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Simulating Organizational Learning from Returns: Simulation of Closed Loop Supply Chains in Military Cases

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ABSTRACT

Advances in new technologies and the management of complex supply networks have allowed firms to make their supply chains more flexible, responsive, and efficient. Organizational learning, improved IT capabilities, and new manufacturing technologies are among the drivers of these supply chain improvements. This study investigates the effectiveness of organizational learning in the context of a Closed-Loop Supply Chain (CLSC). We apply the Monte-Carlo simulation methodology to a case of military CLSC involving line-replaceable units (LRUs). Priority is put on minimizing downtime in the equipment caused by LRU failures. Additionally, we consider costs and the environmental footprint. We incorporate organizational learning into the simulation in two ways. Namely, improved failure rates and shorter lead times. This study presents a set of quantitative assessments on the effectiveness of several organizational learning interventions in a military CLSC. The results indicate that learning leading to product improvement has the largest impact on overall inventory cost reduction. This study contributes to the current research on CLSC value creation by quantifying the concrete implications of specific interventions using realistic data in a military CLSC. In addition, this study contributes to the growing literature on CLSC value creation in general, and in CLSC informational value research more specifically. However, this study focuses on a specific intervention, representing only a few ways in which value can be created in a CLSC. By providing managers with quantitative results regarding CLSC interventions, this research can aid managers in making better decisions regarding CLSC investments.

Keywords: *closed loop supply chain, informational value, monte-carlo simulation, organizational learning, product returns*

1. INTRODUCTION

Closed-Loop Supply Chain (CLSC) management research has been recently garnering increasing attention from many scholars (Guan *et al*., 2020; Peng *et al*., 2020; Mohammed *et al*., 2017; Asim *et al*., 2019). The main goal of a CLSC is not cost reduction but rather the creation of more revenue opportunities (Guide and Van Wassenhove, 2009). Indeed, more recently scholars have argued that CLSC value creation goes beyond direct and short-term revenue generation. Instead, four types of values that firms can generate long-term from CLSC activities have been identified by scholars (Krikke *et al*., 2013; Koppius *et al*., 2014; Schenkel *et al*., 2015): economic value, customer value, environmental value, and informational value.

Information, as a fundamental organizational resource, plays a crucial role in enabling firms to address challenges and generate value (Pellathy *et al*., 2019). Likewise, CLSC informational value can serve as a catalyst for further value creation (Ritola *et al*., 2020). However, what truly sets CLSC informational value apart from external sources of information is that it always sheds light on the specific processes, products, customers, and other organizational resources of the specific firm dealing with their returns and can be thus seen as a source of competitive advantage in dynamic environments (Ritola *et al*., 2022).

More research is required on informational value and its impact on firm performance (Shekarian, 2020). Recent technological developments, often referred to as industry 4.0, have become important in operations management and supply chain management (Sordan, *et al* 2021: Soledispa-Cañarte, *et al*. 2023). Machine learning and data analytics, for instance, have been widely studied and found beneficial for demand forecasting in a traditional supply chain (Aamer, *et al*. 2021). Moreover, much of the existing CLSC literature has focused on IT factors of product return information (Ritola *et al*., 2020). While existing research has focused on exploring the potential benefits of learning from returns, a quantitative assessment of its efficacy along with emerging technologies is missing. At the same time, more research is required on the connection between spare parts inventory management and reverse logistics (Zhang *et al*., 2021). Moreover, the informational aspects of spare parts inventory management, an important part of supply chains (Al-Momani *et al*., 2020) in general and crucial for military supply chains specifically (Zeimpekis *et al*., 2015; Yoho *et al*., 2013), has garnered relatively little attention (Topana *et al*., 2019).

This study brings together the CLSC value creation research stream along with spare parts inventory management with the overall aim of understanding the value of organizational learning in a military CLSC. We undertake a quantitative case study in a single organization, using two exemplary cases of returns to simulate the effectiveness of learning on costs, service levels, and environmental footprint.

This study sheds light on the expected effects and efficacy of specific and novel interventions opened by new developments in CLSC management value creation along with emerging supply chain 4.0 technologies. More specifically, the study contributes to scholarly literature by quantitively measuring the value of these interventions using a case study with real operational data. Managers dealing with decisions to increase their supply chain efficiency can use the results of this study to make better-informed decisions regarding which interventions might be optimal to undertake in their firms.

2. LITERATURE

CLSC management can be defined as "*the design, control, and operation of a system to maximize value creation over the entire life cycle of a product with dynamic recovery of value from different types and volumes of returns over time*" (Guide and Van Wassenhove, 2009, p. 10). A CLSC integrates traditional forward supply chains with a reverse supply chain (Govindan *et al*., 2015). A conceptualization of CLSC flows and functions is depicted in **Figure 1**.

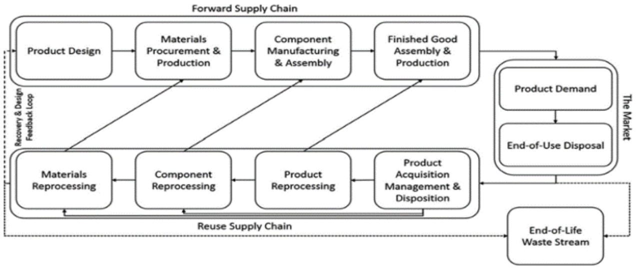

Figure 1 Closed loop supply chain flows and functions (Abbey and Guide, 2017)

CLSC integrates a forward supply chain with a reverse supply chain (**Figure 1**). The underlying goal of a CLSC is not cost reduction but increasing revenue opportunities (Guide and Van Wassenhove 2009) and value creation (Krikke *et al*., 2013; Schenkel *et al*., 2015; Koppius *et al*., 2014). Unlike the forward supply chain, the reverse supply chain deals with uncertain quantities of product returns of different qualities and thus needs to handle different returns in different ways (Rogers and Tibben-Lembke, 1999). A well-run CLSC harbors many benefits (Peng *et al*., 2020), among them is value creation which is enabled by the integration of forward and reverse supply chains (Schenkel *et al*., 2015).

Informational value is a significant part of a CLSC (Röllecke *et al*., 2018; Jayaraman and Luo, 2007). Fundamentally, a CLSC can be considered a dynamic set of processes and routines designed to meet the needs of changing market conditions (Abbey and Guide, 2017), where the informational value of product returns can be used to generate more value (Schenkel *et al*., 2015). This value can be generated by improving processes and products, strategic choices, and by understanding key customers in a better way (Ritola *et al*., 2022). This study focuses on product and process improvement and aims to simulate quantitatively the effects of continuous learning in these areas.

Learning and knowledge management effects have been studied in the context of Reverse Logistics and CLSC management (Ritola *et al*., 2020). Knowledge management, information sharing (Malekinejad *et al*., 2022), and organizational learning can be considered as a set of dynamic capabilities that through specific mechanisms provide fuel for continuous improvement of CLSC (Ritola *et al*., 2022). Among the benefits of implementing organizational learning is improved inventory management. Inventory management has a large impact on system costs and responsiveness (Poursoltan *et al*., 2021). Many studies have focused on spare part forecasting (Croston, 1972; Regattieri *et al*., 2005; Syntetos and Boylan, 2005; Pujawan and Arvitrida, 2010). Maintaining both high service level, without incurring heavy costs is difficult in practice (Pujawan and Arvitrida, 2010).

Figure 2 depicts a framework for creating value from product returns information through dynamic capabilities (Ritola *et al*., 2022). This study provides a qualitative assessment of the efficacy of product and service improvements by focusing on a case study concerning spare parts inventory management with the goal of understanding the learning effects. More specifically, this study measures the impact of product improvements and improved lead times, stemming from analysis based on product returns, inventory management costs, and service level. In addition, integrating repair solutions can drastically reduce footprints (Krikke, 2011). Accordingly, the goal is to use comparative cases to assess the effects of learning rather than primarily to search for optimal decision variables.

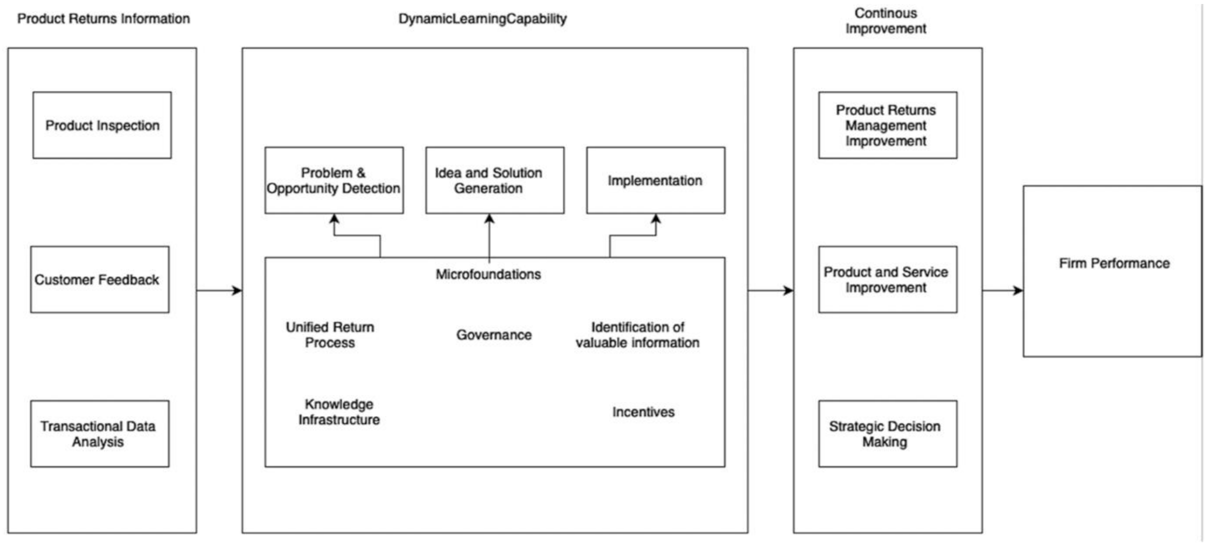

Figure 2 Closed-loop supply chain dynamic capabilities

Inventory management is a major part of supply chain costs (Al-Momani *et al*., 2020). Spare parts management in particular offers unique challenges to organizations as the demand pattern for spare parts is different from final products (Zhang *et al*., 2021). Furthermore, spare parts inventory management is closely related to CLSC management as spare parts can be considered one of the desired outcomes of reverse logistic flows (Pokharel and Muthab, 2009). A large challenge in spare parts inventory management is to achieve both cost-effective inventory management along with the best availability of spare parts (Vaez-Alaei, *et al*., 2018). This study focuses on not finding the optimal configuration of spare part inventory management, but rather on how learning in a CLSC affects costs, service levels, and footprint.

3. METHODOLOGY

A Monte Carlo simulation is used to depict the material flow of the line-replaceable units or LRUs for short. For the purposes of this study, we define LRU as a modular component that can be replaced at the location of operation without the need of additional equipment or arrangements. The material flow process starts when there is an LRU failure, and a replacement is required. The time between failures depends on the specific LRU. In an ideal case, a replacement unit is ready, and the main equipment is used for the replacement. In the case of a process failure, that is if there are no replacements available, a new order must be made. This produces a significant delay as a new replacement needs to be ordered, sometimes manufactured, delivered, and replaced. This means the unit is not working optimally or is not functioning entirely. The goal is to have adequate inventory levels to ensure minimal downtime. Therefore, each scenario is simulated with the objective to have as little downtime as possible. Consequently, the learning effects lead to lower ordering, repair, and holding costs while maintaining the same low downtime levels.

There exists a wide variety of modelling approaches (Saha and Ray, 2019). The choice of Monte-Carlo simulation over all the other approaches was motivated by several factors. Firstly, it can be used to simulate inventory management problems (Zabawa and Mielczarek, 2007), service levels (Pujawan and Arvitrida, 2010), and costs (Zabawa and Mielczarek, 2007). Secondly, a Monte Carlo approach allows for suitable manipulation of the relevant parameters to simulate the learning effects. Thirdly, as compared with other simulation methods, Monte-Carlo simulation approach is particularly suitable for unpredictable demand patterns (Pujawan and Arvitrida, 2010). Since the demand pattern for spare parts is often lumpy (Zhang *et al*., 2021), that is erratic and intermittent (Turrini and Meissner, 2017), the Monte-Carlo approach seems particularly suitable. Lastly, the method is relatively commonly used as well as easy to use (Sonneman, *et al*., 2003), allowing managers to easily adopt this approach for calculating possible CLSC interventions.

The simulation is conducted on exemplary items that represent typical cases of items the case organization handles regularly. These are (1) High-Cost case, and (2) Low-Cost case. In addition to the base case, concerning each exemplary case, a variety of interventions are simulated. These are: (1) Learning to improve the length of the useful life of the product, and (2) Learning to improve the supply chain process and thus reduce lead times. footprints are calculated as follows. Each unit of LRU is assigned a footprint value of 10. This was done because the dataset did not include footprint data and because this study does not aim at measuring the actual footprint but only to measure the impact of learning. The spare parts management literature considers various performance measures such as lead time metrics, cost metrics, service and quality metrics, and assets metrics (Zhang *et al*., 2021). For the purposes of this study, we consider holding costs and ordering costs or in the case of repair, the repair costs as well. In addition, we measure service metrics in the form of uptime and downtime caused by spare parts inventory. Lastly, we consider the environmental footprint by a relative circularity index. Note that the goal of the simulation is not to find the optimal inventory policy, but rather to estimate and compare the effects of the different learning interventions. Also, we simulate situations with lumpier behaviour of key parameters and a circular repair scenario.

4. RESULTS

4.1 Case Introduction

For military organizations, the effective maintenance, repair, and replacement of military equipment are crucial for ensuring operational readiness. Among critical components are LRUs that need to be replaced as quickly as possible when broken, to maintain high service levels, a key performance measure for military organizations. Therefore, the management of LRU inventory takes on great importance. To capture this importance, the effects of learning within the simulations are measured in overall costs, which can be divided into order costs and inventory holding costs. The effects on the service level within the simulations are measured in days of downtime.

The case for this study consists of a firm providing military equipment and the problem concerns inventory management. The dataset comes from a real military equipment supplier and all the data used for case one comes from that dataset. The data for case two was generated to provide a contrasting, Low-Cost case as the items in the data set were all relatively slow-moving and lacked examples of Low-Cost LRU. The data were obtained from a data set used in a previous study (Basten, 2009). **Figure 3** illustrates the process of this study.

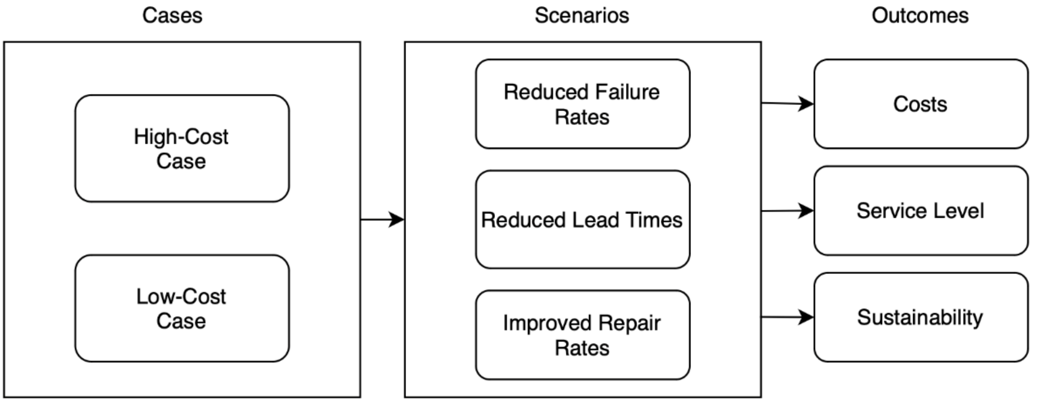

Figure 3 Research process

Each simulation run spans a duration of 730 days (equivalent to two years). Re-order point and order quantity was determined for each simulation based upon the same calculation for each simulation. The Re-order point varied between 3-6 for the High-Cost case and between 32-45 for the Low-cost Case. The order quantality was between 1-7 for High-Cost and between 9-17 for the Low-Cost case. The costs for the High-Cost item category are taken from the datas*et al*ong with holding costs for the Case 1. The case data comes from the High-Cost LRU in the data set and represents a high cost, slow moving case for the purposes of this study. It will be referred to as the High-Cost case throughout the study. The Case 2, named Low Cost, category was generated to form a comparative case with the purpose of analysing a counter case for the case one. The Low-Cost case differs from the High-Cost in that it consists of a low cost, Low-Cost LRU that have shorter lead times as compared to the case 1. Mean time between failures (MTBF), a value from the dataset was used to generate a random dataset using Poisson distribution and this was turned into a probability distribution and cumulative for the variable demand. We followed the same procedure for lead times to generate probability distribution and cumulative distribution for the variable lead time.

Table 1 Case comparison

Case	Case 1. High Cost	Case 2. Low Cost
MTBF	8000 Days	7000 Days
Number of LRU	8 Units	50 Units
Lead Time	240 Days	140 Days
Cost per Unit	50000 €	2000 €

4.2 Poisson Distribution of Failures

The results of the series of simulations using Poisson distribution consist of three performance measures. Total costs, service level, and environmental footprint. They are measured for each case and each learning intervention.
The results of the total costs are depicted in **Figure 4**. A total of twenty simulations were conducted, representing different iterations of product improvement by simulating a reduction in failure rates The base case was established by the data set and each percentage point improvement in failure rates up to 20%. A simulation was carried out between these values for each percentage point. The results indicate that the reduction in total costs is more drastic in the case of the High-Cost case as compared to Low-Cost one.

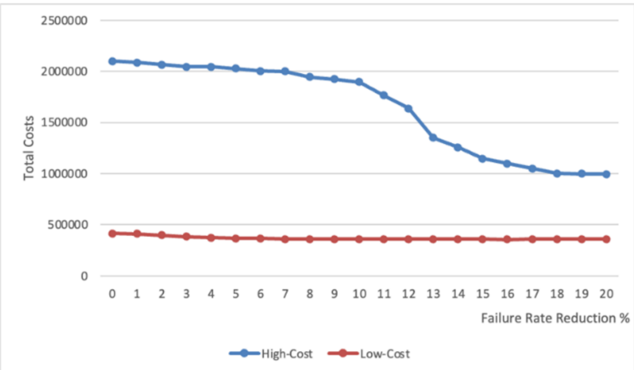

Figure 4 Improved failure rates with Poisson distribution: total costs effects

Figure 4 depicts the cost trends observed across various learning values for the Low-Cost LRU. The costs demonstrate a relatively stable pattern, with noticeable but minimal overall impact. Conversely, the effects in the case of the High-Cost LRU are more pronounced. While the effects remain steadily improving at both ends of the learning curve, there is a larger reduction in costs at around 10% of failure rate reduction and onwards until the effect levels off again. This suggests that the relationship between failure rate reduction and total costs is non-linear and complex. Therefore, the results indicate that that the effects of learning interventions on costs may vary depending on the specific characteristics and cost structure of the LRUs. A plausible explanation for this observation is that beyond a certain threshold of sufficiently low failure rates, the incremental improvements in failure rates no longer yield substantial impacts on cost reduction. This could be attributed to the fact that failures become so rare that the issues caused by long lead times and delays in replacement become relatively insignificant in terms of their effect on overall costs.

The results for reduced lead time scenarios are depicted in **Figure 5**. The results show that improving lead times have less of an impact on the total cost of managing the inventory as compared to improving failure rates. While the impact is noticeable, it is not recommendable to focus on this improvement solely for these purposes, as the impact is relatively small.

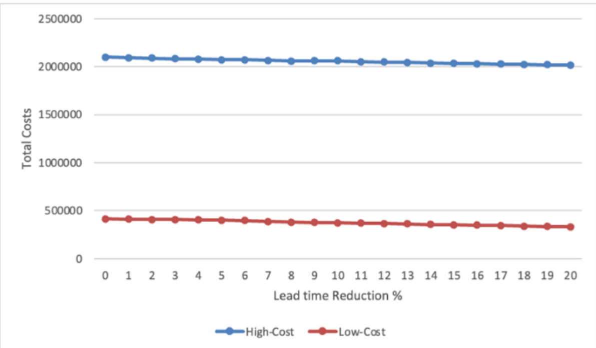

Figure 5 reduced lead times with Poisson distribution: total costs effects

These results indicate that when reduced lead times are compared to reduced failure rates, the cost reduction is much less. A similar pattern can be seen when measuring the service level in downtime. In the case of the Low-Cost LRU, the effect of reduced lead times is relatively small, reducing from of 1044,8 to 1007,4.

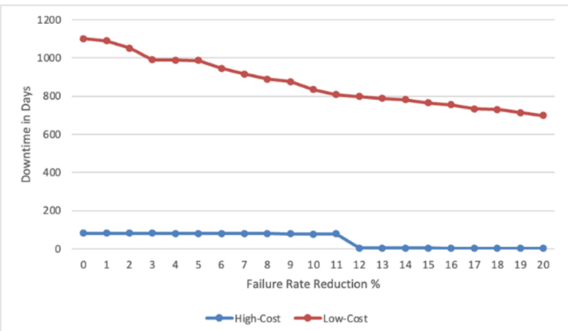

Figure 6 Improved failure rate with Poisson distribution: downtime effects

Figure 6 shows the results reduced failures have on downtime. Reduced failures lead to steady improvement in the Low-Cost case. This result can be explained by the reduced number of overall failures, which means that less time is needed to replace the LRUs. Contrastingly, in the case of the High-Cost case, the line in Figure 6 shows a steady improvement until a point is reached where the downtime drops to several days, down to the lowest time of 1,6 days. This indicates that once a certain level of failure is reached, there is a significant drop in downtime and reaches the average downtime of 1,6 days at the 80% rate.

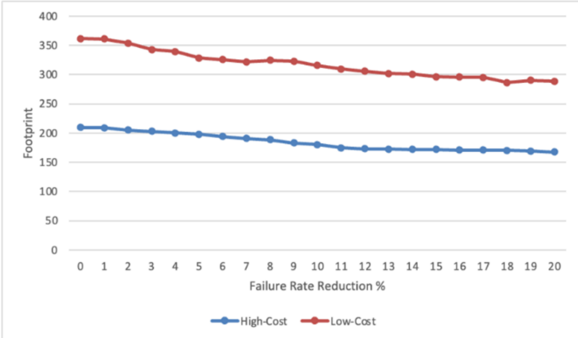

Figure 7 Improved failure rate with Poisson distribution: footprint effects

Figure 7 displays the effects of improved failure rates have on environmental footprint. Importantly, only failure rate improvement and improved repair yields has a significant impact on environmental footprint. Neither improved lead times nor lumpy distribution has a significant impact on footprint. This can be explained by the fact that neither the lead-times nor the distribution of the failures leads to increase or decrease in new product purchases and therefore the footprint remains the same. Therefore, a firm looking to reduce their environmental footprint is better off focusing on failure rate and repair yield improvements. The results suggest a steady reduction in footprint as the life of product increases.

4.3 *Lumpy Distribution of Failures*

In addition to the simulations using a Poisson distribution, a set of simulations was conducted with a lumpier distribution pattern (Pujawan and Arvitrida, 2010). Demand that is erratic and intermittent is said to be lumpy (Turrini and Meissner, 2017). Lumpy distribution of failures was done by manually introducing a 0.01 chance of having four failures for one day while keeping the overall failure constant. The number four is chosen to account for unexpected situations where a sudden surge of failures happens.

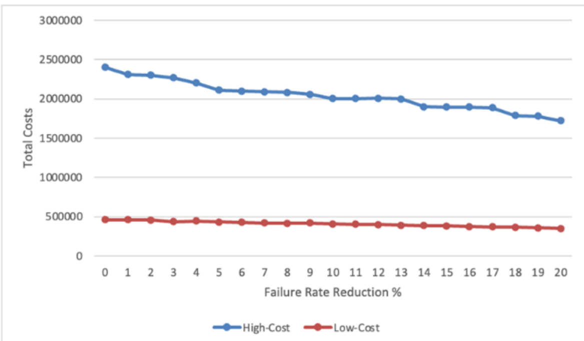

Figure 8 Improved failure rate with lumpy distribution: total costs effects

Figure 8 shows the results of the simulations on product improvement on High-Cost and Low-Cost cases while adopting the lumpy distribution. The results are quite like the results for the simulations based on a Poisson distribution, with the exception that the costs are in each case somewhat higher for both the High-Cost and the Low-Cost LRU. Hence uncertainty costs money. Importantly, in the case of the High-Cost LRU there is no significant drop at any point unlike when using the Poisson distribution. This indicates that the nature of distribution makes it overall harder to design an extremely low-cost inventory management system with high uptime. Improving lead times has a very similar effect to the results shown in the simulations with Poisson distribution as shown in **Figure 4**. **Figure 9** showcases the results in the case of both reduced failures as well as reduced lead times.

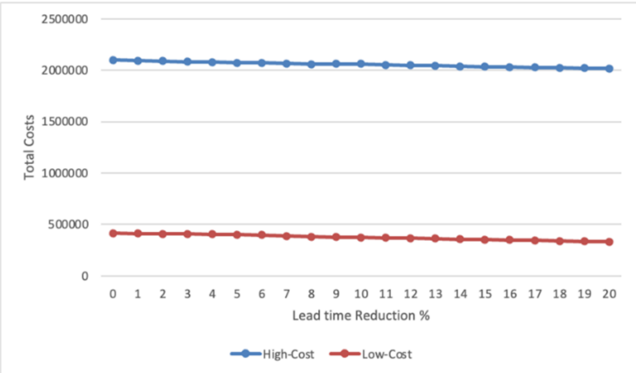

Figure 9 Reduced lead times with lumpy distribution: total costs effects

Figure 9 displays the results of lead time reduction on total costs in a scenario with lumpy failure rates. The results indicate that there is no significant impact on the total costs of reducing lead times in a lumpy distribution of failures scenario as compared to the Poisson distribution one. There is no significant difference in the results between these two distribution scenarios. The effects remain modest for both cases.

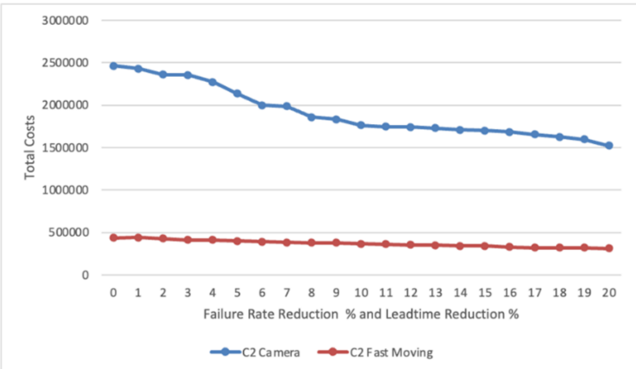

Figure 10 Reduced lead times and improved failure rate with lumpy distribution: total costs effects

The results of these combined improvements are somewhat predictable. The findings indicate that there is no additional benefit from improving both, reduced failures, and reduced lead times, at the same time. Rather the benefit in terms of costs seems to add up to the sum of both improvements if performed independently. As in the case of the previous simulations using lumpy distribution, the impact of combined improvement of lead times product quality is steady and more noticeable in the case of the High-Cost case. Regarding the Low-Cost unit, the results are incremental and small but noticeable.

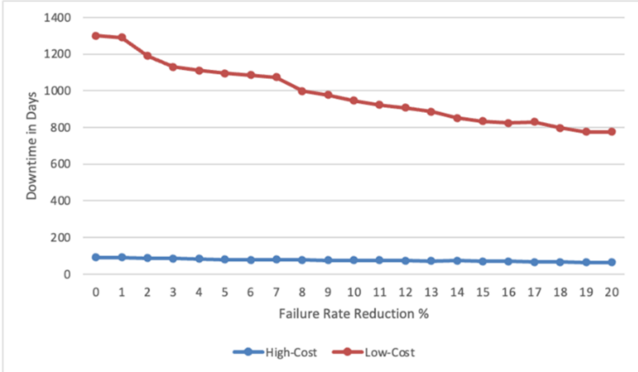

Figure 11 Reduced lead times and improved failure rate with lumpy distribution: total costs effects

Figure 11 shows the impact of product improvements on LRU downtime. Interestingly, again there is no similar point for the High-Cost unit where the downtime drops as drastically as in the case of using Poisson distribution. This can perhaps be explained by the low chance of high number of failures in short period of time introduced by the alternation to the data. Specifically, it prevents a situation where the lead time of new product orders are offset by the rare occurrence and time between failures. Rather the improvement is small throughout the simulations from 0% increased failure rate all the way up to 20%. The same can be said in the case of reduced lead times and in the case of combined improvements (**Figure 9**).

4.4 Repair Scenario

Lastly, we present the results of the repair scenario with Poisson distribution. This scenario assumes the use of repair processes with varying levels of repair yield going from 80% to 100%. While 100% yield being unrealistic, the results are aimed at showing the possible results and provide interesting insights. It is important to note that in this case, both the lead times as well as the costs are lower than buying a new item. **Figure 12** shows the results of the repair scenario simulations on the total inventory costs.

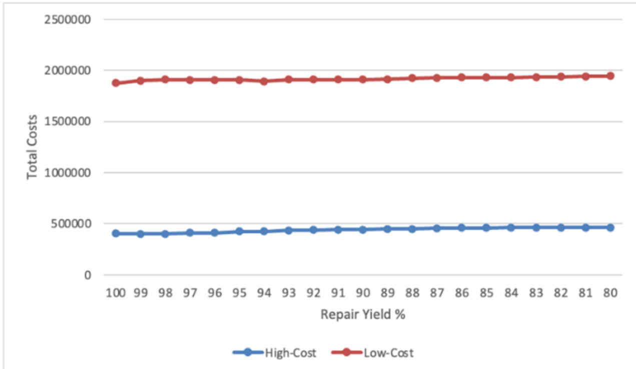

Figure 12 Improved repair yields: total costs effects

The repair option seems to have quite a large impact on total costs. The overall costs are substantially lower in each step of the simulation as the repaired unit is cheaper as compared to a new one. However, the improvement between the different steps of the repair yield remains modest. Therefore, while repairing remains beneficial, the benefits of increasing repair yields seem to be quite modest in terms of total costs of inventory management. This is mirrored in the case of when measuring the improvements in downtime as shown in **Figure 13**.

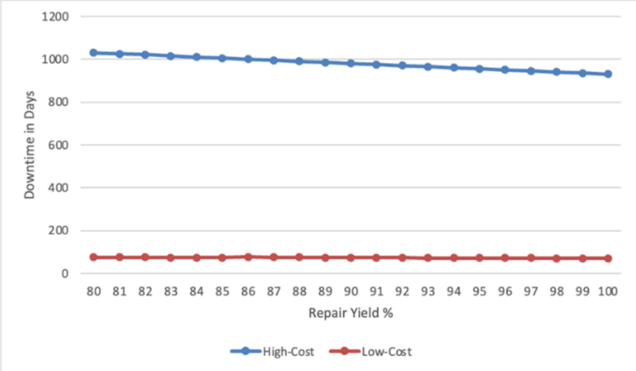

Figure 13 Improved repair yields: downtime effects

The downtime remains lower in each of the repair yield simulation for both the High-Cost as well as the Low-Cost case. However, as in the case when measuring total costs, the benefits when improving the yield are modest. Importantly, it is of real importance whether the repair time is shorter or longer than the lead time of a new product.

Figure 14 shows the impact of repair yield on the footprint of each new required LRU purchased, measured as a value of 10 for each LRU. In this analysis, repairing a product does not involve environmental footprint, and therefore if the repair yield is 100%, there is the footprint is 0. While reaching 100% yield is unrealistic in practice, the results give some indication on the effects of improvements in repair yield. The results suggest that of all the simulated interventions, repair yield improvement has the strongest effect on reducing footprint.

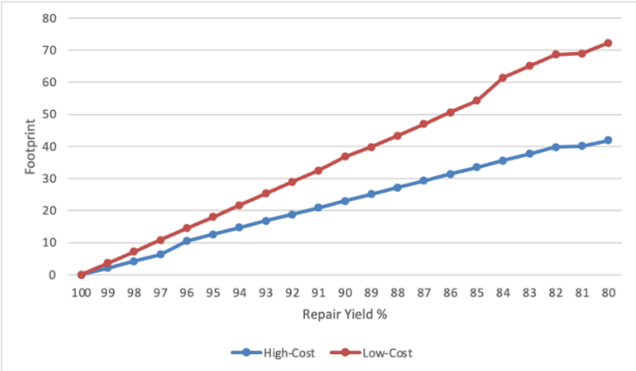

Figure 14 Improved repair yield: footprint effects

5. DISCUSSION AND CONCLUSION

The need for more research combining reverse logistics and spare parts inventory management is identified by a recent literature review (Zhang *et al*., 2021). By bringing together recent developments in CLSC value creation (Schenkel *et al*., 2015; Ritola, *et al*., 2020) with military spare parts inventory management (Zabawa and Mielczarek, 2007; Yoho, *et al*., 2013), this study contributes to the current literature by quantitatively assessing the impact of specific kind of CLSC information (Ritola *et al*., 2022) and by shedding light into the relatively understudied aspects of spare parts inventory management information (Topana *et al*., 2019). More specifically, the effects of two types of learning in a CLSC are simulated. Namely, learning to improve product quality resulting in decreased failure rates and learning to collaborate in a supply chain, leading to reduced lead times.

The results of this study reveal some interesting conclusions regarding the impact of two learning interventions. The largest benefits of the interventions are observed in the case of High-Cost LRU, where the reduced failure rates lead to a significant drop in downtime from 81,3 to 2,2 at 87% of failure rates, after which further improvements are minimal. This indicates that when a threshold of improvement is reached, managing the inventory becomes relatively cheap with the possibility of achieving high equipment uptime. The reason for this result may be that once the mean time between failures becomes long enough, new orders have enough time to arrive, even with long lead times. Moreover, the case analyses indicate that repairing seems to provide better results as compared to buying new LRUs. This finding can be explained by the fact that repair times are shorter than lead times for buying a new item. While this might not be the case in all supply chains, the benefits, when these conditions apply, are substantial. Environment footprint is not affected by lead times nor the distribution of failures and lead times. Therefore, the best way to reduce environmental footprint is to repair the LRUs and focus efforts on both increased repair yield as well as improved failure rates. In conclusion, improving product quality is the most impactful of all interventions in general, as it has the largest impact on both costs, and service levels and has reduces the environmental footprint while other interventions are more context specific.

This study harbours several contributions. This is the first study that to our knowledge quantitatively measures learning effects in the context of spare parts inventory management. Most of the current research in spare parts inventory management focuses on finding and understanding spare parts demand patterns and developing optimal inventory approaches (Zhang *et al*., 2021). The novelty of this research lies in the overall aim of this study and its methodology. Firstly, this study provides a concrete quantitative assessment of value creation from CLSC informational value on a specific part of a CLSC, namely spare parts inventory management. Therefore, this study contributes not only to CLSC value creation research stream (Ritola *et al*., 2022) but also to spare parts inventory management, by bringing new developments in CLSC together with inventory management (Zhang *et al*., 2021) and with the informational and learning aspect of it specifically (Topana *et al*., 2019). Extant literature assesses various distributions to fit spare parts demand (Turrini and Meissner, 2017). Secondly, few studies have studied the relationship between distribution of key parameters and inventory management choices (Turrini and Meissner, 2017). While finding an optimal inventory policy is not the aim of this study, it shows that using a lumpy distribution, often the pattern found among spare parts, causes inventory management to become harder and thus more complicated to manage. Lumpiness creates more uncertainty and has a negative impact on lead times, costs and footprints and reduces the positive effects of learning. Considering actual spare parts demand tends to be lumpy (Zhang *et al*., 2021), the results of this study provide essential guidance by showing a comparison between lumpy distribution and

Poisson distribution. For practitioners, this study may be interesting in two ways. First, it provides quantitative data for decision-making regarding CLSC priorities. The results help decision makers in choosing the correct interventions in the appropriate circumstances in terms of spare parts demand distribution. Second, the simulation model used in this study can be used by managers to assess similar and other related interventions.

Every study has its limitations. The results of this study measure only several benefits of learning from product returns in a CLSC. Firstly, this study measures the benefits in terms of costs, service level, and environmental footprint. However, both interventions can have other benefits as well. In addition, footprint metrics can be more advanced if data is available. In addition, only two types of interventions are considered whereas the learning opportunities of a CLSC extend beyond them (Ritola *et al*., 2020; Ritola *et al*., 2022). For instance, this study does not consider the impact of learning product returns on strategic decision-making. Therefore, more research is required in assessing the impact of other types of interventions and performance measures. Moreover, this research can be extended by assessing the impact of tactical and strategic level learning in a CLSC. For instance, quantitative research in the form of surveys could shed light on the impact of operational CLSC learning and qualitative case studies could prove to be fruitful in highlighting the mechanisms and impact of strategic-level learning. Lastly, emerging areas of interest, such as industry 4.0 technologies (Garrido-Hidalgo *et al*., 2019; Dev *et al*., 2020; Zheng *et al*., 2021) could prove to be an interesting avenue for further research. For instance, in terms of certain LRUs, the use of additive manufacturing could help to drastically reduce the long lead times. Another approach might be to study the use of smart contracts to improve monitoring while minimizing human intervention (Mohril *et al*., 2021).

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