The more the better? The impact of the number and location of product recovery options on the system dynamics in a closed-loop supply chain

Abstract

We investigate the impact of the number and location of product recovery options on the system dynamics in a hybrid closed-loop supply chain (CLSC) system. A CLSC system, commonly observed in industries, such as consumer electronics and automotive, may include one or more product recovery options, such as product repair and core remanufacturing. One important strategic decision is how many recovery options (and in which locations) warrant investment. This is important from a system dynamics perspective where poor dynamic behaviour, such as the bullwhip effect, should be minimised. This motivates us to investigate the impact of the number and locations of recovery options on the dynamic behaviour. We develop a three-echelon CLSC system dynamics model, where demand follows step and sinusoidal functions, representing a sudden sustained shift in demand and seasonally unadjusted demand, respectively. We also consider different return rates to represent the different weights of the product returns received by each echelon of a CLSC system. Our simulation results indicate that, in all scenarios, the bullwhip effect and inventory variance of the CLSC can be reduced significantly in comparison to a traditional supply chain. Moreover, our findings proposed that having more product recovery options in CLSC do not produce better dynamic performance. Besides, the bullwhip effect and inventory variance for upstream supply chain members can be reduced if the product recovery options are located near the end-customer with a high return rate, especially at retailer. Furthermore, return rates play a key role in the bullwhip effect reduction is consistent with prior literature findings. We identify the impact of the location and number of product recovery options in a CLSC system in terms of system dynamics and provides strategic insights for managers to improve their system to reduce the costs of supply chain dynamics.

Keywords: Closed-loop supply chains, System dynamics, Product recovery options, Location and number, Bullwhip effect

1. Introduction

Increased competition and technological innovation contribute to the decrease in the lifecycles of product sales (Sarkar et al. 2017), whereby a tremendous amount of electronic waste is produced, such as mobile phones, personal computers and televisions. In 2016, the amount of global electronic waste was estimated to be 44.7 million tons (Yong et al. 2019) and the value of this fraction of raw material was about 55 billion euros (Balde et al. 2017). Furthermore, the data showed that 70% of the end-life-products in Europe and the United States have reutilisation value (Franke et al. 2006). To avoid waste, closed-loop supply chains (CLSCs) have received a significant amount of attention from practitioners and scholars, since they can remanufacture end-of-life-products by receiving returned products from customers and retaining the value while protecting the environment from waste disposal (Guide & Van Wassenhove 2009). A CLSC system refers to the complete supply chain cycle from purchasing, production, sales, recycling and remanufacturing to final resale, including forward logistics and reverse logistics supported by recycling of end-of-life products (Fleischmann et al. 1997; Stock 1992). Product recovery options include repair, remanufacturing, recycling and refining (Chen Y & Chen F 2019; Wei et al. 2015). Through product recovery options, the CLSCs can generate profits and provide extra positions for operations employees (Dominguez et al. 2019; Guide & Van Wassenhove 2009). Industries, such as consumer electronics (Zhou et al. 2017), automotive (Liu et al. 2018) and furniture manufacturing (Van der Laan & Teunter 2006), operate product recovery options and have an effective circular economy.

For industries thinking about how to develop appropriate designs to fully accomplish the goal of achieving a circular economy (Del Giudice et al. 2020), one important strategic decision is how many recovery options (and in which locations) they should invest in and implement in their CLSCs. From a system dynamics perspective, this is important when poor system dynamics behaviour, particular, the bullwhip effect and high inventory variance, advocated as one of most critical issues in supply chains (Lee et al. 1997; Pastore et al. 2020; Yang et al. 2021), must be considered. The bullwhip effect can cause problems in supply chains associated with costs, such as excessive inventory and machine capacity (Wang & Disney 2016). Thus, understanding the bullwhip effect of CLSCs and reducing their bullwhip levels can help improve their operational performance and economic viability (Hosoda & Disney 2018).

Some studies have focused on the bullwhip and inventory variance of CLSCs, including a single hybrid manufacturing-remanufacturing system or multi-stage CLSCs system. They proposed that bullwhip effect reduction can be resulted from increasing return rate (e.g., Ponte et al. 2020) and information transparency (e.g., Cannella et al. 2016) in either a single or multi-echelon hybrid system. However, some factors have been demonstrated to increase the bullwhip and inventory variance, such as lead time (e.g., Hosoda and Disney 2018), preparation time (Delavar et al. 2022), decentralized configuration (Dominguez et al. 2021), and quality uncertainty (Timbido et al. 2022) and capacity limits (e.g., Huang et al. 2023).

However, these studies focus on the hybrid CLSCs system by considering only remanufacturing option in a single hybrid system, or by assuming that in a multi-echelon hybrid system, no particular recovery options are specified or each echelon has one recovery option. This ignores the fact that the number and location of the product recovery options may impact the bullwhip and inventory variance in CLCSs. More importantly, the common conclusions in the literature derived from the bullwhip effect in CLSCs, such as the benefits of adopting remanufacturing on reducing the bullwhip, may not always hold in CLSCs with a different location and a different number of recovery options.

1.1 Motivation

Motivated by the academic gap and practical observation, the present study focuses on the dynamic performance of a hybrid CLSC, exploring the impact of location and the number of product recovery options on the system dynamics performance. A hybrid CLSC system refers to a system where manufacturing and remanufacturing operations occur simultaneously to produce the same serviceable stock for demand fulfilment (Van der Laan et al. 1999). When enterprises consider transitioning from an open-loop supply chain to a CLSC with many possible product recovery options, they need to think strategically about how many recovery options are required and where they should allocate those options. Therefore, we aim to provide theoretical evidence of and practical insights on how to design a CLSC from the system dynamics perspective. Toward that end, we ask the following research questions:

1. Do more product recovery options in a hybrid CLSC system produce a better system dynamics performance?

2) Where should the product recovery options be located in a CLSC system to improve its dynamic behaviour?

1.2 Contributions

We believe that our paper has the following contributions. First, to the best of our knowledge, this is the first work to theoretically analyze the impact of number and locations of recovery options on system dynamics performance in CLSCs. The effectiveness of models and results are verified under 1) the nonlinear return forbidden environment, 2) different manufacturing/remanufacturing lead time scenarios and 3) industrial demand data. This extends the CLSCs dynamics literature that simply assume recovery options are available/unavailable (e.g. outsourcing) in all echelons of CLSCs, providing in-depth theoretical insights of improving system dynamics performance by strategically designing the number and location of recovery options.

Second, the theoretical and managerial insights derived from this work can contribute to the industries who already adopted or have the intentions to adopt CLSCs. For industries with CLSCs, our findings can guide managers to be aware of supply chain dynamics cost, such as inventory fluctuation, capacity variability and labor hire/fire frequency, based on their existing CLSCs structure characterized by feedback control loop and various physical delays. As the result, company may be able to re-design their existing system structure (e.g. outsource or shift recovery options to different locations of CLSCs) and/or control policies (e.g. forecasting and inventory control) to improve system dynamics performance. For industries with CLSCs adoption intentions, our study can provide strategic suggestions on designing the number and location of recovery options in CLSCs structure from system dynamics perspective. Company thereby can minimize the total cost including the static cost (recovery options investment) and dynamic cost occurred due to the number and locations of recovery options.

The rest of this paper is organised as follows. Section 2 presents relevant background information about and literature on this topic. Section 3 presents our hybrid CLSCs model setting and its development. Section 4 introduces the experiment design. Section 5 presents the results of our system dynamic analysis. Section 6 presents the results of our nonlinear dynamic analysis. Section 7 presents the results of further scenario analysis of lead time. Section 8 presents a summary of the main findings, discussion, conclusions and recommendations for further research.

2. Literature Review

Based on research objectives, we review three themes in the literature: 1) General remanufacturing, recycling and green manufacturing in CLSCs 2) CLSCs with multiple collectors and recovery options and 3) bullwhip of CLSCs

2.1. Research on remanufacturing, recycling and green manufacturing in CLSCs

Green manufacturing is a manufacturing model maximizing environmental protection and resource efficiency throughout the product life cycle to realize circular economy (Abualfaraa et al. 2020; Yin et al. 2020). The research on green manufacturing has been widely carried out by both practitioners and academics. The "3Rs" of environmental approaches, i.e. reduction, remanufacturing and recycling, were proposed by Sarkis and Rasheed as early as 1995. Specifically, reduction are the efforts made by manufacturing firms to reduce waste and recycling collect disposed products and transforms them back into raw materials for remanufacturing. Remanufacturing is a product recovery option that turns used products into as-good-as new conditions (Chen Y & Chen F 2019; Giri & Glock 2022). These three approaches are increasingly being studied in the CLSCs context. Regarding reduction part, the impact of carbon emission and carbon tax in reduction research on CLSCs have been explored. Wang and Wu (2021) found out manufacturer collects returns is optimal for carbon emission reduction in CLSC. The results from Zhang et al. (2022) reveals that higher carbon trading price and a lower investment cost could lead reduction in carbon emissions. Carbon tax has been demonstrated can effectively promote manufacturers to invest in remanufacture to reduce carbon emissions by Luo et al. (2022). In recycling approaches in CLSCs studies, selection of recycling channels could not affect the wholesale and retail prices and market demand for raw materials (Sun et al. 2022); and recycling companies can maximize their profits by presenting their recycling prices online before determining the transfer prices of products collection in the offline (Matsui 2021). Finally, a number of studies focus on the impact of remanufacturing on operations management. Such as in reverse logistics of remanufactured products, uncertainty could be reduced by centralized configuration, resulting in inventory performance improvement (Dominguez et al. 2021). Product recovery modes have been investigated by Chen Y & Chen F (2019), and they found that the emergence of remanufacturing will not make the refurbishing industry disappear. Among the approaches, environmentally relevant carbon emissions are not the subject of our study, but multi-collectors and recovery options are closely related to our research.

2.2 Researches on CLSCs with multiple collectors and recovery options

Given the number and location of recovery options is essentially related to the CLSCs with multiple collectors, we reviewed the relevant literature to position our study. Specifically, manufacturer collection, retailer collection, and third-party collection (TPC) are the three different channel configurations for product collecting that have been taken into consideration in CLSCs (Savaskan et al. 2004). In CLSC, Hong et al. (2015) took into account collecting, advertising, and price choices using centralized and three decentralized models of three different collectors. Competitive dual collection channels between manufacturers and retailers or TPCs were the two approaches Zhao et al. (2017) looked at for choosing an appropriate reverse channel. Wan and Hong (2019) demonstrated remanufacturing and recycling subsidies could increase recovery and enhance the consumption. Wei et al. (2021) investigated how decisions and profits of CLSCs, including one manufacturer, one retailer, and two rival collectors, are impacted by the manufacturer's integration strategies of collecting channels. However, only the three channel configurations suggested by Savaskan et al. (2004) have been researched among the articles mentioned above.

Extensive researches also focus on the operations of general recovery options in CLSCs. The commonly used techniques for recovering products include repair, remanufacturing, recycling and refining (Wei et al. 2015). Papers on the CLSC network and reverse logistics design have explored a variety of solutions for recovering returned goods. Soleimani et al. (2016) and Zhou et al. (2020) integrated recycling, repair, and remanufacturing with a set of recovery rates. Additionally, several research compared the various approaches for recovery to minimum costs (Javid et al. 2019) and maximum profit (Ahmadi & Amin 2019) and customer satisfaction level (Zhou et al. 2020).

All above studies investigated how different selections of collectors in CLSC design affect performance or how different recovery options impact CLSC performance. They considered reducing the static cost to enhance the performance of CLSC. However, these studies ignore the fact that the bullwhip effect that causes dynamic cost in supply chain system is also a significant performance assessment of profitability, as the large deviations between actual demand and amplified order can lead to high costs (Disney and Lambrecht 2008). In the next section we reviewed the research on bullwhip of CLSCs to further highlight our positioning.

2.3 Research on bullwhip of CLSCs

System dynamics is an approach that combines system theory with computer simulation to study the structure and behaviour of system feedback; this approach was developed by Forrester (1961). Within the context of CLSCs dynamics, we categorized these articles into two streams: 1) single hybrid manufacturing-remanufacturing system 2) multi-echelon CLSCs

For the single hybrid manufacturing-remanufacturing system, starting from Tang and Naim (2004), they investigated the impact of different levels of information transparency on the bullwhip effect in CLSC system. Existing literature focuses on the research field of exploring the effects of different operational factors on bullwhip effect, including inventory policies (Zhou et al. 2006; Cannella et al. 2021; Lin et al. 2022), information transparency (Ponte et al. 2020), return yields (Hosoda et al. 2015; Hosoda et al. 2021), return rates (Zhou and Disney 2006; Ponte et al. 2019); lead times (Hosoda and Disney 2018); capacity limits (Dominguez et al. 2019), quality-grading (Ponte et al. 2021) and batching (Ponte et al. 2022).

With multi-echelon CLSC system, Pati et al. (2010) developed a six-echelon CLSC model to study bullwhip effect with assumed AR (1) demand and order-up-to inventory policy. They found out that increasing proportion of recyclable waste (segregation) can cause a reduction in bullwhip. Adenso-Diaz et al. (2012) noticed that the main factors affect the bullwhip effect in reverse supply chain are forecasting methods, inventory adjustment controller, information sharing and demand variability of end customer. Cannella et al. (2016) pointed out improving information transparency and shortening remanufacturing lead time will reduce bullwhip effect in a three-echelon CLSC. Zhou et al. (2017) developed a three-echelon hybrid system and analysed the order and inventory variance at each echelon with remanufacturing uncertainties. They suggested that higher return rate could result in better dynamic performance. Delavar et al. (2022) developed a two-level CLSC model and proposed that increasing preparation time and fixed ordering cost could lead to higher bullwhip effect. In varying levels of information transparency, Dominguez et al. (2020) looked at the impact of remanufacturing lead time variability on bullwhip effect and inventory performance. Dominguez et al. (2021) examined how the bullwhip effect was affected by centralized and decentralized remanufacturing designs and their results revealed that bullwhip effect could be reduced by centralized configuration. Tombido et al. (2022) discovered that having collectors with uncertainties of returned products quantity is less beneficial for CLSCs than one reliable collector. Giri and Glock (2022) observed bullwhip effect was depended on the values of the parameters of an autoregressive moving average pricing process in a three-echelon CLSC. Huang et al. (2023) explored the influence of collectors' stochastic capacity constraint on bullwhip and proposed that bullwhip could be reduced when a collection station with more stable capacity constraint. The studies with multi-echelon CLCS model mainly focused on the influence of factors such as return rate, lead time, information transparency and structure on the dynamic behaviour of the system.

However, all previous research on bullwhip effect of CLSCs, the single hybrid manufacturing-remanufacturing system only considers recovery option of remanufacturing. And some studies with multiple echelon CLSC system have not specified recovery options (e.g., Giri & Glock 2022), or all echelons have one recovery option (e.g., Zhou et al. 2017). As the result, this motives us to explore the dynamics of different number and location of recovery options in a hybrid (i.e. hybrid) CLSC system.

2.4 Summary

Table 1 summarizes the most relevant literatures and positions our paper within exiting literature based on Sections 2.1, 2.2 and 2.3.

From Table 1, our research gap can be highlighted: this is the first study to examine the dynamic performances of including different number and location of recovery options in CLSCs. On the one hand, the non-system dynamics literature focuses on multiple collectors and multiple recovery options. They specify which one or multiple recovery options are investigated and where to collect returned products, either from the same collector or multiple collectors. However, most of recovery options studies did not indicate a specific collector. On the other hand, no studies on system dynamics have investigated multiple recovery options operating in multi-echelon system. They did not specify the recovery options and location of recovery option. Although we adopted the model from Zhou et al. (2017) and they included multiple recovery options with multi-echelon CLSC system, the number of their recovery options remained the same. However, our study considers an important strategic issue: whether or not, and how many recovery options are needed in CLSCs to minimize bullwhip and inventory variance. Thus, this study could help enterprises strategically design their CLSCs when multiple recovery options are available.

	Article	**Collector**					**Recovery options**			
		Retailer	Manufacturer	Supplier	TPC	Collection center	Repair	Remanufacturing	Recycling	Refining
Non-system dynamics	Hong et al. (2015)	√	√		√			√		
	Zhao et al. (2017)	√	√		√			√	√	
	Wan and Hong (2019)	√			√			√	√	
	Wei et al. (2021)	√	√		√			√	√	
	Soleimani et al. (2016)					√	√	√	√	
	Zhou et al. (2020)					√	√	√	√	
	Javid et al. (2019)					√	√		√	
	Zhen et al. (2019)					√		√		
	Ahmadi & Amin (2019)	√				√			√	
	Jerbia et al. (2018)					√		√	√	
System dynamics	Pati et al. (2010)					√			√	
	Adenso-Diaz et al. (2012)					√			√	
	Cannella et al. (2016)		√					√		
	Zhou et al. (2017)	√	√	√			√	√		√
	Dominguez et al. (2020)				√			√		
	Dominguez et al. (2021)	√						√		
	Delavar et al. (2022)					√		√		
	Tombido et al. (2022)		√		√			√		
	Giri and Glock (2022)				√			√		
	Huang et al. (2023)					√		√		
	This paper	√	√	√			√	√		√

Table 1. Summary table of literature review

3. System Dynamic Model

This section describes the preliminaries of our hybrid CLSC system, the main modelling assumptions, the system dynamics model and the model verification. All the notations used in this paper are listed in Table 2.

3.1 Preliminaries

This study considered a three-echelon supply chain, since using single-echelon supply chain models may underestimate the bullwhip effect (Chatfiled 2013). Our three-echelon CLSC system includes a retailer, a manufacturer and a supplier. We adapted a hybrid CLSC with three echelons proposed in the study by Zhou et al. (2017), which is an extension of Tang and Naim (2004). As shown in Figure 1, for each echelon operating the recovery option, we consider a hybrid system where the product recovery process and manufacturing process simultaneously produce a serviceable inventory to satisfy customer demand (Lin et al. 2022). This hybrid system could be applicable in many industries, such as photocopy machines (Zhou et al. 2017), semiconductors (Lin et al. 2018) and plastic products (Xu et al. 2017). If the echelon does not operate the product option, the system will only have the manufacturing process produce the serviceable inventory for customer demand.

Stocks	**Descriptions**
I_{dj}	Target stock level
I_{sj}	Actual serviceable stock level
W_{mj}	Actual manufacturing work-in-process stock
W_{rj}	Actual remanufacturing work-in-process stock
W_{dj}	Desired work-in-process stock
W_{cj}	Products still used by customers
S_{tj}	Reorder point
Flow	
C_{mj}	Manufacturing completion rate
C_{rj}	Recovery option completion rate
D_c	Customer demand
$\widehat{D}_{cj}$	Forecast customer demand
O_{tj}	Order rate
O_{mj}	Manufacturing order rate

O_{rj}	Recovery option order rate
Parameters	
j	Index variable of echelon in the hybrid system
τ_{mj}	Manufacturing pipeline lead time
τ_{rj}	Recovery option pipeline lead time
τ_c	Customer in-use lead time
τ_{wj}	Work-in-process pipeline lead time
τ_{ij}	Time to adjust the serviceable inventory
$\hat{\tau}_{pj}$	Estimated pipeline lead time (achieving a zero-inventory offset error)
τ_{aj}	Exponential smoothing factor
α_j	Return rate at each echelon, $\alpha_j \in (0, 1)$
α_t	Total return rate for the entire supply chain
k	Constant
$\widehat{\sigma}_t$	Estimated standard deviation of forecast error

Table 2. Notations used in this paper

Each echelon can be equipped with product recovery options. In our hybrid CLSC system, the process of handling the returned products by the retailer, manufacturer and supplier is called repairing, remanufacturing and refining, respectively. The connection between each echelon is via receiving the returns from the end-customer and placing the orders to its closest upstream echelon. We also assume the decentralised CLSC system; that is, information, including the customer in-use lead time, return rate, remanufacturing lead time and manufacturing lead time, is shared only within each echelon between the manufacturing and recovery option processes.

Within the CLSC, some of the used products are collected from the end-customer and will be sent to the echelon with the product recovery option. The returned products could be repaired, remanufactured or refined at different echelons, depending on the return rate of the echelon. Therefore, the returned products will not always be sent to the product recovery option at the supplier, where the returned products will be refined. There is a greater chance of the returned products being repaired or refurbished at the product recovery option at the retailer and manufacturer (Zhou et al. 2017). For example, in HP printer cartridge recollection (Zhou et al. 2017), the used cartridges are returned to retailers based on a certain proportion of the sold cartridges; most of them are in good condition and can be refilled and resold right away. Some of them will be sent to the manufacturer for reprocessing or to the supplier for refining the raw materials if it is not possible to refill them. Moreover, the refined raw material, such as plastics, could be used to produce new products in the manufacturing production line. Thus, after the returned products are pushed into the product recovery option of each echelon, the reprocessed products will be added into the serviceable stock to satisfy customer demand.

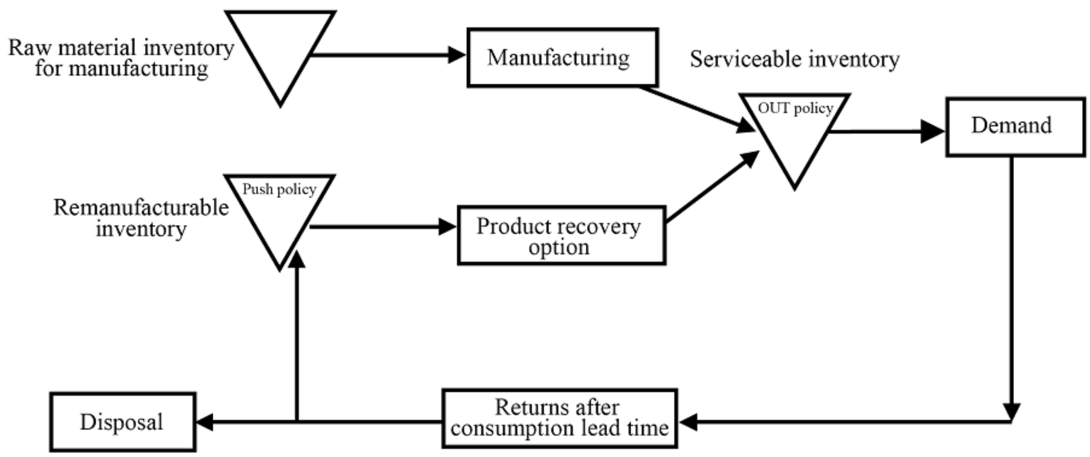


Figure 1. A hybrid CLSC system.

3.2 Assumptions

We developed a three-echelon CLSC system where recovery option and manufacturing production lines satisfy the customer's demand simultaneously. Each echelon manages its own product recovery option and shares the information independently (Ponte et al. 2019). We examined the dynamics of CLSCs at the aggregate level and the forward flow of materials defines a single product or multi-product at an aggregated level. Our model is basically deterministic because we analyse the deterministic cause-and-effect relationships between the variables that lead to complex system dynamics behaviour, including the feedback, delay and nonlinearities presented in a hybrid CLSC. Several assumptions have been made, as discussed below.

Manufacturing and recovery option processing: Recovery option is controlled by a push policy. Under a push policy, all the returned products are either collected and pushed immediately into a product recovery production line or are disposed of after conducting a quality test (Lin et al. 2022). This assumption has been used in other CLSC studies, such as Hosoda and Disney (2018), Hosoda et al. (2015) and Tang and Naim (2004). In our model, all the echelons have their own manufacturing production line. Each manufacturing production line produces new products once the raw materials are delivered from the supplier. All the finished products are stocked in a serviceable inventory to fulfil customer demand. Moreover, the recovery option and manufacturing production lines are assumed to be independent. For both production lines, we assume that there is no capacity limit and the return of orders is allowed. The retailer, manufacturer and supplier have the capability to deal with returns at a different level, such as finished goods, components and raw materials. Moreover, there is no stock point for a serviceable inventory since our study uses a push production strategy where all the products returned by a customer are immediately pushed into the recovery option line. If the serviceable inventory cannot immediately satisfy the customer demand, backorders will be produced, which is referred to as a negative serviceable inventory in this study. Given our system is linear, inventories could be negative or positive depending on the initial inventory level, however, this will not affect our theoretical findings and results. Since we mainly focus on the product recovery options in the CLSC, to simplify the analysis without loss of generality, we assume that the lead times at each echelon in the forward supply chain are the same.

Return rate and quality: Products are assumed to be used by a customer for a specific period of time, and only a proportion of the used products will be returned, while others products will be sent for disposal. In our study, we assumed that all the returned products from the end-customer will be repaired, remanufactured or refined, and the recovered products are as good as new or are perfect substitutions. This is a common assumption in many studies that investigated the dynamics of a CLSC system (Hosoda et al. 2021; Ponte et al. 2019; Zhou et al. 2017). In line with Zhou et al. (2017) and Tang and Naim (2004), we assume that there is a correlation between demand and returns after a consumption lead time, denoted by the return rate (α), where $0 \leq \alpha \leq 1$. It is important to note that we have a fixed total return rate for the entire supply chain system to ensure that the same proportion of sold products are returned. Thus, we could assign different return rates to each echelon to represent differences in the quality of the collected products and investigate the relationship between the location and number of product recovery options on the dynamic performance under different return rates.

CLCS characteristics: Our CLSC system is essentially decentralised where recovery option is governed by push production and managed independently (Dominguez et al. 2021). Each echelon manages its own product recovery option and shares the information independently (Ponte et al.

2019; Zhou et al. 2017). We assume that information about the product recovery option is transparent and shared with the manufacturing process at each echelon, including the lead time, return rate and demand rate (Tang & Naim 2004; Zhou et al. 2017). However, this information is only shared within each echelon (Zhou et al. 2017).

3.3 System dynamics model

Our CLSC model is essentially an adapted order-up-to (OUT) policy including both manufacturing and recovery option productions (Dejonckheere et al. 2004):

$$O_t = S_t - \text{ inventory position} \tag{1}$$

where O_t is the total order rate in period *t*, S_t is the reorder point, the inventory position is the serviceable stock level plus the total work-in-process inventory of manufacturing and recovery option and j ($\forall j = 1, 2, 3$) represents the number of echelons in the hybrid CLSC system; the lower value of *j* indicates that the location of the echelon is closer to the end-customer:

$$O_{tj} = S_{tj} - (I_{sj} + W_{mj} + W_{rj}) \tag{2}$$

The reorder point is updated every period based on:

$$S_{tj} = \widehat{D}_{tj} + k\widehat{\sigma}_{tj} \tag{3}$$

where $\widehat{D}_{tj} = \widehat{D}_{cj} \cdot \hat{\tau}_{pj}$ is the estimated demand rate during the estimated lead time that determines the inventory-offset error (Disney et al. 2006; Zhou et al. 2017). Thus, the reorder point of S_{tj} depends on $\widehat{D}_{cj} \cdot \hat{\tau}_{pj}$ with the addition of a $k\widehat{\sigma}_{tj}$ set as the safety stock (ss_j), following Disney et al. (2006):

$$ss_j = k\widehat{\sigma}_{tj} \tag{4}$$

$$S_{tj} = \widehat{D}_{cj} \cdot \hat{\tau}_{pj} + ss_j \tag{5}$$

By adding parameters of τ_{ij} and τ_{wj}, we can get the generalised OUT policy known as proportional order-up-to (POUT)

$$O_{tj} = \widehat{D}_{cj} + \frac{I_{dj} - I_{sj}}{\tau_{ij}} + \frac{W_{dj} - W_{mj} - W_{rj}}{\tau_{wj}}$$

Additionally, the exponential smoothing forecasting method is applied to estimate $\widehat{D}_{Cj}$ with a smoothing factor τ_{aj} (Zhou et al. 2017):

$$\frac{d_{\hat{D}_{cj}}}{d_t} = \frac{D_c - \hat{D}_{cj}}{\tau_{aj}} \tag{6}$$.

It should be emphasized that more advanced methods may outperform than exponential smoothing method for some pre-determined demand patterns, such as exponential smoothing with additional seasonality (Udenio et al. 2022). Nonetheless, exponential smoothing is a powerful solution that has been widely used in practise due to its simple application, low processing effort and ease of use (Disney et al. 2006). And it is not uncommon that research studies adopted the exponential smoothing method to examine the bullwhip of supply chains system in response to step and deterministic seasonal demand (e.g. Dejonckheere et al. 2002).

The actual serviceable stock (I_{sj}) is equal to the accumulation between inflow (completion rate of recovery option and manufacturing) and outflow (demand). Thus, when customer demand depletes the actual serviceable inventory, the completion rate of the manufacturing and recovery option operations replenishes the actual inventory:

$$\frac{d_{I_{sj}}}{d_t} = C_{mj} + C_{rj} - D_c \tag{7}$$

where the recovery option and manufacturing completion rate is equal to the delayed recovery option and manufacturing order rate (O_{mj} and O_{rj}), which are determined by the work-in-process stock of recovery option and manufacturing (W_{mj} and W_{rj}) and their lead times (τ_{mj} and τ_{rj}). Since we assume τ_{mj} and τ_{rj} are deterministic, the completion rate at which the production units adapt to changes in O_{mj} and O_{rj} could be the production smoothing parameter (Lin et al. 2017).

$$\frac{d_{W_{mj}}}{d_t} = O_{mj} - C_{mj} \tag{8}$$

$$C_{mj} = \frac{W_{mj}}{\tau_{mj}} \tag{9}$$

$$\frac{d_{W_{rj}}}{d_t} = O_{rj} - C_{rj} \tag{10}$$

$$C_{rj} = \frac{W_{rj}}{\tau_{rj}} \tag{11}$$.

Given the 'push' based recovery option assumption, all the returned products from the end-customer will be immediately processed when they arrive at the product recovery option location, so no recoverable inventory exists in our model (Hosoda & Disney 2018; Tang & Naim 2004; Zhou et al. 2017). The number of returned products is equal to the fraction of the products still used by the customer and the in-use lead time. Then:

$$O_{rj} = \frac{W_{cj}}{\tau_c} \tag{15}$$

$$O_{mj} = \ O_{tj} - \frac{W_c j}{\tau_{cj}} \quad (14).$$

Given that only a proportion of the sold products will be returned from the end-customer and collected for recovery option and the proportion of $a_j \forall a_j \in (0,1)$, the first order delay with W_{cj} and τ_{cj} for the rate of returned products should be written as (Zhou et al. 2017):

$$\frac{d_{W_{rj}}}{d_t} = \alpha \cdot D_c - \frac{W_c}{\tau_c} \quad (15).$$

3.4 Model verification

It is necessary to verify the logic and correctness of the model (Sargent 2013). Our model has been verified through a simulation on MATLAB™; some of the main simulation results of our verification process are reported in Table 3. The verification results from Table 3 indicate the logic and correctness of our hybrid CLSC model.

Content	**Description**	**Procedure**	**Results**
Parameters	Reproduce the system's behaviour and be consistent with its findings and results	Regarding the hybrid system and POUT policy, we reproduced the dynamic behaviour of the three-tiered work of Zhou et al. (2017) in responding to a step demand increase by using the same parameter settings: $\tau_{mj} = \tau_{rj} = \tau_{ij}$=8.	The dynamic performance and behaviour of the three-echelon hybrid CLSC is consistent with the model of Zhou et al. (2017): undershoot and overshoot.
Structure and boundaries	Ensure consistency with the system framework and include all essential components.	Relevant studies are used to check the consistency regarding the system descriptions and the	All the important components are included in the hybrid CLSC system model, and the model is cross-checked with

		essential components of a CLSC.	archetypes (Tang & Naim 2004; Zhou et al. 2017).
Extreme conditions	The model is reasonable and logical for extreme situations and values.	We assigned extreme values for the selected model parameters, i.e. τ_{ij}, τ_{wj} and τ_{aj}, and we checked if the system delivers the expected dynamic results (Barlas 1996).	Under extreme conditions, τ_{ij}, τ_{wj} and τ_{aj} will cause the system to respond to a step demand with the expected dynamic results.

Table 3. Verification of the hybrid CLSC model

4. Experimental Design

This section presents the experimental factors and model parameters of our experimental design. We also propose a set of performance measurements for analysing the dynamic behaviour of the CLSCs.

4.1 Experimental factors and parameters

To address research questions, three factors are considered (Table 4): location, number and return rate (α). For the location of the product recovery options, three levels are studied, i.e. retailer (R), manufacturer (M) and the supplier (S) to represent common product recovery options product recovery options include repair/reuse (R), remanufacturing (M), and refining (S) (Chen Y & Chen F 2019; Wei et al. 2015). Regarding the number of product recovery options, four levels including 0, 1, 2, and 3 are assumed to investigate the impact of different number of product recovery on the dynamic performance in CLSCs. Note that 0 represents a traditional forward supply chain without any product recovery option as our study benchmark. Finally, we consider return rate as the experiment factor, due to it is an essential factor influencing the dynamic behaviour of CLSCs (Cannella et al. 2016; Dominguez et al. 2018; Dominguez et al. 2020; Lin et al. 2022). We assumed the total returned rate from end customer is fixed at 0.6 in entire CLSCs, meaning 60% of sold products will be eventually returned to the system for repair, remanufacturer or refine at different echelon of CLSCs. There are two reasons for fixing 0.6 return rate in our simulation study. First, the choice of this value is consistent with previous literature in the multi-echelon CLSCs (Cannella et al. 2021; Zhou et al. 2017). Second, 0.6 return rate or recycle rate can be commonly observed in industries; for example, the automotive industry has a 60% remanufacturing rate (Oakdene Hollins 2004), Australia has a 60% recovery rate of organics and its national resource recycling rate is 60% and recovery rate is 63% (Pickin et al. 2020). Furthermore, as shown in Table 5, we assign different value of return rate to different echelon of CLSCs if the number of recovery options is greater or equal 2, so that different degrees of impact could be analysed by assigning different return rates to each echelon (Cannella et al. 2016; Dominguez et al. 2020). If there are two recovery options, 0.2 and 0.4 are chosen as return rate, while 0.1, 0.2 and 0.3 are determined as return rate if all echelons have recovery options. Setting the return rates at certain values could allow us to compare the upstream and downstream with different weighted return rate. In addition, there has no significant difference among the value of return rates (e.g., 0.1 and 0.5), which is in line with real practice.

Regarding the system parameter settings, τ_{aj}, τ_{ij} and τ_{wj} are determined as16, 8 and 8 based on recommendations by Tang and Naim (2004). This setting has been widely accepted as a 'good setting' for both forward and reverse supply chains system, eliminating the variance in orders and inventory by slowing the system response but not at cost of recovery from demand fluctuations (Tang & Naim 2004; Ponte et al. 2019). Furthermore, following Cannella et al. (2016), Ponte et al. (2019), Tang and Naim (2004) and Zhou et al. (2017), we assumed that the customer in-use lead time is much longer than (re)manufacturing times, and the manufacturing process takes more time than recovery option. Thus, we have selected the value of periods for τ_{mj} =8, τ_{rj}=4, τ_c=32. Note that we also examined the system dynamics performance under the scenario where $\tau_{mj} < \tau_{rj}$ presented in Section 7.

Experiment factors	**Value/label**	
Number of product recovery options	0,1,2,3	
Location of the product recovery options	Retailer (R), Manufacturer(M) and Supplier (S)	
Assigned return rate at each echelon		
Parameters	**Value**	**Source**
α_t	0.6	Cannella et al. (2016); Dominguez et al. (2018);

		Dominguez et al. (2019); Zhou & Disney (2006); Zhou et al. (2017)
τ_{mj}	8	
τ_{wj}	8	Tang and Naim (2004)
τ_{ij}	8	Cannella et al. (2016)
τ_{aj}	16	Zhou et al. (2017)
τ_{c}	32	
τ_{rj}	4	
$\hat{\tau}_{pj}$	$\frac{\left(1-\sum_{n=1}^{j}\alpha_j\right)\cdot\tau_{mj}\ +\alpha_j\tau_{rj}}{1-\sum_{n=1}^{j-1}\alpha_j}$	Zhou et al. (2017)

Table 4. Experiment parameters and factors

4.2 System dynamics performance measurement

In line with previous literature, we used the classic non-financial metrics of bullwhip effect and inventory variance to measure the CLSCs performance (Dominguez et al. 2021; Lin et al. 2022; Tang & Naim 2004; Zhou & Disney 2006; Zhou et al. 2017). It is important to understand the bullwhip effect and inventory variance since both can cause unnecessary costs for a supply chain system (Naim 2006). They can both have a direct impact on supply chain economics (Zhou & Disney 2006). Hence, it is significant to find a way to minimise the bullwhip effect as it has a significant impact on the performance of supply chains. However, dynamic performance from a financial and economic perspective will not be discussed since it is beyond the scope of this paper.

The measurement of system dynamics performance based on two types of demand inputs: step demand and sinusoidal demand. Step input demand indicates a sudden change in demand. It could provide rich information regarding the system's dynamic behaviour (Ponte et al. 2021). Typically, three criteria are usually used to measure order variance and inventory variance with a step input demand (see Figure 2; Lin et al. et al. 2018; Towill et al. 2007). The first criterion is the new equilibrium status of the inventory and order directly related to the customer service level. The second criterion is the transient peak overshoot and undershoot for measuring the bullwhip cost and the number of inventory backlog orders. The overshoot represents the magnitude of the bullwhip effect and the undershoot represents the magnitude of the inventory variance. The third criterion is the inventory and order convergence speed and oscillation. In this study, we mainly focused on overshoot and undershoot with a step input demand since we aimed to explore the bullwhip effect and inventory variance in our developed system.

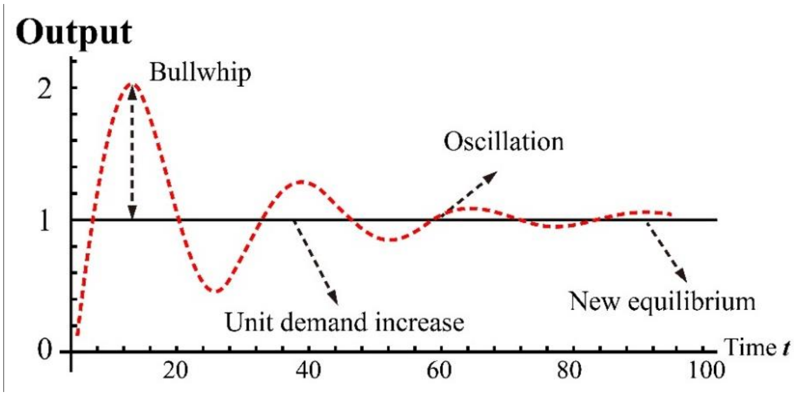


Figure 2. Transient volatility of the orders in responding to a step input demand

Another input to the dynamic system of CLSCs taken into consideration is sinusoidal demand. The deterministic sinusoid demand is a primary source of demand fluctuations as it indicates the seasonal demand (i.e. unadjusted predictable demand data) (Cachon et al. 2007). For sinusoidal demand, an output with the same frequency can generate different amplitudes and phases in a time-invariant linear system. And then its steady-state amplification can be determined as the ratio between the output and input amplitudes, which can evaluate the dynamic performance of the system (Dejonckheere et al. 2003; Jakšic & Rusjan 2008; Udenio et al. 2017), formally

$$Amplitude\ ratio\ (AR) = \frac{amplitude\ of\ order}{amplitude\ of\ demand} \tag{16}$$

Note that AR is also accepted as the measurement of bullwhip at the frequency domain analysis, i.e. maximum AR in the worst-case scenario (Udenio et al. 2022). Noting that real demand patterns are uncommonly ideal sinusoidal and any demand streams can be converted into a sum of sinusoidal waves, and our interest in equilibrium performance is not limited to a sinusoidal demand. Analysis of the associated frequency response plot gives initial insights into the system performance of any demand patterns according to the amplitude of its harmonics components (Dejonckheere et al. 2003). It enables us to determine if and to what degree an ordering policy produces the order and inventory amplification for sinusoidal demand with a specific frequency (Dejonckheere et al.2003; Udenio et al. 2017).

Besides, if stochastic demand (i.i.d) is considered in the analysis in time domain, AR measurement is strongly related to bullwhip measurement. This indicates that the bullwhip effect, which is determined by the ratio of demand variance to order variance (Lee et al. 1997), is proportional to the system's 'noise bandwidth' (i.e., the square of the area below its frequency response plot) (Udenio et al. 2017; Udenio et al. 2022).

4.3 Scenarios

Based on the experimental factor, system parameter settings and demand sources selection, we explored a total of 32 scenarios. The 16 scenarios for each type of demand input and the experimental scenario summary are presented in Table 5. The scenario without a product recovery option is adopted as the benchmark since it could be viewed as a traditional forward supply chain. This benchmark can help us assess the influence of the location and number of product recovery options on the hybrid CLSC system and minimise the bullwhip effect to improve the performance of the hybrid supply chain (Zhou et al. 2017). Total simulation time was set to 1000 periods in Simulink (MATLAB$^{@}$) to ensure that the steady state is reached. To remove the initialisation effects, the records of the first 200 periods of warm-up time were not considered. After 2000 simulation runs for each type of demand input, we obtained data through MATLAB.

Number of product recovery options	**Location of the product recovery option**	**Return rate assigned to each echelon**	**Number of scenarios**
Zero	Forward traditional supply chain	$\alpha_1 = \alpha_2 = \alpha_3 = 0$	1
One	Retailer (*R*) Manufacturer (*M*) Supplier (*S*)	$\alpha_1 = 0.6, \alpha_2 = \alpha_3 = 0$; $\alpha_2 = 0.6, \alpha_1 = \alpha_3 = 0$ $\alpha_3 = 0.6, \alpha_1 = \alpha_2 = 0$	3
Two	Retailer and manufacturer (*R* and *M*) Retailer and supplier (*R* and *S*) Manufacturer and supplier (*M* and *S*)	$\alpha_1 = 0.2, \alpha_2 = 0.4, \alpha_3 = 0$; $\alpha_1 = 0.4, \alpha_2 = 0.2, \alpha_3 = 0$; $\alpha_1 = 0.2, \alpha_3 = 0.4, \alpha_2 = 0$; $\alpha_1 = 0.4, \alpha_3 = 0.2, \alpha_2 = 0$; $\alpha_2 = 0.2, \alpha_3 = 0.4, \alpha_1 = 0$; $\alpha_2 = 0.4, \alpha_3 = 0.2, \alpha_1 = 0$	6
Three	Retailer, manufacturer and supplier (*R*, *M* and *S*)	$\alpha_1 = 0.3, \alpha_2 = 0.2, \alpha_3 = 0.1$; $\alpha_1 = 0.1, \alpha_2 = 0.2, \alpha_3 = 0.3$; $\alpha_1 = 0.2, \alpha_2 = 0.1, \alpha_3 = 0.3$; $\alpha_1 = 0.1, \alpha_2 = 0.3, \alpha_3 = 0.2$; $\alpha_1 = 0.2, \alpha_2 = 0.3, \alpha_3 = 0.1$; $\alpha_1 = 0.3, \alpha_2 = 0.1, \alpha_3 = 0.2$	6

Total number of scenarios:	16

Note: α_1 is the return rate at the retailer, α_2 is the return rate at the manufacturer and α_3 is the return rate at the supplier; the total return α_t of the hybrid system is fixed at 0.6.

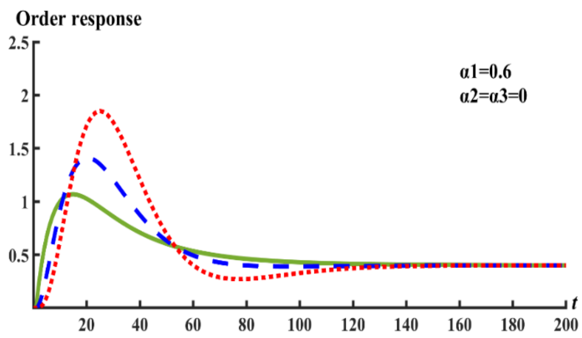
Table 5. Summary of the experimental scenarios for each experimental setting

5. System Dynamic Analysis

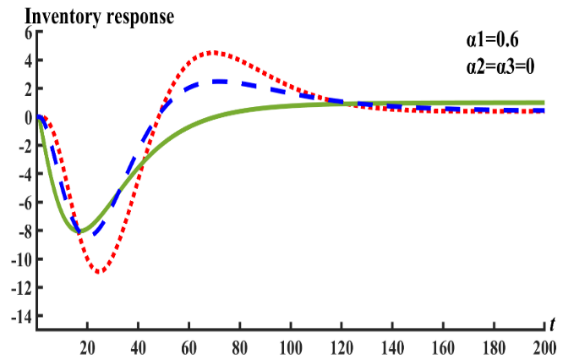
In this section, the simulation results are analysed based on the number of recovery options, according to the critical assumptions considering the CLSC system environment and conditions. Toward that end, we focus on the system dynamics performance of the manufacturing orders and the serviceable inventory. It should be noted that the dynamic response of the recovery options is not discussed in detail given the recovery process used to generate no bullwhip based on the push policy adopted in our CLSCs.

5.1 One product recovery option

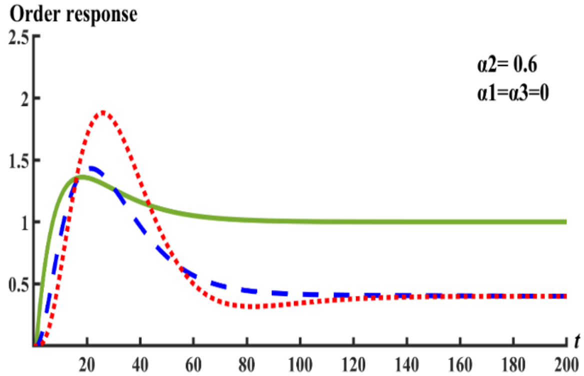
Figure 3 presents the dynamic behaviour of the order and inventory responses with one recovery option in the entire CLSC; thus, all the returned products are processed to this recovery option. Table 6 presents the actual value of the order and inventory responses.



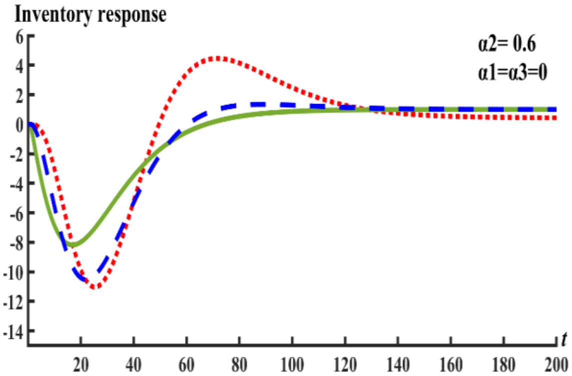
(a). Order response when the recovery option is located at R



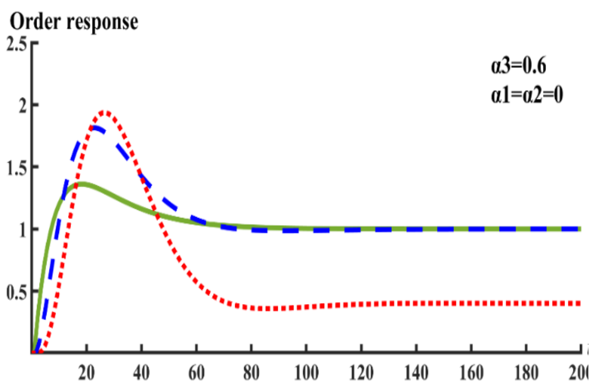
(b). Inventory response when the recovery option is located at R



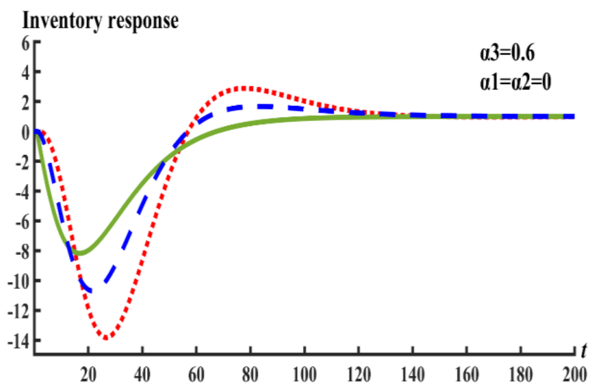
(c). Order response when the recovery option is located at M



(d). Inventory response when the recovery option is located at M



(e). Order response when the recovery option is located at S



(f). Inventory response when the recovery option is located at S

Figure 3. Dynamic performance of a one-product recovery option with a step input demand (green solid line: **Retailer**; blue dashed line: **Manufacturer**; red dotted line: **Supplier**)

		BW				VarI			
Location of the product recovery option	**Return rate (α_i)**	Retailer (R)	Manufacturer (M)	Supplier (S)	**Total**	Retail (R)	Manufactur er (M)	Supplier (S)	**Total**
	$\alpha_1 = \alpha_2 = \alpha_3 = 0$	1.36	1.81	2.39	**5.56**	8.18	10.7	13.93	**32.81**
R	$\alpha_1 = 0.6$	1.07	1.41	1.85	**4.33**	8.06	8.43	10.9	**27.39**
M	$\alpha_2 = 0.6$	1.36	1.43	1.88	**4.67**	8.18	10.54	11.04	**29.76**
S	$\alpha_3 = 0.6$	1.36	1.81	1.94	**5.11**	8.18	10.7	13.83	**32.71**

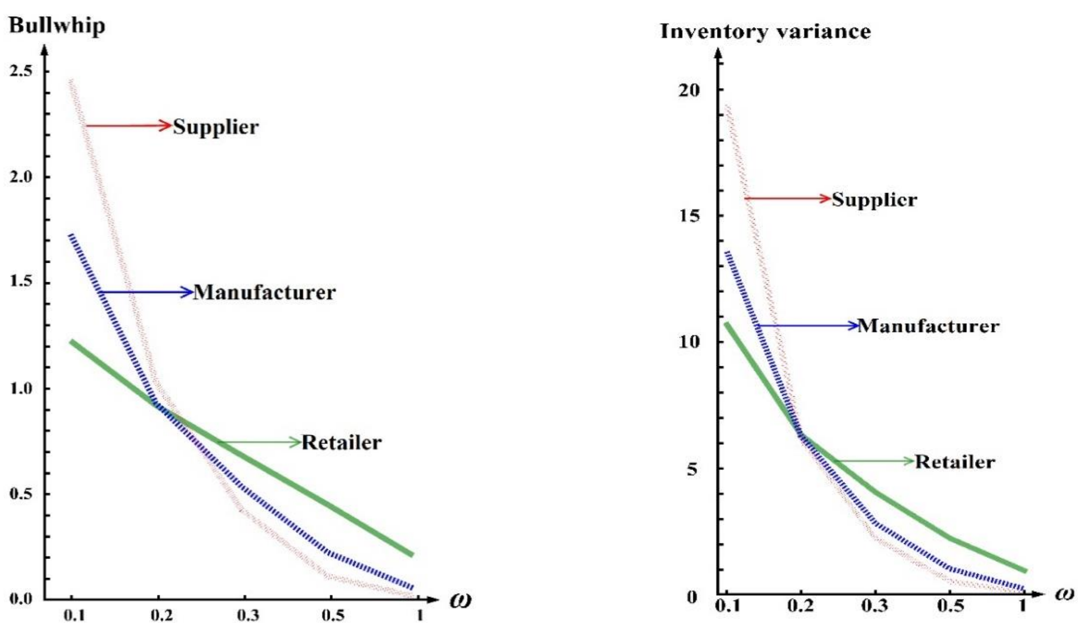
Table 6. Step input demand order and inventory responses of a system with one product recovery option

To analyse the bullwhip effect and inventory variance, the peak value of the dynamic order response and the dynamic inventory response were investigated. The highest value of the dynamic order response represents the magnitude of the bullwhip effect and the lowest value of the dynamic inventory response represents the inventory variance (Lin et al. 2018; Towill et al. 2007). The greater the bullwhip effect and inventory variance, the worse the system's performance. Overall, based on the information presented in Figure 3 and Table 6, there are several findings. First, in comparison to a traditional forward supply chain system, in a CLSC system, the introduction of a recovery option can improve the system dynamics performance including a decrease in the bullwhip effect and inventory variance, although limited improvement is found when the recovery option is located at the supplier echelon. For example, a 32.81 vs 32.71 inventory variance for the supplier is found by comparing a traditional supply chain and a CLSC with the recovery option located at the supplier.

Second, dynamic performance improvement (total bullwhip effect and inventory variance) may decrease as the distance between the product recovery option and the end-customer increases. The minimum overall bullwhip effect (4.33) and inventory variance (27.39) are identified for the scenario where the product recovery option is located at the retailer. However, the maximum overall bullwhip effect and inventory variance (5.11 and 32.71) are found for the case where the product recovery option is located at the supplier. This occurs because the introduction of the recovery option at the retailer not only improves the retailer's system dynamics, it also improves the dynamic performance of the upstream members. For instance, when comparing the production recovery at the supplier (Figure 3e) and the retailer (Figure 3a), the bullwhip effect is reduced from 1.36 to 1.07 for the retailer, from 1.81 to 1.41 for the manufacturer and from 1.94 to 1.85 for the supplier. A similar result can be found for the inventory variance, as shown in Table 6.

Finally, the order and inventory responses may converge to different values in different scenarios, which is driven by the return rate that is assigned (Zhou et al. 2017). For example, the return rates, $\alpha_1 = 0.6$ and $\alpha_2 = \alpha_3 = 0$, indicate that the retailer places 60% fewer orders from the manufacturer and the manufacturer places 60% fewer orders from the supplier. Thus, the final values of the dynamic order response of three echelons converge to 0.4 since they only need to place 40% of the orders from their upstream members to satisfy the demand (see Figure 3a).

However, the system dynamics performance of a CLSC with a one-product recovery option is different if the seasonal demand pattern is assumed. Figure 4 shows a total minimal order and inventory amplitude ratios for each echelon in responding to seasonal demand with a different demand frequency (0.1-1 rad/week). The corresponding numerical values can be found in Appendix A. Overall, the higher the value of ω, the lower the amplitude ratio across the CLSC. This is different from the step input demand as the bullwhip always exists regardless of the location of the product recovery option. More specifically, according to Appendix A, all the echelons produce a bullwhip effect at a frequency of 0.1 and some of the echelons produce a bullwhip effect at a frequency of 0.2 (retailer when $\alpha_2 = 0.6$). However, no echelon generates a bullwhip effect once the demand frequency is equal to or greater than 0.3. This is because the CLSC system acts as an "amplifier" or "filter," depending on the system parameters and the demand frequencies. Under the same system control parameter, low frequencies can be amplified while high frequencies may be filtered from downstream to upstream members of the supply chains (Towill & Del Vechhio 1994; Towill et al. 2007). For instance, when ω = 0.3, 0.5 and 1 rad/week, the bullwhip effect and inventory variance are smaller for the upstream supply chain than the downstream supply chain.



(a). Bullwhip effect

(b). Inventory variance

Figure 4. Performance metrics of each echelon when the sum metrics are minimised in relation to demand frequency (one recovery option; green solid line: **Retailer**; blue dashed line: **Manufacturer**; red dotted line: **Supplier)**

5.2 Two product recovery options

If two product recovery options are available for three-echelon CLSCs, there are three possible location combinations: 1) Retailer & Manufacturer (R&M), 2) Retailer & Supplier (R&S) and 3) Manufacturer & Supplier (M&S). Figure 5 presents the dynamic behaviour of the order and inventory responses in responding to a step demand and Table 7 presents the numerical results. Note: 0.2 or 0.4 are assigned as the return rate for the echelon with the product recovery option. This creates six possibilities/scenarios.

Of the six scenario simulations, the minimum total bullwhip effect (4.4) and inventory variance (28.15) (Table 7), that is, the best-case scenario, can be found when the retailer repairs 40% of the returned products and the manufacturer remanufactures 20% of them. The total maximum bullwhip effect (4.96) and inventory variance (31.83) (Table 7) occur when the product recovery options are processed in the upstream supply chain where the supplier refines 40% of the returned products and the manufacturer remanufactures 20% of them. But one thing to be noted is that there has no much differences between the best-case scenario in two recovery options (4.4) and one recovery option (4.33).

The dynamic performance is always worse for traditional supply chains than CLSCs. However, like traditional supply chains, the bullwhip effect and inventory variance gradually amplify from downstream to upstream along the CLSC in all six possibilities/scenarios. However, when comparing traditional supply chains and the six CLSC possibilities from the aspect of an individual echelon, the reduction in the bullwhip effect and inventory variance is less for the retailer than the manufacturer and supplier. This may be due to the short distance between the retailer and its customers, which does not cause great fluctuations in the inventory. For the manufacturer and supplier, no significant reduction in inventory variance occurs when the recovery options are located at the M&S combination, especially when the supplier refines 40% of the returned products. This has the same impact as the one-recovery option: when two recovery options operate in supply chains, at least one of the recovery options should be located closer to the end-customer.

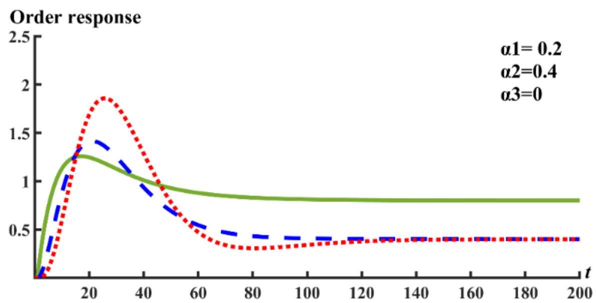
The bullwhip effect increases as the return rate decreases. According to Table 7 and Figure 5, a comparison of the two possibilities for R&M show that when the retailer's return rate is increased and the manufacturer's return rate is decreased, the retailer is the main contributor to the total bullwhip reduction, i.e. bullwhip (α_1=0.4) < bullwhip (α_1=0.2). For the R&S combination, the retailer is still the main contributor to the total bullwhip reduction. Supplier's bullwhip is reduced by the retailer's increased return rate. This is because when the downstream supply chain member has a higher return rate, it will reduce the output of the newly produced items. This is also found in one-recovery option scenarios in which the recovery option that is located at the retailer could improve the dynamic performance of its upstream members. For the M&S combination, when the manufacturer's return rate is increased and the supplier's return rate is decreased, the manufacturer is the main contributor to the total bullwhip reduction.

Based on the results shown in Figure 5, we noticed that unlike the one-recovery option, the final order response values are not always the same for all echelons because the recovery options at the downstream members will impact the order rate of the upstream members. For example, if $\alpha_1 = 0.4$, $\alpha_2 = 0.2$ and $\alpha_3 = 0$, the final value is 0.6 for the retailer and 0.4 for the manufacturer and supplier. However, if $\alpha_1 = 0.4$, $\alpha_2 = 0$ and $\alpha_3 = 0.2$, the final value is 0.6 for the retailer and manufacturer and 0.4 for the supplier. Thus, the final value of the echelon without a product recovery option is equal to and affected by the return rate of its nearest downstream member with a product recovery option.

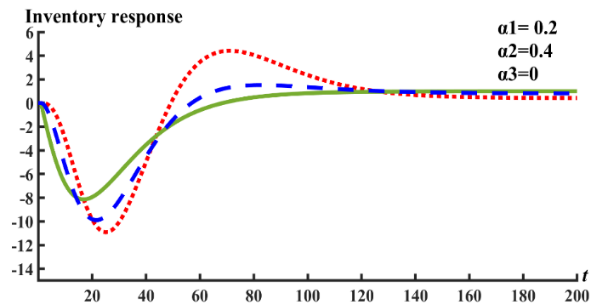
		BW				VarI			
Location of the product recovery option	**Return rate (α_i)**	Retailer (R)	Manufacturer (M)	Supplier (S)	**Total**	Retailer (R)	Manufacturer (M)	Supplier (S)	**Total**
	$\alpha_1 = \alpha_2 = \alpha_3 = 0$	1.36	1.81	2.39	**5.56**	8.18	10.7	13.93	**32.81**
R&M	$\alpha_1 = 0.2$ $\alpha_2 = 0.4$	1.26	1.42	1.86	**4.54**	8.14	9.89	10.92	**28.95**
	$\alpha_1 = 0.4$ $\alpha_2 = 0.2$	1.16	1.4	1.84	**4.4**	8.1	9.21	10.84	**28.15**
R&S	$\alpha_1 = 0.2$ $\alpha_3 = 0.4$	1.26	1.68	1.89	**4.83**	8.14	9.93	12.94	**31.01**
	$\alpha_1 = 0.4$ $\alpha_3 = 0.2$	1.16	1.54	1.86	**4.56**	8.1	9.17	11.98	**29.25**
M&S	$\alpha_2 = 0.2$ $\alpha_3 = 0.4$	1.36	1.69	1.91	**4.96**	8.18	10.65	13	**31.83**

$\alpha_2 = 0.4$ $\alpha_3 = 0.2$	1.36	1.56	1.88	**4.8**	8.18	10.59	12.1	**30.87**

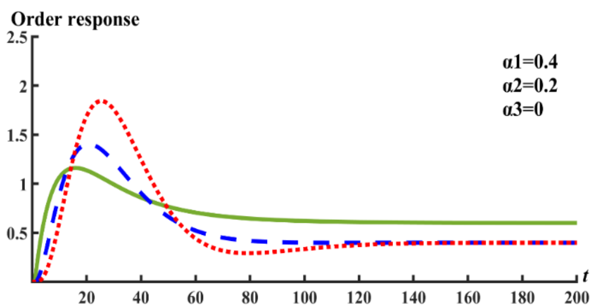
Table 7. Step input demand order and inventory responses of a system with two product recovery options



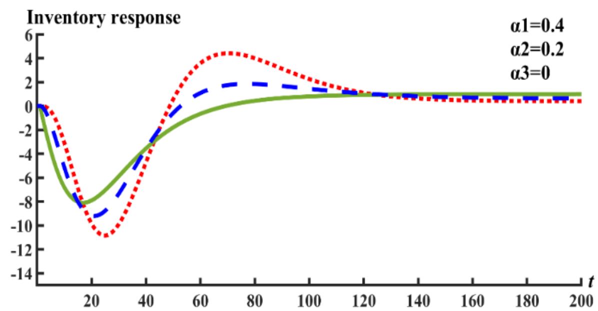
(a). Order response when the recovery options are located at R&M



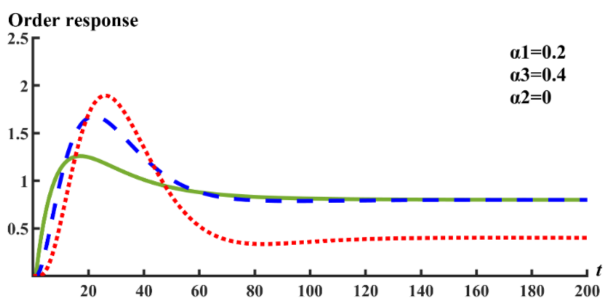
(b). Inventory response when the recovery options are located at R&M



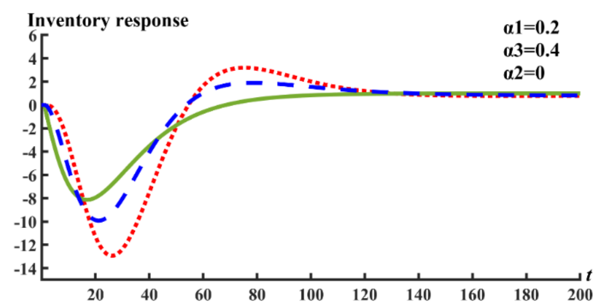
(c). Order response when the recovery options are located at R&M



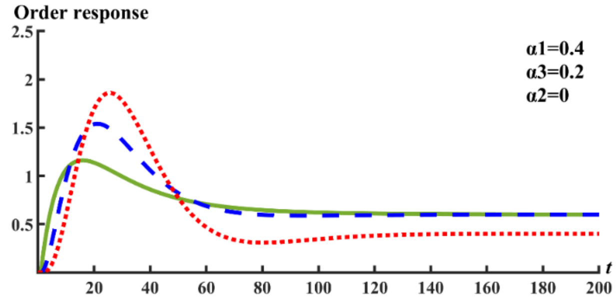
(d). Inventory response when the recovery options are located at R&M



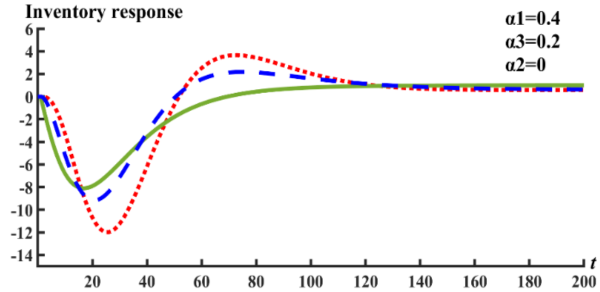
(e). Order response when the recovery options ae located at R&S



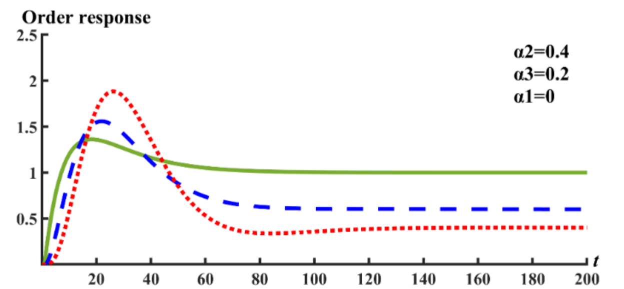
(f). Inventory response when the recovery options are located at R&S



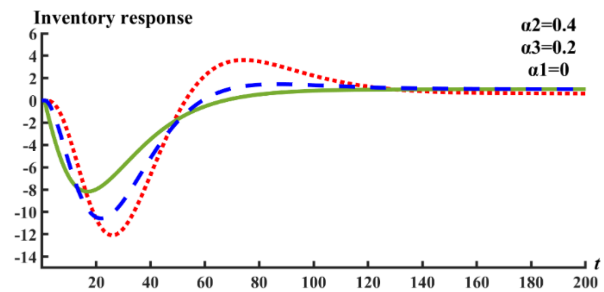
(g). Order response when the recovery options are located at R&S



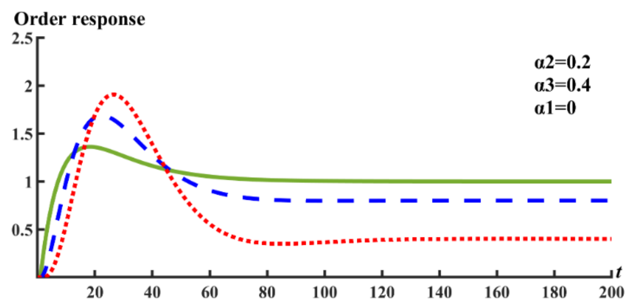
(h). Inventory response when the recovery options are located at R&S



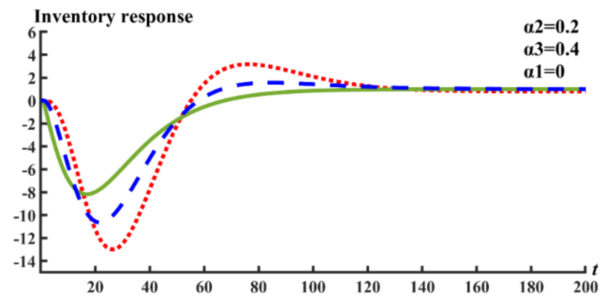
(i). Order response when the recovery options are located at M&S



(j). Inventory response when the recovery options are located at M&S



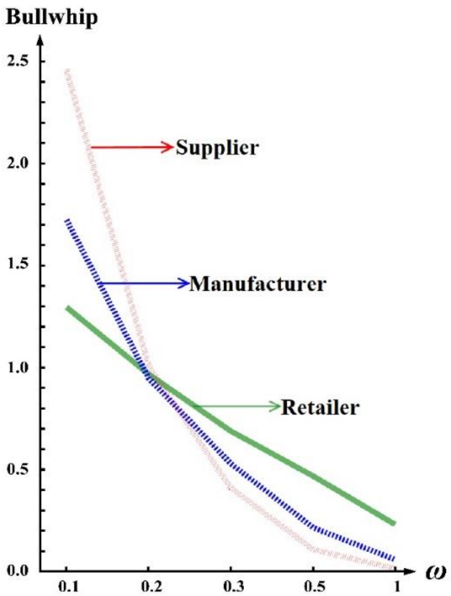
(k). Order response when the recovery options are located at M&S



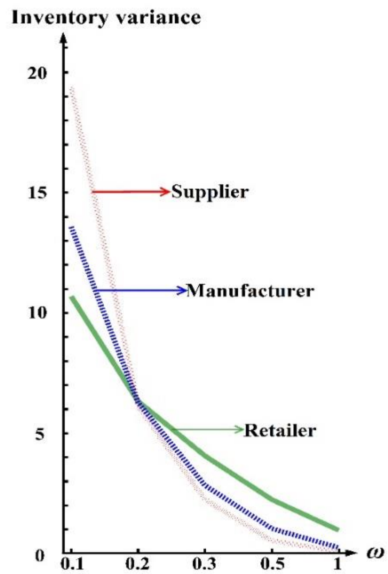
(l). Inventory response when the recovery options are located at M&S

Figure 5. Dynamic performance of two recovery options with step input demand (green solid line: **Retailer**; blue dashed line: **Manufacturer**; red dotted line: **Supplier**)

Figure 6 plots the total minimum order and inventory amplitude ratios of the demand frequency for each echelon with sinusoidal demand (0.1-1 rad/week). Appendix B presents all the numerical results. The result patterns generated for the system with a two-product recovery option are the same as the results for the system with a one-product recovery option. Namely, an increased demand frequency leads to the decreased amplitude ratios of supply chains (Figure 6). Moreover, the high frequencies filter and low frequencies amplify the amplitude ratios along the supply chain.



(a). Bullwhip effect



(b). Inventory variance

Figure 6. Performance metrics of each echelon when the sum metrics are minimised in relation to demand frequency (two recovery options; green solid line: **Retailer**; blue dashed line: **Manufacturer**; red dotted line: **Supplier**)

Overall, the minimum metrics occur when the retailer repairs 40% of the returned products and the manufacturer remanufactures 20% of them. Maximum metrics are generated when the supplier refines 40% of the returned products and the manufacturer reproduces 20% of them (Appendix B). These results are consistent with a unit step demand increase. However, unlike the step input demand results, the decrease in the bullwhip effect is mainly due to the manufacturer and supplier rather than the retailer with a sinusoidal demand. Therefore, locating the recovery options at the downstream members could significantly improve the dynamic performance of the upstream members in supply chains.

5.3 Three product recovery options

Figure 7 illustrates the dynamic order and inventory responses in responding to a step input demand with three recovery options and Table 8 shows the numerical outcomes. Note: 0.1, 0.2 or 0.3 are assigned as the return rate for each echelon, which produces six possibilities/scenarios.

In the presence of three recovery options, the minimum bullwhip effect (4.53) and inventory variance (29.13) (Table 8) are generated at $\alpha_1 = 0.3$, $\alpha_2 = 0.2$ and $\alpha_3 = 0.1$. The maximum bullwhip effect (4.81) and inventory variance (30.95) (Table 8) are produced at $\alpha_1 = 0.1$, $\alpha_2 = 0.2$ and $\alpha_3 = 0.3$. The overall performance indicates that, if the product recovery option is located far from the end-customer, the bullwhip effect increases as the return rate increases.

Consistent with the one- and two-recovery options, a traditional supply chain still generates the worst bullwhip effect and inventory variance in all scenarios with three-recovery options. Moreover, the dynamic performance is amplified from the downstream to upstream members of the supply chain. From the individual echelon perspective, the reduction in bullwhip effect and inventory variance is still the least at the retailer while it is the greatest at the supplier in a CLSC comparing to a traditional supply chain. Thus, the existence of three recovery options is more beneficial to the upstream members of a supply chain.

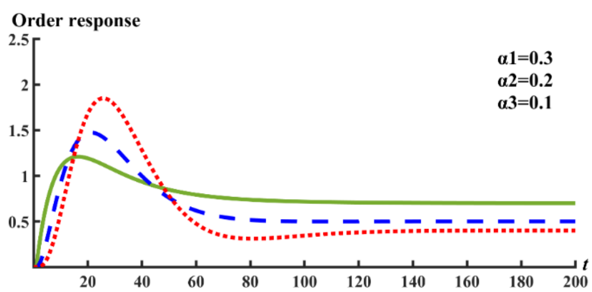
Based on Table 8 and Figure 7, the higher return rate at the downstream supply chain, the lower the bullwhip effect and inventory variance across the CLSC. For instance, the total bullwhip effect and inventory variance is 4.53 and 29.13, respectively, when $\alpha_1 = 0.3$, $\alpha_2 = 0.2$ and $\alpha_3 = 0.1$. However, if the return rate of the retailer is decreased to 0.1, the return rate of the manufacturer remains the same and the return rate of the supplier increases to 0.3, the total bullwhip effect and inventory variance are significantly increased to 4.81 and 30.95, respectively. Moreover, a higher return rate at an individual echelon does not indicate that it has a better dynamic performance than other echelons. For example, a higher return rate at an upstream member does not reduce its bullwhip effect and inventory variance more than that of a downstream member, i.e. $\alpha_3 = 0.3$.

Figure 7 indicates that, unlike one- and two-recovery option systems, every echelon's final value of order response is not the same for all possibilities. This is because each echelon has a recovery option with a different return rate, which will affect the orders placed to its upstream supply chain.

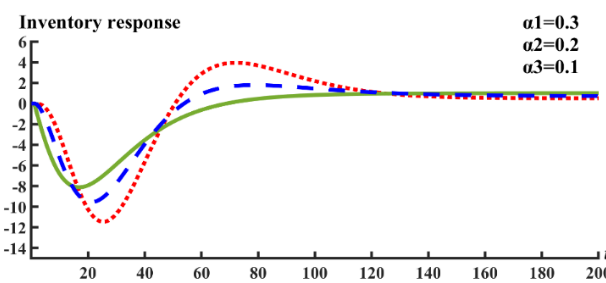
		BW				VarI			
Location of the	**Return rate (α_i)**	Retailer (R)	Manufacturer (M)	Supplier (S)	**Total**	Retailer (R)	Manufacturer (M)	Supplier (S)	**Total**

product recovery option									
R, M & S	$\alpha_1 = \alpha_2 = \alpha_3 = 0$	1.36	1.81	2.39	**5.56**	8.18	10.7	13.93	**32.81**
	$\alpha_1 = 0.3$ $\alpha_2 = 0.2$ $\alpha_3 = 0.1$	1.21	1.47	1.85	**4.53**	8.12	9.56	11.45	**29.13**
	$\alpha_1 = 0.1$ $\alpha_2 = 0.2$ $\alpha_3 = 0.3$	1.31	1.62	1.88	**4.81**	8.16	10.27	12.52	**30.95**
	$\alpha_1 = 0.2$ $\alpha_2 = 0.1$ $\alpha_3 = 0.3$	1.26	1.61	1.88	**4.75**	8.14	9.92	12.48	**30.54**
	$\alpha_1 = 0.1$ $\alpha_2 = 0.3$ $\alpha_3 = 0.2$	1.31	1.55	1.87	**4.73**	8.16	10.25	12.05	**30.46**
	$\alpha_1 = 0.2$ $\alpha_2 = 0.3$ $\alpha_3 = 0.1$	1.26	1.48	1.86	**4.6**	8.14	9.9	11.48	**29.52**
	$\alpha_1 = 0.3$ $\alpha_2 = 0.1$ $\alpha_3 = 0.2$	1.21	1.54	1.86	**4.61**	8.12	9.55	11.98	**29.65**

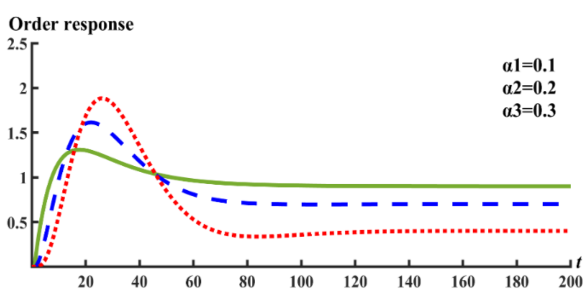
Table 8. Step input demand order and inventory responses of a system with three product recovery options



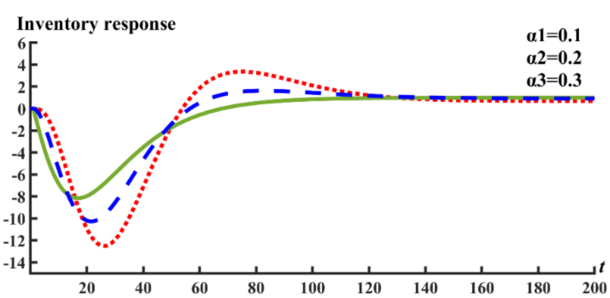
(a). Order response for $\alpha_1 = 0.3$, $\alpha_2 = 0.2$, $\alpha_3 = 0.1$



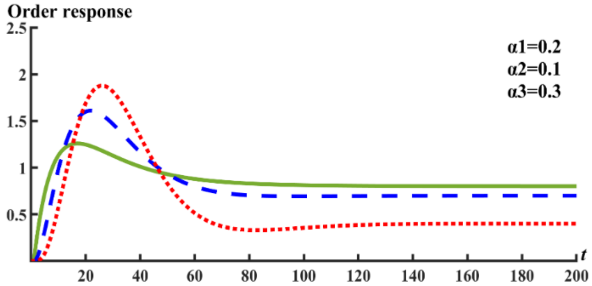
(b). Inventory response for $\alpha_1 = 0.3$, $\alpha_2 = 0.2$, $\alpha_3 = 0.1$



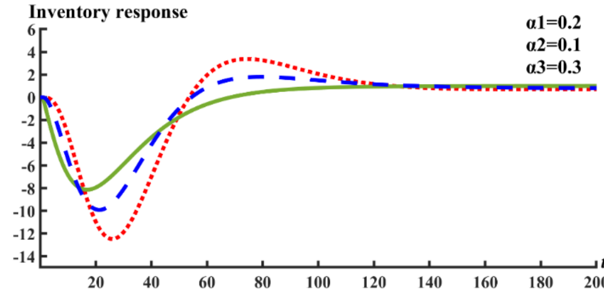
(c). Order response for $\alpha_1 = 0.1$, $\alpha_2 = 0.2$, $\alpha_3 = 0.3$



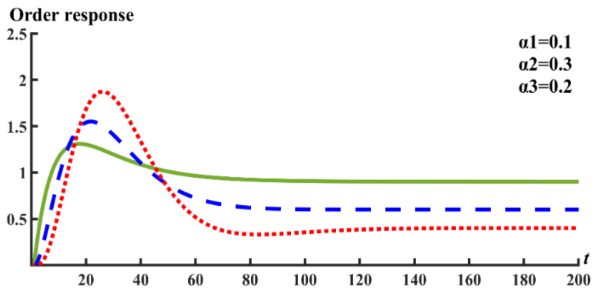
(d). Inventory response for $\alpha_1 = 0.1$, $\alpha_2 = 0.2$, $\alpha_3 = 0.3$



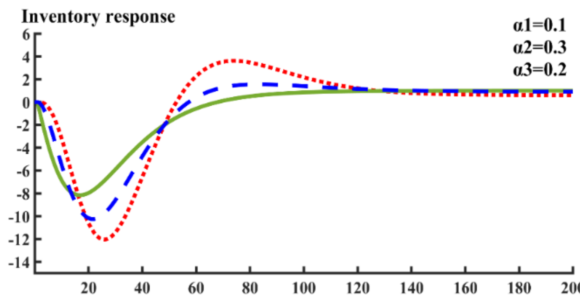
(e). Order response for $\alpha_1 = 0.2$, $\alpha_2 = 0.3$, $\alpha_3 = 0.1$



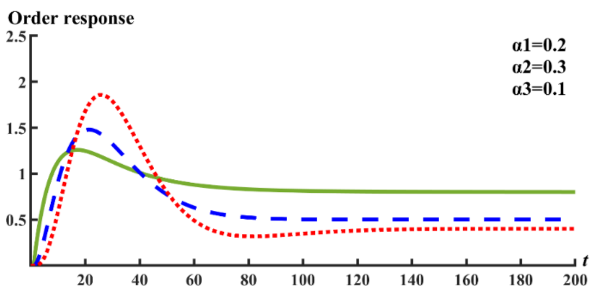
(f). Inventory response for $\alpha_1 = 0.2$, $\alpha_2 = 0.3$, $\alpha_3 = 0.1$



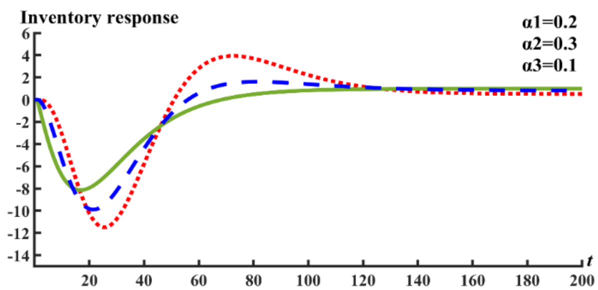
(g). Order response for $\alpha_1 = 0.1$, $\alpha_2 = 0.3$, $\alpha_3 = 0.2$



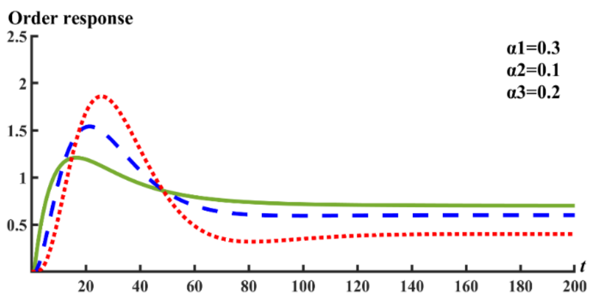
(h). Inventory response for $\alpha_1 = 0.1$, $\alpha_2 = 0.3$, $\alpha_3 = 0.2$



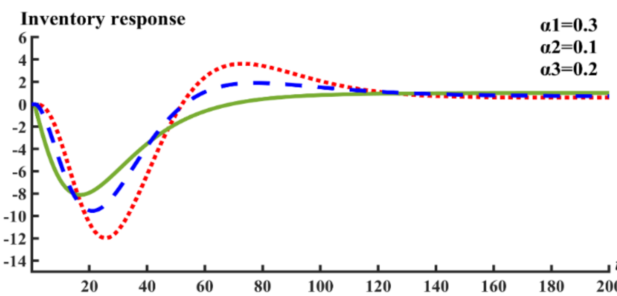
(i). Order response for $\alpha_1 = 0.2$, $\alpha_2 = 0.3$, $\alpha_3 = 0.1$



(j). Inventory response for $\alpha_1 = 0.2$, $\alpha_2 = 0.3$, $\alpha_3 = 0.1$



(k). Order response for $\alpha_1 = 0.3$, $\alpha_2 = 0.1$, $\alpha_3 = 0.2$

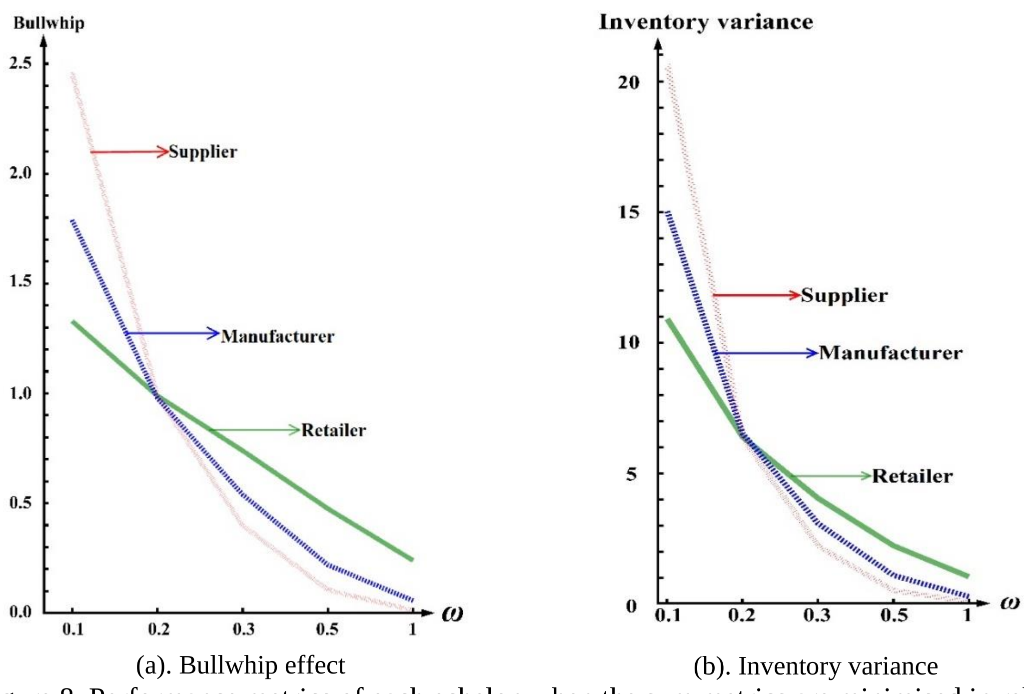


l). Inventory response for $\alpha_1 = 0.3$, $\alpha_2 = 0.1$, $\alpha_3 = 0.2$

Figure 7. Dynamic performance of three product recovery options with a step input demand (green solid line: **Retailer**; blue dashed line: **Manufacturer**; red dotted line: **Supplier**)

Appendix C presents the simulation results of three recovery options with a sinusoidal demand and Figure 8 plots the minimal total amplitude ratios for each echelon regarding the demand frequency (0.1-1 rad/week). Overall, the comparison reveals that the total amplitude ratios decrease as the demand frequency increases. This is in line with the results of the previous two conditions.

The minimal total amplitude ratios occur at $\alpha_1 = 0.3$, $\alpha_2 = 0.2$ and $\alpha_3 = 0.1$, while the maximum occur at $\alpha_1 = 0.1$, $\alpha_2 = 0.2$ and $\alpha_3 = 0.3$. This finding agrees with the step input demand results. At a low frequency, $\omega = 0.1$ rad/week, we found that the bullwhip effect gradually increases from the downstream supply chain members to the upstream members. However, at other frequencies, our results indicate that the higher the demand frequency, the smaller the bullwhip effect from the downstream to upstream members. From the perspective of an individual echelon, the trend is for the bullwhip effect to decrease as the demand frequency increases.



(a). Bullwhip effect (b). Inventory variance

Figure 8. Performance metrics of each echelon when the sum metrics are minimised in relation to demand frequency (three recovery options; green solid line: **Retailer**; blue dashed line: **Manufacturer**; red dotted line: **Supplier**)

6. Numerical study

To verify our linear outcomes in a more complex and realistic CLSC system, we explored the performance metrics by adding a non-negative order constraint. A non-negative order constraint is one of the most common nonlinearities present in real-world supply chain systems. Note that we used the same deterministic values in this setting as in our linear setting so it is possible to compare the linear and nonlinear results. We also tested the non-negative order constraint using sinusoidal demand with the frequency at 0.1.

6.1 Non-negative order constraint

Non-negative order constraint is also known as a forbidden return constraint, where a customer is not allowed to return products to the seller due to exceeded inventory unless there are quality issues (Wang et al. 2023). Exceeded inventory is presented as a negative demand; this means the returned products cause a decrease in the stock level of demand in a specific period and an increase in the inventory level (Wang et al. 2014). However, the orders for suppliers are restricted to non-negative values (Wang et al. 2023). The non-negative order constraint can be applied to represent the real-world forbidden return phenomenon between customers and suppliers. For example, in the personal computer industry, the forbidden return policy is usually agreed upon between manufacturers and suppliers (Lin & Naim 2019). By adding the non-negative order constraint, we assume the manufacturing orders are always positive. Thus, it is forbidden to send orders back to the suppliers in our system, which is in line with most real-world cases. We added the non-negative order constraint by setting up the saturation variable with a lower limit of 0 and an upper limit of 100000 (i.e. unlimited production capacity). All the other settings are identical to those used in the linear conditions.

Table 9 presents our simulation outcomes under a non-negative order constraint with a sinusoid demand frequency of 0.1. Comparing the information presented in Appendixes A, Appendix B, Appendix C and Table 9, the linear condition findings are robust in a nonlinear environment with a non-negative order constraint. In one-, two- and three-product recovery option scenarios, the overall supply chain dynamic performance is optimal when the retailer has the highest proportion of returned products and the manufacturer has the second-highest proportion. In line with the linear results, having a product recovery option for a downstream supply chain member with a higher return rate improves the dynamic performance of its upstream member. Furthermore, an increased return rate significantly decreases the amplitude ratio, leading to a lower bullwhip effect.

		BW				**VarI**			
Location of the product recovery option	**Return rate (α_i)**	Retailer (R)	Manufacturer (M)	Supplier (S)	**Total**	Retailer (R)	Manufacturer (M)	Supplier (S)	**Total**
	$\alpha_1 = \alpha_2 = \alpha_3 = 0$	1.43	2.04	2.91	**6.38**	10.96	15.64	22.32	**48.92**
R	$\alpha_1 = 0.6$	1.24	1.53	1.76	**4.53**	10.67	13.51	20.8	**44.89**
M	$\alpha_2 = 0.6$	1.43	1.52	1.77	**4.72**	10.96	15.05	20.49	**46.5**
S	$\alpha_3 = 0.6$	1.43	2.04	1.82	**5.29**	10.96	15.64	21.49	**48.09**

Table 9a. One-product recovery option

		BW				**VarI**			
Location of the product recovery option	**Return rate (α_i)**	Retailer (R)	Manufacturer (M)	Supplier (S)	**Total**	Retailer (R)	Manufacturer (M)	Supplier (S)	**Total**
	$\alpha_1 = \alpha_2 = \alpha_3 = 0$	1.43	2.04	2.91	6.38	10.96	15.64	22.32	48.92
R&M	$\alpha_1 = 0.2$ $\alpha_2 = 0.4$	1.36	1.52	1.755	4.635	10.87	14.52	20.35	45.74
	$\alpha_1 = 0.4$ $\alpha_2 = 0.2$	1.3	1.519	1.755	4.574	10.77	13.91	20.3	44.98
R&S	$\alpha_1 = 0.2$ $\alpha_3 = 0.4$	1.36	1.943	1.815	5.118	10.87	14.93	20.76	46.56
	$\alpha_1 = 0.4$ $\alpha_3 = 0.2$	1.3	1.93	1.812	5.042	10.77	14.23	20.07	45.07
M&S	$\alpha_2 = 0.2$ $\alpha_3 = 0.4$	1.43	1.92	1.812	5.162	10.96	15.41	20.68	47.05
	$\alpha_2 = 0.4$ $\alpha_3 = 0.2$	1.43	1.84	1.805	5.075	10.96	15.18	19.89	46.03

Table 9b. Two-product recovery option

		BW				**VarI**			
Location of the product recovery option	**Return rate (α_i)**	Retailer (R)	Manufacturer (M)	Supplier (S)	**Total**	Retailer (R)	Manufacturer (M)	Supplier (S)	**Total**
	$\alpha_1 = \alpha_2 = \alpha_3 = 0$	1.43	2.04	2.91	6.38	10.96	15.64	22.32	48.92
R, M & S	$\alpha_1 = 0.3$ $\alpha_2 = 0.2$ $\alpha_3 = 0.1$	1.33	1.73	1.8	4.86	10.82	14.62	19.67	45.11
	$\alpha_1 = 0.1$ $\alpha_2 = 0.2$ $\alpha_3 = 0.3$	1.39	1.89	1.807	5.087	10.91	15.04	20.28	46.23

$\alpha_1 = 0.2$ $\alpha_2 = 0.1$ $\alpha_3 = 0.3$	1.36	1.89	1.808	5.058	10.87	14.8	20.32	45.99
$\alpha_1 = 0.1$ $\alpha_2 = 0.3$ $\alpha_3 = 0.2$	1.39	1.84	1.803	5.033	10.91	14.92	19.87	45.7
$\alpha_1 = 0.2$ $\alpha_2 = 0.3$ $\alpha_3 = 0.1$	1.36	1.72	1.798	4.878	10.87	14.57	19.64	45.08
$\alpha_1 = 0.3$ $\alpha_2 = 0.1$ $\alpha_3 = 0.2$	1.33	1.84	1.81	4.98	10.82	14.45	19.94	45.21

Table 9c. Three-product recovery option

Table 9. Non-negative order constraint responses with ω = 0.1 rad/week

However, it is interesting to note that the retailer is not affected by the non-negative order constraint since its demand is always positive. The bullwhip effect is slightly decreased for the upstream members in comparison to the linear condition due to the non-negative constraint. This is due to the inclusion of a non-negative order policy where the increase in time adjustment in serviceable inventory leads to the decrease in the bullwhip level. Unlike the bullwhip effect, the inventory variance increases slightly due to the non-negative constraint. In other words, a non-negative order constraint could help reduce the bullwhip effect but amplify the inventory variance. Moreover, a non-negative order constraint can reduce the total bullwhip effect.

7. Further Scenario Analysis

The influence of lead time in a CLSC has been studied extensively in the literature. Shortening manufacturing lead time (Ponte et al. 2020; Zhou et al. 2006) and consumption lead time (Zhou et al. 2017) could benefit both bullwhip and inventory variance. Shortening the remanufacturing lead time could improve the system's dynamic performance (Cannella et al. 2016; Zhou et al. 2017) but it might also have a negative impact on inventory dynamics (Hosoda & Disney 2018). In general, the consumption lead time and manufacturing lead time are always longer than the remanufacturing lead time (Cannella et al. 2016; Ponte et al. 2019; Tang & Naim 2004). However, in real-world cases, the remanufacturing lead time may be longer than the manufacturing lead time. Since products are not designed to facilitate disassembly in the remanufacturing process (Sundin & Bras 2005), it could take longer to conduct a quality test, disassemble the cores and remanufacture products. Thus, in this section, we discuss the results of a scenario analysis to explore the relationship between lead times and system dynamics with a step input demand and we verify whether the results are consistent in these scenarios. The numerical results are showed in Appendix D, Appendix E and Appendix F.

7.1 Normal system (τ_{mj}>τ_{rj})

In the normal system, we assume τ_{mj}>τ_{rj} and τ_{mj}=16, which represent most of real-world cases. The values of rest parameters are the same. The order variance and inventory variance were measured using step input demand, while $\tau_{rj}$is set as 2, 4 or 8. The results are still valid in the normal system with a step input demand after changing the values of τ_{rj} and setting τ_{mj} to 16, i.e. more recovery options do not indicate better performance or help reduce the bullwhip effect and inventory variance. The decrease in the bullwhip effect could be greatest when the retailer repairs all the returned products in all the scenarios. If there is more than one recovery option in the CLSC, operating the recovery option process at the supply chain members closer to the end-customer and with a higher return rate could help increase the dynamic performance. We also found that when the recovery option lead time increases, the order and inventory variance also increase, simultaneously. Therefore, a longer recovery option lead time results in a worse overall CLSC performance in comparison to a shorter recovery option lead time.

7.2 Fast system (τ_{mj}<τ_{rj})

The fast system refers to a CLSC in which the manufacturing lead time is shorter than the remanufacturing lead time. For instance, in the automotive industry, the remanufacturing process could be complex and less predictable than in traditional manufacturing since disassembly could cause damage to the cores and high levels of testing are required (Giutini & Gaudette 2003; Pawlik et al. 2013). Thus, remanufacturing could need a longer lead time than manufacturing to achieve high-quality products. Unlike a normal system, we fixed τ_{rj} at 16 but changed the value of $\tau_{mj}$to 2, 4 or 8 to ensure that the manufacturing lead time is always shorter than the remanufacturing lead time. Again, we remained the values of the rest parameters.

There are several essential results. First, like the normal system, the fast system gradually amplifies the bullwhip effect and inventory variance along supply chain as the distance from the end-customer increases. We found that the fast system (τ_{mj}<τ_{rj}) outperforms the normal system (τ_{mj}>τ_{rj}) in terms of the sum of the bullwhip effect and inventory variance for all τ_{mj} and τ_{rj} settings. Moreover, the most significant finding was that the previous results no longer hold in the fast system for a step input demand. Thus, repairing all returned products at the retailer does not necessarily produce a better CLSC performance. The results indicate that the number of recovery options that produces the minimal bullwhip effect among all the scenarios is still one. However, the recovery option should set a higher return rate and be located farther from the end-customer; that is, at the supplier. In the scenarios with one, two or three recovery options, the location of the recovery options that can diminish inventory variance changes with τ_{mj}. As τ_{mj} increases from 2 to 8, the location of the recovery options slowly changes from the location farthest from the end-customer to the one closest to the customer. The higher return rate also varies from the most distant supply chain member to the closest member. Among all the scenarios, the minimal bullwhip effect and inventory variances occur at τ_{mj}= 2 with one recovery option located at the supplier. With two and three recovery options, locating them in the upstream supply chain and at a supplier results in a higher return rate; this can result in a greater decrease in the inventory variance but a higher bullwhip effect than in a traditional supply chain. This may cause uncertainties in the system, such as resource allocation (Zhou et al. 2017). Nevertheless, as τ_{mj} increases, the bullwhip effect gradually decreases than in a traditional supply chain.

7.3 End-of-life system (τ_c)

We define the end-of-life system as a CLSC system in which the returned products have different consumption times. In real-world cases, products, such as food, could be called back because of quality issues. The consumption lead time of such products is very short because when problems are revealed, the products will be called back immediately. Some products are recycled at the end of their lifecycle, and they have a very long consumption lead time. To determine the impact of the length of consumption lead time for our topic, we assigned consumption lead times of 2, 4, 8, 16, 32, 64 or 128 and kept the other settings the same.

The results demonstrate that our linear findings still hold in this system. The bullwhip effect is decreased more in cases when the recovery option is closer to the end-customer and the return rate is higher. Additionally, the optimal number of product recovery options is one, and the location is at the retailer. In comparison to the normal system, the overall bullwhip effect and inventory variance are smaller in the end-of-life system. Like the normal system, in the end-of-life system the bullwhip effect and inventory variance increase as the value of the variable increases (τ_c and τ_{mj}). We also found that the longer the customers keep the products, the worse the performance. Both order variance and inventory variance can be increased significantly due to a long consumption lead time.

7.4. Industrial case analysis

In this section, based on Goltsos et al. (2019), we applied real industrial data from Qioptiq Company to verify the effectiveness and functionality of our model. Qioptiq is a global defence and aerospace integrated logistics supplier (managing flows and repairs), operating within various commercial and state military supply chains (SCs) globally. The company deals with 15 electronic night vision, thermal (IR) and image enhancing visual aid equipment for the dismounted soldier (head-mounted, weapon-mounted, and hand held). The company provided a partially redacted raw output of their information system (15 SKUs) in the form of transactional data. The author refers to Goltsos et al. (2019) for further details of company supply chain and data. Basically, we select 3 data set contains 11 years, 7 years and 9 years demand data. Demand is intermittent in nature, that is, demand (returns) occurring periods are interspersed by a varying number of periods with no demand at all. We follow company's inventory control policy by applying the order-up-to (OUT) policy with exponential smoothing (setting$\tau_{wj} = \tau_{ij} = 1$) to verify our results and findings. All results are shown in Table 10.

It can be concluded that the effectiveness of the theoretical model and findings can be verified in industrial data environment. For three sets of industrial data, compared with the traditional supply chain without any recovery options, introducing recovery options could significantly reduce the bullwhip and inventory variance. For instance, the total bullwhip effect decreases from 6.917 to 5.593 after implementing the recovery option at the retailer for data set one. For the CLSC with two recovery options, it is evident to see that having recovery options at the locations closer to the end customer, especially when retailer has a higher return rate, will decrease total bullwhip (3.406) and inventory variance (27.42) for data set two (Table 10). However, locating the recovery options with a higher return rate at upstream will produce worse dynamic performance. To be noted, in one- and two recovery options, the values of their total lowest bullwhip effect are no much difference, which is observed in linear setting as well.

If the CLSCs has three recovery options, similar findings can be observed. Traditional supply chain always produces the highest bullwhip effect and inventory variance comparing the CLSCs. Also, upstream members with higher return rate always generate higher bullwhip effect and inventory variance than downstream members. For example, in Table 10, the total bullwhip and inventory variance is 3.812 and 25.42, respectively, when $\alpha_1 = 0.1$, $\alpha_2 = 0.2$ and $\alpha_3 = 0.3$. However, if the return rate of retailer increases to 0.3, while decreasing the return rate of supplier to 0.2, a reduction of overall bullwhip (3.696) and inventory variance (23.81) can be observed.

		Quantity and location of recovery processes in closed-loop supply chain															
		Traditional	One recovery process			Two recovery processes						Three recovery processes					
	Location		R	M	S	R & M		R & S		M & S		R, M & S					
	Return rate (α_i)	$\alpha_1 = \alpha_2 = \alpha_3 = 0$	$\alpha_1 = 0.6$	$\alpha_2 = 0.6$	$\alpha_3 = 0.6$	$\alpha_1=0.2$ $\alpha_2=0.4$	$\alpha_1=0.4$ $\alpha_2=0.2$	$\alpha_1=0.2$ $\alpha_3= 0.4$	$\alpha_1=0.4$ $\alpha_3= 0.2$	$\alpha_2=0.2$ $\alpha_3= 0.4$	$\alpha_2=0.4$ $\alpha_3= 0.2$	$\alpha_1=0.3$ $\alpha_2=0.2$ $\alpha_3= 0.1$	$\alpha_1=0.1$ $\alpha_2=0.2$ $\alpha_3= 0.3$	$\alpha_1=0.2$ $\alpha_2=0.1$ $\alpha_3= 0.3$	$\alpha_1=0.1$ $\alpha_2=0.3$ $\alpha_3= 0.2$	$\alpha_1=0.2$ $\alpha_2=0.3$ $\alpha_3= 0.1$	$\alpha_1=0.3$ $\alpha_2=0.1$ $\alpha_3= 0.2$
Data Set One	Total BW	6.917	5.593	5.866	6.274	5.654	5.524	5.959	5.707	6.056	5.896	5.614	5.892	5.841	5.808	5.673	5.703
	Total VarI	41.27	32.54	38.14	44.92	35.91	33.94	40.48	36.326	40.62	40.35	35.97	40.34	39.29	39.20	36.98	37.15
Data Set Two	Total BW	4.276	3.44	3.626	3.875	3.489	3.406	3.676	3.516	3.742	3.642	3.464	3.638	3.604	3.587	3.501	3.517
	Total VarI	33.52	26.37	30.47	36.01	28.85	27.42	32.72	29.53	33.251	32.45	29.14	32.54	31.79	31.62	29.87	30.14
Data Set Three	Total BW	4.477	3.634	3.795	4.054	3.662	3.583	3.858	3.701	3.915	3.812	3.638	3.812	3.782	3.759	3.673	3.696
	Total VarI	26.4	21.75	24.51	27.87	23.27	22.25	25.56	23.47	26.61	25.45	23.20	25.42	24.9	24.84	23.72	23.81

Table 10. Bullwhip effect and inventory variance generated from industrial data

8. Discussion, summary and conclusion

In this section, we summarised all main findings and compared them with previous literature shown in Table 11. In addition, we provide managerial implications regarding our main findings and conclude our contributions and future directions.

	Main findings	Prior literature
One recovery option	• System dynamics performance can be improved if the recovery options is located to the closer to the end-customer.	
	• Adoption of recovery option at retailer not only improves the dynamic performance of retailer but also the entire upstream members	
	• Order variance decreases as the increase of demand frequency, thus no bullwhip will be generated.	Observed in the traditional supply chains (Towill et al. 2007) and CLSCs (Lin et al. 2022)
Two recovery options	• To reduce order and inventory variance in CLSC, at least one of the recovery options should locate closer to the end-customer	
	• CLSCs with a higher return rate generates the lower bullwhip effect and inventory variance	Consistent with Cannella et al. (2016), Dev et al. (2017), Pati & Kumar (2010), Tang & Naim (2004); Zhou & Disney (2006); Ponte et al. (2020) Supported industries, HP CLSCs (Zhou et al. 2017)
	• An increased demand frequency leads to decreased bullwhip effect and inventory variance	Consistent with Ponte et al. (2020) and Lin et al. (2022)
Three recovery options	• Bullwhip effect increases from the downstream to the upstream members at low demand frequency	Consistent with Dejonckheere et al. (2004) in a traditional supply chain system
	• For an individual echelon, bullwhip effect decrease as the demand frequency increases.	Different from the u-shaped relation in a traditional supply chain (Dejonckheere et al. 2002) and a single hybrid CLSC (Lin et al. 2022).
Non-negative constraint	• A non-negative order constraint reduce the bullwhip effect but amplify the inventory variance	Consistent in the traditional single echelon, serial and divergent supply chain literature (Chatfield & Pritchard 2013; Dominguez et al. 2015; Lin & Naim 2019; Lin et al. 2017).

Lead times	• A longer recovery option lead time results in a worse overall CLSC performance	Consistent with Cannella et al. (2016), Tang & Naim (2004), Zhou & Disney (2006); Zhou et al. (2017), Ponte et al. (2020)
	• Fast system ($\tau_{mj} < \tau_{rj}$) outperforms the normal system ($\tau_{mj} > \tau_{rj}$) in terms of the sum of the bullwhip effect and inventory variance	Consistent with Hosoda et al. (2015) and Hosoda & Disney (2018) found that shorten remanufacturing lead time could worsen inventory dynamics and costs.

Table 11. Summary table of main findings and prior literature

Specifically, for the number of product recovery processes with a step input demand and a sinusoidal demand, the CLSC system with one recovery option delivered the best performance. If the input is sinusoidal demand, the total bullwhip effect and inventory variance decrease as the demand frequency increases. The highest bullwhip effect and inventory occur at a low frequency of 0.1, while the lowest occurs at a high frequency of 1. Thus, the results do not indicate that the more product recovery options, the better its performance will be.

Regarding the location of the product recovery option, the recovery option operated at the retailer with a return rate of 0.6 will produce the minimal amount of bullwhip effect and inventory variance. However, there has no much difference between the minimal bullwhip generated from recovery options located at retailer and manufacturer when retailer has a higher return rate. It can be concluded that the bullwhip effect can be reduced when the product recovery option is located near the end-customer. Moreover, the benefit derived from the downstream members with higher return rates is that could have a reduction on the bullwhip of upstream members.

Overall, our results demonstrate that locations and number of recovery options with different return rates can significantly influence the dynamic performance of CLSCs. All main finding holds for both step input demand and sinusoid demand in different systems. In addition, our findings are consistent with literature regarding the impact of return rate on the dynamics of CLSCs (Cannella et al. 2016; Dev et al. 2017; Tang & Naim 2004; Zhou & Disney 2006; Zhou et al. 2017), which demonstrate that increasing the return rate has a positive impact on CLCS dynamics. The echelons with higher return rates produced a lower bullwhip effect than the echelons that only have forward manufacturing operations. However, a higher return rate may negatively impact the dynamic metrics in CLSCs if information other than customer demand is shared between echelons (Hosoda

& Disney 2018; Ponte et al. 2020). In addition, from an individual echelon perspective in three recovery options condition with a sinusoid demand, our system with POUT policy does not generate a u-shaped relationship between frequency and bullwhip as in traditional supply chain (Dejonckheere et al. 2002) and a single hybrid system (Lin et al. 2022) with OUT policy.

Based on our main findings, we derived the following managerial implications:

1) *For industries with CLSCs adopted*. If the company has only one recovery option, the return rate of this recovery option needs to be increased as high as possible to reduce the bullwhip effect and the performance of the whole system. For example, the clothing industry with their own remanufacturing process (Dissanayake & Sinha 2015), should consider to enhance the return rate of their recovery option process. If the company has implemented two recovery options, e.g. the bottled water industry, see Papen & Amin (2019), and then the company should increase the return rate of the recovery option that is closer to the end customer (e.g. retailer) to improve dynamic performance. For those companies with three recovery options, managers should make the return rate be the highest at the most downstream and lowest at the most upstream to reduce the bullwhip effect and inventory variance. For example, for printer industries (Zhou et al. 2017), they should focus on how to increase the return rate of repairing at retailer and reduce the return rate of refining at supplier, thus to reduce the bullwhip effect.
2) *For industries with intentions to adopt CLSCs*. Among all possibilities of location and number of recovery options, one recovery option located at the nearest location to the end customer results lower bullwhip and inventory variance. Also, high return rate can further benefit from improved system dynamics performance. Since the bullwhip effect has no much difference in one recovery option and two recovery options under certain conditions, if the company plans to invest in two recovery options, then it is better to locate them at downstream, where are closer to the end customer. If the company has sufficient funds to invest in three recovery options, it is significant to ensure that the return rate at the most downstream location is the highest and at the most upstream location is the lowest in order to minimize the bullwhip effect. For example, the clothing industry previously used the third-party company with recovery option of repairing, remanufacturing and recycling (Masoudipour et al. 2017), and intent to invest their own recovery options. So the company should pay attention to return rate at the

most downstream location and at the most upstream location in order to optimize its system performance.

3) *The impact of return rate.* The high return rate not only improve dynamic performance of the specific echelon itself, but also the upstream members of CLSCs. Thus, for those industries/companies with multiple/single recovery option(s), managers should encourage high return rate at the downstream echelon via, e.g. various trade-in schemes with end customers and collaboration with third-party collectors, to improve the system dynamics performance of their entire CLSCs.
4) *The impact of lead times*. Overall, manufacturing and recovery option lead times reduction can significantly improve system dynamics performance of the CLSCs. However, company need to carefully think about their lead time characterises of CLSCs, i.e. relations between recovery option and manufacturing lead times. Industries/companies' CLSCs systems characterised by fast systems (recovery option lead times is longer than manufacturing lead times, e.g. automotive engine remanufacturing) *outperform* the normal system (recovery option lead times is shorter than manufacturing lead times, e.g. automotive remanufacturing industry, e.g. HP printer remanufacturing) regarding bullwhip and inventory variance. It should be noted that for fast system, if the recovery option lead times is much longer than manufacturing lead times, CLSCs may generate very high bullwhip (even higher than open loop supply chains), thus company may prioritize to the bullwhip reduction strategies such as improve forecasting and inventory feedback control, or outsourcing their remanufacturing to avoid high supply chain dynamics cost

To conclude, we developed a three-echelon CLSC to investigate the different number of product recovery options at different locations with assigned return rates in CLSCs. Our study contributes to both supply chain dynamics theory and practice. Theoretically, this is the first work to strategically examine the impact of number of locations of recovery options on bullwhip and inventory variance, extending the supply chain dynamics literature that assume recovery options are located in all echelons of CLSCs or without specifying particular recovery option. The results are robust verified by nonlinear environment and industrial data. Step and sinusoid demand provides rich and robust insights of order and inventory dynamic behavior. The dynamics of different return rate are assessed, offering in-depth understanding of interaction effect between return rate and recovery options on dynamic performance. Furthermore, the sensitivity of manufacturing and remanufacturing lead times is analysed to understand the impact of different lead time scenarios on system dynamics performance.

Practically, industries who already adopted CLSCs can benefit from our study. We offer in-deep understanding of the impact of CLSCs system structure (inventory feedback, manufacturing and recovery option delays and nonlinearities) with different number and locations of recovery options on bullwhip and inventory variance, thus guide companies to re-think their CLSCs structure and/or control policies to minimize system dynamics cost. For example, given the great impact of locating the recovery option on bullwhip and inventory variance at upstream supplier site, outsourcing such recovery option to third party remanufacturer may become a good alternative to reduce total cost. Also, those industries with CLSCs adoption intentions can strategically design their recovery options based our study findings. Static recovery option investment and dynamic cost can be synthesized together to minimize the total cost. This is particular the case for those high-volume, low-cost product (e.g. bottle reuse and recycling) where supply chain dynamics cost plays an important role in influencing total cost.

Several future research opportunities are provided based on this paper. First, the CLSC setting could be tested with a pull system commonly found in practice. Second, the system dynamics could be investigated with other options that consider for the remanufactured work-in-process inventory when computing the reorder point (e.g., Hosoda & Disney 2018; Ponte et al. 2020). Other nonlinearity situations could be considered, such as capacity constraints. Also, stochastic properties, such as return time variability or uncertainty regarding the volume of the returns (e.g. Framinan 2022), and return patterns of sequential products could be further studied. Finally, a cost function can be developed and relevant optimisation studies can be considered in terms of the bullwhip effect and inventory variance.

References

Abualfaraa, W, Salonitis, K, Al-Ashaab, A & Ala'raj, M 2020, 'Lean-green manufacturing practices and their link with sustainability: a critical review', *Sustainability*, vol. 12, no. 3, pp. 1-21.

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*, vol. 135, no. 2, pp. 917–928 .

Ahmadi, S & Amin SH 2019, 'An intergrated chance constrained stocastic model for mobile phone closed-loop supply chain netweork with supplier selection', *Journal of Cleaner Production,* vol. 226, pp. 988-1003.

Balde, CP, Forti, V, Gray, V, Kuehr, R & Stegmann, P 2017, 'The global e-waste monitor-2017', *United Nations University (UNU) International Telecommunication Union (ITU) & International Solid Waste Association (ISWA)*, Bonn/Geneva/Vienna.

Barlas, Y 1996, 'Formal aspects of model validity and validation in system dynamics', *System Dynamics Review*, vol. 12, no. 3, pp. 183-210.

Cachon, GP, Randall, T & Schmidt, GM 2007, 'In search of the bullwhip effect, *Manufacturing & Service Operations Management,* vol. 9, no. 4, pp. 457–479.

Cannella, S, Bruccoleri, M & Framinan, JM 2016, 'Closed-loop supply chains: what reverse logistics factors influence performance?', *International Journal of Production Economics,* vol.175, pp. 35-49.

Cannella, S, Ponte, B, Dominguez, R & Framinan JM 2021, 'Proportional order-up-to policies for closed-loop supply chains: the dynamic effects of inventory controllers', *International Journal of Production Research,* vol. 59, no. 11, pp. 3323-3337.

Chatfield, DC 2013, 'Underestimating the bullwhip effect: a simulation study of the decomposability assumption', *International Journal of Production Research,* vol. 51, no. 1, pp. 230-244.

Chatfield, DC & Pritchard, AM 2013, 'Returns and the bullwhip effect', *Transportation Research Part E: Logistics and Transportation Review*, vol. 49, no. 1, pp. 159-175.

Chen, Y & Chen, F 2019, 'On the competition between two modes of product recovery: remanufacturing and refurbishing', *Production and Operations Management*, vol. 28, no. 12, pp. 2983-3001.

Dejonckheere, J, Disney, SM, Lambrecht, MR & Towill, DR 2002, 'Transfer function analysis of forecasting induced bullwhip in supply chains', *International Journal of Production Economics*, vol. 78, no. 2, pp. 133-144.

Dejonckheere, J, Disney, SM, Lambrecht, MR & Towill, DR 2004, 'The impact of information enrichment on the bullwhip effect in supply chains: A control engineering perspective', *European Journal of Operational Research*, vol. 153, no. 3, pp 727-750.

Delavar, H, Gilani, H &Sahebi H 2022, 'A system dynamics approach to measure the effect of information sharing on manufacturing/remanufacturing systems' performance', *International Journal of Computer Integrated Manufacturing*, vol. 35, no. 8, pp. 859-872.

Del Giudice, M, Chierici, R, Mazzucchelli, A & Fiano, F 2020, 'Supply chain management in the era of circular economy: the moderating effect of big data', *The International Journal of Logistics Management*, vol. 32, no. 2, pp. 337-356.

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

Disney, SM, Towill, DR & Warbuton, R 2006, 'On the equivalence of control theoretic, differential, difference equation approaches to modeling supply chains', *International Journal of Production Economics*, vol. 101, pp. 194-208.

Disney, SM & Lambrecht MR 2008, 'On replenishment rules, forecasting, and the bullwhip effect in supply chains, *Foundations and Trends in Technology, Information and Operations Management*, Vol. 2, No. 1, pp1–80.

Dissanayake, G & Sinha, P 2015, 'An examination of the product development process for fashion remanufacturing', *Resources, Conservation and Recycling*, vol. 104, pp. 94-102.

Dominguez, R, Cannella, S, Barbosa-Póvoa, AP & Framinan, JM 2018, 'OVAP: A strategy to implement partial information sharing among supply chain retailers, *Transportation Research Part E: Logistics and Transportation Review*, vol. 110, pp. 122-136.

Dominguez, R, Cannella, S & Framinan, JM 2015, 'On returns and network configuration in supply chain dynamics', *Transportation Research Part E: Logistics and Transportation*, vol. 73, pp. 152-167.

Dominguez, R, Cannella, S & Framinan, JM 2021, 'Remanufacturing configuration in complex supply chains', *Omega*, vol. 101, 102268.

Dominguez, R, Cannella, S, Ponte, B & Framinan, JM 2020, 'On the dynamics of closed-loop supply chains under remanufacturing lead time variability', *Omega*, vol. 97, 102106.

Dominguez, R, Ponte, B, Cannella, S & Framinan, JM 2019, 'On the dynamics of closed-loop supply chains with capacity constraints', *Computers & Industrial Engineering*, vol. 128, pp. 91–103.

Fleischmann, M, Bloemhof-Ruwaard, JM & Dekker, R 1997, 'Quantitative models for reverse logistics: A review', *European Journal of Operational Research*, vol. 103, no. 1, pp.1-17.

Forrester, JW 1961, *Industrial dynamics*, MIT Press, Cambridge.

Framinan, JM 2022, *Modelling Supply Chain Dynamics*, Springer Cham.

Franke, C, Basdere, B & Ciupek, M 2006, 'Remanufacturing of mobile phones- capacity, program and facility adaptation planning', *Omega*, vol. 34, no.6, pp. 562-570.

Giri, BC & Glock, CH 2022, 'The bullwhip effect in a manufacturing/remanufacturing supply chain under a price-induced non-standard ARMA (1, 1) demand process', *European Journal of Operational Research*, vol. 301, no. 3, pp. 458-472.

Giutini, R & Gaudette, K 2003, 'Remanufacturing: The next great opportunity for boosting US productivity', *Business Horizons*, vol. 46, no. 6, pp. 41-48.

Goltsos, TE, Ponte, B, Wang S, Liu, Y, Naim, MM & Syntetos, AA 2019, 'The boomerang returns? Accounting for the impact of uncertainties on the dynamics of remanufacturing systems', *International Journal of Production Research*, vol. 57, no. 23, pp. 7361-7394.

Guide, VDR & Van Wassenhove, LN 2009, 'OR FORUM- The evolution of closed-loop supply chain research', *Operations Research,* vol. 57, no. 1, pp. 10-18.

Hong, X, Xu, L, Du, P & Wang W 2015, 'Joint advertising pricing and collection decisions in a closed-loop supply chain, *International Journal of Production Economics,* vol. 167, pp. 12-22.

Hosoda, T & Disney, SM 2018, 'A unified theory of the dynamics of closed-loop supply chains', *European Journal of Operational Research,* vol. 269, no. 1, 313–326.

Hosoda, T, Disney, SM & Gavirneni, S 2015, 'The impact of information sharing, random yield, correlation, and lead times in closed loop supply chains', *European Journal of Operational Research,* vol. 246, no.3, pp. 827–836.

Hosoda, T, Disney, SM & Zhou, L 2021, 'The yield rate paradox in closed-loop supply chains', *International Journal of Production Economics,* vol. 239, 108187.

Jakšic, M & Rusjan, B 2008, 'The effect of replenishment policies on the bullwhip effect: A transfer function approach' *European Journal of Operational Research,* vol. 184, no. 3, pp. 946–961.

Huang, S, Lu, H, Lin, J & Ponte, B 2023, 'On the dynamics of return collection in closed-loop supply chains', *International Journal of Production Research.*

Javid, GN, Ramez, K & Ehsan S 2019, 'A robust fuzzy mathematical programming model for the closed loop supply chain network design and a whale optimization solution algorithm, *Expert Systems with* Applications, vol. 116, pp. 454-471.

Lee, HL, Padmanabhan, V & Whang, SJ 1997, 'Information distortion in a supply chain: The bullwhip effect', *Management Science,* vol. 43, no. 4, pp. 546–558.

Lin, J & Naim, MM 2019, 'Why do nonlinearities matter? The repercussions of linear assumption on the dynamic behaviour of assemble-to-order systems', *International Journal of Production Research*, pp. 6424-6451.

Lin, J, Naim, MM, 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,* vol. 194, pp.135–152.

Lin, J, Spiegler, VLM, & Naim, MM 2018, 'Dynamic analysis and design of a semiconductor supply chain: a control engineering approach', *International Journal of Production Research,* vol. 56, no. 13, pp. 4585-4611.

Lin, J, Zhou, L, Spiegler, VLM, Naim, MM & Syntetos, AA 2022, 'Push or Pull? The impact of ordering policy choice on the dynamics of a hybrid closed-loop supply chain', *European Journal of Operational Research,* vol. 300, no. 1, pp. 282-295.

Liu, B, Chen, D, Zhou, W, Nasr, N, Wang, T, Hu, S & Zhu, B 2018, 'The effect of remanufacturing and direct reuse on resource productivity of China's automotive production', *Journal of Cleaner Production*, vol.194, pp. 309-317.

Luo, R, Zhou, L, Song, Y & Fan, T 2022, 'Evaluating the impact of carbon tax policy on manufacturing and remanufacturing decisions in a closed-loop supply chain', *International Journal of Production Economics*, vol. 245, 108408.

Masoudipour, E, Amirian, H & Sahraeian, R 2017, 'A novel closed-loop supply chain based on the quality of returned products', *Journal of Cleaner* Production, vol. 151, pp. 344-355.

Matsui, K 2021, 'Optimal timing of acquisition price announcement for used products in a dual recycling channel reverse supply chain', *European Journal of Operational Research*, vol. 300, no. 2, pp. 615-632.

Naim, MM 2006, 'The impact of the net present value on the assessment of the dynamic performance of e-commerce enabled supply chains', *International Journal of Production Economics*, vol. 104, no. 2, pp. 382-393.

Oakdene Hollins 2004, ‘Remanufacturing in the UK: a significant contributor to sustainable development?’, *Resource Recovery Forum,* Pagefast Limited, UK.

Organization for Economic Cooperation and Development (OECD) 2022, *Global Plastics Outlook: Policy Scenarios to 2060,* OECD Publishing, Paris.

Papen, P & Amin, SH 2019, ‘Network configuration of a bottled water closed-loop supply chain with green supplier selection’, *Journal of Remanufacturing,* vol. 9, pp. 109-127.

Pastore, E, Alfieri, A, Zotteri, G & Boylan, JE 2020, ‘The impact of demand parameter uncertainty on the bullwhip effect’, *European Journal of Operational Research,* vol. 283, no. 1, pp. 94-107.

Pati, RK, Vrat, P, & Kumar, P, 2010, ‘Quantifying bullwhip effect in a closed loop supply chain’, *Opsearch,* vol. 47, no. 4, pp. 231–53.

Pawlik, E, Ijomah, W & Corney, J 2013, ‘Current state and future perspective research on lean remanufacturing- focusing on the automotive industry’, *IFIP Advances in Information and Communication Technology,* vol. 397, pp. 429-436.

Pickin, J, Wardle, C, O’Farrell, K, Nyunt, P & Donovan S 2020, *National Waste Report 2020,* Blue Environment, AU.

Ponte, B, Cannella, S, Dominguez, R, Naim, MM & Syntetos, AA 2021, ‘Quality grading of returns and the dynamics of remanufacturing’, *International Journal of Production Economics*, vol. 236, 108129.

Ponte, B, Cannella, S, Dominguez, R, Cannella, S & Framinan, JM 2022, ‘The implications of batching in the bullwhip effect and customer service of closed-loop supply chains’, vol. 244, 108379.

Ponte, B, Framinan, JM, Cannella, S & Fominguez, R 2020, ‘Quantifying the bullwhip effect in closed-loop supply chains: the interplay of information transparencies, return rates, and lead times’, *International Journal of Production Economics*, vol. 230, 107798.

Ponte, B, Naim, MM & Syntetos, AA 2019, ‘The value of regulating returns for enhancing the dynamic behaviour of hybrid manufacturing-remanufacturing systems’, *European Journal of Operational Research,* vol. 278, no. 2, pp. 629–645.

Ponte, B, Puche, J, Rosillo, R, & de la Fuente, D 2020, "The effects of quantity discounts on supply chain performance: Looking through the Bullwhip lens", *Transportation Research Part E: Logistics and Transportation Review*, vol. 143, 102094.

Sarkis, J & Rasheed, A 1995, 'Greening the manufacturing function', *Business Horizons*, vol. 38, no. 5, pp. 17-27.

Sargent, RG 2013, 'Verification and validation of simulation models', *Journal of Simulation*, vol. 7, no. 1, pp. 12-24.

Sarkar, B, Ullah, M & Kim, N 2017, 'Environmental and economic assessment of closed-loop supply chain with remanufacturing and returnable transport items', *Computers & Industrial Engineering*, vol. 111, pp. 148-163.

Savaskan, RC, Bhattacharya, S & Van Wassenhove, LN 2004, 'Closed-loop supply chain models with product remanufacturing', *Management Science*, vol. 50, no. 2, pp. 239-252.

Soleimani, H, Seyyed-Esfahani, M & Shirazi, MA 2016, 'A new multi-criteria scenario-based solution approach for stochastic forward/reverse supply chain network design' *Annals of Operations Research*, vol. 242, no. 2, pp. 399-421.

Stock, JR 1992, *Reverse logistics*, Council of logistics Management, Oak Brook, Illinois.

Sun, Q, Chen, H, Long, R, Li, Q & Huang, H 2022, 'Comparative evaluation for recycling waste power batteries with different collection modes based on Stackelberg game', *Journal of Environmental Management*, vol. 312, no.15, 114892**.**

Sundin, E & Bras, B 2005, 'Making functional sales environmentally and economically beneficial through product remanufacturing', *Journal of Cleaner Production*, vol. 13, no. 9, pp. 913-925.

Tang, O & Naim, MM 2004, 'The impact of information transparency on the dynamic behaviour of a hybrid manufacturing/remanufacturing system', *International Journal of Production Research*, vol. 42, no. 19, pp. 4135–4152.

Tombido, L, Louw, L, van Eeden, J & Zailani, S 2022, "A System Dynamics Model for the Impact of Capacity Limits on the Bullwhip Effect (BWE) in a Closed-Loop System with Remanufacturing", *Journal of Remanufacturing*, vol. 12, no. 1, pp. 1–45.

Towill, DR & Del Vecchio, A 1994, 'The application of filter theory to the study of supply chain dynamics', *Production Planning & Control*, vol.5, no.1, pp. 82-96.

Towill, DR, Zhou, L & Disney, SM 2007, 'Reducing the bullwhip effect: Looking through the appropriate lens', *International Journal of Production Economics*, vol. 108, no. 1–2, pp.444–453.

Udenio, M, Vatamidou, E & Fransoo, JC 2022, 'Exponential smoothing forecasts: Taming the bullwhip effect when demand is seasonal', *International Journal of Production Research*, https://doi.org/10.1080/00207543.2022.2048114.

Udenio, M, Vatamidou, E, Fransoo, JC & Dellaert, N 2017, 'Behavioral causes of the bullwhip effect: An analysis using linear control theory', *IISE Transactions*, vol. 49, no. 10, pp.980–1000.

Van der Laan, EA, Salomon, M, Dekker, R & Van Wassenhove, LN 1999, 'Inventory control in hybrid systems with remanufacturing', *Management Science*, vol. 45, no. 5, pp. 733-747.

Van der Laan, EA & Teunter, RH 2006, 'Simple heuristics for push and pull remanufacturing policies', *European Journal of Operational Research*, vol. 175, no. 2, pp. 1084–1102.

Wan, N & Hong, D 2019, 'The impacts of subsidy policies and transfer pricing policies on the closed-loop supply chain with dual collect channels', vol. 224, pp. 881-891.

Wang, X & Disney, SM 2016, 'The bullwhip effect: Progress, trends and directions', *European Journal of Operational Research*, vol. 250, no. 3, pp. 691–701.

Wang, X, Disney, SM & Ponte, B 2023, 'On the stationary stochastic response of an order-constrained inventory system', *European Journal of Operational Research*, vol. 304, no. 2, pp. 543-557.

Wang, X, Disney, SM & Wang, J 2014, 'Exploring the oscillatory dynamics of a forbiddent returns inventory system', *International Journal of Production Economics*, vol. 147, pp. 3-12.

Wang, Z & Wu, Q 2021, ‘Carbon emission reduction and product collection decision in the closed-loop supply chain with cap-and-trade regulation’, *International Journal of Production Research,* vol. 59, no. 14, pp. 4359-4383.

Wei, J, Chen, W & Liu, G 2021, ‘How manufacturer’s integration strategies affect closed-loop supply chain performance’, *International Journal of Production Research,* vol. 59, no. 14, pp. 4287-4305.

Wei, S, Tang, O & Sundin, E 2015, ‘Core (product) acquisition management for remanufacturing: a review’, *Journal of Remanufacturing,* vol. 5, no. 4.

Xu, Z, Pokharel, S, Elomri, A & Mutlu, F 2017, ‘Emission policies and their analysis for the design of hybrid and dedicated closed-loop supply chains’, *Journal of Cleaner Production,* vol. 142, pp. 4152-4168.

Yang, Y, Lin, J, Liu, G & Zhou, L 2021, ‘The behavioural causes of bullwhip effect in supply chains: A systematic literature review’, *International Journal of Production Economics,* vol. 236, 108120.

Yin, S, Zhang, N & Li, B 2020, ‘Enhancing the competitiveness of multi-agent cooperation for green manufacturing in China: An empirical study of the measure of green technology innovation capabilities and their influencing factors’, *Sustainable Production and Consumption,* vol. 23, pp. 63-76.

Yong, YS, Lim, YA & Ilankoon, IMSK 2019, ‘An analysis of electronic waste management strategies and recycling operations in Malaysia: Challenges and future prospects’, *Journal of Cleaner Production*, vol. 224, pp. 151-166.

Zhao, J, Wei, J & Li, M 2017, ‘Collecting channel choice and optimal decisions on pricing and collecting in a remanufacturing supply chain, *Journal of Cleaner Production*, vol. 167, pp. 530-544.

Zhang, C, Tian, Y & Han, M 2022, ‘Recycling mode selection and carbon emission reduction decisions for a multi-channel closed-loop supply chain of electric vehicle power batter under cap-and-trade policy’, *Journal of Cleaner Production*, vol. 375, no. 15, 134060.

Zhou, J, Xia, W, Wang, K, Li, H & Zhang, Q 2020, 'Fuzzy bi-objective closed-loop supply chain network design problem with multiple recovery options', *Sustainability*, vol. 12, pp. 6770.

Zhou, L & Disney, SM 2006, 'Bullwhip and inventory variance in a closed loop supply chain', *OR Spectrum*, vol. 28, no. 1, pp. 127–149.

Zhou, L, Naim, MM & Disney, SM 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*, vol. 183, pp. 487–502.

Zhou, L, Naim, MM, Tang, O & Towill, DR 2006, 'Dynamic performance of a hybrid inventory system with a Kanban policy in product recovery option', *Omega*, vol. 34, no. 6, pp. 585–598.