm{r_{3,p}(t)} \in \mathbb{N}$
$\mathrm{rb_{3,p}(t)}$	Remanufacturing backlog of product type p at time unit t	$\mathrm{rb_{3,p}(t)} \in \mathbb{N}$
$\mathrm{rc_{3,p}(t)}$	Remanufacturing completion rate of product type p at time unit t	$\mathrm{rc_{3,p}(t)} \in \mathbb{N}$
$\mathrm{tr_1(t)}$	Repair time in the factory	$\mathrm{tr_1(t)} \in [0, 1] \cap\mathbb{R}$
$\mathrm{TI_{2,p}(t)}$	Target inventory of product type p in the retailer at time t	$\mathrm{TI_{2,p}(t)} \in \mathbb{N}$
$\mathrm{TW_{2,\ p}(t)}$	Target work in progress of product type p in the retailer at time t	$\mathrm{TW_{2,\ p}(t)} \in \mathbb{N}$
$\mathrm{W_{2,p}(t)}$	Delivery work in progress of product type p at time t	$\mathrm{W_{2,p}(t)} \in \mathbb{N}$
$\mathrm{y_{3,p}(t)}$	Percentage of the customer demand for the returns of product type p at time unit t	$\mathrm{y_{3,p}(t)} \in [0, 1] \cap\mathbb{R}$

Table 1 (*continued*)

Symbol	Description	Domain
Performance indicators		
$\mathrm{FR_p}$	Fill Rate of product type p	$\mathrm{FR_p} \in [0, 1] \cap\mathbb{R}$
$\mu I_{1,p}$	Average factory inventory level of product type p	$\mu I_{1,p} \in \mathbb{R}$
$\mathrm{OrVr_p}$	Order rate variance ratio of product type p	$\mathrm{OrVr_p} \in \mathbb{R}^+$

quantity, $O_{2,p}(t)$, at each time unit t:

$$O_{2,p}(t) = max\left\{\widehat{d}_{2,p}(t) + \beta \bullet \left(TW_{2,p}(t) - W_{2,p}(t) + TI_{2,p}(t) - I_{2,p}(t)\right); 0\right\} \tag{10}$$

The order quantity is composed of the forecasted demand, $\widehat{d}_{2,p}(t)$, the delivery work-in-progress gap, $TW_{2,p}(t) - W_{2,p}(t)$, and the inventory gap, $TI_{2,p}(t) - I_{2,p}(t)$. The forecasted demand is calculated using the exponential smoothing method:

$$\widehat{d}_{2,p}(t) = \alpha_{ret} \bullet d_{2,p}(t) + (1 - \alpha_{ret})\widehat{d}_{2,p} \bullet (t-1) \tag{11}$$

The work-in-progress gap and the inventory gap depend on the target work-in-progress, $TW_{2,p}(t)$, and target inventory, $TI_{2,p}(t)$, respectively, which are calculated as follows:

$$TW_{2,p}(t) = LT \bullet \widehat{d}_{2,p}(t) \tag{12}$$

$$TI_{2,p}(t) = \varepsilon \bullet \widehat{d}_{2,p}(t) \tag{13}$$

2.3. Remanufacturer

At each time unit t, the remanufacturer receives units of products as returns, $r_{3,p}(t)$, from the customer. $r_{3,p}(t)$ represents a percentage, $y_{3,p}(t)$, of the customer demand, $d_{2,p}(t)$. $y_{3,p}(t)$ assumes values in the range of [0, 1] and it is assumed to be normally distributed with mean $\mu_{a\%}$ and variance $\sigma^2_{a\%}$. These returns are shipped to the remanufacturer after a consumption lead-time, LT_c, and are calculated as follows:

$$r_{3,p}(t) = y_{3,p}(t) \bullet d_{2,p}(t - LT_c) \tag{14}$$

These units of returns are subject to a remanufacturing process that is characterized by a remanufacturing capacity constraint, ψ_p. ψ_p is a parameter that depends on the coefficient of remanufacturing capacity, $CoCr$, as follows:

$$\psi_p = CoCr \bullet \mu_{a\%} \bullet \mu_{d_p} \tag{15}$$

Therefore, at each time unit t, it can be calculated the number of units of products remanufactured, $rc_{3,p}(t)$, which depends on the remanufacturing lead time LT_r and the remanufacturing capacity constraint, ψ_p, as follows:

$$rc_{3,p}(t) = min\left\{r_{3,p}(t - LT_r - 1) + rb_{3,p}(t-1); \psi_p\right\} \tag{16}$$

where $rb_{3,p}(t\text{-}1)$ is the remanufacturing backlog calculated as:

$$rb_{3,p}(t) = max\left\{r_{3,p}(t - LT_r - 1) + rb_{3,p}(t-1) - \psi_p; 0\right\} \tag{17}$$

2.4. Key performance indicators

The performance of the CLSC model at hand are evaluated based on three response variables: i) fill rate, FR_p; ii) average factory inventory level, $\mu I_{1,p}$; iii) order rate variance ratio, $OrVr_p$. The fill rate measures the customer service level of the CLSC by considering the ratio between the units of products delivered by the retailer and the customer demand (Chinello, Herbert-Hansen, & Khalid, 2020):

$$FR_p = \left(\frac{1}{T - T_{warm}} \bullet \sum_{t=T-T_{warm}-1}^{T} \frac{C_{2,p}(t)}{d_p(t)}\right)\% \tag{18}$$

The average factory inventory level is considered to estimate the holding costs of this node (Fu, Ionescu, Aghezzaf, & De Keyser, 2015) and it is calculated as:

$$\mu I_{1,p} = \frac{1}{T - T_{warm}} \bullet \sum_{t=T-T_{warm}+1}^{T} I_{1,p}(t) \tag{19}$$

Finally, the order rate variance ratio ($OrVr_p$) is the widely adopted performance metric to measure the BWE of the supply chain (Fussone, Dominguez, Cannella, & Framinan, 2022; Vicente, Relvas, & Barbosa-Póvoa, 2018). In this work, we adopt a version of the $OrVr_p$ which is formulated as the ratio of the variabilities of demand between the two echelons of the CLSC, expressed in terms of standard deviation:

$$OrVr_p = \frac{\sigma_{O_{2,p}}}{\sigma_{d_p}} \tag{20}$$

It can be noticed that all the metrics are computed without considering the T_{warm} period to avoid the randomness effect in the performance evaluation.

3. Production control policies

The PCP is used by the factory to decide when a changeover operation is needed to switch from one product type to another. Considering that the manufacturing system of the factory is characterized by production flow time F and the production work-in-progress, the forecasted inventory level $\widehat{I}_{INP}(t)$ is used by each PCP to carry out the decision-making about changeovers (Corsini, Costa, Cannella, et al., 2022; Costa et al., 2020). The forecasted inventory level is calculated as follows:

$$\widehat{I}_{1,p}(t) = max\left\{I_{1,p}(t) + F \bullet \left(\chi_p - \widehat{d}_{1,p}(t)\right);\ -k \bullet \mu_{d_p}\right\} \tag{21.a}$$

In this work, we consider the well-established HCP (Elhafsi & Bai, 1996) and the IMHCP (Assid et al., 2014). Furthermore, we have slightly modified HCP and IMHCP to fit the specific CLSC requirements. As a result, we defined two additional PCPs named CLSC-HCP and CLSC-IMHCP, respectively. Briefly, these PCPs incorporate the mean return rate in the $\widehat{I}_{INP}(t)$ calculation, as follows:

$$\widehat{I}_{1,p}(t) = max\left\{I_{1,p}(t) + F \bullet \left(\chi_p - \widehat{d}_{1,p}(t) + \mu_{a\%} \bullet \widehat{d}_{1,p}(t)\right); -k \bullet \mu_{d_p}\right\} \tag{21.b}$$

3.1. Hedging Corridor policy

The aim of the PCPs is to cope with the inventory and capacity shortages arising from production stoppages due to changeovers and failures. To this end, HCP and CLSC-HCP protect the manufacturing system by building a positive target inventory level defined by a maximum inventory threshold Z_p. It is calculated by considering the inventory threshold factor (z), and the mean value of the customer demand (μ_{d_p}) as follows:

$$Z_p = z \bullet \mu_{d_p} \tag{22}$$

To make decisions about changeovers, the maximum inventory threshold is compared with the forecasted inventory level as in Fig. 2. Precisely, shows the variation of the current and forecasted inventory levels when HCP or CLSC-HCP are used as PCP by the factory. The continuous line is the current inventory level $I_{INP}(t)$, while the forecasted inventory level $\widehat{I}_{INP}(t)$ is depicted with the dashed line. Looking at mark 1 of Fig. 2, a changeover event occurs when the forecasted inventory level exceeds the maximum inventory threshold. In this case, the residual changeover time $CO_{1,p'p}(t)$ is set equal to the changeover time δ and, then, Eq. (1) can be expressed as follows:

$$CO_{1,p'p}(t) = \delta \quad if\ INP_{1,p'}(t-1) > \ and\ \widehat{I}_{1,p'}(t) \geqslant Z_{p'} \tag{1.a}$$

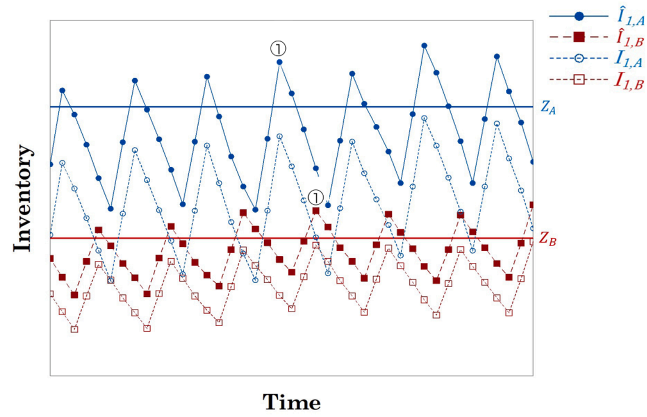


Fig. 2. The current and forecasted inventory level when the HCP or CLSC-HCP are adopted.

3.2. Improved Modified Hedging Corridor policy

The IMHCP, introduced by Assid et al. (2014), is a variant of the well-established HCP. Differently from HCP that looks only at the maximum inventory threshold Z_p (see Eq. (22)), the aim of IMHCP is to anticipate product changeovers when a backlog scenario could occur. To this end, IMHCP is characterized by three different thresholds, that are the maximum inventory threshold Z_p, the minimum inventory threshold a_p and the safety threshold b_p. The minimum inventory threshold depends on Z_p and on a parameter φ that can assume values between 0 and 1. a_p is calculated as follows:

$$a_p = \varphi \bullet Z_p \tag{23}$$

On the other hand, the safety threshold b_p is used to alert when the inventory level is low and can become negative. Therefore, b_p depends on δ and μ_{d_p} as follows:

$$b_p = \delta \bullet \mu_{d_p} \tag{24}$$

Fig. 3 shows that if IMHCP or CLSC-IMHCP are adopted as PCP, the decision about product changeover is made based on two different alternatives. In the first condition (see mark 1 in Fig. 3), a changeover event occurs if the forecasted inventory level of the product p' being manufactured is higher than the related minimum inventory threshold and, simultaneously, the current inventory level of the alternative product type p is lower than the related safety threshold. The second condition is the same of HCP or CLSC-HCP policies since it compares the

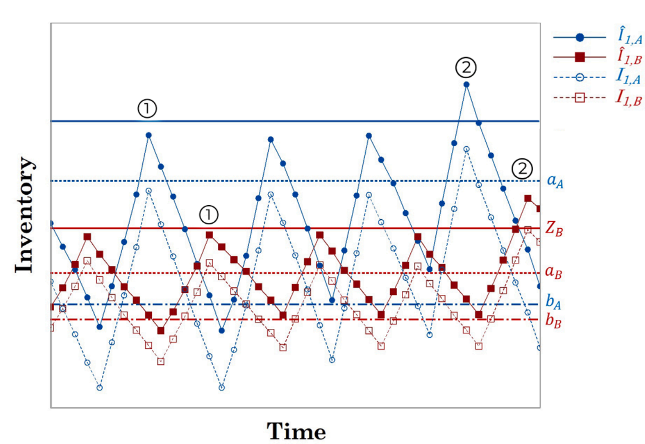


Fig. 3. The current and forecasted inventory level when the IMHCP or CLSC-IMHCP are adopted.

forecasted inventory level of the product p' being manufactured with the related maximum inventory threshold. Therefore, Eq. (1) can be expressed as follows:

$$CO_{1,p'p}(t) = \delta \text{ if } INP_{1,p'}(t-1) > \text{ and } \begin{cases} \widehat{I}_{1,p'}(t) \geqslant a_{p'} \text{ and } I_{1,p}(t) < b_p \\ \widehat{I}_{1,p'}(t) \geqslant Z_{p'} \end{cases} \tag{1.b}$$

4. Experimental analysis

This section deals with the experimental campaign carried out to investigate the dynamics of the CLSC model at hand. For this purpose, a full-factorial Design Of Experiments (DOE) was built (see Table 2). As stated in Kleijnen (2005), "*Because simulation - treated as a black box -implies experimentation with a model, DOE is essential.*" In fact, the majority of works using a simulation approach for analysing SC dynamics adopt the DOE (see *e.g.* Chatfield, Kim, Harrison, & Hayya, 2004, Kim, Chatfield, Harrison, & Hayya, 2006, Ponte et al., 2022 or Fussone, Dominguez, Cannella, & Framinan, 2023). This approach allows systematically varying key inputs parameters and observing their effects on SC behavior. In fact, through the use of DOE in combination with statistical methods, it can be identified the influence (main effects and interactions) of key inputs on model outputs, leading to valuable insights and recommendations for SC managers and decision-makers.

The DOE is composed of 8 experimental factors: 3 factors related to the remanufacturer stage (*i.e.*, $\mu_{a\%}$, $\sigma^2_{a\%}$, and $CoCr$) and the other 5 related to the manufacturing system of the factory (*i.e.*, PCP, χ_p/μ_{d_p}, δ, λ, z). Each experimental factor varies at three levels, with the exception of PCP that varies at four levels. Considering that 10 replicates were included in the experimental campaign, then, $3^7 \bullet 4 \bullet 10 = 87,480$ runs were executed. These simulation runs were obtained through the simulation model based on discrete-time difference equations coded in Matlab r2021® on a workstation equipped with an INTEL i9-9900 3.6 GHz 10 core CPU, 32 Gb DDR4 2,666 MHz RAM and Win 10 PRO OS. The values of the exogenous factors are consistent with relevant studies from the literature dealing with both forward and reverse multi-echelon SC dynamics problem (as for example Sterman, 1989; Chatfield et al., 2004; Tang & Naim, 2004; Dejonckheere, Disney, Lambrecht, & Towill, 2004; Towill, Zhou, & Disney, 2007; Zhou et al., 2017; Dominguez et al., 2019, 2020; Cannella et al., 2021; Ponte et al., 2022, among others). The next sub-sections analyze the outcomes arising from the experimental campaign.

Table 2
Design of experiments.

Parameters			Symbol		Value
Mean customer demand of product type A			μ_{d_A}		100
Mean customer demand of product type B			μ_{d_B}		50
St. Dev. Demand / Mean Demand			σ_{d_p}/μ_{d_p}		0.10
Forecasting factor			α		0.30
Proportional controller			β		0.30
Safety stock factor			ε		1
Delivery lead-time			LT		2
Flow time			F		2
Threshold of lost sales factor			k		2
Consumption lead-time			Tc		32
Remanufacturing lead-time			Tr		4
Time horizon			T		2000
Warm-up period			$Twarm$		200
Experimental factors	**Symbol**	**Level I**	**Level II**	**Level III**	**Level IV**
Production control policy	PCP	HCP	CLSC-HCP	IMHCP	CLSC-IMHCP
Mean of return rate	$\mu_{a\%}$	0.25	0.50	0.75	–
St. Dev. of return rate	$\sigma_{a\%}$	0.15	0.30	0.45	–
Coefficient of remanufacturing capacity	$CoCr$	0.75	1.00	1.25	–
Nominal production capacity / mean demand	χ_p/μ_{d_p}	2.50	3.00	3.50	–
Changeover time	δ	1.00	2.00	3.00	–
Failure rate	λ	0.05	0.10	0.15	–
Inventory threshold factor	z	8.00	9.00	10.00	

4.1. ANOVA analysis

The influences of the eight experimental factors were analyzed through a series of analyses of variance (ANOVA) at 95 % until the second-order interactions. To do this, Minitab® 17 commercial package was used. It can be noticed that only product type A is considered in the analyses as no significant difference came out from the outputs of the ANOVA analyses related to the two product types. Fig. 4 illustrates the ANOVA table of the three key performance indicators. The impact of each experimental factor is significant whether the *p*-value is lower than 0.05. The significance of the experimental factors on the performance measures is further exacerbated by *F*-values. High *F*-values represent a relevant significance of the experimental factor under investigation. Furthermore, Yu, Semeraro, and Matta (2018) pointed out that the significant factors are usually identified by a F-value larger than 50. In light of the aforementioned consideration, each experimental factors have a significant impact on the performance measures, with the exception of the standard deviation of the return rate. This experimental factor presents an *F*-value lower than 50 in terms of both fill rate and order rate variance ratio. The experimental factors that mostly affect the fill rate and the order rate variance ratio are PCP, $\mu_{a\%}$ and δ, while, in terms of average factory inventory level are $\mu_{a\%}$, δ and z. As for the interaction between the experimental factors, the most influencing interactions for all the performance measures are PCP * $\mu_{a\%}$, PCP * δ, $\mu_{a\%}$ * χ_p/μ_{d_p} and $\mu_{a\%}$ * δ. Finally, it is worth pointing out that, for each response variable, the impact of the replications, named "blocks", can be considered not significant since they present *F*-values lower than 50.

4.1.1. Fill rate

This sub-section analyses the results in terms of the fill rate of the CLSC model under investigation with the main effect plots in Fig. 5. As for PCP, the well-established HCP and the CLSC-HCP assure the highest values of fill rate in comparison with the IMHCP and CLSCL-IMHCP policies. In fact, the CLSC-HCP achieves similar performance to HCP and assures a fill rate higher than 95 %. As expected, the mean return rate enables the CLSC to increase the fill rate. The main effect plots of the standard deviation of the return rate confirm the findings of the ANOVA table, *i.e.*, the values of this experimental factor are almost equal to the mean fill rate and, then, it can be considered not significant. Similarly to the work of Dominguez et al. (2019), high values of remanufacturing capacity support the CLSC in increasing the fill rate, while the nominal production capacity, changeover, failure rate, and inventory threshold factors show the same trend of the SCs model with production capacity constraints (Corsini et al., 2021; Costa et al., 2020). Fig. 6 shows the most interesting interaction plot. Fig. 6-a reports the interaction PCP * $\mu_{a\%}$. The interaction reveals that low values of mean return rate increase the difference in terms of fill rate between the PCPs. When the mean return rate assumes high values (*e.g.* 0.75), the fill rate of the PCPs are similar and in the range of 95 % and 100 %. It can be noticed that there is a wide range of performance when the mean return rate assumes low values. In particular, IMHCP is strongly affected by passing from 0.50 to 0.25 of the mean return rate since it revealed a reduction of almost 15 % of the fill rate. In fact, when the mean return rate is equal to 0.50, IMHCP presents a similar performance compared to HCP and CLSC-HCP, while when the return rate is lower, the performance is similar to CLSC-IMHCP. Fig. 6-b shows the interaction PCP * δ. From this interaction, it can be pointed out the strong influence of the changeover time on the performance of the CLSC. When the changeover time is equal to 1, the differences between the PCPs are not significant and the fill rate is

Analysis of Variance

		FR		μI_1		OrVr	
Source	DF	F-Value	P-Value	F-Value	P-Value	F-Value	P-Value
Model	152	2443.20	0.000	5539.52	0.000	2456.39	0.000
Blocks	9	1.74	0.074	3.98	0.000	13.10	0.000
Linear	17	13106.43	0.000	41739.23	0.000	14661.37	0.000
PCP	3	13035.83	0.000	41002.36	0.000	13895.66	0.000
$\mu_{a\%}$	2	37855.29	0.000	86680.58	0.000	34016.53	0.000
$\sigma_{a\%}$	2	30.35	0.000	2.87	0.057	7.13	0.001
CoCr	2	4742.47	0.000	14562.31	0.000	4232.13	0.000
χ_p/μ_{dp}	2	4366.25	0.000	10745.76	0.000	2361.07	0.000
δ	2	36517.75	0.000	69690.25	0.000	51017.45	0.000
λ	2	572.99	0.000	1074.27	0.000	760.49	0.000
z	2	7765.77	0.000	110523.87	0.000	11383.39	0.000
2-Way Interactions	126	1178.90	0.000	1050.83	0.000	984.21	0.000
PCP*$\mu_{a\%}$	6	3181.67	0.000	5347.30	0.000	1230.94	0.000
PCP*$\sigma_{a\%}$	6	1.54	0.159	0.89	0.498	2.98	0.006
PCP*CoCr	6	349.64	0.000	243.33	0.000	138.33	0.000
PCP*χ_p/μ_{dp}	6	151.09	0.000	152.12	0.000	140.48	0.000
PCP*δ	6	4351.13	0.000	3708.17	0.000	4371.25	0.000
PCP*λ	6	14.68	0.000	5.55	0.000	4.43	0.000
PCP*z	6	779.21	0.000	168.03	0.000	708.33	0.000
$\mu_{a\%}$%*$\sigma_{a\%}$	4	80.24	0.000	266.70	0.000	92.82	0.000
$\mu_{a\%}$%*CoCr	4	999.89	0.000	250.34	0.000	673.94	0.000
$\mu_{a\%}$%*χ_p/μ_{dp}	4	6496.23	0.000	6067.60	0.000	6759.24	0.000
$\mu_{a\%}$%*δ	4	10780.95	0.000	9548.65	0.000	8464.33	0.000
$\mu_{a\%}$%*λ	4	262.45	0.000	187.71	0.000	293.02	0.000
$\mu_{a\%}$%*z	4	874.15	0.000	47.31	0.000	347.72	0.000
$\sigma_{a\%}$%*CoCr	4	41.15	0.000	59.07	0.000	25.54	0.000
$\sigma_{a\%}$%*χ_p/μ_{dp}	4	18.34	0.000	16.14	0.000	21.60	0.000
$\sigma_{a\%}$%*δ	4	8.53	0.000	7.69	0.000	6.27	0.000
$\sigma_{a\%}$%*λ	4	0.17	0.953	0.11	0.980	0.13	0.971
$\sigma_{a\%}$%*z	4	0.99	0.410	2.08	0.080	4.05	0.003
CoCr*χ_p/μ_{dp}	4	514.61	0.000	506.02	0.000	409.15	0.000
CoCr*δ	4	876.03	0.000	586.99	0.000	628.18	0.000
CoCr*λ	4	31.82	0.000	20.68	0.000	28.91	0.000
CoCr*z	4	214.33	0.000	15.73	0.000	93.20	0.000
χ_p/μ_{dp}*δ	4	613.14	0.000	826.60	0.000	327.42	0.000
χ_p/μ_{dp}*λ	4	76.29	0.000	60.38	0.000	55.51	0.000
χ_p/μ_{dp}*z	4	21.95	0.000	17.15	0.000	254.55	0.000
δ*λ	4	84.33	0.000	30.36	0.000	107.27	0.000
δ*z	4	1883.50	0.000	144.75	0.000	2505.45	0.000
λ*z	4	12.90	0.000	1.09	0.362	9.26	0.000

Model Summary	R-sq	R-sq(adj)	R-sq(pred)
FR	80.96%	80.93%	80.90%
μI_1	90.60%	90.59%	90.57%
OrVr	81.04%	81.01%	80.98%

Fig. 4. ANOVA table.

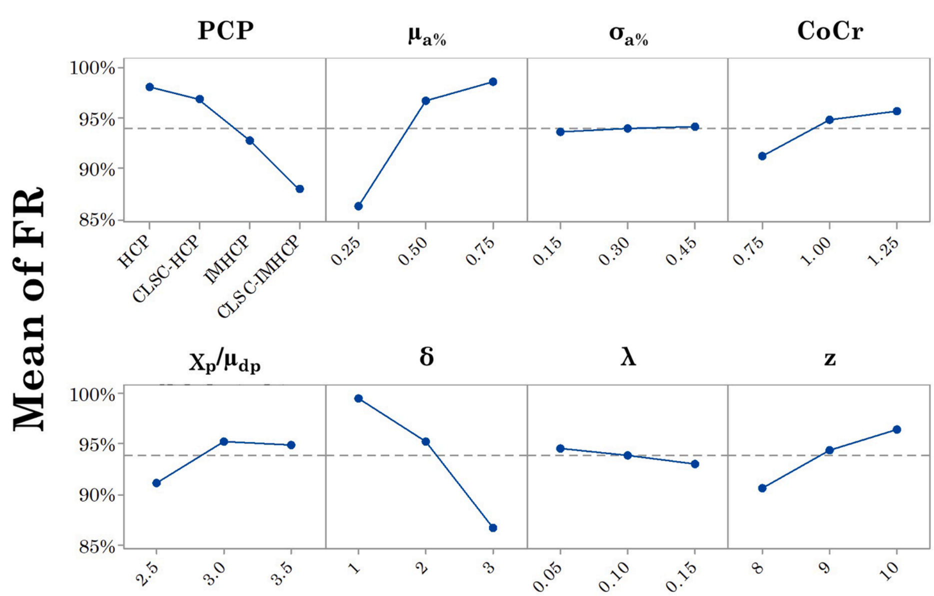


Fig. 5. Main effect plots for the fill rate.

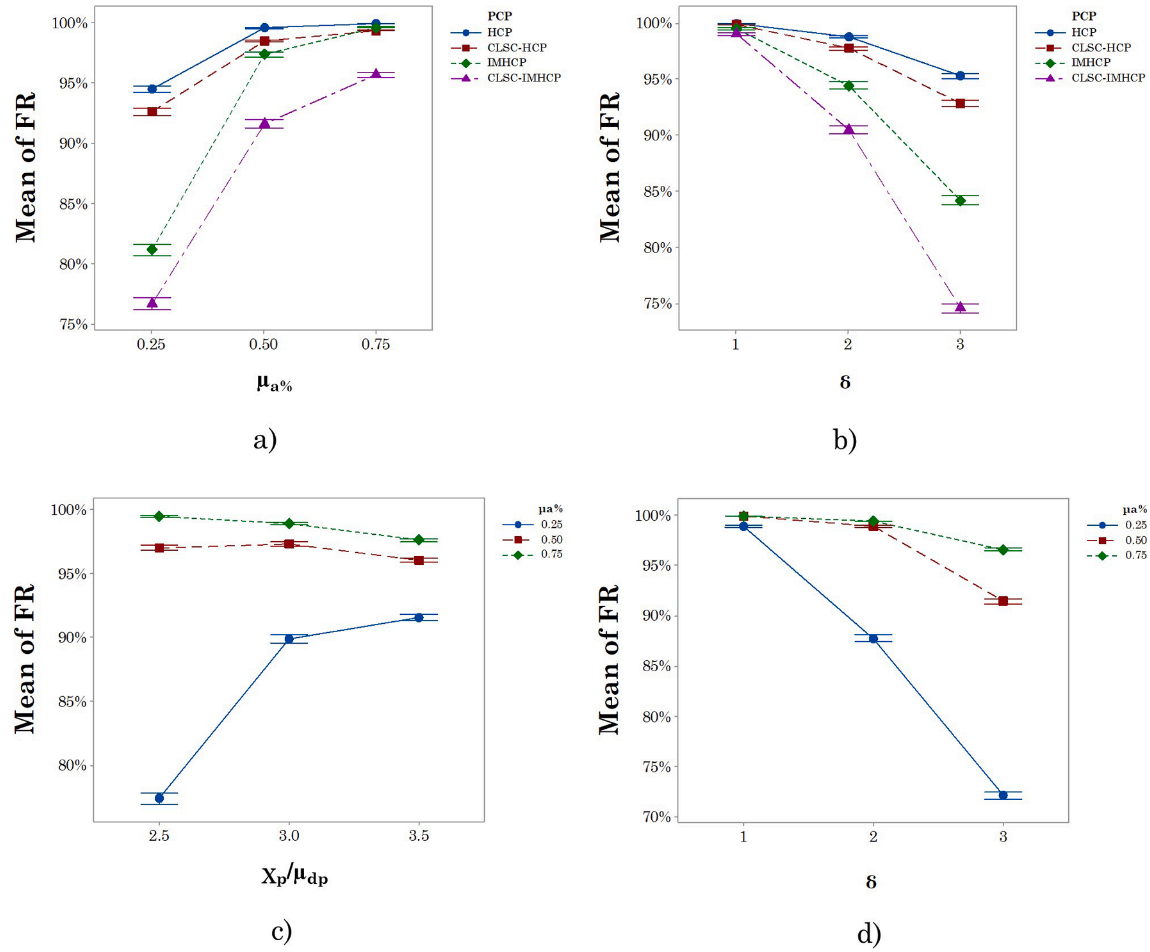


Fig. 6. Most significant interaction plots for the fill rate.

almost equal to 100 %. On the other hand, high changeover times negatively bias the fill rate of the CLSC, and the differences between the PCPs are relevant. Fig. 6-c illustrates the interaction $\mu_{a\%}$ * χ_p/μ_{d_p}. It can be noticed that when the mean return rate is equal to or higher than 0.50, there is no particular difference between the values of the nominal production capacity. Surprisingly, high values of nominal production capacity slightly reduce the fill rate, since a higher number of production stoppages occur in the system (see Fig. 7). On the other hand, when the mean return rate is equal to 0.25 an increment of nominal production capacity positively influences the fill rate indicator of the CLSC. Finally, Fig. 6-d shows the interaction $\mu_{a\%}$ * δ. For low changeover times, the factory does not take benefit from the mean return rate. On the other hand, for high values of changeover times, the mean return rate represents strong support for achieving high performance in terms of fill rate.

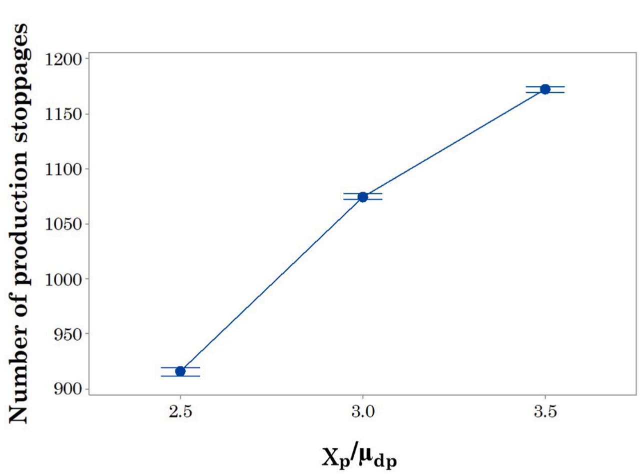


Fig. 7. Influence of the nominal production capacity in terms of number of production stoppages.

4.1.1.1. Average factory inventory level. This sub-section concerns the analysis of the results related to the average factory inventory level. Fig. 8 depicts the main effect plots. The first finding to point out is related to the influence of PCPs on the average inventory level. Indeed, it can be noted that the CLSC variants of the PCPs allow the factory to reduce the average inventory level, In particular, CLSC-IMHCP is the policy that achieves the best performance in terms of average factory inventory level. The remanufactured units of products directly increase the factory inventory level and, therefore, high values of mean return rate and remanufacturing capacity constraints involve an increment of the average inventory level, as expected. Interestingly, due to the number of production stoppages (see Fig. 7) high values of nominal production capacity and changeover time reduce the average inventory level. Finally, the impact of the failure rate and the inventory threshold is similar to the work of Costa et al. (2020). The inventory threshold is the most influencing factor and the difference between each experimental level of average factory inventory level is relevant. Fig. 9 illustrates the most influencing interaction plots. In Fig. 9-a it can be seen the interaction between PCP and the mean return rate. The figure reveals that the mean return rate mainly affects the performance of IMHCP. In fact, for low values of mean return rate (*e.g.* 0.25), IMHCP assures good performance in terms of average inventory level, while, for high values

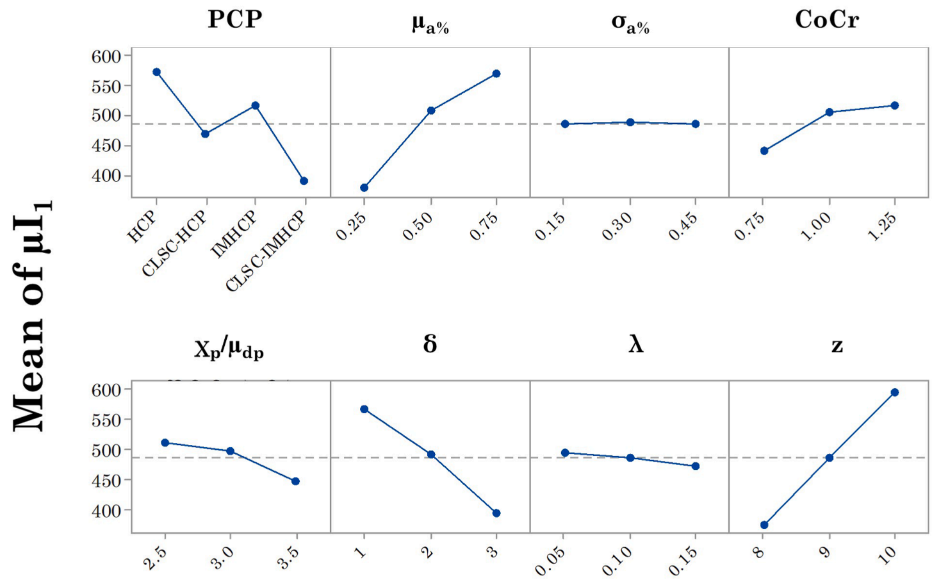


Fig. 8. Main effect plots for the average factory inventory level.

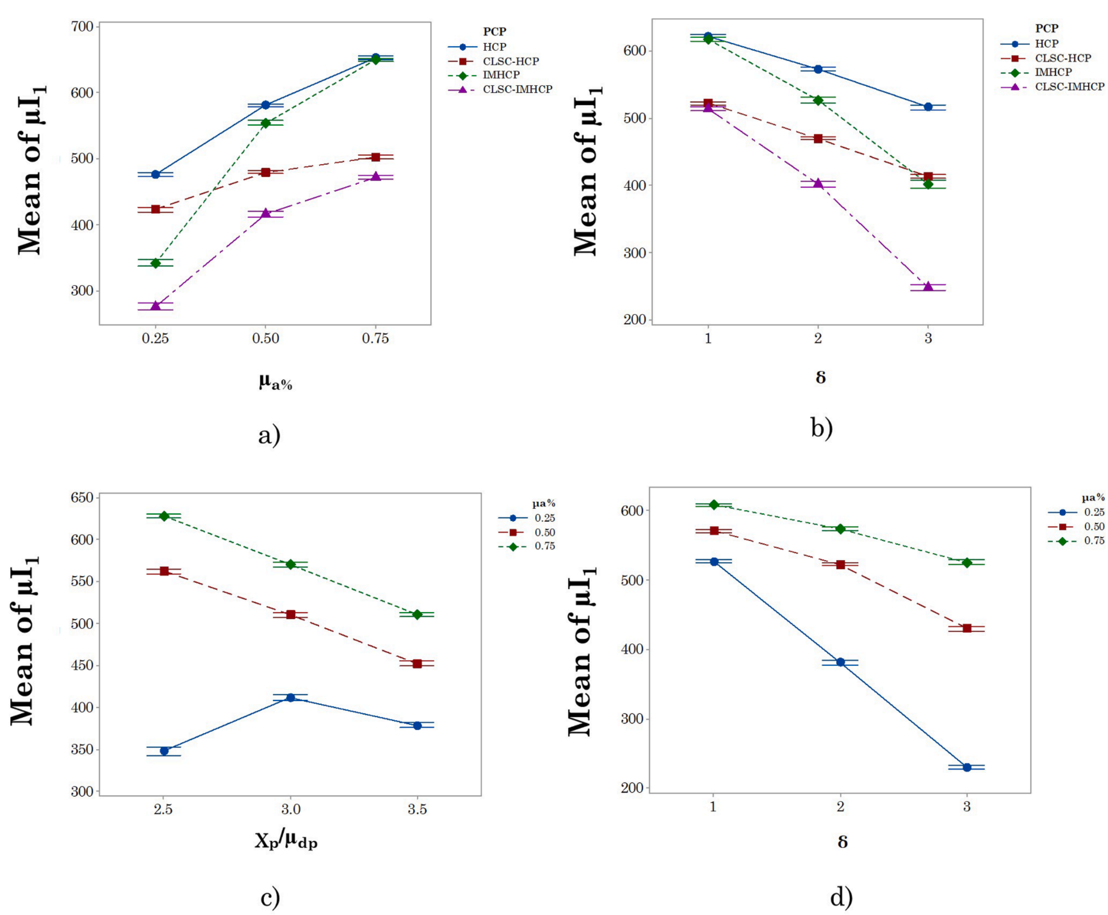


Fig. 9. Most significant interaction plots for the average factory inventory level.

of mean return rate, the performance worsens and becomes similar to HCP. Fig. 9-b shows the interaction between the mean return rate and changeover time pointing out interesting findings. When the changeover time is low (*e.g.* 1 time unit), the difference between HCP and IMHCP is not significant. The same happens between the CLSC variants of the PCPs. On the other hand, high values of changeover times involve a relevant reduction of average inventory level when the factory adopts IMHCP or its CLSC variant. In particular, when the changeover time is set to high values, the impact of IMHCP and CLSC-HCP on the average factory inventory level is similar. Fig. 9-c shows the interaction between the mean return rate and the nominal production capacity. This interaction mainly reflects the individual impact of the nominal production capacity on the performance measure. In fact, high values of nominal production capacity involve a high number of production stoppages and, then, the average factory inventory level is reduced. However, when the nominal production capacity and the mean return rate are set to low values (*e.g.* 2.5 and 0.25, respectively), a reduction of the performance measure can occur due to frequent backlog scenarios. It is confirmed by the same interaction in Fig. 6-c that causes fill rate values lower than 80 %. Finally, Fig. 9-d reveals that the effect of the changeover time is damped by high values of the mean return rate.

4.1.1.2. Order rate variance ratio. This sub-section investigates the impact of the experimental factors on the order rate variance ratio by reporting the main effect plots in Fig. 10 and the interaction plots in Fig. 11. Looking at the main effect plots, the graph reveals that the HCP strategy and its CLSC variants allow the structure to reduce the order rate variance ratio, while IMHCP and CLSC-IMHCP involve high values of order rate variance ratio (*i.e.*, higher than 1.5). As for the remanufacturing process, it can be noticed that the return flows of material support the CLSC to reduce the order rate variance ratio. In fact, high values of both the mean return rate and remanufacturing capacity constraint cause a reduction of this performance measure. As for the experimental factors related to the production capacity constraint of the factory, interestingly, the changeover time and factory inventory threshold have a relevant influence on the order rate variance ratio. Specifically, low values of changeover times and high values of factory inventory threshold reduce the order rate variance ratio of the whole CLSC. On the other hand, also high values of nominal production capacity and low values of failure rate allow the CLSC to reduce this performance indicator. However, their influence seems to be weak in comparison with the other experimental factors. Looking at the interaction plots, Fig. 11-a and Fig. 11-b reveal that IMHCP and CLSC-IMHCP are the PCPs that mostly suffer the lower values of mean return rate and the high values of changeover time. Fig. 11-c shows that the order rate variance ratio particularly worsens when the mean return rate and the nominal production capacity are set to lower values. Finally, Fig. 11-d reveals that the high values of mean return rate allow the CLSCL to reduce the negative impact of high values of changeover time in terms of order rate variance ratio.

4.2. Bicriteria analysis for the production control policies

The outcomes emerging from the numerical analyses reveal that enhancing the fill rate or mitigating the BWE (measured by the order rate variance ratio) often leads to an increase in the average factory inventory level and vice-versa. Consequently, a challenging task for the CLSC managers would consist of finding the optimal balance between these performance indicators. Motivated by these findings, a bicriteria analysis was conducted to go beyond the single-objective evaluations and to guide CLSC managers in evaluating and selecting the PCP that offers the most favourable trade-off between different performance indicators. To this end, all possible pairs of performance indicators were assessed, *i.e.*: 1) fill rate – average factory inventory level, 2) order rate variance ratio – average factory inventory level, and 3) fill rate – order rate variance ratio. Then, performance indicators (PI_{norm}) were normalized and the 'Bicriteria Index' (BI) to be minimized was introduced. The BI was calculated using the following formula:

$$BI = \omega \bullet PI^1_{norm} + (1-\omega)\bullet PI^2_{norm} \tag{25}$$

where ω is a weight ranging from 0 to 1. To normalize the performance indicators, we employed the following formulas:

$$FR_{norm} = (FR - FR_{max})/(FR_{max} - FR_{min}) \tag{26}$$

$$\mu I_{1norm} = (\mu I_1 - \mu I_{1min})/(\mu I_{1max} - \mu I_{1min}) \tag{27}$$

$$OrVr_{norm} = (OrVr - OrVr_{min})/(OrVr_{max} - OrVr_{min}) \tag{28}$$

As the BI objective must be minimized, the FR_{norm} is calculated by the difference between FR - FR_{max} in the numerator (see Eq. (26) and must be minimized as well. The minimum and maximum values of the performance indicators are: $FR_{max} = 1$, $FR_{min} = 0$, $\mu I_{1max} = 874.81$, $\mu I_{1min} = 0$, $ORVR_{max} = 6.17$ and $ORVR_{min} = 1$. Notably, upper and lower bounds mentioned above were set on the basis of the numerical outputs obtained by the DOE. Whether fill rate and average factory inventory level are considered (*i.e.*, $PI^1_{norm} = FR_{norm}$ and $PI^2_{norm} = \mu I_{1norm}$), Fig. 12 shows the average BI values obtained by each PCP at varying the weight w. It emerges that:

- When ω is set to 1, then considering only the fill rate, the best policy is HCP, confirming the outcomes obtained from the ANOVA analysis;
- When ω is set to 0.9, the best trade-off is achieved by HCP and CLSC-HCP.
- When ω is between 0.6 and 0.8, CLSC-HCP is the most effective policy.

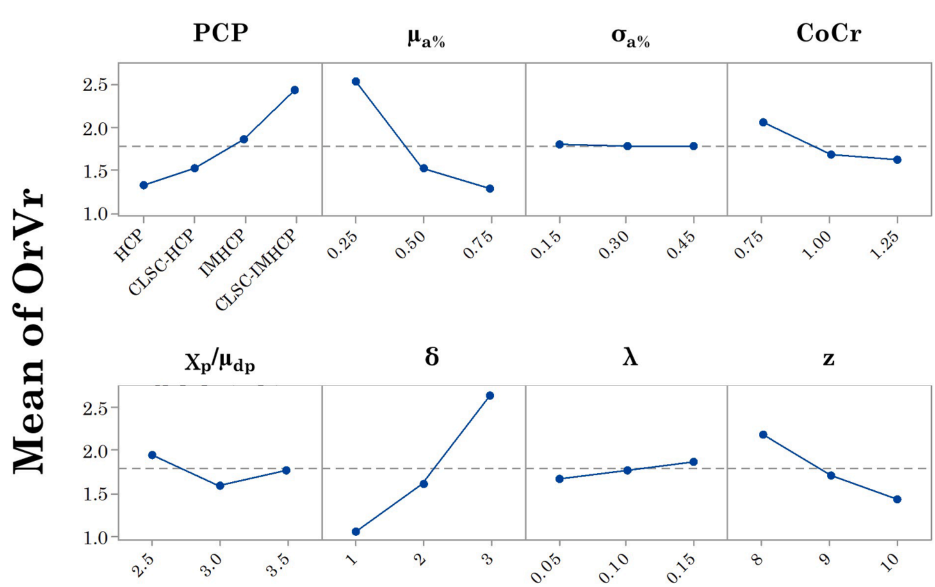


Fig. 10. Main effect plots for the order rate variance ratio.

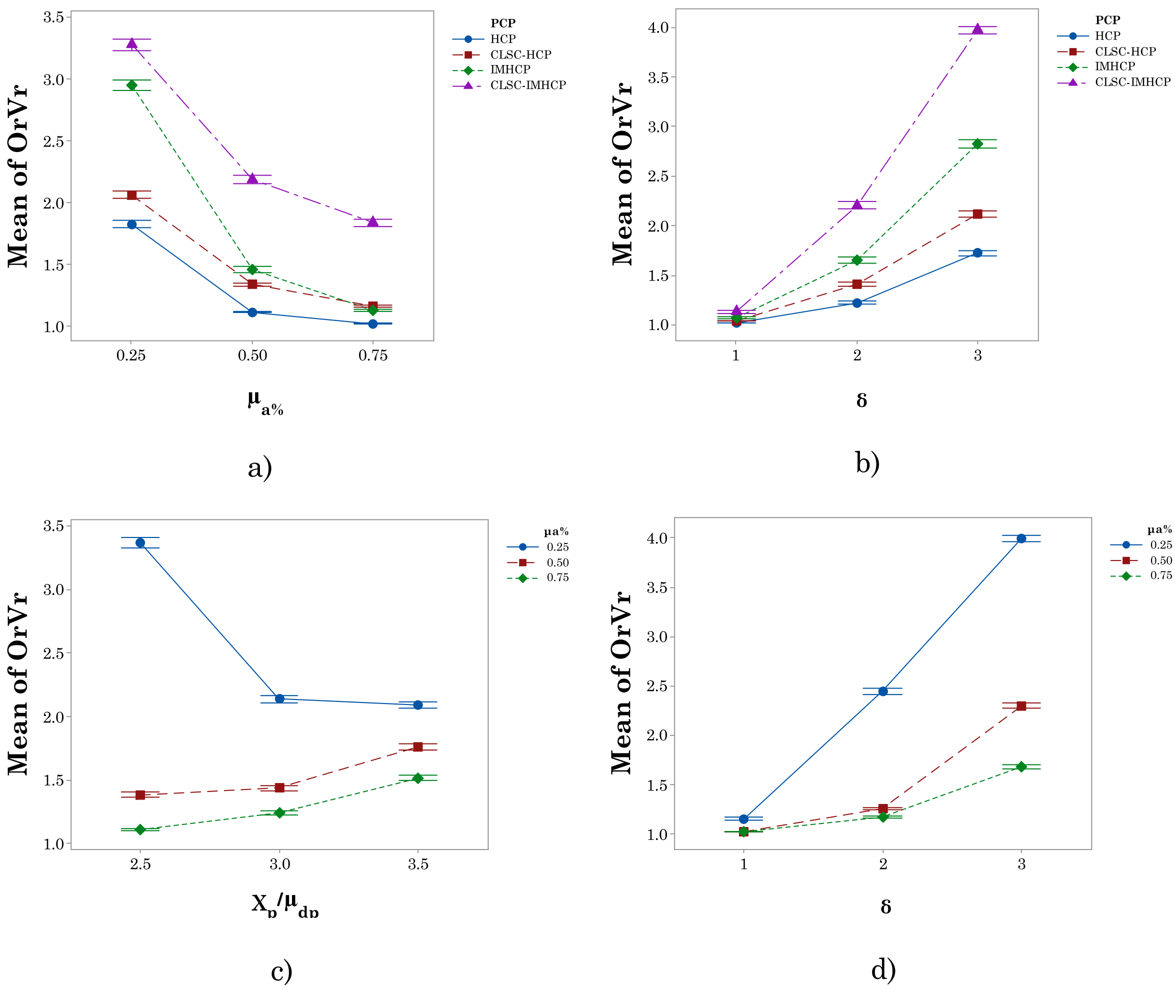


Fig. 11. Most interesting interaction plots for the order rate variance ratio.

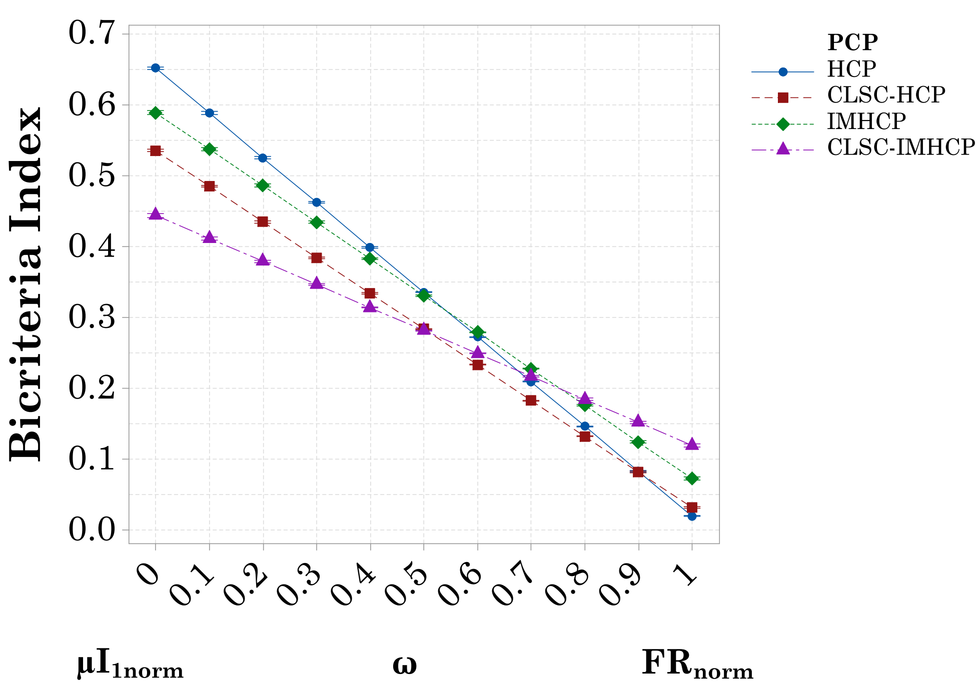


Fig. 12. Bicriteria analysis in terms of fill rate and average factory inventory level.

- When ω is set to 0.5, the best trade-off is reached by CLSC-HCP and CLSC-IMHCP.
- When ω is lower than 0.5, the best balance of performance is assured by CLSC-IMHCP.
- When ω is equal to 0, only the average factory inventory level is considered. In this case, the results reflect the ANOVA analysis, where the CLSC-IMHCP policy is the most-suitable policy to reduce the average factory inventory level.

Fig. 13 shows the Bicriteria analysis for the order rate variance ratio and the average factory inventory level (*i.e.*, $PI^1_{norm} = OrVr_{norm}$ and $PI^2_{norm} = \mu I_{1norm}$) and it can be noticed that:

- When ω is set equal to 1, considering only the order rate variance ratio, the most-suitable policy is HCP, as showed by the ANOVA analysis;
- When ω is between 0.8 and 0.9, the best trade-off is gained by HCP.
- When ω is set between 0.4 and 0.7 for, CLSC-HCP is the most effective policy.
- When ω is lower than 0.4, the best balance of performance is obtained by CLSC-IMHCP.
- When ω is equal to 0, then considering only the average factory inventory level, CLSC-IMHCP is the most-suitable policy to reduce this metric, confirming the ANOVA results.

Finally, Fig. 14 considers the balance between the fill rate and the order rate variance ratio (*i.e.*, $PI^1_{norm} = FR_{norm}$ and $PI^2_{norm} = OrVr_{norm}$). In this case, HCP stands out as the most suitable policy for CLSC dynamics to maximize the fill rate and minimize the order rate variance ratio.

4.3. Sensitivity analysis on delivery lead-time

In this section, the impact of delivery lead-time in terms of fill rate, average factory inventory level and order rate variance ratio of the CLSC is studied. Recently, global events such as the COVID-19 pandemic are considerably affecting the performance of supply chains. In particular, these disruptive events are causing a sudden increase in delivery lead-times (Corsini, Costa, Fichera, & Framinan, 2022). The scope of this analysis is to assess the impact of high values of delivery lead-time on the performance of the CLSC at hand. To this end, we selected the configuration of the previous DOE (see Table 2) that assures the highest value of the fill rate. In accordance with the ANOVA analysis in Section 4.1.1, the considered SC is characterized by the following values: PCP = HCP; $\mu_{a\%} = 0.75$; $\sigma_{a\%} = 0.3$; $CoC_r = 1.25$; $\chi_p/\mu_{d_p} = 3.5$; $\delta = 1$; $\lambda = 0.05$; $z = 10$. The delivery lead-time varies at three levels: 2, 10 and 20 time units. 10 replicates were considered in this analysis to avoid the randomness effect on the results. Fig. 15 shows the impact of the delivery lead-time on the three KPIs. The results revealed that an increase in lead-time involves a deterioration of the performance of the CLSC. As for the fill rate, it can be noticed that a significant reduction is caused by the highest values of delivery lead time (*i.e.*, $LT = 20$). On the other hand, any increment in delivery lead-time involves a sudden deterioration of the average factory inventory level and order rate variance ratio.

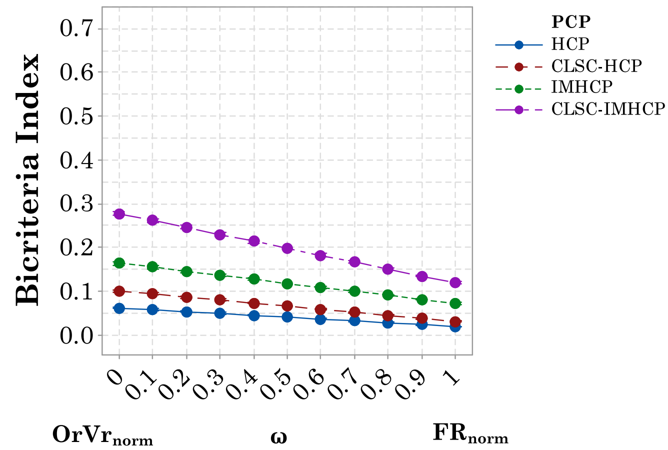


Fig. 14. Bicriteria analysis in terms of fill rate and order rate variance ratio.

5. Findings and managerial implications

Since there are numerous insights in this paper, we now summarize the main findings that contribute to the advancement of the CLSC literature by increasing our understanding of the impact of PCPs on fill

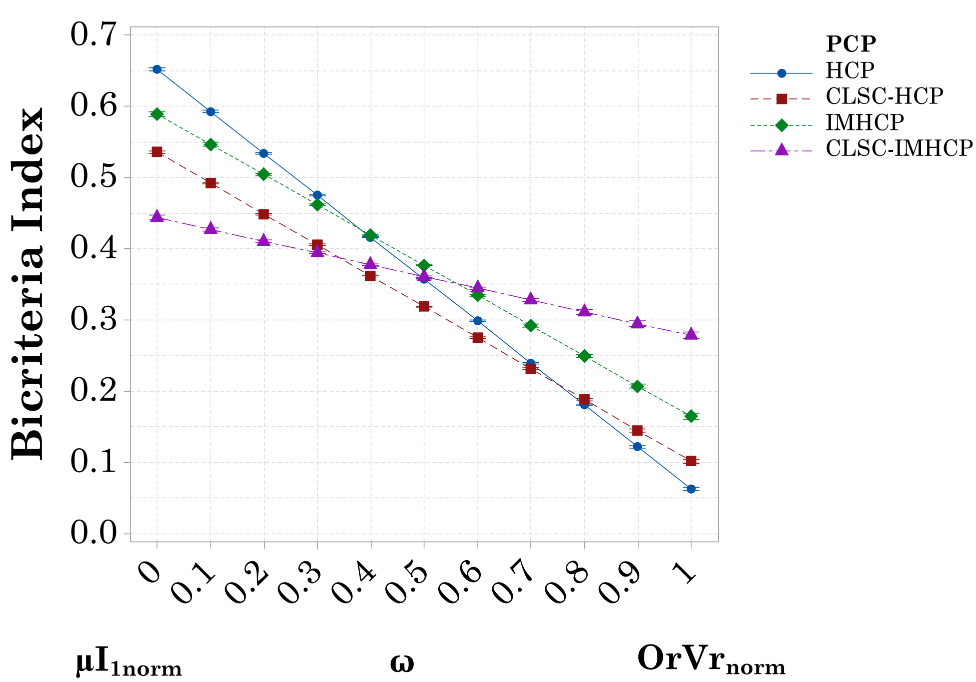
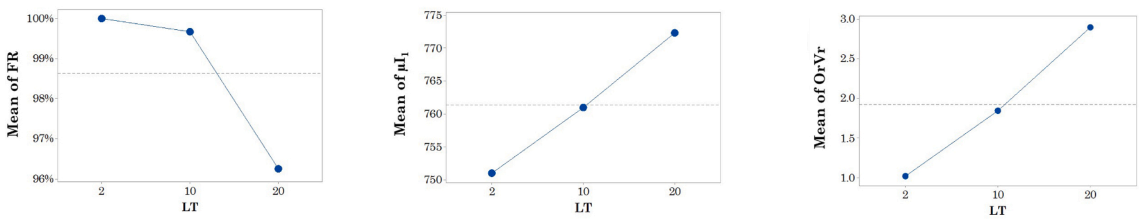


Fig. 13. Bicriteria analysis in terms of order rate variance ratio and average factory inventory level.



a) b) c)

Fig. 15. Sensitivy analysis of delivery lead-time in terms of a) fill rate, b) average factory inventory level and c) order rate variance ratio.

rate, factory inventory level, and BWE in a multi-product environment. After that, we evaluate the main implications of these findings for managerial decision-making.

1. *Impact of PCPs.* The analyses of results revealed that HCP is the most suitable policy for maximizing the fill rate and mitigating the bullwhip effect in CLSCs. On the other hand, CLSC-IMHCP is the most effective PCP in minimizing the factory inventory level. According to the numerical results, an increase in the fill rate or the mitigation of the bullwhip effect leads to an increase in the factory inventory level and vice-versa. Therefore, a Bicriteria analysis was conducted to identify the PCP that gains the best trade-off between the performance indicators. CLSC-HCP and CLSC-IMHCP emerged as the best PCPs when the aim is to balance the fill rate versus the factory inventory level and the order variance ratio versus the factory inventory level. Instead, if the goal is to maximize the fill rate and mitigate the bullwhip effect, HCP is the most suitable PCP.
2. *Impact of changeover time.* The changeover time decreases the factory inventory level and the fill rate and increases the order rate variance ratio. These phenomena are more significant for IMHCPs, CLSC-PCPs, and CLSCs with low average return rates.
3. *Impact of the mean return rate.* The mean return rate increases the factory inventory level and the fill rate (the increase is generally higher for IMHCPs). On the contrary, the order rate variance ratio decreases.
4. *Impact of the production capacity.* Increasing the production capacity increases the fill rate and decreases the order rate variance ratio, while it has a low impact on the factory inventory level if the mean return rate is low. When the mean return rate is medium or high, on the contrary, increasing the production capacity decreases the factory inventory level and increases the order rate variance ratio, due to the high number of production stoppages.
5. *Impact of the remanufacturing capacity.* Increasing the remanufacturing capacity increases the factory inventory level and fill rate, and decreases the order rate variance ratio.
6. *Impact of the delivery lead-time.* The results arising from the sensitivity analysis revealed that an increment in delivery lead-time causes a deterioration of all the three KPIs of the CLSC.

Now we discuss the key implications of this set of findings for managerial practice, in particular by providing useful suggestions to implement the advocated principles of the circular economy in supply chains in several industries, *e.g.* computers, cameras, medical equipment, automobile engines and aircrafts, among others. In our problem, the incorporation of capacity constraints in CLSC is a critical aspect that reflects the challenges faced by industries aiming to operate in a sustainable and environmentally responsible manner. Our study aims to offer valuable insights for decision-makers in industries (such as automotive, electronics, aerospace, industrial equipment sectors among others) where the closed-loop supply chain is a prevalent operational model. In these sectors, the presence of production capacity constraints can influence the planning of remanufacturing activities, in order to maintain a steady flow of remanufactured products in the market and meet demand and ensure operational continuity for customers. Then, we aim to provide CLSC professionals with helpful suggestions on how to appropriately manage multi-product closed-loop production and distribution systems. First of all, CLSC managers should focus on return policies that assure a high return rate, and the reason is twofold. On one hand, this is the main goal of CLSCs, as these structures are meant to achieve a high level of circularity and save raw materials and energy. On the other hand, our findings show that medium to high return rates results in high fill rates. As a drawback, these high return rates may cause some inefficiencies in inventory management (due to the uncertainty in the reverse flow), and thus the factory inventory level may be increased. On the other hand, the CLSC should be configure with adequate manufacturing and remanufacturing capacities, to be able to quickly respond to variations in the production of new products or to handle the inherent variability of the reverse flow of used and remanufactured products. As a consequence, the CLSC will be more reactive to unforeseen events, and this results in lower inventories and a higher fill rate as well. However, managers of such CLSCs should invest carefully in increasing the production capacity, since the combination of high production capacity and mean return can involve production stoppages and, as a consequence, an increase of the BWE.

In addition to these settings, the changeover time also has a relevant impact on the CLSC performance and should be considered by managers. Thus, it is recommended the CLSC managers undertake all possible actions to avoid the detrimental impact of high changeover times on the performance of CLSC, such as implementing the Single Minute Exchange of Die (SMED) methodology that can reduce the changeover time (Da Silva & Godinho Filho, 2019). Finally, the inventory threshold factor has a direct impact on performance, increasing the factory inventory level and fill rate, and decreasing the BWE. Therefore, it should be chosen ad-hoc according to the Retailer's orders variability in the final CLSC setting, to minimize the factory inventory level while maintaining the desired fill rate.

6. Conclusions and future directions

The existing body of literature related to the dynamics of CLSCs often assumes unlimited capacity. Only a few studies have studied the implications of capacity restrictions in the manufacturing and/or remanufacturing processes, revealing the importance of considering capacity restrictions in the analysis of CLSCs. Nonetheless, these studies have considered the production of a single product and simple capacity restrictions, but factories in the real world often produce different products, and thus they need to allocate capacity for the production of such products, requiring the adoption of a proper PCP.

This work contributes to the literature on CLSCs dynamics by addressing the impact of different PCPs on the dynamic performance of a multi-product, multi-echelon, capacitated CLSC. To do so, a CLSC with a factory, a retailer, and a remanufacturer has been modelled using discrete-time difference equations. The factory produces two different products and consists of a failure-prone manufacturing system with a production line that is not able to manufacture both types of product simultaneously. For that reason, the production line requires changeover operations to switch from one product type to another. To address the impact of PCPs, four PCPs have been considered in the study, which are the well-established HCP, IMHCP and two variants of these PCPs adapted to the CLSC, *i.e.*, CLSC-HCP and CLSC-IMHCP.

The simulation study consists of a full-factorial Design Of Experiments, composed of 8 experimental factors: the mean of returns of products, the variance of returns of products, the coefficient of remanufacturing capacity, the adopted PCP, the ratio between the nominal production capacity and the mean customer demand, the changeover time, the failure rate of the production system and the inventory threshold factor. The CLSC performance has been addressed by the fill rate, the factory inventory level, and the order rate variance ratio.

We found that PCPs and changeover time have a significant impact on the CLSC performance. Specifically, HCP is the most effective PCP to maximize the fill rate and mitigate the BWE, while IMHCP allows minimizing the average factory inventory level. The changeover time decreases the factory inventory level and fill rate and increases the BWE. We also found numerous significant interactions between these and the other factors of the study. To provide insightful recommendations for professionals, a Bicriteria Analysis has been performed. The results suggest to adopt CLSC-HCP and CLSC-IMHCP to find an effective trade-off between fill rate versus average factory inventory level and order rate variance ratio versus average factory inventory level, while HCP is recommended when the aim is to maximize the fill rate and mitigate the BWE. The selection of the PCP should be accompanied by adequate manufacturing and remanufacturing capacities, to be able to quickly respond to variations in the production of new products or to handle the inherent variability of the reverse flow of used and remanufactured products.

In the context of future research, our study is confined to the scenarios defined by the proposed DOE. An avenue for future research could involve exploring the effectiveness of various PCPs under different market conditions within CLSC systems. This could provide valuable insights into the robustness and adaptability of production control strategies across a broader spectrum of CLSC scenarios. Future research can focus on the impact of different PCPs not only in CLSCs but also in novel sustainable production–distribution structures (*e.g.* Symbiotic SCs, Turken & Geda, 2020). A further research avenue is represented by studying the impact of PCPs on different CLSC structures, such as divergent and convergent multi-echelon systems. In light of the recent pandemic emergency, it can be of benefit to investigate the efficiency of different PCPs in CLSCs under uncertainty in production and distribution lead-time, and when the system is characterized by destructions in forward and reverse material and information flow.

CRediT authorship contribution statement

Roberto Rosario Corsini: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data Curation, Writing – original draft, Writing – review & editing, Visualization. **Salvatore Cannella:** Conceptualization, Methodology, Investigation, Resources, Writing – original draft, Writing – review & editing, Supervision, Project administration, Funding acquisition. **Roberto Dominguez:** Conceptualization, Methodology, Investigation, Resources, Writing – original draft, Writing – review & editing, Supervision, Project administration, Funding acquisition. **Antonio Costa:** Conceptualization, Methodology, Investigation, Resources, Writing – original draft, Writing – review & editing, Supervision, Project administration, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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