THE ANALYSIS OF BULLWHIP EFFECT ON A MULTI-ECHELON CLOSED-LOOP SUPPLY CHAIN WITH ORBIT SIZE-DEPENDENT RETURN FLOWS

by

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All the best to every reader of this thesis!

ABSTRACT

THE ANALYSIS OF BULLWHIP EFFECT ON A MULTI-ECHELON CLOSED-LOOP SUPPLY CHAIN WITH ORBIT SIZE-DEPENDENT RETURN FLOWS

Companies that embrace product recovery as a beneficial business option are more competitive, better compliant with government regulations, optimizing their operational processes, and efficiently balancing their return flows. However, uncertainty in timing, quantity, and quality of returns leads to various difficulties particularly in multi-echelon closed-loop supply chains. In this study, a multi-echelon hybrid production system with return flows where a single type of product demand is met by manufacturing new products and remanufacturing returned cores is analyzed under the periodic review (r, S). The efficient use of inventory replenishment systems in hybrid supply chains is particularly important as the variance of such systems is higher than traditional supply chains due to a higher level of uncertainty. Orders placed upstream have the potential of increasing order variability or namely, the bullwhip effect. In hybrid systems, the main goal is to bring the products in use (*i.e.*, orbit) back to the system through collection channels. Accurate prediction of returns is key as incorrect estimation leads to a gradual increase in variance. Unlike most existing literature, we assume that demands and returns are correlated and define the *return rate* as a function of the number of products in use *viz.* orbit size, the expected lifetime of a product in orbit, and the probability of return to the reverse supply chain at the end of use. Then, we propose a new method to foresee the returns under the orbit size knowledge and examine the bullwhip behaviour under environmental factors (*e.g.*, review periods, return probabilities, and average product lifetime). Thus, we evaluate the value of orbit size information under stationary and impulse demand.

ÖZET

KULLANIMDAKİ ÜRÜN SAYISINA BAĞLI GERİ DÖNÜŞ AKIŞI OLAN ÇOK KATMANLI KAPALI DÖNGÜ TEDARİK ZİNCİRİNDE KAMÇI ETKİSİNİN ANALİZİ

Ürün kurtarmayı faydalı bir iş seçeneği olarak gören şirketler, operasyonel süreçlerini optimize ederek ve devlet düzenlemelerine uyarak daha rekabetçi bir konumda yer alırlar. Ancak, geri dönüşlerin zamanlaması, miktarı ve kalitesindeki belirsizlik, çok katmanlı kapalı döngü tedarik zincirlerinde çeşitli zorluklara yol açmaktadır. Bu çalışmada, tek tip ürün talebinin, yeni ürünler üreterek ve kullanılmış geri dönen ürünleri yeniden üreterek karşılandığı bir hibrit üretim sisteminde periyodik inceleme (r, S) altında analiz edilmektedir. Hibrit tedarik zincirlerinde envanter yenileme sisteminin verimli kullanımı özellikle önemlidir çünkü bu tür sistemlerde, belirsizliğin daha yüksek olması nedeniyle varyans geleneksel tedarik zincirlerinden daha yüksek gözlemlenir. Katmanlar arası yukarı yönde verilen siparişler, artan sipariş değişkenliği veya başka bir deyişle kamçı etkisi potansiyeline sahiptir. Hibrit sistemlerde hedef, ömrü biten ürünleri toplama kanalları aracılığıyla sisteme geri kazandırmaktır. Hatalı geri dönüş tahmini, tüm katmanlar arasında kademeli bir varyans artışına yol açtığından, geri dönüşlerin doğru tahmini kritiktir. Mevcut literatürden farklı olarak, talep ve dönüşlerin ilişkili olduğunu varsayıyoruz ve geri dönüş oranını; kullanımdaki ürünün sayısının, beklenen ömrünün ve geri dönme olasılığının bir fonksiyonu olarak tanımlıyoruz. Daha sonra, kullanımdaki ürün sayısı bilgisi altında geri dönüşleri öngören yeni bir method geliştirerek çevresel faktörler (*örn.*, inceleme süreleri, geri dönüş olasılıkları ve ortalama ürün ömrü) altında kamçı davranışını inceliyoruz. Böylece, kullanımdaki ürün sayısı bilgisinin değerini düzenli ve anlık talep yapısı altında değerlendiriyoruz.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF SYMBOLS

D_t	Daily demand at time t
$\bar{D}$	Estimated daily demand
DSL	Desired service level
k	Echelon
L	Order delivery lead time
$\bar{L}$	Estimated order delivery lead time
m	Number of historical periods to be tracked in moving average
OS_t	Orbit size at time t
p	Return probability
PL	Production lead time
r	Review period
R	Return quantity during lead time
$\bar{R}$	Estimated return quantity during lead time
RL	Remanufacturing lead time
S	Order-up-to level
s_D^2	Estimated variance of daily demand
s_L^2	Estimated variance of order delivery lead time
s_R^2	Estimated variance of return quantity
s_X^2	Estimated variance of lead time demand
SL	Shipment lead time
X_t	Lead time demand for a review period at time t
$\bar{X}$	Estimated lead time demand
Y	Lifetime distribution of a single product in use
z	Safety factor
γ	Average product lifetime
θ	Daily demand rate
λ	Rate parameter of exponential distribution

μ	Mean parameter of log-normal distribution
σ^2	Variance parameter of log-normal distribution

LIST OF ACRONYMS/ABBREVIATIONS

AFR	Average Fill Rate
ANOVA	Analysis of Variance
ANS	Average Net Stock
ARI	Advanced Return Information
BWE	Bullwhip Effect
CE	Circular Economy
CLSC	Closed-Loop Supply Chain
CPFR	Collaborative Planning, Forecasting, and Replenishment
CV	Coefficient of Variation
DIST	Distributor
EPA	Environmental Protection Agency
FIFO	First-Come-First-Served
FR	Fill Rate
ICT	Information and Communication Technology
IESC	Information Enriched Supply Chain
LTD	Lifetime Distribution
NS	Net Stock
NSA	Net Stock Amplification
OEM	Original Equipment Manufacturer
OUT	Order-Up-To
RET	Retail
RFID	Radio Frequency Identification
RL	Reverse Logistics
SEP	Sensor Embedded Products
VMI	Vendor Managed Inventory
WEEE	Waste Electrical and Electronic Equipment Directive
WHSA	Wholesaler

1. INTRODUCTION

1.1. Background

In a world where globalization has become more widespread, the enormous needs of the end consumers are met with increasing new production. During the production process, besides primary resources such as capital and labor, the need for many natural resources such as energy, water, and raw materials increases essentially [1]. As a result of environmental effects, the legal obligations that organizations must fulfill have emerged over the years. In the 1970s, regulations and concerns were raised for the first time in the US by the Environmental Protection Agency (EPA) regarding the amount of waste and pollution that industry releases into the environment [2]. This was followed by the Waste Electrical and Electronic Equipment Directive (WEEE) adopted in 2003 in Europe [3]. Such directives have encouraged reverse supply chain activities. As a result, there are numerous reasons for collecting end-of-life products from the perspective of organizations and customers, and it is a widespread belief that remanufacturing will gradually become an inevitable subject in the near future. Consequently, the industry has evolved into a phase where they realize the importance of limited natural resources, adopt more environmentally friendly and sustainable production processes, and promote the recovery of any resources as much as possible. Beyond demonstrating their responsibility to environmental concerns, the revaluation of a used product to be utilized in the manufacturing process has attracted global companies such as Kodak, Canon, Fuji, Xerox, IBM, Hewlett-Packard, and Lucent [4]. In addition for companies adopting product recovery as a beneficial business option, optimizing operational processes and complying with environmental government regulations help the company be more competitive [5].

As Circular Economy (CE) addresses the problem of waste disposal and resource scarcity, it is defined as an emerging strategy for an alternative solution to the traditional open-ended system in which a win-win approach is adopted using an economic and value perspective [6]. CE has drawn the attention of scientists and practitioners to the effective management of Reverse Logistics (RL) processes. According to the Reverse Logistics and Sustainability Council [7], RL is a sequential process of collecting, sorting, inspecting and transporting products from the point of consumption through retailers or third-party collectors for re-value creation. The concept of RL includes not only the delivery of products from the final consumer to the related sites but also the proper disposal of substances considered to be harmful to the environment [8]. Figure 1.1 depicts the main RL processes in a conventional supply chain.

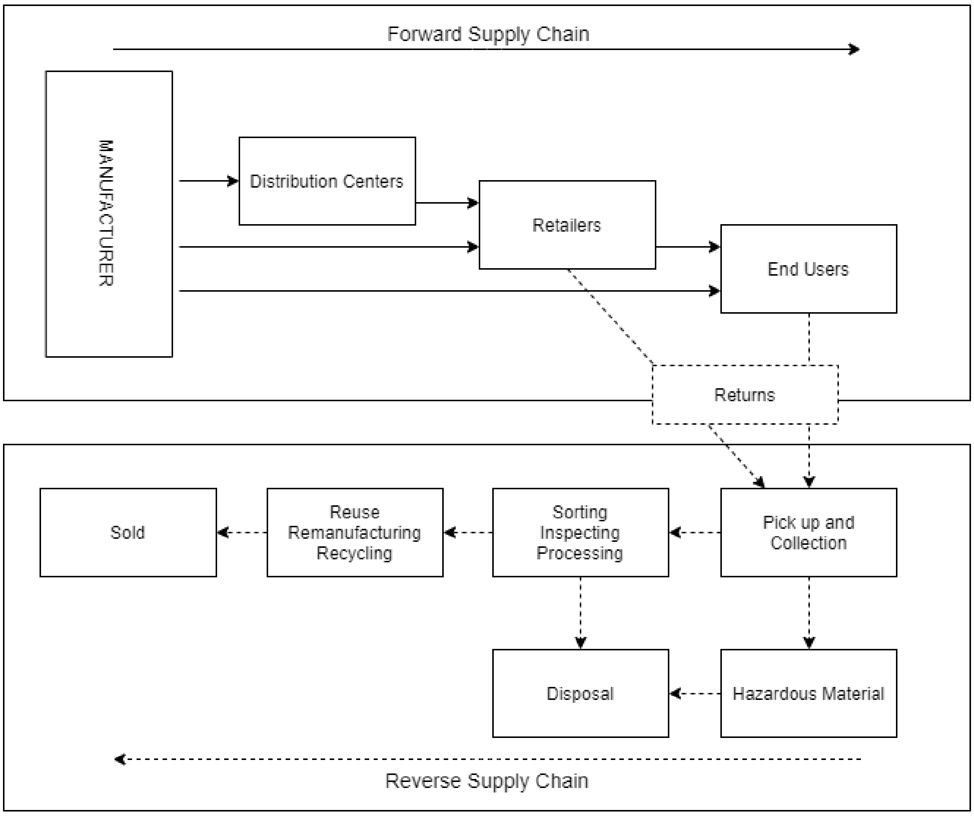


Figure 1.1. Reverse logistics processes.

Various recovery methods can be applied to products returned after usage. This might be direct reuse that only requires cleaning or minor reprocessing, reuse, refurbishing, or it may require serious repair. The most challenging but the most beneficial among the recovery options is remanufacturing [9]. Remanufacturing, one step further from typical recovery methods, is making the product returned from consumer usage as good as the newly produced product with minimum effort and resources [10]. Typically, the benefit to be gained from remanufacturing is much greater than recycling, usually the most applied recovery method, even though it depends on the product to be remanufactured [11]. Recycling is often applied in the paper, metal, and plastic industries and is seen as the last option among recovery methods [9]. However, remanufacturing requires a more comprehensive preparation, as the regained product is entirely disassembled, parts and modules are inspected, replaced or repaired, and reassembled into a new product. Moreover, the integration between forward logistics (producer-to-consumer) and reverse logistics (consumer-to-producer) further complicates the progress of supply chain processes.

With the widespread utilization of returned products in producing as good as new products, a new Closed-Loop Supply Chain (CLSC) concept is introduced [12]. Closed loops consist of two-way supply chains in which a product is returned to the Original Equipment Manufacturer (OEM) and re-enters its original forward logistics activities [13]. Figure 1.2 depicts a comprehensive CLSC structure. In such economic systems, reverse flows are critical as there is uncertainty in the timing, quantity, and quality of returned products.

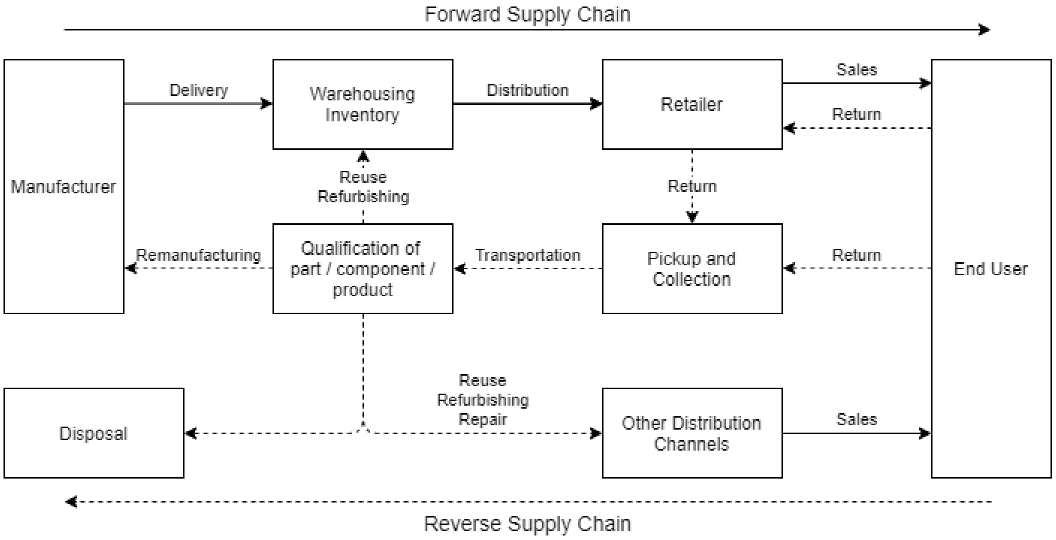


Figure 1.2. Closed-loop supply chain.

On the other hand, the Bullwhip Effect (BWE), one of the most frequently encountered problems in the supply chain system, is more pronounced in CLSCs due to uncertainty of returns. The bullwhip phenomenon, discovered in the last century, mainly arises as a result of demand signal processing by supply chain actors [14, 15]. The BWE is mainly related to the increase of variance of orders placed between echelons of the supply chain [16]. A general representation of this increase across the supply chain echelons is given in Figure 1.3. The presence of the BWE leads to crucial consequences such as stock exhaustion, additional costs (*e.g.*, inventory holding, ordering, backorder, and shipment), and eventually inadequate service levels.

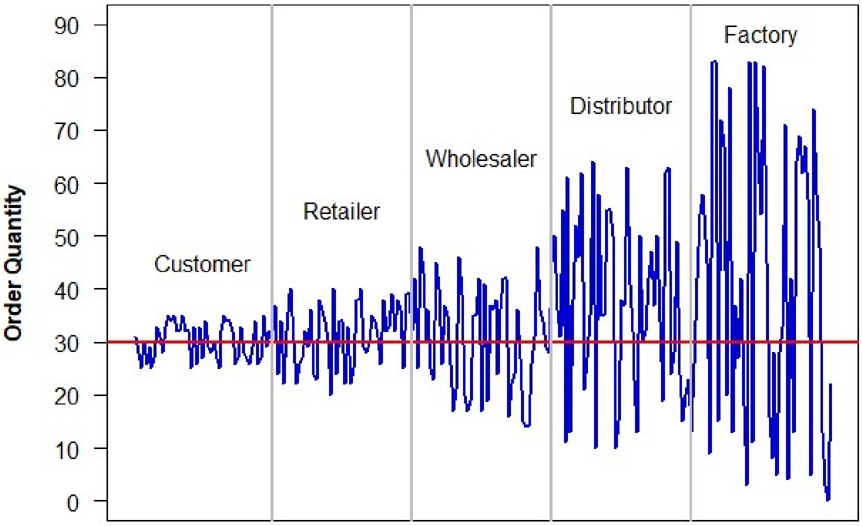


Figure 1.3. General representation of bullwhip effect.

1.2. Aim and Scope of Study

With the prominence of supply chain activities in the last century, the bullwhip phenomenon has become more visible. While the multi-echelon forward supply chain is already a complex system, the structure becomes even more complicated with the integration of RL activities. In particular, with the addition of remanufacturing processes to the traditional supply chain framework, production and inventory management require additional coordination. In a CLSC system, products returned from usage are incorporated into new production processes. This additional stream inevitably affects production decisions. Moreover, the uncertainty in the timing, quantity, and quality of returned products leads to various difficulties in integrated supply chain processes such as production and remanufacturing planning, inventory management, and timely distribution management. The alteration in production planning with the integration of remanufacturing processes significantly influences the inventory replenishment processes of supply chain actors. As typical results of BWE in RL processes, preparation and delivery of the orders might be delayed, dynamic inventory computations might be miscalculated, and inventory costs might be multiplied. Especially in supply chain systems that adopt the make-to-stock inventory approach, incomplete order replenishment from the upstream echelon puts the downstream echelon in a difficult situation and may lead to sales losses.

In addition, many versions of the most widely used forecasting methods, such as moving average or exponential smoothing, are developed in literature and practice to be used for demand and return estimation. While these forecasting methods are convenient to be applied in the forward supply chain, they are not very suitable for forecasting returns since the relationship between sales and returns is ignored [17]. Therefore, there is a need to develop a detailed model that includes the correlation between sales and returns. However, it is a common belief that supply chain actors are still challenged by the uncertainty in timing, quantity, and quality of products returning from reverse flow. To extend the insights into returns, we define the *return rate* as a function of the number of products in use, the expected lifetime of the product in use, and the probability of returning an end-of-life product, and create an environment in which the OEM predicts returns with the knowledge of orbit size. Therefore, we measure the value of orbit size information by analyzing the impact of this innovative estimation method on the BWE.

Recognizing that these problems add complexity to the research field, it is first planned to examine the BWE experienced in a multi-echelon CLSC, which estimates returns with the traditional moving average method and applies the periodic review (r, S) system. We consider this review system because of its prevalence in the literature and practice and, in particular, the efficacy of examining the BWE. Meanwhile, we measure the value of the return flow by comparing this model to a traditional supply chain without reverse supply chain. Then, we analyze the impact of system inputs such as review period, return probability, and average product lifetime with the help of sensitivity analysis in the system that predicts returns under orbit size knowledge. Also, the value of the orbit size information is measured by examining the improvement rates on order and stock variability. In the literature, a system in which return estimation is applied within the orbit size information and examined in terms of BWE has not been discussed. While the majority assumed demand and return flows are entirely independent processes, only a few works agreed that they are correlated; however rate of returns is still not defined as a function that depends on the number of products in use. Beyond the orbit size information, we also consider the case where the return quantities are exactly known in advance. As a result, we discuss the three different methods of obtaining the return quantities under stationary and impulse demand, and we evaluate when the orbit size information is more beneficial.

We model this wide-ranging problem in Python programming language using discrete-event simulation modeling with process iteration, as it is thought to be best integrated with the periodic review system.

1.3. Organization of This Thesis

The remainder of this dissertation is organized as follows: In Chapter 2, the comprehensive literature review on CLSC and BWE is presented. In Chapter 3, the methodology of the proposed model is detailed, the parameter set and performance measures are introduced, and the model is verified. Chapter 4 covers the numerical analysis, which includes behavioral and sensitivity analyses with various experiments. Chapter 5 lastly concludes the main findings and contributes to future studies.

2. LITERATURE REVIEW

This chapter provides an insight into CLSC structure and the BWE occurring across supply chain actors and critically discusses the literature on these research areas. The aim here is to advance a theoretical basis for the research topic of this thesis and review the existing knowledge in the literature, identify potential gaps in the literature, and approach these gaps in this study.

First, demand amplification, as recently called BWE, is introduced, and their importance, causes, and available solutions are indicated. Looking at the historical development of the BWE in the literature, these phases are called "The Production and Inventory Control Era" before 1959, "The Production Smoothing Era" between the years 1959 and 1969, "The Development of Control Theory" between the years 1969 and 1989, "The Beer Game Phase" between the years 1989 and 1997, "The BWE Rediscovery Phase" between the years 1997 and 2000, and lastly "The BWE Avoidance Phase" since 2000 [18]. The BWE, which has been the subject of many phases, has become one of the biggest problems of the last century experienced in the supply chain.

Second, previous works are compiled considering a CLSC with remanufacturing. It seems that BWE and CLSC will continue to be essential subjects of research for many more decades. While examining the methods applied in modeling such problems, the ease, and prevalence of the discrete-event simulation modeling approach, especially in supply chain systems, are highlighted in the following chapter.

2.1. Literature Review on Bullwhip Effect

The issue of the BWE is one of the major problems encountered in supply chain management and has been extensively studied with many aspects in literature. The order variance that increases along the supply chain echelons is referred to as the "demand amplification" [19] and, more commonly, as the BWE [20]. With the evolution of inventory management from being a necessary business function to being the core business unit, damping the BWE has become essential. This problem, faced by many executives, was examined for the first time in Jay Forrester's studies using systems dynamics simulations [21, 22]. Many studies on this subject have been encouraged with these pioneer works, and this problem has been rediscovered as the importance of the supply chain has increased in the late 1990s [23–26].

Holweg and Disney [18] referred to three main methodological approaches for supply chain analysis: the continuous-time approach, the discrete-time approach, and the frequency domain approach - also known as the control theory. These approaches are methodologically independent of each other but have significantly influenced each other over the years. In all approaches, the demand pattern is assumed to be deterministic or stochastic, which converges to a stationary mean in the long run. The main reason for this assumption is that when the demand is not assumed to have a natural mean, the variance values get infinite, which makes it impossible to calculate the order variances between echelons along the supply chain. Especially in stochastic models, it is challenging to obtain co-variances between the inventory levels and the forecast error along with lead-time [27].

Continuous-time models are based on the idea that all system states are constantly observed, so the flow rates in the system are the focus. Since possible incoming events are continuously evaluated, there is no need for periodic review, and the trigger in the replenishment policy is the inventory levels themselves. Simon [28] by using Laplace transform and Forrester [21] by developing the DYNAMO system dynamics simulation take the lead of the continuous-time approach. The approach has been further developed in the area of system dynamics, and promising contributions have been made, especially in demand signals amplifications in the multi-echelon supply chain [29–31].

Discrete-time models applied in the supply chain are based on the idea that inventory records are updated at periodic time intervals. In practical terms, although customers are purchasing products at any time, inventory control and production planning are done at pre-determined time intervals. Norbert Wiener's [32] pioneering work on the discrete-time approach created new study areas in the field of inventory control, proved worth working on production and inventory control problems, and encouraged many studies on this problem. Besides, Lee's reputed articles based on the stochastic approach were made in the context of the discrete-time approach [20, 33].

Third, the frequency domain, or the control theory approach, emerged in the 20th century, influenced by both the discrete and continuous approaches. Focusing on z-transforms and Order-Up-To (OUT) inventory policy, the control theory has become a well-known approach today and continues to develop [34–37].

In production-inventory systems, order replenishment policies are defined as a sequence of procedures or rules that include the timing and quantity information of consecutive orders, and the gap between the number of items needed in the production or procurement process and the on-hand inventory level is completed in each replenishment process in order to meet the customer demand at the desired service level [38]. A standard classification of replenishment rules is based on scheduling the review of the inventory level (*i.e.*, periodic and continuous review systems). Since demand signal processing are seen as a significant cause of the BWE, the study field on inventory replenishment policies has attracted considerable attention [15, 39].

Several studies examining the BWE included the periodic review OUT inventory policy into their models due to its popularity in academia and industry [14,39–43]. The periodic review is more preferred than the continuous review when the supply chain actors accept orders only at regular intervals or when ordering costs are relatively higher than inventory review costs. [38,44]. In this policy, the replenishment order is generated to fulfill the difference between target and current inventory position. The inventory position refers to on-hand inventory plus on-order inventory minus backorders [39]. This replenishment policy in several applications advocates the gradual transition to a new OUT level S and the recalculation of S in every review period. If the new S is lower or higher than the previous value, monitoring and predicting changes in demand becomes the key to establishing a smooth changeover to the new steady state in the gradual transition [37, 39, 45].

One of the first studies examining BWE in the literature was conducted by Magee [46]. Magee built a discrete-time inventory model that uses z-transform to solve a classic OUT policy with minimum mean square error demand forecasting. Magee defined the BWE as:

$$BWE = \frac{Variance\ of\ orders}{Variance\ of\ demand} = \frac{\sigma^2_{orders}}{\sigma^2_{demand}} \tag{2.1}$$

where the defined BWE in this way is still being used in current literature as the comparison measure.

Deziel and Eilon [34], and afterward, Disney and Towill [37] obtained analytical closed-form solutions for the inventory variance in a classic OUT policy with exponential smoothing forecasting. Bertrand [47] evaluated the bullwhip and inventory variance in a sophisticated production and inventory control problem that aims to minimize shortage and holding inventory costs and to meet a 95% service level at the same time.

Beer Game, which has an important place in the literature of BWE, was formally introduced by Sterman [29] by building a discrete-time participative model; however, its essence was based on the participative version of Forrester's [21] supply chain model. Sterman shows that the individuals in the game were adjusting themselves over time to make the best decision on inventory management, and this describes the behavior of independent supply chain actors. Beer Game inspired many articles and was intensively studied in simulation-based [48–50], analytically research [51, 52], and web-based [53–57].

Lee's [20, 33] two popular articles pointed to four leading causes of the BWE: demand signal processing, rationing game, order batching, and price promotions. The demand signal is a message that is transmitted to an upper echelon to inform that products are required, so it is a significant element of information for demand planners in the supply chain. Demand signal processing is an application where target inventory and safety stock levels are constantly updated according to the inventory replenishment rule and demand forecasting method. The supply chain actors are certainly influenced by the inventory replenishment policy and the lead times. Physical and informational delays are another significant issue since lead-time is an essential parameter in calculating OUT level S, safety stock, and reorder point [44]. A new order is triggered in some replenishment policies when the stock level drops below a threshold called the reorder point [58]. Lee *et al.* [59] afterward published another article investigating the factors that cause the BWE by reflecting it into the real world. They proposed methods to diminish the BWE phenomenon, but these observations were limited to the forward supply chain.

Since the late 1980s, the authors' primary purpose dealing with the BWE has been to identify the causes of the BWE in the interactions between supply chain actors considered to be optimized locally and to develop solution methods to reduce order variances. Many studies investigated whether the BWE can be controlled by sharing information among echelons, and establishing called the collaboration in the supply chain [14, 20, 33, 39, 60]. The idea behind the collaboration is to find out the global solution for the entire supply chain [61]. Local optimization often leads to a global disharmony in the supply chain, as each echelon replenishes demand from downstream without directly considering the market. Information visibility is considered to be the first step towards attaining collaboration in supply chains [61,62]. Many studies concentrated on measuring the value of information sharing along multi-echelon supply chains, focusing on sharing customer demand information [14,15,25,39,60–65]. Chen *et al.* [25] quantified the BWE in a multi-echelon collaborative supply chain using stochastic approaches in discrete-time and argued that information sharing benefits. Collaboration in the supply chain reduces the BWE [14,25,37,66–71], limits bulk orders [72], reduces inventory holding costs by providing inventory stability [73–75], and thus improves customer service level [76]. Besides, the negative impact of order smoothing on the level of customer service is mostly eliminated through synchronized supply chains [77]. The debate about the BWE phenomenon shifted to the expanded strategies to dampen the BWE by collaborating in the supply chain through Information Enriched Supply Chain (IESC), Collaborative Planning, Forecasting, and Replenishment (CPFR), and Vendor Managed Inventory (VMI) [62, 78]. While it has been argued that demand visibility is a key element to the remedy of the BWE, recent models show that in some cases, all the shared information across echelons can already be obtained from orders placed thanks to the structure of the traditional supply chain and thus information sharing has no value. Raghunathan [79] showed that sharing downstream lead-time information with upstream echelons has no benefit. Indeed, the jury still seems undecided about whether there is a benefit in sharing demand information among supply chain actors.

Forecasting methods for demand or lead times, which have various versions in the literature and the practice, are another powerful discussion affair. Hosoda and Disney [80] examined bullwhip and inventory variance based on common forecasting methods such as moving average, exponential smoothing, and minimum mean square error. Gilbert [81] studied classical OUT inventory policy in a multi-echelon supply chain with minimum mean square error forecasting in a stochastic environment. Adaptive forecasting techniques other than conventional methods have also been developed in practice. Industrial engineering researchers, in particular, are encouraged to redefine collaborative multi-echelon supply chain models based on an innovative order smoothing replenishment rule [60, 63]. It is possible to design smoothing replenishment rules that have a balancing effect on orders. Balakrishnan *et al.* [82] and Disney *et al.* [83] presented an inventive smoothing replenishment rule with a proportional controller. Costantino *et al.* [84] developed a smoothing inventory replenishment rule based on control charts and compared it to a classical OUT replenishment policy. Other demand forecasting models have also been developed in order to reduce BWE [45, 85]. Besides, supply chain actors need to keep additional inventory to buffer against demand forecast uncertainty for future sales speculation and lead times in delivering orders in transit from the factory to the consumer [27]. In conclusion, many articles examining the BWE showed that the bullwhip and inventory variance issue could be damped by selecting the proper forecasting method and order replenishment policy [14,25,40,84,86], reducing delivery lead times [25,40,84,86], and enhancing the collaboration level across the supply chain echelons [14, 15, 25, 39, 60, 84, 87, 88].

The problem of the BWE, which is one of the biggest dilemmas encountered in the supply chain, and which has been the subject of literature research for almost half a century, has not yet been solved with today's academic knowledge. Furthermore, the increase in complexity in supply chains will inevitably bring other problems in addition to this problem, as is the case with CLSC today. As a result, it seems that we will be encountering this problem for many more decades, both in the literature and in practice.

2.2. Literature Review on Closed-Loop Supply Chain

CLSCs combine forward and reverse supply chain operations to enhance the economic and ecological value. The forward supply chain is the process of materials flowing from suppliers to the factory for production and then from the factory to retailers for sale and purchased by the end-user [89]. The reverse supply chain, which is complementary to the forward supply chain, is the process by which collectors accept returned products from end-users and then reintroduce them to the supplier and factory for product recovery. RL has become a critical business sector in recent years and mainly consists of collection, inspection, separation, disassembly, reprocessing, reuse, remanufacturing, recycling and disposal. A practical application of these activities leads to optimization of resource use, waste reduction, minimized environmental pollution, increased regain, balanced production lines, and saving in operational costs. Therefore, CLSC management develops the economic situation of an organization and thus provides a competitive advantage in the market [90]. In general, product recovery is seen as the basis for developing an industrial system that is both environmentally and economically sustainable.

Several recovery methods can be applied to products, components, parts, or cores returned after usage. However, remanufacturing is the most appealing process among product recovery options, with its capability to enhance the value of returns [91]. On the other hand, it also brings various challenges to overcome. Although many of these problems have been clarified, the lack of guidelines for managing remanufacturing and related operations limited the growth of preferences to integrate remanufacturing into business processes, and so the current literature regarding the CLSC with remanufacturing is still limited [92].

The majority of works within the context of CLSC and RL are based on the typical assumption that demand and return flows are uncorrelated. The following inventory systems established under periodic or continuous inventory review applying various methodologies such as the Markovian, system dynamics, and simulation approaches. Heyman [93] developed a single-item inventory system in which returned cores affect the stock level as demand arrives. Returned items can be repaired to meet future demand or be disposed of, requiring an admission control of returns. This was conceived as a single-server queueing problem where the return and demand processes follow the Poisson process, PUSH production control is adopted, and production and remanufacturing lead times are not considered. Muckstadt and Isaac [94] examined a single-product inventory system in which return and demand processes are independent and constant production and remanufacturing lead times are introduced. Optimal policy parameters were found in single-echelon and two-echelon supply chains under the continuous review system (Q, r) by establishing a cost model. Van der Laan *et al.* [95] extended the single-echelon supply chain model suggested in [94] introducing the disposal option and performed a numerical analysis for continuous review system parameters s and Q. Fleischmann *et al.* [96] designed a conventional uncapacitated continuous review system (s, Q) in which demand and returns follow Poisson processes and derived an optimal control policy for the cases where return flows are allowed and not allowed. They considered production lead-time, holding cost, backlogging cost, and fixed ordering cost while ignoring remanufacturing lead-time and cost. Fleischmann and Kuik [97] extended the same setup and derived an optimal control policy for a conventional continuous review system (s, S). Buchanan and Abad [98] derived an optimal inventory control policy for periodic review returnable systems, in which the usage rates of in-use products are distributed exponentially, and the returns over a given period are a stochastic function of the quantity of products in use. They introduced two state variables (*e.g.*, number of products in-use and on-hand inventory) based on the dynamic programming method. Fleischmann *et al.* [99] designed a CLSC, in which IBM uses product returns as a source of spare parts, as an analytical inventory control model, and a simulation model. IBM was advised to take advantage of all product return opportunities as long as there is an uncovered demand. Toktay *et al.* [100] modeled a closed queue network for Kodak's single-use camera and evaluated ordering policies that minimized costs such as purchasing, inventory holding, and lost sales. They proposed a heuristic method for adaptive forecasting method, acknowledging the uncertainty in the return flows. With the system dynamics approach, the CLSC examples are studied in the electrical and electronic equipment supply chains [101] and the automotive industry [102].

Simpson [103] derived a three-parameter optimal policy for repairable inventory system defined by the dependent values of the repair up-to-level, the purchase up-to-level, and the scrap down-to-level. In this study, the periodic review r is fixed, and the delivery lead times of purchased and repaired items are zero. This article, published in 1978, made significant contributions to the literature within the context of recoverable inventory systems. Inderfurth [104] also showed that the policy introduced in [103] is optimal in the case of identical non-zero deterministic lead times for production and remanufacturing. The severe influence of lead times on the complexity of optimal policy is highlighted, and it is shown how procurement, remanufacturing, and disposal decisions can be evaluated for periodic review systems. De Croix *et al.* [105] analyzed the base-stock inventory policy for a multi-echelon supply chain with an infinite horizon. They showed that the stationary base-stock policy is optimal in cases with non-negative demand. De Croix [4] extended the repairable inventory systems proposed in [103] and

[104] by integrating the multi-echelon supply chain network of [105] without disposal option.

De Croix and Zipkin [106] considered an assembly system with returns of components or end products for a single product. They found that as the rate of return, the variability of returns, and the quantity of recovered components increased, the inventory holding and backorder costs also increased. Whether product recovery operations diminish overall system costs depends on the greatness of the extra inventory holding and backorder costs compared to potential cost savings in procurement. Extending the previous work, De Croix *et al.* [107] proposed an assemble-to-order system with returns of components or end products for multi-product under a base-stock policy at the component level over an infinite horizon. They showed that product-based returns information is relatively less valuable than demand information, but tracking both types of information incredibly beneficial.

Salomon *et al.* [108] studied a simple hybrid production system with remanufacturing for durable products and conducted a numerical analysis under the PUSH-remanufacturing policy (*i.e.*, all returned cores are remanufactured as soon as possible regardless of the return quantity) and the PULL-remanufacturing policy (*i.e.*, all returned cores are remanufactured as lately as possible and the timing of remanufacturing activities depends on the demand for new products and the supply of returned products). Van der Laan *et al.* [109] extended the PUSH and PULL remanufacturing control systems described in [108] to evaluate the effects of lead-time period and lead-time variability on expected costs in hybrid production systems. Although neither of these control systems is optimal, it is easy and common to implement in practice. The key takeaways from the numerical analysis are that production lead-time has a greater impact on total costs than remanufacturing lead-time, and a greater remanufacturing lead-time and greater variability in production lead-time result in cost reductions in some cases. Van der Laan *et al.* [110] compared conventional systems to hybrid production systems with integrated PUSH or PULL remanufacturing control policies. The managerial insights based on numerical analysis are that even if the return flow is less than demand intensity, it may not be economically beneficial to remanufacture all returned cores, and it might be helpful for OEMs to monitor the correlation between demand and returns as uncertainty in the timing and quality of returned cores becomes more predictable. Van der Laan and Salomon [111] also demonstrated that planned disposal is economically beneficial due to lower variation in PUSH and PULL remanufacturing control systems. Besides, to control the PULL production system, Korugan and Gupta [112] proposed an adaptive kanban control method for hybrid production systems based on a stochastic queueing network approach. The proposed adaptive method performs better than static control methods in total costs, as kanbans balance new production and remanufacturing capacities.

Shi *et al.* [113] examined optimal policy for production and pricing in a CLSC, where the OEM has two channels of new and remanufactured products to meet demand and explored the effects of uncertainty in returns and demand. Shi *et al.* [114] then studied optimal production planning for a multi-product CLSC with a Lagrangian relaxation-based approach, considering uncertainty both in return and demand. Lee *et al.* [115] presented a dynamic optimization approach that integrates production and inventory decisions in a decentralized reverse manufacturing system with retailer collection. Pan *et al.* [116] made a general inference for dynamic lot-sizing problems in a CLSC in which production, remanufacturing, and disposal capacities are limited, using a dynamic programming algorithm.

Guide and Wassenhove [117] argued that product life cycles are getting shorter and shorter, thus encouraging CLSC applications both in academia and industry. As the number of short lifecycle product offerings increases, recovery processes at CLSC become more complex, particularly where capacity is limited. Georgiadis *et al.* [118] studied the effect of product lifecycle on capacity planning and showed that lifecycle characteristics influence capacity planning policies of collection and remanufacturing. As an extension of previous work, Georgiadis and Athanasiou [119] examined the effect of two-product joint lifecycles on remanufacturing capacity planning. Vlachos *et al.* [120] studied the dynamic capacity planning of remanufacturing considering economic and environmental concerns, using the system dynamics approach.

In addition to the reasons for the reusing of returned products, CLSCs are generally uncontrollable on the supply side, which introduces three dimensions of uncertainty: Timing, quantity, and quality of returned products. Such uncertainties in product returns cause additional complexity to CLSCs with remanufacturing. Regarding returns uncertainty in timing, the exact moment is mostly unknown at which a single end-of-life product is returned. Additional uncertainty in timing appears in practice as the end-user is not compelled to deliver the product to the collection channels immediately, either because the product on hand becomes valueless or because the product is replaced for a new product.

Uncertainty in quality indicates the condition of the returned product. End-users sometimes claim that a product does not work properly because they misunderstood how to operate it correctly or changed their minds. These types of returns are referred to as false failure returns or non-defective [121]. In practice, especially for warranty returns, the quality variability is high as the existence of false failure returns is not known with complete certainty. As the increased variability of the quality status of used products is one of the significant parameters in the reverse supply chain, Zikopoulos [122] studied a remanufacturing system in which the classification of quality information of returned cores is used. Behret and Korugan [123] developed a hybrid production system based on the approach of the queuing networks. In the study, returned products are classified and graded according to their quality conditions, and for each class, remanufacturing lead-time, remanufacturing costs, recovery rates, and disposal costs are determined. The quality-based grading of returned cores provides significant cost savings in the cases of higher return rates.

Legislation, contracts, incentive systems, monitoring, and forecasting are prevalent ways to diminish the uncertainty in product returns [124]. Legislation is beyond the sphere of the impact of an organization. While contracts and incentive systems are valuable activities, they do not provide certainty. Any practical information of the returned product is useful to be tracked and used for forecasting. However, the forecasting of the reverse flows is one of the significant challenges encountered in CLSCs. The issues related to reverse flow of products in use are still not widely explored in the context. The quantity of returned products is practically stochastic and requires estimation for various supply chain operations such as inventory management and production/remanufacturing planning. Mashhadi *et al.* [125] developed a stochastic optimization model to deal with uncertainties in market demand and the quality and quantity of returns. Existing publications in the literature generally use purchase or delivery information [126] or consider the information about actual returns [127] in order to estimate returns. Besides, in rental/leasing systems, the timing of the return is partially or fully known in advance; therefore, no serious effort is needed to estimate the returns [128].

Ketzenberg *et al.* [129] explored the value of information and the value of partial information to reduce the impact of these uncertainties. Expanding the previous work, Ketzenberg [130] explored the value of information in capacitated a CLSC, adding capacity utilization uncertainty. Ilgin and Gupta [131] proposed the application of Sensor Embedded Products (SEP) to advance CLSC system performance, particularly in relation to the high level of uncertainty regarding disassembly efficiency due to missing and non-functional components. Visich [132] suggested that Radio Frequency Identification (RFID) technology can be used efficaciously to reduce uncertainties over product returns and track partially or fully in-use products. As the cost of RFID technology decreased, it became a promising tool for clarifying product return processes.

Most of the available literature deals with quantifying BWE for the traditional forward supply chain, so the number of studies examining the CLSC and the BWE phenomenon together is considerably limited. Moreover, those examined generally apply great relaxations to their models. Zhou *et al.* [133], Zhou and Disney [134], and Huang and Wang [135] investigated a hybrid production/remanufacturing system for the BWE examination and showed that CLSCs with return product flow have relatively lower inventory variance and hence lower the BWE. They also investigated the impact of information distortion, return rate, and remanufacturing lead-time on inventory and order variability. Tang and Naim [135] examined the impact of different levels of information transparency encountered in remanufacturing processes on the BWE and showed that when a high degree of information transparency in the CLSC is provided, system performance improves even when the uncertainty in the reverse flow is high. Das and Dutta [136] compared a CLSC with a fuzzy demand and collection rate to a traditional forward supply chain, evaluating order variability. Pati *et al.* [137] developed an analytical solution to measure the BWE in a six-echelon CLSC where each echelon follows an OUT inventory replenishment policy and an minimum mean square error estimation method for recyclables such as paper and plastics. To expand insights on BWE encountered in CLSCs, this article is an attempt to measure the value of information on the number of products in use to be used for return estimation and the impact of the review period, return probability, and product reliability on BWE in a CLSC where demands and returns are totally correlated.

In hybrid production/remanufacturing systems, the correlation between demand streams and return streams is a significant issue. While the majority of researchers disregard this relationship, they instead consider a typical assumption of independent flows. These works generally assume zero return lead-time for products in use and a fixed rate of return estimation. The acknowledgment of such assumptions makes examining the system all the easier while detracting from reality. de Brito [138] demonstrated that stochastic models often use the assumption that demand and returns are independent and concluded that this traditional assumption needs to be abandoned. Zerhouni *et al.* [139] analyzed a hybrid production/remanufacturing system in which returns and demands are strongly correlated. In other words, a satisfied demand is being used with a stochastic return lead-time, then triggers a return of the used product with a certain probability. To study the system, the assumption of instantaneous lead-time was relaxed by Cheung and Yuan [140], and make-to-stock queues with a single exponential server were adopted to model capacitated production process by Veatch and Wein [141], and Ha [142]. They emphasized that when the return lead-time is introduced, it complicates the system considerably. With numerical analysis, it was observed that ignoring the dependence between demands and returns leads to a significant increase in total costs. Gayon *et al.* [143] and Flapper *et al.* [144], respectively, considered a capacitated single-item production and inventory control system where customers pre-announce product demands and returns. Demands and return announcements follow independent Poisson processes. After a randomized return lead-time, the customer makes an announcement, and the return of the product may be triggered or canceled. The main purpose is to evaluate the value of advanced information of demand and return under continuous review. The make-to-stock queue framework [145] is adopted to review this, and two-dimensional state space is generated to track both the end-product inventory and the announced returns using a Markovian approach. According to the numerical analysis results, using advanced return information can result in a 5% reduction in total cost, which may not seem much, but when compared to the net profit of an organization, this gain might be pretty substantial. The CLSC appears to be most advantageous when return lead-time is not too short or too long. Besides, in cases where backorders are allowed, the cost reduction can reach up to 23%. When advance information of demand and return are available together, the total costs are significantly diminished due to reducing uncertainties and a more explicit system. Mitra [146] examined a two-echelon CLSC with correlated stochastic demands and returns under periodic review system. This paper reveals that a higher rate of return leads to lower demand variability, the availability of information considerably cuts down the expected costs, and CLSCs do not cost more than traditional forward supply chains as long as the economic value of the returns is recovered. Kiesmüller and van der Laan [147] investigated a single-product periodic review inventory model (r, S), in which returns generate new demands, and constant lead times are introduced. However, they assumed a fixed probability of being returned instead of estimating using lead times (*i.e.*, product usage, shipment, and remanufacturing lead times). In a finite planning horizon, the cases where the returns are dependent and independent are compared, and numerical analysis shows that the average cost is lower in the dependent case. Yuan and Cheung [126] examined a continuous review (s, S) inventory system with merchandise returns for retail businesses. They derived the system operating characteristics based on a queuing perspective and proposed the optimal replenishment parameters for the review system. In this model, the products in use after exponential return lead-time are either returned with a certain probability or retained by the customer. With the assumption that return flows depend on demand flows, the results provided essential insights (*i.e.*, effects of partial returns) for rental/leasing businesses.

As a contribution to the literature, we consider a system where the returns are dependent on the satisfied demands by taking the number of products in use. Further, we propose a new return estimation method by defining the return rate as a function of the orbit size (*i.e.*, the number of products in use), the expected lifetime of a product in orbit (*i.e.*, the return lead-time), and the probability that the product being reintroduced into the reverse supply chain at the end of its use. Therefore, satisfying a demand has a direct and indirect effect on CLSC. On the other hand, we examine the many unusual research questions that arise with the orbit structure brought to the literature. Considering the valuable information that products sold have, we investigate the influence of the correlation between the demand and return processes on the new production decision and the inventory replenishment decisions of supply chain actors, thus examining the BWE across the entire CLSC. Kokkinaki *et al.* [148], and Van Nunen and Zuidwijk [149] claimed that the products in the field could be monitored with the effective use of Information and Communication Technology (ICT) tools. However, it is pretty challenging to know or predict the orbit size at the exact moment, so we focus on evaluating the value of orbit size information.

3. METHODOLOGY: DISCRETE-EVENT SIMULATION MODELING

This chapter provides the research approach, the description of the proposed model, and the verification of the simulation model. Before going into the details of the model, we present the methodology of discrete-event simulation modeling that is a common approach in modeling the supply chain problems. In particular, we explain our model with an emphasis on the conceptual problem addressed at CLSC. Then, we verify with other models in the literature to test the robustness of our simulation model.

3.1. Research Approach

The comprehensive problem to be addressed in this study is integrated with discrete-event simulation modeling. Here, an analytical method such as steady-state queueing network analysis was not preferred as it would have to deal with high-dimensional state spaces to model a large-scale CLSC structure. Thus, we developed the supply chain with the help of object-oriented modeling in the Python programming language. Discrete-event simulation is a common method for modeling problems within the context of CLSC (*e.g.*, in [150, 151]) and BWE (*e.g.*, in [152, 153]). The analysis of discrete-event simulation begins with forming a conceptual model of the problem. The detailed description of the system to be modeled is explained in the next section of this chapter. Then, the simulation environment is created by defining entities, resources, and queues in accordance with procedures and rules. Once the model appears to be working properly, it is verified by comparing it to the results of other analytical models that have been tested for accuracy in the research field. Subsequently, the numerical analysis is carried out with the experimental parameters.

3.2. Description of the Model

In this study, a four-echelon hybrid make-to-stock production system with return flows where a single type of product demand is met either by manufacturing new products or remanufacturing returned cores is analyzed under a periodic review system for inventory replenishment. Similar to [139], we assume that the remanufactured products are as good as new, that is, demand does not differentiate between new and remanufactured products. To that end, we model and simulate a single-product inventory system for hybrid production within the context of multi-echelon CLSCs. Even though the single-item inventory system is unusual in genuine supply chains, it is a common assumption that is widely accepted in the literature to analyze the supply chains [142, 154–156].

The difficulty of modeling the inventory system in a multi-echelon CLSC reveals the need to focus our research on two primary processes: the forward supply chain and the reverse supply chain. These processes include various operations, including new production, preparation and shipment of ready-made products, sales, collection and inspection of used products, remanufacturing, and disposal.

Here, the model consists of four echelons, including end-user, retailer, wholesaler, distributor, and OEM, or namely echelon $k = 0$, 1, 2, 3, and 4, respectively. Figure 3.1 depicts the system under consideration. Demands arrive at the bottom echelon (*i.e.*, retailer) one by one following independent exponential interarrival times with daily rate λ. When demand arrives, if there is sufficient stock in the retail inventory, the demand is satisfied, and the product usage begins. In case of stock out, the sales are lost as the make-to-stock inventory method is adopted, and back-ordering is not considered at the retail level. The daily demand is represented by $D \,\tilde{}\, Exp(\lambda)$, with estimated mean by $\bar{D}$, and estimated variance by s_D^2. Once a product is sold, it is being used with an exponential usage rate γ before it is returned or disposed of. With the probability of $1 - p$, the product is disposed of after use, while with the probability of p, the end-of-life product is reintroduced into the reverse supply chain. The returned cores are collected, inspected, and parts deemed suitable for remanufacturing are stored in recoverable/remanufacturable inventory. The OEM remanufactures the returned cores in recoverable inventory with remanufacturing lead-time ρ, and then places them into the serviceable inventory. We assume that all collected products are recoverable. The OEM makes a new production decision periodically by reviewing its return history in order to meet the expected order quantity to be placed by the top echelon (*i.e.*, distributor). The system generates planned new products with new production lead-time, θ, and then places them into the serviceable inventory in order to satisfy the demand. As with the OEM, all other independent supply chain actors manage their inventories according to the periodic review system (r, S) as described in the previous paragraph.

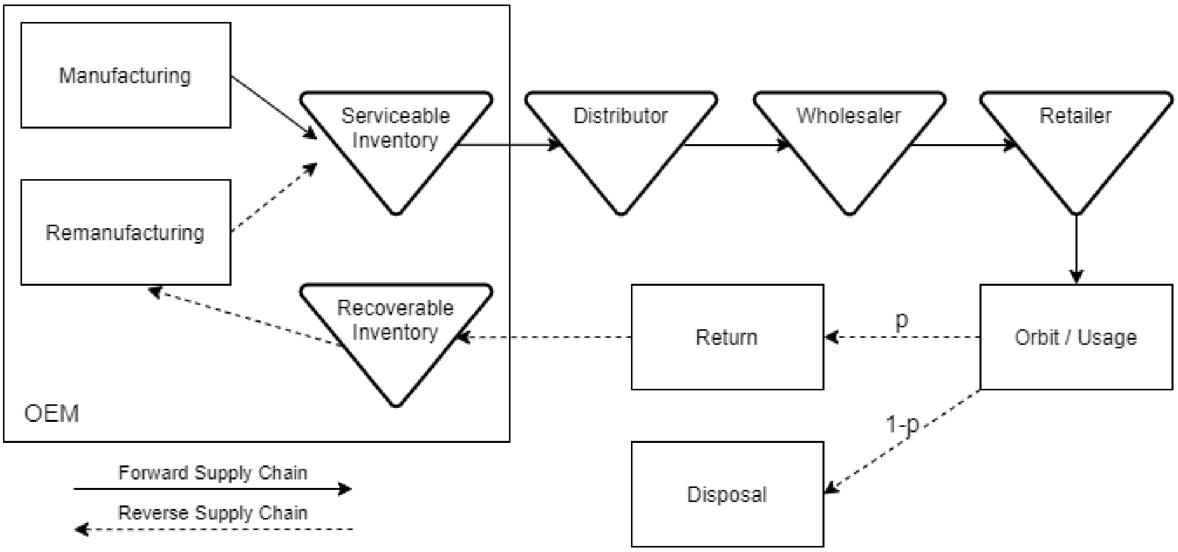


Figure 3.1. Multi-echelon closed-loop supply chain model with return flows.

Supply chain actors, namely echelons, typically carry out inventory management and follow a particular inventory replenishment policy independent of each other by keeping sufficient inventory to minimize the inventory holding costs while delivering the orders placed by the downstream echelon on time, *viz.* providing the desired service level. Here, the periodic review system (r, S) is integrated into our simulation model due to its widespread use in literature and practice [38, 44] and the ability to examine the BWE better [14,39–43]. The r-value represents the periodic review interval at which the inventory replenishment procedures are performed, while the S-value represents the target inventory or OUT level desired to be reached at each periodic review. While the r-value is pre-determined by the supply chain actors, the S-value is constantly updated as needed in every review period, as it specifically concerns the quantity of orders placed and the stock to be held. To be able to update the S level, each echelon uses a forecasting technique to foresee the future demand during lead-time based on historical data. Due to the nature of the periodic review system, echelon k at time t cannot benefit from the information about the order placed by downstream echelon $k-1$, until time $t+r$. To give an example for better understanding, at the beginning of each review period, the retailer forecasts its lead-time demand, updates its OUT level S, places a replenishment order to the wholesaler (*i.e.*, the upper echelon of retail) as much as the difference between the target stock level and the inventory position. The inventory position is basically on-hand inventory (*i.e.*, net stock) plus on-order inventory (*i.e.*, pipeline inventory) since back-ordering is not considered. The goal is here to order an adequate quantity that will bring the inventory position back up to the OUT level S in order to secure the on-hand inventory level during lead-time. Each order is filled on a first-come-first-served (FIFO) basis. Upon the information of the order placed to the wholesaler, the order is prepared with a preparation lead-time and then delivered to the retailer with a shipment lead-time. The order preparation lead-time is directly related to the current net stock level, and the quantity of the order placed, while the order shipment lead-time is an environmental factor for our model and is constant. At the moment that the incoming order information is received, the wholesaler may not have enough inventory on hand to meet the incoming order, in this case, the preparation time and therefore the delivery time of the order may be extended; otherwise, the delivery lead-time is simply equal to the shipment lead-time, since the preparation lead-time is zero. Put simply, the order delivery process typically encompasses the order preparation and shipment sub-processes (*i.e.*, order delivery lead-time, L, is equal to the sum of order preparation lead-time, and shipment lead-time, SL). We here assume that the quantity of orders placed will be fully satisfied in advance but with a bit of order preparation delay in case of instant stock out. The wholesaler and distributor follow these processes autonomously in the same way, and all these actions occur simultaneously. Since the discrete-event simulation model with process iteration is preferred, simultaneous events are easily integrated. For better understanding, the change in inventory level over time at the echelon is seen in Figure 3.2 as an example where the review period is seven days, and the order delivery lead-time is three days.

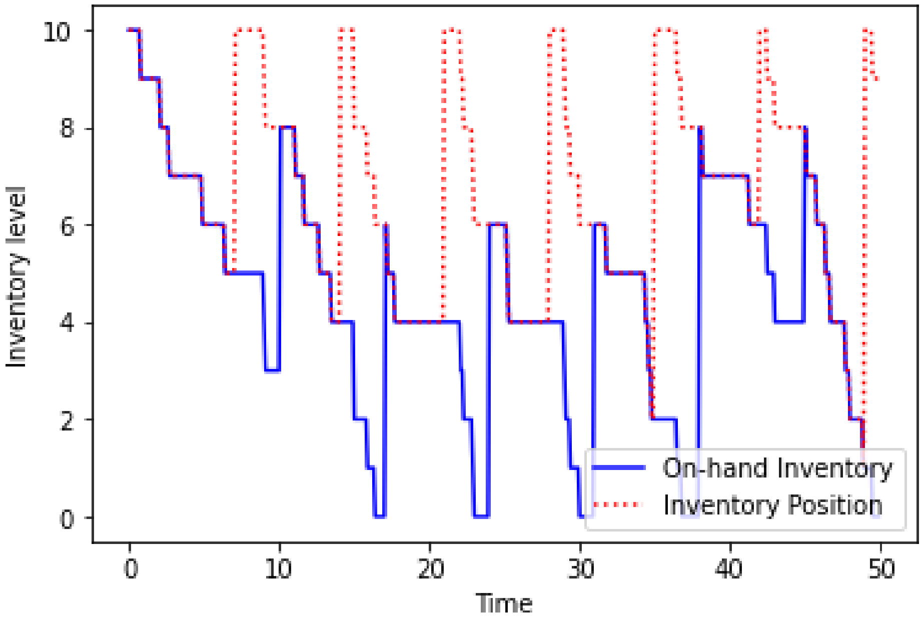


Figure 3.2. Inventory control chart.

We consider the computations behind the inventory replenishment procedures at each echelon in more detail. Let X be the demand during the lead-time or called the protection period $L + r$ according to [27], with an estimated mean of $\bar{X}$, and estimated variance of s_X^2. As a reminder, r represents the review period, and L represents the order delivery lead-time. Then, the lead-time demand for a review period at time t turned into the following summation:

$$X_t = \sum_{i=0}^{L+r} D_{t+i}. \tag{3.1}$$

The OUT level S (*i.e.*, target inventory level or base-stock level) is examined at all echelons at each review period and updated as needed. The OUT level S is critical for ordering the correct quantity in order to maintain an adequate number of products in inventory throughout the protection period time $L + r$ and calculated as follows:

$$S = \bar{X} + z \cdot s_X \tag{3.2}$$

where the z value in the formula represents the safety factor that is z ˜ $N(0, 1)$, and takes a value according to the desired service level (*e.g.*, $z = 2.0$ at the service level of 97.72%).

To determine the OUT level S and ultimately meet the desired service level, supply chain actors estimate the lead-time demand mean $\bar{X}$ and its standard deviation s_X using historical data as follows:

$$\begin{aligned} \bar{X} &= \bar{D} \cdot (\bar{L} + r) \\ s_X^2 &= (\bar{L} + r) \cdot s_D^2 + \bar{D}^2 \cdot s_L^2. \end{aligned} \tag{3.3}$$

To forecast $(\bar{D}, s_D^2)$ at each echelon k, moving average with historical m-period is used. In the absence of seasonality in demand, the moving average is known as an effective estimation method [157]. Likewise, to forecast $(\bar{L}, s_L^2)$ at each echelon k, moving average with historical m-period is used as well. Even though the shipment lead-time between echelons is introduced as a constant value, there is a delay in the preparation and so delivery of orders in cases of stock out. Therefore, supply chain actors must consider this valuable information when updating the OUT level S and include lead-time estimation in their calculations. Otherwise, more out-of-stock cases may occur as this leads to a lower forecast of lead-time demand than expected and subsequently lower the OUT level S and the quantity of orders placed.

When return flows are considered, in addition to the above calculations, the OEM (*i.e.*, $k = 4$) estimates the return quantity it will receive during the protection period using historical return data in each review period and then uses this information to update the S as follows:

$$S = \bar{X} + z \cdot s_X - (\bar{R} + z \cdot s_R) \tag{3.4}$$

where R is the quantity of returned cores during the protection period $L+r$, estimated by $\bar{R}$, and s_R^2.

We examine our model in three prominent cases to have knowledge about returns. First, we consider the case where a moving average method is used for return flow estimation, as is the case with estimating orders to be placed in the forward supply chain, and no extra information is available. Later, we propose a new return estimation method in the presence of real-time orbit size information by defining *return rate* as a function of the orbit size, the expected lifetime of a single product in orbit, and the return probability. Lastly, we examine the case of access to advanced return information where the OEM can be fully aware of the market through some actions.

3.2.1. Return Estimation Using Moving Average

To forecast $(\bar{R}, s_R^2)$ at echelon $k = 4$ (*i.e.*, the OEM), moving average with historical m-period is used. At the beginning of each review period, the OEM forecasts its lead-time demand and amount of cores to return, updates its OUT level S, takes a decision of production quantity as much as the difference between the target stock level and the inventory position. The goal is here to produce an adequate quantity that will bring the inventory position back up to the OUT level S in order to secure the serviceable on-hand inventory level during lead-time. The presence of a reverse supply chain makes production planning flexible but makes it challenging with possible errors in return estimation. Under- or overestimating returns lead to several consequences for the OEM and then the entire supply chain. All supply chain echelons use the moving average method for inventory operations in both forward and reverse supply chains in this baseline scenario. Besides, traditional forecasting methods such as moving average and exponential smoothing preferred in forward supply chains are not rather suitable for return estimation due to often neglecting the correlation between sales and returns [17]. However, this is not the case for study because we propose a return estimation procedure that includes the relationship between demands and returns in the following scenarios.

3.2.2. Return Estimation Based on Orbit Size

After relaxing many assumptions usually encountered in traditional CLSCs, we observe that a general model needs to be developed to predict the returns of end-of-life products. Since the critical role of return estimation in CLSCs is common to all, we take this study one step further and focus on developing a better forecasting method in case of knowing the number of products in use (*i.e.*, orbit size) in real-time and examine whether the BWE on the multi-echelon CLSC can be damped. In this way, the payoffs of the OEM gathering more information about the market are also examined.

We propose a new method that uses real-time orbit size information for periodically estimating returns. Here the return rate is a function of current orbit size, expected lifetime of a single product in orbit, and probability of return. Thus, $(\bar{R}, s_R^2)$ at echelon $k = 4$ (*i.e.*, OEM) and time t are estimated as follows:

$$\begin{aligned}\bar{R} &= \frac{OS_t \cdot p}{E[Y]} \cdot r \\ s_R^2 &= \frac{OS_t \cdot p}{Var(Y)} \cdot r\end{aligned} \tag{3.5}$$

where the p-value represents the probability that an end-of-life product to be returned to the reverse supply chain, the r-value represents the review period, and OS_t describes the orbit size at time t.

Let Y be the lifetime distribution of a single product in use. The lifetime distribution is the basis of reliability engineering and defines the probability of failure or return of a sold product over time. Although there are various lifetime distributions for modeling reliability data, we focus on Exponential or Log-normal distributions as they best describe the service life of the products considered and the behavior of the end-user. The expected value (mean) and variance of the particular distributions are given in the following Table 3.1.

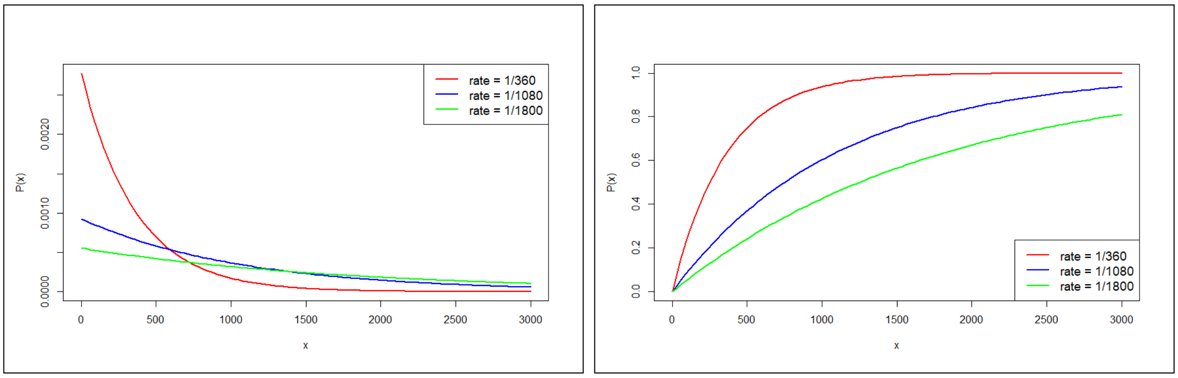
Table 3.1. Mean and variance of distributions.

Distribution of Y	E[Y]	Var(Y)
Exponential (λ)	$1/\lambda$	$1/\lambda^2$
Log-normal (μ, σ^2)	$e^{\mu+\sigma^2/2}$	$(e^{\sigma^2} - 1) \cdot e^{2\mu+\sigma^2}$

The exponential distribution is the widely used statistical distribution for components or systems with a constant average failure rate. In an exponential distribution, the rate parameter represented as λ is the constant failure rate per unit time and $\lambda = \frac{1}{MTBF}$, where $MTBF$ is the mean time between failures. Since the exponential distribution is the unique continuous distribution with useful properties such as memorylessness and constant rate, it is quite suitable for examining reliability functions [158]. In exponential distributions, the coefficient of variance (*i.e.*, the ratio of the standard deviation to the mean value) is always equal to one. As examples for products with short and long usage time, the probability density function and cumulative distribution function of exponential distribution are given in Figure 3.3.

The log-normal distribution is another commonly used statistical distribution for general reliability analysis. When the natural logarithm of Y (the times-to-failure) is distributed as normal with mean μ and variance σ^2, the random variable Y follows the log-normal distribution (*i.e.*, Y ˜ $lnorm(\mu_Y, \sigma_Y^2)$). To generate a log-normal distribution with the desired mean and variance, the following transformations are applied:

$$\mu = log\left(\frac{\mu_Y^2}{\sqrt{\mu_Y^2 + \sigma_Y^2}}\right) \tag{3.6}$$
$$\sigma^2 = log\left(1 + \frac{\sigma_Y^2}{\mu_Y^2}\right).$$

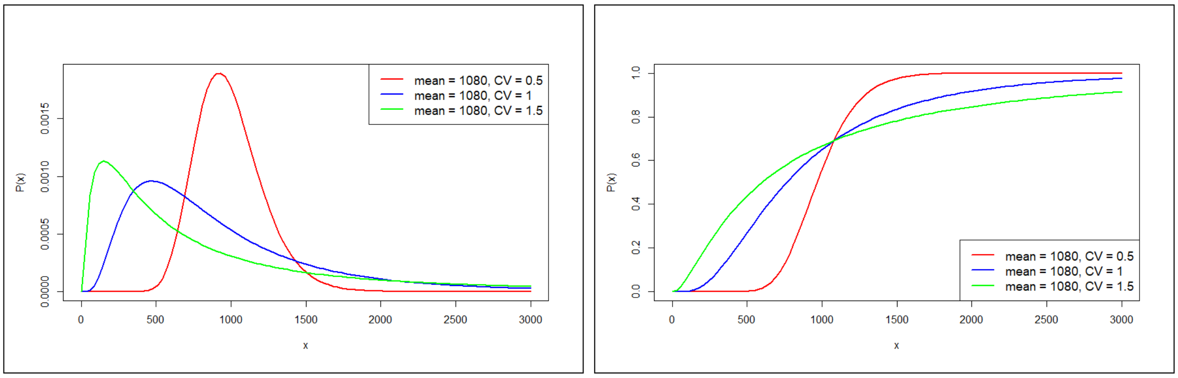


(a) Probability density function (b) Cumulative distribution function

Figure 3.3. Probabilistic graphs of exponential distribution for products with an average lifespan of 1, 3 and 5 years.

The log-normal distribution is a very convenient model since it takes only positive absolute values, and the coefficient of variance can take various values. Therefore, it is ideal for analyzing variability by examining situations such as keeping the mean constant and increasing or decreasing the variance parameter. Here we make an assumption that the mean of product lifetime is equal to the mean of the log-normal distribution. As examples for products with the same average lifespan but the different coefficient of variance values, the probability density function and cumulative distribution function of log-normal distribution are given in Figure 3.4. In order to obtain these plots, first, the transition from the parameters of Y itself into the natural logarithm parameters was applied.

When the purchased appliance requires many repairs over time, the end-user might lose faith and decide not to repair the appliance again after a few repairs. The literature shows that most end-users do not see repair as an option, preferring to either replace it or dispose of it [159]. The log-normal distribution is capable of revealing such end-user behavior as it provides a right-skewed distribution.



(a) Probability density function

(b) Cumulative distribution function

Figure 3.4. Probabilistic graphs of log-normal distribution for products with different coefficients of variance.

3.2.3. Advanced Return Information

In this part, we assume that the amount of return is fully known beforehand, rather than using the return estimation methods mentioned earlier. Naturally, this is basically not an estimation method; $\bar{R}$ is exact, and s_R^2 is equal to zero. As noted in the work of Flapper *et al.* [144], and Khawan and Hausman [160], uncertainties in the timing and quantity of returns are reduced in such a real-life application when an end-user has to announce return information after purchasing a product. The tenant must indicate whether or not to continue with the lease close to the expiration. Industries can also obtain such information with great accuracy through the bring-old take-new campaigns and the agreements with retailers and third-party collectors. Thus, unnecessary or incorrect returns can be prevented in systems that operate within the ARI information.

We included ARI in our model to analyze these real-life applications under our model specifications and mainly compare it with the case of orbit size-based return estimation. In order to measure the value of orbit size information, comparing with the case where the return amounts are fully known in advance will provide valuable outputs.

In our system, this certainty is achieved by using pre-generated random numbers in the simulation environment. When the simulation is run, a set of random numbers is generated depending on the seed, and the return timings are obtained based on this set of random numbers. Accordingly, the number of returns that will occur during the OEM's lead time demand is known and used with certainty in advance.

3.3. Performance Measures

Before the several experiments are designed, the performance measures of interest are determined. This study aims to conduct a scenario analysis basically in terms of the demand amplification, the corresponding performances on inventory and order stability, and service levels observed throughout the supply chain. To this end, three performance measures are taken into account in the simulation runs; bullwhip effect ratio, net stock amplification, and average fill rate.

3.3.1. Bullwhip Effect Ratio

The BWE is widely used in the literature as a standard performance measure, especially in systems with a multi-echelon supply chain structure [25, 44]. The order variance that increases across the supply chain is referred to as the "demand amplification" [19] and, more commonly, as the BWE [20]. Based on the periodic review system (r, S), the orders are placed at each periodic review r of the echelon k. The BWE is basically defined as the ratio of the order variance at the echelon k to the order variance at the customer level:

$$BWE_k = \frac{\sigma^2_{order}\ at\ echelon\ k}{\sigma^2_{demand}\ at\ customer\ level} \tag{3.7}$$

where $k = 1$, 2, 3, and 4.

3.3.2. Net Stock Amplification

Net Stock Amplification (NSA) proposed by Disney *et al.* [37] is to measure the level of inventory stability. This measure quantifies net stock variability relative to demand variability:

$$NSA_k = \frac{\sigma^2_{net\ stock}\ at\ echelon\ k}{\sigma^2_{demand}\ at\ customer\ level} \tag{3.8}$$

where $k = 1$, 2, 3, and 4. An amplification in inventory instability may be observed upstream of the supply chain [63]. Besides, an increased NSA leads to higher holding and lost sales costs and poor cycle service level [44].

Net stock assessments are generally made at the beginning and end of a specific period. According to the periodic review system (r, S), these specific periods are basically the review periods, so the net inventory countings are assumed to be made at each periodic review.

3.3.3. Average Fill Rate

The Fill Rate (FR) is the fraction at which demand or incoming order can be satisfied through instant stock availability, with no backorders or loss of sales. The FR is a popular performance indicator among practitioners since it represents the rate of satisfied demand. While FR is measured as the ratio of the number of demands served to the total number of demands at each periodic review interval at time t, Average Fill Rate (AFR) is measured by averaging FRs:

$$\begin{aligned} FR_{k,t} &= \frac{\mathbf{E}[min(X, NS)]}{\mathbf{E}[X]} \cdot 100 \qquad (3.9) \\ AFR_k &= \frac{\sum_t FR_{k,t}}{r_{eff}} \end{aligned}$$

where k = 1, 2, 3, and 4. The FR is observed and computed when there is a positive incoming order. Therefore, the average of the FRs is divided by the total number of review periods r_{eff} in which the incoming order is positive, rather than by dividing by the total number of review periods.

AFR is generally used as the representative of the cycle service level. These two indicators that are often confused with each other represent the same level and are highly correlated with exceptional circumstances (*e.g.*, when the demand pattern is too sparse or erratic).

3.4. Model Verification

To verify our model, we compare our simulation results with the results of two other analytical models that have been tested for accuracy in this research area. Since the final version of the simulation model we established covers the forward and reverse logistics and also echelons, we made some adjustments in our simulation model in order to compare with published models in the literature. In order to do this, we adapted the model features and parameters to the models in the literature. First, we evaluated our model, assuming that there is no product return flow, and tested the accuracy of inventory replenishment processes. The order variances that the downstream echelon transmitted to the upstream echelon are tracked for comparison. Then, we obtained the BWE ratio at each echelon k in the supply chain and evaluated them as a comparison measure. The main purpose of verification here is not to replicate the works in the literature but to determine that our simulation model runs as expected.

First, we verified our simulation model with the work of Dejonckheere *et al.* [39], whose BWE has been studied from a control engineering perspective. For comparison, we constructed a four-echelon supply chain where customer demands reach the retail, orders reach the wholesaler, distributor, and factory, respectively, and an external supplier fulfills the factory's orders. We set a model in which the demand distribution is normally distributed with a mean of 100 products and a standard deviation of 10 products, the moving average period is 19 days to be used in demand forecasting, the delivery lead-time is fixed 3 days, there is a safety period of 2 days instead of the safety factor z, that is, the protection time is $L + 2 = 3 + 2 = 5$. The comparison results of order standard deviation and BWE are given in Table 3.2.

Table 3.2. Model validation with Dejonckheere *et al.* [39]: mean order standard deviations and mean BWE ratios (in parentheses).

	Customer	Retailer	Wholesaler	Distributor	Factory
Dejonckheere *et al.* [39]	10.00	12.90	17.30	23.91	33.81
	-	(1.67)	(2.99)	(5.72)	(11.43)
Model with Dejonckheere *et al.* [39] specifications	10.03	12.96	17.37	24.00	33.93
	-	(1.67)	(3.00)	(5.73)	(11.44)

Second, we verified our simulation with the work of Chatfield *et al.* [14], whose model was established with the discrete-event simulation approach. While the structure of the model in the first comparison remains the same, there are minor differences in parameters. This time, we set a model in which the demand distribution is normally distributed with a mean of 50 products and a standard deviation of 10 products, a restriction of negative orders, the moving average period is 15 days to be used in demand forecasting, the average running time is to be used in lead-time forecasting, the delivery lead-time is gamma distributed with a shape parameter of 4 days and a scale parameter of 1, a safety factor $z = 2$, that is, the protection time is $L + 1$. The comparison results of order standard deviation and BWE are given in the Table 3.3.

While obtaining these results, a simulation period of 5500 days (-500 days for the warm-up period) and 30 repetitions were applied. The comparison shows that the results of the simulation model we established are very similar to reference models in the literature; as a result, our model is based on a solid basis and gives a high level of confidence to proceed with the numerical analysis.

Table 3.3. Model validation with Chatfield *et al.* [14]: mean order standard deviations and mean BWE ratios (in parentheses).

	Customer	Retailer	Wholesaler	Distributor	Factory
Chatfield *et al.* [14]	10.00	14.90	22.83	33.93	48.75
	-	(2.22)	(5.21)	(11.51)	(23.77)
Model with Chatfield *et al.* [14] specifications	10.02	14.94	22.88	34.01	48.85
	-	(2.22)	(5.21)	(11.52)	(23.77)

4. NUMERICAL ANALYSIS

The development of the conceptual model and then the simulation model, and its verification, led us to the ultimate step of discrete-event simulation modeling, which comprised behavior analysis centering on the simulation parameters in order to attain main findings, specifically to evaluate how events and factors change the effect of the system on performance measures. In other words, the main purpose of simulation and numerical analysis is not to predict a future event but to evaluate possible and meaningful scenarios under particular conditions and assumptions [161].

The main intention of this study is to analyze whether the BWE can be damped by observing the change of OEMs' production decisions and supply chain actors' inventory replenishment decisions under the periodic review (r, S) system in a CLSC where returns depend on the orbit size (*i.e.*, the number of products in-use). Before reaching this ultimate goal, the answers were sought to specific problems encountered in CLSC by gradually examining our detailed simulation model. First of all, by introducing return flows into our simulation model, we consider a CLSC that uses a traditional forecasting method (*i.e.*, the moving average) for return size estimation, as is the case with demand forecasting in the forward supply chain. These estimation methods, preferred in forward supply chains, are not rather suitable for return estimation due to the often disregarded correlation between sales and returns [17]. Consequently, there is an obvious need to develop an elaborative model, including the relationship between sales and returns, to predict the returns of end-of-life products. To expand insights on returns, we evolve our model into one where the return estimation is based on orbit size by updating the return estimation method that the OEM uses at each review period. As indicated in the literature review, the orbit size can actually be observed partially or even fully with adequate investment and the advanced tools (*e.g.*, SEP [131], RFID [132], and ICT [148, 149]). In addition to orbit size information, the average lifespan of a single product in use and the probability that the end-of-life product will not be disposed of and reintroduced into the reverse supply chain are also essential to predict returns. Thus, the effect of an innovative forecasting method on the performance measures of the system and the value of orbit size information are analyzed. Lastly, we assume that the return quantities are known precisely in advance and do not require any estimation. Industries can obtain such information with great accuracy when an end-user needs to announce return information after purchasing a product through the bring-old take-new campaigns and the agreements with retailers and third-party collectors. As a result, we measure the value of advanced return information under our model specifications and compare three different tools that help the OEM to get knowledge about the returns.

As presented in Chapter 3, all considered assumptions regarding production, remanufacturing, and inventory systems are used for developing a simulation analysis, with a particular focus on the returns process. To summarize the assumptions: uncontrollable disposals may occur at the end of the product's useful life probabilistically; back-ordering at the retail level is disregarded instead make-to-stock and lost sales is considered; the transportation lead-time of the items collected from the returns to the OEM is ignored as it is quite small compared to the product's lifetime; the single-item capacity of collection, remanufacturing and production activities, and inventories of supply chain actors are assumed to be infinite.

In the numerical analysis, the changes in the behavior of the system performance measures related to the BWE with different levels of parameters are examined. The system performance measures introduced in Chapter 3 are summarized in Table 4.1.

Table 4.1. System performance measures.

BWE	Bullwhip effect ratio
NSA	Net stock amplification
AFR	Average fill rate

Table 4.2. Model inputs.

Parameter	Description
θ	Daily demand rate
r	Review period
PL	Production lead time
RL	Remanufacturing lead time
SL	Shipment lead time
DSL	Desired service level
m	Number of moving average periods
LTD	Product lifetime distribution
γ	Average product lifetime
CV	Coefficient of variation
p	Return probability

Various simulation runs are executed according to the values of the input parameters given in Table 4.2. The θ represents the daily demand rate, and demands arrive at echelon k one by one following independent exponential interarrival times. The review period, r, represents the intervals (*e.g.*, daily and weekly) for supply chain actors to review their inventory levels. Production and remanufacturing lead times represent the required times to get products ready-to-serve to satisfy demand, regardless of quantity. The shipment lead-time represents the timespan it takes for the prepared order to reach the target echelon. The DSL represents the level at which supply chain actors desire to meet incoming demand, and the echelons hold a safety stock proportional to the coefficient corresponding to the DSL value in the normal distribution. The m value represents the number of periods that supply chain actors take into account retrospectively in the moving average method for estimating demands or returns. LTD represents the lifetime distribution of a single product, and CV represents the coefficient of variation of the distribution. The CV values are valid for the log-normal distribution since CV equals one in the exponential distribution. Within the scope of product reliability, some analysis can be conducted using exponential distribution for durable or non-durable products and also for fast-moving or slow-moving products. With the log-normally distributed product lifetime, multifarious experiments with different levels of CV can be examined. Finally, the return probability, p, represents the likelihood of an end-of-life product to be collected and reintroduced into reverse supply chain operations.

Specifically, we focus on the analysis that investigates the effect of five parameters on system performance measures. We found that the daily demand rate, θ, is not significant as long as it is stationary, so we take the demand rate of 1 per day for simplification. We examine the cases where the demand pattern is non-stationary later in this study. Since we consider an uncapacitated production/remanufacturing system, the lead-time parameters (*i.e.*, production and remanufacturing) are out of scope, and we take them as 3 days on a fixed basis regardless of the quantity. No lower or upper limit was considered for production and remanufacturing since the main purpose here is to experience the consequences of the BWE; adding capacity may make it challenging to observe this effect. We also treat the shipment lead-time as 3 days so that we assume equal levels of order shipment across the echelons. Since the lead-times are taken into account equally when calculating the OUT level S in all echelons, we can more accurately observe the behavioral change of CLSC over other parameters of concern.

Later in this chapter, we first consider the case where the daily demand rate is stationary, and we discuss the experimental results for input parameters of interest and different methods of obtaining return information. Then, we consider the impulsive buying effect where the daily demand rate is not stationary, and we observe the continuing impact of the BWE on the supply chain.

4.1. Bullwhip Effect on a Multi-Echelon Closed-Loop Supply Chain

This section focuses on the performance measures mainly related to the BWE, where three different methodologies foresee the returns in a CLSC where demand and returns are totally correlated. First, we consider the traditional moving average method for reverse flow estimation, as practiced in the majority of the study done within the context of CLSC. Then, we define the *return rate* as a function of the orbit size, the expected lifespan of a product in orbit, and the probability that the end-of-life product being reintroduced into the reverse supply chain. Lastly, we consider the case where the return flow is known in advance and does not require any additional return estimation. Thus, we measure the value of return flow, orbit size information, and advanced return information.

In this way, the value ranges of the input parameters are given in Table 4.3, thus creating a total of 1620 experiments (3 review periods × 3 desired service levels × 2 number of periods for moving average × 6 life time distributions × 5 return probabilities × 3 ways of obtaining return information). While obtaining the results, a simulation period of 4000 days (-400 days for warm-up period) in each experiment and 30 repetitions are performed.

Table 4.3. Parameter values.

Parameter	Value
r	(1, 7, 15)
DSL	(0.5, 0.7, 0.9)
m	(15, 30)
LTD	$exp(1/360)$, $exp(1/720)$, $exp(1/1080)$ $lnorm(720, 180^2)$, $lnorm(720, 720^2)$, $lnorm(720, 2880^2)$
p	(0.1, 0.3, 0.5, 0.7, 0.9)

4.1.1. Return Estimation Using Moving Average

As a first step, we focus on scenario analysis in a multi-echelon CLSC that uses a traditional forecasting method for returns without considering the orbit size information. The changes in the behavior of BWE-related performance measures with different review periods, desired service levels, number of moving average periods, average product lifetime, product lifetime variability, and return probabilities, respectively, are examined in a CLSC where returns are estimated by using the moving average method with m-period historical data as in the forward supply chain. Then we measure the value of return flow by comparing it to the traditional supply chain with no return.

4.1.1.1. Impact of Review Periods. At this stage, we consider three different experiments in which the review periods are incrementally increased. We consider the daily, 7-day, and 15-day periodic review periods for comparison. The practice with the daily review is called base stock policy, and it usually gives stable results in terms of inventory variability but is costly and challenging to manage. For a better understanding of the comparisons, we perform visualization and statistical tests. The performance measures on the echelons by review periods is given in Figures 4.1 and 4.3 as an average of 30 runs. The retail is abbreviated as RET, the wholesaler as WHSA, and the distributor as DIST. As a first impression, the BWE in base stock policy shows an upward linear increase across echelons, while in the cases of the review period is 7 and 15 days, it follows a similar pattern like the BWE ratio is low in the lower echelons but high in the upper echelons. In the first two echelons (*i.e.*, retailer and wholesaler), minimal BWE is experienced when the review period is 7 days. At the same time, in the last two echelons (*i.e.*, distributor and OEM), the minimum is observed in the base stock policy. According to this experiment set, the highest amplification in terms of BWE at all echelons is observed when the review period is 15 days.

With the visualization, it is evident that the parameter of the review period shows significant and ordinal interaction. However, we examine whether the BWE experienced in the echelons is statistically significantly different by applying one-way Analysis of Variance (ANOVA) test at each echelon. We then focus on the difference ranges between these cases at the 95% confidence interval through Tukey's range test. The output of one-way ANOVA and Tukey's range test at each echelon is given in Figure 4.2. Before the application, it is checked that the assumptions for the ANOVA testing are satisfied at each stage. The observations are obtained randomly and independently, and the data at each factor level is normally distributed.

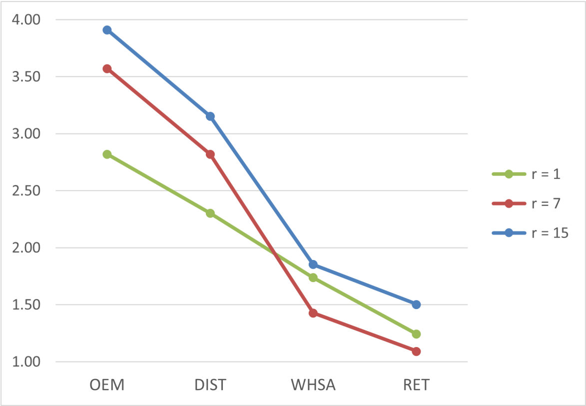
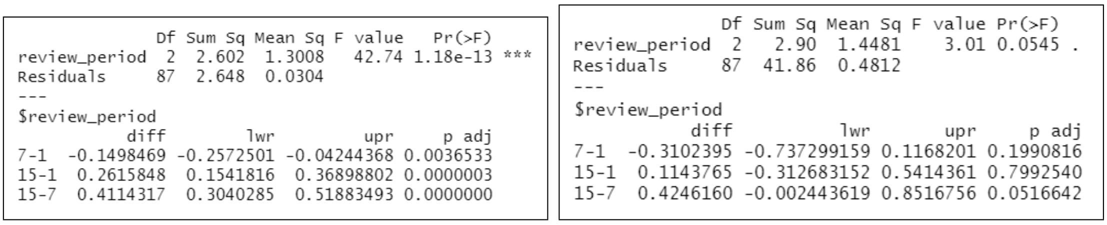


Figure 4.1. BWE comparison by review periods, $r = (1,\ 7,\ 15)$, $DSL = 0.9$, $m = 30$, $LTD = exp(1/720)$, $p = 0.5$.

At the retail echelon, there are significant differences between the review periods, as the p-value is much smaller than the significance level of 0.05 and highlighted with "***" in the output. The degrees of freedom is basically 89 (3 scenarios × 30 replications - 1). Since the ANOVA test is significant, we can proceed to apply Tukey's range test for conducting multiple pairwise-comparison. The mean differences between pairs are shown under the "diff" column, and the lower and upper limits at the 95 percent confidence level are under the "lwr" and "upr" columns, respectively. It is concluded that there is also a significant difference between all pairwise groups due to the adjusted p-values being less than 0.05. For instance, the mean difference between cases with a review period of 7 days and cases with a daily review period was observed as -0.15 ± 0.107 at the 95% confidence interval. From another perspective, we can also say that the difference is significant since this range does not contain the zero value. Unlike the retail, we cannot say that there are significant differences at the wholesaler echelon between the review periods, even in the pairwise comparison of 7-day and 15-day periodic reviews. Based on the distributor and OEM, there are significant differences only in the pairwise comparison of the 1-day and 15-day periodic reviews. As a result of the comparison of period reviews, the base stock policy draws a different linear pattern compared to the 7-day and 15-day periodic reviews. The 15-day periodic review has the same pattern as the 7-day periodic review, where BWE is experienced lower in the first echelons and higher in the upper echelons but with an upward margin.

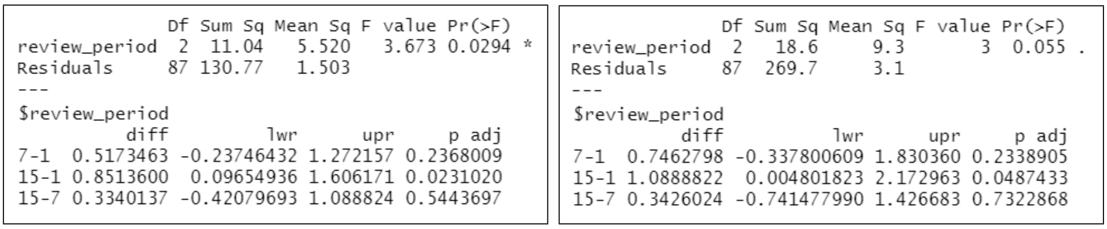


```
              Df Sum Sq Mean Sq F value   Pr(>F)
review_period  2  2.602  1.3008   42.74 1.18e-13 ***
Residuals     87  2.648  0.0304
---
$review_period
            diff        lwr         upr     p adj
7-1   -0.1498469 -0.2572501 -0.04244368 0.0036533
15-1   0.2615848  0.1541816  0.36898802 0.0000003
15-7   0.4114317  0.3040285  0.51883493 0.0000000
```

(a) Retail

```
              Df Sum Sq Mean Sq F value Pr(>F)
review_period  2   2.90  1.4481    3.01 0.0545 .
Residuals     87  41.86  0.4812
---
$review_period
            diff          lwr       upr     p adj
7-1   -0.3102395 -0.737299159 0.1168201 0.1990816
15-1   0.1143765 -0.312683152 0.5414361 0.7992540
15-7   0.4246160 -0.002443619 0.8516756 0.0516642
```

(b) Wholesaler



```
              Df Sum Sq Mean Sq F value Pr(>F)
review_period  2  11.04   5.520   3.673 0.0294 *
Residuals     87 130.77   1.503
---
$review_period
          diff         lwr      upr     p adj
7-1  0.5173463 -0.23746432 1.272157 0.2368009
15-1 0.8513600  0.09654936 1.606171 0.0231020
15-7 0.3340137 -0.42079693 1.088824 0.5443697
```

(c) Distributor

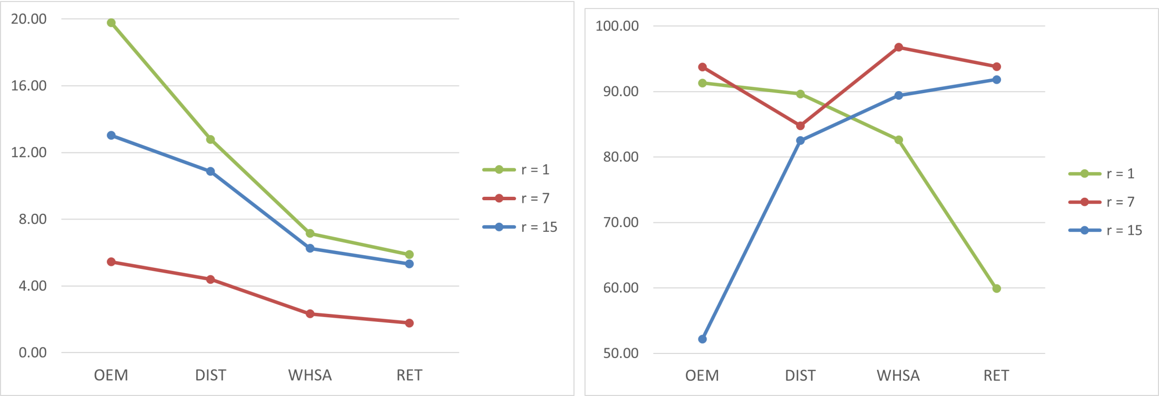
```
              Df Sum Sq Mean Sq F value Pr(>F)
review_period  2   18.6     9.3       3  0.055 .
Residuals     87  269.7     3.1
---
$review_period
          diff          lwr      upr     p adj
7-1  0.7462798 -0.337800609 1.830360 0.2338905
15-1 1.0888822  0.004801823 2.172963 0.0487433
15-7 0.3426024 -0.741477990 1.426683 0.7322868
```

(d) OEM

Figure 4.2. Outputs of one-way ANOVA and Tukey's range tests (factor: review periods (1, 7, 15) and response variable: BWE ratio at echelon).

From Figure 4.3, the NSA in base stock policy shows an upward linear increase across echelons with an exceptionally steep rise in the top echelon, while in the cases of the review period is 7 and 15 days, they again follow a similar pattern like the NSA is low in the lower echelons but high in the upper echelons. According to this set of experiments, the lowest NSA at all echelons is experienced by a large margin when the review period is 7 days. In daily and 15-day periodic reviews, the performance measurement is high, leading to higher holding and lost sales costs and thus lower service level.

Also from Figure 4.3, the AFR in base stock policy shows a steady upward improvement across echelons and there is a disordinal interaction in the cases of 7-day and 15-day periodic reviews. Based on this set of experiments, we can say that the situation with the review period of 7 days gives the best instant service levels. On the other hand, the daily and 15-day periodic reviews give quite the opposite results, with a regular increase at the daily review and a decreasing trend at the 15-day review. Although the DSL is pre-determined as 90 percent, AFR is observed as 60 percent at the retail echelon with the daily periodic review system and 52 percent at the OEM echelon with the 15-day periodic review system. In cases where the AFR is low, there is a delay in responding to incoming requests immediately.



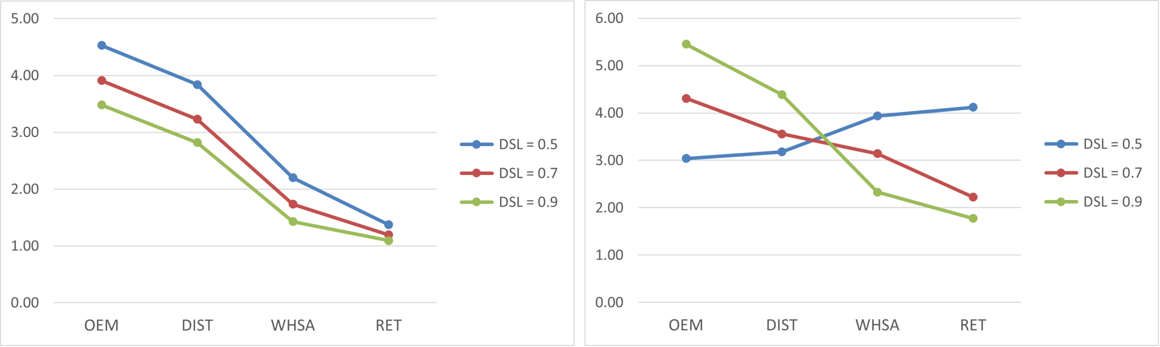
(a) NSA

(b) AFR

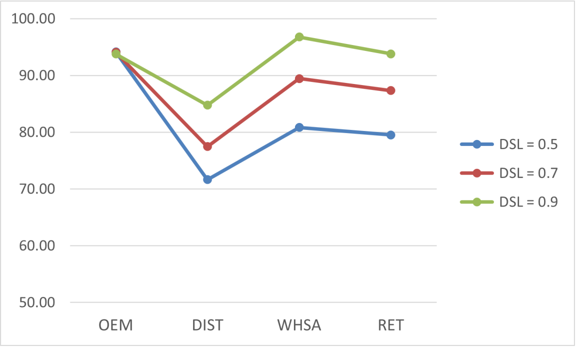
Figure 4.3. NSA and AFR comparison by review periods, $r = (1, 7, 15)$, $DSL = 0.9$, $m = 30$, $LTD = exp(1/720)$, $p = 0.5$.

4.1.1.2. Impact of Desired Service Levels. The development of performance measures in three different experiments, in which the desired service levels are increased incrementally, are given in Figure 4.4. Supply chain actors operating at the 50 percent of DSL keep the stocks in the exact amounts they foresee, while those operating at the 90 percent level keep an additional safety stock, taking into account the variability in demand and returns.

With the increase of DSL, the BWE ratios decrease in all echelons. By increasing the level of safety stock, echelons increase the quantity of orders placed so that less order variability can be observed. It is possible to interpret this situation in a similar way over AFR rates. It observed that keeping the safety stock, taking into account the variability in demand and returns, increases the instant inventory availability, that is, the AFR. In other words, safety stock helps echelons have the correct quantity of inventory at the right time. In terms of NSA, the NSA observed in echelons gradually increases as the quantity of safety stock increases. However, the NSA gradually decreases along with the echelons if the safety stock is not held. This is because the first echelons are subject to higher inventory variability, ignoring the variability in demands.



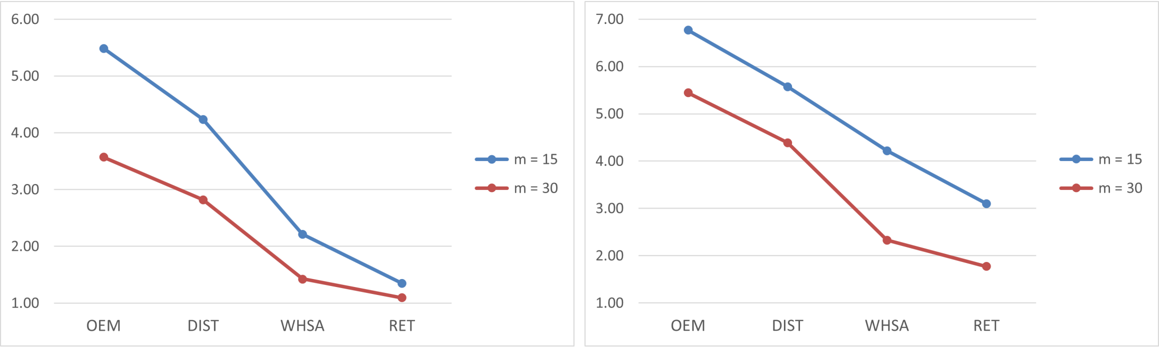
(a) BWE (b) NSA



(c) AFR

Figure 4.4. Comparison by desired service levels, $r = 7$, $DSL = (0.5, 0.7, 0.9)$, $m = 30$, $LTD = exp(1/720)$, $p = 0.5$.

4.1.1.3. Impact of Number of Moving Average Periods. In this part, the effect of the number of moving average periods is examined. For comparison, we consider the moving average method with 15-periods and 30-periods. The development of performance measures is given as in Figure 4.5. In terms of BWE, a significant difference is clearly visible in all echelons. As the number of moving average periods increases, the system can take more stable actions since sudden changes have a lower impact, thus damping the BWE.



(a) BWE (b) NSA

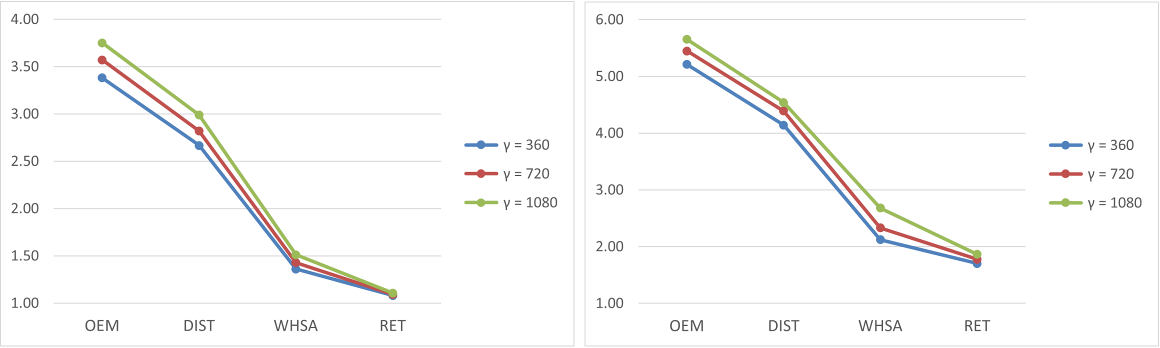
(c) AFR

Figure 4.5. Comparison by number of moving average periods, $r = 7$, $DSL = 0.9$, $m = (15, 30)$, $LTD = exp(1/720)$, $p = 0.5$.

NSA measures show an upward linear increase across echelons. As with BWE, the NSA can be damped as the number of moving average period increases, revealing that this is a significant factor for CLSCs. According to this experimental group, the highest NSA across all tiers is experienced when the number of periods is 15 and may have higher holding costs, lost sales, and therefore lower service level in this scenario where fewer periods are tracked.

Although DSL was pre-determined to be 90 percent, the AFR is observed to be above 90 percent and quite similar in three echelons, excluding the distributor. According to this set of experiments, the distributor echelon bears the greatest impact in the multi-echelon CLSC. The increase in the number of tracked periods impacts improving the service level at all echelons.

4.1.1.4. Impact of Average Product Lifetime. This part examines three different experiments in which the average product life is varied. By considering the products with an average life of 1, 2, and 3 years, the impact of slow and fast consumed products on the bullwhip behavior is observed as in Figure 4.6.



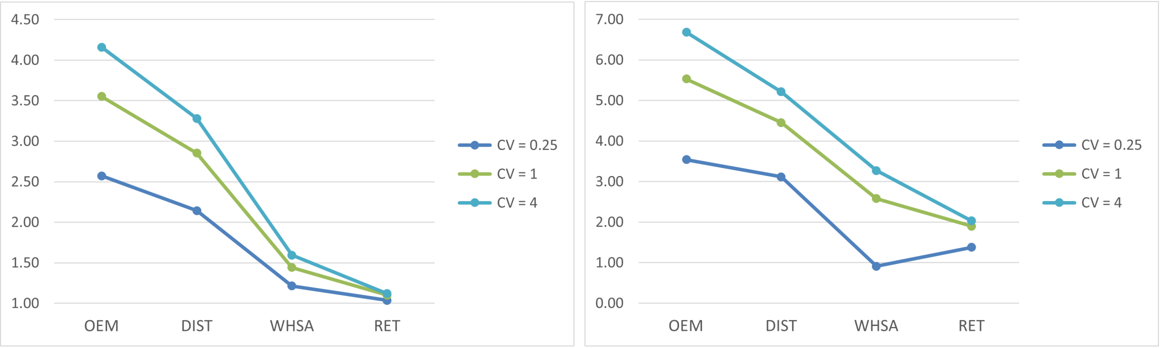
(a) BWE (b) NSA

(c) AFR

Figure 4.6. Comparison by average product lifetimes, $r = 7$, $DSL = 0.9$, $m = 30$, $LTD = (exp(1/360), exp(1/720), exp(1/1080))$, $p = 0.5$.

Considering a mature market, although there is no significant difference between performance measures, BWE and NSA increase at all echelons with prolonged average life of the product. Fast-consumption products are more beneficial for CLSC systems because product cycles are completed faster, the collected products constantly feed the remanufacturing line, and the new production line is relieved. On the other hand, there is no significant difference between the AFR rates, and the distributor is once again the echelon that faced the challenge of not keeping sufficient instant inventory.

4.1.1.5. Impact of Product Lifetime Variability. In this part, 3 different product types with log-normally distributed product lifetime with different coefficients of variation are examined, taking the average lifespan equal to 2 years. Thus, the impact of low and high variability products on bullwhip behavior is observed as in Figure 4.7.



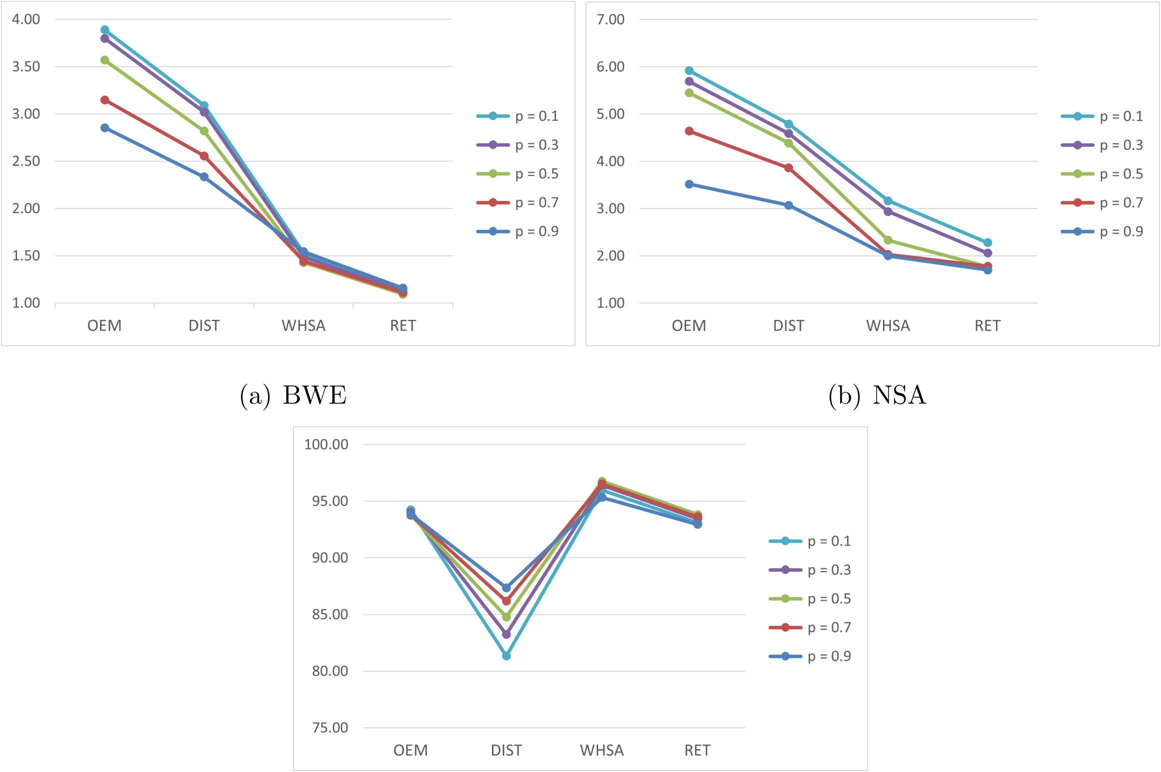
(a) BWE (b) NSA

(c) AFR

Figure 4.7. Comparison by coefficients of variation, $r = 7$, $DSL = 0.9$, $m = 30$, $LTD = (lnorm(720, 180^2), lnorm(720, 720^2), lnorm(720, 2880^2))$, $p = 0.5$.

With the increase in CV, BWE and NSA ratios increase significantly at all echelons. Accurate estimation of the timing and quantity of returns is key in CLSCs, and such uncertainties are less observed in product types with lower lifetime variability. With the formation of a mature market, an estimation method that considers retrospective returns begins to forecast more accurately for such products. Due to the nature of uncertainty, return estimation deviates from the accuracy with increasing product lifetime variability, and the echelons are subject to much higher inventory and order variability, as shown in Figure 4.7. A similar interpretation can be made for AFR measurements. While great improvements are seen with low product life variability, significant reductions of down to 75 percent are observed in other cases, particularly at the distributor echelon.

4.1.1.6. Impact of Return Probability. The performance measures of three different experiments, in which the return probabilities are incrementally increased, are examined in this part. While the impact of return probabilities in CLSC is a common research area, few studies examine the BWE [162]. As analyzed in Figure 4.8, the CLSC structure appears to dampen inventory and order variability, as is the effect seen with the increased probability of returns.



(a) BWE

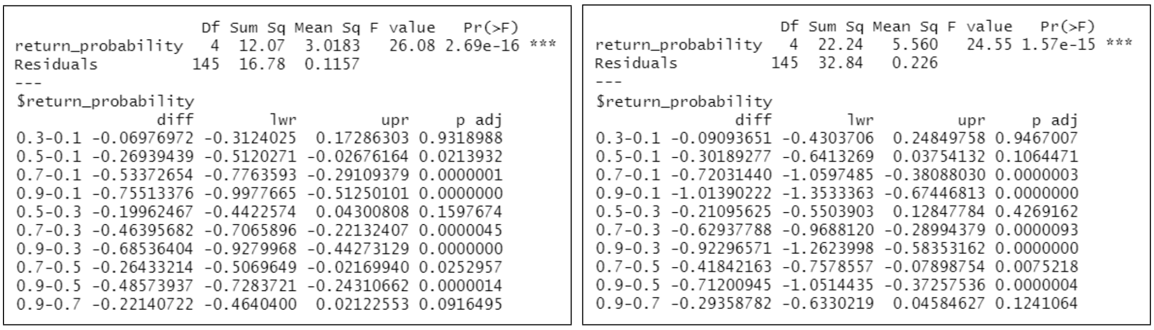
(b) NSA

(c) AFR

Figure 4.8. Comparison by return probabilities, $r = 7$, $DSL = 0.9$, $m = 30$, $LTD = exp(1/720)$, $p = (0.1, 0.3, 0.5, 0.7, 0.9)$.

In terms of BWE, while there is no significant difference in the first two echelons (*i.e.*, retail and wholesaler), the differences caused by the return possibilities in the last two echelons (*i.e.*, distributor and OEM) are seen more clearly. However, in general, they follow the same pattern. As the probability of return increases, the BWE rate decreases at the echelons, revealing the positive impact of the reverse supply chain.

In the following Figure 4.9, the output of one-way ANOVA and Tukey's range test at distributor and OEM echelons is given. According to the parameter set, while it is seen that there is no significant difference between the pairs with close return rates (*e.g.*, 0.1 and 0.3 or 0.7 and 0.9), there are significant differences between all other pairs. As a result, it is determined that the probability of return has a significant impact on BWE, especially for the last two echelons (*i.e.*, distributor and OEM).



```
                   Df Sum Sq Mean Sq F value   Pr(>F)    
return_probability   4  12.07  3.0183   26.08 2.69e-16 ***
Residuals          145  16.78  0.1157                     
---
$return_probability
               diff        lwr         upr     p adj
0.3-0.1 -0.06976972 -0.3124025  0.17286303 0.9318988
0.5-0.1 -0.26939439 -0.5120271 -0.02676164 0.0213932
0.7-0.1 -0.53372654 -0.7763593 -0.29109379 0.0000001
0.9-0.1 -0.75513376 -0.9977665 -0.51250101 0.0000000
0.5-0.3 -0.19962467 -0.4422574  0.04300808 0.1597674
0.7-0.3 -0.46395682 -0.7065896 -0.22132407 0.0000045
0.9-0.3 -0.68536404 -0.9279968 -0.44273129 0.0000000
0.7-0.5 -0.26433214 -0.5069649 -0.02169940 0.0252957
0.9-0.5 -0.48573937 -0.7283721 -0.24310662 0.0000014
0.9-0.7 -0.22140722 -0.4640400  0.02122553 0.0916495
```

(a) Distributor

```
                   Df Sum Sq Mean Sq F value   Pr(>F)    
return_probability   4  22.24   5.560   24.55 1.57e-15 ***
Residuals          145  32.84   0.226                     
---
$return_probability
               diff        lwr         upr     p adj
0.3-0.1 -0.09093651 -0.4303706  0.24849758 0.9467007
0.5-0.1 -0.30189277 -0.6413269  0.03754132 0.1064471
0.7-0.1 -0.72031440 -1.0597485 -0.38088030 0.0000003
0.9-0.1 -1.01390222 -1.3533363 -0.67446813 0.0000000
0.5-0.3 -0.21095625 -0.5503903  0.12847784 0.4269162
0.7-0.3 -0.62937788 -0.9688120 -0.28994379 0.0000093
0.9-0.3 -0.92296571 -1.2623998 -0.58353162 0.0000000
0.7-0.5 -0.41842163 -0.7578557 -0.07898754 0.0075218
0.9-0.5 -0.71200945 -1.0514435 -0.37257536 0.0000004
0.9-0.7 -0.29358782 -0.6330219  0.04584627 0.1241064
```

(b) OEM

Figure 4.9. Outputs of one-way ANOVA and Tukey's range tests (factor: return probabilities (0.1, 0.3, 0.5, 0.7, 0.9) and response variable: BWE ratio at echelon).

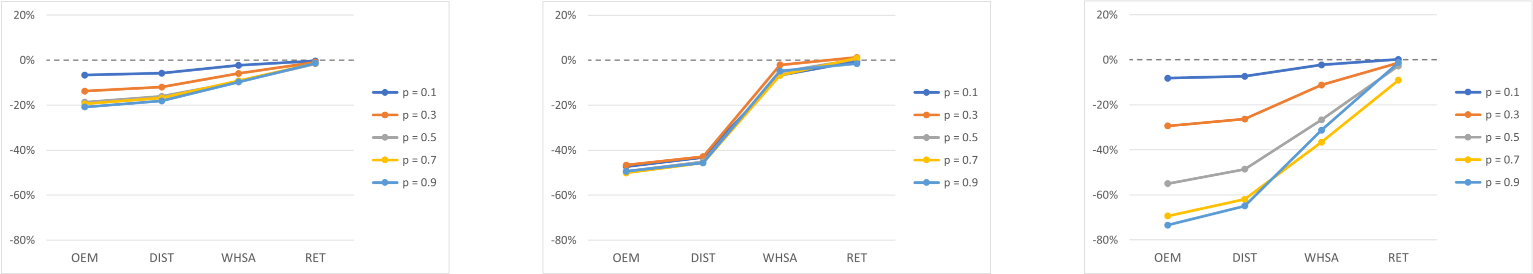
As with BWE ratios, NSA measures show an upward increase across echelons. The NSA can be damped as the probability of return increases, revealing that this is an important factor for CLSCs. According to this set of experiments, the lowest NSA across all echelons is experienced when the probability of return is 0.9, especially in the last two echelons with a great margin. On the other hand, lower return flow can result in higher holding costs, lost sales, and thus lower service level.

Although DSL was pre-determined to be 90 percent, the fill rate is observed to be above 90 percent and quite similar in three echelons, excluding the distributor. According to this set of experiments, the distributor echelon bears the greatest impact in the multi-echelon CLSC. In addition to the low fill rates, the probability of return has a significant effect on this echelon, and the increase in the probability of return has the impact of enhancing the service level. In cases where the probability of a return is low, there might be delays in responding immediately to incoming demands, especially at the distributor echelon.

4.1.1.7. Value of Return Flow.

We evaluate the performance metrics with a set of parameters considering a traditional multi-echelon supply chain with no return flow and a multi-echelon CLSC. Our aim here is to observe the value of the return streams by comparing the systems with the average parameter set without being too detailed since this section is the main focus of the literature.

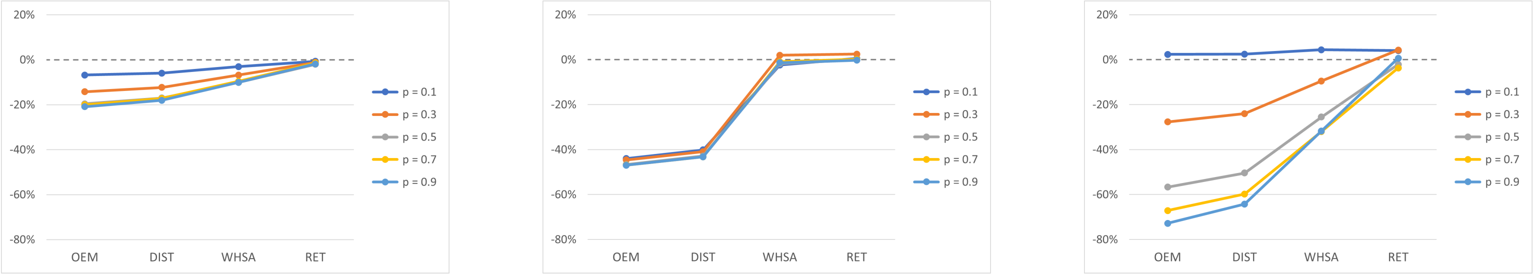
The developments of the performance measures are given in Figure 4.10 according to the mentioned supply chain types. As can be seen from the figure, return flows with remanufacturing relieve the supply chain system, decrease the order and inventory variability, and increase the instant service level. The improvement rates differ for the different review periods, CVs, return probabilities, and even each echelon. Compared to the traditional multi-echelon supply chain with no return flow, order variability can be reduced by up to 21 percent in the base-stock policy, up to 50 percent in the 7-day periodic review, and up to 73 percent in the 15-day periodic review. Except for some particular circumstances (*e.g.*, where a 15-day periodic review is applied, CV is high, and return is unlikely), these results demonstrate once again how beneficial remanufacturing is a business option.



(a) $r = 1$, $CV = 0.25$

(b) $r = 7$, $CV = 0.25$

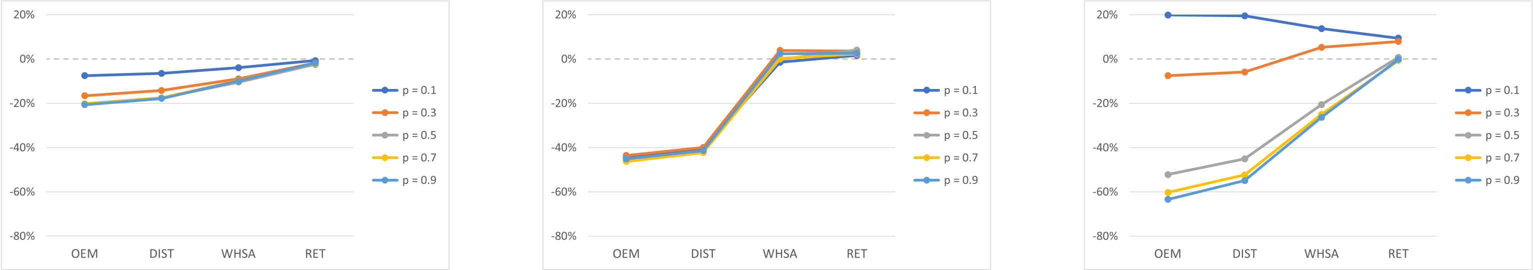
(c) $r = 15$, $CV = 0.25$



(d) $r = 1$, $CV = 1$

(e) $r = 7$, $CV = 1$

(f) $r = 15$, $CV = 1$



(g) $r = 1$, $CV = 4$

(h) $r = 7$, $CV = 4$

(i) $r = 15$, $CV = 4$

Figure 4.10. Value of return flow, $r = (1,\ 7,\ 15)$, $DSL = 0.9$, $m = 30$, $LTD = (lnorm(720, 180^2),\ lnorm(720, 720^2),\ lnorm(720, 2880^2))$, $p = (0.1,\ 0.3,\ 0.5,\ 0.7,\ 0.9)$.

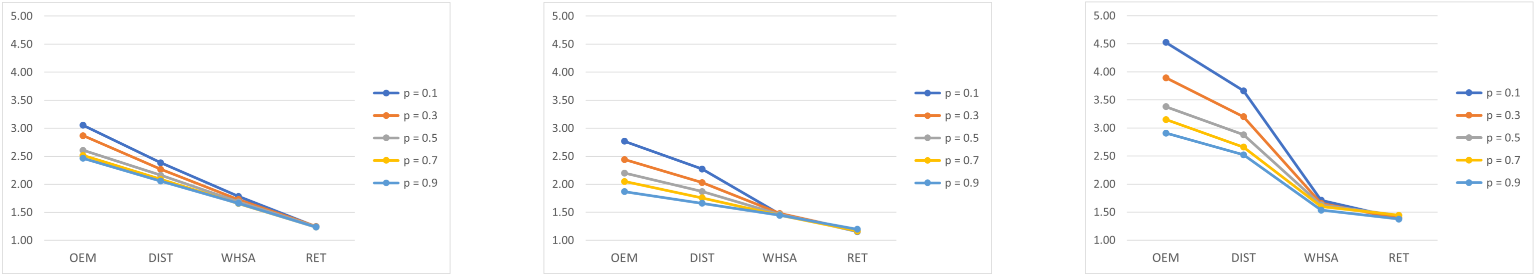
4.1.2. Return Estimation Based on Orbit Size

After analyzing the impact of the system parameter set on a CLSC that estimates returns using the moving average method and measuring the value of return flows by comparing it to a conventional multi-echelon supply chain with no return streams, the behavior of the BWE with a return estimation methodology that takes orbit size information into account is discussed here. For this, we define the *return rate* as a function of orbit size, the average lifetime of a single product in orbit, and the probability of reintroducing the end-of-life product into the reverse supply chain.

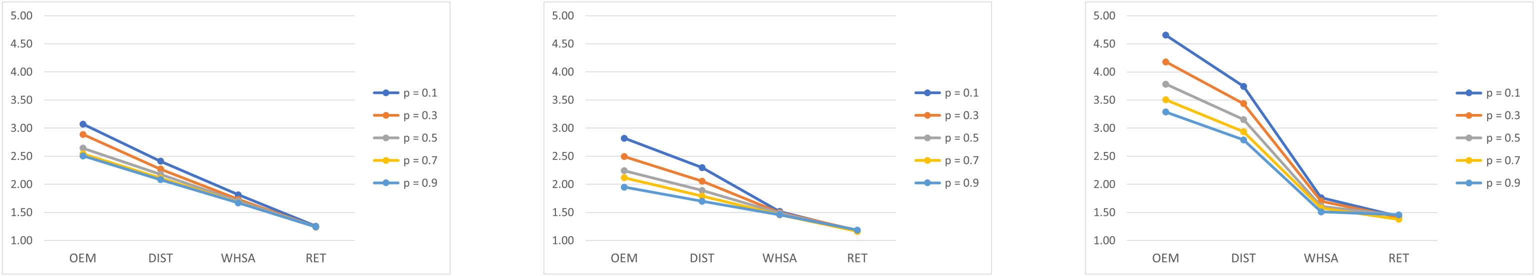
The changes in the bullwhip behavior are examined with different review periods, average product lifetime, product lifetime variability, and return probabilities. Then, to measure the value of orbit size information, we compare it to a CLSC reviewed in the previous section, which estimates returns with the traditional moving average method and focuses on ratios of change on the performance measures.

4.1.2.1. Sensitivity Analysis on Bullwhip Behaviour. In Figure 4.11, nine graphs in which the BWE ratios of the selected experiments at the echelons are plotted according to the probability of return. The plots in the lines belong to the experiments where the average life of a product is one year (*i.e.*, $\gamma = 360$), two years (*i.e.*, $\gamma = 720$), and three years (*i.e.*, $\gamma = 1080$), respectively. Going from left to right, they include experiments with daily, 7-day, and 15-day review periods, respectively.

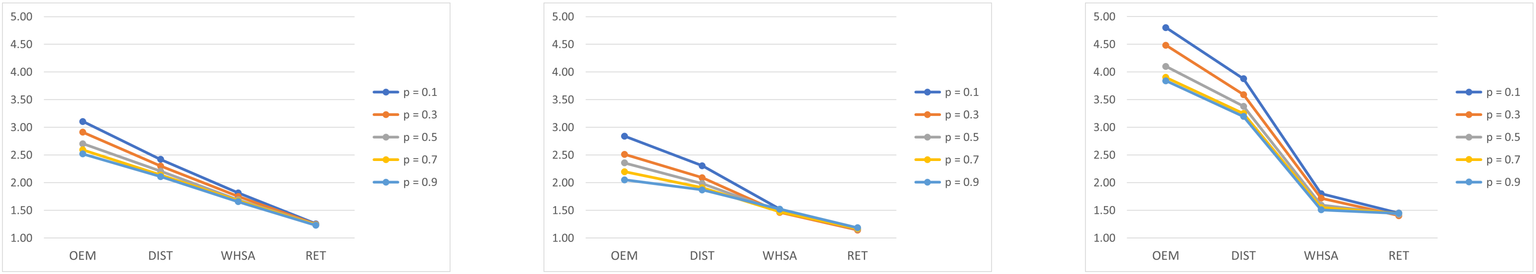
From Figure 4.11, it is clearly seen that BWE ratios increase as the review period gets longer, which becomes more visible, especially in the last two echelons. As discussed in Figure 4.1, the increase in the review period in estimating returns by the moving average method tends to increase order variability between echelons. Since the return quantities to be estimated in the base stock policy are on a daily basis, they contain less uncertainty than the cases of 7-day and 15-day periodic reviews. In this responsive periodic review, which can react more quickly to the variability in demand and returns, the BWE is also observed at a low level.



(a) $r = 1$, $\gamma = 360$ (b) $r = 7$, $\gamma = 360$ (c) $r = 15$, $\gamma = 360$



(d) $r = 1$, $\gamma = 720$ (e) $r = 7$, $\gamma = 720$ (f) $r = 15$, $\gamma = 720$



(g) $r = 1$, $\gamma = 1080$ (h) $r = 7$, $\gamma = 1080$ (i) $r = 15$, $\gamma = 1080$

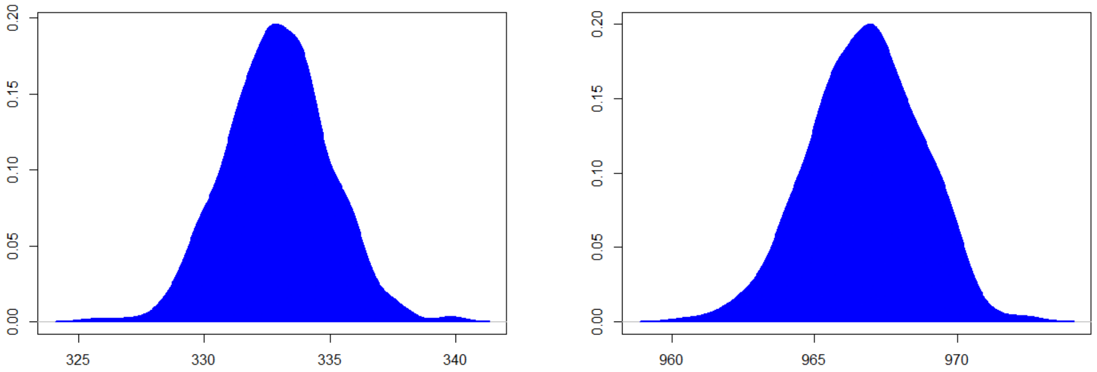
Figure 4.11. Sensitivity analysis on BWE, $r = (1,\ 7,\ 15)$, $DSL = 0.9$, $m = 30$, $LTD = (exp(1/360),\ exp(1/720),\ exp(1/1080))$, $p = (0.1,\ 0.3,\ 0.5,\ 0.7,\ 0.9)$.

Table 4.4. Improvement rates of BWE at distribution echelon with increased return probability, r = (1, 7, 15), $DSL = 0.9$, $m = 30$, $LTD = (exp(1/360), exp(1/720), exp(1/1080))$, p = (0.1, 0.3, 0.5, 0.7, 0.9).

r	γ	$p = 0.1$	$p = 0.3$	$p = 0.5$	$p = 0.7$	$p = 0.9$
1	360	-	4.9%	4.7%	3.3%	1.4%
	720	-	4.9%	4.5%	3.2%	1.3%
	1080	-	4.9%	4.0%	3.2%	1.3%
7	360	-	10.7%	7.8%	6.1%	5.9%
	720	-	9.8%	7.1%	5.2%	7.2%
	1080	-	6.9%	5.4%	3.5%	1.6%
15	360	-	12.6%	9.9%	7.6%	5.3%
	720	-	8.2%	8.0%	7.2%	4.9%
	1080	-	7.4%	5.8%	3.8%	1.7%

In addition, return probabilities appear to have a significant impact in all chosen experiments. The echelons experience low order variability as the probability of return increases. While significant differences are observed, especially in the last two echelons, these differences become more evident with longer review period. In particular, the improvement rate in BWE between the return parameters decreases with the increase of the return probability, that is, a significant difference is observed between 10 percent and 30 percent returns, while the difference between 70 percent and 90 percent returns still persists, but is low. The improvement rates of BWE observed in the distribution echelon with the increased probability of return for the selected experiments are represented in Table 4.4. In the base stock policy, the difference in improvement rates between average product lifetimes is considerably low. An improvement of 4.9 percent is seen when the probability of return increases from 10 percent to 30 percent for both cases. At the same time, an improvement of approximately 1.3 percent is seen when the probability of return increases from 70 percent to 90 percent. The BWE differences between the return parameters are more dramatic for fast-consuming products and the 15-day periodic review. As the return probability gets closer to 100 percent, the system starts to operate as the rental/leasing system, the need for new production decreases, and the system maintains itself with reverse flows.

Increasing the average lifetime of the product slightly increases the BWE experienced in the echelons. The variability in the lifetime of slowly consumed products is higher, making it difficult to estimate the returns. In addition, an increase in the average lifetime of the product causes an increase in the number of products in use and thus inventories in the echelons. The marginal probability distributions of the orbit size are as shown in Figure 4.12. Considering that the average demand is taken as 1 per day for experimental purposes, orbit size in marginal distributions is observed to be lower than 360 and 1080 levels due to lost sales in the retail echelon over time.

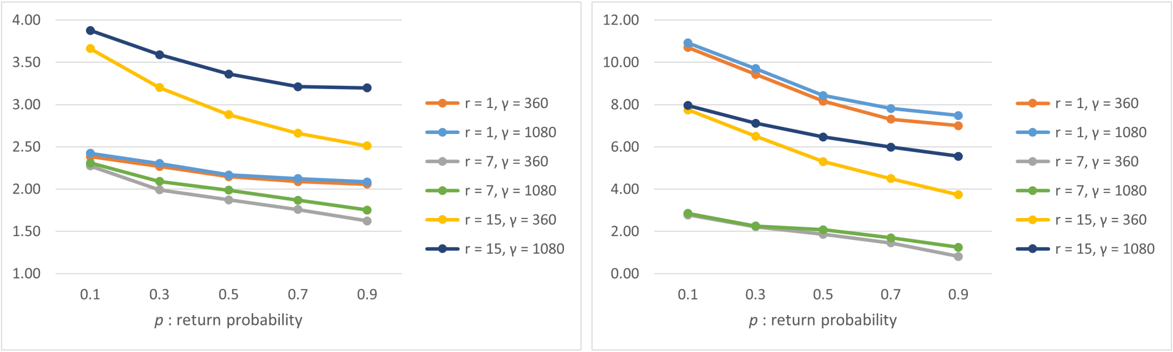


(a) $\gamma = 360$

(b) $\gamma = 1080$

Figure 4.12. Marginal probability distributions of orbit size, $r = 7$, $DSL = 0.9$, $m = 30$, $LTD = (exp(1/360), exp(1/1080))$, $p = 0.5$.

In order to further visualize the relationship between the review periods, average product lifetimes, and return probabilities, the BWE ratios observed at the distributor echelon are presented as in the first plot in Figure 4.13. It can be said that all three parameters have a significant impact on the order variability. A linear trend is observed in the probability of return; in all experiments, it decreases as the probability of return increases. The worst-case is observed by a large margin in the 15-day periodic review, while the best-case is observed in the 7-day periodic review. There is almost no difference between product average lifetimes in base stock policy, but lower variability is observed in fast-consuming products. This difference can be seen more clearly in the 7-day and 15-day periodic reviews. In all periodic reviews, the best pair is the fast-consuming products with a 90 percent return probability, while the worst pair is the slow-consuming products with a 10 percent return probability.

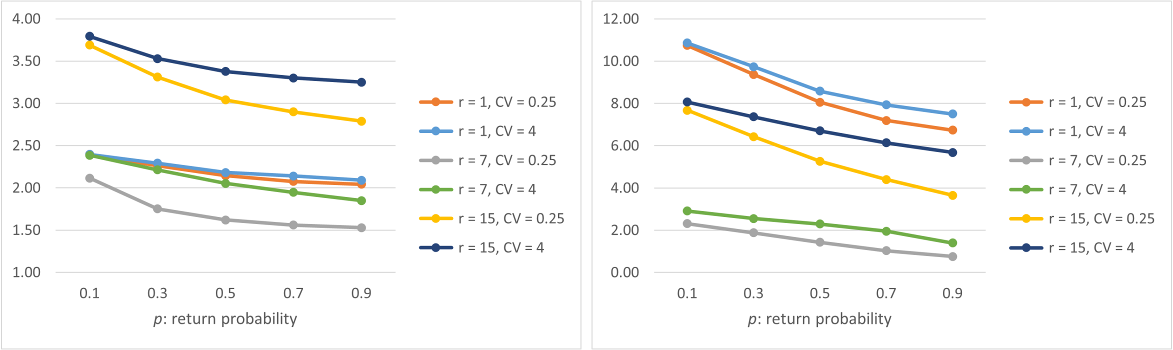


(a) BWE (b) NSA

Figure 4.13. Sensitivity analysis on performance measures at distributor echelon, $r = (1,\ 7,\ 15)$, $DSL = 0.9$, $m = 30$, $LTD = (exp(1/360),\ exp(1/1080))$, $p = (0.1,\ 0.3,\ 0.5,\ 0.7,\ 0.9)$.

From the second plot in Figure 4.13, it can be said that the situation is slightly different for NSA ratios. This time the highest net stock imbalances are observed in the daily periodic review. Due to the variability in demand and returns, the variability in net stocks increases with the daily review of stocks. The 7-day periodic review, on the other hand, has by far the lowest NSA ratios here as in the BWE ratios, thus yielding the results with the lowest inventory and order variability in the distribution echelon of this review policy. Once again, in all periodic reviews, the best pair is fast-consuming products with a higher return probability, and the worst pair is slow-consuming products with a lower return probability.

It is also possible to conduct the same experiments with different product life variabilities. We examine the relationship of CV to bullwhip behaviour for a product with an average lifespan of 2 years. To examine the behavior of CV, we preferred the log-normal distribution, which is often used in the literature for product reliability. The development of performance measures observed at the distributor echelon is presented as in Figure 4.14. We get a result similar to the previous analysis, where the comparison between slow or fast consumed products was examined. In all periodic reviews, the best pair is the products with low CV and high probability of return, while the worst pair is the products with high CV and low probability of return. As a result of inventory and order variability, the fast-consuming products with lower CV are the most suitable product type for CLSC, especially when combined with the high probability of return.

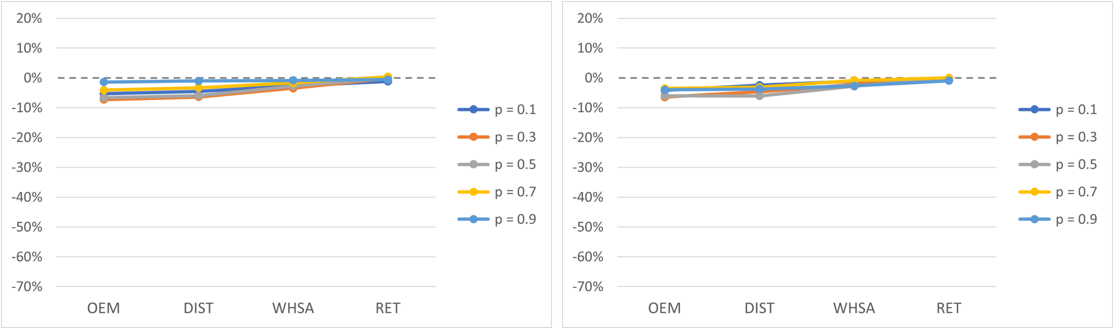


(a) BWE

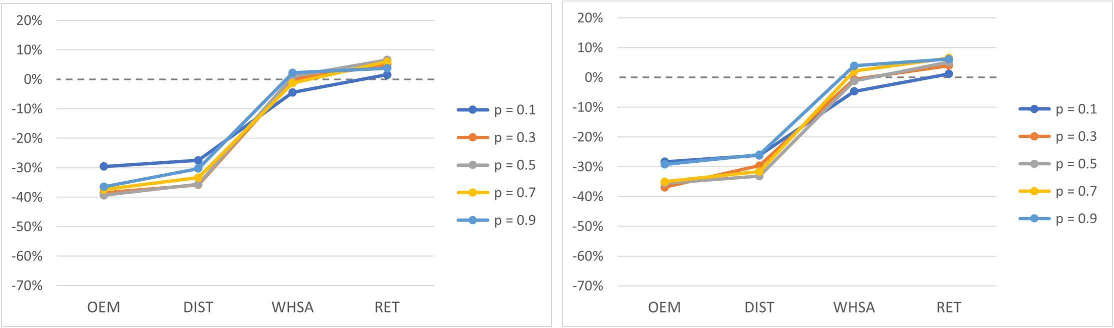
(b) NSA

Figure 4.14. Sensitivity analysis on performance measures at distributor echelon, $r = (1,\, 7,\, 15)$, $DSL = 0.9$, $m = 30$, $LTD = (lnorm(720, 180^2),\, lnorm(720, 2880^2))$, $p = (0.1,\, 0.3,\, 0.5,\, 0.7,\, 0.9)$.

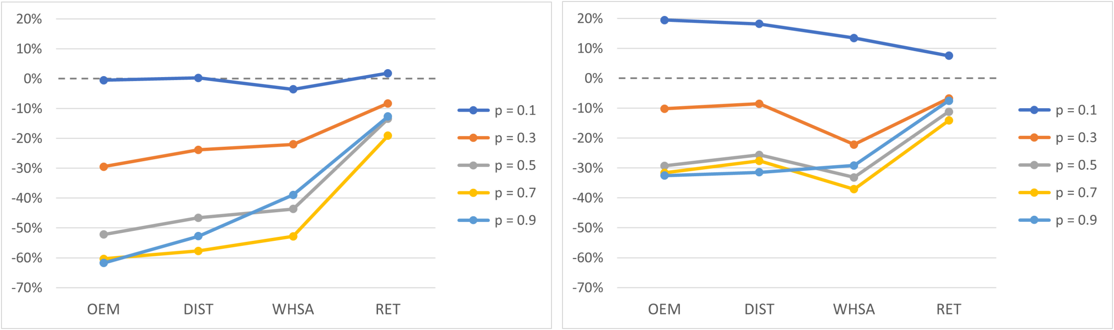
4.1.2.2. Value of Orbit Size Information. We compare the multi-echelon CLSCs, where the return estimation is based on the moving average method and the orbit size information by evaluating the performance metrics with a given set of parameters. Thus, we aim to measure the value of orbit size information by observing how well the return timing and quantity estimation made within the orbit size information yields compared to the traditional method. According to the mentioned return estimation methods, the proportional change of the BWE ratio in the echelons is given in Figure 4.15. The changes in the negative direction show how beneficial the orbit size information is, while the positive changes show how this information harms the echelon.



(a) $r = 1$, $\gamma = 360$ (b) $r = 1$, $\gamma = 1080$



(c) $r = 7$, $\gamma = 360$ (d) $r = 7$, $\gamma = 1080$



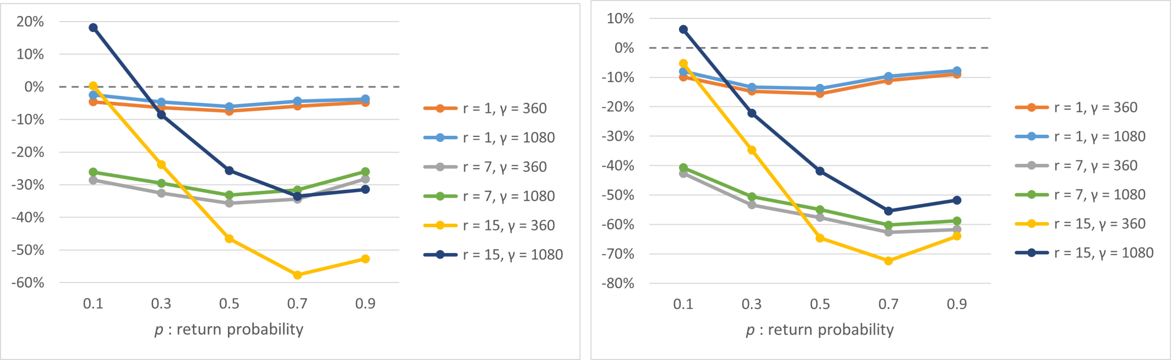
(e) $r = 15$, $\gamma = 360$ (f) $r = 15$, $\gamma = 1080$

Figure 4.15. Value of orbit size information on BWE, $r = (1, 7, 15)$, $DSL = 0.9$, $m = 30$, $LTD = (exp(1/360), exp(1/1080))$, $p = (0.1, 0.3, 0.5, 0.7, 0.9)$.

As seen in Figure 4.15, the importance of the orbit size information varies based on different review periods, product average lifetimes, and return probabilities. In the base stock policy, the order variability experienced at echelons has improved around 0 to 10 percent, regardless of product average life or probability of return. More drastic changes are seen in the 7-day periodic review. While the first two echelons generally show worsening, the last two echelons show significant improvement, up to

36% in the distributor and 39% in the OEM. However, the outputs differ considerably in the 15-day periodic review according to the probability of return and the average product lifetime. It is seen that the existence of orbit information is not beneficial in the case of low return flows and even affects the BWE ratios adversely. However, as the probability of return increases, the rate of improvement increases gradually. While the best recovery is usually seen in the wholesaler echelon, with the exception of 90% returns, the improvement rates increase as the echelon level increases, and the best improvement is seen in the OEM echelon. The reason why such a situation is encountered with a 90% return probability might be due to the fact that the need for new production has gradually decreased as the return probability approaches 100% and the system has turned into a circular economy business model. On the other hand, average product lifetimes also have a significant impact. For example, in the 15-day periodic review, the presence of orbit size information can lead to an improvement of up to 37% in slow-consumption products and up to 62% in fast-consumption products in order variances.

To further visualize the value of orbit size information, the improvement rates of BWE ratios observed at the distributor echelon are presented as in Figure 4.16. According to the improvement rates in order and inventory variability compared to the moving average method, it is difficult to make certain interpretations on how the best or worst improvements are achieved. A progressively greater improvement is observed up to a 50 percent probability of return, after which there is still an improvement, but the improvement rate decreases. We mentioned that the presence of orbit size information is not so beneficial in cases where the probability of return is low. Here, on the other hand, as the probability of return approaches 100 percent, the efficiency of the moving average return estimation method increases as well. In particular, at the distributor echelon, we observe the value of orbit size information to be most useful, especially when the probability of return is between 50 and 70 percent. While the base stock policy usually has the lowest improvement rates, the 7 and 15-day periodic reviews have the highest improvement rates depending on the probability of return and average product lifetime. In daily and 7-day periodic reviews, we observe that the average product lifetime does not significantly differ, but higher improvement rates for fast-consumed products. On the other hand, the average product lifetime becomes a critical parameter in the 15-day periodic review. In terms of BWE, slow-consumption products can improve up to 34 percent, while fast-consumption products can improve up to 58 percent. Likewise, in terms of NSA, slow-consumption products can improve up to 55 percent, while fast-consumption products can improve up to 72 percent. As a result, orbit size information becomes more valuable when the probability of return is not very low, periodic reviews are at longer intervals, and products in use are consumed quickly.



(a) BWE

(b) NSA

Figure 4.16. Value of orbit size information at distributor echelon, $r = (1,\ 7,\ 15)$, $DSL = 0.9$, $m = 30$, $LTD = (exp(1/360),\ exp(1/1080))$, $p = (0.1,\ 0.3,\ 0.5,\ 0.7,\ 0.9)$.

4.2. Bullwhip Behaviour Under Impulse Demand

This section discusses the impact of impulse demand on inventory and order stability under different ways of obtaining returns information. Wadhwa *et al.* [163] addressed the need to examine supply chain structures under dynamic demands. We consider the demand impulses as non-stationary demand fluctuations in which the average demand increases upwards for a certain period, but then the average demand returns to its original state. This can be defined as the impulsive buying effect of the end-user at seasonal times, such as sales promotions or end-of-period sales bonuses.

Although these fluctuations last for a short time, their effects are gradually observed in the whole supply chain and remain relatively long [164].

As seen in Figure 4.17, an impulse can be defined by two metrics: amplitude and length. For experimental purposes, we take the average demand and the amplitude as 10 units per day and the impulse length as 30 days. 400 days are again reserved for the warm-up period, followed by a 30-day single-time impulse, and the simulation runs for another 720 days. Then, 30 replications are taken for each simulation experiment. The impact of this variability on system performances and the inventory level of each supply chain actor in the time series are examined during the 2-year simulation run.

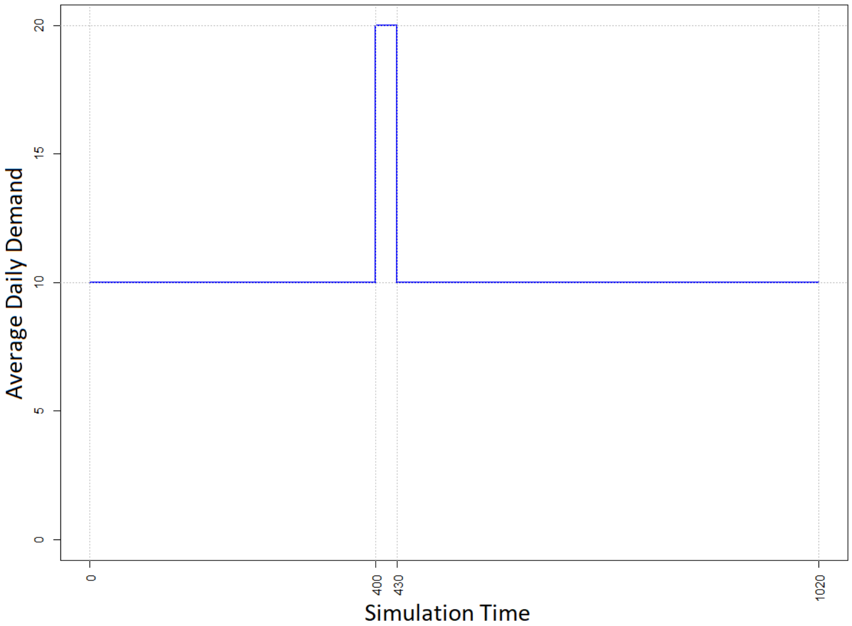
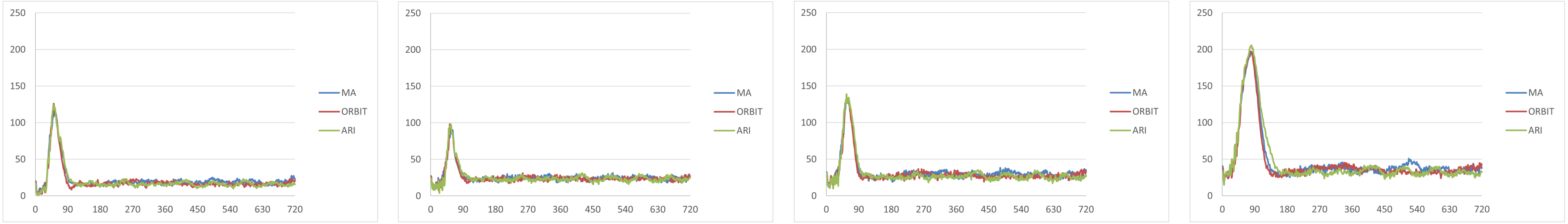


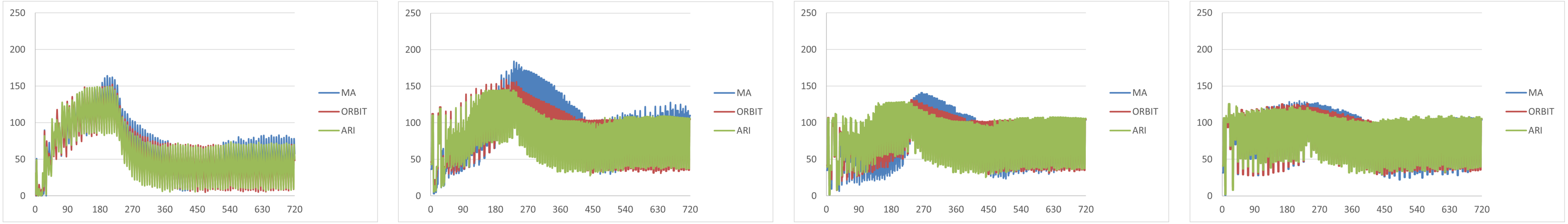
Figure 4.17. Representation of impulse demand over simulation time.

4.2.1. Impact of Review Periods

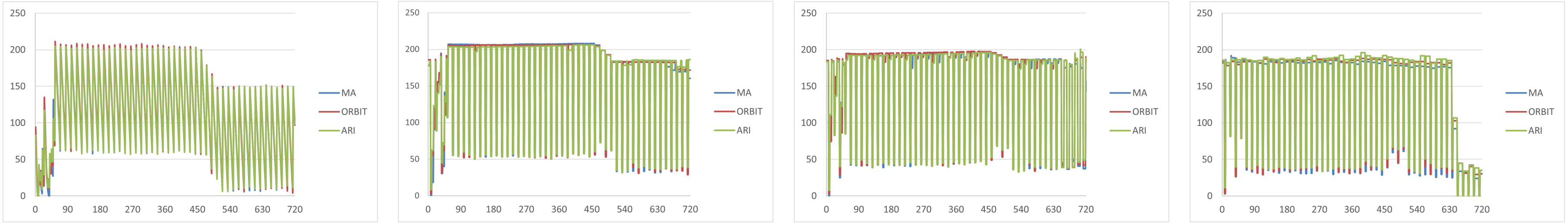
The on-hand inventory levels of the echelons during the 2 years after the impulse demand for 30 days is plotted as in Figure 4.18 for different review periods under different ways of obtaining returns information.



(a) RET, $r = 1$ (b) WHSA, $r = 1$ (c) DIST, $r = 1$ (d) OEM, $r = 1$



(e) RET, $r = 7$ (f) WHSA, $r = 7$ (g) DIST, $r = 7$ (h) OEM, $r = 7$



(i) RET, $r = 15$ (j) WHSA, $r = 15$ (k) DIST, $r = 15$ (l) OEM, $r = 15$

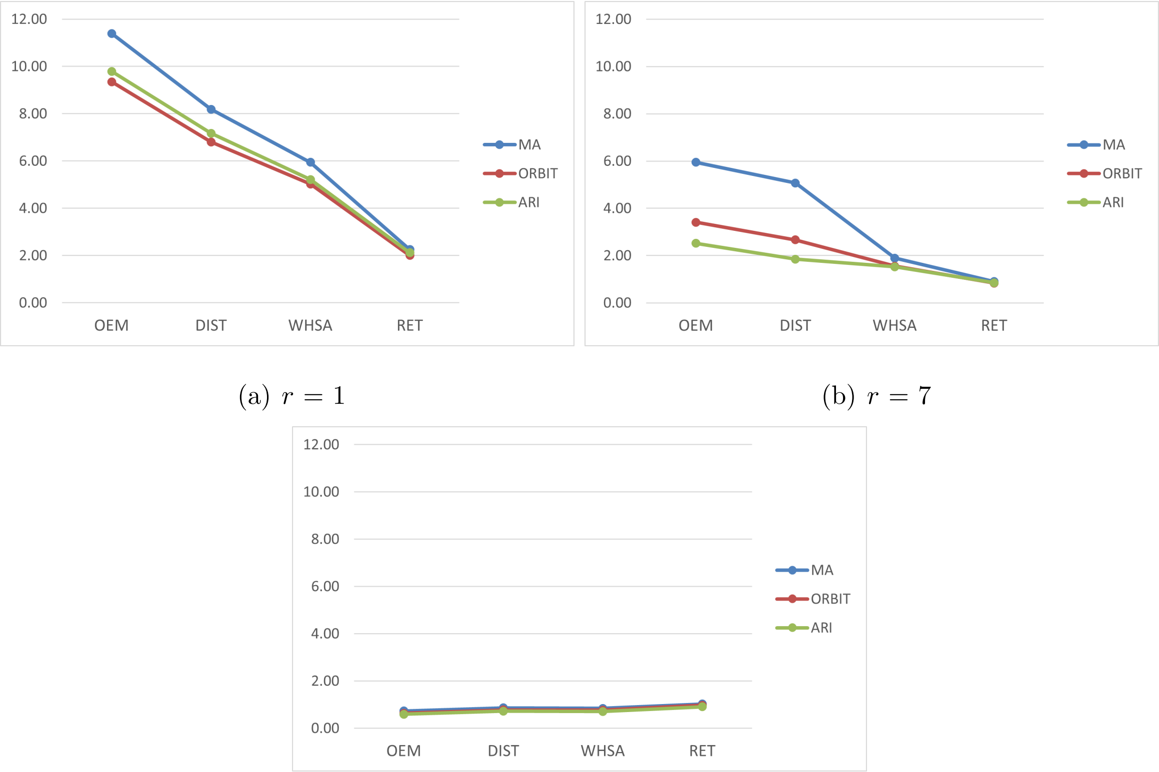
Figure 4.18. Net stock levels under impulse demand by review periods, $r = (1, 7, 15)$, $DSL = 0.9$, $m = 30$, $LTD = exp(1/360)$, $p = 0.5$.

In the early periods, lost sales may occur with the unexpected increase in demand. However, the supply chain echelons begin to anticipate the new demand over time better, and they make an effort to accumulate inventory. When the impact of impulsive demand begins to wane, this time, the echelons begin to deplete their stocks, which are considerably high relative to actual demand. Although the length of impulsive demand is limited to 30 days, its impact on inventory levels is experienced much longer. Another critical point here is that the effect of impulse demand varies considerably for different review periods. In the base stock policy, the echelons were able to react more quickly to the impulse demand and recover in just 60 days, as they reviewed inventory levels on a daily basis. While the highest inventory level is observed in the OEM echelon, the peak observed at the retail echelon is also quite dramatic, with demand coming directly to retail. On the other hand, as the review period increases, so does time required for inventory levels to return to their original state. In the 7-day periodic review, although the impulse demand is limited to 30 days, it takes 200 days for retail to peak at the inventory level, while its effect in the upper echelons gradually gets even longer. It took approximately 450 days, that is, 15 times the length of impulsive demand, to return the inventory level to its original levels in all echelons. In the 15-day periodic review, we observe a much longer impact. With the impulse demand, all echelons brought the inventory levels to around 200 products and remained at these levels for a long time. As a result, with the increase in inventory review frequency, the effects of impulse demand can be damped more easily and quickly. With the increase of the review period, the impulse demand becomes more difficult to perceive, and the impact of the impulse demand remains in the system for much more extended periods. The peak inventory level observed is also higher with the increase of the review period. Thus, with the impact of impulse demand, much higher inventory holding costs occur in a situation where the review period is high.

From Figure 4.18, it is also possible to compare the ways of obtaining return information in terms of inventory variability, and the base stock policy and the 15-day periodic review followed a fairly similar pattern. More evident differences are seen in the 7-day periodic review. While the return estimation method using the moving average resulted in higher inventory levels and variability in all echelons, the system followed slightly more stable and lower inventory levels within the knowledge of ARI. The system operating with orbit size information provided a result between these two methods, and it shows that the existence of orbit size information is valuable as it shows lower inventory level and variability compared to the moving average method.

It is possible to observe net stock variability from time-series graphs, but it is not entirely possible to make inferences about order quantities and variability. The observed BWE ratios in the echelons with the impact of impulse demand are shown in Figure 4.19. The fact that the review period has a significant impact on the BWE has been discussed previously as well as in Figures 4.1 and 4.11. Although the base stock policy gives a more stable result in terms of inventory levels and variability, the highest order variability among the review periods is observed. This is due to the daily ordering of the quantity needed to meet the impulsive demand. Thus, the supply chain actor reaches the desired inventory level faster, but the upper layer may be affected by high order variability. In the 15-day periodic review, there is no gradual increasing BWE between the echelons. As a result, shorter the periodic review period when an impulse demand occurs, the lower the inventory variability but, the higher the BWE they are exposed to. Likewise, longer the review period, the lower the BWE, but the more they suffer from inventory quantities and variability.

From Figure 4.19, the highest BWE ratios except the 15-day periodic review experiment are observed with a large difference in the moving average method, especially in the 7-day periodic review, among the ways of obtaining return information. While the lowest BWE is seen in the system operating within the orbit size information in the base stock policy, it is seen in the presence of ARI in the 7-day periodic review. As a result, the periodic review itself is the most affecting the system. Moreover, a 50 percent probability of return is considered for this set of experiments. Therefore, we observe that the return probability is an important factor and orbit size information is especially valuable in cases of impulse demand for base stock policy. Analysis of the probability of return is given later in the study.



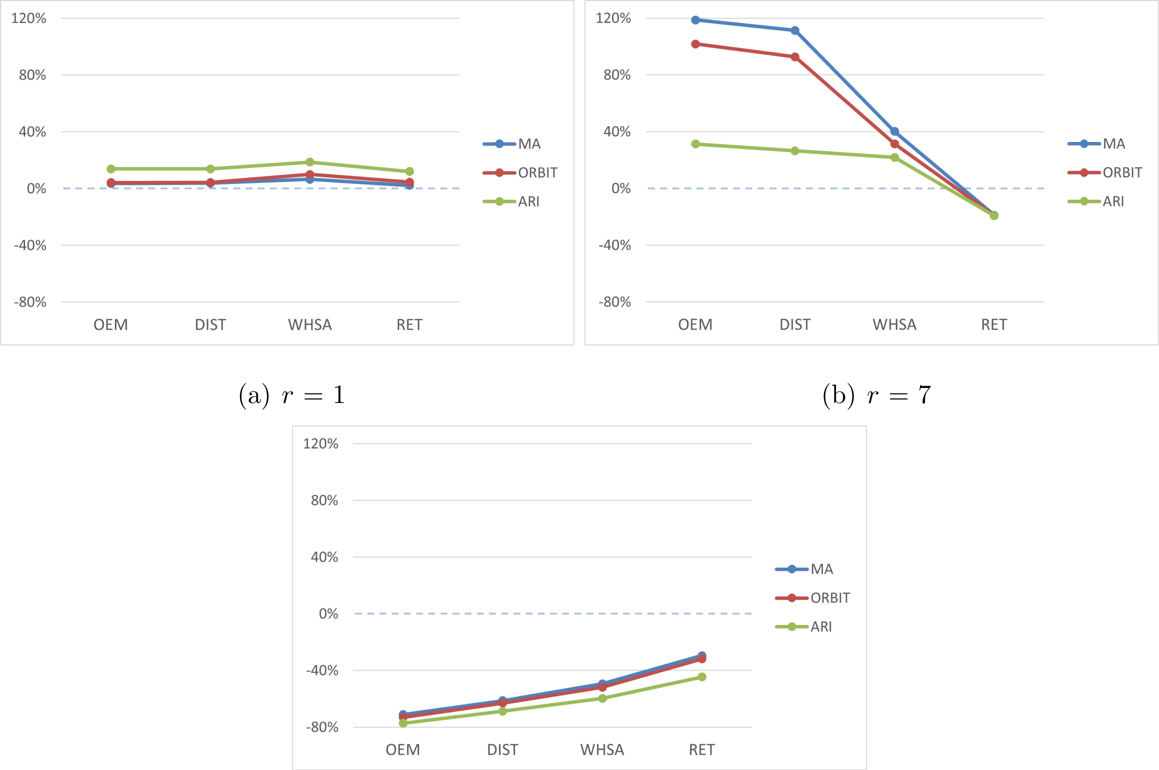
(a) $r = 1$

(b) $r = 7$

(c) $r = 15$

Figure 4.19. BWE ratios under impulse demand by review periods, $r = (1,\ 7,\ 15)$, $DSL = 0.9$, $m = 30$, $LTD = exp(1/360)$, $p = 0.5$.

In order to measure the impact of impulse demand on methods and periodic reviews, it is meaningful to compare the systems operating with the impulse demand and the original average demand. For this, we ran a system without impulsive demand under the exact simulation specifications. In Figure 4.20, the percentage changes in BWE ratios with the impact of impulse demand are given. In the base stock policy, it is seen that impulse demand does not affect the system much. This is due to the ability of supply chain actors to place the necessary orders on a daily basis to achieve desired inventory levels and satisfy actual demand. In this periodic review, it is the system operating within the knowledge of ARI that was most affected. The reason for this is that BWE ratios are observed to be much lower than other methods in the systems where there is no impulse demand. In the 7-day periodic review, the BWE observed in the first echelon decreased with the impact of impulse demand in all methods. But then, especially in the last two echelons, systems that make return estimation with moving average and orbit size information were significantly affected. This demonstrates that impulsive demand is an important fact for these periodic review policies. Another important reason why such an increase is observed in the system, which works with the knowledge of orbit size, is that it has the lowest BWE rates in the absence of sudden demand. The root cause for this can be interpreted as the probability of return; we have previously examined the significant effect of the probability of return on the orbit size information in Figures 4.8 and 4.11. In the 15-day periodic review, the BWE observed in the system decreased significantly with the arrival of the impulse demand. This is because the net stock fluctuation in the echelons with the impact of the impulse demand lasts quite longer, and the system has not been adversely affected.



(a) $r = 1$

(b) $r = 7$

(c) $r = 15$

Figure 4.20. Impact of impulse demand on changes in BWE ratios by review periods, $r = (1, 7, 15)$, $DSL = 0.9$, $m = 30$, $LTD = exp(1/360)$, $p = 0.5$.

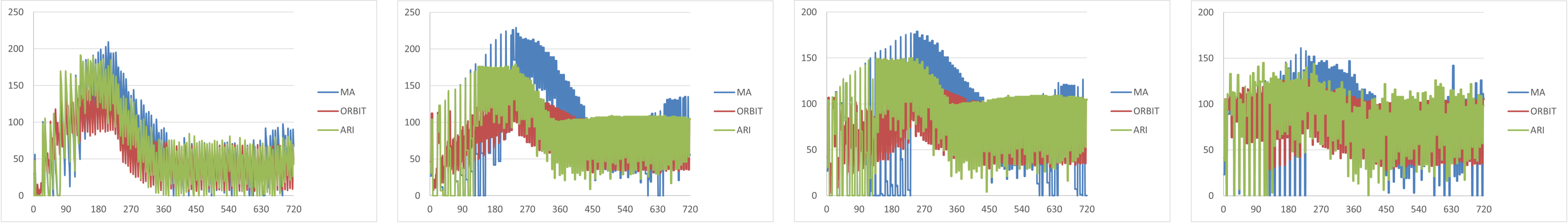
4.2.2. Impact of Return Probabilities

The on-hand inventory levels of the echelons during the 2 years after 30 days of impulse demand is plotted as in Figure 4.21 for different return probabilities. The impact of impulse demand varies considerably for different return probabilities and ways of obtaining returns information. When the probability of a return is low, each echelon has more regular inventory levels and a lower peak. Uncertainties in timing and quantity of returns are observed at a lower level since the system operates like a traditional forward supply chain due to considerably low probability of return. Most of the orders that the OEM has to fulfill are met by new production, while a small proportion are met by return flows. The fluctuations in inventory levels can be further reduced by knowing the returns in advance. As discussed in Figures 4.15 and 4.16, it is seen that the presence of orbit size information does not benefit the system when the probability of return is low, but contributes significantly as the probability of return increases.

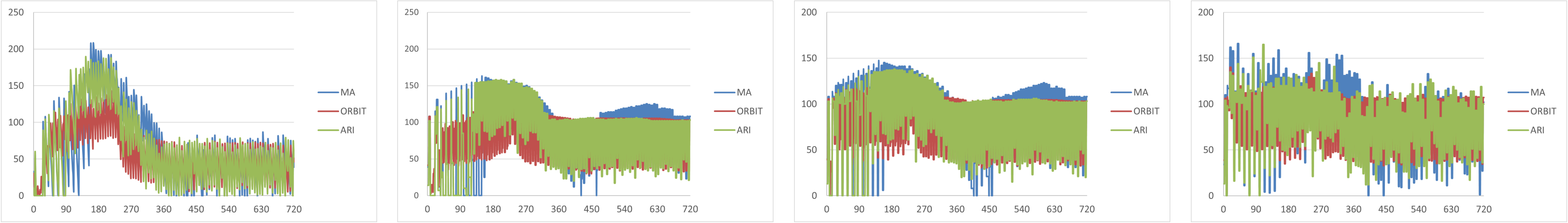
In a CLSC with a 50 percent probability of return, significant deviations are observed in the inventory levels of each echelon due to the impact of impulse demand. This time, the lowest deviations and a more regular inventory level are seen in orbit size-based return estimation and so the value of orbit size information has increased and the burden of uncertainty in returns has been alleviated. An irregular stock structure emerged with the return estimation using the moving average, and the effect of the impulse demand lasted longer.

From Figure 4.21, a CLSC with a 90 percent return gives very similar results to a CLSC with a 50 percent return. Again, the system has the most stable inventory structure, with orbit size-dependent return estimation. However, with the probability of return approaching 100 percent, a significant improvement is observed in the inventory levels of the system with return estimation using the moving average method. With the decrease in the need for new production, the estimation accuracy of the moving average method on returns considerably increases.

(a) RET, $p = 0.1$ (b) WHSA, $p = 0.1$ (c) DIST, $p = 0.1$ (d) OEM, $p = 0.1$



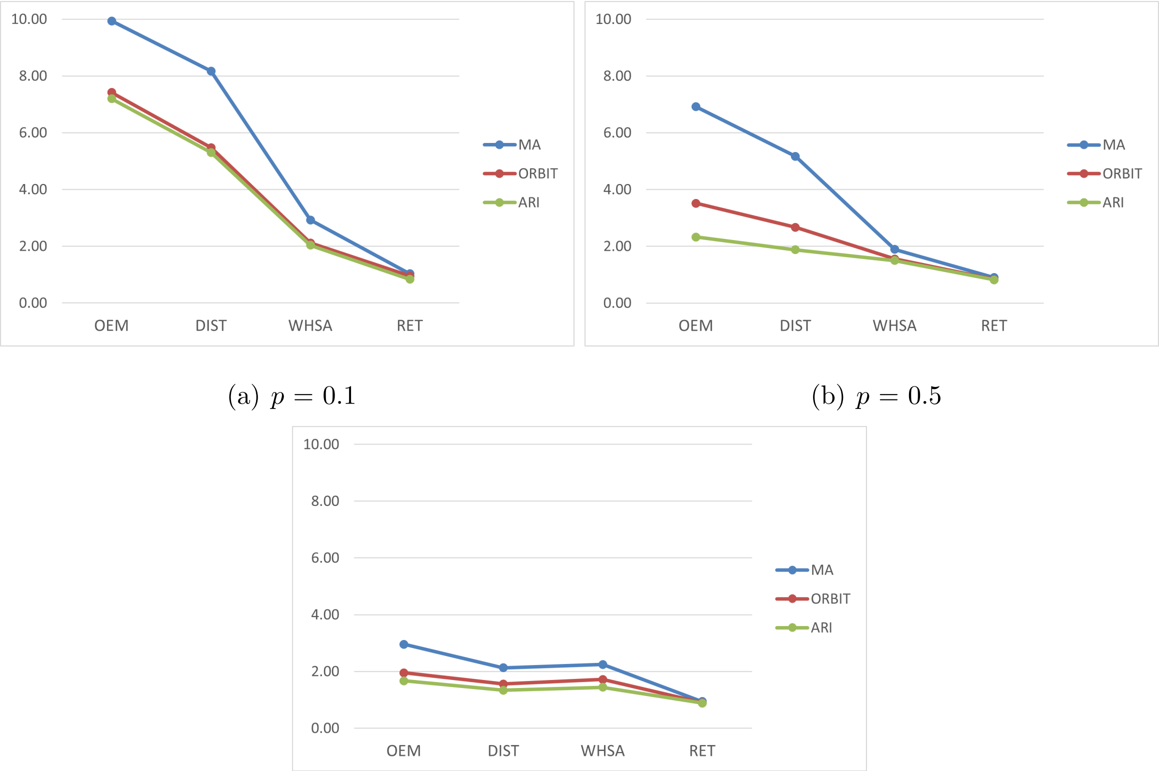
(e) RET, $p = 0.5$ (f) WHSA, $p = 0.5$ (g) DIST, $p = 0.5$ (h) OEM, $p = 0.5$



(i) RET, $p = 0.9$ (j) WHSA, $p = 0.9$ (k) DIST, $p = 0.9$ (l) OEM, $p = 0.9$

Figure 4.21. Net stock levels under impulse demand by return probabilities, $r = 7$, $DSL = 0.9$, $m = 30$, $LTD = exp(1/360)$, $p = (0.1, 0.5, 0.9)$.

The observed BWE ratios in the echelons with the impact of impulse demand are shown in Figure 4.22. As previously discussed in Figures 4.8 and 4.11, there is a significant decrease in order variability observed in the system as the probability of return increases. So, return flows have a relaxing effect on the supply chain structure. In all three different return probabilities, the lowest BWE is observed in the system with the advanced return information. In contrast, the highest BWE is observed in the system based on return estimation using moving average, especially in the last two echelons. The system with the orbit size-dependent return estimation, on the other hand, gives results close to the system with the advanced return information. As a result, the presence of orbit size information has the impact of dampening the BWE even under instantaneous demand.



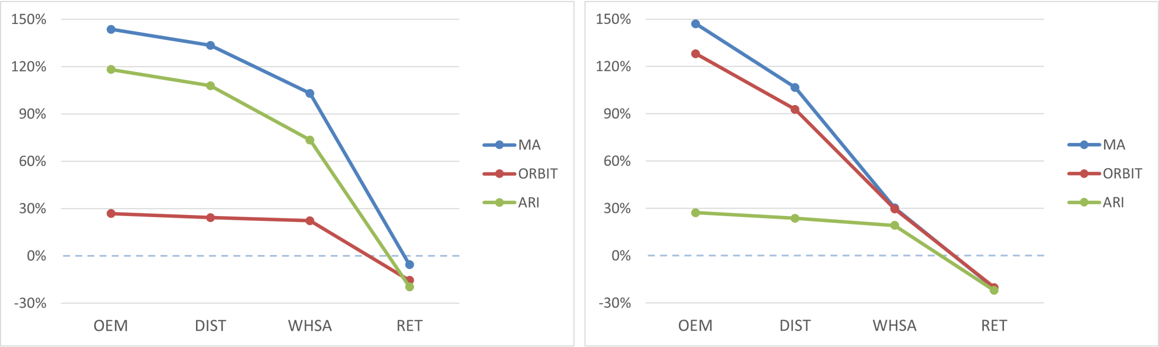
(a) $p = 0.1$

(b) $p = 0.5$

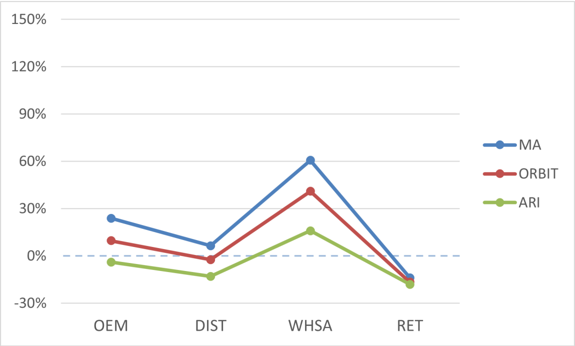
(c) $p = 0.9$

Figure 4.22. BWE ratios under impulse demand by return probabilities, $r = 7$, $DSL = 0.9$, $m = 30$, $LTD = exp(1/360)$, $p = (0.1, 0.5, 0.9)$.

In Figure 4.23, the percentage changes in BWE ratios with the impact of impulse demand are given for different return probabilities. When the probability of return is low, the system with orbit size-dependent returns is least affected by impulse demand. This is because it already has a high BWE in the absence of impulse demand. If there is a 50 percent return probability, the same situation applies to the system based on advanced return information. In all return probabilities, the one most affected by the impulse demand is the system that uses the moving average to forecast the returns. When the probability of return approaches 1, all three systems are less affected by impulse demand. Since the system maintains itself largely with returns, the variability due to new production has decreased. The instant encouragement of new production meets excess demand.



(a) $p = 0.1$ (b) $p = 0.5$



(c) $p = 0.9$

Figure 4.23. Impact of impulse demand on changes in BWE ratios by return probabilities, $r = 7$, $DSL = 0.9$, $m = 30$, $LTD = exp(1/360)$, $p = (0.1,\ 0.5,\ 0.9)$.

5. CONCLUSION

The main intention of this study is to analyze the Bullwhip behavior by observing the change of OEMs' production decisions and supply chain actors' inventory replenishment decisions under the periodic review (r, S) system in a CLSC where returns and demands are totally correlated. Recognizing that supply chain structures also need to be examined under a non-stationary demand pattern, we examined our discrete-event simulation model under stationary and impulse demand. While demand signal processing is a sufficient factor for the BWE in the forward supply chain, considering our CLSC structure reveals that return flows are also an important factor for net stock and order variability. Aware of this, we introduce a new return function based on the number of products in use and focus on the improvements of this return estimation method on system performance measures. We observed that the orbit size is correlated with the S levels of the supply chain actors. We believe that the quality of information on returns is driving BWE by influencing the stability of the lead time demand estimating process. Less stable forecasting processes result in more erratic S levels, which inevitably result in greater order variability. The results show that CLSC is heavily influenced by the demand pattern, review period, probability of return, and average product lifespan. While the stationarity of demand causes a more stable periodic review system to be seen, inventory replenishment policy can be changed entirely with an impulse demand. On the other hand, we do not believe that adjustments to the periodic inventory (r, S) system, in which the S level is updated at each inventory review period based on historical data, are always beneficial; they occasionally predispose the system to increase inventory and order variability or reduce service level.

Numerical analysis shows that the inclusion of return flows greatly relieves the supply chain. Compared to the traditional supply chain, lower inventory and order variability and a higher level of service are observed. In the base stock policy, the most stable BWE is observed, while at the same time, the highest inventory variability is observed. For instance, implementing a 7-day periodic review instead of a daily or

15-day review would be a logical choice for supply chain actors from the perspective of BWE and NSA. We see that products consumed quickly and have a high return probability are much more compatible with the CLSC structure. Likewise, the CLSC can be further disburdened by keeping a greater safety stock with a higher desired level of service or more stable lead time demand forecasting with a higher number of moving average periods.

Opting for return estimation based on orbit size information over traditional estimation methods is beneficial in many cases. For example, in the distributor tier, improvements in net inventory variability of up to 72 percent and order variability of up to 58 percent were observed. As in the moving average, we observe that the system is affected by low stock and order variability, especially with the preference of 7-day periodic review in CLSC, which was established for a product that is consumed quickly and has a high probability of return. Shortening the average product lifetime and increasing the return probability continually improve the system performance. However, as the return probability gets closer to 100 percent, the system starts to operate as the rental/leasing system, the need for new production decreases and the system maintains itself with reverse flows. Since the prediction accuracy of the moving average method on the return increases considerably, the improvement rates decrease slightly with the increase of the probability of the return.

With the presence of impulse demand, the inventory structure is completely changing. In the early periods, lost sales occur with the unexpected increase in demand. Then, the supply chain echelons begin to anticipate the new demand over time better, and they make an effort to accumulate inventory. With longer periodic reviews, the length of response to variability in demand pattern also increases so that the base stock policy can take action faster. However, it is subject to high net stock and order variability in order to maintain the rapid reaction. We also reveal that the presence of orbit size information does not provide effective results for situations where the probability of return is low. On the other hand, while systems operating with orbit size-based return estimation and advanced return information show very similar results, the highest inventory and order variability was observed in the system based on the moving average return estimation, with the effect of impulsive demand. With the presence of orbit size information without the need for advanced return information, the bullwhip and inventory variability observed from the system can be prevented to a large extent.

Our proposed model deals with the widely preferred periodic review system. As future work, we aim to expand our study by integrating various PUSH and PULL systems for production and remanufacturing decisions of other discrete and continuous inventory replenishment policies. Besides, we fixed production, remanufacturing, and shipment lead times for experimental purposes in this study. We aim to incorporate stochastic lead times, an important research topic in supply chains, into our simulation environment.

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