Computers & Industrial Engineering 128 (2019) 91–103

Contents lists available at ScienceDirect

Computers & Industrial Engineering

journal homepage: www.elsevier.com/locate/caie

On the dynamics of closed-loop supply chains with capacity constraints

Roberto Dominguez[a], Borja Ponte[b], Salvatore Cannella[c,a,*], Jose M. Framinan[a]

[a] Industrial Management and Business Administration Department, University of Seville, Spain
[b] Department for People and Organisations, The Open University, UK
[c] DICAR, University of Catania, Italy

ARTICLE INFO

Keywords:
Bullwhip effect
Supply chain dynamics
Reverse logistics
Capacity limitations
Simulation

ABSTRACT

In this paper, we investigate the dynamic behavior of a closed-loop supply chain with capacity restrictions both in the manufacturing and remanufacturing lines. We assume it operates in a context of a twofold uncertainty by considering stochastic demand and return processes. From a bullwhip perspective, we evaluate how the four relevant factors (specifically, two capacities and two sources of uncertainty) interact and determine the operational performance of the system by measuring the variability of the manufacturing and remanufacturing lines and the net stock. Interestingly, while the manufacturing capacity only impacts on the forward flow of materials, the remanufacturing capacity affects the dynamics of the whole system. From a managerial viewpoint, this work suggests that capacity constraints in both remanufacturing and manufacturing lines can be adopted as a fruitful bullwhip-dampening method, even if they need to be properly regulated for avoiding a reduction in the system capacity to fulfill customer demand in a cost-effective manner.

1. Introduction

An almost-ubiquitous problem occurring in supply chains (SC) is the so-called bullwhip effect (BWE) (Lee, Padmanabhan, & Whang, 1997), which refers to the phenomenon by which even small variations in customer demand may generate high alterations in upstream production for suppliers (Dominguez, Cannella, & Framinan, 2014; Huang, Hung, & Ho, 2017; Lin, Naim, Purvis, & Gosling, 2017). This has important implications in real-life SCs (see e.g. Zotteri, 2013; Isaksson & Seifert, 2016; Chiang, Lin, & Suresh, 2016; Trapero & Pedregal, 2016; Jin, DeHoratius, & Schmidt, 2017; de Oliveira Pacheco, Cannella, Lüders, & Barbosa-Povoa, 2017; Lin, Spiegler, & Naim, 2017; Pastore, Alfieri, & Zotteri, 2017). Indeed, recent empirical works have shown that the BWE may emerge in two-thirds of firms from USA (Bray & Mendelson, 2012) and China (Shan, Yang, Yang, & Zhang, 2014). Besides, its consequences are, by nature, global and impact both developed and developing countries, as pointed out by the European Central Bank (Altomonte, Mauro, Ottaviano, Rungi, & Vicard, 2012), the European Bank for Reconstruction and Development Working (Zavacka, 2012) and the World Bank (Ferrantino & Taglioni, 2014). Some of the consequences of BWE are excess of inventory, poor customer service and inaccurate demand forecasts (Trapero, Kourentzes, & Fildes, 2012). In the last two decades, different efforts to explain and reduce the BWE have emerged and these continue to grow (Wang & Disney, 2016). However, even if a number of advances have been made for limiting BWE, there is still substantial room for improvement. More specifically, after conducting the most recent literature survey on the BWE, Wang and Disney (2016) identify several opportunities for future research, such as BWE in complex systems, with pricing considerations, in service chains, and with research competition. Among those opportunities, two stand out, i.e.: investigating the BWE in capacity-constrained environments and exploring this phenomenon in Closed-Loop SCs (CLSCs).

Manufacturing firms are fundamental in supporting modern economies (Trapero, Kourentzes, & Fildes, 2015). Consequently, studying the impact of manufacturing capacity constraints in SC dynamics has become an important research area in the past years. Capacity constraints usually refer to considering upper limits in the order sizes placed to suppliers, or upper limits in the orders' acceptance channel. For example, this may be due to restrictions in the manufacturing resources. In this regard, literature has shown that such interpretation of capacity can stabilize the orders and generate a smoothing effect on production (see e.g., Evans & Naim, 1994; Chen & Lee, 2012; Shukla & Naim, 2017; Ponte, Wang, de la Fuente, & Disney, 2017; Framinan, 2017). However, and at the same time, these restrictions may negatively impact on inventory holding costs and customer service level (Cannella, Ciancimino, & Marquez, 2008; Hussain, Khan, &

* Corresponding author.
E-mail addresses: rdc@us.es (R. Dominguez), borja.ponte-blanco@open.ac.uk (B. Ponte), cannella@unict.it, cannella@us.es (S. Cannella), framinan@us.es (J.M. Framinan).

https://doi.org/10.1016/j.cie.2018.12.003

Available online 08 December 2018
0360-8352/

Sabir, 2016; Nepal, Murat, & Chinnam, 2012; Spiegler & Naim, 2014). In general, works dealing with the implications of capacity limits on the dynamic performance of the SC are relatively scarce (Ponte et al., 2017) and, to the best of authors' knowledge, their subject of study is a traditional forward SC as opposed to the emerging CLSC setting.

In a CLSC, recycling and/or remanufacturing activities — which involve taking back products from customers after their consumption and returning them to the SC for the recovery of added-value by reusing the whole product or part of it (Genovese, Acquaye, Figueroa, & Koh, 2017) — are implemented (Jerbia, Kchaou Boujelben, Sehli, & Jemai, 2018). CLSC archetypes are the desired business model for companies due to the potential value recovery, environmental sustainability, and special importance given by the customers (Jabbarzadeh, Haughton, & Khosrojerdi, 2018). In the last decade, some works have been exploring the dynamic characteristics of CLSCs, specifically by focusing on how some key factors of this structure (e.g., the return yields, the remanufacturing lead-time, and the adoption of different order policies) may impact on the performance in terms of BWE, inventory stability and customer service level. Particularly, most of studies have shown that increasing return yields can reduce the BWE (see e.g., Tang & Naim, 2004; Zhou & Disney, 2006; Hosoda, Disney, & Gavirneni, 2015; Cannella, Bruccoleri, & Framinan, 2016; Zhao et al., 2018). However, to the best of the authors' knowledge, these studies assume infinite production capacity.

In the light of the above-mentioned considerations, we argue that exploring the dynamic behavior of a CLSC by understanding how a limitation in the capacity of the manufacturing and remanufacturing lines impacts on SC performance can be reasonably considered a major challenge for OM communities. Hence, in this work we aim to shed light on this topic and, to fulfill the research objective, we model a CLSC via difference equations (Riddalls, Bennett, & Tipi, 2000) characterized by a limitation in both manufacturing and remanufacturing operations. Moreover, given the need of modern SCs for surviving and thriving in turbulent and volatile environments (Wikner, Naim, Spiegler, & Lin, 2017), we consider stochasticity in both the return yield and the customer demand. Thus, we perform a rigorous Design of Experiments (DoE) considering four key factors, i.e., (1) the variability of the return yield, (2) the capacity factor of the manufacturer, (3) the capacity factor of the remanufacturer, and (4) the variability of the customer demand. In short, the results of this works reveal that a low capacity in the remanufacturer may smooth the BWE in the fabrication of both new and remanufactured products while maintaining a good inventory performance. However, if capacity is reduced below certain threshold value, it can also generate detrimental consequences in terms of inventory holding costs and customer service level. From a managerial point of view, this work suggests that imposing capacity limits in both remanufacturing and manufacturing processes can be adopted as a bullwhip-dampening method. In order to the set suitable capacity of both lines, managers should also take into account the degree of uncertainty of both the market demand and the return yield.

The rest of the paper is organized as follows. Section 2 presents a literature review of studies dealing with BWE, capacity constraints and CLSCs. Section 3 details the model of the capacitated CLSC and the key performance indicators employed. Section 4 describes the experimental design, while Section 5 shows the results obtained from the simulations. Section 6 contains the summary of findings and managerial implications. Finally, Section 7 presents the main conclusions of the work.

2. Literature review

In this section, we first provide an overview of the previous works investigating the BWE in capacitated SCs. Later, we summarize the relevant literature exploring the dynamics of CLSCs. As discussed in the previous section, although a number of contributions have been produced in these areas separately, we are not aware of any work jointly investigating these two aspects.

2.1. The impact of capacity constraints on supply chains

In BWE literature, the problem of capacity constraints has been considered in relatively few studies. These are usually developed by adopting modelling and simulation techniques, given the mathematical complexity introduced by the capacity limit in the form of a non-linearity. Among these works, to the best of the authors' knowledge, Evans and Naim (1994) can be considered the first one. Via differential equation modelling, the authors conclude that the capacity constraints may improve the behavior of SC in terms of BWE, but at the expense of reducing the inventory service levels. Essentially, Evans and Naim (1994) show for the first time that an unconstrained SC does not always produce the best performance. De Souza, Zice, and Chaoyang (2000), using system dynamics, conclude that SC performance can be seriously affected by capacity shortages. In this fashion, they suggest that capacity planning is central to the dynamics of the SC. Analogously, Helo (2000), also via system dynamics, suggests that a limited capacity negatively impacts on the responsiveness of the SC. Vlachos and Tagaras (2001), through both analytical methods and simulation, show that imposing capacity limits damages the system's response, particularly for long production lead times. Similarly to Evans and Naim (1994), Wilson (2007), through system dynamics modelling, finds out that short-term limitations on capacity may produce a poor customer service level; however, they can improve the SC behavior. Analogously, Cannella et al. (2008), via differential equations modelling, show that the BWE can be reduced if capacity limits are imposed, but they also can create a significant stock-out phenomenon. Boute, Disney, Lambrecht, and Van Houdt (2009), via analytical methods, demonstrate that inflexible limits on capacity generate stochastic lead times and thus they amplify the desired inventory on-hand and, in general, the operational costs. Interestingly, Juntunen and Juga (2009), via discrete-event simulation, show that the fill rate does not necessarily improve by increasing the capacity limitation in distribution. Contrarily, Hamdouch (2011), by adopting a network equilibrium method, shows that capacity limitations generate poor market response and SC behavior. Nepal et al. (2012), via differential equations modelling, report that capacity restrictions do not have a significant impact on order variability but, in contrast, it can strongly affect the stability of the inventory. Chen and Lee (2012), via mathematical analysis, and in line with those studies showing the benefits of capacity constraints in terms of BWE reduction, argue that considering a fixed capacity in SC mitigates this phenomenon. Spiegler and Naim (2014), via system dynamics, show that capacity restrictions have a negative effect on both inventory and service customer levels, even if it emerges a positive impact on the 'backlash' effect (i.e., BWE on transportation). In line with most of the previous studies, Hussain et al. (2016), using differential equations modelling, show that restrictions in the order size due to capacity limitation may avoid "phantom" large orders, a similar conclusion to that by Shukla and Naim (2017) via system dynamics modelling. Ponte et al. (2017) show that the capacity limit can be optimized to reduce SC costs by looking at the trade-off between improved order stability and reduced inventory performance. Finally, Framinan (2017) analytically demonstrates that if capacity refers to the rejection of orders in excess of a given threshold, then capacity dampens the BWE.

In summary, the above-mentioned studies have reported somewhat contradictory results regarding the impact of capacity constraints on the dynamics of SCs. However, most of them agree on the positive effect of the capacity limitations on the BWE, since these restrictions dampen order variability. At the same time, they observe that this improvement is generally achieved at the expense of a decreased trade-off between service level and inventory holding requirements. However, it is interesting to highlight that all the previous studies have been conducted in the context of traditional, or open-loop, SCs. In this sense, none of the studies investigates how capacity limitations may impact the dynamics of CLSCs, particularly when these affect to both the forward and reverse flow of materials.

2.2. The dynamics of closed-loop supply chains

Following from the previous discussion, the BWE has largely boosted the attraction of researchers over the last decades in what we may label as traditional, or open-loop, SCs (see e.g. Wang & Disney, 2016). These cover the unidirectional flow of materials between the point at which the raw materials are extracted, upstream, and that at which the product is consumed and ends up in landfill, downstream. However, this archetype is becoming obsolete in many practical settings, as SCs are evolving towards closed-loop variants in a bid to mitigate environmental impacts and exploit economic opportunities derived from circular economy models (Genovese et al., 2017; Govindan, Soleimani, & Kannan, 2015). In this sense, the so-called CLSCs capture a bidirectional flow of materials: on the one hand, the traditional downstream flow, from suppliers to customers; on the other hand, the reverse flow, in the opposite direction. The reverse flow covers the collection of used products and their recovery up to operating standards, for examples through recycling and/or remanufacturing processes. It should be noted that the forward and reverse flow are subject to different uncertainties. While the dynamics of the former, and thus those of traditional SCs, are heavily influenced by the consumer demand uncertainty; the dynamics of the reverse flow of materials, and thus those of CLSCs, are greatly impacted by the uncertainty on the volume, timing, and quality of the returned products (Ferguson, Guide, Koca, & Souza, 2009; Souza, 2013). Given that the characteristics of these emerging SCs significantly differ from those of traditional SCs, research on new business models that efficiently integrate both flows of materials becomes necessary (Goltsos, Ponte, Wang, Liu, Naim, & Syntetos, in press; Guide, Harrison, & Van Wassenhove, 2003).

In the BWE literature, the CLSC archetype has still received relatively little attention, as pointed out by recent reviews of the literature (Braz, De Mello, de Vasconcelos Gomes, & de Souza Nascimento, 2018; Goltsos et al., in press). Historically, the work by Tang and Naim (2004) can be considered the first effort in analyzing the BWE in a CLSC in the form of a hybrid manufacturing/remanufacturing system. The authors, via control theory, study three ad-hoc order policies. They conclude that increasing recollected products and operating with higher information transparency on the pipeline of the remanufacturer strongly improves the performance of the CLSC. Also by means of a control theoretic approach, Zhou and Disney (2006) analyze the impact of lead times and return rates on the inventory variance and demand amplification phenomenon. Zanoni, Ferretti, and Tang (2006) use a discrete-event simulation model to carry out a comparative study between four different replenishment rules in terms of order amplification. They show how the BWE of the downstream (forward) flow in the SC can be reduced in the dual policy, while the BWE of the upstream flow (reverse) can be mitigated by using the shifted pull policy. Pati, Vrat, and Kumar (2010) use a statistical analysis on a six-stage reverse SC and conclude that the reverse flow does not experience a demand amplification. By means of agent-based simulation, Adenso-Díaz, Moreno, Gutiérrez, and Lozano (2012) analyze the impact of 12 factors in both the forward and the reverse flow of materials and do not detect significant differences between the performances of the two considered SC structures in terms of order rate amplification. Turrisi, Bruccoleri, and Cannella (2013), via difference equation modelling, propose a novel replenishment rule to coordinate the upstream and downstream flows in a CLSC and show that a reduction of BWE can be obtained by increasing the volume of returns. However, they do not find significant differences in terms of inventory variance. Analogously, Corum, Vayvay, and Bayraktar (2014) employ a discrete-event simulation model to show that a CLSC allows reducing the BWE phenomenon. Hosoda et al. (2015), via analytical methods, study the impact of the correlation between demand and returns, and observe that increasing the yield may have a negative effect in terms of inventory variability. Cannella et al. (2016) employ difference equation modelling to show that shifting from a forward SC to a CLSC always generates benefits in terms of inventory and order variances, both in stable and turbulent market scenarios. Dev, Shankar, and Choudhary (2017), via difference equation modelling, conclude that, in a CLSC, continuous-review policies outperform periodic-review policies from a BWE perspective. Zhou, Naim, and Disney (2017) consider different return qualities in a three-echelon supply chain, using control theory, and show that a higher return yield decreases the BWE. The magnitude of this reduction depends on the combination of control parameters (i.e., the degree of return yield at each echelon and the lead times in the CLSC). Hosoda and Disney (2018), via analytical methods, explore the so-called 'lead time paradox' in CLSCs, which refers to the scenarios in which increasing the remanufacturing lead time may decrease the SC cost. They show that shortening the remanufacturing lead time does not contribute to lower inventory costs but could generate some other benefits, such as lower capacity cost and in-transit inventory. Sy (2017) employs system dynamics to analyze a hybrid production-distribution system and show that, under three scenarios, the centralization of the customer demand information attenuates the BWE. Similarly, Zhao et al. (2018) study, via system dynamics, the impact of three ordering policies that differ on the degree of shared information in the CLSC. In line with literature on information sharing, they conclude that the use of centralized demand information in a vendor managed inventory system reduces both order and inventory variability.

To sum up, previous studies show a lack of consensus on the impact of the relevant CLSC parameters on the BWE and inventory variability of such systems. While some studies observed that the dynamics of CLSCs may be improved by increasing the return yield, other studies concluded the opposite impact. Similarly, some studies concluded that reducing remanufacturing lead times translates into an increased performance of CLSCs, while others reported the previously mentioned lead time paradox. As remarked by Cannella et al. (2016) and Zhao et al. (2018), these conflicting results may depend on different SC configurations and modelling assumptions. There is no doubt, however, about the key role of information transparency for improving the dynamic behavior of CLSCs. Integrating the forward and reverse flow of materials in a cost-effective manner has proven to be greatly facilitated by the information exchange between them. Finally, it is important to emphasize that there is no evidence on how a CLSC performs if capacity limitations are considered both in the forward and reverse flow of materials.

3. Closed-loop supply chain model

Fig. 1 provides an overview of the hybrid manufacturing/remanufacturing system considered in this research work, together with its main parameters. This CLSC is described in detail in the following paragraphs. A summary of the notation employed for describing the CLSC model is provided in Table 1.

The CLSC integrates both manufacturing and remanufacturing processes into the same SC and operates on a discrete-time basis, being the time unit t. We consider two sources of stochasticity, i.e., the consumer demand (d_t) and the returns (r_t). As usually assumed in this field, the demand is drawn from an independent and identically distributed

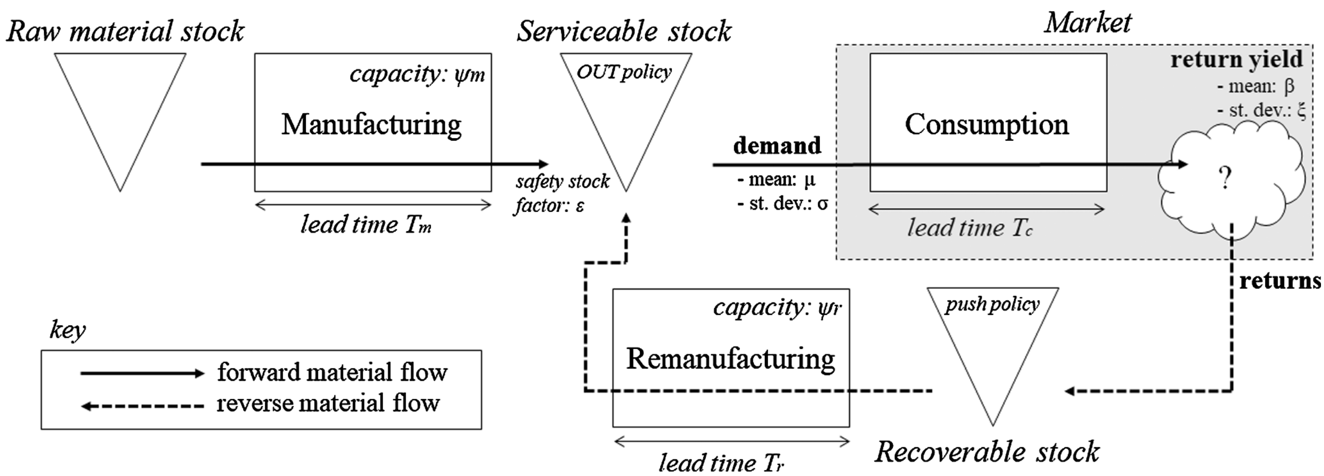

Fig. 1. Structure of the hybrid manufacturing/remanufacturing system.

(i.i.d.) random variable (x_t) following a normal distribution with mean μ and standard deviation σ, being the coefficient of variation $CV_d = \sigma/\mu$, which is constrained to only positive values. That is,

$$d_t = \max\{x_t, 0\}, \, x_t \to N(\mu, \sigma^2). \tag{1}$$

In order to account for the stochasticity of the returns, we model the return yield (z_t), i.e., the percentage of sold products that come back to the SC after consumption, through an i.i.d. random variable (y_t) following a normal distribution with mean β and standard deviation ξ, being the coefficient of variation $CV_r = \xi/\beta$, which has been constrained to values between 0 and 1. This approach allows us to model the returns as the product of the yield and the demand before a constant consumption lead time T_c. In this sense, this variable has been constrained to prevent negative values from happening, which would be meaningless in practice.

$$r_t = y_t d_{t-T_c}, \, y_t = \min\{\max\{z_t, 0\}, 1\}, \, z_t \to N(\beta, \xi^2). \tag{2}$$

Each period t, the operation of the hybrid manufacturing/remanufacturing system can be divided into three sequential stages, which are detailed below, including the associated mathematical formulation.

3.1. Stage I: Reception, settling and feeding

At the beginning of each period t, the serviceable inventory receives the product from both the manufacturer (new products) and remanufacturer (assuming as-good-as-new products), once the processes have been completed after the respective constant lead times T_m and T_r. In this sense, the serviceable inventory is ready for facing the consumer demand that will be received during this period. Moreover, the raw material inventory provides the manufacturing equipment with the quantity required according to the order issued at the end of the previous period. Similarly, the returns collected during the previous period are fed into the remanufacturing process, which hence operates according to a push policy—Hosoda and Disney (2018) justifies that this common assumption fits well with the ethics of sustainability.

In this regard, we note that the capacity constraints of the manufacturing and remanufacturing process, respectively ψ_m and ψ_r, play a key role. Taking into consideration the capacity required for both processes under a steady state defined by the mean values μ (for the demand) and β (for the returns), that is, $(1-\beta)\mu$ for the manufacturing process (i.e. the average net demand) and $\beta\mu$ for the remanufacturing process (i.e. the average returns); we define the coefficients of capacity as $CoC_m = \psi_m/[(1-\beta)\mu]$ and $CoC_r = \psi_r/[\beta\mu]$. Note that these

Table 1
Notation of the CLSC model.

Variables			
o_t	Order quantity	rc_t	remanufacturing completion rate
d_t	customer demand in period t	rb_t	remanufacturing backlog
$\hat{d}_t$	market demand forecast at the end of period t	x_t	random variable for demand in the period t
r_t	returns in the period	w_t	work-in-progress
is_t	serviceable stock	z_t	return yield in period t
ss_t	safety stock	tw_t	target work-in-progress
ns_t	net stock	y_t	random variable for the return yield
mb_t	manufacturing backlog		
Parameters and statistics			
CV_d	coefficient of variation of demand	ψ_m	capacity constraint of the manufacturing process
CV_r	coefficient of variation of the return yield	ψ_r	capacity constraint of the remanufacturing process
σ	standard deviation of the random variable simulating the demand	T_p	Estimated pipeline lead time
μ	mean of the random variable simulating the demand	T_m	manufacturing lead time
α	demand forecast smoothing factor	T_r	remanufacturing lead time
β	mean of the random variable simulating the return yield	T_c	consumption lead time
ξ	standard deviation of the random variable simulating the return yield	t	time unit
ε	safety stock factor	Σ_{mc}	standard deviation of the manufacturing completion rate
CoC_m	coefficient of manufacturing capacity	Σ_{rc}	standard deviation of the remanufacturing completion rate
CoC_r	coefficient of remanufacturing capacity	Σ_{ns}	standard deviation of the net stock

coefficients inform about the excess capacity available in relative terms to the mean required. We note that to ensure the stability of the system, both must be greater than the unity.

Under these circumstances, the manufacturing completion rate responds to the order placed $T_m + 1$ periods ago, as long as there is enough capacity available, by

$$mc_t = \min\{o_{t-T_m-1} + mb_{t-1}, \psi_m\}. \tag{3}$$

As Eq. (3) illustrates, it is also necessary to consider the manufacturing backlog (mb_t) which measures the pending orders that could not be processed when required and will be delivered as soon as capacity becomes available. This variable can be expressed by

$$mb_t = \max\{o_{t-T_m-1} + mb_{t-1} - \psi_m, 0\}. \tag{4}$$

It can be easily checked that if $o_{t-T_m-1} + mb_{t-1} \geq \psi_m$, the manufacturing system has no pending work, i.e. $mb_t = 0$, while $o_{t-T_m-1} + mb_{t-1} < \psi_m$ would result in pending orders, i.e. $mb_t > 0$.

The rationale employed for modelling the remanufacturing line is similar, assuming that it operates according to a push policy. For this reason, the remanufacturing completion rate (rc_t) corresponds to the returns collected $T_r + 1$ periods ago, as long as the remanufacturing capacity allows it, by

$$rc_t = \min\{r_{t-T_r-1} + rb_{t-1}, \psi_r\}; \tag{5}$$

while the remanufacturing backlog (rb_t) would be expressed as

$$rb_t = \max\{r_{t-T_r-1} + rb_{t-1} - \psi_r, 0\}. \tag{6}$$

Overall, the on-hand serviceable stock, or initial stock (is_t), which is available for fulfilling the demand received during the period can be expressed as a function of the net stock (ns_t), or excess on-hand inventory at the end of the previous period, by

$$is_t = ns_{t-1} + mc_t + rc_t. \tag{7}$$

3.2. Stage II: Manufacturing, serving, and returns collection

During period t, orders from consumers are received. These are satisfied as long as on-hand inventory is available. In this sense, the final position of this inventory can be expressed as

$$ns_t = is_t - d_t, \tag{8}$$

where positive values of this variable refer to holding and negative values indicate stock-outs, which will be satisfied as soon as possible (ideally, at the beginning of the next period).

In this regard, the on-order inventory, or work-in-progress (w_t), at the end of the period can be obtained by

$$w_t = w_{t-1} + (o_{t-1} - mc_t) + (r_{t-1} - rc_t). \tag{10}$$

Note that we are implicitly assuming that it takes one period to gather the collected returns and evaluate their state. The work-in-progress represents the sum of the products that have been ordered but not yet received in the serviceable inventory plus the returns that have been collected but not yet completely remanufactured. This is a relevant variable as it provides the decision makers with important information about the current state of the system.

At the same time, during period t, returns are collected and stored in the recoverable inventory. Similarly, both the manufacturing and remanufacturing processes are considered to be ongoing.

3.3. Stage III: Updating, forecasting, and sourcing

At the end of each period, a new order is issued to manufacture new products. In this sense, we are implicitly assuming that the serviceable inventory is operated via a discrete-review policy. To this end, we employ an order-up-to (OUT) replenishment model, which is widely used in real-world scenarios (Dejonckheere, Disney, Lambrecht, & Towill, 2003). We note that, as pointed out by Axsäter (2003), these periodic-review inventory models are generally easier to implement and less expensive to operate than continuous-review models, where the inventory is constantly reviewed.

It is relevant to highlight that the OUT model has been adapted to closed-loop scenarios by employing the same rationale that the type-3 OUT model developed by Tang and Naim (2004). More specifically, an order is placed to cover the fraction of the demand that cannot be satisfied through remanufactured products. We selected the type-3 system, as it was shown to make the best use of the available information both from the manufacturing and remanufacturing processes. As in Tang and Naim (2004)'s proposal, the order quantity is obtained as the sum of three gaps: (i) the gap between the forecasted demand ($\hat{d}_t$) and the actual number of remanufactured products; (ii) the gap between the target, or safety stock (ss_t), and the current level of the on-hand inventory; and (iii) the gap between the target (tw_t) and the current work-in-progress; as per the following equation,

$$o_t = \max\{(\hat{d}_t - rc_t) + (ss_t - ns_t) + (tw_t - w_t), 0\}. \tag{11}$$

Note that we have constrained the order quantity to only positive values, which means assuming that the serviceable inventory is not allowed to return the excess inventory to the raw material inventory (if it were the case). In this sense, we are capturing a common real-world feature of inventory systems.

The previous equation requires the calculation of the demand forecast, the safety stock, and the target work-in-progress. First, we assume that the demand is estimated through the minimum mean square error (MMSE) forecast of the statistical variable that define its behavior, which is its conditional expectation (e.g. Disney, Maltz, Wang, & Warburton, 2016). For i.i.d. demand, that is:

$$\hat{d}_t = \mu. \tag{12}$$

Regarding the safety stock, we adopt a simple but used model (e.g. Cannella et al., 2016) that estimates it as the product of the safety stock factor ε and the demand forecast, by

$$ss_t = \varepsilon \hat{d}_t. \tag{13}$$

Thus, the factor may be interpreted as the number of future periods against which the node aims to be protected. Finally, the target work-in-progress is obtained as the product of the pipeline estimate T_p and the demand forecast, according to:

$$tw_t = T_p \hat{d}_t. \tag{14}$$

Note that the pipeline estimate has been adjusted, according to the setting proposed by Tang and Naim (2004), as an average of the manufacturing and remanufacturing lead times weighted by the return yield. These authors show that this is the only configuration that avoids a long-term drift in the position of the serviceable inventory. Given that in their case they assumed a constant return yield, we have adapted their proposed equation by employing the average of the variable that define the yield's behavior, i.e. $T_p = (1 - \beta)T_m + \beta T_r$.

3.4. Key performance indicators

We assess the behavior of the CSLC using three main performance indicators based on the pioneering works of Tang and Naim (2004) (i.e., manufacturing completion rate, net stock) and Zanoni et al. (2006) (i.e., remanufacturing completion rate). More specifically, we measure the standard deviations of these three variables over time, i.e. manufacturing completion rate (Σ_{mc}), remanufacturing completion rate (Σ_{rc}), and net stock (Σ_{ns}), as they provide more concise and comparable insights on the BWE of both manufacturing and remanufacturing processes as well as on inventory holding costs. Below, we discuss in detail the rationale behind the adoption of these metrics.

Disney, Gaalman, and Hosoda (2012) explore several cost functions that can be employed to assigned capacity-related costs to stochastic production rates. They show that in guaranteed-capacity models — i.e., where an opportunity cost is incurred if the production is lower than the guaranteed capacity and an overtime cost is incurred when the production rate is higher than the guaranteed capacity —, the minimum production cost is proportional to the standard deviation of the manufacturing rate if both costs are proportional to the volume. While it is true than in other costs models this perfect relationship may be broken, it can be considered that the standard deviation of the manufacturing completion rate provides a good understanding on the behavior of the capacity-related production costs in the SC. The same rationale applies for the standard deviation of the remanufacturing completion rate.

Similarly, Kahn (1987) demonstrate that the minimum inventory cost is linearly related to the standard deviation of the net stock, where holding (for positive net stocks) and stock-out (for negative net stocks) are considered and these are proportional to the volume. Again, this pure relationship may not hold for other cost models; but the variability of net stock can still be interpreted as a good indicator of the inventory performance of the SC under a specific configuration. In this sense, Disney & Lambrecht (2008) state that the variability of the net stock determines the echelon's ability to meet a service level in a cost-effective manner.

4. Experimental design

In this section, the effect of capacity constraints on the performance of the hybrid manufacturing/remanufacturing system is explored using an experimental design. To do so, we focus on the coefficients of capacity of both the manufacturer and remanufacturer processes, i.e., CoC_m and CoC_r. As highlighted previously, these parameters express the capacity limits of the manufacturing and remanufacturing line in relative terms to the average capacity required. In order to understand their effect in a wide range of scenarios, we explore several levels of both factors. These levels are chosen according to the following considerations:

- To ensure the long-term stability of the system, CoC_m and CoC_r must be greater than the unity, i.e., the manufacturing system needs to be able to meet the average net demand and the remanufacturing system needs to be able to process the average returns.
- Preliminary simulation experiments revealed that the three performance metrics tend to stabilize as the relevant coefficients of capacity increase, like in the traditional SC (see e.g. Ponte et al., 2017). More specifically, this happens for $CoC_m > 3$ and $CoC_r > 3$, as per Σ_{mc} and Σ_{rc} (these values are lower for Σ_{ns}). Thus we exclude from the analysis the region above these values, since they give no further information about the system.

Since these parameters are the effects of interest in our study, we analyze several levels for each capacity, in intervals of 0.5. Specifically, they range from 1.1 (the system operates close to its maximum capacity) to 3.1 (the system has sufficient spare capacity and behaves similarly to an unconstrained system), i.e. $CoC_m = \{1.1, 1.6, 2.1, 2.6, 3.1\}$ and $CoC_r = \{1.1, 1.6, 2.1, 2.6, 3.1\}$.

As it seems reasonable, several research studies (see e.g. Ponte et al., 2017) have shown that the impact of capacity constraints on the dynamics of SCs strongly depends on the variability of the sources of stochasticity. For this reason, we introduce the variability of the random variables generating the demand and the return yield in the experimental design. Again, we do it through relative instead of absolute values, i.e., the coefficients of variations. In both cases, we employ three levels. In the former, $CV_d = \{0.15, 0.30, 0.45\}$, as they are inside the common interval of variability of demands for retailers according to Dejonckheere et al. (2003). In the latter, $CV_r = \{0.20, 0.40, 0.60\}$, which also covers a wide enough interval that allows us to explore the impact of capacity where there is a strong correlation between demand and returns (yield variability low) and where this correlation is small (yield variability high). It is important to note that these factors can be interpreted as uncontrollable factors, as opposed to the coefficient of capacities that may be understood as controllable factors.

The rest of the parameters have been defined as fixed. In this regard, the mean demand has been set to $\mu = 100$ units per period, while the average return yield has been set to $\beta = 0.5$. For the lead times, we explore a scenario where the manufacturing and remanufacturing lead times are equal, $T_m = T_r = 4$. The reason behind this decision is that it represents a "target scenario", according to the conclusions by Hosoda and Disney (2018). While it is common to assume that remanufacturing lead times are shorter than manufacturing lead times (e.g. Tang & Naim, 2004), Hosoda and Disney (2018) show that the aforementioned lead time paradox —according to which reducing remanufacturing lead times has a negative impact on SC performance— is very likely to appear in these scenarios. To avoid this from happening, the authors highlight the benefits of shortening the manufacturing lead time until both lead times are equal. Note that other authors have also considered equal lead times, e.g. Teunter and Vlachos (2002). Furthermore, we have considered a consumption time of $T_c = 32$ in order to illustrate that this tends to be significantly higher than the rest of lead times in the CLSC (e.g. Tang & Naim, 2004). Lastly, we employ $\varepsilon = 1$ for the safety stock policy. The same value is used in Cannella et al. (2016).

Table 2
Experimental design protocol.

Experimental factors		Role	Levels
Coefficient of manufacturing capacity	CoC_m	Controllable	1.1, 1.6, 2.1, 2.6, 3.1
Coefficient of remanufacturing capacity	CoC_r	Controllable	1.1, 1.6, 2.1, 2.6, 3.1
Coefficient of variation of the demand	CV_d	Uncontrollable	0.15, 0.30, 0.45
Coefficient of variation of the return yield	CV_r	Uncontrollable	0.20, 0.40, 0.60
Fixed factors			
$\mu = 100$, $\beta = 0.5$, $T_m = 4$, $T_r = 4$, $T_c = 32$, $\varepsilon = 1$			
Experimental approach			
Type of DoE		Full factorial	
No. of experiments		225	
No. of replications		10	
No. of simulation runs		2250	
Simulation parameters			
Time horizon		2100 periods	
Warm-up period		100 periods	

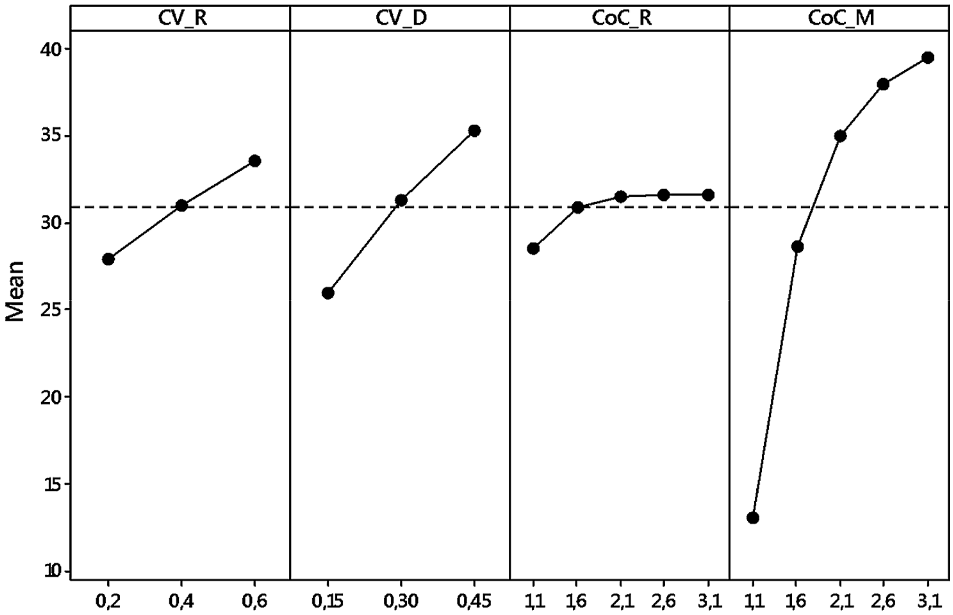

Fig. 2. Main effects plot for Σ_{mc}.

From this perspective, we have designed a full factorial experiment, based on exploring the 225 scenarios resulting from combining the different values of the selected factors (5 × 5 × 3 × 3). Each scenario has been explored through 10 different simulations of 2100 periods, where the first 100 periods are not considered for the results reported to avoid the impact of the initial state of the system. The number of replications aims to reduce the confidence intervals, and hence increase the soundness of our results. Overall, Table 2 summarizes the experimental design protocol.

5. Results

In this section, we analyze the results obtained from the simulations for the metrics Σ_{mc}, Σ_{rc}, and Σ_{ns} using Minitab. Numerical results from ANOVA are shown in Appendix A. The three main assumptions of the ANOVA (i.e. normality, homoscedasticity, and independence of cases) were checked and validated prior to the analysis.

We note that the three models (Σ_{mc}, Σ_{rc}, and Σ_{ns}) show highly adjusted R^2, thus confirming their reliability, as the observed performance variations are well explained by the variations in the experimental factors. Furthermore all factors and their two-way interactions are statistically significant at a 95% confidence level ($p < 0.05$), with the exceptions of CoC_m (and all its associated two-way interactions) for Σ_{rc}, as outlined below. Therefore, in all these cases ($p < 0.05$) we can reject the null hypothesis that there is no difference in means between groups.

In the following paragraphs, we first analyze the main effects of the four experimental factors (i.e., CoC_m, CoC_r, CV_d, and CV_r), and then we investigate the first order interactions.

5.1. Main effects

The main effects plots are shown in Figs. 2–4. The main effect of CV_d is not discussed in detail here, as the impact of demand variability on

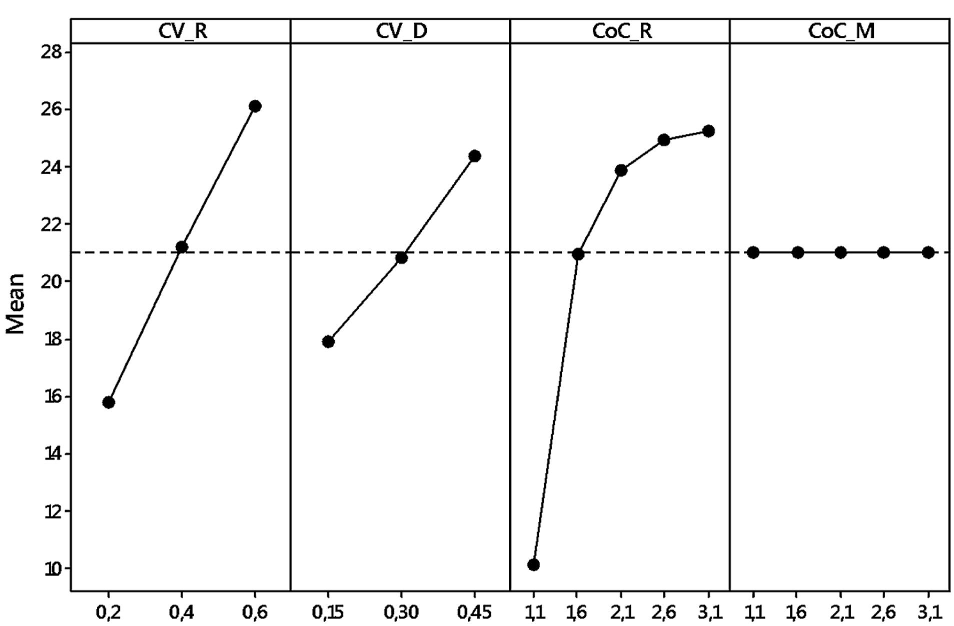

Fig. 3. Main effects plot for Σ_{rc}.

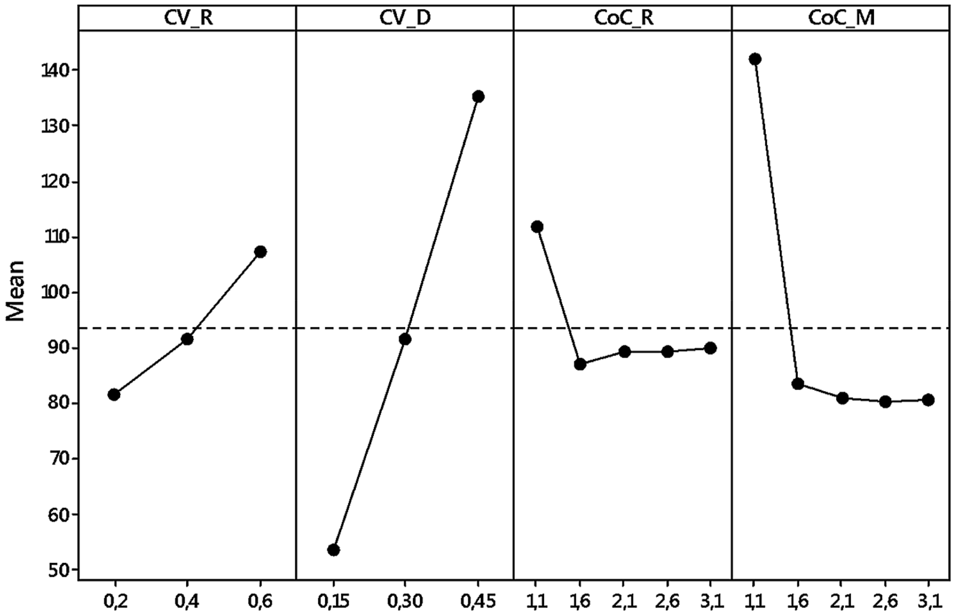

Fig. 4. Main effect plots for Σ_{ns}.

the dynamics of SCs is well known in the problem-specific literature. Meanwhile, the main effect of CV_r confirms previous results in CLSCs, such as those provided by Hosoda et al. (2015). As it can be expected, the variability of indicators Σ_{mc}, Σ_{rc} and Σ_{ns} increases as the coefficient of variation of the return yield grows. This illustrates how returns uncertainty negatively impacts on the dynamic behavior of CLSC.

Our results show that the main effect of CoC_m is similar to that in previous studies of capacitated systems in traditional forward SCs. It can be seen from Fig. 2 that reducing this factor results in a lower Σ_{mc}, and this decrease is more significant as CoC_m becomes closer to 1. Nevertheless, Σ_{ns} slightly increases by reducing CoC_m, and a sudden increase is observed when CoC_m is below 1.6. This finding is aligned with previous studies (Cannella et al., 2008; Spiegler & Naim, 2014; Hussain et al., 2016; Ponte et al., 2017, among others) reporting that a reduction in the capacity of the manufacturer acts as a BWE limiter at the expense of decreasing the SC capacity to fulfill consumer demand in time. Interestingly, we do not find evidences of a significant impact of CoC_m on Σ_{rc}, which can be interpreted as consequence of the push policy employed in the recoverable inventory.

The main effect of CoC_r on Σ_{rc} is similar to that of CoC_m on Σ_{mc} (both curves have similar shapes). The effect of CoC_r on Σ_{ns} also has similar features as that of CoC_m on Σ_{ns}, i.e., reducing CoC_m has almost no impact on Σ_{ns} for medium and high values of this parameter, while a sudden increase of Σ_{ns} is observed for values of CoC_m below 1.6. However, the strength of the sudden increase of Σ_{ns} is lower for CoC_r than for CoC_m. Finally, we observe that CoC_r does have a significant impact on Σ_{mc}. In fact, since the reverse flow is considered in the order policy of the manufacturer, and the remanufacturer is governed by a push policy, the

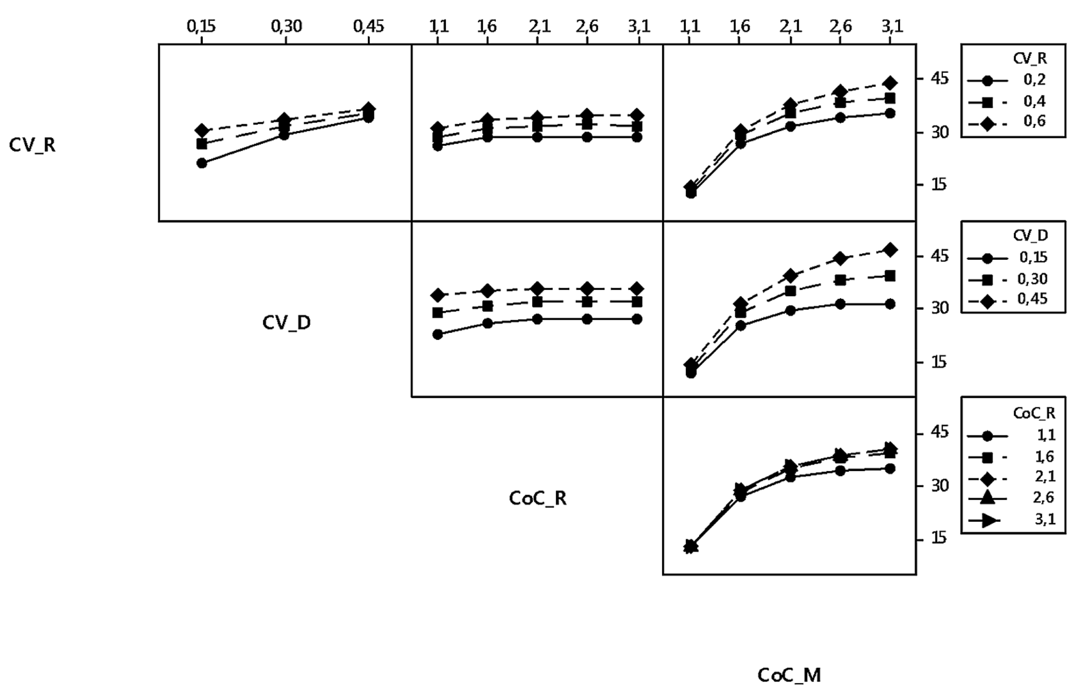

Fig. 5. Interaction plot for Σ_{mc}.

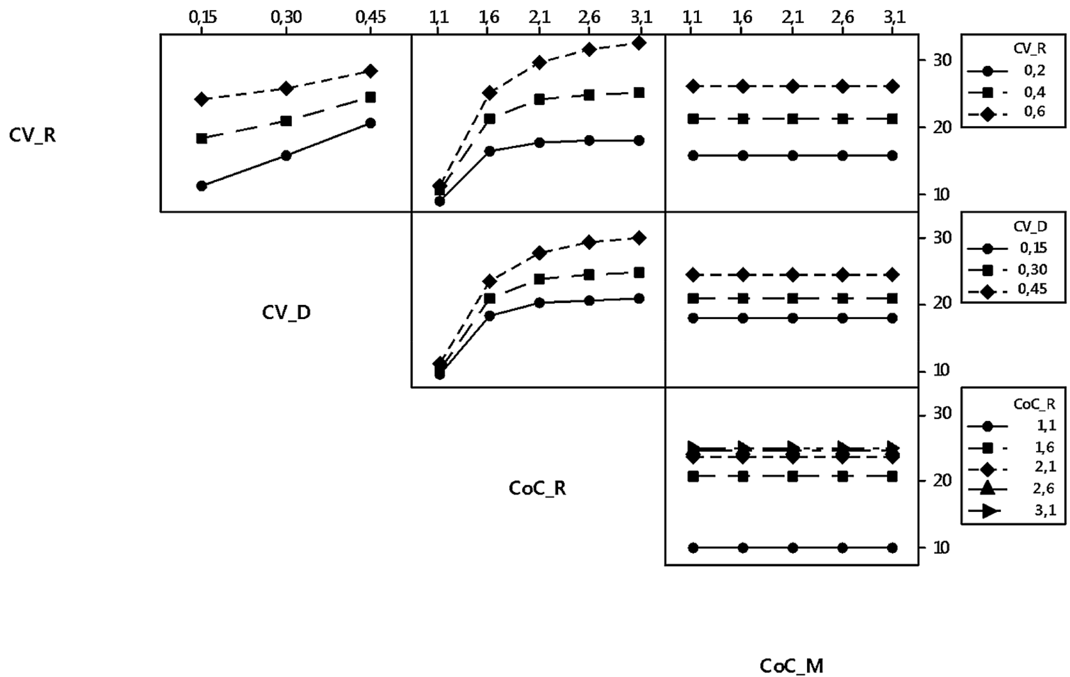

Fig. 6. Interaction plot for Σ_{rc}.

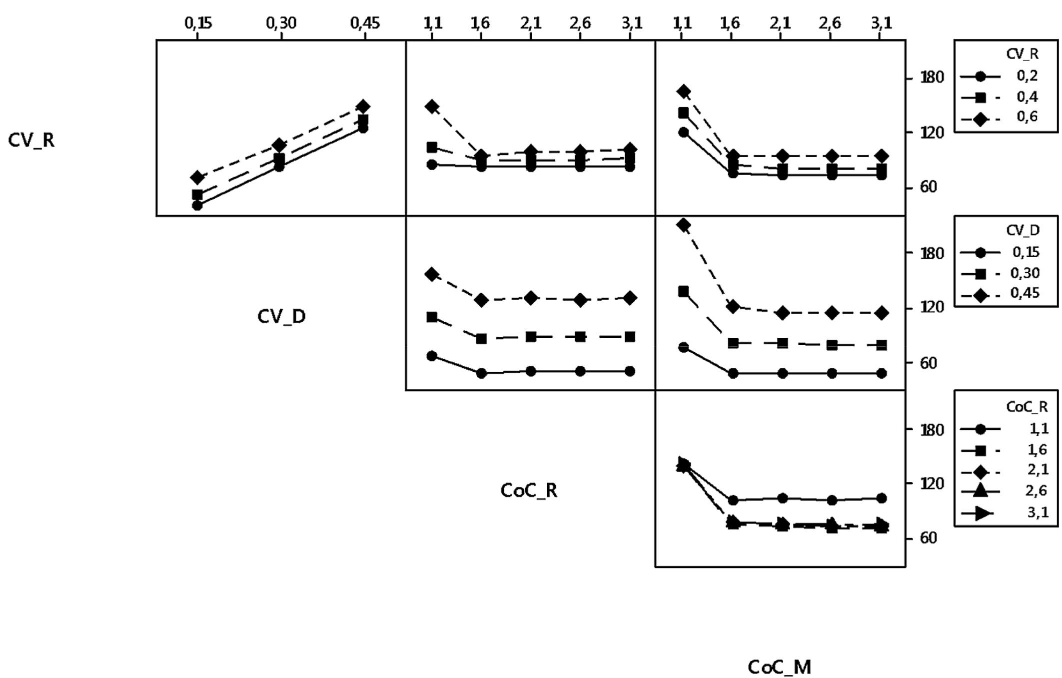

Fig. 7. Interaction plot for Σ_{ns}.

effect caused in Σ_{rc} by increasing/decreasing CoC_r has direct implications on Σ_{mc}. This result implies that reducing CoC_r between 2.6 and 1.6 slightly reduces Σ_{mc}, while a more significant reduction is observed for values between 1.6 and 1.1. Clearly, the impact of CoC_r on Σ_{mc} is always lower than the impact of CoC_m.

5.2. Interactions

The first order interactions are shown in Figs. 5–7. Firstly, looking into Fig. 5, we observe significant interactions between CoC_m and the other three factors. These interactions are particularly strong for the factors CV_d and CV_r (see also *F*-Values in Appendix A), i.e., the reduction obtained for Σ_{mc} by decreasing CoC_m is more significant for higher values of CV_d and CV_r. The interaction between CoC_m and CoC_r is only observed for very low values of CoC_r (CoC_r = 1,1), where Σ_{mc} is less sensitive to CoC_m. CoC_r shows relatively lower interaction strength with CV_d and CV_r. This result implies that reducing CoC_r from 2.1 to 1.1 produces a higher reduction of Σ_{mc} for lower/higher values of CV_d and CV_r, respectively, being the former interaction more significant than the latter (see also *F*-Values in Appendix A). Finally, there is also a significant interaction between CV_d and CV_r. Thus, we can conclude that Σ_{mc} is more sensitive to CV_r for lower values of CV_d.

In Fig. 6 the interaction plots for Σ_{rc} are shown. As CoC_m has no impact on Σ_{rc}, the most significant interactions take place between CoC_r and the other two factors, CV_d and CV_r, being more significant the interaction with the latter factor (see *F*-Values in Appendix A). More specifically, the reduction of Σ_{rc} resulting from reducing CoC_r is more significant for higher values of CV_d and CV_r.

Finally, we analyze the interaction plots for Σ_{ns} (see Fig. 7). The most significant interactions take place between CoC_m and CV_d, and between CoC_r and CV_r, being the former more significant than the latter (see *F*-Values in Appendix A). More specifically, it can be observed that, when CoC_m is reduced below 2.1, the increase in Σ_{ns} is higher for high values of CV_d. Similarly, when CoC_r is reduced below 1.6 the increase in Σ_{ns} is more pronounced for high values of CV_r.

6. Summary of findings and managerial implications

We now summarize the main findings and contributions of our work. We also present interesting implications for managers, suggesting different ways to improve the dynamic performance of a capacitated CLSC.

(1) The capacity restriction in the manufacturing line of a CLSC limits the BWE suffered by the manufacturer (like in a traditional forward SC). This limitation is more significant when the return yield and/or the customer demand present high variability. However, the capacity constraints of the manufacturing line has no significant impact on the BWE suffered by the remanufacturer.

Firstly, we reassert the evidence that capacity constraints may improve the dynamic performance of a SC by reducing the BWE of the manufacturer. As a practical implication, managers may consider to smooth the manufacturing process by limiting its maximum capacity, obtaining a higher performance improvement as the capacity limit becomes lower. This effect is especially important when there is a turbulent market demand or when the return yield is very uncertain. However, the limitation in the capacity of the manufacturing line does not affect the BWE of the remanufacturing line.

(2) The capacity restriction of the remanufacturing line in a CLSC limits the BWE suffered by the remanufacturer, especially when the return yield and/or the customer demand present high uncertainty. In addition, the capacity constraints of the remanufacturing line may enable to reduce the BWE suffered by the manufacturer, especially for high variability of the return yield and/or low variability of the customer demand.

This novel finding allows one to understand the impact of the capacity constraints of the remanufacturing line on the dynamic behavior of capacitated CLSCs. Limiting the capacity of the remanufacturing line has a positive impact on the stability of the remanufacturing process, also obtaining higher improvements as the capacity limit decreases. As in the previous case *(1)*, this impact is especially important when the market demand or the return yield present very variable conditions. In addition, the manufacturing line may also benefit from the limitation of the remanufacturing capacity, but in a lower magnitude. More specifically, this benefit could be only appreciated when the capacity of the remanufacturing line is below a certain threshold value (see Fig. 5). Furthermore, this effect is exacerbated when there is a high uncertainty of the return yield and (contrarily to the previous case) a more stable market demand. In summary, in capacitated (real-life) CLSCs, a way to improve the dynamic behavior of both manufacturing and remanufacturing lines is to limit the capacity of the remanufacturing line, which is able to indirectly smooth instabilities in the manufacturing line.

(3) Reducing either the capacity of the manufacturing line (particularly in case of high variability of customer demand) or the remanufacturing line (particularly in case of high variability of the return yield) below a certain threshold value has a strong negative impact on the variability of the net stock. This negative impact is more sensitive to the capacity of the manufacturing line than to the capacity of the remanufacturing line.

This finding goes in countertendency with the previous findings, since it highlights the negative impact of capacity limitations of both lines on the variability of the net stock. While reducing capacity of the manufacturing/remanufacturing lines produce a continuous improvement in terms of BWE, the variability of the net stock does not present significant changes until a threshold capacity value is reached. From that point on, the variability of the net stock suddenly increases as the capacity is smaller (see Fig. 7). Interestingly, such threshold value seems to be very similar for both lines.

In the light of the above findings, we would recommend managers of CLSCs to strategically consider the capacity planning of both manufacturing and remanufacturing processes. In fact, while the capacity of the manufacturing line has a major effect on the dynamics of the SC, the capacity of the remanufacturing line also plays an important role. By limiting both capacities (i.e., avoiding over-capacitated manufacturing/remanufacturing processes), it is possible to smooth the production of both new and remanufactured products. This decision needs to be taken carefully, since reducing capacity limits over a capacity threshold may have a negative impact on the dynamics of the net stock, thus increasing costs related to inventory holding costs and stock-outs. In this sense, and considering that both lines may share a common capacity threshold, it would be advisable to reduce the capacity of both processes until such threshold is achieved, thus smoothing both processes while maintaining a good performance of the net stock. Additional capacity reduction over such threshold could be recommended only after a proper trade-off analysis between inventory holding costs/target customer service level and production and remanufacturing costs. Finally, uncertainty in market demand and return yield accentuates the positive and negative effects discussed above. Thus, if the SC is characterized by uncertainty in both market demand and return yields, managers would be more willing to reduce capacity of both processes in order to alleviate the negative consequences of such uncertainties, while, in the other hand, more consideration should be given to overstepping the capacity threshold.

7. Conclusions

In this paper we explore the dynamic behavior of a capacitated CSLC. To do so, we modelled a hybrid manufacturing/remanufacturing system characterized by a capacity limitation in both manufacturing and remanufacturing processes. We adopted difference equation modelling approach and a rigorous DoE for assessing the impact of four key factors, i.e., the variability of the return yields, the capacity factor at the manufacturing line, the capacity factor at the remanufacturing line, and the variability of the customer demand. The most interesting result concerns the impact on the BWE of the remanufacturer capacity, which may influence the dynamics of the manufacturer. More specifically, capacity constraints in the remanufacturer line may create a smoothing effect in the fabrication of both new and remanufactured products, but it can also generate detrimental consequences in terms of the trade-off between inventory holding costs and customer service level. From a managerial viewpoint, this work suggests that capacity constraints in both remanufacturing and manufacturing processes can be adopted as a BWE-dampening method. However, a proper tuning of these constraints should take into account the market environment and the degree of uncertainty in the return yield.

As this work is the first attempt to explore the dynamics of a CLSC with capacity constraints in both manufacturing and remanufacturing processes, it is clear that future research is needed to deepen our analysis. Firstly, more complex and real-life CLSC structures need to be analyzed (e.g., multi-echelon and divergent structures; see Dominguez, Cannella, Barbosa-Póvoa, & Framinan, 2018; Cabral & Grilo, 2018). As we do not focus on the impact of remanufacturing and manufacturing lead times, further studies may explore the effect of the interaction between lead times and capacity constraints, and investigate how such limits affect the “lead-time paradox” advocated by Hosoda et al. (2015). Also, we assumed an i.i.d. demand, but other demand processes can also be studied, such as the auto-correlated demand (see e.g. Babai, Boylan, Syntetos, & Ali, 2016). Furthermore, modelling the capacity is still an issue, since all the complexities of a real manufacturing system cannot be captured by considering a limitation in order quantity, limitation to the orders placed to suppliers or limitation to the orders' acceptance channel. Thus, new studies may consider load-dependent lead times, by adopting empirical results from scheduling theory (see e.g. CT-TP curve and clearing functions; see Orcun, Uzsoy, & Kempf, 2009; Mönch, Fowler, & Mason, 2013). Finally, the impact of inventory obsolescence (Babai, Dallery, Boubaker, & Kalai, in press) should also be explored in capacitated CLSCs.

Acknowledgements

We are grateful to the anonymous referees and the editorial team, as their suggestions allowed us to improve earlier versions of this manuscript. This research was supported by the Italian Ministry of Education, University and Research (Rita Levi Montalcini fellowship programme), by the University of Seville (V/VI PPIT-US), and by the Spanish Ministry of Science and Innovation, under the project PROMISE with reference DPI201680750P.

Appendix A

See Table A1–A3.

Table A1
Analysis of variance for Σ_{mc}.

Source	DF	Adj SS	Adj MS	F-value	P-value
Analysis of variance					
Model	64	271,018	4,234.7	5,897.49	0.000
Linear	12	255,121	21,260.0	29,608.22	0.000
CV_R	2	11,569	5,784.4	8,055.74	0.000
CV_D	2	32,461	16,230.7	22,604.00	0.000
CoC_R	4	3094	773.6	1,077.35	0.000
CoC_M	4	207,996	51,999.0	72,417.44	0.000
2-Way Interactions	52	15,898	305.7	425.78	0.000
CV_R*CV_D	4	3,910	977.5	1,361.27	0.000
CV_R*CoC_R	8	140	17.5	24.36	0.000
CV_R*CoC_M	8	2,380	297.5	414.26	0.000
CV_D*CoC_R	8	392	49.0	68.21	0.000
CV_D*CoC_M	8	7,928	990.9	1,380.06	0.000
CoC_R*CoC_M	16	1,149	71.8	100.01	0.000
Error	2,185	1,569	0.7		
Lack-of-Fit	160	1,059	6.6	26.31	0.000
Pure Error	2,025	510	0.3		
Total	2,249	272,587			
Model summary					
	S	R-sq	R-sq(adj)	R-sq(pred)	
	0.847376	99.42%	99.41%	99.39%	

Table A2
Analysis of variance for Σ_{rc}.

Source	DF	Adj SS	Adj MS	F-value	P-value
Model	64	140,479	2,195.0	8,930.68	0.000
Linear	12	127,987	10,665.6	43,394.85	0.000
CV_R	2	40,370	20,184.8	82,125.35	0.000
CV_D	2	15,792	7,896.1	32,126.66	0.000
CoC_R	4	71,825	17,956.3	73,058.44	0.000
CoC_M	4	0	0.0	0.12	0.975
2-Way Interactions	52	12,492	240.2	977.41	0.000
CV_R*CV_D	4	1,699	424.7	1,727.83	0.000
CV_R*CoC_R	8	7,819	977.4	3,976.79	0.000
CV_R*CoC_M	8	1	0.1	0.33	0.956
CV_D*CoC_R	8	2,969	371.2	1,510.22	0.000
CV_D*CoC_M	8	1	0.1	0.29	0.970
CoC_R*CoC_M	16	3	0.2	0.80	0.682
Error	2,185	537	0.2		
Lack-of-Fit	160	159	1.0	5.34	0.000
Pure Error	2,025	378	0.2		
Total	2249	141,016			
Model summary					
	S	R-sq	R-sq(adj)	R-sq(pred)	
	0.495762	99.62%	99.61%	99.60%	

Table A3
Analysis of variance for Σ_{ns}.

Source	DF	Adj SS	Adj MS	F-value	P-value
Model	64	4,800,665	75,010.0	393.86	0.000
Linear	12	4,300,608	358,384.0	1,881.78	0.000
CV_R	2	255,206	127,603.0	670.01	0.000
CV_D	2	2,531,326	1,265,663.0	6,645.65	0.000
CoC_R	4	190,786	47,697.0	250.44	0.000
CoC_M	4	1,323,291	330,823.0	1,737.06	0.000
2-Way Interactions	52	500,057	9,616.0	50.49	0.000
CV_R*CV_D	4	3397	8,49.0	4.46	0.001
CV_R*CoC_R	8	145,543	18,193.0	95.53	0.000
CV_R*CoC_M	8	35,780	4,472.0	23.48	0.000
CV_D*CoC_R	8	6958	870.0	4.57	0.000
CV_D*CoC_M	8	264,422	33,053.0	173.55	0.000
CoC_R*CoC_M	16	43,957	2,747.0	14.43	0.000
Error	2185	416,133	190.0		
Lack-of-Fit	160	51,399	321.0	1.78	0.000
Pure Error	2025	364,734	180.0		
Total	2249	5,216,798			

Model summary

	S	R-sq	R-sq(adj)	R-sq(pred)
	13.8004	92.02%	91.79%	91.54%

References

Adenso-Díaz, B., Moreno, P., Gutiérrez, E., & Lozano, S. (2012). An analysis of the main factors affecting bullwhip in reverse supply chains. *International Journal of Production Economics, 135*(2), 917–928.

Altomonte, C., Mauro, F. D., Ottaviano, G., Rungi, A., Vicard, V. (2012). Global value chains during the great trade collapse: A bullwhip effect? European Central Bank. Working Paper Series 1412.

Axsäter, S. (2003). Supply chain operations: Serial and distribution inventory systems. *Handbooks in Operations Research and Management Science, 11*, 525–559.

Babai, M. Z., Boylan, J. E., Syntetos, A. A., & Ali, M. M. (2016). Reduction of the value of information sharing as demand becomes strongly auto-correlated. *International Journal of Production Economics, 181*, 130–135.

Babai, M. Z., Dallery, Y., Boubaker, S., & Kalai, R. (2018). A new method to forecast intermittent demand in the presence of inventory obsolescence. *International Journal of Production Economics*. https://doi.org/10.1016/j.ijpe.2018.01.026 (in press).

Boute, R. N., Disney, S. M., Lambrecht, M. R., & Van Houdt, B. (2009). Designing replenishment rules in a two-echelon supply chain with a flexible or an inflexible capacity strategy. *International Journal of Production Economics, 119*(1), 187–198.

Bray, R. L., & Mendelson, H. (2012). Information transmission and the bullwhip effect: An empirical investigation. *Management Science, 58*(5), 860–875.

Braz, A. C., De Mello, A. M., de Vasconcelos Gomes, L. A., & de Souza Nascimento, P. T. (2018). The bullwhip effect in closed-loop supply chains: A systematic literature review. *Journal of Cleaner Production, 202*, 376–389.

Cabral, I., & Grilo, A. (2018). Impact of business interoperability on the performance of complex cooperative supply chain networks: A case study. Complexity, 2018, Article ID 9213237.

Cannella, S., Bruccoleri, M., & Framinan, J. M. (2016). Closed-loop supply chains: What reverse logistics factors influence performance? *International Journal of Production Economics, 175*, 35–49.

Cannella, S., Ciancimino, E., & Marquez, A. C. (2008). Capacity constrained supply chains: A simulation study. *International Journal of Simulation and Process Modelling, 4*(2), 139–147.

Chen, L., & Lee, H. L. (2012). Bullwhip effect measurement and its implications. *Operations Research, 60*(4), 771–784.

Chiang, C. Y., Lin, W. T., & Suresh, N. C. (2016). An empirically-simulated investigation of the impact of demand forecasting on the bullwhip effect: Evidence from US auto industry. *International Journal of Production Economics, 177*, 53–65.

Corum, A., Vayvay, Ö., & Bayraktar, E. (2014). The impact of remanufacturing on total inventory cost and order variance. *Journal of Cleaner Production, 85*, 442–452.

de Oliveira Pacheco, E., Cannella, S., Lüders, R., & Barbosa-Povoa, A. P. (2017). Order-up-to-level policy update procedure for a supply chain subject to market demand uncertainty. *Computers & Industrial Engineering, 113*, 347–355.

De Souza, R., Zice, S., & Chaoyang, L. (2000). Supply chain dynamics and optimization. *Integrated Manufacturing Systems, 11*(5), 348–364.

Dejonckheere, J., Disney, S. M., Lambrecht, M. R., & Towill, D. R. (2003). Measuring and avoiding the bullwhip effect: A control theoretic approach. *European Journal of Operational Research, 147*(3), 567–590.

Dev, N. K., Shankar, R., & Choudhary, A. (2017). Strategic design for inventory and production planning in closed-loop hybrid systems. *International Journal of Production Economics, 183*, 345–353.

Disney, S. M., & Lambrecht, M. R. (2008). On replenishment rules, forecasting, and the bullwhip effect in supply chains. *Foundations and Trends® in Technology, Information and Operations Management, 2*(1), 1–80.

Disney, S. M., Gaalman, G., Hosoda, T. (2012). Review of stochastic cost functions for production and inventory control. In 17th International Working Seminar of Production Economics (pp. 117–128).

Disney, S. M., Maltz, A., Wang, X., & Warburton, R. D. (2016). Inventory management for stochastic lead times with order crossovers. *European Journal of Operational Research, 248*(2), 473–486.

Dominguez, R., Cannella, S., Barbosa-Póvoa, A. P., & Framinan, J. M. (2018). OVAP: A strategy to implement partial information sharing among supply chain retailers. *Transportation Research Part E: Logistics and Transportation Review, 110*, 122–136.

Dominguez, R., Cannella, S., & Framinan, J. M. (2014). On bullwhip-limiting strategies in divergent supply chain networks. *Computers & Industrial Engineering, 73*, 85–95.

Evans, G. N., Naim, M. M. (1994). The dynamics of capacity constrained supply chains. In Paper presented at the International System Dynamics Conference, Stirling (pp. 28–35).

Ferguson, M., Guide, V. D., Jr, Koca, E., & Souza, G. C. (2009). The value of quality grading in remanufacturing. *Production and Operations Management, 18*(3), 300–314.

Ferrantino, M. J., & Taglioni, D. (2014). Global value chains in the current trade slowdown. *World Bank Economic Premise, 137*, 30.

Framinan (2017). Capacity considerations in the bullwhip effect in supply chains: The effect on lead times. In Paper presented at the 11th Conference on Stochastic Models of Manufacturing and Service Operations. June 4–9, 2017, Acaya, Italy.

Genovese, A., Acquaye, A. A., Figueroa, A., & Koh, S. L. (2017). Sustainable supply chain management and the transition towards a circular economy: Evidence and some applications. *Omega, 66*, 344–357.

Goltsos, T. E., Ponte, B., Wang, S., Liu, Y., Naim, M. M., & Syntetos, A. A. (2018). The boomerang returns? Accounting for the impact of uncertainties on the dynamics of remanufacturing systems. *International Journal of Production Research*. https://doi.org/10.1080/00207543.2018.1510191 (in press).

Govindan, K., Soleimani, H., & Kannan, D. (2015). Reverse logistics and closed-loop supply chain: A comprehensive review to explore the future. *European Journal of Operational Research, 240*(3), 603–626.

Guide, V. D. R., Harrison, T. P., & Van Wassenhove, L. N. (2003). The challenge of closed-loop supply chains. *Interfaces, 33*(6), 3–6.

Hamdouch, Y. (2011). Multi-period supply chain network equilibrium with capacity constraints and purchasing strategies. *Transportation Research Part C: Emerging Technologies, 19*(5), 803–820.

Helo, P. T. (2000). Dynamic modelling of surge effect and capacity limitation in supply chains. *International Journal of Production Research, 38*(17), 4521–4533.

Hosoda, T., & Disney, S. M. (2018). A unified theory of the dynamics of closed-loop supply chains. *European Journal of Operational Research, 269*(1), 313–326.

Hosoda, T., Disney, S. M., & Gavirneni, S. (2015). The impact of information sharing, random yield, correlation, and lead times in closed loop supply chains. *European Journal of Operational Research, 246*(3), 827–836.

Huang, Y. S., Hung, J. S., & Ho, J. W. (2017). A study on information sharing for supply chains with multiple suppliers. *Computers & Industrial Engineering, 104*, 114–123.

Hussain, M., Khan, M., & Sabir, H. (2016). Analysis of capacity constraints on the backlog bullwhip effect in the two-tier supply chain: A Taguchi approach. *International Journal of Logistics Research and Applications, 19*(1), 41–61.

Isaksson, O. H., & Seifert, R. W. (2016). Quantifying the bullwhip effect using two-

echelon data: A cross-industry empirical investigation. *International Journal of Production Economics, 171*, 311–320.
Jabbarzadeh, A., Haughton, M., & Khosrojerdi, A. (2018). Closed-loop supply chain network design under disruption risks: A robust approach with real world application. *Computers & Industrial Engineering, 116*, 178–191.
Jerbia, R., Kchaou Boujelben, M., Sehli, M. A., & Jemai, Z. (2018). A stochastic closed-loop supply chain network design problem with multiple recovery options. *Computers and Industrial Engineering, 118*, 23–32.
Jin, M., DeHoratius, N., & Schmidt, G. (2017). In search of intra-industry bullwhips. *International Journal of Production Economics, 191*, 51–65.
Juntunen, J., & Juga, J. (2009). Controlling the bullwhip with transport capacity constraints. *International Journal of Services and Standards, 5*(2), 160–171.
Kahn, J. A. (1987). Inventories and the volatility of production. *The American Economic Review,* 667–679.
Lee, H. L., Padmanabhan, V., & Whang, S. (1997). The bullwhip effect in supply chains. *Sloan Management Review, 38*(3), 93.
Lin, J., Naim, M. M., Purvis, L., & Gosling, J. (2017). The extension and exploitation of the inventory and order based production control system archetype from 1982 to 2015. *International Journal of Production Economics, 194*, 135–152.
Lin, J., Spiegler, V. L., & Naim, M. M. (2017). Dynamic analysis and design of a semiconductor supply chain: A control engineering approach. *International Journal of Production Research,* 1–27.
Mönch, L., Fowler, J. W., Mason, S. (2013). Production planning and control for semiconductor wafer fabrication facilities: Modeling, analysis, and systems (Vol. 52). Springer Science Business Media.
Nepal, B., Murat, A., & Chinnam, R. B. (2012). The bullwhip effect in capacitated supply chains with consideration for product life-cycle aspects. *International Journal of Production Economics, 136*(2), 318–331.
Orcun, S., Uzsoy, R., & Kempf, K. G. (2009). An integrated production planning model with load-dependent lead-times and safety stocks. *Computers Chemical Engineering, 33*(12), 2159–2163.
Pastore, E., Alfieri, A., & Zotteri, G. (2017). An empirical investigation on the antecedents of the bullwhip effect: Evidence from the spare parts industry. *International Journal of Production Economics*. https://doi.org/10.1016/j.ijpe.2017.08.029.
Pati, R. K., Vrat, P., & Kumar, P. (2010). Quantifying bullwhip effect in a closed loop supply chain. *Opsearch, 47*(4), 231–253.
Ponte, B., Wang, X., de la Fuente, D., & Disney, S. M. (2017). Exploring nonlinear supply chains: The dynamics of capacity constraints. *International Journal of Production Research, 55*(14), 4053–4067.
Riddalls, C. E., Bennett, S., & Tipi, N. S. (2000). Modelling the dynamics of supply chains. *International Journal of Systems Science, 31*(8), 969–976.
Shan, J., Yang, S., Yang, S., & Zhang, J. (2014). An empirical study of the bullwhip effect in China. *Production and Operations Management, 23*(4), 537–551.
Shukla, V., & Naim, M. M. (2017). Detecting disturbances in supply chains-the case of capacity constraints. *International Journal of Logistics Management, 28*(2), 398–416.
Souza, G. C. (2013). Closed-loop supply chains: A critical review, and future research. *Decision Sciences, 44*(1), 7–38.
Spiegler, V. L., & Naim, M. M. (2014). The impact of freight transport capacity limitations on supply chain dynamics. *International Journal of Logistics Research and Applications, 17*(1), 64–88.
Sy, C. (2017). A policy development model for reducing bullwhips in hybrid production-distribution systems. *International Journal of Production Economics, 190*, 67–79.
Tang, O., & Naim, M. M. (2004). The impact of information transparency on the dynamic behaviour of a hybrid manufacturing/remanufacturing system. *International Journal of Production Research, 42*(19), 4135–4152.
Teunter, R. H., & Vlachos, D. (2002). On the necessity of a disposal option for returned items that can be remanufactured. *International journal of production economics, 75*(3), 257–266.
Trapero, J. R., Kourentzes, N., & Fildes, R. (2012). Impact of information exchange on supplier forecasting performance. *Omega, 40*(6), 738–747.
Trapero, J. R., Kourentzes, N., & Fildes, R. (2015). On the identification of sales forecasting models in the presence of promotions. *Journal of the operational Research Society, 66*(2), 299–307.
Trapero, J. R., & Pedregal, D. J. (2016). A novel time-varying bullwhip effect metric: An application to promotional sales. *International Journal of Production Economics, 182*, 465–471.
Turrisi, M., Bruccoleri, M., & Cannella, S. (2013). Impact of reverse logistics on supply chain performance. *International Journal of Physical Distribution & Logistics Management, 43*(7), 564–585.
Vlachos, D., & Tagaras, G. (2001). An inventory system with two supply modes and capacity constraints. *International Journal of Production Economics, 72*(1), 41–58.
Wang, X., & Disney, S. M. (2016). The bullwhip effect: Progress, trends and directions. *European Journal of Operational Research, 250*(3), 691–701.
Wikner, J., Naim, M. M., Spiegler, V. L., & Lin, J. (2017). IOBPCS based models and decoupling thinking. *International Journal of Production Economics, 194*, 153–166.
Wilson, M. C. (2007). The impact of transportation disruptions on supply chain performance. *Transportation Research Part E: Logistics and Transportation Review, 43*(4), 295–320.
Zanoni, S., Ferretti, I., & Tang, O. (2006). Cost performance and bullwhip effect in a hybrid manufacturing and remanufacturing system with different control policies. *International Journal of Production Research, 44*(18–19), 3847–3862.
Zavacka, V. (2012). The bullwhip effect and the Great Trade Collapse. European Bank for Reconstruction and Development Working Paper no. 148.
Zhao, Y., Cao, Y., Li, H., Wang, S., Liu, Y., Li, Y., & Zhang, Y. (2018). Bullwhip effect mitigation of green supply chain optimization in electronics industry. *Journal of Cleaner Production, 180*, 888–912.
Zhou, L., & Disney, S. M. (2006). Bullwhip and inventory variance in a closed loop supply chain. *OR Spectrum, 28*(1), 127–149.
Zhou, L., Naim, M. M., & Disney, S. M. (2017). The impact of product returns and remanufacturing uncertainties on the dynamic performance of a multi-echelon closed-loop supply chain. *International Journal of Production Economics, 183*, 487–502.
Zotteri, G. (2013). An empirical investigation on causes and effects of the Bullwhip-effect: Evidence from the personal care sector. *International Journal of Production Economics, 143*, 489–498.