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

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

Abstract

In this paper, we investigate the dynamic behaviour 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, the 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 fulfil customer demand in a cost-effective manner.

Keywords: Bullwhip effect; supply chain dynamics; reverse logistics; capacity limitations; simulation.

1. INTRODUCTION

An almost-ubiquitous problem occurring in supply chains (SC) is the so-called bullwhip effect (BWE) (Lee et al. 1997), which refers to the fact that even small variations in customer demand may generate high alterations in upstream production for suppliers (Huang et al. 2017, Lin et al. 2017, Dominguez et al. 2014). This phenomenon has important consequences in real-life SC (see e.g. Zotteri 2013, Isaksson and Seifert 2016, Chiang et al. 2016, Trapero and Pedregal 2016, Jin et al. 2017, de Oliveira Pacheco et al. 2017, Lin et al. 2017, Pastore et al. 2017). Indeed, recent empirical works have shown that BWE may emerge in two-thirds of firms from USA (Bray and Mendelson 2012) and Chine (Shan et al. 2014) and that its consequences are, by nature, global and impact both developed and developing countries, as pointed out by the European Central Bank (Altamonte et al. 2012), the European Bank for Reconstruction and Development Working (Zavacka et al. 2012) and by the World Bank (Ferrantino and Taglioni 2014). Some of the consequences of BWE are excess of inventory, poor customer service and poor product forecasts (Trapero et al. 2012). In the last two decades, different efforts to explain and reduce the BWE have emerged and continue to grow (Wang and 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 system, with pricing considerations, in service chain, with research competition, etc. Among those, two stand out, i.e.: investigating the BWE under capacity-constrained and the dynamics of Closed-Loop SC (CLSC).

Manufacturing firms are fundamental in supporting most modern economies (Trapero et al. 2015). Consequently, studying the impact of manufacturing capacity constraints in SC dynamics has been an issue in the past years. Capacity constraints usually refer to considering limits on the order sizes placed to suppliers, or limits on the orders' acceptance channel. 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 and Naim 1994, Chen and Lee 2012, Shukla and Naim 2017, Ponte et al. 2017, Framinan 2017). However, these restrictions may negatively impact on inventory holding costs and customer service level (Cannella et al. 2008, Nepal et al. 2012, Spiegler and Naim 2014, Hussain et al. 2016). In general, works dealing with the implications of capacity limits on the dynamics 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 a CLSC.

In a CLSC, recycling and remanufacturing activities – *i.e.*, taking back products from customers and returning them to the original manufacturer for the recovery of added-value by reusing the whole product or part of it (Genovese et al. 2017) — are implemented (Jerbia et al. 2018). CLSC design is the desired business model for companies due to the potential value recovery, environmental sustainability, and special importance given by the customers (Jabbarzadeh et al. 2018). In the last decade, some works have been exploring the characteristic the CLSC, specifically by focusing on how some key factors of this structure (e.g., the percentage of 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 the percentage of return yields can reduce the BWE (see e.g., Tang and Naim 2004, Zhou and Disney 2006, Hosoda et al. 2015, Cannella et al. 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 results, we argue that exploring the dynamics behavior of a capacitated 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 fulfil the research objective, we model a CLSC via difference equation modelling (Riddals et al. 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 et al. 2017), we consider stochasticity in both the return yield and the customer demand. Thus, we perform a rigorous Design of Experiment (DoE) considering four key

factors, *i.e.*, (1) the variability of the return yields, (2) the capacity factor of the manufacturer, (3) the capacity factor of the remanufacturer, and (4) the variability of the customer demand. The results of this works reveal that a low capacity in the remanufacturer may smooths the bullwhip effect 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 nodes, managers should also take into account 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 CLSC. 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 provide an overview of the previous works investigating the BWE assuming capacity constraints, or in a CLSC. As discussed in the previous section, although a number of contributions have been produced in this 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 constraint has been addressing in few studies, usually developed by adopting methodologies based on the dynamics of the systems (i.e., control theory and what-if simulation, such as continuous and discrete-event simulations). Among these work, to the best of the authors' knowledge, Evans and Naim (1994) can be considered the seminal work. Via differential equation modelling, the authors conclude that the capacity constraints may improve the behavior of SC in terms of bullwhip effect and inventory stability, 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 response. Contrarily, De Souza et al. (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 for the dynamics of the SC. Analogously, Helo (2000), also via system dynamics, suggests that a limited capacity negatively impact the responsiveness of the SC. Vlachos and Tagaras (2001), by adopting both analytical methods and simulation, show that imposing capacity limits reduces

the system's response, particularly for long production lead-time. 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 is reduced if capacity limits are imposed, but they also can create a significant stock-out phenomenon. Boute et al. (2009), via analytical method, demonstrate that inflexible limits on capacity generate stochastic lead times and thus they amplifies the desired inventory on-hand and, in general, the operational costs. Juntunen and Juga (2009), via discrete event simulation show, in line with previous studies, 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. Interestingly, Nepal et al. (2012), via differential equations modelling, report that capacity restriction does not have a significant impact on the order variability but, in contrasts, it can strongly affect the stability of the inventory. Chen and Lee (2012), via mathematical analysis, in line with those studies showing the benefits of capacity constraints in terms of BWE reduction, argue that considering a fixed capacity in SC reduces the BWE. Contrarily, 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 value, a similar conclusion to that by Shukla and Naim (2017) via system dynamics modelling. 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, most of the above-mentioned studies have reported contradictory results regarding the impact of capacity constraints on the dynamics of the SC. However, most of them, by adopting different methodological approaches, agree on the positive impact of the capacity limitations on BWE since these restrictions dampen order variability. Overall, none of the studies investigates how capacity limitations may impact the dynamics of a CLSC, particularly when these affect to both manufacturer and remanufacturer.

2.2. The dynamics of closed-loop supply chains

In BWE literature, similarly to the capacity-constrained SC, the CLSC has not been receiving special attention. Only in the last few years, thanks to the challenges advocated by the sustainability principles, an increasing number of studies dealing with the impact of considering both forward and reverse flows has been detected. Historically, the work of Tang and Naim (2004) can be considered the first effort in

analyzing the BWE in a CLSC. The authors, via difference equation modelling, study three ad-hoc order policies for hybrid manufacturing/remanufacturing systems. They conclude that increasing recollected products and operating with higher information transparency on the pipeline of the remanufacturer may strongly improve the performance of a CLSC. By using control theory, Zhou and Disney (2006) analyze the impact on the inventory variance and demand amplification of a combined "in-use" and remanufacturing lead-time and the return rate. Zanoni et al. (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 reduced in the shifted pull policy. Pati et al. (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 et al. (2012) analyze the impact of 12 factors in both forward and reverse SC and do not detect significant differences between the performances of the two SC structures in terms of order rate amplification. Turrisi et al. (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 return rate of recollected products. However, they do not find significant differences in terms of inventory variance. Analogously, Corum et al. (2014) employ a discrete-event simulation model to show that a CLSC allows reducing the demand amplification phenomenon. Hosoda et al. (2015), via analytical methods, study the impact of the correlation between demand and returns, and show 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 turbulence market scenarios. Dev et al. (2017), via difference equation modelling, conclude that, in a CLSC, continuous review policies outperform the periodic review policies in terms of BWE. Zhou et al. (2017) study the quality of recollected product in different levels of the SC using difference equation modelling, 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 (2017), via analytical method, explore the so-called "lead time paradox" in CLSCs, which refers to the scenarios in which increasing the remanufacturing lead-time sometimes decreases the 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 analyse a hybrid production-distribution system and show that, under three scenarios, and show that the centralization of the customer demand information reduces the BWE.. Similarly, Zhao et al. (2018) study, via system dynamics, the impact of three orders policies based on the degree of shared information in a CLSC. In line

with literature on information sharing, they conclude that centralized demand information and a vendor managed inventory reduce both bullwhip and inventory variability.

In summary, previous studies show a lack of consensus on the impact of BWE and inventory variance when a CLSC is the subject of research. As remarked by Cannella et al. (2016) and Zhao et al. (2018), these conflicting results may depend on different SC configurations and modelling assumptions, particularly with respect to the remanufacturing lead-time. However, it can be noticed a general agreement on the impact of the return yield, as most studies note that the BWE can be reduced by increasing the percentage of products recollected from the market for remanufacturing. However, to the best of the authors' knowledge, there is no evidence on how a CLSC performs if capacity limitations are considered both in the forward and reverse production flows.

3. CLOSED-LOOP SUPPLY CHAIN MODEL

Figure 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.
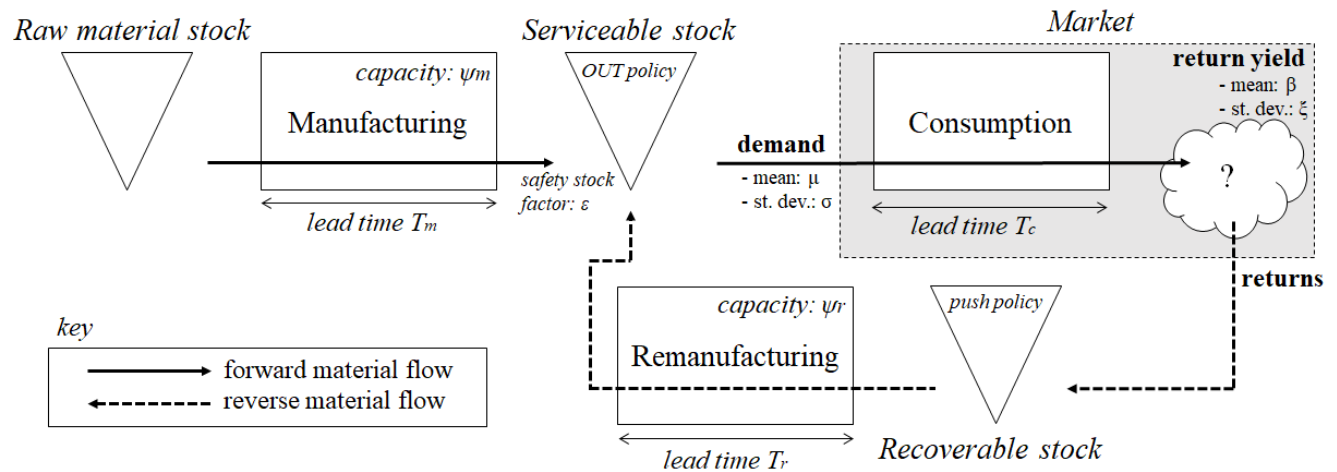

Figure 1. Structure of the hybrid manufacturing/remanufacturing system.

The CLSC modelled 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 an independent and identically distributed (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, as a 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. Similarly, 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) processes, once these 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 (2017) 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. If we take into consideration the capacity required for both processes under a stability situation 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 $CoC_r = \psi_m/[\beta\mu]$. Note that these coefficients inform about the excess capacity available in relative terms. 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 capacity available, by

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

As Equation (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 considered 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 if 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, or, 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 account for 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. We note that this is a relevant variable as it provides the decision makers with relevant 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 et al., 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 variable that define its behavior, which is its conditional expectation (e.g. Disney et al., 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 it aims to be covered. 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 was 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 behaviour 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 use 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/remanufacturing processes and on inventory holding costs. Below, we discuss in detail the rationale behind the adoption of these metrics.

Disney et al. (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 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 does 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 and 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 in relative terms. 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 stability of the system, CoC_m and CoC_r must be greater than the unity (i.e. the manufacturing system is able to meet the average net demand and the remanufacturing system is able to process the average returns).
- Thanks to preliminary simulation experiments we notice that the three performance metrics tend to stabilize as the relevant capacities increase. More specifically, this happens for $CoC_m>3$ and $CoC_r>3$, for 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 capacities are the effects of interest in our study, we adopt five levels for each capacity factor, allowing a more precise representation of the main effects and their interactions. Specifically, they range from 1.1 (the system operates close to its capacity) to 3.1 (the system has sufficient spare capacity) with intervals of 0.5, 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 the relative instead of the absolute values, *i.e.*, the coefficients of variations. In both cases, we employ three levels. In the former,

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$CV_d = \{0.15, 0.30, 0.45\}$, 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 are interpreted 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 (2017). While it is common to assume that remanufacturing lead times are shorter than manufacturing lead times (e.g. Tang and Naim, 2004), Hosoda and Disney (2017) show that a 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 (2003). 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 and Naim, 2004). Lastly, we employ $\varepsilon = 1$ for the safety stock policy. The same value is used in Cannella et al. (2016).

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 x 5 x 3 x 3). Each scenario has been explored through 10 different simulations of 2,100 periods, where the first 100 periods are not considered for the results reported to avoid the impact of the initial situation of the system. The number of replications aims to reduce the confidence intervals, and hence increase the soundness of our results. Overall, Table 1 summarizes the experimental design protocol.

Table 1. 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 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	2,250
Simulation parameters	
Time horizon	2,100 periods
Warm-up period	100 periods

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. the normality, homoscedasticity and the independence of cases) were checked and validated prior to the analysis.

We note from the numerical results that the three models (Σ_{mc}, Σ_{rc}, and Σ_{ns}) show highly adjusted R², 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 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 continue with the analysis of the first order interactions.

5.1. Main Effects

The main effects plots are shown in Figures 2 to 4. The main effect of CV_d is not discussed in detail, as the impact on demand variability on the dynamics of SCs is very well known in literature. Meanwhile, the main effect of CV_r confirms previous results in CLSCs, such as those provided by Hosoda et al. (2015). As it seems foreseeable, it can be seen that the variability of indicators Σ_{mc}, Σ_{rc} and Σ_{ns} increases with the coefficient of variation of the return yield. This illustrates how returns uncertainty negatively impact 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 Figure 2 that reducing this factor results in a lower Σ_{mc}, and this decrease is more significant as CoC_m becomes closer to 1. Contrarily, Σ_{ns} slightly increases by

reducing CoC_m, and a sudden increase is observed when CoC_m is below 1.6. This finding confirms previous studies (Cannella et al. 2008, Spiegler and 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, while maintaining a low value of the net stock variability. However, if the capacity of the manufacturer is reduced below a certain threshold value, the variability of the net stock suddenly increases, thus diminishing the benefits obtained in terms of BWE reduction. 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 a similar behavior than that of CoC_m on Σ_{ns}, *i.e.*, reducing CoC_m has almost no impact on Σ_{ns}, while a sudden increase of Σ_{ns} is observed for values of CoC_m below 1.6. However, 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 effect caused in Σ_{rc} by increasing/decreasing CoC_r has a direct impact 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.
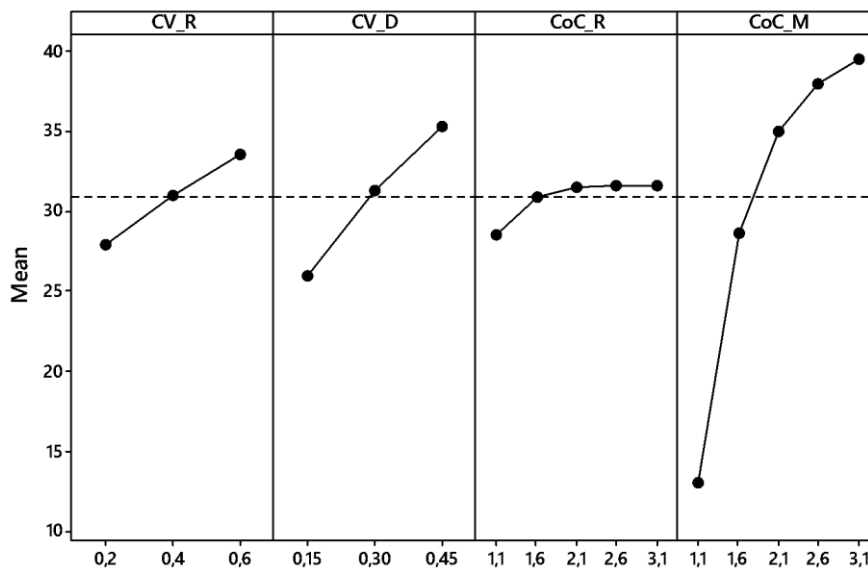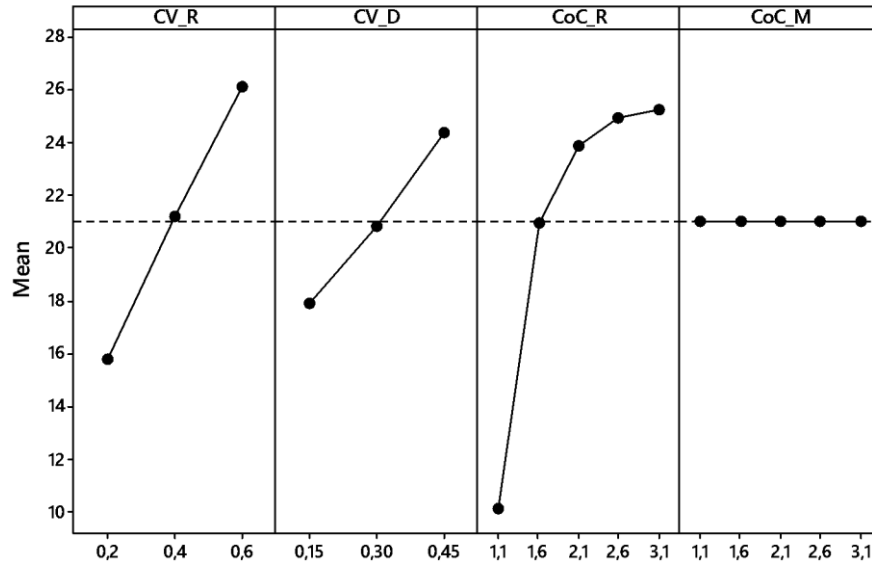

Figure 2. Main effects plot for Σ_{mc}.

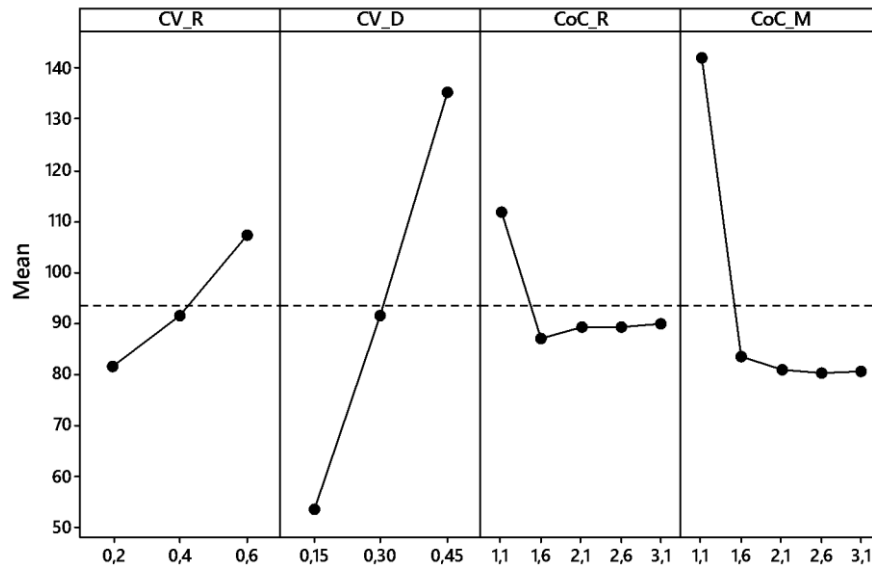*Figure 3.* Main effects plot for Σ_{rc}.

Figure 4. Main effect plots for Σ_{ns}.

5.2. Interactions

The first order interactions are shown in Figures 5 to 7. Firstly, looking into Figure 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 reducing 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 less

interaction 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 Figure 6 the interaction plots for Σ_{rc} are shown. Assuming that 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 o_NSt (see Figure 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 higher values of CV_d. Similarly, when CoC_r is reduced below 1.6 the increase in Σ_{ns} is higher for higher values of CV_r.
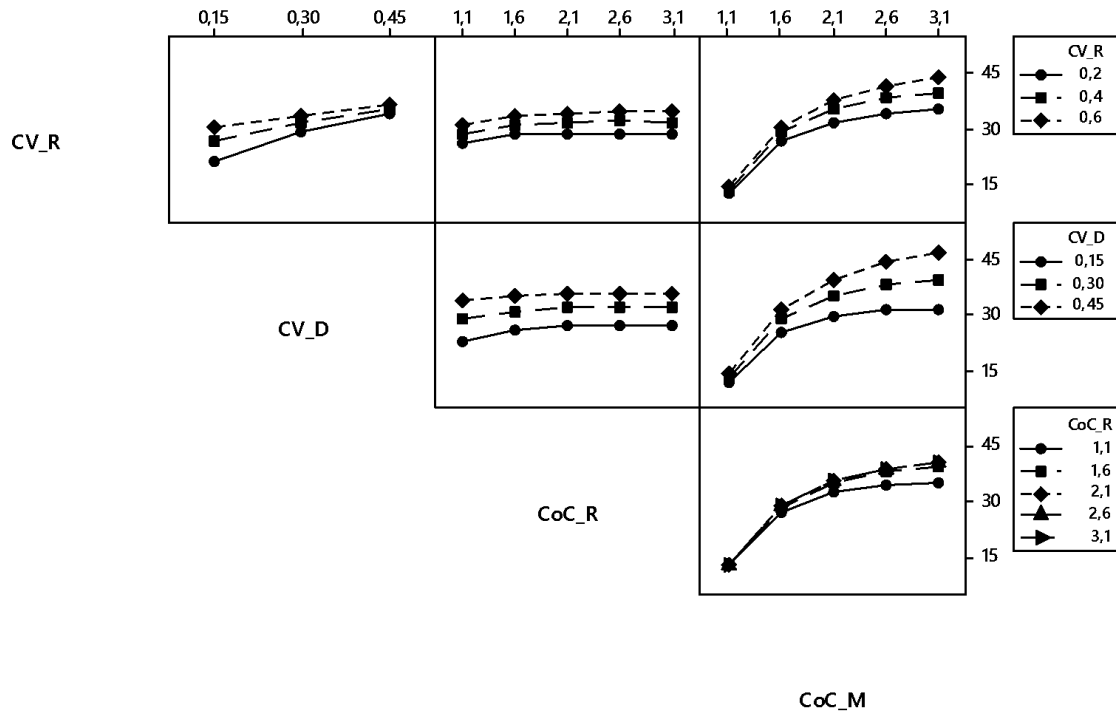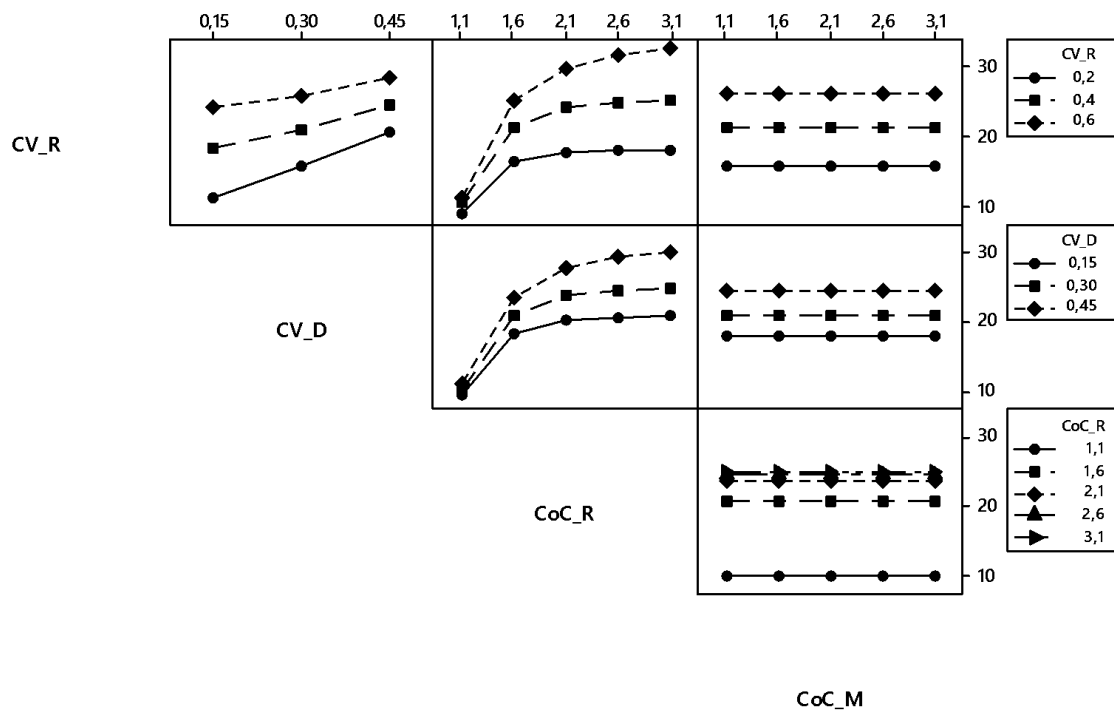

Figure 5. Interaction plot for Σ_{mc}.

Figure 6. Interaction plot for Σ_{rc}.
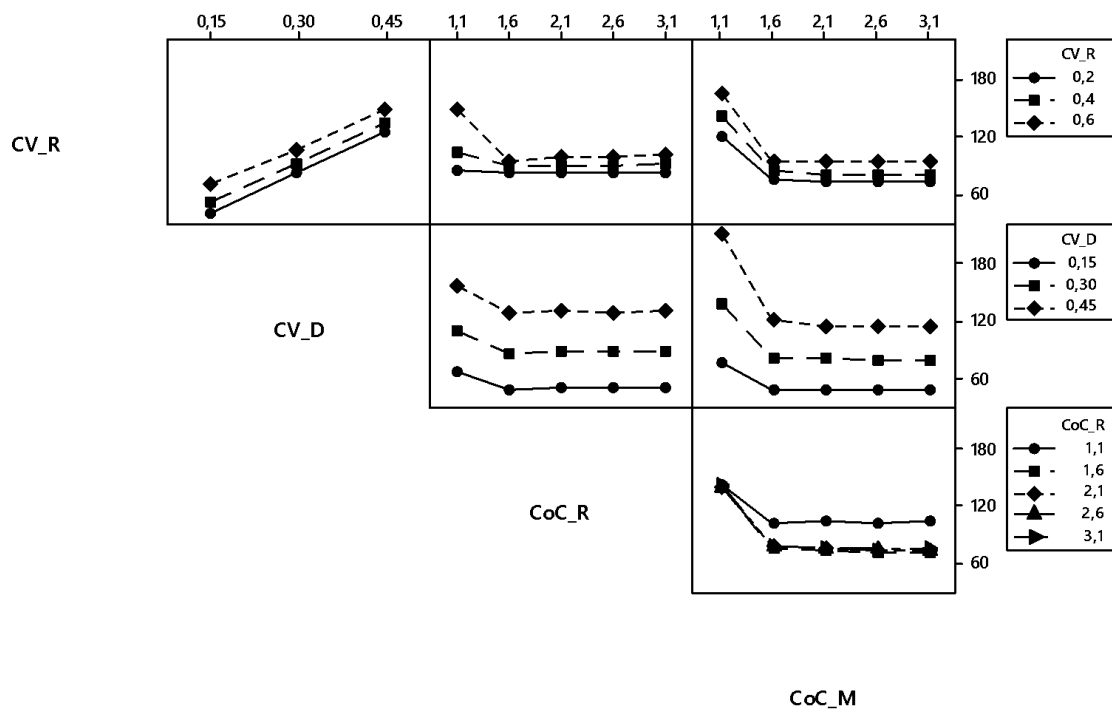

Figure 7. Interaction plot for Σ_{ns}.

6. SUMMARY OF FINDINGS AND MANAGERIAL IMPLICATIONS

We now summarize the main findings and contributions of our work. These are summarized in three different findings, referring to the different performance metrics (*i.e.*, the BWE of the manufacturing and the remanufacturing line, and the variability of the net stock). We present also 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 placed by the manufacturer (as in a traditional forward SC). This limitation is more significant when the return yield or the customer demand present higher variability. However, the capacity constraints of the manufacturing line has no significant impact on the BWE of the remanufacturing line.

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 is 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 of the remanufacturing line, especially when the return yield or the customer demand present higher uncertainty. In addition, the capacity constraints of the remanufacturing line may limit the BWE of the manufacturing line, especially for high variability of the return yield or low variability of the customer demand.

This novel finding allows 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 limits gets to lower values. 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 maybe also be benefited 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 Figure 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 further method for improving 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 a high variability of customer demand) or the remanufacturing line (particularly in case of a high variability of the return yield) below a certain threshold value has a negative impact on the variability of the net stock. However, 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 limitation of both lines on the variability of the net stock. While reducing capacity of the manufacturing/remanufacturing lines produce a continuous improvement in terms 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 Figure 7). Interestingly, such threshold value seems to be very similar for both lines (around 160% of the mean customer demand).

In the light of the above findings, we would recommend managers of a CLSC to take cautious decisions on the capacity planning of both manufacturing and remanufacturing processes. In fact, while the capacity of the manufacturing line has a major effect on the dynamic of the SC, the capacity of the remanufacturing line may also play 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 dynamic 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, thus smoothing both processes while maintaining a good performance of the net stock. Additional capacity reduction over such capacity threshold could be recommended only after a proper trade-off analysis between inventory holding costs/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 mono-echelon SC with reverse flow 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 manufacturing line, the capacity factor at the remanufacturing line and the variability of the customer demand. The most interesting results concerns the impact on the BWE of the remanufacturer capacity, which may influence the dynamics of the manufacturer. More specifically, a low capacity 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 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 degree of uncertainty of 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 works is needed to deepening our analysis. Firstly, more complex and real-life CLSC structures need to be analysed (*e.g.*, multi-echelon, divergent structure, Dominguez et al. 2018, Cabral and 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 these variables, such as the "lead-time paradox" advocated by Hosoda et al. 2015. Also, we assumed an i.i.d. demand, but other demand structures can be studied, such as the auto-correlated demand (see *e.g.* Babai et al. 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, further studies modelling load-dependent lead time, by adopting empirical from scheduling theory (see e.g. CT-TP curve, clearing functions, etc. Orcun, 2009, Mönch, 2013). Finally, the impact of inventory obsolescence (Babai et al. 2018) should also be explored in capacitated CLSCs.

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Appendix A

Table A.1. Analysis of Variance for Σ_{mc}.

```
Analysis of Variance

Source                DF  Adj SS   Adj MS   F-Value  P-Value
Model                 64  271018   4234,7   5897,49   0,000
  Linear              12  255121  21260,0  29608,22   0,000
    CV_R               2   11569   5784,4   8055,74   0,000
    CV_D               2   32461  16230,7  22604,00   0,000
    CoC_R              4    3094    773,6   1077,35   0,000
    CoC_M              4  207996  51999,0  72417,44   0,000
  2-Way Interactions  52   15898    305,7    425,78   0,000
    CV_R*CV_D          4    3910    977,5   1361,27   0,000
    CV_R*CoC_R         8     140     17,5     24,36   0,000
    CV_R*CoC_M         8    2380    297,5    414,26   0,000
    CV_D*CoC_R         8     392     49,0     68,21   0,000
    CV_D*CoC_M         8    7928    990,9   1380,06   0,000
    CoC_R*CoC_M       16    1149     71,8    100,01   0,000
Error               2185    1569      0,7
  Lack-of-Fit        160    1059      6,6     26,31   0,000
  Pure Error        2025     510      0,3
Total               2249  272587


Model Summary

      S    R-sq  R-sq(adj)  R-sq(pred)
0,847376  99,42%    99,41%      99,39%
```

Table A.2. Analysis of Variance for Σ_{rc}

```
Analysis of Variance

Source                DF  Adj SS   Adj MS   F-Value  P-Value
Model                 64  140479   2195,0   8930,68   0,000
  Linear              12  127987  10665,6  43394,85   0,000
    CV_R               2   40370  20184,8  82125,35   0,000
    CV_D               2   15792   7896,1  32126,66   0,000
    CoC_R              4   71825  17956,3  73058,44   0,000
    CoC_M              4       0      0,0      0,12   0,975
  2-Way Interactions  52   12492    240,2    977,41   0,000
    CV_R*CV_D          4    1699    424,7   1727,83   0,000
    CV_R*CoC_R         8    7819    977,4   3976,78   0,000
    CV_R*CoC_M         8       1      0,1      0,33   0,956
    CV_D*CoC_R         8    2969    371,2   1510,22   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               2185     537      0,2
  Lack-of-Fit        160     159      1,0      5,34   0,000
  Pure Error        2025     378      0,2
Total               2249  141016


Model Summary

      S    R-sq  R-sq(adj)  R-sq(pred)
0,495762  99,62%    99,61%      99,60%
```

Table A.3. Analysis of Variance for Σ_{ns}

```
Analysis of Variance

Source                   DF    Adj SS    Adj MS  F-Value  P-Value
Model                    64   4800665     75010   393,86    0,000
  Linear                 12   4300608    358384  1881,78    0,000
    CV_R                  2    255206    127603   670,01    0,000
    CV_D                  2   2531326   1265663  6645,65    0,000
    CoC_R                 4    190786     47697   250,44    0,000
    CoC_M                 4   1323291    330823  1737,06    0,000
  2-Way Interactions     52    500057      9616    50,49    0,000
    CV_R*CV_D             4      3397       849     4,46    0,001
    CV_R*CoC_R            8    145543     18193    95,53    0,000
    CV_R*CoC_M            8     35780      4472    23,48    0,000
    CV_D*CoC_R            8      6958       870     4,57    0,000
    CV_D*CoC_M            8    264422     33053   173,55    0,000
    CoC_R*CoC_M          16     43957      2747    14,43    0,000
Error                  2185    416133       190
  Lack-of-Fit           160     51399       321     1,78    0,000
  Pure Error           2025    364734       180
Total                  2249   5216798


Model Summary

      S    R-sq  R-sq(adj)  R-sq(pred)
13,8004  92,02%     91,79%      91,54%
```