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Proportional order-up-to policies for closed-loop supply chains: The dynamic effects of inventory controllers

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Abstract: Increasing the understanding of the management of closed-loop supply chains (CLSCs) is fundamental to accelerate the much-desired transition towards the circular economy. From this perspective, we investigate the value of proportional order-up-to policies (POUT) policies and the adjustment of their inventory controllers in these systems. These policies are often used to improve the performance of traditional supply chains due to their ability to cope with the damaging bullwhip effect; however, they have not been sufficiently studied in CLSCs. Through a difference equation modelling approach, we show that POUT policies are also a valuable instrument for enhancing the CLSC dynamics. Specifically, we find that the POUT model outperforms the traditional order-up-to policy in a hybrid manufacturing/remanufacturing system, yielding significant cost savings. To optimise the key trade-off between order and inventory variability, the tuning of the inventory controllers needs to consider not only the cost structure of the CLSC but also the average return rate. Therefore, managers should react to increasing levels of circularity by lowering the setting of the controllers' time constant. In the light of our findings, we suggest two strategies for aligning the calibration of the POUT controllers and the forecasting methods to increase the performance of CLSCs.

Keywords: system dynamics; bullwhip effect; closed-loop supply chain; remanufacturing system; proportional order-up-to.

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1. INTRODUCTION

1.1 Context, background and problem statement

In traditional supply chains, the proportional order-up-to (POUT) replenishment policy represents a common instrument through which to improve the system dynamics; see, among many others, Dejonckheere et al. (2003), Gaalman (2006), Cannella and Ciancimino (2010), Wang and Disney (2017), and Priore et al. (2019). This policy refers to a generalisation of the well-known order-up-to (OUT) model in which the orders are issued to partially, rather than totally, recover the gap between the target inventory position and the available inventory (both on-hand and work-in-progress). The amount of the gaps to recover is defined by two decision parameters, which, from a control-theoretic standpoint (see Ivanov et al., 2018, for a review of the applications of this methodology to operations and supply chain management, and Ivanov et al., 2020, for an example), can be named as the *inventory controllers*.

The main benefits of the POUT policy arise from its ability to cope with the bullwhip effect, see e.g. Disney et al. (2006). Specifically, this policy allows for a mitigation of the supply chain members' over-reactions to changes in demand, which reduces the upstream propagation of the damaging bullwhip phenomenon. However, the POUT policy often has a negative impact on inventory variability, potentially resulting in high stock-out occurrence and/or large holding requirements, see e.g. Gaalman (2006). Therefore, a fundamental trade-off between order and inventory variability emerges (Disney et al., 2020). This trade-off needs to be carefully considered by supply chain managers, who need to accurately calibrate their inventory controllers according to the conditions where they operate; for instance, Potter and Disney (2010) show the application of a POUT policy in the UK-based grocery retailer Tesco.

In line with the previous discussion, POUT policies have been widely used and investigated in forward supply chains as they are very effective bullwhip-limiters. In addition, they have been used in closed-loop supply chains (CLSCs), which are gaining attention in modern societies as a stepping-stone towards the desired circular economy (Govindan et al., 2015; Goltsos et al., 2019; Kazemi et al., 2019; Wei et al., 2020; Guo et al., 2020). In particular, POUT polices were firstly adopted in closed-loop supply chains (CLSCs) by Tang and Naim (2004), whose work is often recognised as the first study in the field of CLSC dynamics (Goltsos et al., 2019). Other recent works have also used POUT models to study the dynamics of CLSCs, including Cannella et al. (2016), Zhou et al. (2017), and Ponte et al. (2019a).

However, in such studies, very little attention has been given to the analysis of how the decision or control parameters of the POUT policy (i.e. the inventory controllers) should be adjusted in CLSC settings. Indeed, most works implicitly assume that they can be configured as in traditional supply chains. That is, while the impact of the controllers and their tuning have been systematically analysed in forward supply chains under numerous scenarios (to cite a few, Dejonckheere et al., 2003; Cannella and Ciancimino, 2010; Dominguez et al., 2014; Ponte et al., 2017a; Priore et al., 2019), the POUT model has been clearly understudied in CLSC studies, despite their growing importance nowadays.

To the best of the authors' knowledge —supported by the recent review of the CLSC dynamics literature conducted by Goltsos et al. (2019)—, only three works have considered the effects of inventory controllers in CLSC settings, namely, those by Zhou and Disney (2006), Zhou et al. (2006), and Adenso-Diaz et al. (2012). Zhou and Disney (2006) employ the same POUT policy as in traditional supply chain. Through control theory, they provide analytically the values of the inventory controllers that minimise supply chain costs. Zhou et al. (2006) also use control theory to study a Kanban policy in the reverse flow of materials, and explore the impact of several parameters, including the inventory controllers. They observe opposite effects of the controllers in terms of order and inventory variabilities

—as in traditional systems. Adenso-Diaz et al. (2012) use a closed-loop variant of the popular Beer Game, which they name the Cider Game, to analyse the impact of 12 factors on a CLSC managed with a POUT policy. They find that the bullwhip effect of CLSCs is minimised by using low values of the inventory controllers, which also applies for traditional supply chains. Nevertheless, they do not consider the inventory implications of such configurations.

These prior works arguably shed some light on the dynamics generated by the inventory controllers of POUT replenishment policies in CLSCs. Nonetheless, it is important to note that (1) the POUT policies used in these previous works have not been adapted to the CLSC setting; and (2) the uncertainty in these CLSC scenarios has been constrained to demand uncertainty only. In this fashion, these prior studies have not considered the intrinsic uncertainty in the return process, related to the quantity and/or the quality of the returned products, which is a defining characteristic of many real-world CLSCs (Zikopoulos et al., 2017; Abbey and Guide, 2018; Goltsos et al., 2019). As a consequence, there are no clear directives and recommendations regarding the setting of inventory controllers in a wide range of real-world CLSC scenarios with POUT policies specifically designed for these closed-loop systems.

1.2 Objective and methods

Motivated by the above-mentioned considerations, this work aims to explore the calibration of the inventory controllers of POUT policies for CLSCs that face a twofold uncertainty, i.e. demand and returns.

To do so, we adapt the conventional POUT policy to CLSCs following the guidelines developed by Tang and Naim (2004) in their *type-3* system. We model the supply chain via a difference equation approach and assess its dynamic behaviour in terms of the said key trade-off between order and inventory variability. To provide comprehensive findings on the underlying effects of the controller under several operational scenarios, we adopt a full factorial experimental design (Evers and Wan, 2012). In this sense, we consider four key factors: (1) the time constant of the POUT controllers; (2) the exponential smoothing factor of the demand forecast; (3) the mean return rate, capturing the level of circulatory in the CLSC; and (4) the coefficient of variation of the return rate, accounting for the degree of uncertainty in the return channel. With the simulation results, we statistically infer the main effects of the inventory controllers on CLSCs and how these decision parameters interact with the other key operational parameters.

In brief, the results of this work reveal that, while the economic value of the inventory controllers is relatively higher in traditional systems, the POUT policy may also substantially outperform the traditional OUT model in CLSCs. In this sense, we find that large operational cost savings can be reached by appropriately tuning the inventory controllers, considering both the cost structure of the CLSC and the average return rate. Interestingly, we show that uncertainty in the volume of returns provokes a considerable reduction in the cost performance of the CLSC, but should not affect significantly the tuning of the controllers. Moreover, we propose two roadmaps to strategically align the POUT replenishment policy with an exponential smoothing forecasting method to improve the operational performance of the system. Finally, we also discuss the robustness of the CLSC to variations in the setting of the controllers.

The rest of this paper is structured as follows. Section 2 provides detail on the CLSC model and the performance metrics. Section 3 describes and justifies the design of experiments. Section 4 presents and discusses the results obtained in the simulations. Section 5 summarises the main findings and provides an overview of their implications for CLSC professionals. Finally, Section 6 concludes and identifies important directions for future research.

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2. CLOSED-LOOP SUPPLY CHAIN MODEL

2.1 Structure, assumptions, and mathematical formalisation

Our research is concerned with hybrid manufacturing/remanufacturing systems (HMRSs), which integrate manufacturing and remanufacturing operations to satisfy the demand of customers (Aras et al., 2006). This closed-loop supply chain structure is common in practice when manufactured and remanufactured products are perfect substitutes, such as in the spare parts industry (Souza, 2013). HMRSs have been widely explored in the literature due to their practical relevance and their rich dynamic behaviour (including Tang and Naim, 2004; Zhou and Disney, 2006; Zhou et al., 2006; Cannella et al., 2016; Hosoda and Disney, 2018; Dominguez et al., 2019; Ponte et al., 2019a).

The mathematical model of the HMRS is defined by Eqs. (1)-(11), shown in Table 1. To model the HMRS dynamics, we assume three stages per period: (I) Reception; (II) Serving; and (III) Sourcing. This is in line with previous works in the CLSC literature, e.g. Dominguez et al. (2019). The three above-mentioned stages are described in detail below.

Table 1. Mathematical model of the CLSC.

Variable	*Equation*	*No.*
Manufacturing completion rate, mc_t	$mc_t = o_{t-T_m-1}$	(1)
Remanufacturing completion rate, rc_t	$rc_t = r_{t-T_r-1}$	(2)
Initial stock, is_t	$is_t = ns_{t-1} + mc_t + rc_t$	(3)
Customer demand, d_t	$d_t = \max\{x_t, 0\}, x_t \to N(\mu, \sigma^2)$	(4)
Customer returns, r_t	$r_t = y_t d_{t-T_c}, y_t = \min\{\max\{z_t, 0\}, 1\}, z_t \to N(\beta, \xi^2)$	(5)
Net stock, ns_t	$ns_t = is_t - d_t$	(6)
Work-in-progress, w_t	$w_t = w_{t-1} + (o_{t-1} - mc_t) + (r_{t-1} - rc_t)$	(7)
Production order, o_t	$o_t = \max\left\{(\hat{d}_t - rc_t) + \frac{1}{T_i}(ss_t - ns_t) + \frac{1}{T_w}(tw_t - w_t), 0\right\}$	(8)
Demand forecast, $\hat{d}_t$	$\hat{d}_t = \alpha d_t + (1-\alpha)\hat{d}_{t-1}$	(9)
Safety stock, ss_t	$ss_t = \varepsilon \hat{d}_t$	(10)
Target work-in-progress, tw_t	$tw_t = T_p \hat{d}_t$	(11)

Stage (I) - Reception. This takes place at the start of each period, *t*, when the position of the serviceable inventory increases due to receiving new (manufactured) products and as-good-as-new (remanufactured) products. The former responds to the production orders placed $T_m + 1$ periods ago, where T_m is the manufacturing lead time, as per Eq. (1). The latter corresponds to the products collected from the market, i.e. customer returns, $T_r + 1$ periods ago, where T_r is the remanufacturing lead time, according to Eq. (2)[iv]. This entails considering that the remanufacturing line

[iv] $T_m + 1$ and $T_r + 1$ apply in Eqs. (1) and (2), respectively, as production orders are issued and the returns are accounted for at the end of the period, i.e. in the *Sourcing* stage, while the products are received when the period starts, i.e. in the *Reception* stage.

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operates on the basis of a push policy. That is, returns are processed as soon as they are received at the remanufacturer site, which is a common assumption in HMRS studies (e.g. Tang and Naim, 2004; Hosoda and Disney, 2018). The initial position of the stock, available for satisfying customer demand during this period, is then defined by Eq. (3).

Stage (II) - Serving. Now, customer demand is received and satisfied from the serviceable inventory. Also, returns are collected in the recoverable inventory. In line with Eq. (4), we model the stochastic demand with an independent and identically distributed (i.i.d.) random variable, x_t, that follows a normal distribution with mean μ and standard deviation σ, where $CV_d = \sigma/\mu$ is the coefficient of variation. Demand is truncated to non-negative values. We also consider uncertainty in the collection channel, which, as discussed before, applies to most CLSCs in practice (Goltsos et al., 2019). We use a stochastic return rate, y_t, which is modelled through an i.i.d. random variable, z_t, that follows a normal distribution with mean β and standard deviation ξ, where $CV_r = \xi/\beta$ is the coefficient of variation. The return rate, constrained to the interval [0, 1], defines the percentage of sold products that return to the HMRS after the consumption lead time, T_c. In this sense, Eq. (5) expresses the returns as a function of the past demand.

As demand is received, the position of the serviceable inventory decreases. At the end of period *t*, the position of the serviceable inventory is denoted as the *net stock*, see Eq. (6). Note that $ns_t > 0$ refers to holding products at the end of *t*, while $ns_t < 0$ would reveal stock-outs, indicating unsatisfied demand that will need to be meet when inventory becomes available (if possible, at the start of *t*+1). In addition, the work-in-progress at the end of *t*, representing the products that are within the manufacturing and remanufacturing lines (and have not been received yet at the serviceable inventory) is defined by Eq. (7). Note that the work-in-progress increases due to the orders issued and the returns collected in the last period (o_{t-1}, r_{t-1}) and decreases due to the completion rates (mc_t, rc_t).

Stage (III) - Sourcing. Finally, a new production order is placed to satisfy the portion of the demand that cannot be meet through remanufactured products. To this end, we employ a POUT replenishment policy. We adapt the traditional POUT policy to closed-loop settings as per the type-3 system[v] developed by Tang and Naim (2004), shown in Eq. (8). T_i and T_w, which need to be regulated by the operations manager, are decision parameters that can be named as the time constant of the inventory controllers. They define the portion of the gap between the target and the actual inventory (T_i for the on-hand inventory, and T_w for the work-in-progress) to be accounted for by the replenishment rule. The order is constrained to positive values, i.e. excess products cannot be returned to the supplier.

In addition to the controllers, the configuration of the POUT policy requires the consideration of the demand forecasting method, the safety stock model, and the target work-in-progress policy. For the forecasting method, we adopt an exponential smoothing, see Eq. (9). This is a common forecasting procedure among practitioners (Petropoulos et al., 2014). Here, α is the smoothing factor, and determines the sensitivity of the forecasting rule to changes in demand. For the safety stock model, we use a simple but industrially popular model that obtains the safety stock as the product of the demand forecast and the safety stock factor, ε, according to Eq. (10); see e.g. Cannella et al. (2016). The decision parameter ε determines the level of protection against stock-outs. Last, we define the target work-in-progress as the product of the demand forecast and the estimate of the pipeline lead time T_p, according to Eq. (11); see e.g. Lin et al. (2017). The pipeline estimate, a control parameter that also needs to appropriately adjusted

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[v] Tang and Naim (2004) showed that the type-3 system, which considers both the manufacturing and remanufacturing information within the work-in-progress, makes the best use of the available information in the HMRS.

to improve the performance of the CLSC, can be calibrated following the proposal by Tang and Naim (2004)[vi], that is, $T_p = (1-\beta)T_m + \beta T_r$. Their study demonstrates that this configuration allows managers to prevent a serviceable inventory offset from happening, which would be detrimental from the perspective of inventory performance.

2.2 Key performance metrics

In this work, we consider both the production and inventory implications of replenishment rules. This provides a wider perspective from which to investigate CLSC performance, given that production smoothness and inventory performance are strongly interrelated, as discussed in Section 1. The metrics we use are summarised in Table 2.

Table 2. Key performance metrics of the CLSC.

Metric	*Equation*	*No.*
Order Variability Ratio, OVR	$OVR = \dfrac{var(o_t)}{var(d_t)}$	(12)
Inventory Variability Ratio, IVR	$IVR = \dfrac{var(ns_t)}{var(d_t)}$	(13)
Variability trade-off metric, J	$J = k_o\sqrt{OVR} + k_i\sqrt{IVR}$	(14)

To measure production smoothness, we employ the Order Variability Ratio, OVR, often referred to as the Bullwhip Ratio (e.g. Disney et al., 2020). This compares the variance of production orders to that of customer demand, see Eq. (12). This metric is indicative of the production efficiency, as it related to variable, capacity-related production costs. To consider inventory performance, we use the Inventory Variability Ratio, IVR, sometimes named as Net Stock Amplification (e.g. Ponte et al., 2020). This is the quotient of the variance of net stocks to that of customer demand, see Eq. (13). When supply chains are appropriately controlled, minimising IVR results in a reduction of the sum of holding and backlog costs, as discussed by Disney and Lambrecht (2008).

Frequently, OVR and IVR offer conflicting recommendations. Indeed, OVR can sometimes be reduced at the expense of increasing IVR and vice versa. This can be named as the *order-inventory variability trade-off* in supply chains (e.g. Disney and Lambrecht, 2008), highlighting the need for studying simultaneously the production and inventory implications of inventory policies. This perspective makes convenient to define a unified metric that considers order and inventory variabilities at the same time. In Eq. (14), we define the variability trade-off metric J as the weighted average of the square roots of OVR and IVR[vii], where k_o and k_i indicate the weight of both terms ($0 \leq \{k_o, k_i\} \leq 1$, $k_o + k_i = 1$). The metric J can be interpreted as an objective function to be minimised in supply chains (Priore et al., 2019), where k_o and k_i are uncontrollable parameters that can be obtained from the unit costs of over-ordering,

[vi] We note that in their type-3 system, the return rate is fixed. We have adapted their equation to the stochastic scenario under consideration in this work by replacing the return yield by the mean of the stochastic variable that defined its behaviour.

[vii] We use the square root, as the production and inventory-related costs tend to be closely related to the square roots of OVR and IVR, respectively. Indeed, in some specific cost models, the square root of the metrics and the costs are linearly related, see Ponte et al. (2017b).

under-ordering, storage, and stock-outs; see Ponte et al. (2017b). In this sense, $k_o > k_i$ reveals that order variability is more costly than inventory variability, and as such minimising OVR should be prioritised, while IVR would illustrate the opposite scenario.

2.3 Parameter diagram and model implementation

To sum up, Figure 1 represents the parameter diagram of the system under consideration. In the central area, we can see the structure and the two flows of materials of the HMRS (i.e. forward, in solid line, and reverse, in dashed line), including the fundamental processes (manufacturing, remanufacturing, and consumption) and inventories (raw materials, serviceable, and recoverable). The top of Fig. 1 displays the uncontrollable parameters, which impact the three performance indicators previously described and represented in the bottom right corner. Also at the bottom, Fig. 1 shows the decision or control parameters, through which the operations or supply chain management team can improve the performance of the CLSC. Finally, we note that the difference equation model described in this section has been implemented in MATLAB R2018b to carry out the experimental design discussed in the next section.

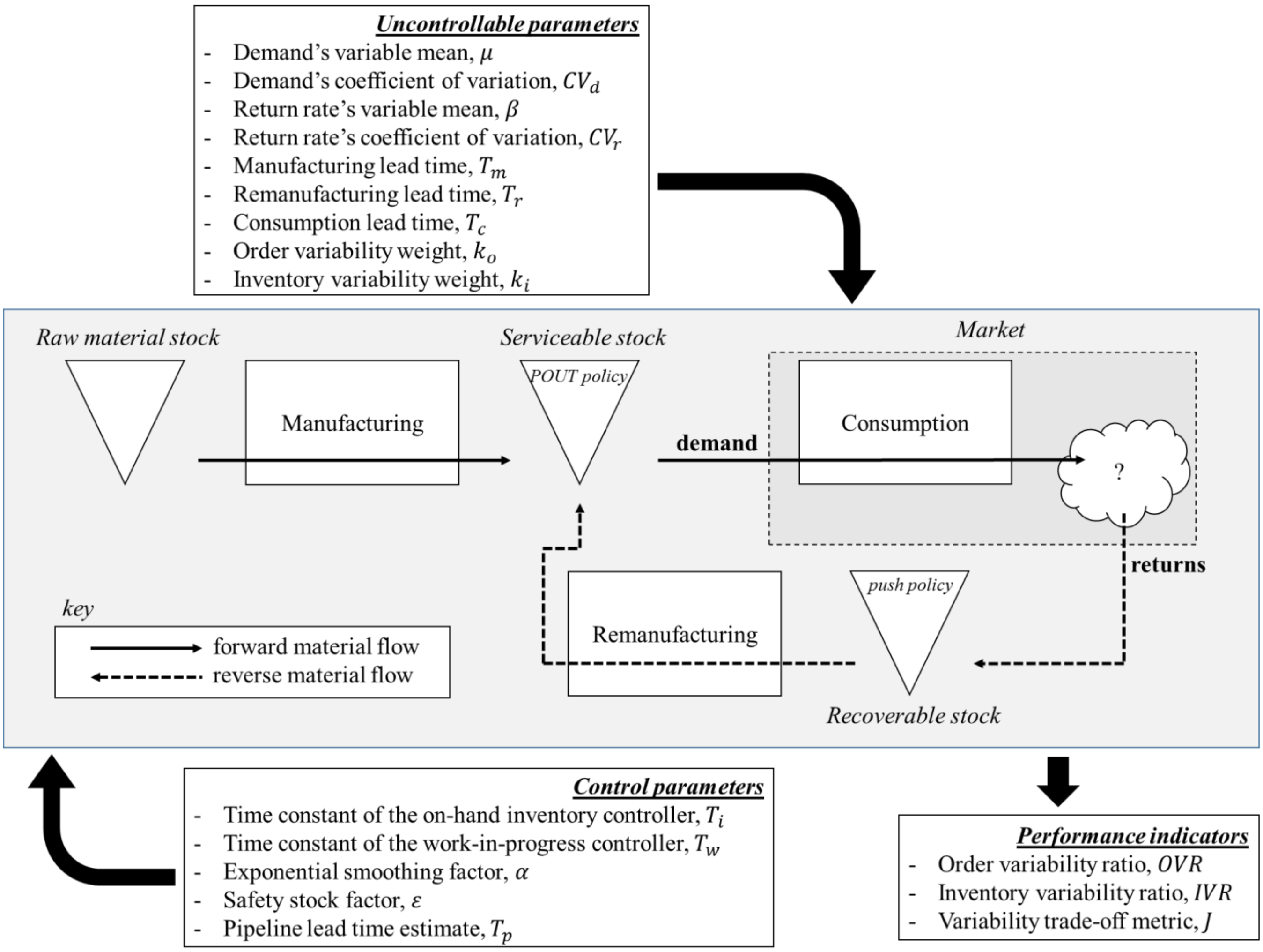

Figure 1. Parameter diagram, including performance indicators, of the HMRS under consideration.

3. DESIGN OF EXPERIMENTS

3.1 Control parameters

With most of the CLSC dynamics literature investigating the impact of uncontrollable parameters, we here consider the dynamic effects of control parameters. We aim to provide professionals with prescriptive guidance on how to appropriately manage inventories in circular economy supply chains through POUT replenishment policies. To this end, we explore a wide range of scenarios through a planned experimental design, which is presented in this section.

As shown in Figure 1, there are five control parameters in the CLSC. To pursue the research objectives of this article, our analysis concentrates on the influence of the time constants of the inventory controllers, T_i and T_w. We analyse exclusively the so-called Deziel-Elion case (Deziel and Eilon, 1967), in which $T_i = T_w$, a particularly interesting case due to its properties that is often employed in the real world, see e.g. Cannella and Ciancimino (2010). Future research may be aimed at investigating the generic case in which T_i and T_w are regulated independently. Therefore, we select $T_i = T_w$ as one of the experimental factors. To provide a deep understanding on the impact of $T_i = T_w$ and generate valuable insights on how to tune the inventory controllers, we consider eight levels, specifically, $T_i = T_w = \{1, 2, 4, 8, 16, 32, 64, 128\}$. Note that, for $T_i = T_w = 1$, the POUT policy is equivalent to the classic OUT model.

We also consider the effects of the forecasting mechanism, through the exponential smoothing factor α. By studying the interactions between both decision parameters (i.e. $T_i = T_w$ and α), we will explore how to align replenishment policies and forecasting methods in CLSCs to improve the system performance. For α, values between 0.05 and 0.2 are generally recommended (Teunter et al., 2011). One of the reasons behind that is that the bullwhip effect increases dramatically as α grows, see Chen et al. (2000). In this case, we define four levels, specifically, $\alpha = \{0, 0.1, 0.2, 0.3\}$. Notice that $\alpha = 0$ results in a static forecast, $\hat{d}_t = \hat{d}_0\ \forall t$. For i.i.d. demand, this is a minimum mean squared error (MMSE) forecast if $\hat{d}_0$ matches the conditional expectation of the demand (Disney et al., 2016). In contrast, $\alpha = 0.3$ illustrates a scenario with room for improvement, where the forecast is relatively sensitive to changes in demand.

For the sake of the focus of this article, we have not incorporated the safety stock factor ε and the pipeline lead team estimate T_p into the experimental design; rather, they have been considered as fixed factors. For the former, we use $\varepsilon = 1$. This means that the serviceable inventory is protected against one (extra) period, which may be interpreted as a reasonable decision when stock-outs should be avoided, and demand and returns are uncertain; see e.g. Cannella et al. (2016). Finally, for the latter, we employ in all cases the suggestion by Tang and Naim (2004), $T_p = (1-\beta)T_m + \beta T_r$. Otherwise, the inventory performance of the system would be dramatically penalised due to the inventory drift.

3.2 Uncontrollable parameters

We also include two uncontrollable parameters in the experimental design: the mean of the variable that defines the return rate, β, and its coefficient of variation, CV_r. By exploring the interactions of these parameters with $T_i = T_w$, we expect to provide managers with useful guidelines of how to tune their inventory controllers. We consider four levels for β, specifically, $\beta = \{0, 0.25, 0.5, 0.75\}$. Interestingly, $\beta = 0$ represents the traditional, forward supply chain. This analysis thus will allow us to compare our findings on the regulation of the controllers with those for the traditional, widely studied setting, as well as to study how increasing the level of circularity should affect the design of the controller. Second, CV_r represents uncertainty in the return process, which also may have important effects on the control of CLSCs by means of POUT policies. We also consider four levels for this parameter, $CV_r = \{0, 0.2, 0.4, 0.6\}$. Note that $CV_r = 0$ represents the ideal case in which demand and returns are perfectly correlated with lag T_c, which facilitates the integration of the forward and reverse flow of materials (see Ponte et al., 2019b).

Regarding the weights k_o and k_i, we do not directly include them as parameters in the experimental design. However, for each simulation run, we measure the variability trade-off metric J under three different cost structures: (i) $k_o = k_i = 0.5$, representing a scenario in which both sources have the same impact on the economic performance; (ii) $k_o = 0.75$, $k_i = 0.25$, representing a scenario in which order variability is more damaging and then reducing it should be prioritised; and (iii) $k_o = 0.25$, $k_i = 0.75$, representing the opposite scenario. In this sense, we attempt to capture insights on how the balance between k_o and k_i should affect the tuning of the controllers in CLSC settings.

Finally, the rest of uncontrollable parameters in Figure 1 have been defined as fixed. Further investigations of their interactions with $T_i = T_w$ may also be of interest but are beyond the scope of this article. For the demand characterisation, we adopt $\mu = 100$ and $CV_d = 0.3$. This degree of variability fits well with that faced by many real-world retailers, see Dejonckheere et al. (2003). Regarding the lead times, we study probably the most common case in practice, in which the consumption lead time is the longest one in the HMRS, and remanufacturing used products takes less time than manufacturing new ones. Indeed, this is a common assumption in CLSC dynamics studies, such as those reviewed in Section 1 (e.g. Tang and Naim, 2004), although a lead time paradox has been identified when this occurs (Hosoda and Disney, 2018)[viii]. Taking these issues into consideration, we use $T_c = 16$, $T_m = 4$, $T_r = 2$.

3.3 Experimental approach

The combination of the four parameters selected results in 512 scenarios to be explored (that is, 8×4×4×4). Given the low experimental effort of the modelling techniques and the software used, we simulate all of them through a full factorial design. Indeed, each scenario has been investigated through 10 simulation runs (i.e. replications). The length of each run has been fixed as 2,100 periods, where the first 100 periods have been defined as a warm-up horizon and hence their results have not been considered[ix]. Overall, our experimental approach is summarised in Table 3.

Table 3. Design of experiments and overview of the simulation protocol.

Experimental factors		*Role*	*Levels*
Time constant of the inventory controllers	$T_i = T_w$	Control	1, 2, 4, 8, 16, 32, 64, 128
Exponential smoothing factor	α	Control	0, 0.10, 0.20, 0.30
Return rate's variable mean	β	Uncontrollable	0, 0.25, 0.50, 0.75
Return rate's coefficient of variation	CV_r	Uncontrollable	0, 0.20, 0.40, 0.60

[viii] Prior studies have observed that under some circumstances HMRSs benefit from 'artificially' increasing remanufacturing lead times. This paradox was investigated by Hosoda and Disney (2018) and, in general, occurs when these lead times are shorter than manufacturing lead times, as the production ordering rule cannot make the best use of the information on the return channel.
[ix] The length of the simulation runs, the duration of the warm-up period, and the number of replications have been selected to ensure the stability of the supply chain response and the replicability of our results.

Fixed factors	
$\mu = 100$, $CV_d = 0.3$, $T_m = 4$, $T_r = 2$, $T_c = 16$, $\varepsilon = 1$, $T_p = (1-\beta)T_m + \beta T_r$.	
Experimental approach	
Type of design	Full factorial
No. of scenarios	512
No. of replications	10
No. of simulation runs	5,210
Simulation parameters	
Simulation length	2,100 periods
Warm-up horizon	100 periods

4. RESULTS AND DISCUSSION

4.1 Analysis of variance

In this section, we present the numerical results of the experiments, analyse them through statistical inferential techniques, and discuss the main insights. To this end, we have conducted an analysis of variance (ANOVA) test for the results obtained in each of the three cost structures of the variability trade-off metric J. Table 4 summarises the outcome of these tests. The three models show very good fit with the results of the simulation runs, in all cases with R^2_{adj}>95%. In addition, we find that the main effects of the four experimental factors are statistically significant at a 95% confidence level (p<0.05). Therefore, in all cases we reject the null hypothesis that there is no difference in means between groups. Regarding the interactions, all of them have shown to be statistically significant (p<0.05), except that between the return rate's coefficient of variation, CV_r, and the exponential smoothing factor, α, in the third cost structure (characterised by $k_o = 0.75, k_i = 0.25$). In the following subsections, we address separately the main effects of the inventory controllers' time constants, with $T_i = T_w$, and their interactions with α, β, and CV_r.

Table 4. Results of the ANOVA tests.

Source	$J\ (k_o = 0.25, k_i = 0.75)$			$J\ (k_o = 0.5, k_i = 0.5)$			$J\ (k_o = 0.75, k_i = 0.25)$		
	DF	*F*-value	*p*	*DF*	*F*-value	*p*	*DF*	*F*-value	*p*
CV_r	3	803.152	<0.001	3	1,197.892	<0.001	3	2,750.728	<0.001
β	3	4,302.761	<0.001	3	5,269.609	<0.001	3	8,925.154	<0.001
α	3	1,523.655	<0.001	3	963.477	<0.001	3	656.161	<0.001
T_i	7	2,122.378	<0.001	7	1,660.278	<0.001	7	3,503.383	<0.001
$CV_r * \beta$	9	255.810	<0.001	9	318.240	<0.001	9	551.844	<0.001
$CV_r * \alpha$	9	8.187	<0.001	9	5.619	<0.001	9	1.867	0.052

$CV_r * T_i$	21	31.263	<0.001	21	32.319	<0.001	21	35.280	<0.001
$\beta * \alpha$	9	27.139	<0.001	9	15.969	<0.001	9	107.259	<0.001
$\beta * T_i$	21	432.792	<0.001	21	499.272	<0.001	21	783.299	<0.001
$\alpha * T_i$	21	731.094	<0.001	21	805.732	<0.001	21	1,067.162	<0.001
			R^2_{adj} = 95.4%			R^2_{adj} = 95.6%			R^2_{adj} = 97.3%

4.2 Main effects analysis: The impact of the inventory controllers in closed-loop supply chains

Looking at the F-values of the individual factors, it can be noted that the impact of β on J is more significant as k_o grows (and, thus, k_i decreases), i.e. when the costs of OVR increase in relative terms to those of IVR. This is in line with the existing literature on CLSC dynamics, as the impact of the volume of returns on order variability (OVR) is clearer than that on inventory variability (IVR); see Tang and Naim (2004), Cannella et al. (2016), and Ponte et al. (2019b). The same is observed for CV_r. That is, as k_o grows, the consequences of returns uncertainty become more significant. However, the opposite trend is observed for α, which has a higher impact on J when $k_i > k_o$. The main effects of these three factors will not be analysed in detail here, since they are not within the scope of this work — they have been widely studied in prior works. As discussed before, we will focus on the inventory controller.

Figure 2 shows the main effects of T_i for the three cost structures. Importantly, the results make clear that T_i needs to be appropriately adjusted to optimise the performance of CLSCs. That is, POUT policies have the potential to outperform OUT policies in CLSCs, but the improvement occurs as long as T_i is accurately calibrated. Hence, an in-depth analysis of the trade-off between production smoothness and inventory performance, which may be conducted through the convex metric J, is required to tune the inventory controllers in CLSCs, as in traditional systems. In this sense, we observe in the three structures that as the time constant increases from $T_i = 1$ (i.e. the conventional OUT model) the cost performance of the HMRS can be improved. However, from a certain point —which should be interpreted as the 'optimal' setting of T_i—, the sum of bullwhip- and inventory-related costs, represented by J, grows.

Taking the above into account, we observe that the cost structure of the system plays an important role in the optimal adjustment of T_i. Specifically, we see that, to minimise J, T_i should adopt higher values as k_o increases. This can be explained from the perspective that increasing T_i tends to reduce OVR, often at the expense of increasing IVR (e.g. Disney and Lambrecht, 2008); therefore, as k_o grows, managers should also opt in CLSCs for higher values of T_i. For example, when $k_o = 0.25$, the minimum J is obtained for $T_i \approx 4$ (Figure 2-a), while the time constant should be increased to $T_i \approx 8$ when $k_o = 0.5$ (Figure 2-b), and to $T_i \approx 16$ when $k_o = 0.75$ (Figure 2-c). Naturally, these are only estimations of the actual optimum, as they are restricted by the values of T_i selected in our experimental design.

Moreover, we find that the performance of CLSCs is moderately robust to some variations around the optimal setting of the controller; however, considerably under- or over-estimating the optimal T_i (i.e. selecting a T_i significantly below or above the optimal) may dramatically increase the costs in the HMRS. Indeed, the downsides of over-estimating T_i may outweigh the benefits of using the inventory controller, especially for low values of k_o, see Figure 2-a. In contrast, the impact of under-estimating T_i, as long as $T_i > 1$, may just undermine the benefits provided by the controller. Finally, and in line with prior notes, we underline that the operational benefits derived from using POUT replenishment policies in CLSCs is higher as the relative importance of OVR in the computation of J grows.

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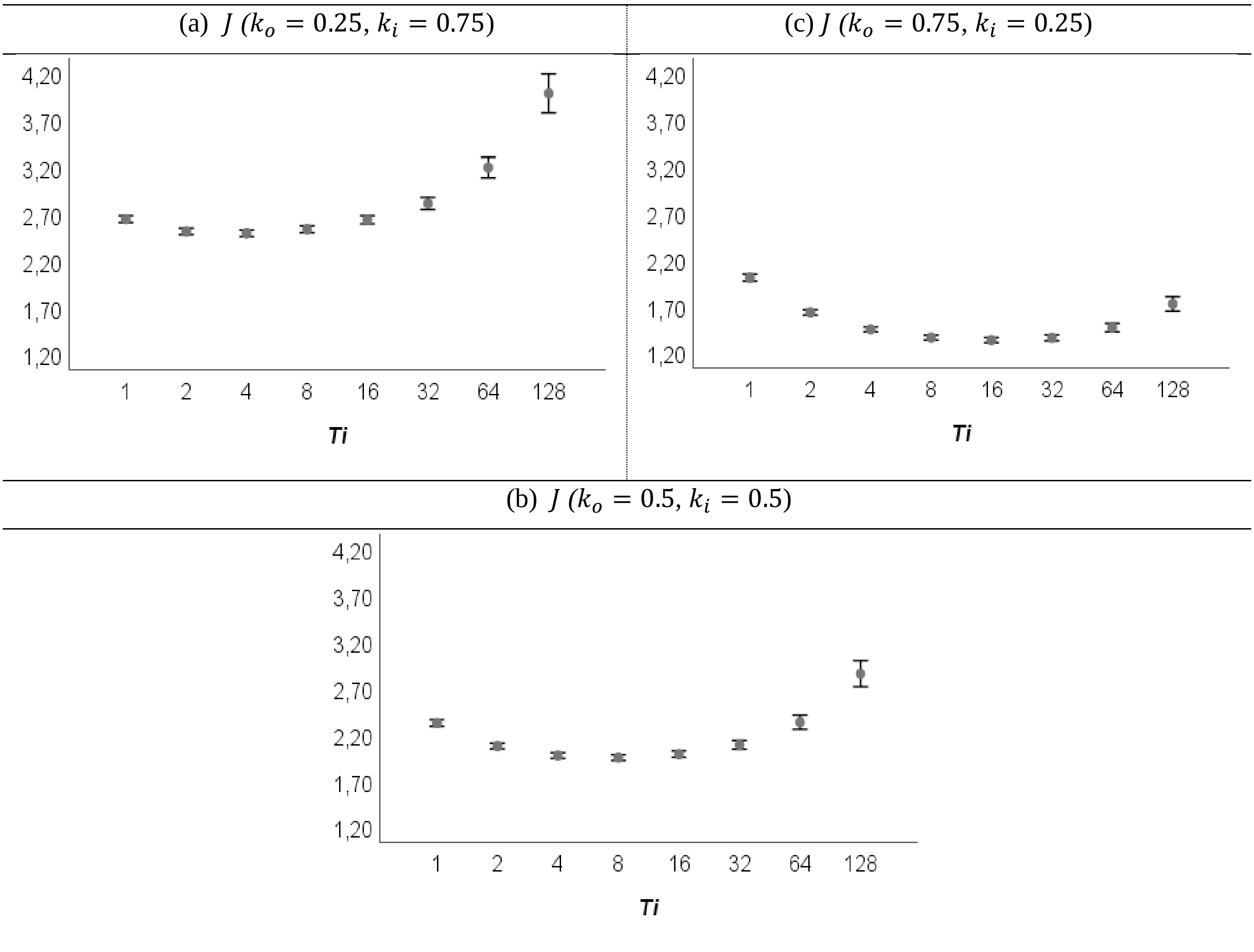

Figure 2. Main effects of T_i for different cost structures.

4.3 Interaction analysis: Setting inventory controllers in different closed-loop scenarios

The main effects study provides general insights into the impact of the POUT controller on the dynamic performance of the CLSC. However, the actual impact of T_i on J depends, sometimes to a large extent, on the levels of the other experimental factors. To evaluate the strength of the relevant interplays (those of T_i with α, β, and CV_r), we look at the two-way interactions provided by the ANOVA, also shown in Table 4. First, we can see that the interaction $CV_r * T_i$, despite being statistically significant, shows a low strength; note that the F-values are low for the three structures. This means that the impact of T_i on J is only slightly affected by the uncertainty of returns, expressed through CV_r; i.e. tuning the controllers for improving the performance of CLSCs can be effectively done without considering the intrinsic variability of the return rate. Therefore, we will not further discuss this interaction. Instead, we will focus on the other two interactions, $\beta * T_i$ and $\alpha * T_i$, which show significantly higher F-values for the three cost structures.

Two-level interaction between the inventory controller and the average return rate. Figure 3 exhibits the interaction $\beta * T_i$ for the three cost structures. From the inspection of the graphs, we can observe that the impact of T_i on J depends significantly on β, that is, on the level of circularity in the CLSC. Therefore, β needs to be considered in depth when designing inventory controllers for HMRSs. Also, it is interesting to note that the traditional supply chain outperforms the CLSC for the three costs structures, to a large extent due to the effects of a twofold (demand plus returns) uncertainty in this CLSC model.

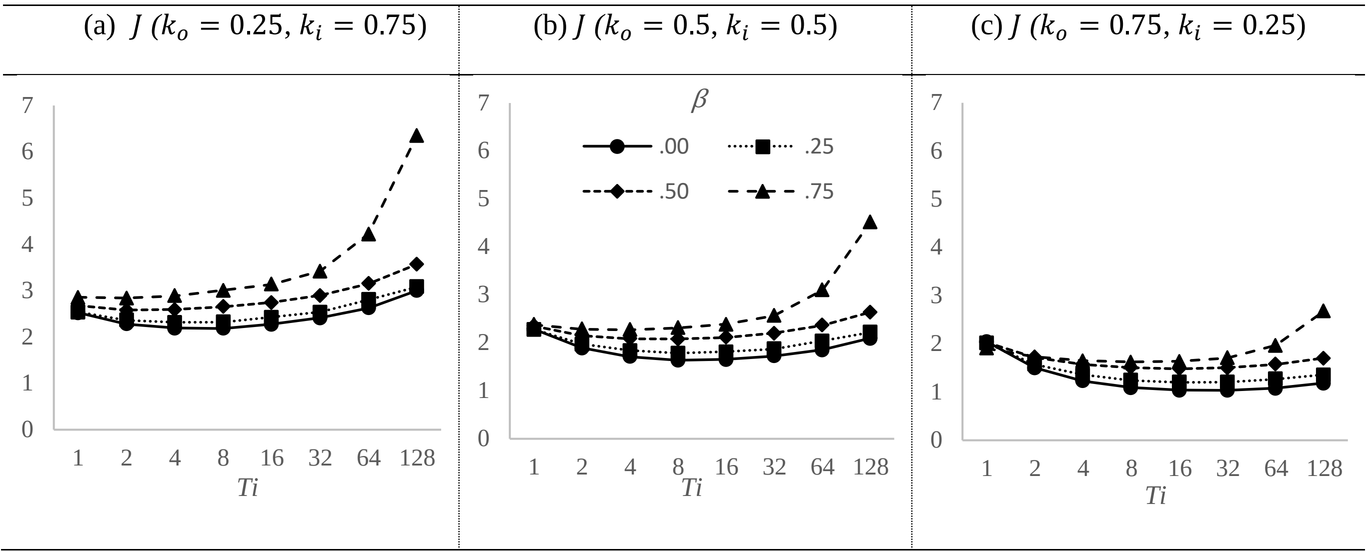

Figure 3. Interaction $\beta * T_i$ for different cost structures.

For the first cost structure ($k_o = 0.25$), increasing T_i significantly improves the operational performance of the CLSC when $\beta = 0$ (i.e. the traditional supply chain), achieving the minimum J between $T_i = 4$ and $T_i = 8$. However, as β grows, we observe that there is less room for improvement in the operational costs of the CLSC, and the minimum J is obtained for lower values of the inventory controller. For instance, the time constant that minimises J is between $T_i = 2$ and $T_i = 4$ for $\beta = 0.50$. This important finding suggests that, in the CLSC under analysis, the value of the inventory controller is higher in traditional systems than in CLSCs. Indeed, in this case ($k_o = 0.25$), for high return rates there might be no clear benefit derived from incorporating the inventory controller into the replenishment rule; e.g. when $\beta = 0.75$, increasing T_i from $T_i = 1$ does not yield clear benefits in terms of CLSC performance.

A similar behaviour can be seen in Figure 3 for the other two cost structures. The only difference is that, since T_i is more effective in reducing J for high values of k_o, in these cases it is also possible to improve J for large volumes of returns by appropriately calibrating T_i. Finally, we note that the negative impact of over-estimating T_i on J increases as β grows, and it is especially serious for the cost scenario in which IVR should be prioritised (i.e. $k_i = 0.75$).

Two-level interaction between the inventory controller and the exponential smoothing parameter. Figure 4 looks in detail at the interaction $\alpha * T_i$. We observe that the impact of T_i on the HMRS performance is also very sensitive to the forecasting procedure and the value of the key factors. Therefore, the POUT controller needs to be adjusted in combination with the exponential smoothing parameter with the objective of minimising J. Both decision parameters, α and T_i, should not be treated independently in the design of CLSCs, as this would lead to sub-optimal performance.

In particular, we highlight that $\alpha = 0$ (i.e. a static forecast $\hat{d}_t = \mu$, which is a MMSE technique for i.i.d. demand) should not be used in conjunction with high values of T_i, given that this would generate large inefficiencies that result in excessive operational costs. Therefore, T_i should take relatively low values in the case of $\alpha = 0$; in particular, $T_i \approx 1$ for $k_o = 0.25$, $T_i \approx 2$ for $k_o = 0.5$, and $T_i \approx 4$ for $k_o = 0.75$. In contrast, higher values of the T_i should be selected in case of adopting an exponential smoothing method with α within the interval [0.1, 0.3]. In this case ($\alpha > 0$), Figure 3 suggests that closed-loop managers should opt for a higher T_i as k_o increases. For example, if $\alpha = 0.2$, we obtain $T_i \approx 8$ for $k_o = 0.25$, $T_i \approx 16$ for $k_o = 0.5$, and $T_i \approx 32$ for $k_o = 0.75$; in any case, notice that T_i is significantly higher than for static forecasts. Also, the benefits of adopting a POUT replenishment rule are higher as α increases.

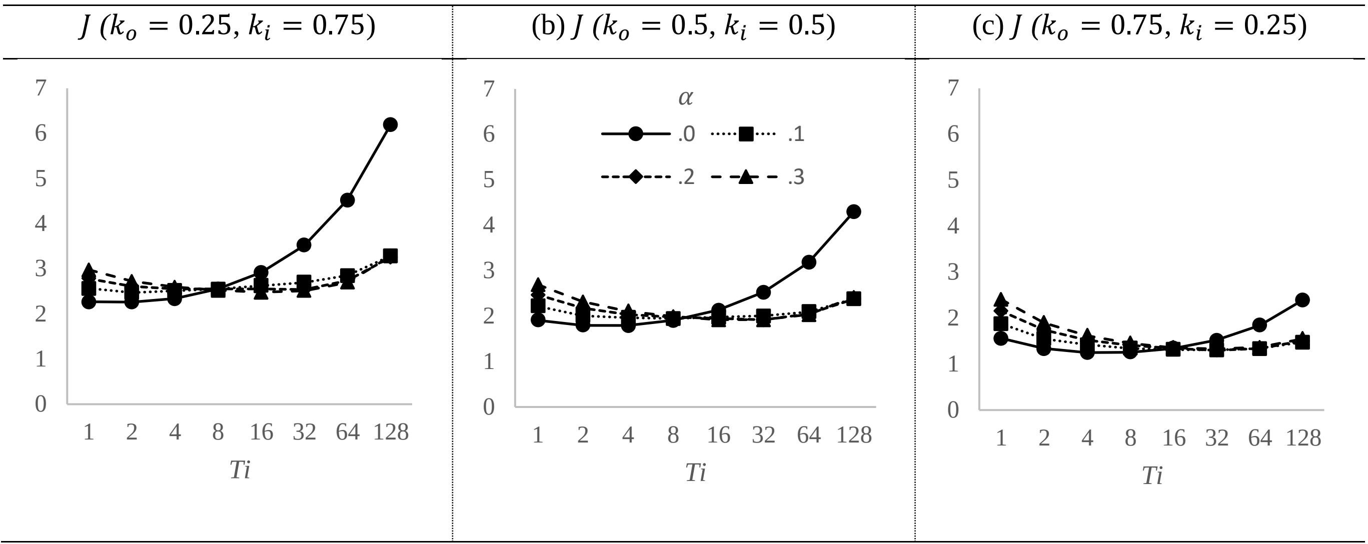

Figure 4. Interaction $\alpha * T_i$ for different cost structures.

It is also interesting to note that for low T_i there are meaningful differences in the CLSC performance for the different values of α. However, for high values of T_i the differences caused by α are marginal, as long as $\alpha > 0$. Another interesting observation is that for $\alpha > 0$ the cost performance of the CLSC is more robust to variations in T_i, that is, the impact of over-estimating T_i is significantly higher in the case of static forecasting.

Following from the previous discussion, we conclude that there may be two different strategies for improving the performance of the HMRS based on the strategic combination of α and T_i. First, managers may opt for a static forecasting, looking for the MMSE solution that minimises forecasting errors, along with a low regulation of the controller's time constant. Alternatively, they may select an exponential smoothing forecast with $\alpha > 0$, dynamically reacting to changes in demand, together with a high regulation of the time constant. In this case, it becomes crucial to appropriately regulate the value of T_i, mainly depending on the values of k_o and k_i, whose impact is higher than that of α. In the first strategy, the static forecasting approach helps managers to mitigate the bullwhip phenomenon (i.e. OVR), while the low regulation of T_i cares about the inventory performance (i.e. IVR)[x]. In contrast, in the second strategy, high values of T_i allow for a large reduction of bullwhip (i.e. OVR) while the exponential smoothing with $\alpha > 0$ considers the changes in demand and would help them to meet the customer in a cost-effective way (i.e. IVR).

5. MANAGERIAL IMPLICATIONS

This paper is concerned with the exploration of POUT replenishment policies in CLSC environments. Specifically, we study the configuration of inventory controllers in HMRSs. We consider both the production and inventory implications of the replenishment policy, as both impact the economic performance of the system and that they are generally strongly interrelated. In this section, we provide an overview of the main findings of our work and discuss their relevance for professionals in CLSCs. Some of these findings and implications are important as they extend the knowledge on inventory controllers in traditional inventory systems to circular economy supply chains; while others are specific to CLSCs settings, providing new perspectives on inventory management through POUT policies.

[x] T_i may be interpreted as the time to adjust the inventory; thus, low values will benefit the satisfaction of customer demand.

(1) POUT replenishment policies outperform the conventional OUT policy in CLSCs.

This work should encourage practitioners in CLSCs that employ OUT replenishment policies for the management of their inventories to incorporate the controllers into their policies. Our results show that the controller may yield strong economic benefits in CLSC settings. Such benefits emerge from finding an appropriate trade-off between production efficiency and customer service level in the CLSC. This applies to the three cost structures studied; however, it should be noted that the scope for improvement derived from the inventory controller increases as bullwhip-related costs become more important. All in all, these findings confirm that the known benefits of the inventory controller in the traditional supply chain (see e.g. Disney and Lambrecht, 2008) also apply to the CLSC scenario.

(2) The value of the inventory controller is maximised in the forward supply chain.

Having highlighted the economic benefits derived from the use of the inventory controller in CLSC settings, our results show that the economic value of the controller is higher in traditional supply chains than in CLSCs. Indeed, we have found that, when the CLSC is characterised by high volumes of returns (represented by β) and low relative importance of bullwhip-related costs (represented by k_o), the classic OUT policy emerges as the most appropriate solution. That is, the value of the inventory controller in CLSCs decreases as β grows and as k_o reduces.

(3) The regulation of the inventory controller needs to carefully consider the cost structure of the CLSC.

The actual economic benefits derived from the implementation of inventory controllers depend on the ability of the management team to appropriately tune them. To realise the cost savings by tuning correctly the controllers, CLSC managers need to carry out a thorough analysis of the interplays between order and inventory variabilities. We have observed that the optimal adjustment of the controllers is very sensitive to the cost structure in the CLSC. When capacity-related production costs are especially important, inventory managers should opt for high values of the time constant with the aim of prioritising bullwhip reduction. In contrast, when inventory-related costs are very high and customer satisfaction needs to be prioritised, lower values of the time constant are preferable. This confirms that the rationale for designing inventory controllers is the same in CLSCs as in traditional inventory systems.

(4) CLSCs are more robust to non-optimal values of the inventory controllers than traditional systems, and the underestimation of the optimal value is less damaging than the overestimation.

We recognise that the difficulty of finding the exact optimal configuration for the inventory controller in a realistic setting may deter some CLSC managers from implementing the POUT policy in their supply chains. In this regard, it is important to point out that the performance of the CLSC is robust to some reasonable degree of variations around the actual optimum, approx. from $0.5T_i^*$ up to $2T_i^*$, where T_i^* is the optimal value of the controller's time constant (see Figure 2). In this regard, it is interesting to note that the robustness of CLSCs to variations in the controller is higher than that of traditional systems (see Figure 3). That is, near-optimal configurations would also be able to yield high economic benefits in CLSCs. Only if the time constant was dramatically over-estimated, the CLSC costs would increase —as compared to the classic OUT policy. In this regard, over-estimating T_i^* is especially damaging for high return rates, while under-estimating T_i^* would only undermine the benefits provided by the POUT implementation.

(5) There are two roadmaps for strategically setting the replenishment policy and the forecasting method.

The interplays between the time constant of the inventory controller in a POUT policy and the constant of an exponential smoothing forecasting method play a major role in CLSC performance. Thus, the controller needs to be designed in conjunction with the forecasting rule. Importantly, we suggest two strategies for enhancing the dynamics of CLSCs based on the coordinate design of replenishment and forecasting. The first one uses a static forecasting (i.e. $\alpha = 0$) together with a low regulation of the controller's time constant (i.e. low T_i). Here, the forecasting method acts as a bullwhip-limiter, and the POUT policy is established for effectively satisfying customer demand. The second one combines exponential smoothing forecasts (i.e. $\alpha > 0$, preferably with $\alpha \leq 0.2$) with a high calibration of the time constant (i.e. high T_i). Now the roles are reversed: the POUT policy focuses on mitigating bullwhip, and the dynamic forecasting attends to customer demand variations. In our experiments, there are no significant differences between the performance offered by both strategies; however, misaligned combinations of the replenishment policy and the forecasting method (e.g. $\alpha = 0$ and high T_i; or $\alpha > 0$ and low T_i) result in meaningful inefficiencies and high operating costs. Thus, each organisation should opt for that strategy that is more feasible in practical terms and/or serves better other purposes. Note that static forecasting may be risky if the mean demand is unknown (and the ideal MMSE forecasts become unachievable); therefore, the second strategy may be more appropriate in these cases.

(6) Companies need to react to increasing levels of circularity by re-adjusting the setting of inventory controllers. Modern societies currently find themselves in the pursuit of circular economic models, motivated by environmental, social and economic considerations. This makes that the return rate in many real-world CLSCs will continuously increase over the next few years. In our paper, we have observed that the configuration of inventory controllers in CLSCs employing POUT replenishment models also need to consider the volume of returns, represented by β. In this regard, we reveal that, as β grows, T_i should be decreased. Under these circumstances, to maximise the value of the inventory controllers and with the aim of reducing costs, companies will need to adapt their configuration by decreasing the value of the time constant as the level of circularity increases over time.

(7) Return uncertainty damages CLSC performance but should not alter the design of inventory controllers. Although we have not focused on the individual effects of uncontrollable decision parameters, we have clearly perceived the negative effects of uncertainty in the return channel on the dynamics of the CLSC. This helps to explain why the CLSC performs worse than the traditional system in the different scenarios considered (see Figure 3). However, uncertainty in the volume of returns (considered through CV_r) should not significantly affect the design of the controllers. In line with the previous points, the regulation of POUT policies should mainly take into consideration other uncontrollable factors, including the cost structure of the system (modelled by k_o and k_i) and the mean return rate (represented by β), as well as the interactions with other control factors, such as the forecasting parameters (e.g. α); however, the degree of variability in the volume of returns barely impact the controller's optimal adjustment.

6. CONCLUDING REMARKS

The environmental gains derived from circular economies need to be enabled by the cost-effective operation of CLSCs in practice. Establishing and configuring appropriate replenishment policies is of major importance, as they control the flow of materials across the supply chain. To this end, CLSC managers need to consider two sides of the same coin: the inventory implications —i.e. the balance between customer service level and inventory investment— and the production implications —i.e. the variability of production and transportation schedules— of such policies.

In this work, we have explored in detail the implementation of POUT policies in CLSCs, which incorporate two inventory controllers into the conventional OUT replenishment rule. We have shown that these policies, like in traditional supply chains, allow for a significant improvement of the dynamics of CLSCs, which has an economic value. Nonetheless, to realise the cost savings, professionals need to tune accurately the controllers of their POUT models with the aim of finding the appropriate trade-off between inventory and order variability.

We have provided practitioners with key insights on how to calibrate their inventory controllers under a range of realistic CLSC scenarios. To optimise the system performance, they should opt for higher values of the time constant of the controllers as the importance of the capacity-related costs increases (relative to that of the inventory costs). Also, they should react to growing volumes of returns by reducing the regulation of the time constant. However, interestingly, the level of uncertainty in the return channel should not affect the tuning of the controller.

We have also suggested two strategies for the management of CLSCs based on the combination of the replenishment rule and the forecasting method. Importantly, we have shown that both need to be regulated coherently; otherwise, large inefficiencies may damage the performance of the CLSC. In this sense, static forecasting methods, such as MMSE for i.i.d. demands, should be used in conjunction with the adoption of low values of the inventory controller's time constant, while exponential smoothing forecasts are better combined with higher values of the time constant.

This work does not only provide advances in the CLSC dynamics literature but also aims to stimulate the development of further research efforts. It can be highlighted that the (traditional) supply chain literature offers effective methods, widely validated, for reducing the bullwhip effect and satisfying customer demand in a cost-effective manner under different scenarios, and have extensively explored the regulation of the relevant decision parameters. These methods include smoothing replenishment models, advanced forecasting techniques, and information sharing structures. However, the CLSC dynamics literature has barely considered the development of such methods and the setting of control parameters so far. Thus, it is not clear if the same methods work in CLSC settings and/or how they need to be adapted to accommodate the characteristics of the emerging CLSC context, such as the uncertainty in the returns.

Therefore, a promising research stream is to analyse how classical bullwhip-dampening strategies can be successfully introduced in CLSCs. Some unanswered questions that come to mind are: should the (re)manufacturing lead time affect the tuning of inventory controllers?, how can POUT policies be adapted to CLSC settings to maximise the value of the controllers?, could CLSCs benefit from the unequal tuning of the two controllers?, and what information should be shared between the nodes in the forward and reverse flows of materials to enhance the dynamics of CLSCs?

Furthermore, the impact of the inventory controllers do not need to be only assessed from the lens of CLSC efficiency but also from a resilience perspective. That is, the design of POUT policies should also consider the response of the CLSC in the event of disruptions in the materials and information flows, such as those caused by the current COVID-19 pandemic (Ivanov et al., 2020a,b; Ivanov and Dolgui, 2020). Under such circumstances, the bullwhip effect coexists with the ripple effect of disruptions, yielding consequential interactions (Dooley, 2010; Dolgui et al., 2020).

These are just a few of the numerous open research problems in the discipline of CLSC dynamics. Contributions in these directions would help modern societies address crucial sustainability challenges, thus allowing for a more solid connection between the environmental and economic benefits of the much-needed transition to a circular economy.

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