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Mitigating the Bullwhip Effect and Enhancing Supply Chain Performance through Demand Information Sharing: An ARENA Simulation Study

Ahmed Esmail Mohamed & Kim Tuan Anh Huynh
University of Southern Denmark, Campusvej 55, DK-5230 Odense M, Denmark
Ahmed.esmail.mohamed19@gmail.com & tuananhfb.hcmc@gmail.com

Abstract

The supply chain is a network of organizations that collaborate and leverage their resources to deliver products or services to end-customers. In today's globalized and competitive market, organizations must specialize and form partnerships to gain a competitive edge. To thrive in their respective industries, organizations need to prioritize supply chain coordination, as it is integral to their business processes. Supply chain management focuses on the collaboration of organizations within the supply chain. However, when each echelon member optimizes their goals without considering the network's impact, it leads to suboptimal performance and inefficiencies. This phenomenon is known as the Bullwhip effect, where order variability increases as it moves upstream in the supply chain. The lack of coordination, unincorporated material and information flows, and absence of ordering rules contribute to poor supply chain dynamics. To improve supply chain performance, it is crucial to align organizational activities. Previous research has proposed solutions to mitigate the Bullwhip effect, which has been a topic of intense study for many decades. This research aims to investigate the causes and mitigations of the Bullwhip effect based on existing research. Additionally, the paper utilizes ARENA simulation to examine the impact of sharing end-customer demand information. As far as we are aware, no study has been conducted to deeply simulate the bullwhip effect using the ARENA simulation. Previous studies have investigated this phenomenon, but without delving into its intricacies. The simulation results offer potential strategies to mitigate the Bullwhip effect through demand information sharing.

Keywords: Supply Chain Management, Bullwhip effect, Inventory management, ARENA simulation, Information sharing, forecasting technique, Demand variability.

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1 Introduction

The term "supply chain management" can sometimes be confused with the term "logistics" and seen as overlapping, depending on the organization's definition (R. R. Lummus et al., 2001). Several articles mention that the word "logistics" was derived from the French word "Logistiek," which referred to the role of the Marshall of lodging for finding accommodation for soldiers during the era of Napoleon Bonaparte (Azmi et al., 2017; Rhonda R. Lummus & Vokurka, 1999; Van Creveld, 2004).

The Council of Supply Chain Management Professionals (CSCMP) (2018) defines logistics management as follows: *"Logistics management is that part of supply chain management that plans, implements, and controls the efficient, effective forward and reverse flow and storage of goods, services, and related information between the point of origin and the point of consumption in order to meet customers' requirements."* Logistics management encompasses various activities, including inbound and outbound transportation management, inventory management, materials handling, warehousing, supply/demand planning, procurement, production planning and scheduling, packaging and assembly, and customer service (Grant, 2017). Logistics is generally seen as within one firm, although it manages flows between the firm and its suppliers and customers (R. R. Lummus et al., 2001).

Modern business management no longer competes as independent entities but rather as supply chains. Mentzer et al. (2001) define a supply chain as "*a set of three or more entities (organizations or individuals) directly involved in the upstream and downstream flows of products, services, finances, and/or information from a source to a customer."* The supply chain is not only a chain of businesses with one-to-one, business-to-business relationships, but also a network of multiple businesses and relationships (Lambert et al., 1998). The management of multiple relationships across the supply chain is described as supply chain management (Lambert et al., 1998). The term "Supply Chain Management" (SCM) was introduced by a group of professional consultants back in the 1980s (Grant, 2017; Mohamed, A. E. 2021) and has grown in popularity compared to the term "Logistics Management." Since the 1980s, the concept of supply chain management has gained traction as firms realized the benefits of collaborative relationships within and beyond their own companies (Rhonda R. Lummus & Vokurka, 1999). Supply Chain Management focuses on various activities starting from the gathering of raw materials until the final product reaches the consumer. According to the Council of Supply Chain Management Professionals (CSCMP) (2018), SCM encompasses the planning and management of all activities involved in sourcing and procurement, conversion, and all logistics management activities. Importantly, it also includes coordination and collaboration with channel partners, which can be suppliers, intermediaries, third-party service providers, and customers. Mentzer et al. (2001) define SCM as *"the systematic, strategic coordination of the traditional business functions and the tactics across these business functions within a particular company and across businesses within the supply chain, for the purposes of improving the long-term performance of the individual companies and the supply chain as a whole."* SCM represents a network of interrelated businesses that connect resources, raw materials, transportation, production, and distribution of material resources, information, and financial flows to ultimately provide goods and services (Wang & Gupta, 2013; Mohamed, A. E. 2023). It comprises all logistics management activities as well as manufacturing operations and encompasses the coordination of all processes and activities across marketing, product design, sales, information technology, and finance (Grant, 2017).

Coordination plays a crucial role in enhancing the effectiveness of supply chain performance, and one key mechanism of supply chain coordination is the flow of information between each echelon in the supply chain network. To optimize efficiency in the current market environment, it is essential to coordinate production, inventory, location, and logistics among supply chain members Ensuring high-order fill rates and on-time delivery rates are fundamental for maintaining customer service at its most basic level. However, in a multi-echelon supply chain, a lack of coordination among chain members can result in each stage optimizing its objectives without considering the impact on the entire supply chain network, leading to impaired overall performance.

Moreover, when end-customers place higher demand orders, the information tends to amplify and move with high variability as each participant aims to protect their inventory from depletion or backorders, leading to increased replenishment for safety stocks upon receiving the order. This lack of coordination causes time delays at each stage of the supply chain, resulting in demand amplification from customers. This phenomenon, known as the Bullwhip Effect, is characterized by order variability being larger than demand variability. This distortion of demand exacerbates further as it moves up the supply chain, with upstream sites exhibiting greater variability than downstream sites.

The Bullwhip Effect has been a subject of interest for decades and has been observed in numerous real-market situations. The effect was first noticed by Procter and Gamble, who observed that the variability of diaper orders from distribution centers could not be solely attributed to fluctuations in end-customer demand. A similar pattern of demand variability was observed in the case of Hewlett-Packard, where orders placed by resellers to the printer division exhibited greater swings and variation than customer demand, and orders to the company's integrated circuit division displayed even worse swings. The phenomenon was initially described by Jay Forrester, who referred to it as demand amplification or the Forrester Effect. The term "Bullwhip Effect" was later popularized by Lee et al. (1997), who analyzed operational causes of the Bullwhip Effect and proposed countermeasures to mitigate its impact on the supply chain. Since then, numerous research studies have been conducted to investigate the causes, impacts, and countermeasures of the Bullwhip Effect, including studies by Chen et al. (1998, 2000), Disney et al. (2005), Croson & Donohue (2003, 2005, 2006), Geary et al. (2006), and Disney & Wang (2016).

The purpose of this paper is twofold. Firstly, it aims to review the causes and countermeasures of the Bullwhip Effect identified in previous research studies. Secondly, it will conduct a simulation to illustrate the impact of information sharing on the Bullwhip Effect in a supply chain under specific conditions.

1.1 Research Objectives:

The objectives of this paper are to review the identified causes and countermeasures of the Bullwhip Effect from previous research and to construct a simulation model to examine the impact of the Bullwhip Effect in a supply chain under different end-customer demand information sharing strategies. The simulation will consider a supply chain consisting of four echelon members: retailer, distributor, manufacturer, and external supplier. For simplicity, all stages in the simulation model will employ the same inventory policy, forecasting technique, ordering policy, constant replenishment lead-time, and review interval. The simulation outcomes will be used to analyze the impact of end-customer demand information sharing on the Bullwhip Effect in a supply chain.

1.2 Methodology:

In the field of social sciences, research plays a crucial role in studying social relationships and addressing social problems through the application of scientific procedures. According to Kothari (2004), research is a systematic process that involves stating a problem, formulating hypotheses, collecting, and analyzing data, and reaching conclusions to enhance our understanding of a phenomenon. Its aim is to uncover hidden aspects of a problem and discover new knowledge. Consequently, research provides intellectual satisfaction by shedding light on phenomena and enabling researchers to analyze problems efficiently.

There are two fundamental approaches to research: quantitative and qualitative. Quantitative research is primarily concerned with measuring quantities or amounts. It involves quantifying problems by generating and converting numerical data into statistical calculations. On the other hand, qualitative research obtains non-numerical data and is mainly associated with exploratory research. It is conducted to gain an understanding of underlying reasons, opinions, and motivations behind social phenomena.

Within the quantitative research approach, there are sub-classifications such as inferential, experimental, and simulation methods. The inferential method involves forming a database that helps determine characteristics and then inferring those characteristics to the sample population. Experimental research is a systematic and scientific approach in which researchers manipulate one or more variables to observe their effects on other variables. Simulation methods construct artificial environments to generate relevant conditions and data. By representing the behavior of a process over time, simulation helps establish models for understanding future conditions (Kothari, 2004).

Furthermore, Wang and Disney (2016) pointed out that early research on the Bullwhip effect employed empirical,

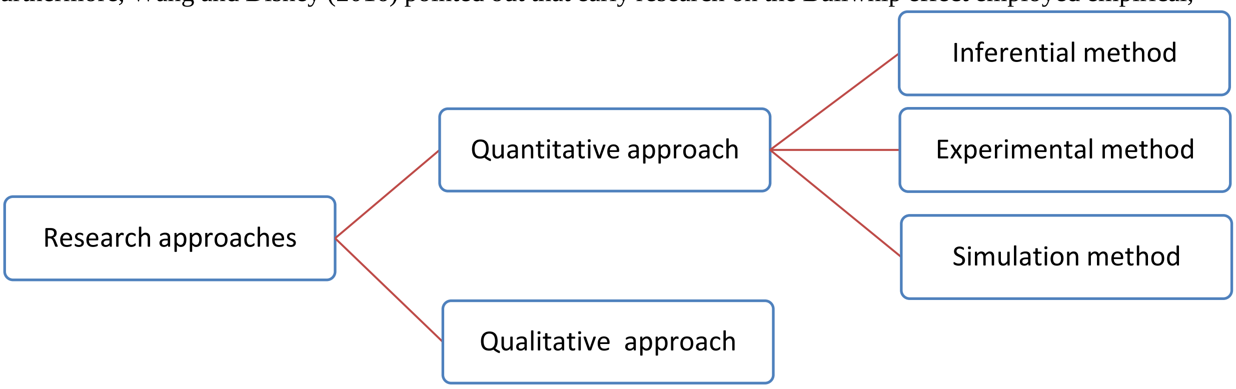


Figure 1-1: Research approach (Kothari, 2004)

experimental, analytical, and simulation-based methods. These methods can be explained as follows:

Empirical studies on the Bullwhip effect involve collecting and analyzing historical data on demand, sales, shipments, and production. Information about firms or the supply chain is also required for analysis. This approach helps trace the causes of the Bullwhip effect and measure the performance of implemented remedies (Wang and Disney, 2016).

Experimental methods use laboratory experiments to examine the factors and mechanisms that affect the Bullwhip effect. They focus on the behavioral and psychological aspects of decision-makers in relation to forecast techniques, replenishment, or production settings. Experimental methods test previous theories in controlled environments to reduce the impact of external disturbances, thus improving the accuracy of the experimental outcomes (Wang and Disney, 2016).

Analytical methods utilize mathematical models to quantify the Bullwhip effect and its causes accurately. They contribute to improving and providing solutions for preventing and eliminating the Bullwhip effect (Wang and Disney, 2016). Additionally, Alony & Munoz (2007) stated that using analytical methods helps understand the behavior of a model and the effects of information sharing on the Bullwhip effect. Analytical methods provide insights into restrictive industrial settings and are useful for obtaining simple insights.

Simulation methods enable a realistic understanding of the Bullwhip effect through numerical and computational illustrations. Simulations are employed when complex mathematical models exceed analytical capabilities (Wang and Disney, 2016). Furthermore, Alony & Munoz (2007) pointed out that simulation models are created to address stochastic properties of the supply chain as they allow for a detailed description of the supply chain. Additionally, simulation models help assess the discovery and formalization of small parts of the social world. They enable humans to understand the consequences of their decisions on the performance of a supply chain.

Considering the various research approaches and methods used to study the Bullwhip effect, this paper will employ a quantitative approach, specifically the simulation method. This choice is suitable for this research because it allows for the manipulation of research questions and simulating the impact of the Bullwhip effect in a supply chain under different information sharing strategies.

2 Literature review of the Bullwhip effect:

Supply chain management encompasses the flow of both materials and information within the supply chain, with the latter directly influencing internal activities such as production scheduling, inventory control, and delivery plans (Lee et al., 1997). Effective supply chain management decisions can result in cost reductions for organizations, including transportation, sourcing, stock-outs, storage, and disposal costs. To achieve these benefits, supply chain members must recognize their role within a complex network and understand the interdependencies between chain participants. Information flows from downstream partners play a crucial role in the supply chain, and any inefficiencies can lead to the phenomenon known as the Bullwhip effect (Wang & Disney, 2016).

The Bullwhip effect was first observed by logistics executives at Procter and Gamble, who noticed unexplainable order patterns for their best-selling diapers. Similarly, Hewlett-Packard experienced significant variations in orders placed by resellers compared to end customers, with even greater fluctuations in orders for their integrated circuits division. Jay Forrester (1961) was among the first researchers to study the variation in demand, and his work became known as the Forrester Effect. Using a system dynamics model, Forrester demonstrated how demand increased within a four-echelon production inventory distribution system, emphasizing the relationship between industrial dynamics and time-varying behavior of organizations (Forrester, 1961). This research inspired other scholars to develop management games, such as the Beer Distribution Game, to illustrate and quantify the

Bullwhip effect. Regardless of whether the game is played by students, managers, or economists, the results consistently show that ordering patterns are more significant at upstream sites compared to downstream sites. John Sterman (1989) further validated the Bullwhip effect in the beer game, attributing it to misperception of feedback or systematic irrational behavior.

Jack Burbidge (1961) proposed a methodology for controlling production and inventory related to the Bullwhip effect problem. Burbidge demonstrated that traditional stock control procedures based on Economic Order Quantity logic tend to amplify demand variabilities throughout the supply chain. Burbidge also provided the initial definition of the Bullwhip effect, stating that demand variations increase with each transfer when demands for products are transmitted through a series of inventories using stock control. In recent decades, the Bullwhip effect has garnered increased attention from researchers, leading to numerous studies shedding light on the subject from various perspectives. Lee et al. (1997) provided a comprehensive definition of the Bullwhip effect, describing it as the phenomenon where orders to suppliers exhibit larger variance than sales to buyers (i.e., demand distortion),

Figure 2-1: Increasing the variability of orders up the supply chain (Lee et al., 1997)

and this distortion propagates upstream in an amplified form (i.e., variance amplification) (Lee et al., 1997, p.546). The distortion of demand information has significant cost implications for upstream members of the supply chain, affecting production schedules and inventory planning efficiency.

Lee et al. (1997) built upon previous research by Forrester (1961) and Sterman (1989), as well as economists such as Holt et al. (1960), Blinder (1982), Blanchard (1983), Caplin (1985), and Blinder (1986). While Forrester assumed certain behaviors and Sterman assumed a lack of full rationality and misperceptions, Lee et al. (1997) employed mathematical models to illustrate the consequences of institutional structure and optimizing behaviors of supply chain members. The focus shifted from deriving an optimal decision rule for managers to understanding the outcomes of rational decision making. Consequently, the implications for optimal practices suggested that addressing the institutional and inter-organizational infrastructure would be more effective in controlling the Bullwhip effect compared to previous approaches focused on behavioral practices (Forrester) and individual education (Sterman) (Lee et al., 1997).

Inventory is highlighted as a crucial buffer for smoothing production in response to demand fluctuations, enabling manufacturers to take advantage of economies of scale. This perspective suggests that the variance in production time series should be smaller than the variance in demand time series. However, empirical research in macroeconomics (e.g., Blanchard, 1983) has shown that the variance of production time series is greater than that of demand. Lee et al.'s (1997) work complements these studies by adopting a managerial perspective and incorporating the Bullwhip effect into the framework of classical inventory theory.

Existing literature on the Bullwhip effect generally categorizes the causes into two main groups: behavioral causes and operational causes. Behavioral causes focus on social and cognitive psychology theories to study operational performance (Gino & Pisano, 2008). This perspective is typically examined in laboratory settings to eliminate operational causes. On the other hand, operational causes have been extensively studied and involve technical inefficiencies in both the supply chain and internal organizational structures. These operational causes encompass factors such as lead-time, non-synchronized systems, and the number of echelons in the supply chain.

2.1 Behavioral causes:

The causes of behavior have primarily been examined through laboratory tests and case studies. In contrast to operational causes, the behavioral perspective focuses on cognitive limitations, particularly bounded rationality. These cognitive limitations restrict rational decision-makers from making optimal decisions, leading to demand variability. Individuals are bound by rationality when it comes to indirect or non-linear feedback loops (Sterman, 1989, 2000).

Regarding decision-making, decision-makers treat supplier lead-time and customer lead-time as exogenous factors (J. Sterman, 2006). They perceive the lead-time of their supply chain partners as beyond their control, assuming that changes in their orders won't affect the supplier's lead-time (J. Sterman, 2006). However, if all organizations adopt this viewpoint, a positive feedback loop is established, significantly impacting supplier lead-time. Ultimately, this rational goal-seeking behavior harms these organizations. Furthermore, managers tend to overreact to changes in demand (Disney et al., 2005). They often read too much into historical demand data as it evolves over time, leading to over-optimism and confusion between forecasts and goals. Croson & Donohue (2002) and Sterman (1989) discovered that decision-makers typically lack a clear understanding of what is available in the supply chain, which introduces some form of decision bias. This behavioral cause of the bullwhip effect is closely linked to the operational demand signal processing.

Rather than focusing on changing institutional and inter-organizational infrastructure, authors have emphasized behavioral causes (Croson & Donohue, 2003, 2005, 2006; J. Sterman, 2000; J. D. Sterman, 1989). They propose that changing behavior can be achieved by providing decision-makers with more information and promoting organizational learning. Organizations should strive to improve mental models and adjust decision-making processes to account for interdependency, feedback, time delays, and other complexities inherent in modern supply chains.

2.2 Operational causes:

Lee et al. (1997) identified the primary causes of the bullwhip effect as demand signal processing, price fluctuation, order batching, and the rationing game. These causes were chosen because they represent common effects observed in supply chains. Retailers rely on demand signals from the market to predict future demand. Subsequently, these predicted demands are used to batch orders, aiming to achieve economies of scale in ordering and transportation. Demand signal processing and order batching are closely linked as they are driven by individual members of the supply chain who seek to optimize their internal inventory management operations. Rationing often occurs in product markets during the growth phase of a product's life cycle when demand exceeds supply. Price fluctuations are typically observed in mature product categories where manufacturers strive to gain market share. Both price variation and the rationing game respond to market dynamics. Lee et al. (1997) argued that all these causes stem from information distortion somewhere within the supply chain when optimizing behaviors of supply chain members occur.

Additionally, Chen et al. (2000) and Geary et al. (2006) identified additional causes that contribute to the bullwhip effect, including lead-time, forecasting methods, lack of transparency, and the number of echelons in the supply chain. Each of these causes will be discussed further.

2.2.1 Demand signal processing:

Lee et al. (1997) identifies inaccurate information and demand forecasting as primary sources of demand distortion. Demand signal processing involves adjusting inventory parameters in response to replenishment orders, often deviating from original demand due to rational adjustments. This practice leads to erratic responses to downstream demands, fueled by poor information sharing and inaccurate forecasts.

Demand forecasts are frequently based on historical data, potentially leading to unreliable predictions of future demand. Biases can arise from individual supply chain members' distinct goals, causing inaccuracies. Aligning member goals and creating incentives can reduce these biases.

Increasing inventory levels to avoid stockouts can inadvertently inflate demand and trigger the bullwhip effect (Dai et al., 2017). Safety stock accumulation due to forecasted orders contributes to this effect, particularly with extended lead times and multiple supply chain organizations.

Distorted demand signals from retailers spread upstream, intensifying with longer lead times and more organizations in the chain, as each adds safety stock based on their forecasts (Dai et al., 2017). Both information and physical product flows are affected, leading to inaccurate forecasts throughout the chain and amplifying divergence from end-customer demand, causing the bullwhip effect (Chen et al., 2000).

To enhance demand forecasts, strategies like lead-time reduction and improved information sharing are suggested. Centralizing demand information across the supply chain enables better data sharing and accuracy (Chen et al., 2000).

2.2.2 Order batching:

Hussain & Drake (2011) discuss how conflicting objectives among supply chain members influence ordering and production decisions. These conflicts arise from considerations like quantity discounts for retailers and economies of scale for manufacturers. The inventory manager's goal is to balance these competing aims while minimizing inventory.

Order batching involves grouping orders for upstream members in the supply chain. It offers benefits such as lowered costs, advantageous incentives, and transportation advantages. This practice leverages economies of scale in ordering, production, or transportation. However, orders often occur at set intervals, leading to unsynchronized supply with demand. This irregular ordering pattern causes suppliers to face erratic demand patterns, characterized by spikes followed by lulls (Lee et al., 1997). These order batches introduce demand variability, which is amplified as it propagates through the supply chain due to rounding up to batch sizes. This phenomenon, known as the bullwhip effect, contributes to longer cycle and delivery times (Cachon & Lariviere, 1999).

2.2.3 Price fluctuation:

Price fluctuations in the economy involve varying product prices, influenced by strategies like promotions, discounts, and coupons (Lee et al., 1997). However, these fluctuations can distort demand due to customers buying excess quantities during discounts, causing irregular buying patterns and demand variability (Dai et al., 2017). Pricing strategy, crucial for demand, must align with supply policies; temporary low prices can lead to short-term demand spikes (Lu et al., 2012). Fluctuations impact both upstream and downstream supply chain segments, exacerbating the bullwhip effect with more companies changing prices, increasing order variance (Lee et al., 1997).

2.2.4 Rationing and shortage gaming:

Supply shortages occur when demand significantly surpasses available supply. In response, manufacturers often implement rationing strategies by allocating products proportionally to customer orders. One of the primary causes of supply shortages is the miscalculation of demand by various members in the supply chain (Lee et al., 1997).

When customers encounter a supply shortage, they are aware of the limited availability of products. As a result, they tend to inflate their actual needs when placing orders to ensure their true demand is fulfilled. However, once the demand subsides, these customers may abruptly cancel their orders (Lee et al., 1997). This behavior distorts the supplier's perception of demand, leading to overproduction. It parallels the phenomenon of excessive ordering without fully considering previously placed orders that are pending fulfillment. Ultimately, this distorted demand information contributes to the occurrence of the bullwhip effect.

2.2.5 Forecasting methods:

The significance of supply chain forecasting extends beyond estimating demand at different levels of the supply chain. It involves addressing complex coordination and sharing of end-customer demand data among supply chain members. In this context, various forecasting techniques have been investigated to understand their effects on the bullwhip effect, such as moving average, exponential smoothing, and minimum mean squared error (MSE) (Lee et al., 1997).

Lee et al. (1997) laid the groundwork by using an *AR(1)* demand processing model to analyze a two-echelon supply chain with an order-up-to level policy. Building on this, Chen et al. (2000) expanded the study by applying exponential smoothing and moving average techniques to explore the influence of forecasting on the bullwhip effect. Their findings highlighted the role of regular demand signal processing in increasing order variance, contributing to the bullwhip effect. Additionally, incorporating more customer demand information into the forecast reduced variability, emphasizing the importance of smoother forecasts for mitigating the bullwhip effect. The authors noted that exponential smoothing and moving average methods produced varying results in different demand scenarios.

Chandra and Grabis (2005) examined the bullwhip effect in a two-stage supply chain with serially correlated demand. They evaluated forecasting techniques like moving average, exponential smoothing, and the naive MEAN method in auto-regressive models. Auto-regressive models demonstrated better inventory performance compared to moving averages and exponential smoothing, suggesting their forecasting efficiency. Exponential smoothing resulted in lower inventory sizes than moving averages, while the MEAN forecast underperformed in an auto-regressive model.

Hosoda and Disney (2006) used an *AR(1)* demand processing model in a three-echelon supply chain with moving average forecasting. They found a correlation between the bullwhip effect and net inventory variance at different supply chain stages.

Duc et al. (2008) explored the bullwhip effect in a two-echelon supply chain with a base stock inventory policy and moving average forecast under an *ARIMA(1,1)* demand process. Their study concluded that while the bullwhip effect might not always occur, the values of auto-regressive and moving average parameters influence its likelihood.

The reviewed literature predominantly focused on simpler two-stage supply chains and employed straightforward forecasting methods like moving average and exponential smoothing under *AR(1)* and *ARIMA(1,1)* demand processing models (Hosoda and Disney, 2006; Duc et al., 2008).

2.2.6 Lead-time:

Lead-time refers to the duration for delivering products downstream in the supply chain, encompassing order processing, production, logistics, and information transfer. Longer lead-times have been associated with increased order variability and play a key role in calculating safety stock (Lee et al., 1997; Chen et al., 1999; Chen et al., 2000; Wang et al., 2008). Combined with review periods, lead-time multiplicatively influences the bullwhip effect (Lee et al., 1997).

Chatfield et al. (2004) simulated a four-echelon chain with varied inventory sharing and gamma-distributed lead-times. They found that information quality affects the bullwhip effect by influencing lead-time demand forecasting stability and accuracy. Unstable or inaccurate forecasts lead to higher order variability.

Kim et al. (2006) assessed the bullwhip effect in a serial supply chain under periodic review (R, S) with fixed interval (R=1). Deterministic or stochastic lead-times were shown to significantly inflate demand variance upstream, contributing to the bullwhip effect. Agrawal et al. (2007) explored deterministic lead-time impact in a two-echelon serial chain using order-up-to policy, concluding that reducing lead-time is an effective bullwhip effect mitigation strategy.

Michna et al. (2019) analyzed a simple two-echelon chain with autoregressive demand. They found lead-time to be a major bullwhip effect driver, particularly when both lead-times and demands are stochastic. Accurate information collection based on realized lead-times was recommended for effective forecasting.

2.2.7 Lack of transparency:

The bullwhip effect can be attributed to a lack of transparency in operations, which hampers the efficient functioning of the supply chain. A key aspect of achieving optimal supply chain performance is the seamless flow of demand information across each stage. Consequently, sharing demand information among network members becomes imperative. Several researchers have investigated this subject extensively.

Lee et al. (1997) and Lee et al. (2000) studied a two-stage supply chain and found that sharing information benefits upstream partners by reducing inventory and costs. This effect is particularly pronounced with highly correlated and variable demands over a long lead-time.

Agrawal et al. (2007) examined a two-echelon supply chain, considering lead-time and information sharing. They concluded that while information sharing minimally reduces order variance, lead-time reduction is more advantageous.

Viswanathan et al. (2007) analyzed a four-echelon supply chain assuming all members access end-customer demand data. Their findings revealed that operational costs decrease across all supply chain echelons.

Sohn and Lim (2008) revealed in their research that information sharing doesn't always optimize supply chain performance. Yet, selecting an appropriate information sharing policy can effectively alleviate the bullwhip effect.

Lotfi et al. (2013) investigated how information integration impacts supply chain performance. Their results highlighted that sharing information benefits supply chain members through inventory and cost reduction, substantial bullwhip effect reduction, and enhanced overall performance.

2.2.8 Number of echelons:

The bullwhip effect, defined as the amplification of demand variability as one moves up the supply chain, suggests that an increase in the number of echelons corresponds to a greater impact of the bullwhip effect. Geary et al. (2006) argue that a supply chain with a minimum number of echelons allows for optimal inventory levels, mitigating the bullwhip effect.

Paik and Bagchi (2007) further assert that the level of echelons within a supply chain contributes to demand variation. They note that the addition of more echelons not only leads to longer material and information lead-times but also introduces more decision points, ultimately increasing the variability of orders. Consequently, individuals within the supply chain face a more erratic ordering pattern, resulting in the emergence of the bullwhip effect.

2.3 Mitigation of the bullwhip effect:

The bullwhip effect, a well-established concept in operations management and supply chain research, contradicts supply chain objectives of customer value and waste-free just-in-time availability (Lee et al., 1997). Its negative consequences include increased costs, substantial when production/ordering fluctuations outweigh inventory holding costs. Bullwhip costs impact workforce, machine use, upstream inventory, relationships, workload, and forecasting (Wang & Disney, 2016), leading to higher inventory holding costs, inefficient production, and risks to customer service (Wang & Disney, 2016). This effect strains retailer-supplier relations and escalates operational, transportation costs, harming competitiveness (Nienhaus et al., 2006).

Efforts to alleviate the bullwhip effect are crucial for operational efficiency. Wang & Disney (2016) present dominant opinions from 20 years of bullwhip research:

- Rational/irrational decisions trigger the bullwhip effect.
- Under specific conditions, it can be lessened or eradicated.
- Accurate forecasts, smaller batches, shorter lead times help.
- Supply chain integration, collaboration, transparency, centralized decisions aid reduction.

2.3.1 Demand signal processing:

In the realm of demand signal processing, the distortion of demand intensifies when retailers update their orders based on revised demand forecasts instead of actual customer demand. This leads upstream suppliers to adjust their forecasts to avoid shortages when receiving these orders. This propagation of demand forecast updates along the supply chain amplifies the initial signal, causing greater fluctuations as it progresses upstream. This results in distorted demand signals for upstream members, causing inefficiency and costly production.

To tackle the problem of dual forecasting as information traverses the supply chain stages, Lee et al. (1997) suggests enhancing information sharing among members. This prevents multiple demand forecast updates. Sharing raw demand data with upstream members enables them to adjust forecasts directly. Methods like Electronic Data Interchange (EDI), Vendor Managed Inventory (VMI), and Continuous Replenishment Program (CRP) facilitate this sharing. Chen et al. (2000) proposes using forecasting techniques generating smooth forecasts, maintaining stable mean and standard deviation estimates over time, as a means to mitigate the bullwhip effect. Reducing intermediaries in the supply chain is another strategy to achieve this, as it can lead to smoother demand forecasts. Furthermore, shorter lead times counteract the bullwhip effect by resulting in smaller safety stocks and more accurate forecasts. Additionally, shorter lead times accelerate order delivery to customers, aligning with actual market demand more effectively.

2.3.2 Order batching:

Batch ordering is influenced by two primary factors: the periodic review system and replenishment order processing costs. To address periodic review-related challenges, Lee et al. (1997) suggests granting suppliers access to retailer-level sales and inventory data to diminish demand distortion. This enables suppliers to plan production and inventory based on actual sales, reducing reliance on retailer orders. Furthermore, reducing transaction costs can curtail the need for batch ordering; implementing Electronic Data Interchange (EDI) systems, for instance, can trim ordering costs and batch sizes.

Transportation costs also prompt large batch orders. Often, companies opt for full truckloads, despite infrequent replenishments from suppliers, due to cost-effectiveness. A solution is ordering full truckloads with various products, not just one. This approach not only mitigates the bullwhip effect but also heightens ordering costs. Third-party logistics (3PL) can be advantageous, offering feasibility for smaller batch sizes, amalgamation of full truckloads from different suppliers, and potential economies of scale.

Hussain & Drake (2011) demonstrated that smaller batch sizes and balanced demand can curtail demand variability linked to order batching. Employing smaller batches brings benefits like better product alignment, lowered risk of delays, reduced inventory costs from smaller warehouses, and enhanced flexibility.

2.3.3 Price variation:

Lee et al. (1997) suggests that a straightforward approach to mitigate the bullwhip effect arising from forward buying is to reduce offering price discounting to retailers. Instead, they propose alternative pricing policies such as Everyday Low Price (EDLP) or a combination of Continuous Replenishment Program (CRP) and rationalized wholesale pricing. Implementing an Activity-Based Cost (ABC) system can also aid retailers in recognizing the excessive costs associated with forward buying and diversions. Additionally, the adoption of an ABC system facilitates the effective implementation of the EDLP strategy.

2.3.4 Rationing and shortage gaming:

In their study, Lee et al. (1997) suggests various solutions to address shortage supply in the supply chain. One strategy involves the supplier allocating items proportionally among retailers based on their past order records. Sharing information regarding the manufacturer's inventory and capacity with retailers can also help alleviate the rationing game. However, despite information sharing, shortage gaming may still occur when retailers place larger advance orders for seasonal sales. To effectively leverage information sharing, it is vital for manufacturers to continuously update their production schedule and capacity in response to market demand from downstream members. Additionally, suppliers can discourage retailers from exaggerating their needs and canceling orders by implementing stricter returns and cancellation policies. By adopting these measures, the occurrence of shortage gaming can be limited, resulting in reduced risks and improved supply chain performance.

2.3.5 Forecasting methods:

Forecasting methods are crucial for estimating average demand and its variability, which is essential in determining adequate capacity. Chen et al.'s 2000 study investigated the impact of forecasting techniques on the bullwhip effect under a periodic order-up-to level policy. They noted that forecast activities are necessary to prevent the bullwhip effect, even though practical implementation requires forecasting throughout the supply chain.

To reduce the bullwhip effect, Chen et al. (2000) recommended using moving average forecasts over exponential smoothing. Geary et al. (2006) also highlighted the significant influence of forecasting method selection on the bullwhip effect, causing demand information mismatches that escalate up the supply chain.

Numerous time series modeling approaches, including moving average, exponential smoothing, auto-regression, and auto-regression moving average, have been studied for measuring the bullwhip effect. Moving average and exponential smoothing are preferred due to their robustness, adaptability to nonlinear methods, and ease of use.

In conclusion, organizations should align their choice of forecasting method with their operational needs to effectively process demand forecasts.

2.3.6 Lead-time:

Order information progression within the supply chain undergoes stages that frequently introduce delays in logistics and information flow. These delays contribute significantly to the need for increased safety stock in upstream levels. Longer lead-times exacerbate the potential for demand prediction errors, giving rise to the detrimental bullwhip effect that undermines overall supply chain efficiency.

Lee et al. (1997) emphasizes that tackling lengthy replenishment lead-times effectively entails their reduction. They advocate adopting the Quick Response strategy as a countermeasure against extended lead-times.

Chen et al. (2000) present various countermeasures to trim lead-times. These include instituting lead-time contracts with suppliers, elevating order frequency, sharing sales data and forecasts with suppliers, and leveraging extensive demand data when facing prolonged lead-times.

Implementing these strategies empowers businesses to mitigate the adverse repercussions of lead-time delays and cultivate a more seamless and productive supply chain network.

2.3.7 Lack of transparency:

Information sharing is a pivotal strategy for mitigating the bullwhip effect in supply chains. When supply chain members exchange data, they gain a deeper understanding of received orders, especially how retailer orders reflect end-customer demand and replenishment requirements. This comprehension helps avoid errors in interpreting demand (Croson & Donohue, 2003). The sharing of Point-of-sale (POS) data, a common practice, effectively reduces the bullwhip effect. Analyzing POS data offers insights into genuine demand and order drivers beyond relying solely on forecasts (Lee et al., 2000). Information sharing also facilitates initiatives like Quick Response, Efficient Consumer Response, and Continuous Replenishment programs, benefiting both downstream and upstream partners (Lee et al., 2000).

The extent of information sharing reflects supply chain relationships and opportunities for improvement. Weak relationships and low service levels correlate with order variability. Consequently, sharing downstream inventory and direct end-customer demand data significantly reduces order variability throughout the supply chain (Chen et al., 2000; Croson & Donohue, 2003). Significantly, this collaborative information sharing also enhances the performance of upstream facilities (Lee et al., 2000; Croson & Donohue, 2006).

2.3.8 Number of echelons:

Geary et al. (2006) stress that to mitigate the bullwhip effect and create an efficient supply chain, it's essential to minimize the number of echelons in the chain. This isn't solely about maintaining ideal inventory levels, but also about ensuring timely delivery of these minimal stocks to the right places.

Paik & Bagchi (2007) recognize a trade-off between rectifying demand distortions and reducing intermediaries in the supply chain. While this approach can enhance supply chain performance, it might lead to conflicts among existing members. Thus, a meticulous supply chain restructuring is needed to avert unnecessary conflicts.

By finding a middle ground between reducing echelons and managing potential conflicts, supply chains can optimize their operations and enhance overall efficiency.

2.3.9 Behavioral perspective:

The bullwhip effect in supply chains arises from behavioral factors that lead to decision-making biases. Supply chain managers' decisions can be influenced by misinterpreting demand data, resulting in overly optimistic forecasts and confusion between forecasts and targets. Overreactions to customer complaints can further amplify the bullwhip effect (Disney et al., 2005).

Cognitive limitations worsen the situation due to the supply chain's complexity and uncertainty. Decision-makers often lack a clear understanding of resources and information, exacerbating the bullwhip effect. Limited data access and difficulty assessing supply chain status are common issues (Sterman, 1989; Croson & Donohue, 2003).

To address these challenges, strategies include sharing point-of-sale, inventory, and demand data among supply chain partners for improved decision-making (Wang & Disney, 2016). Centralizing ordering decisions reduces fluctuations caused by local demand variations (Wang & Disney, 2016). Accurate forecasting techniques are vital, minimizing variability in demand signals (Wang & Disney, 2016).

Integration across the supply chain is key. Information integration shares product flow and inventory data, while organizational integration ensures effective collaboration (Wang & Disney, 2016). Geary et al. (2006) recommend behavioral countermeasures, including suitable control systems, efficient time management, transparent information access, and synchronized activities.

By tackling these factors and implementing countermeasures, supply chains can reduce the bullwhip effect and enhance performance.

3 The framework of supply chain network

This section provides an overview of the structure of the supply chain model, which primarily consists of several members: manufacturer, distributor, wholesaler, retailer, and end-customer. The manufacturer is assumed to have unlimited external suppliers for raw materials.

The supply chain integrates business processes from end-customers to original suppliers who provide goods, services, or information that add value for the end-customers. To ensure an uninterrupted and timely flow of materials to customers, it is crucial to have high-quality information and precise timing of relevant information among all members of the chain. Supply chain performance relies on the operations of all members, with each entity striving to optimize their organization to meet customer demand and prevent inventory stock-outs.

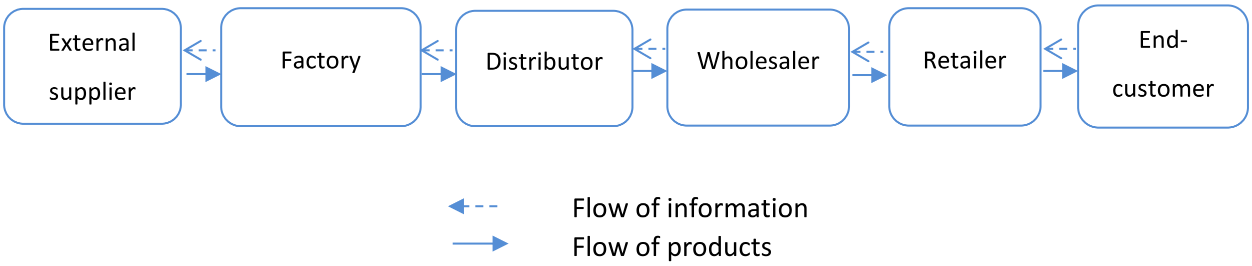


Figure 3-1: A multi-echelon supply chain (Costantino at el., 2015)

The activities in the supply chain begin with the end-customer, who sends demand orders to their upstream partners. The upstream members then receive these customer orders and engage in various activities such as fulfilling demand, adjusting inventory parameters, and placing replenishment orders with their suppliers. This process continues throughout the entire supply chain. During this horizontal timeline, each stocking node performs the following tasks sequentially:

- Receiving incoming replenishment orders from downstream members and updating their on-hand inventory.
- Receiving shipments from upstream stocking nodes, fulfilling demand orders, and backordering any unfulfillable demand. Partial order filling is used when there is insufficient stock to meet the entire demand order.
- Updating the inventory parameters using demand forecast information derived from recently observed demand data.
- Placing replenishment orders with upstream partners to adjust the inventory position.

3.1 Inventory policy:

This sub-section will explain the different types of inventories used at each stocking point. Inventory refers to stocks or items used to support production (such as raw materials and work-in-process items), supporting activities (such as maintenance, repair, and operating supplies), and customer service (such as finished goods and spare parts). Inventory is a valuable resource for companies, but they aim to avoid excessive inventory as it takes up space and capital. Additionally, in supply chains with short life cycle products, there is a significant risk of inventory becoming obsolete. Inventory drivers, which are business conditions that necessitate holding inventory, are also taken into consideration. By effectively managing and controlling these drivers, companies can reduce the need for inventory in the supply chain.

Wang & Disney (2016) suggest that uncertainties are one of the main factors leading to the bullwhip effect in the supply chain. Geary et al. (2006) identify four types of uncertainty related to the bullwhip effect: process uncertainty, supply uncertainty, demand uncertainty, and control uncertainty. Process uncertainty pertains to a company's internal activities required to meet production delivery targets. Supply uncertainty refers to poor supplier performance that hinders value-added processes. Demand uncertainty relates to discrepancies between actual end-customer demand and orders placed by customers within companies. Control uncertainty is associated with information flow and how companies process customer orders into production targets and supplier raw materials. The degree of uncertainty has a direct impact on the bullwhip effect and supply chain integration. Thus, inventory drivers related to "uncertainty in supply or demand" are considered, as they are closely related to the causes of the bullwhip effect.

When companies face supply or demand uncertainty, they need to hold more safety stock and hedge inventory due to the unreliable and ever-changing demands over time. This leads to the bullwhip effect. To address such uncertainties, it is crucial to determine whether supply uncertainty or demand uncertainty needs to be reduced, and then focus on reducing that factor (Bozarth & Handfield, 2016). For example, supply uncertainty caused by poor quality can be significantly reduced through business cycle or quality improvement programs. Additionally, forecasts can help mitigate demand uncertainty to some extent.

According to Barlas & Gunduz (2011), in a supply chain with *i* identical stocking points (*i=1,2,...,N)*, each echelon replenishes its upstream partner *(i+1)* at time *t*. The terminology used for inventory is as follows:

On-hand stock: Refers to all items that are physically available on the shelves. It is important to note that on-hand stock cannot have a negative value. It increases with the arrival of new inventory and decreases when items are shipped out.

$$OH_{i,t} = OH_{i,t-1} + \left(A_{i,t} - S_{i,t}\right) \qquad (3.1)$$

Where $A_{i,t}$ is the arrivals to echelon i and $S_{i,t}$ is the shipment to meet the customer demand from echelon i in period t.

In-transit inventory: Refers to items that have been shipped by the upstream partner but have not yet arrived.

$$IT_{i,t} = IT_{i,t-1} + \left(S_{i+1,t} - A_{i,t}\right) \qquad (3.2)$$

Where $S_{i+1,t}$ can be known as the stock on-order which has been ordered but not shipped by the upstream stocking note.

Shipment requirement: Is the sum of demand $D_{i,t}$ and backorder $BO_{i,t-1}$

$$SR_{i,t} = D_{i,t} + BO_{i,t-1} \qquad (3.3)$$

If there is sufficient on-hand inventory, the required amount is shipped immediately. However, if the on-hand inventory is inadequate, the unfulfilled portion of the orders is backlogged.

$$S_{i,t} = min\left(SR_{i,t}; OH_{i,t}\right) \qquad (3.4)$$

Net stock: Is defined as the on-hand after the backorders are subtracted.

$$NS_{i,t} = OH_{i,t} - BO_{i,t} \qquad (3.5)$$

Opposite to on-hand stock, this quantity can become negative because of backorders. If there is not enough on-hand stock, the order will be partly filled, and the rest will be backordered. The size of the backorder will therefore be the negative size of net stock.

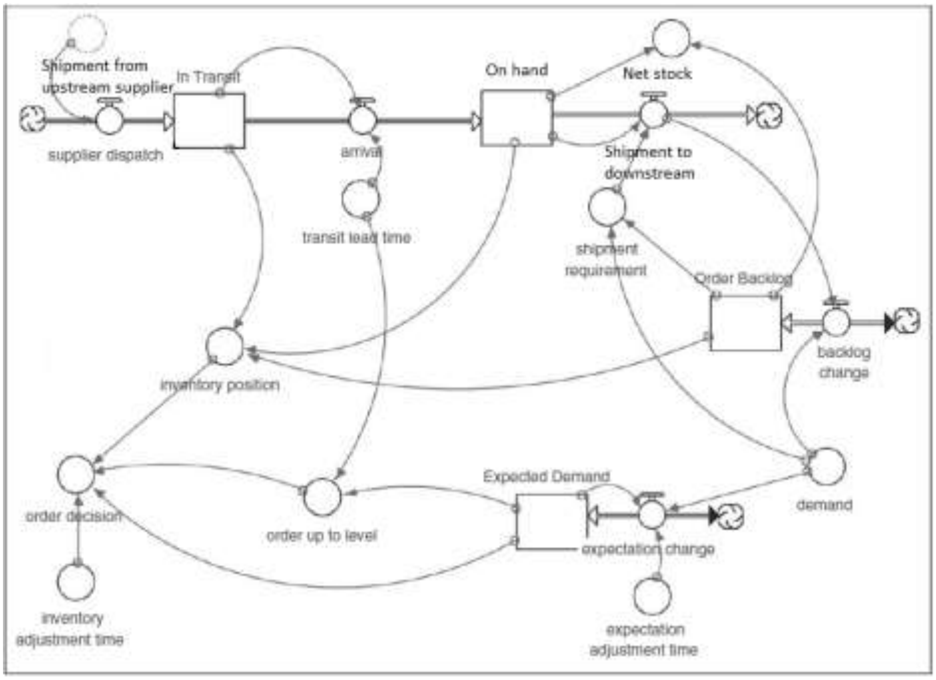


Figure 3-2: General flow stock of the supply chain model (Barlas & Gunduz, 2011)

Inventory position is defined as:

$IP_{i,t} = OH_{i,t} + IT_{i,t} - BO_{i,t}$

(3.6)

Safety stock: is the average level of net stock just before a replenishment order arrives. Thus, a positive safety stock provides a buffer against larger-than-average demand during the effective replenishment lead time. On the other hand, safety stock is an extra inventory that companies hold to prevent them from uncertainties. Moreover, companies do not want to plan to use their safety stock, it is there because of uncertainties in demand or replenishment lead time. With the allowance of backorders, the safety stock can be of negative quantity (Silver et al., 2017).

Additionally, it is important to make clear what will happen to customer orders if items are out-of-stock. Hence, there will be two extreme cases:

Complete backordering: Under this scenario, any demand that cannot be fulfilled from the available stock will be backordered and eventually filled with a partial replenishment.

Complete lost sales: occur when demand cannot be satisfied and is essentially lost, often seen at the retailer level within the supply chain. This situation prompts customers to seek alternative retailers to fulfill their needs.

In terms of inventory policy decision-making, Silver et al. (2017) emphasizes key factors such as the frequency of inventory reviews, timing of replenishment orders, and order size. These considerations are closely linked to the demand process. When dealing with deterministic demand, decision-making becomes straightforward due to the ability to calculate inventory status at all points in time. Replenishment orders are initiated when inventory levels reach a predefined point, often zero. The order quantity is commonly determined using the Economic Order Quantity (EOQ) model.

In contrast, under probabilistic demand, determining the inventory status becomes more challenging as it requires significant resources such as labor and computer time. Additionally, the less frequently the inventory status is reviewed, the longer the period needed to satisfy desired customer service. Companies can choose to place replenishment orders early and carry extra stock or wait to minimize carrying costs. However, this approach carries the risk of inadequate provision of customer service, resulting in potential costs in the form of lost sales. It becomes a trade-off between these two boundaries.

There are various replenishment policies, but two commonly used ones are the periodic review, replenishment interval, order-up-to level policy, and the continuous review, reorder point, order quantity model. However, under probabilistic demand and considering the research on the Bullwhip effect, researchers assume that each echelon of the supply chain implements an adaptive base-stock policy known as the Up-to-order (S) policy for replenishment. The inventory position is reviewed at regular intervals (e.g., daily, weekly, monthly), and a replenishment order is placed to raise the inventory position to an order-up-to or base-stock level whenever it drops to or below the re-order point (s). Both the review interval and the order-up-to level are decision variables. Therefore, the following types of inventory systems will be introduced.

3.1.1 Order-point, Order-Up-to-Level $(\boldsymbol{s}, \boldsymbol{S})$ system:

The Order-Point, Order-Up-to-Level (s, S) system is an inventory management policy that involves continuous review of inventory levels. When the inventory reaches the re-order point (s), an order is placed to bring the inventory level back up to the order-up-to level (S). However, since demand varies over time, the replenishment quantity also becomes variable.

The (s, S) system is often referred to as a min-max system because the inventory position is always between a minimum value of (s) and a maximum value of (S), except for a possible temporary drop below the re-order point. One advantage of the (s, S) system is the flexibility of variable order quantities. However, companies that adopt this system may make more frequent errors, and some prefer the predictability of a fixed order quantity, especially

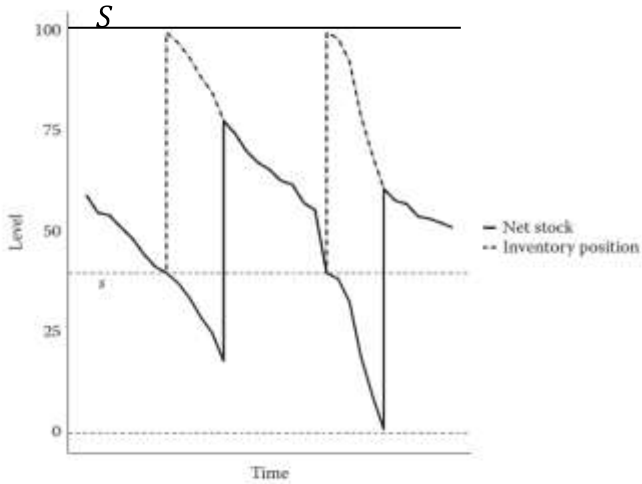


Figure 3-3: The (s, S) policy (Silver et al, 2017)

if it aligns with packaging or handling requirements (Silver et al., 2017).

3.1.2 Periodic-Review, Order-Up-to-Level (R, S) system:

In the periodic-review system, the company periodically checks the inventory level of an item at fixed intervals (R) and replenishes enough stock to bring it to a predetermined level (S). The order quantity (Q) is determined using the formula: $Q = S - I$, where S is the target stock level, and I is the inventory position at the time of review (Bozarth & Handfield, 2016).

$$Q = S - I \qquad (3.7)$$

Compared to order point systems, the periodic-review system is preferred for coordinating the replenishment of related items, which can result in significant cost savings. Additionally, the (R, S) system offers the opportunity to adjust the order-up-to level (S) regularly, making it suitable for accommodating changes in demand patterns. However, the periodic-review system has varying replenishment order quantities over time and incurs higher inventory holding costs compared to continuous-review systems (Silver et al., 2017).

3.1.3 (R, s, S) System:

The (R, s, S) system combines elements of both continuous and periodic review systems. Under this policy, the inventory level is reviewed every R unit of time, and a decision is made whether to place an order to bring the inventory to the predetermined level (S). If the inventory position is at or below the reorder point (s), an order is placed to raise the inventory position to the level (S). Otherwise, no action is taken until the next review period.

The main distinction between the (s, S), (R, S), and (R, s, S)) systems is that the reorder point is only implemented in the (s, S) and (R, s, S) policies. Furthermore, the (s, S) policy is a special case when $R = 0$, and the (R, S) policy is a special case when $s = S - 1$. In other words, the (R, s, S) system is a periodic version of the (s, S) system, and the (R, S) system is a periodic implementation of the (s, S) system when $s = S - 1$.

The (R, s, S) system can result in lower total costs for replenishment, carrying, and shortages compared to other systems. However, it is generally more challenging to understand and implement than other policies. The (R, s, S) system is commonly used in practice, even when point-of-sale (POS) equipment allows for continuous review of inventory positions (Silver et al., 2017).

The comparison between (R, s, S) system and (R, S) system is illustrated in figure 3-4 below.

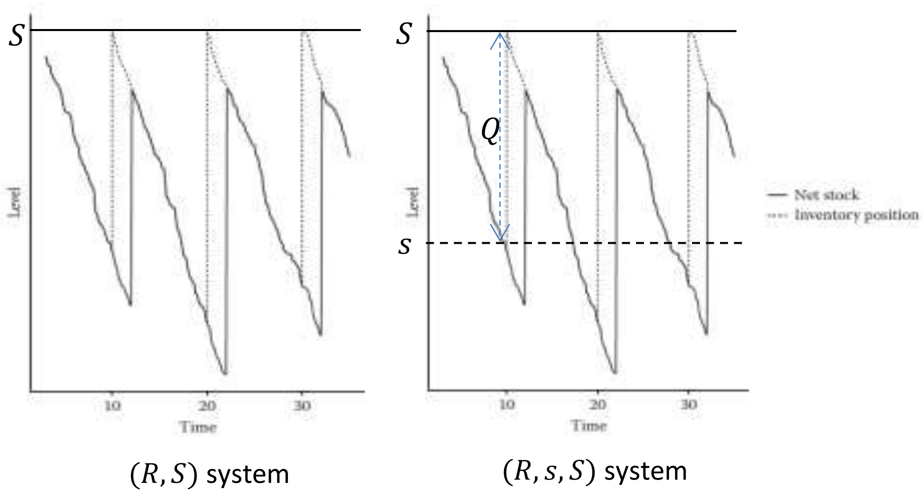


Figure 3-4: The comparison between (R, S) and (R, s, S) review system with $R = 10$ units (Silver et al., 2017)

3.2 Replenishment process:

3.2.1 Correlated demand:

In this section, we consider a simple model of a two-echelon supply chain consisting of a retailer and a supplier to study the manipulation of the demand process. The retailer, in period t, places an order q_t to the manufacturer, who then fulfills the demand D_t using their on-hand stock. The model assumes a fixed order lead time denoted as L, which is independent of the replenishment order sizes and the ordering period. Orders placed at the end of period t will be received at the beginning of period $t + L$. Additionally, backlogs are allowed in case of excess demands, and negative orders (return of excess inventory without cost) between stages are permitted, assuming the standard deviation σ is smaller than the mean demand μ, as assumed by Lee et al. (1997).

Most researchers, including Lee et al. (1997), consider customer demand to follow an auto-regression *AR(1)* demand processing model with temporal correlation. The demand signal at the retailer stage is processed as follows:

$$D_t = \mu + \rho D_{t-1} + \epsilon_t \qquad (3.8)$$

$= \mu/(1-\rho)$ *and* $Var(D_t) = \frac{\sigma^2}{(1-\rho^2)}$. Note that if $\rho = 0$, the demands are i.i.d with mean μ and variance σ^2.

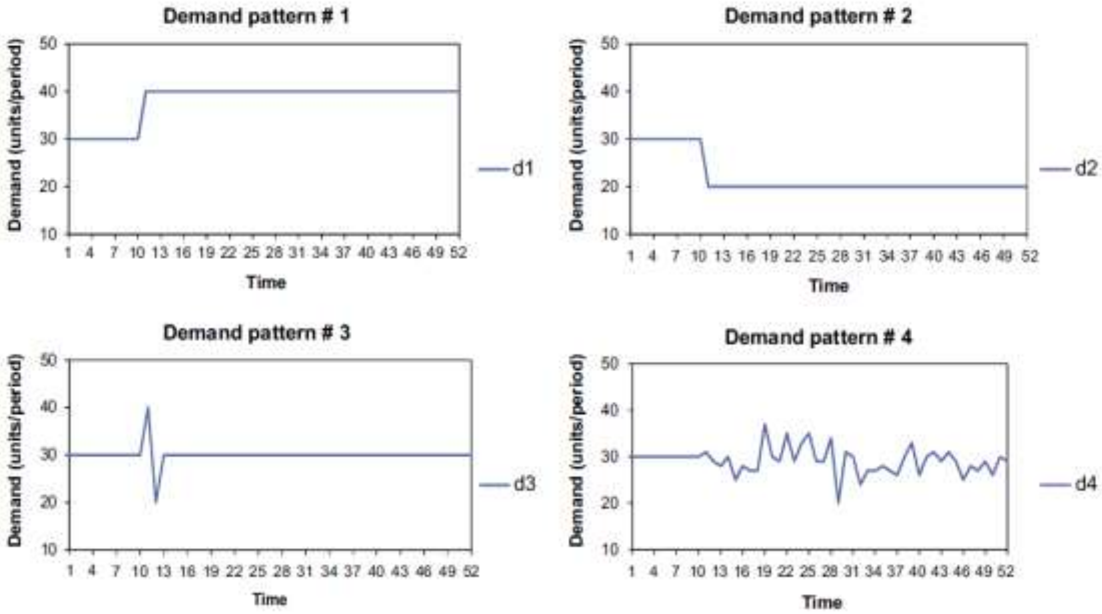


Figure 3-5: Different types of demand pattern (Costantino et al., 2015)

Here, μ is a nonnegative constant, ρ is a correlation parameter with $|\rho| < 1 to$ ensure covariance stationarity of the demand process, and the error terms ϵ_t are independent and identically distributed (i.i.d) with a mean of 0 and variance σ^2. The expected demand and variance of demand faced by the retailer can be calculated as $E(D_t) = \mu/(1-\rho)$ and $Var(D_t) = \frac{\sigma^2}{(1-\rho^2)}$., respectively. Notably, when ρ = 0, the demands are i.i.d with a mean of μ and variance of σ^2. **Figure 3-5** provides a visualization of demand variations under different inputs.

The figure demonstrates four demand structures associated with deterministic and probabilistic demand assumptions. For deterministic demand, we assume a constant level of 30 units per period with limited variability starting from period $t = 11$. Stochastic customer demand follows a normal distribution with a mean demand $\mu = 30$ and variance $\sigma^2 = 3$. The figure illustrates the response of the supply chain under various conditions. The first three demand patterns exemplify highly non-stationary demand, while under stochastic demand, unexpected and substantial changes in demand result from factors such as price changes, discounts, promotions (demand pattern 1 and 2), or advance demand (demand pattern 3). It is worth noting that most research on the bullwhip effect utilizes demand signals from the first and fourth demand patterns, as highlighted by Costantino et al., 2015.

3.2.2 Ordering process:

In the (R, S)policy, which is a periodic review system, the inventory is raised to the order-up-to level (S) every R unit of time. The predefined level S_t can be determined by the lead time demand using the formula:

$$S_t = \widehat{D}_t^{L+R} + z\hat{\sigma}_t^{L+R} \quad (3.9)$$

Here, $\widehat{D}_t^{L+R}$ represents the estimated mean lead-time demand, $\hat{\sigma}_t^{L+R}$ is the estimated standard deviation of the *(L+R)* period forecast error, and *z* is the normal z-score that corresponds to a given service level. The z-score can be obtained from a standard normal cumulative distribution function table, which is shown in Appendix 1. A higher z-score value indicates a lower probability of stockout.

The optimal order-up-to level *(S)* can be estimated based on inventory holding costs and shortage costs, as suggested by Heyman & Sobel (1984), Duc et al. (2008), and Bozarth & Handfield (2016). However, since accurately estimating these costs is often challenging, the approach of using the service level is commonly employed to determine the order-up-to level.

The order quantity q_t is calculated as:

$$q_t = S_t - S_{t-1} + D_{t-1} \quad (3.10)$$

Here, S_t represents the order-up-to level in period t, which is the inventory level at the beginning of the period after the order is placed.

In the (s, S) review system, a replenishment order is made when the inventory position drops to or below the reorder point (s), and the order is placed to bring the inventory position to level S. Barlas & Gunduz (2011), Bozarth & Handfield (2016), and Silver et al. (2017) suggest an appropriate correspondence between the continuous and periodic review systems, where *(R+L)* is used for L and S is used for s. Thus, the reorder point (s) and order-up-to level *(S)* can be expressed using the following equations:

$$s_t = \widehat{D}_t^{L} + z\hat{\sigma}_t^{L} \quad (3.11)$$

$$S_t = s_t + EOQ_t \quad (3.12)$$

Where $\widehat{D}_t^{L}$ represents the estimated mean lead-time demand,, $z\hat{\sigma}_t^{L}$ is the safety stock at time t and EOQ_t represents the optimal economic order quantity given by $EOQ_t = \sqrt{\frac{2*\bar{D}_t*ordering\ cost}{holding\ cost}}$ with $\bar{D}_t$ is the average demand at time t.

The order quantity Q_t is expressed as:

$$Q_t = S_t - I_t \quad (3.13)$$

Here, I_t represents the inventory position at the review interval.

As mentioned earlier, the (*R*,*s*,*S)* system is a periodic version of the *(s*,*S*) system with specific R review intervals. Therefore, the ordering pattern in the (*R*,*s*,*S*) system follows the same process as the (*s*,*S)* system, which includes:

$$s_t = \widehat{D}_t^{L+R} + z\hat{\sigma}_t^{L+R}$$

$$S_t = s_t + EOQ_t$$

And

$Q_t = S_t - I_t$

3.3 Forecasting method:

A forecast is an estimate of the future level of a variable (Bozarth & Handfield, 2016). This variable can include factors such as demand, supply, and price. One particular type of forecast is demand forecasting, which involves estimating the quantity of a product that will be purchased. Demand forecasting plays an important role in both short-term and long-term production planning and decision-making related to inventory management.

Forecasting future demand is essential for making informed decisions about replenishment orders. Inventory management and production planning rely on accurate predictions of future demand. In situations where the supply chain members do not have precise information about the true demand process, they resort to forecast techniques to estimate future demand and adjust their inventory parameters accordingly. As demand is adjusted periodically, the order-up-to level becomes adaptive and updated in each period.

To effectively measure the mean and variance of demand during the lead-time, two widely used forecasting methods are employed. These methods are as follows:

- Moving average:

The moving average is a simple technique used to estimate demand data over a specific period, where N represents the parameter indicating the number of periods considered. The moving average calculates the average demand during the given period using the following formula:

$$\widehat{D}_t = \frac{1}{N}\sum_{i=1}^{N} D_{t-i} = \frac{1}{N}(D_{t-1} + D_{t-2} + \cdots + D_{t-N}) \qquad (3.14)$$

For the forecast of lead time demand, it is computed using the following formula:

$$\widehat{D}_t^L = L \times \widehat{D}_t = \frac{L}{N}\sum_{i=1}^{N} D_{t-i} \qquad (3.15)$$

Therefore, the standard deviation of the lead time demand forecast error in period t is calculated as follows:

$$\hat{\sigma}_t^2 = \frac{1}{N-1}\sum_{i=1}^{N}\left(D_{t-i} - \widehat{D}_t\right)^2 \qquad (3.16)$$

where $(D_{t-i} - \widehat{D}_t)$ is a single period forecast error

$$(\hat{\sigma}_t^L)^2 = L \times \hat{\sigma}_t^2 = \frac{L}{N-1}\sum_{i=1}^{N}\left(D_{t-i} - \widehat{D}_t\right)^2 \qquad (3.17)$$

$$\hat{\sigma}_t^L = \sqrt{L} \times \hat{\sigma}_t = \sqrt{L} \times \sqrt{\frac{\sum_{i=1}^{N}(D_{t-i} - \widehat{D}_t)^2}{N-1}} \qquad (3.18)$$

Due to the availability of new demand information every period, the estimated values of $\widehat{D}_t^L$ and $\hat{\sigma}_t^L$ are subject to change in each period. As a result, the order-up-to inventory policy is also updated accordingly in every period.

- Exponential smoothing:

When employing exponential smoothing as a forecasting technique under the same policy and demand process setting, the estimate of future demand during the period can be expressed as follows:

$$\widehat{D}_{t+i} = \alpha D_{t-i} + (1-\alpha)\widehat{D}_{t-i} \tag{3.19}$$

Here, α represents the smoothing constant, where $0 < \alpha < 1$. It is important to note that the current forecast $\widehat{D}_t$ is a weighted average of the previous period's demand and the previous period's forecast demand. The value of α determines the relative weight assigned to the current period's demand. Consequently, the estimation of the total expected demand over *L* lead time periods is calculated using the following equation:

$$\widehat{D}_t^L = L \times \widehat{D}_t = L\left[\alpha D_{t-1} + (1-\alpha)\,\widehat{D}_{t-1}\right] \tag{3.20}$$

In this equation, L represents the number of lead time periods, α is the smoothing constant, $\hat{D}_t$ is the current forecast, D_{t-1} is the previous period's demand, and $\hat{D}_{t-1}$ is the previous period's forecast demand.

The standard deviation of the lead time forecast error is calculated in the same way as in the moving average. The formula to calculate it is as follows:

$$\hat{\sigma}_t^L = \sqrt{L} \times \sqrt{Var\left(D_t^L - \widehat{D}_t^L\right)} = \sqrt{L} \times \sqrt{\frac{\sum_{i=1}^{N}(D_{t-i} - \widehat{D}_t)^2}{N-1}} \tag{3.21}$$

In this equation, $\hat{\sigma}_t^L$ represents the standard deviation of the lead time forecast error, *L* is the number of lead time periods, D_{t-i} represents the actual demand in period *i*, and $\hat{D}_t$ is the forecasted demand in the current period. The formula calculates the variance of the difference between the actual and forecasted demand values over the specified number of periods, and the square root of the result provides the standard deviation.

3.4 Information sharing in supply chain:

Supply chain management involves coordinating the flow of finished goods and information among chain members. Information flows, inventory management, and production plans are communicated in both directions between downstream and upstream members. Sales information and forecasted demand flow from downstream stages to upper stages. Therefore, effective, and timely information sharing between stages plays a vital role in integrating the supply chain, enabling more efficient coordination, collaborative sales and production planning, and meeting customer service level requirements.

However, in pursuit of competitive advantages, each member of the supply chain often focuses primarily on optimizing their own organization, without considering the broader perspective of other members within the local supply chain. As a result, two types of information sharing strategies exist in the supply chain: decentralized information sharing and centralized information sharing. The definitions of these strategies, as explained by Lee et al. (2000) and Sohn and Lim (2008), are as follows:

- Decentralized information sharing:

Decentralized information sharing refers to a strategy where members of the supply chain do not share information with each other. Only the retailer has access to end-customer demand information. Consequently, the information transmitted between stages is limited to the downstream member's order demand to the upper partner. The upstream member then estimates their forecast and updates their inventory parameters based on the received demand order information. As a result, the demand forecast deviates from the original end-customer demand as it moves through the upstream sites, leading to demand variance in the supply chain.

- Centralized information sharing:

In the centralized information sharing strategy, end-customer demand information is shared among all members of the supply chain. This means that upstream members not only have access to demand order information from the nearest downstream members but also to end-customer demand data. They can estimate and update their inventory parameters based on the complete set of end-customer demand data. By forecasting from end-customer demand, the expected future demand aligns more closely with the original customer demand, resulting in improved forecasting accuracy and reduced demand variance throughout the supply chain.

The illustration of how information sharing strategies works is briefly shown is figure 3-6.

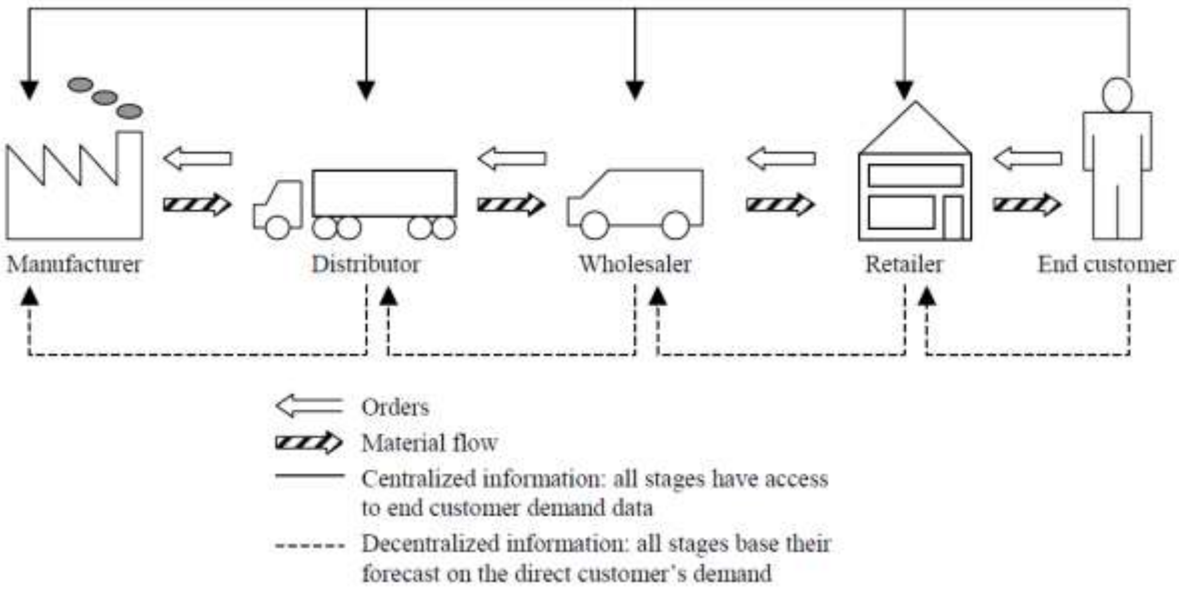


Figure 3-6: The two types of information strategy in supply chain management (Merkuryev & Petuhova, 2002)

4 Simulation Method

4.1 Choice of simulation type:

Simulation modeling involves creating an artificial environment to replicate real-world processes and behaviors, aiding in understanding and predicting future conditions (Kothari, 2004). It utilizes artificial data to recreate diverse real system conditions, often employing mathematical formulas (Bozarth & Handfield, 2016). Such models offer advantages such as process experimentation without real-world impact, time compression for faster analysis, and "what-if" scenario assessment. However, they can lack realism, be costly to develop, and might not provide optimal solutions.

This research focuses on simulating supply chain performance, particularly regarding the impact of sharing end-customer demand information on the bullwhip effect. Two strategies are studied: decentralized information (no sharing) and centralized information (sharing). Discrete-event and continuous simulation modeling are discussed as approaches. Continuous simulation suits dynamic aspects, while discrete-event modeling examines operational initiation. The chosen approach for this study is discrete-event simulation due to its ability to simulate product and information flows. Selecting appropriate software is crucial; it should be flexible, efficient, and scalable for complex systems like supply chains.

4.2 ARENA Software:

ARENA, developed by Rockwell Corporation, is a versatile simulation software widely employed in domains like manufacturing and supply chain management. It encompasses logistics, warehousing, distribution centers, customer service, planning, and internal processes. It features object libraries for system modeling and employs the SIMAN simulation language, categorized into blocks (logic constructs) and elements (statistical data facilities) (Altiok & Melamed, 2007).

Modules in ARENA are vital modeling components, selected from templates, and composed of SIMAN blocks and/or elements for complex systems (Altiok & Melamed, 2007).

A typical ARENA session involves:

- Selecting module/block icons from templates and placing them on the model canvas.
- Establishing graphical connections between modules for transactional/controlling flows.
- Parameterizing modules using a text editor.
- Writing case-insensitive code within modules, allowing mixed-case use.
-

ARENA offers simulation optimization via opt quest and includes modules like Arena Input Analyzer (for distribution fitting) and Arena Output Analyzer (for simulation experiments) (Altiok & Melamed, 2007).

4.3 Bullwhip effect performance measure:

The Bullwhip effect is defined as a phenomenon in which order variability increases as orders move upstream in the supply chain. This variability can be quantified using measures such as the coefficient of variation, variance, or standard deviation. In most mathematical models, the variance is commonly used for convenience. Therefore, the measurement of the bullwhip effect involves comparing the variance of demand with the variance of orders. This comparison can be expressed either as a ratio or a difference. An amplification of the bullwhip effect is indicated by a ratio significantly larger than one or a difference greater than zero (Wang & Disney, 2016; Cachon et al., 2007).

$$Bullwhip\ effect\ ratio = \frac{Variance\ of\ order}{Variance\ of\ demand}$$

4.4 Simulation procedure:

The simulation is designed to demonstrate the information flow and ordering coordination among echelon members of the supply chain under different information sharing strategies. The following sections will provide detailed explanations of the assumptions, procedure, and design of the simulation model.

Phase 1: Generation of End-Customer Demand and Forecasting

In this phase, the simulation generates demand for the retailer based on the autoregression *AR(1)* demand processing model proposed by Lee et al. (1997) (refer to section 3.2.1). The demand for the retailer is generated using the following formula:

$$D_t = \mu + \rho D_{t-1} + \epsilon_t$$

Parameters such as μ, ρ, $D_{t-1}$and ϵ_t are assumed to have specific values. All members of the supply chain employ the same forecasting techniques, namely moving average and exponential smoothing, to estimate the expected demand.

Phase 2: Ordering decision

During each re-planning cycle, the specific forecasting technique is used to estimate the expected demand based on past observed demand data. Using the calculated future demand, the lower-stage member determines an order quantity to be placed with the upper-stage partner. The forecasting parameters are re-estimated as the schedule moves one period forward, and more demand information becomes available at the upstream stage. After the lead time, the downstream echelon receives the delivery shipped by the upstream stocking point. At the end of the period, the actual demand is realized, and the demand is fulfilled using on-hand inventory, with any remaining unfulfilled demand being backlogged. It's important to note that, to capture real-world supply chain dynamics, unfulfilled demand is backlogged in all stages. In other words, the retailer stage no longer faces lost sales; instead, the unsatisfied demand is backlogged at the retailer's store, similar to other echelon members of the supply chain.

Phase 3: Production and delivery decision

The upstream stocking point receives orders from its downstream members and makes production and planning decisions based on the available information. Two cases are considered:

a) When there is no information sharing, the downstream does not share any information with the upstream partner regarding their actual demand. The upstream echelon makes production decisions solely based on the direct orders placed by the downstream stage.

b) When information sharing occurs, the upstream is given access to the end-customer demand, allowing production decisions to be made based on the estimation of end-customer demand.

At the end of each period, after the current period's production is completed, the upstream stage decides on shipping from its on-hand inventory. If the on-hand inventory is sufficient to fulfill all downstream orders (including backorders), they are filled accordingly. If the on-hand inventory is insufficient, the downstream stock point will be allocated a proportionate supply to fulfill its orders (including backorders), and any shortages will be backlogged.

These processes are repeated until ordering, production, and delivery decisions are made for the entire simulation period. Consequently, all relevant data from the simulation will be collected and analyzed to assess the bullwhip effect in the supply chain.

4.5 Simulation general assumption:

The simulation model focuses on a four-echelon supply chain comprising a retailer, distributor, manufacturer, and external supplier. The following assumptions are made:

- Simulation Duration: The simulation runs for a period of 3000 days.
- Replenishment Lead Time: The fixed lead time for replenishment is set at 2 days.
- Review Interval: The review interval for inventory management is set at 4 days.
- Uniform Settings: All echelons in the supply chain employ the same (*R, s, S)* review system, ordering policy, exponential smoothing as a forecasting method, lead time, review interval, service level, and initial on-hand inventory.
- Information Sharing Settings: To ensure fair comparison of the bullwhip effect, both the simulation of decentralized information and centralized information sharing adopt identical settings, including inventory review system, ordering policy, forecasting technique, replenishment lead time, review interval, service level, and initial on-hand inventory.
- Deterministic Lead Time and Review Interval: The lead time (*L)* and review interval (*R*) remain fixed and deterministic across the supply chain.
- Order Availability: There is no ordering lead time; once an order is placed, it immediately becomes available to the upstream stage as a demand order.
- Unlimited Shipment Capacity: The shipment capacity between adjacent echelons in the supply chain is considered unlimited, allowing a single truckload to accommodate complete shipments to downstream stages at any given period.
- Unlimited On-Hand Inventory Capacity: The on-hand inventory capacity at different supply chain echelons is assumed to be unlimited.
- Shortage Handling: Shortages are to be fulfilled as quickly as possible, following a first-come-first-served pattern.
- Unit of Measurement: The material exchanged among supply chain members is measured in units.
- Backlogging: All echelon members, including the retailer, distributor, and manufacturer, experience complete backlogging when facing shortages.
- Cost Parameters: The ordering cost is set at 70, the holding cost at 0.2, and the shortage cost at 140.

These assumptions provide a framework for conducting the simulation and analyzing the dynamics of the supply chain with respect to the bullwhip effect.

The equations presented in Section 3.1 and Section 3.2 are utilized to define and calculate various state variables at each echelon member. These state variables include:

$$OH_{i,t} = OH_{i,t-1} + (A_{i,t} - S_{i,t}) \quad (3.1)$$

$$IT_{i,t} = IT_{i,t-1} + (S_{i+1,t} - A_{i,t}) \quad (3.2)$$

$$SR_{i,t} = BL_{i,t} + D_{i,t} \quad (3.3)$$

$$S_{i,t} = min(SR_{i,t}; OH_{i,t}) \quad (3.4)$$

$$NS_{i,t} = OH_{i,t} - BO_{i,t} \quad (3.5)$$

$$IP_{i,t} = OH_{i,t} + IT_{i,t} - BO_{i,t} \quad (3.6)$$

$$s_t = \widehat{D}_t^L + z\hat{\sigma}_t^L \quad (3.11)$$

$$S_t = s_t + EOQ_t \quad (3.12)$$

$$Q_t = S_t - I_t \quad (3.13)$$

The simulation model, as shown in Figure 4-1, is initialized with zero on-hand inventory units in each echelon. Additionally, at the beginning of the time horizon, there is no backlog in any echelon. The service level is set to meet 97% of the expected demand in all echelons, corresponding to a z-score of 1.9. The determination of the z-score is derived from Appendix 1.

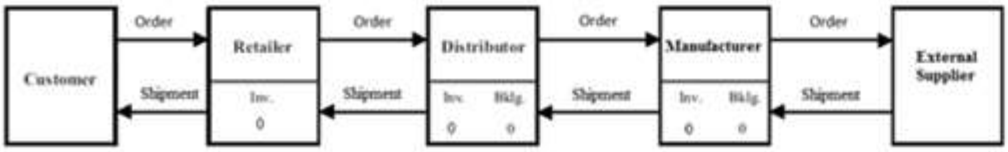
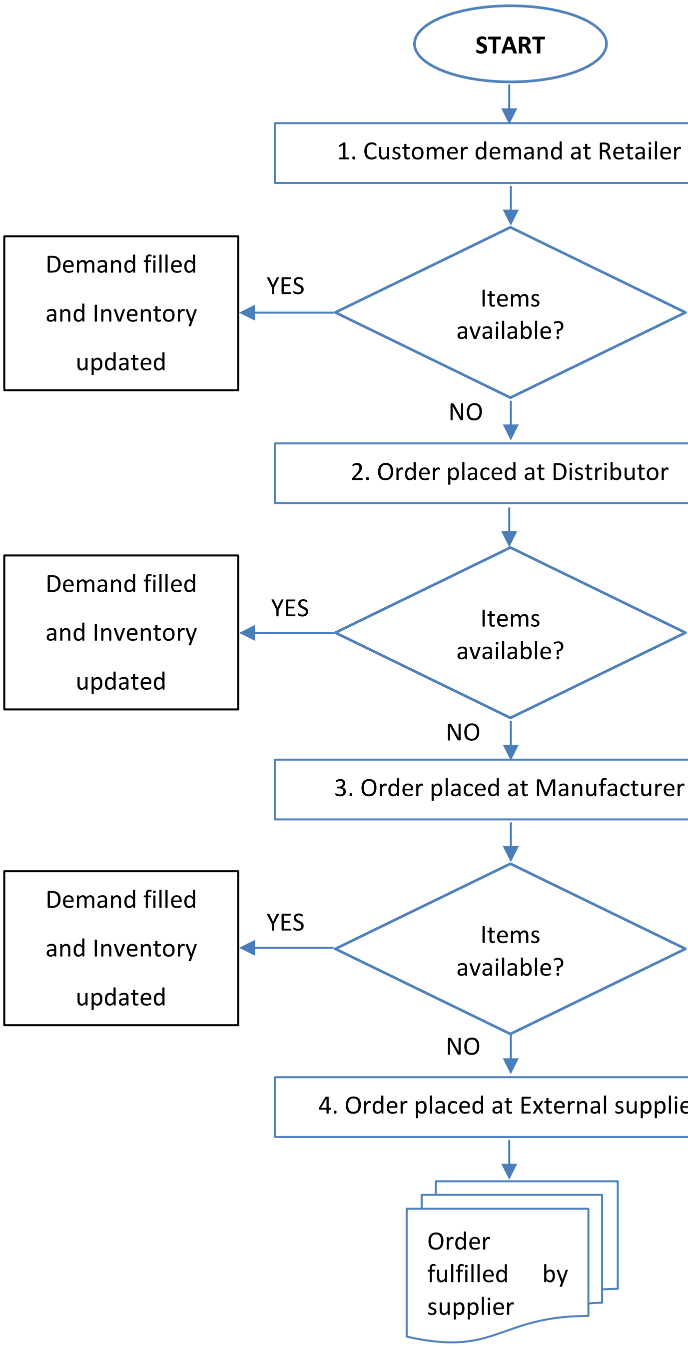


Figure 4-1: The balance state setting of the simulation (Author)

Modeling logic used in multi-echelon supply chain modeling:



Details of Variables and Attributes Used in Modeling and Simulation of Multi-Echelon Supply Chain:

Figure 4-2: Modeling logic for simulation (Author)

Sr. No	Variables	Meaning
1	Inventory_Retailer	Inventory capacity at Retailer
2	InventoryPosition_Retailer	Current inventory status of Retailer
3	ReorderPoint_Retailer	Reorder level at Retailer

4	TargetStock_Retailer	Target level inventory at Retailer
5	Backorder_Retailer	Backorder of Retailer
6	Inventory_Distributor	Inventory capacity at Distributor
7	InventoryPosition_ Distributor	Current inventory status of Distributor
8	ReorderPoint_ Distributor	Reorder level at Distributor
9	TargetStock_ Distributor	Target level inventory at Distributor
10	Backorder_Distributor	Backorder of Distributor
11	Inventory_Manufacturer	Inventory capacity at Manufacturer
12	InventoryPosition_ Manufacturer	Current inventory status of Manufacturer
13	ReorderPoint_ Manufacturer	Reorder level at Manufacturer
14	TargetStock_ Manufacturer	Target level inventory at Manufacturer
15	Backorder_Manufacturer	Backorder of Manufacturer
16	Q_R	Order quantity by Retailer
17	Q_D	Order quantity by Distributor
18	Q_M	Order quantity by Manufacturer
19	Order_Distributor	Order placed by Wholesaler to Distributor
20	Order_Manufacturer	Order placed by Distributor to Manufacturer
21	Order_Supplier	Order placed by Manufacturer to Supplier
22	AvailableForBackorder_Retailer	Current status of backorders at Retailer
23	AvailableForBackorder_Distributor	Current status of backorders at Distributor
24	AvailableForBackorder_Manufacturer	Current status of backorders at Manufacturer
25	ReviewInterval	Review period at each echelon (R = 4)
26	LeadTime	Replenishment lead-time at each echelon (L = 2)
Sr. No	**Attributes**	**Meaning**
1	UnsatisfiedPortionDemand_Retailer	Unsatisfied portion demand at Retailer
2	UnsatisfiedPortionDemand_Distribiutor	Unsatisfied portion demand at Distributor
3	UnsatisfiedPortionDemand_ Manufacturer	Unsatisfied portion demand at Manufacturer
4	CUSTOMER_DEMAND	Customer demand
5	REATAILER_DEMAND_FORECAST	Customer demand forecast at Retailer
6	RETAILER_STDEV	Standard deviation of lead-time demand forecast at Retailer
7	RETAILER_AVERAGE_DEMAND	Average demand at Retailer
8	DC_DEMAND_FORECAST	Demand forecast at Distributor
9	DC_STDEV	Standard deviation of lead-time demand forecast at Distributor
10	DC_AVERAGE_DEMAND	Average demand at Distributor
11	MN_DEMAND_FORECAST	Demand forecast at Manufacturer
12	MN_STDEV	Standard deviation of lead-time demand forecast at Manufacturer
13	MN_AVERAGE_DEMAND	Average demand at Manufacturer

Table 4-1: Details of variables and attributes used in modeling and simulation

4.6 Modeling and simulation on ARENA:

4.6.1 Supply chain simulation in Decentralized information:

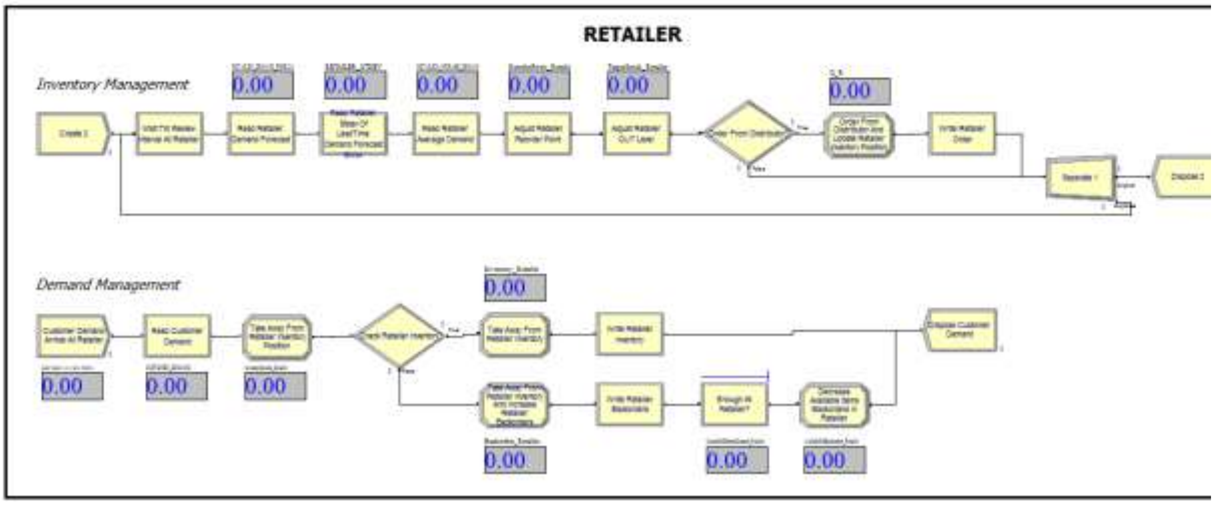


Figure 4-3: The Retailer simulation model

The first stage of the supply chain is the **"*Retailer*"**, which is designed as shown in Figure 4-3. The retailer activities consist of two segments: demand management and inventory management. In the demand management segment, customer demand is received and fulfilled, while the inventory management segment triggers replenishment orders by updating the reorder point and order-up-to level. Let's delve into each segment in detail, starting with the demand management segment.

The demand management segment begins with the description of the Retailer model, specifically the Demand

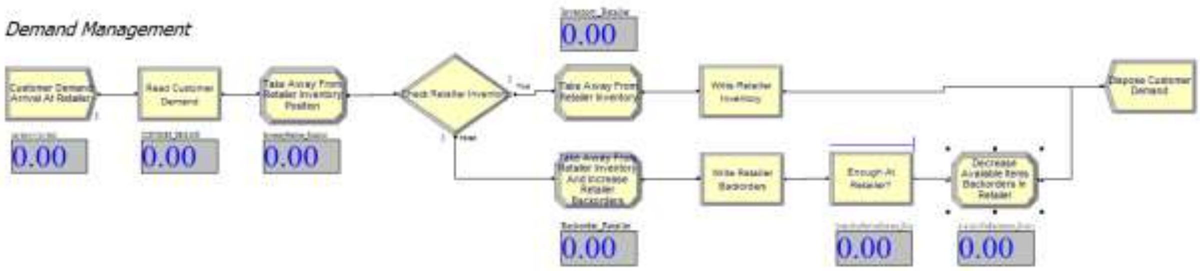


Figure 4-4: Demand Management model of Retailer

segment. The module called "***Customer Demand Arrival At Retailer***" initiates the stream of customer arrivals with a single-unit demand quantity (Figure 4-5). This module creates entities and releases them into the system. The *Interarrival time* is set at a constant value of ***1***, meaning that one customer arrives at the retailer every day. Once an entity is created, it leaves the module.

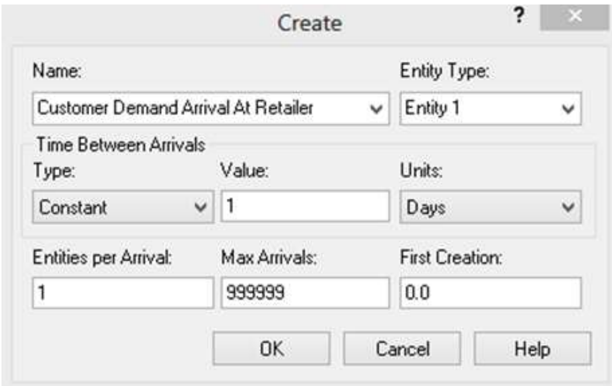


Figure 4-5: The dialog box of Create module Customer Demand Arrival Retailer

The entity "**ReadWrite"** module that is responsible for interacting with a specific data source to either read or write data. In this case, the module is specifically designed to read customer demand from an Excel spreadsheet file.

When the "***Read Customer Demand module"*** is executed, it accesses the Excel file and retrieves the customer demand information. It then assigns this value to an attribute called "***CUSTOMER_DEMAND"***. Attributes are variables or properties that hold specific values within a program or system (Figure 4-6).

Figure 4-6: The dialog box of ReadWrite module Read Customer Demand

After that, the entity proceeds to the "***Take Away From Retailer Inventory Position***" (Figure 4-7), an "***Assign"*** module where the variable "***InventoryPosition_Retailer"*** is decreased by the value of the "***CUSTOMER_DEMAND"*** attribute.

Next, the entity enters the "***Decide***" module (Figure 4-8) which is called "***Check Retailer Inventory"***, the Decide module tests whether there is sufficient on-hand inventory to fulfill the end-customer demand.

Figure 4-7: The dialog box of Assign module Take Away From Retailer Inventory Position

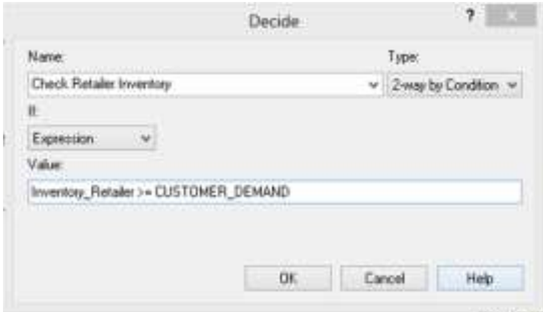


Figure 4-8: The dialog box of Decide module Check Retailer Inventory

If the condition "***Inventory_Retailer ≥ CUSTOMER_DEMAND***" holds true, the entity takes the True exit and enters the "***Assign***" module, which is called "***Take Away From Retailer Inventory***". In this module, the on-hand inventory is decremented by the value of the "***CUSTOMER_DEMAND***" attribute. The entity then proceeds to the "***ReadWrite***" module, which is called "***Write Retailer Inventory***". This "***ReadWrite***" module writes the value of the variable "***Inventory_Retailer***" to an Excel spreadsheet file named "***Retailer Inventory***" (Figure 4-9 and 4-10).

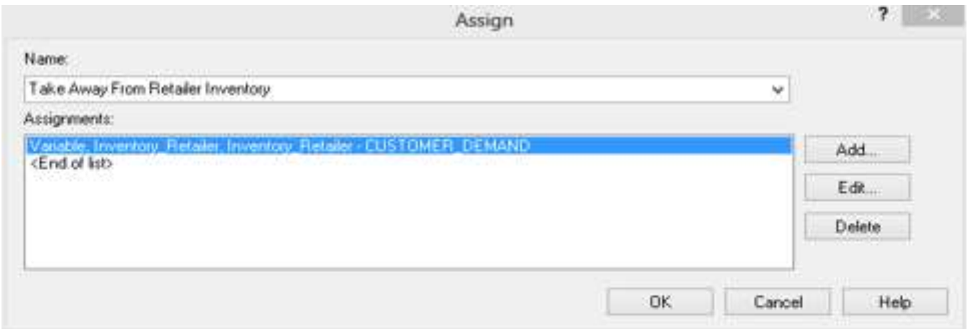


Figure 4-9: The dialog box of Assign module Take Away From Retailer Inventory

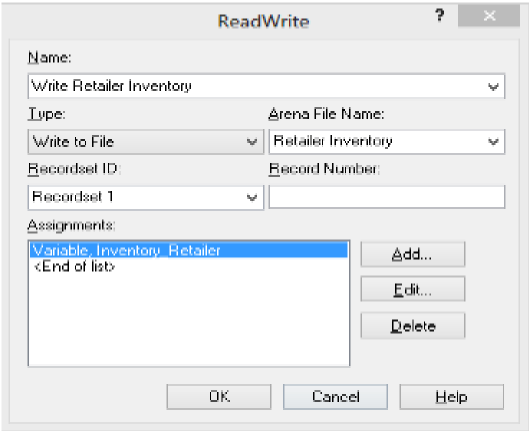


Figure 4-10: The dialog box of ReadWrite module Write Retailer Inventory

If the condition "***Inventory_Retailer < CUSTOMER_DEMAND***" holds true, indicating insufficient on-hand inventory, the entity takes the False exit. The current demand is fully backlogged at the retailer stage, and the entity enters to the "***Assign"*** module, which is called "***Take Away From Retailer Inventory And Increase Retailer Backorders***". In this module (Figure 4-11), three assignments are performed: decreasing the "***Inventory_Retailer"*** variable to zero, increasing the "***UnsatisfiedPortionDemand_Retailer"*** attribute, and incrementing the "***Backorder_Retailer"*** variable.

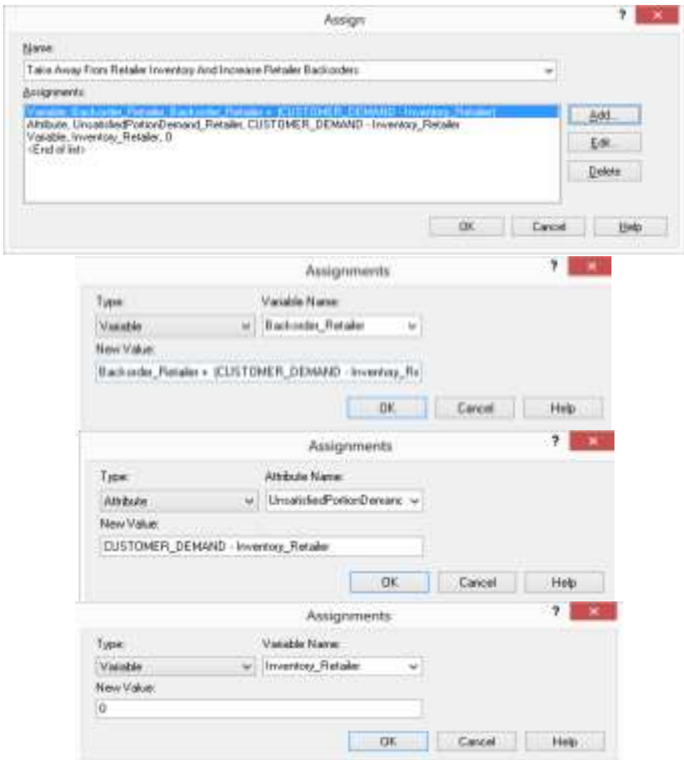


Figure 4-11: The dialog box of Assign module Take Away From Retailer Inventory And Increase Retailer Backorders

The entity transitions from the "***Assign"*** module to the "***ReadWrite"*** module, specifically called "***Write Retailer Backorders"***. In this module, the variable "***Backorder_Retailer"*** is written to the designated Excel spreadsheet

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file named “***Retailer Inventory”***, capturing the value of the backorders from the retailers. Figure 4-12 illustrates the dialog box of the “***ReadWrite”*** module.

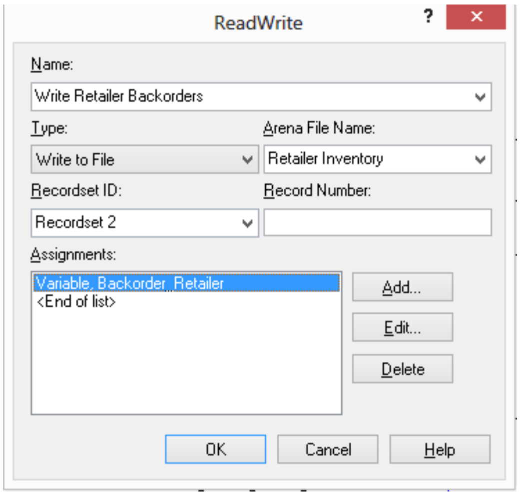

Figure 4-12: The dialog box of ReadWrite module Write Retailer Backorders

The entity then proceeds to the “***Hold”*** module, known as “***Enough At Retailer***?”, where it remains detained until a sufficient inventory accumulates at the Retailer to fulfill the backorders during stock-out periods. In other words, the entity is held in the “***Hold”*** module until enough inventory becomes available to satisfy the remaining demand. A variable named “***AvailableForBackorders_Retailer***” is created to be compared with the attribute “***UnsatisfiedPortionDemand_Retailer***”. The module keeps the entity detained until the condition ***“AvailableForBackorders_Retailer ≥ UnsatisfiedPortionDemand_Retailer”*** is met. Once the condition is satisfied, the entity is released and proceeds to the “***Assign”*** module called “***Decrease Available Items For Backorders In Retailer***”, where the variable “***AvailableForBackorders_Retailer***” is decremented by the value of the attribute “***UnsatisfiedPortionDemand_Retailer***”. The dialog boxes illustrating the processing of backorders in the Retailer are shown in Figure 4-13.

Finally, regardless of whether the entity follows the True exit or the False exit in the “***Decide”*** module, it reaches its conclusion at the “***Dispose”*** module named “***Dispose Retailer Demand***”. This module serves as an exit point for the model.

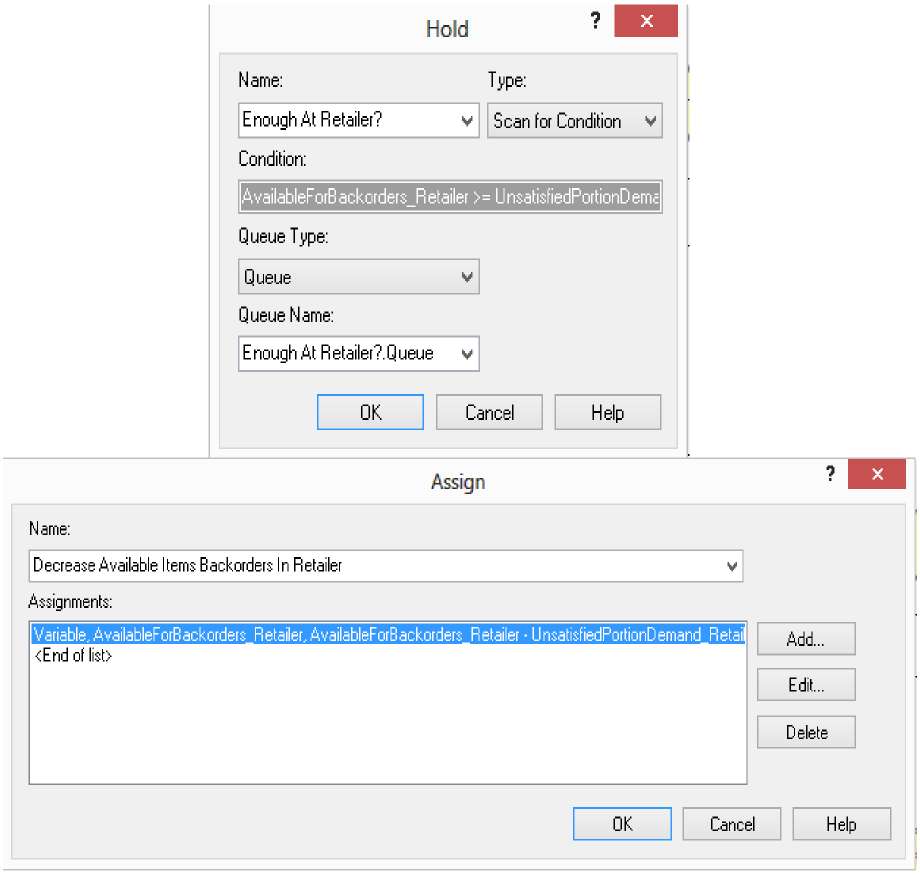

Figure 4-13: Dialog boxes of processing backorders in Retailer

Now that we have provided a detailed explanation of the Demand management segment of the Retailer, let's move on to describing the Inventory management segment. The Inventory management model is illustrated in Figure 4-14.

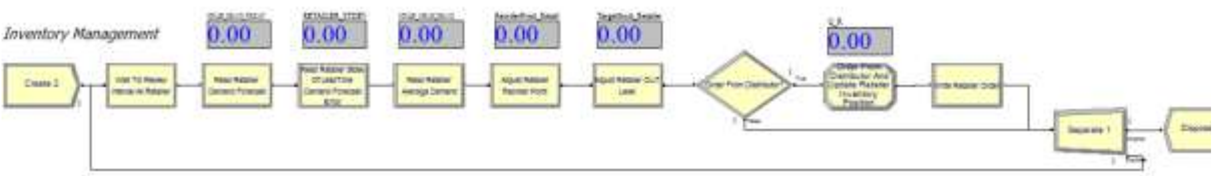

Figure 4-14: The model of Inventory management of the Retailer

In the inventory management segment, the "***Create***" module named "***Create 2***" generates a single entity within the model. Unlike the demand management segment, where a larger number of entities representing customers are allowed to enter the model, the inventory management segment only releases a constant single entity as a control entity. The dialog box of the "***Create***" module is displayed in Figure 4-15.

The entity then proceeds to enter a "***Delay***" module called ***"Wait Till Review Interval At Retailer"***. This "***Delay***" module is utilized to introduce a specific time delay to the entity, which aligns perfectly with the review interval of $R=4$ days. Once the entity enters this "***Delay***" module, it is detained for a period of 4 days until it is released to the next module. The dialog box of this "***Delay***" module is shown in Figure 4-16.

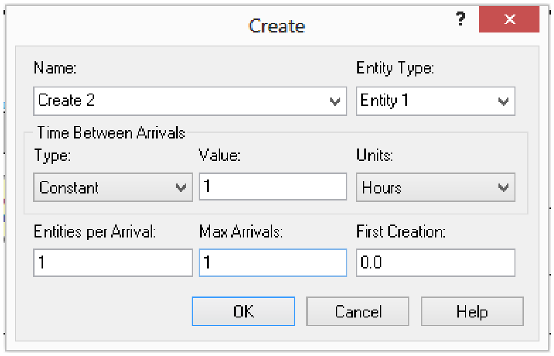

Figure 4-15: The dialog box of Create module in Retailer Inventory management segment

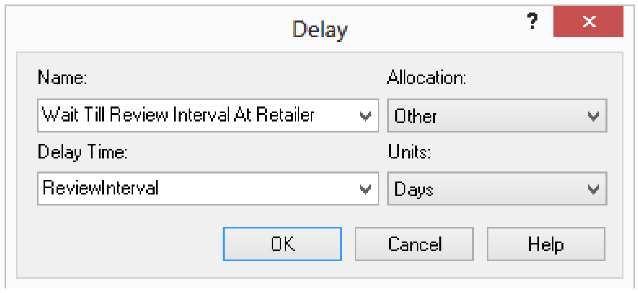

Figure 4-16: The dialog box of Delay module Wait Till Review Interval At Retailer

After the 4-day period in the "***Delay"*** module, the entity proceeds to the "***ReadWrite"*** module called "***Read Retailer Demand Forecast***". In this module, the attribute "***RETAILER_DEMAND_FORECAST***" is assigned the value from a specific Excel spreadsheet file called "***Customer Demand Data***". The entity then continues to the next two modules: ***"Read Retailer Stdev Of LeadTime Demand Forecast Error"*** and **"*Read Retailer Average Demand*"**. In these modules, the values of the standard deviation of lead-time demand forecast error ('***RETAILER_STDEV***') and the average demand ('***RETAILER_AVERAGE_DEMAND***') are assigned to their respective attributes from the same Excel spreadsheet named "***Customer Demand Data***". These attribute values are used for the calculation of the variables "***ReorderPoint_Retailer***" and "***TargetStock_Retailer***", which will be explained shortly. The dialog boxes for these three "***ReadWrite"*** modules are displayed in Figure 4-17.

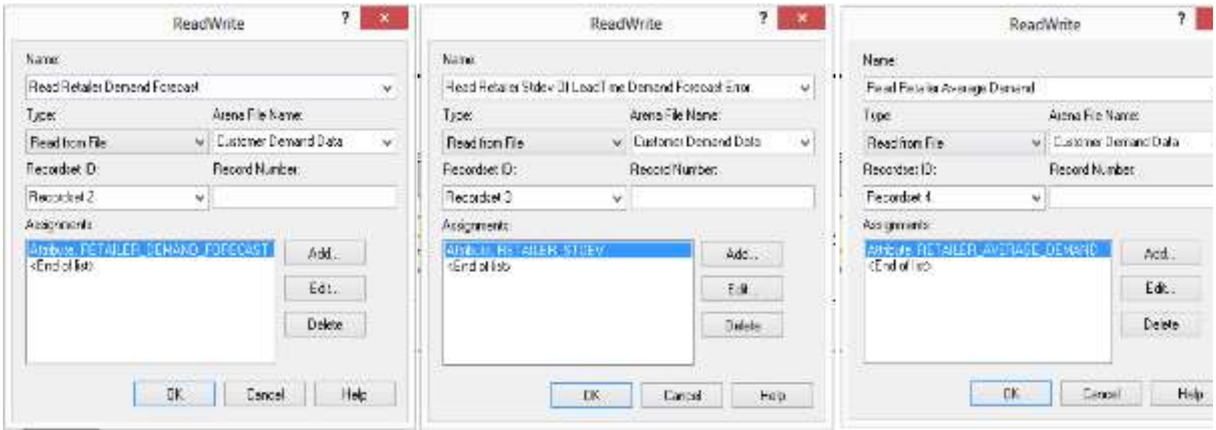

Figure 4-17: The dialog boxed of ReadWrite module in processing Retailer forecast attributes

The entity now proceeds to the next module which is named "***Adjust Retailer Reorder Point"***. This is "***Adjust Variable"*** module and is used to adjust variables in the model. In this model, the reorder point of retailer whose variable is "***ReorderPoint_Retailer"*** is updated using the value of attributes "***RETAILER_DEMAND_FORECAST***, ***RETAILER_STDEV"***, and z-score = 1.9 which represent the service level of 97%. Moreover, the values of variables "***ReviewInterval"*** and "***LeadTime"*** are also used to estimate the retailer reorder point. The dialog box of "***Adjust Variable"*** module is shown in figure 4-18

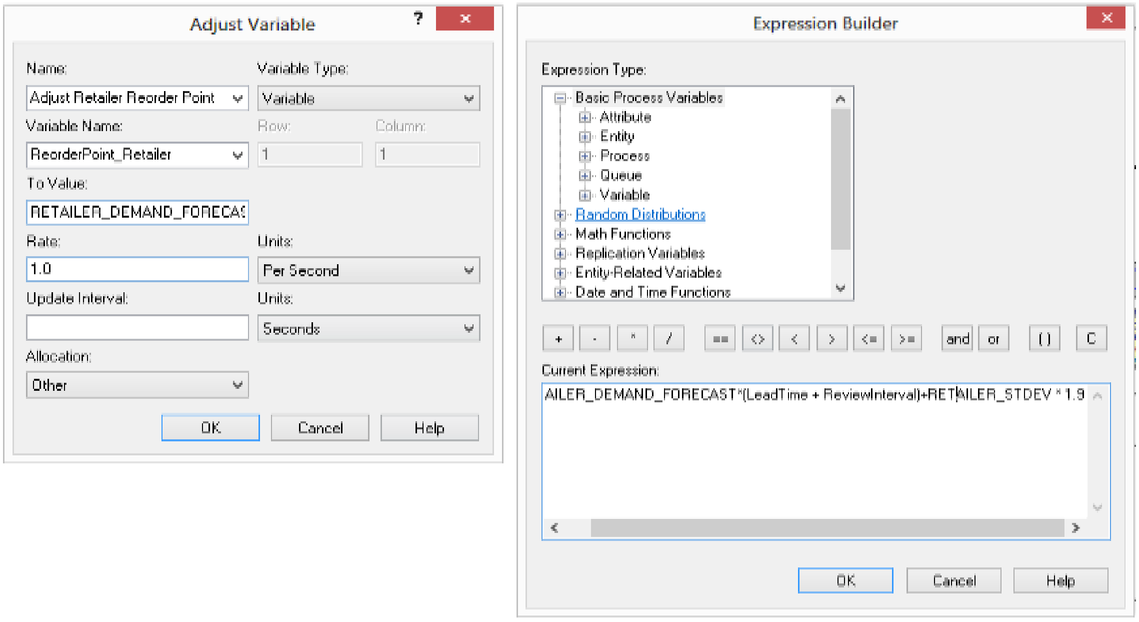

Figure 4-18: The dialog box of Adjust Variable module Adjust Retailer Reorder Point

The entity proceeds to another "***Adjust"*** module, named "***Adjust Retailer OUT Level***". In this module, the value of the variable "***TargetStock_Retailer***" is determined based on the variable "***ReorderPoint_Retailer***", the attribute ***"RETAILER_AVERAGE_DEMAND***", the ordering cost (set at 70), and the holding cost (set at 20). These factors are taken into account to estimate the appropriate target stock level for the retailer. The dialog box for the "***Adjust Variable***" module is displayed in Figure 4-19.

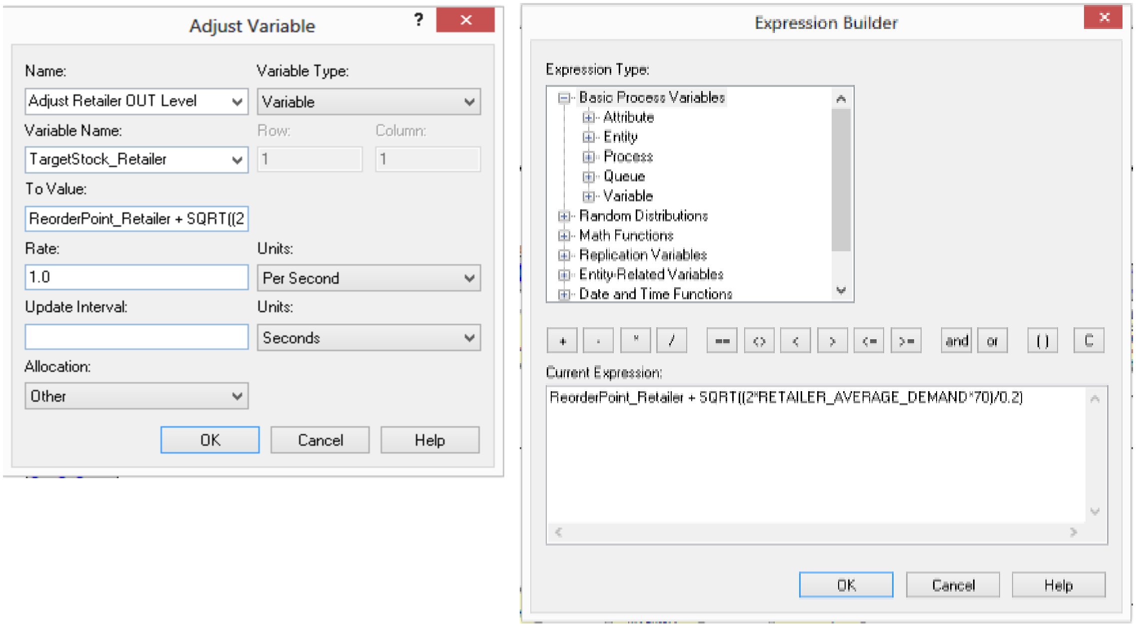

Figure 4-19: The dialog box of Adjust module Adjust Retailer OUT Level

The entity then proceeds to the "***Decide***" module called ***"Order From Wholesaler?"***. In this module, it checks whether the retailer's inventory position has fallen below the reorder point. As a result, there are two possible outcomes. If the condition ***"InventoryPosition_Retailer ≤ ReorderPoint_Retailer"*** holds true, the entity takes the True exit and subsequently enters the ***Assign*** module named ***"Order From Wholesaler And Update Retailer Inventory Position"***. Otherwise, the entity takes the False exit.

In the True exit path, the entity enters the "***Assign***" module called ***"Order From Distributor And Update Retailer Inventory Position"***. Within this module, three assignments are performed. The first assignment is to place an order with the Distributor by setting the variable ***"Order_Distributor"*** to 1. This action promptly releases a pending order entity that is currently detained in the "***Hold***" module named ***"Shall we release Retailer Order?"*** within the Distributor's inventory management segment. The second assignment sets the retailer's order quantity, calculated as *Q_R = TargetStock_Retailer - InventoryPosition_Retailer*. Finally, the last assignment updates the retailer's inventory position by setting the variable *InventoryPosition_Retailer = InventoryPosition_Retailer + Q_R*. This ensures an immediate update to the retailer's inventory position. The dialog box of the "***Assign***" module and its corresponding assignments are displayed in Figure 4-20.

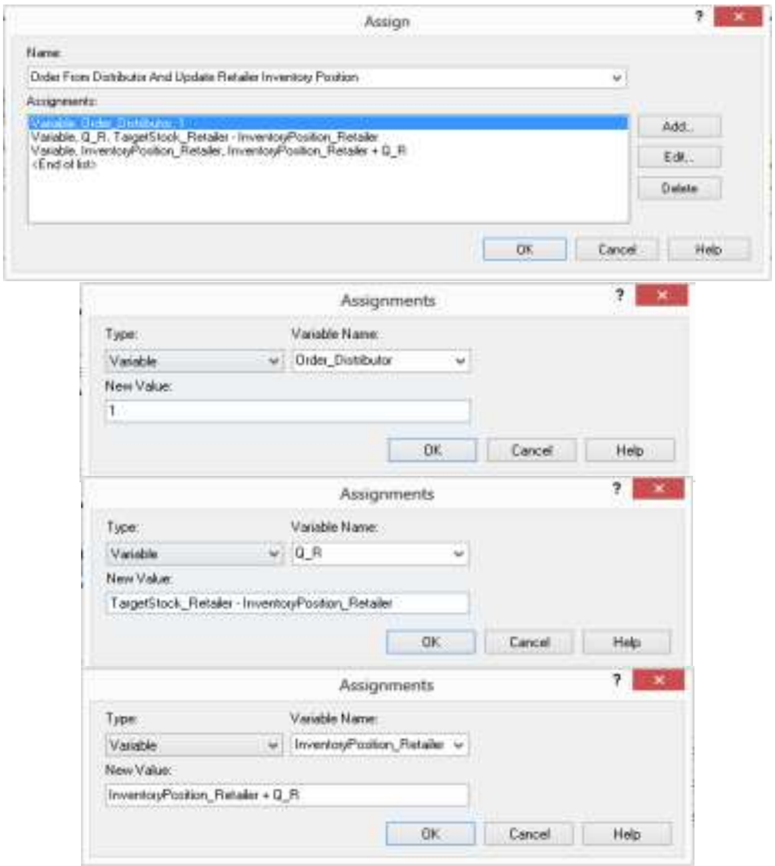

Figure 4-20: The dialog box of Assign module Order From Distributor And Update Retailer Inventory Position

On the True exit branch, the entity continues to enter the "***ReadWrite"*** module named ***"Write Retailer Order"***, which is responsible for writing the value of variable *Q_R* to a specific Excel spreadsheet file called "***Retailer Order***". The functionality of the "***ReadWrite"*** module is depicted in Figure 4-21. Regardless of the exit path taken, the entity proceeds to the Separate module named ***"Separate 1"***. This module serves the purpose of duplicating the entity. The original entity then exits the model through the "***Dispose"*** module, while the duplicated entity loops back to the "***Delay"*** module ***"Wait Till Review Interval At Retailer"***, where it awaits another 4-day period for the next inventory review.

Figure 4-21: The dialog box of ReadWrite module Write Retailer Order

The Retailer model segment has now been thoroughly explained. The next segment to be described is the Distributor model segment.

The Demand management and Inventory management segments of the Distributor are depicted in Figure 4-22.

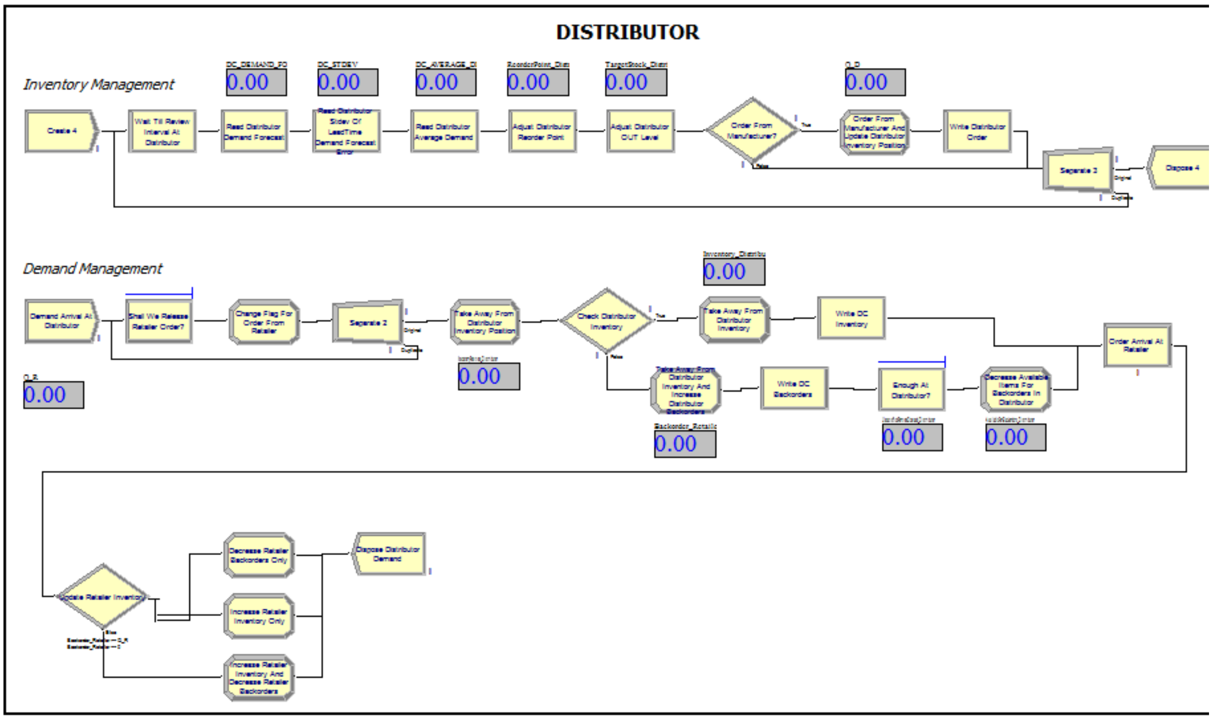

Figure 4-22: The simulation model of Inventory management and Demand management of the Distributor

Firstly, let's delve into the Demand management segment of the Distributor. A detailed depiction of the Distributor's Demand management can be found in Figure 4-23.

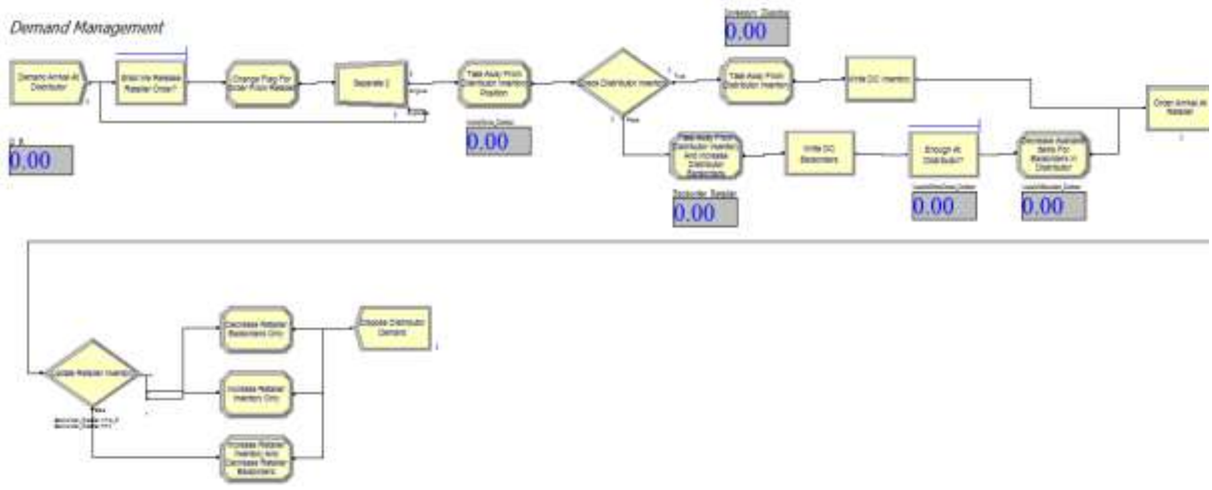

Figure 4-23: The simulation of Demand management segment of the Distributor

Demand arrives at the Distributor through the "***Create***" module named ***"Demand Arrival At Distributor"***. This module generates a single entity at time 0 and releases it into the model. The entity then enters the "***Hold***" module called ***"Shall We Release Retailer Order?"***. The "***Hold***" module is utilized to queue the entity until a specific condition becomes true. In the Distributor model, the ***Hold*** module holds the entity until the variable ***"Order_Distributor"*** equals 1. The dialog box for this "***Hold***" module is displayed in Figure 4-24

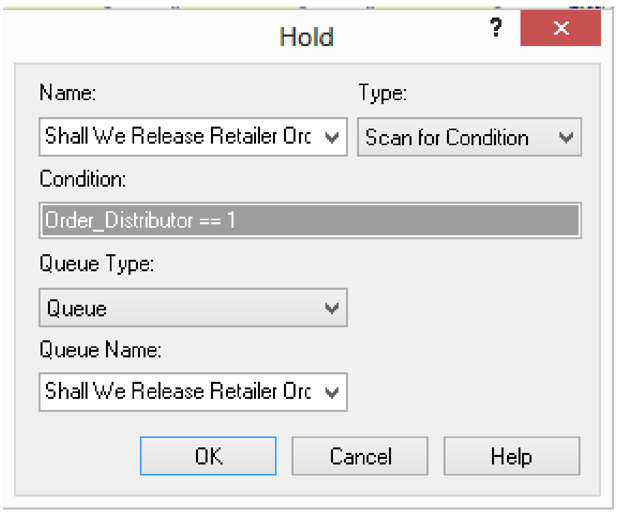

Figure 4-24: The dialog box of Hold module Shall We Release Retailer Order?

The entity proceeds to the "***Assign***" module named ***"Change Flag For Order From Retailer"*** and sets the variable ***"Order_Distributor"*** to a new value of *0*. This action signals back to the Retailer that the distributor has received the retailer's order, allowing for a new order to be placed. Next, the entity enters the "***Separate***" module called ***"Separate 2"***, which duplicates itself. The duplicated entity loops back to the "***Hold***" module to generate the next pending order from the retailer, while the original entity continues to the ***Assign*** module called ***"Take Away From Distributor Inventory Position"***. In this module, the variable ***"InventoryPosition_Wholesaler"*** is decremented by the value of variable *Q_R*, representing the retailer's order quantity. The entity then proceeds to the "***Decide***" module named ***"Check Distributor Inventory"*** to verify if the distributor has sufficient inventory to fulfill the retailer's order. This test results in two possible outcomes. If the condition *'Inventory_Distributor* $\geq$ *Q_R* ' holds true, the entity takes the True exit and proceeds to the "***Assign"*** module called "Take Away From Distributor Inventory", where the variable ***"Inventory_Distributor"*** is decremented by the value of *Q_R*. Additionally, the entity enters the "***ReadWrite"*** module named ***"Write Distributor Inventory"*** to assign the value of the variable "***Inventory_Distributor"*** to a specific Excel spreadsheet file named ***"DC Inventory"***. The functionality of the "***ReadWrite"*** module is shown in Figure 4-25.

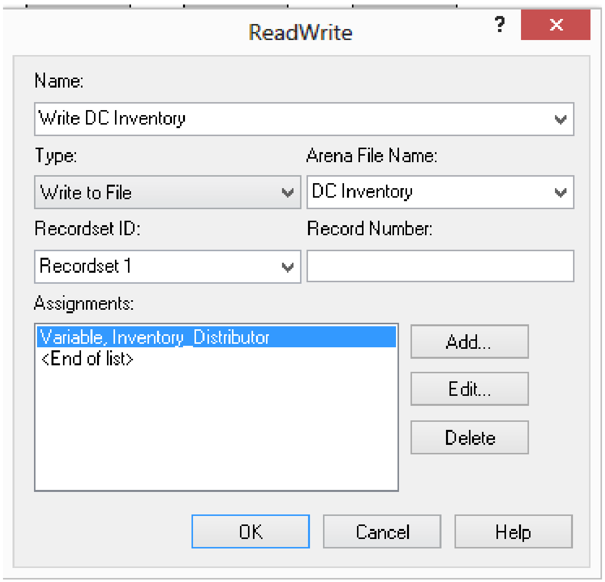

Figure 4-25: The dialog box of ReadWrite module Write DC Inventory

Figure 4-25 displays the dialog box of the "***ReadWrite"*** module, specifically the "***Write DC Inventory"*** module.

In the next step, if the condition *Inventory_Distributor* < *Q_R* is met, the entity takes the False exit to the "***Assign"*** module, which is called "***Take Away From Distributor Inventory And Increase Distributor Backorders"***. In this scenario, the same logic as in the retailer backorder setting is applied. When the demand cannot be fully satisfied, it is backordered from the Manufacturer, and the retailer's demand is only partially fulfilled. Consequently, three assignments are performed within the module, as depicted in Figure 4-26:

- The backorder level is increased by the shortage.
- The attribute "***UnsatisfiedPortionDemand_Distributor"*** is assigned the unsatisfied portion of the demand.
- The Distributor's inventory is set to a new value of zero.

Subsequently, the entity proceeds to the "***ReadWrite"*** module called ***"Write Distributor Backorders"***. Here, it writes the value of the variable "***Backorder_Distributor"*** to a specific Excel spreadsheet file named "***DC Inventory"***. The entity then moves on to the "***Hold"*** module, referred to as ***"Enough In DC?,"*** where it remains detained until sufficient inventory accumulates in the wholesaler to fulfill backorders during stock-out periods. In other words, the entity is held in this "***Hold***" module until enough inventory becomes available to satisfy its unsatisfied portion. A variable named "***AvailableForBackorders_Distributor***" is created to compare with the attribute "***UnsatisfiedPortionDemand_Distributor***". The module keeps the entity detained until the condition "**AvailableForBackorders_DC ≥ UnsatisfiedPortionDemand_DC**" is met. Once the condition is satisfied, the entity is released and proceeds to the "***Assign***" module called Decrease Available Items For Backorders In Distributor, where the variable "***AvailableForBackorders_Distributor***" is decremented by the value of the attribute "***UnsatisfiedPortionDemand_Distributor***". The dialog boxes illustrating the processing of backorders in the Distributor are shown in Figure 4-27.

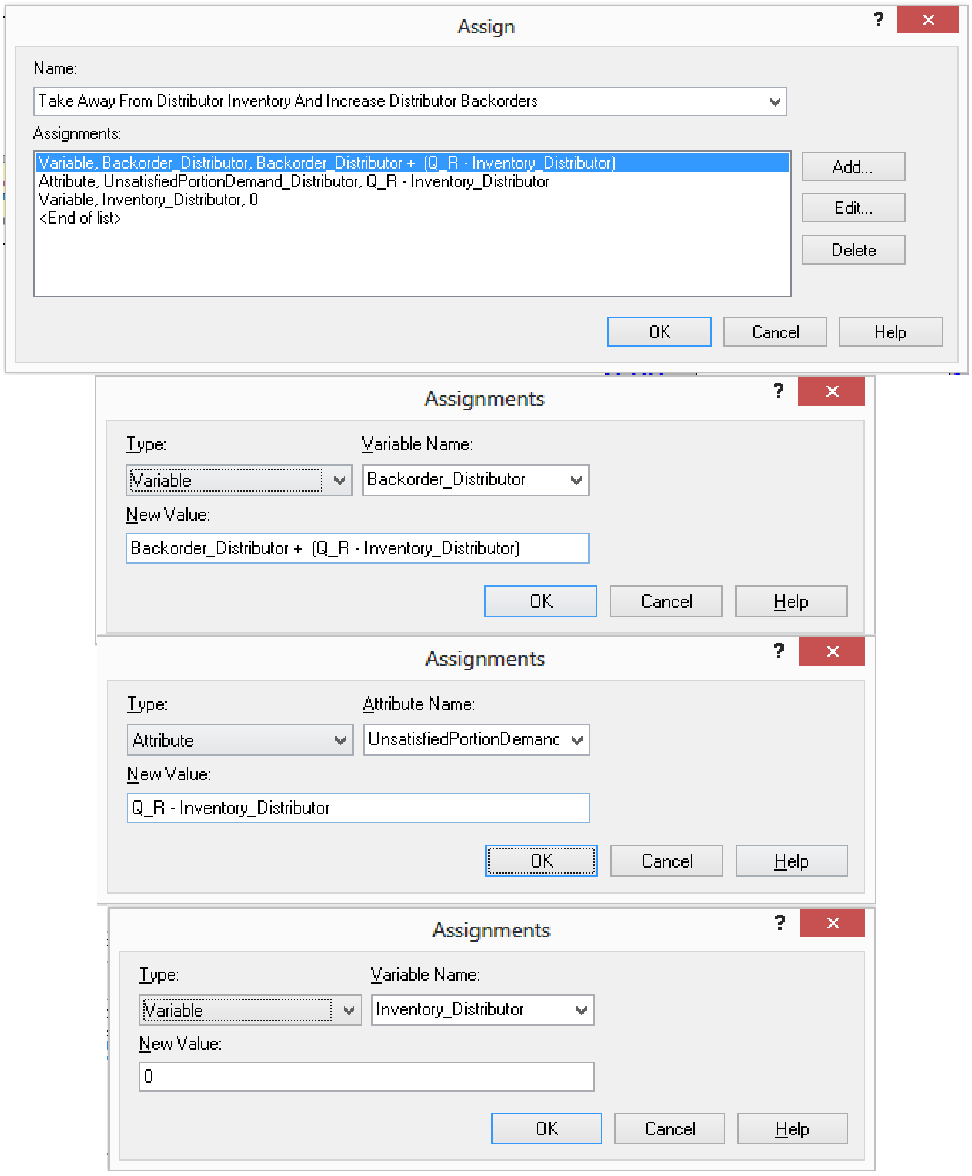

Figure 4-26: The dialog box of Assign module Take Away From Distributor Inventory And Increase Distributor Backorders

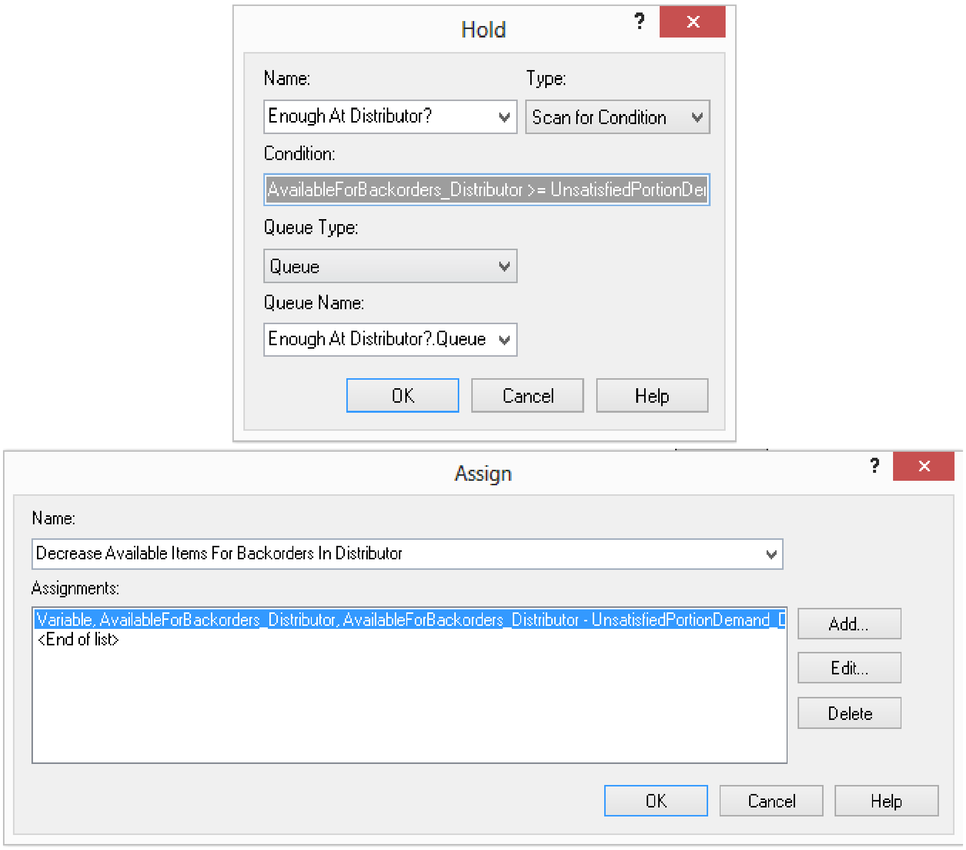

Figure 4-27: The dialog box processing backorders of Distributor

The retailer's order entity is now prepared for shipment to the retailer, whether it is fulfilled by on-hand inventory or through backorders. Assuming that orders are processed sequentially, the "***Process***" module called ***"Order Arrival At Retailer"*** is utilized. This module models the transportation delay from the distributor to the retailer, commonly known as lead time. The value of the variable *LeadTime* is set at 2 days and remains constant throughout the simulation. Figure 4-28 displays the dialog box associated with this module.

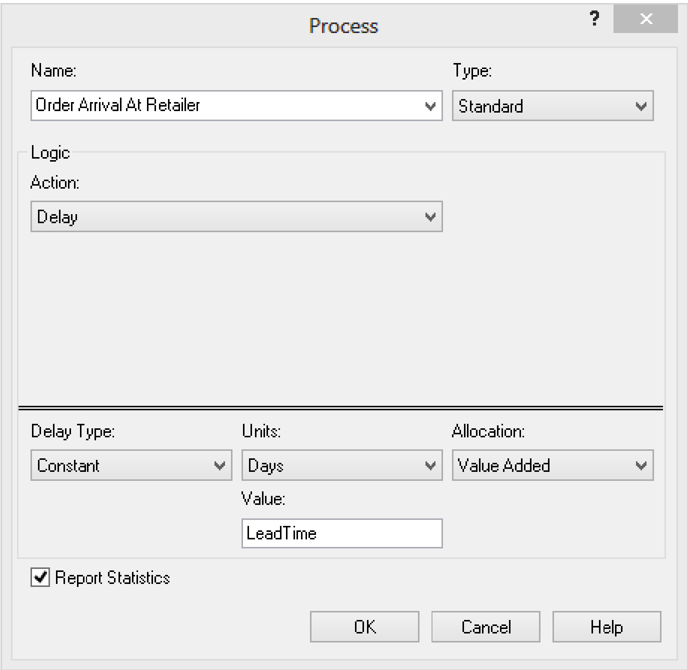

Figure 4-28: The dialog box of Process module Order Arrival At Retailer

The order entity then enters the "***Decide"*** module known as ***"Update Retailer Inventory",*** where three possible outcomes are considered:

- If the condition $Backorder\_Retailer \geq Q\_R$ is met, the entity proceeds to the "***Assign"*** module called ***"Decrease Retailer Backorders Only".*** Here, the variable "***Backorder_Retailer"*** is decremented by the value of Q_R, while the variable AvailableForBackorders_Retailer is incremented by Q_W.
- If the condition "**Backorder_Retailer"** = 0 holds, the entity takes the exit for the "***Assign"*** module called ***"Increase Retailer Inventory Only"***. In this case, "**Inventory_Retailer"** is incremented by the value of Q_R.
- If the condition $0 < Backorder\_Retailer < Q\_R$ *is* satisfied, the entity proceeds to the Assign module called "Increase Retailer Inventory And Decrease Retailer Backorders." Here, "**Inventory_Retailer"** is set to $Inventory\_Retailer + Q\_R - Backorder\_Retailer$, "**AvailableForBackorders_Retailer"** is incremented by "**Backorder_Retailer"**, and "**Backorder_Retailer"** is set to zero.

Finally, the order entity is disposed of in the Dispose module known as ***"Dispose Distributor Demand".*** The dialog box displaying the update of retailer inventory is shown in Figure 4-29.

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The Demand management segment of the Distributor has now been thoroughly explained. Next, we will discuss the Inventory management segment of the Distributor. The Inventory management segment of the Distributor is identical to the inventory management segment of the Retailer, with the only difference being how attributes such as distributor demand forecast, distributor standard deviation of lead-time forecast demand error, and distributor average demand are read from a specific Excel spreadsheet file. Therefore, there is no further explanation needed for the inventory management procedures, except for how the attribute values—namely, Distributor demand forecast **(DC_DEMAND_FORECAST)**, Distributor standard deviation of lead-time demand forecast error **(DC_STDEV)**, and Distributor average demand **(DC_AVERAGE_DEMAND)**—are introduced to the system. The dialog boxes demonstrating the reading of values for the distributor's attributes are shown in Figure 4-30.

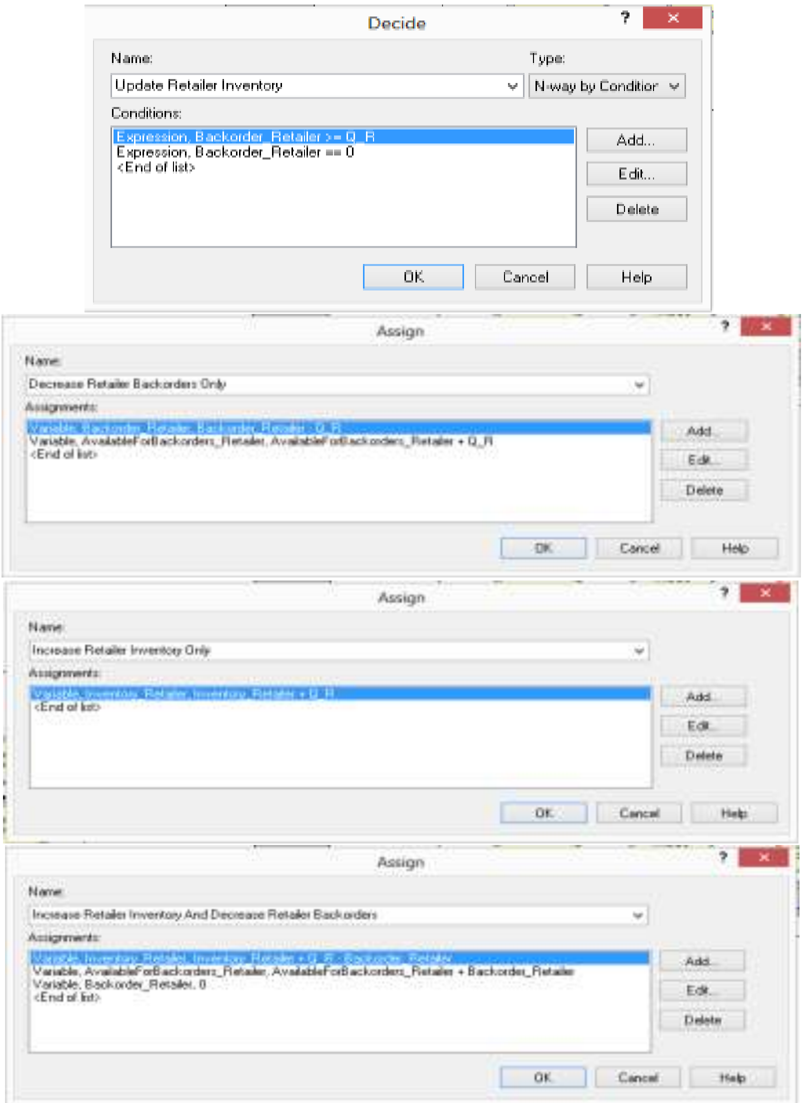

Figure 4-29: The dialog box of performing updating Retailer inventory

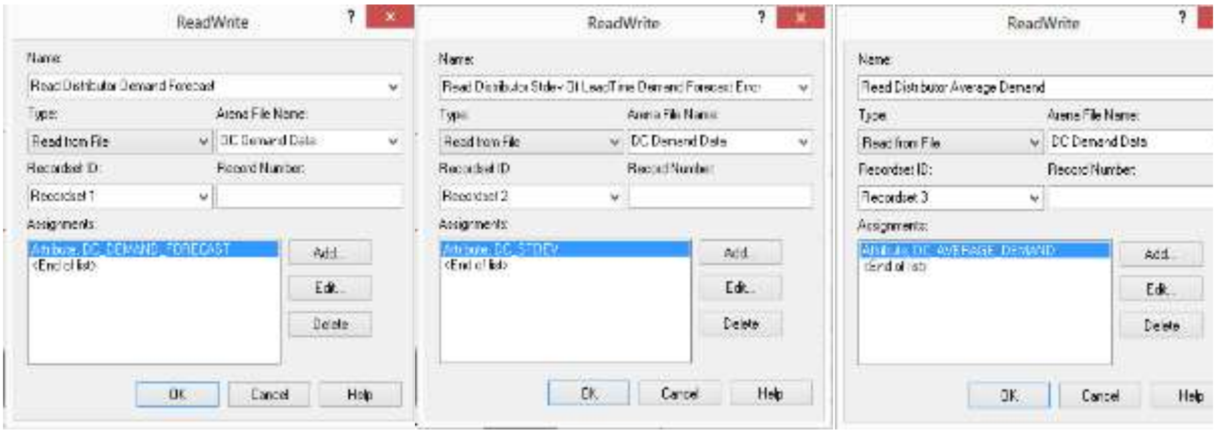

Figure 4-30: The dialog box of reading value for Distributor's attributes

The detailed explanation of the entire Distributor model has been provided. The Demand management segment and Inventory management segment of the Manufacturer are designed in a similar manner to the corresponding segments of the Distributor model. Therefore, there is no need for further explanation on how the Manufacturer segments are constructed. The key difference lies in how attribute values, namely Manufacturer demand forecast ***(MN_DEMAND_FORECAST)***, Manufacturer standard deviation of lead-time demand forecast error ***(MN_STDEV)***, and Manufacturer average demand ***(MN_AVERAGE_DEMAND)***, are assigned values from a specific Excel spreadsheet file named ***"MN Demand Data".*** The dialog boxes illustrating the reading of values for the manufacturer's attributes are shown in Figure 4-31.

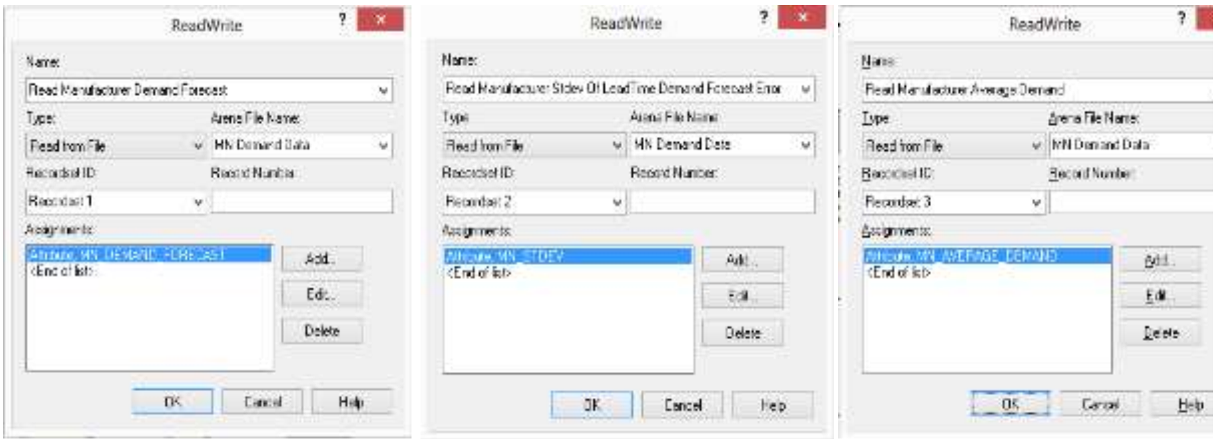

Figure 4-31: The dialog box of reading value for Manufacturer's attributes

The last model in this decentralized information simulation of the supply chain is the model of the External Supplier. This section will now continue to describe the activities of the external supplier. The external supplier is assumed to have an unlimited supply of products available for the manufacturer, and therefore, it does not engage in inventory management activities. The sole role of the external supplier is to fulfill the order demand from the manufacturer. The demand management segment of the external supplier is depicted in Figure 4-32.

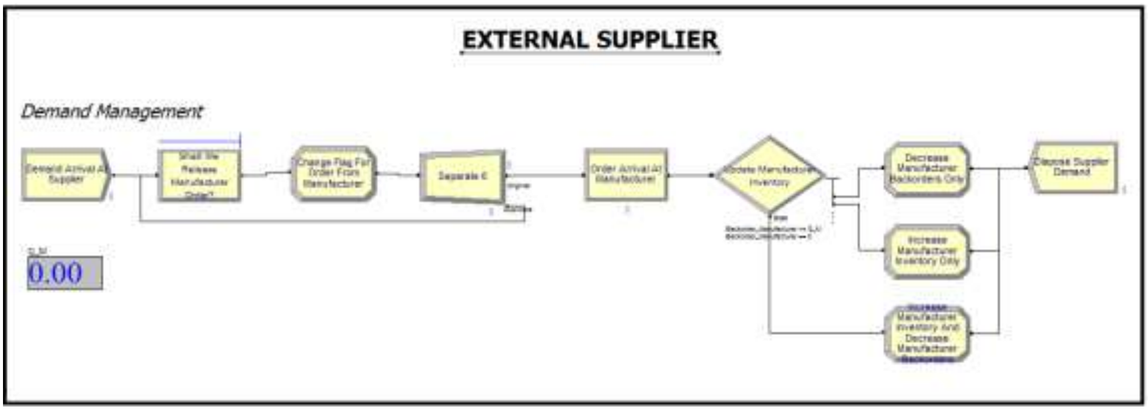

Figure 4-32: The simulation of Demand management segment of External Supplier

A single order entity is created and released into the "***Hold"*** module called ***"Shall We Release Manufacturer Order?"***. Here, it waits until the manufacturer places an order **(Order_Supplier = 1)**. Once the order is received, a signal is sent back to the manufacturer indicating that the supplier has received the order, and a new order can be placed. The Separate module is utilized to duplicate the entity and send it back to the "***Hold"*** module to wait for a new order, while the original order entity continues its progression through the system. The order entity then waits for 2 days in the "***Delay"*** module before proceeding to the "***Decide"*** module to send back the order quantity and update the manufacturer's inventory.

The simulation of the supply chain in decentralized information has now been fully explained. Each member of the supply chain echelon bases their demand forecast on the demand order received from their immediate downstream. The order quantity, backorder quantity, and inventory of each echelon member are written to specific Excel spreadsheet files to measure the bullwhip effect. The results will be presented in the upcoming section.

4.6.2 Supply chain simulation in Centralized information:

The simulation of the supply chain in centralized information is identical to the simulation of the supply chain in decentralized information, which has been described in detail in the previous sub-section. Assumptions such as forecasting technique, inventory policy, ordering policy, review interval, and lead time remain the same. The key difference is that in centralized information, all stages of the supply chain have access to end-customer demand information, allowing each member to base their forecasting on this data. In contrast, in the decentralized information model, only the retailer has access to end-customer demand data.

While it may seem confusing that all stages of the supply chain receive the same demand information and potentially order the same quantity from their upstream partner, it is important to note that the literature review highlights the distortion and amplification of demand signals as they propagate upstream in the supply chain, leading to increased variance (Dai et al., 2017). By using the same end-customer demand data for forecasting across all echelon members, the variance of demand and the standard deviation of the lead-time demand forecast error can be mitigated. Additionally, the order quantity is influenced by target stock and inventory position. Regardless of whether all stages forecast based on the same demand data, the inventory position is still reduced by the order quantity from the immediate downstream stage, irrespective of whether sufficient on-hand inventory exists. At the review interval, the inventory position is compared to the reorder point to determine if replenishment should be initiated.

Returning to the simulation, the demand management segment for all echelon members of the supply chain is designed in the same way as the simulation model in the decentralized information setting. The difference lies in the inventory management segment between the models. Therefore, this section will describe the inventory management segment of the retailer, distributor, and manufacturer in the centralized information simulation.

The inventory management segment of the retailer is executed exactly as in the retailer simulation using decentralized information (refer to figures 4-14), as the retailer has access to end-customer demand data, resulting in the same forecast. The attribute values "***RETAILER_DEMAND_FORECAST", "RETAILER_STDEV"***, and "***RETAILER_AVERAGE_DEMAND"*** is sourced from a specific Excel spreadsheet file named **"Customer Demand Data".** These attributes are used to estimate the retailer's reorder point and order-up-to level, enabling the retailer to determine whether to place a replenishment order with their upstream partner. If a replenishment order is placed, the order quantity is recorded in a dedicated Excel spreadsheet file called "Retailer Order."

Next, we will delve into the description of the inventory management segment of the distributor, which is depicted in Figure 4-33.

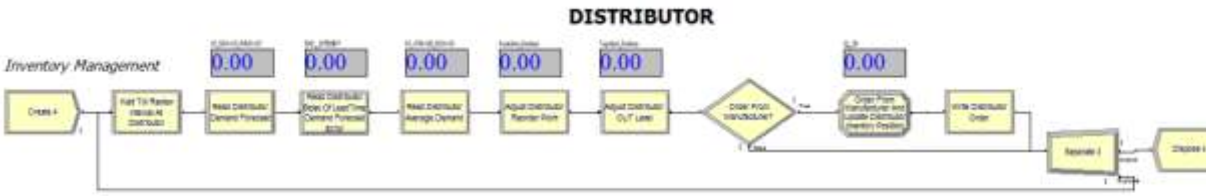

Figure 4-33: The simulation of inventory management segment of the Distributor

The inventory management procedure for the distributor is identical to that of the retailer. A single entity is created and released into the system, then delayed in the "***Hold"*** module called ***"Wait Till Review Interval At Distributor"*** for 4 days. The entity proceeds to the "***ReadWrite"*** modules to read and update the values of the attributes "**DISTRIBUTOR_DEMAND_FORECAST, DISTRIBUTOR_STDEV"**, and "**DISTRIBUTOR_AVERAGE_DEMAND"** from a specific Excel spreadsheet file named **"Customer Demand Data",** which is the same file used for demand forecasting at the retailer level. The entity continues through the system to the "***Adjust Variable"*** module, where the variables "**ReorderPoint_Distributor"** and "**TargetStock_Distributor"** are adjusted. Subsequently, the entity enters the "***Decide"*** module to determine whether a replenishment order quantity should be placed with the manufacturer. If an order is placed, the value of variable *Q_D* is written to a specific Excel spreadsheet file named **"DC Order".** If no replenishment is needed, the entity exits the "***Decide"*** module without placing an order. In both cases, the entity then enters the "***Separate"*** module, where the original entity is disposed of through the "***Dispose***" module, while the duplicated entity loops back to the "***Delay***" module to wait for the next review interval, which occurs every 4 days. The dialog boxes illustrating the processing of the distributor's attributes through the "***ReadWrite***" modules are displayed in Figure 4-34.

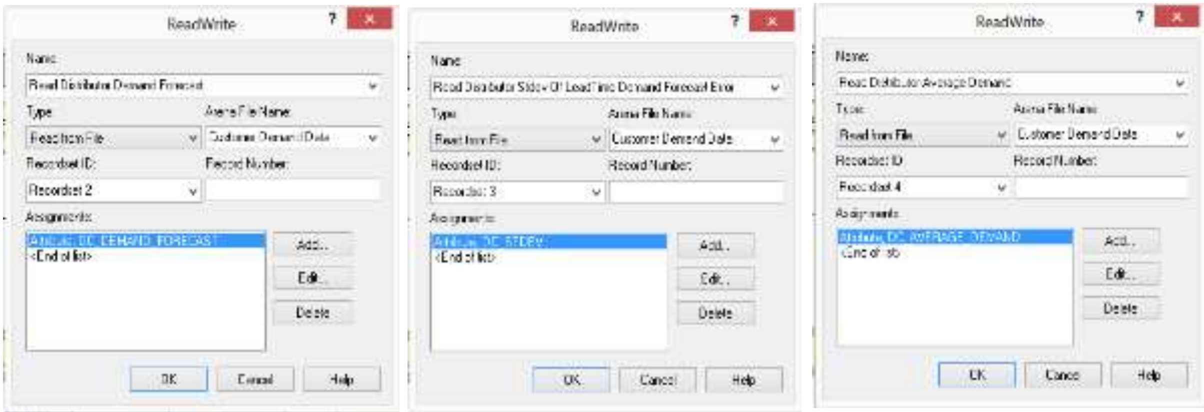

Figure 4-34: The dialog box of processing the Distributor's attributes in centralized information

The inventory management segment of the manufacturer follows the same procedure as the retailer and distributor. Specifically, the attributes **"MN_DEMAND_FORECAST"**, **"MN_STDEV"**, and **"MN_AVERAGE_DEMAND"** in the manufacturer's model are updated with values from a specific Excel spreadsheet file named **"Customer Demand Data".** The remaining steps in the system are identical to those of the retailer and distributor. Therefore, no further explanation of this segment is necessary. The dialog boxes illustrating the processing of the manufacturer's attributes through the "***ReadWrite***" modules are displayed in Figure 4-35.

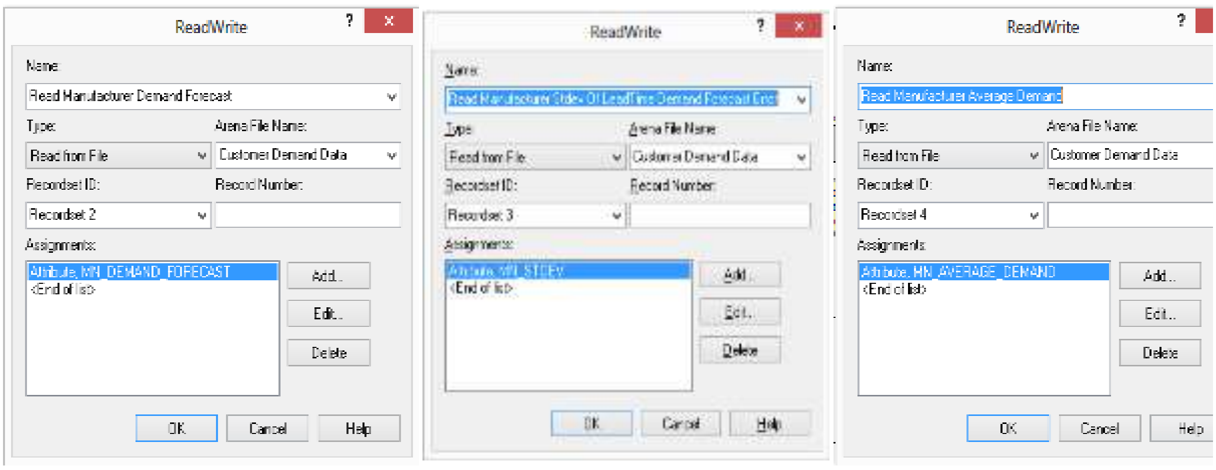

Figure 4-35: The dialog box of processing the Manufacturer's attributes in centralized information

The simulation model of the supply chain in centralized information has been thoroughly discussed. The results obtained from this simulation will be presented in the subsequent section.

The complete simulation models of the supply chain, both in decentralized information and centralized information, can be found in Appendix 2.

5 Simulation results analysis

Verification and Validation:

Verification is performed at the end of the model's operationality to ensure that programming errors within the model and its scope are not affected by any errors, oversights, or bugs (Sharma et al., 2019). Therefore, verification of the supply chain simulation model is a spontaneous process that considers the number of replications it undergoes. In this model, an acceptable level (α) of 5% is assumed. To ensure that the model functions well and enhances its relevance and confidence level, the necessary replications of the simulation model need to be calculated using the following formula (Kelton et al., 2003):

$$n = \frac{z_{\alpha/2}^2 \sigma^2}{d^2} \qquad (5.1)$$

Where n is the required replications, z refers to the critical value from the standard normal table at the assumed confidence level, σ refers to the standard deviation of the simulation, and d, where $d = 100(1 - a)\%$, is a confidence level closely related to the acceptable level α.

For a confidence level of 95% and a standard deviation of 3.75 for the simulation, the number of required replications is 60.

Simulation set-up:

The simulation is set up to run for 3000 days with 60 replications. Running multiple replications helps synchronize and reduce simulation variance. The simulation assumes a supply chain with a service level of 97%, meaning it should be able to deliver 97% of the orders on time. The end-customer demand arrival process is assumed to be similar in stock-out and non-stock-out situations. Additionally, all echelons of the supply chain start with no on-hand inventory, and the re-order point and target stock are set to zero. While this may not be an optimal state, it represents an equilibrium where each echelon member is in an equal condition.

Results and analysis:

The objective of the simulation model is to illustrate the bullwhip effect, specifically the variability of demand in the supply chain. The simulation model measures the impact of the bullwhip effect under different information sharing strategies: decentralized information sharing and centralized information sharing. To facilitate a better comparison between the two strategies, the assumptions made in both models are similar, with the only difference being how each echelon estimates forecasting based on the information sharing strategy.

The outcomes of the simulation are presented in Table 5-1 and Table 5-2 (refer to Appendix 3 and 4 for all 60 replications).

Standard deviation of demand under decentralized information				
Replication	End-customer	Retailer	Distributor	Manufacturer
10	16.92	68.38	498.90	5350.71
20	17.41	66.87	500.78	5135.95
30	17.28	69.04	516.81	5951.92
40	17.48	69.73	485.25	5487.82
50	17.33	69.17	482.85	5303.88
60	16.56	65.72	503.27	5628.04
Aggregation	17.12	67.54	485.34	5309.31

Table 5-1: Standard deviation of demand under decentralized information

Standard deviation of demand under centralized information				
Replication	End-customer	Retailer	Distributor	Manufacturer
10	16.92	89.20	169.14	228.69
20	17.14	85.84	152.15	183.93
30	17.28	91.18	149.15	211.01
40	17.48	90.69	168.40	214.97
50	17.33	91.63	154.28	206.73
60	16.56	88.28	162.38	212.07
Aggregation	17.12	89.13	156.37	212.14

Table 5-2: Standard deviation of demand under centralized information

For ease of analysis, the interpretation of the results will mainly focus on aggregated data rather than individual replication data.

The aggregated results of the overall replications show that the standard deviation of demand and order increases as we move further along the supply chain under both information sharing strategies. Specifically, in the case of decentralized information sharing, the variability of demand exhibits a significant increase, approximately 310 times larger between the manufacturer and end-customer. In contrast, under centralized information sharing, the variance of order slightly increases as we move forward in the supply chain, with the variability of demand in the manufacturer being around 12 times larger than that of the end-customer. Therefore, the results indicate that the variability of demand and order is significantly reduced in centralized information sharing compared to decentralized information sharing.

To further analyze the presence of the bullwhip effect in the supply chain under the two strategies, the bullwhip effect ratio is introduced. The results are presented in Table 5-3 and Table 5-4 (refer to Appendix 3 and 4 for all 60 replications).

Bullwhip effect under decentralized information			
Replication	Retailer	Distributor	Manufacturer
10	4.04	7.30	10.73
20	3.84	7.49	10.26
30	4.00	7.49	11.52
40	3.99	6.96	11.31
50	3.99	6.98	10.98
60	3.97	7.66	11.18
Aggregation	3.95	7.19	10.96

Table 5-3: Bullwhip effect under decentralized information

Bullwhip effect under decentralized information			
Replication	Retailer	Distributor	Manufacturer
10	5.27	1.90	1.35
20	4.93	1.77	1.21
30	5.28	1.64	1.41
40	5.19	1.86	1.28
50	5.29	1.68	1.34
60	5.33	1.84	1.31
Aggregation	5.21	1.76	1.36

Table 5-4: Bullwhip effect under centralized information

The aggregated results of the bullwhip effect ratio in the two information sharing strategies reveal interesting insights. In the case of decentralized information sharing, the bullwhip effect ratios show a significant increase from the retailer stage to the manufacturer stage, with a ratio of 5.21 at the retailer stage and 1.36 at the manufacturer stage. This demonstrates that the bullwhip effect has a substantial impact on the supply chain under decentralized information. On the other hand, in the case of centralized information sharing, the bullwhip effect still exists, despite sharing end-customer demand data across all stages of the supply chain. However, the ratios are not considerably high and decrease from 5.21 to 1.36 as we move towards the end-echelon of the supply chain.

Interestingly, the bullwhip effect ratios are significantly reduced at the distributor and manufacturer stages, with the ratios fluctuating around 1. Moreover, the manufacturer's bullwhip effect ratio is lower than that of the distributor, indicating that the manufacturer experiences the least distortion compared to the distributor and retailer. These findings align with the research conducted by Lee et al. (2000), which suggests that the effective use of information sharing improves the performance of upstream sites, with the upstream echelons benefiting the most.

To facilitate a better comparison between the bullwhip effect ratios of the two strategies, an overall bullwhip effect ratio is introduced. According to Merkuryev et al. (2002), measuring the bullwhip effect ratio of the entire supply chain involves calculating the average value using the following equation:

$$Average\ supply\ chain\ bullwhip\ effect\ ratio = \frac{\sum_{i=1}^{n} BE_i}{n} \qquad (5.2)$$

BE_i is the bullwhip effect ratio in stage i

n is the number of stages in the supply chain

Therefore,

$$Average\ supply\ chain\ bullwhip\ effect\ ratio = \frac{BE\ ratio\ at\ Retailer + BE\ ratio\ at\ Distrributor + BE\ ratio\ at\ Manufacturer}{3} \qquad (5.3)$$

For a visual representation of the standard deviation of demand and order, as well as the bullwhip effect ratio in both information sharing strategies, please refer to Figure 5-1 and Figure 5-2.

The overall bullwhip effect ratios are shown in table 5-5:

Overall bullwhip effect ratio	
Decentralized information	Centralized information
7.37	2.78

Table 5-5: Overall bullwhip effect ratio

From the aggregated results, it is evident that implementing demand information sharing significantly reduces the bullwhip effect in the supply chain. In particular, the bullwhip effect is reduced by approximately 2.5 times in

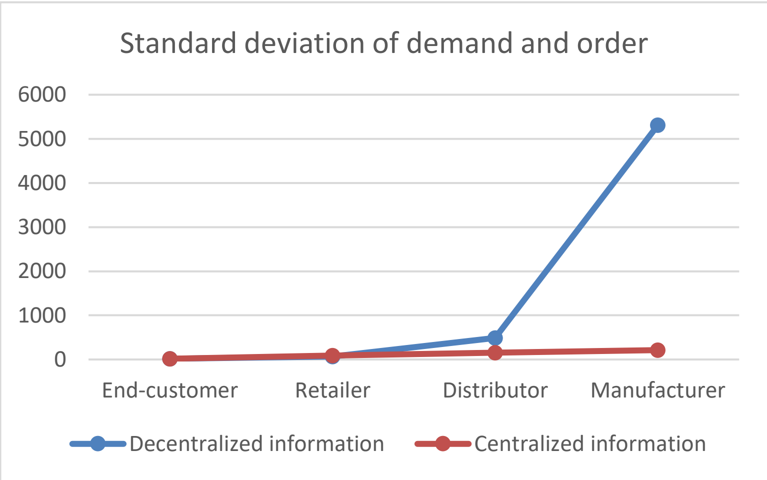

Figure 5-1: Standard deviation of demand and order

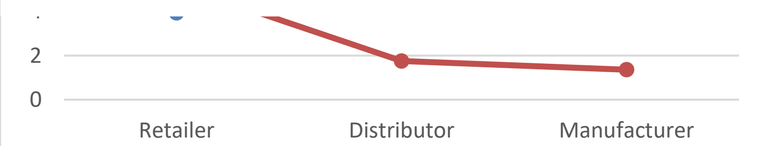

Figure 5-2: Bullwhip effect ratios of supply chain members

centralized information sharing compared to decentralized information. This reduction highlights the effectiveness of sharing demand information in mitigating the bullwhip effect.
This reduction in the bullwhip effect within the supply chain can be attributed to the value of information sharing. In the absence of sharing end-customer demand, each stage in the supply chain forecasts expected demand based on the replenishment orders received from downstream. This forecasting activity occurs at every echelon, exacerbating the demand variability as it propagates upstream. With each stage making replenishment forecasts based on the previous stage's orders, the demand variability increases as it moves further along the supply chain.

In contrast, when the end-customer demand is shared among all members of the supply chain, the variance of orders is reduced. Each member has access to the same end-customer demand data, and although they still forecast expected future demand, they do so use the shared information. Therefore, the standard deviation of demand, lead-time forecast, reorder point, and target stock are the same for each member at every period. The timing of replenishment orders, however, varies among the echelons due to their respective review intervals. Each echelon waits for its review interval and then places its replenishment order accordingly. This leads to different reorder points and target stocks for each echelon. The order quantity is influenced by the target stock and inventory position, which is affected by backorders. When making replenishment orders, backorders from previous periods are included in the order quantity by subtracting the target stock from the inventory position.

Under centralized information sharing, the original demand information is not exacerbated multiple times as each echelon forecasts based on the original order waveform. As a result, the variance of orders does not fluctuate significantly as it moves up the supply chain, leading to a reduction in the bullwhip effect.

However, evaluating the performance of the supply chain solely based on the bullwhip effect is not sufficient. The variance of net stock also provides valuable insights from a different perspective. Higher net stock variance requires more safety stock, leading to increased holding and shortage costs, lower service levels, and higher average inventory costs per period. The net stock amplification ratio, proposed by Disney and Lambrecht (2008), is used to measure the bullwhip effect in the supply chain and is expressed as the ratio of the variance of net stock to the variance of demand.

$$Net\ stock\ amplification\ ratio = \frac{Variance\ of\ Net\ stock}{Variance\ of\ Demand} \qquad (5.4)$$

The variance of net stock is closely related to inventory and order costs. A higher net stock variance indicates more frequent changes in ordering patterns, resulting in increased ordering and holding inventory costs. Additionally, increased inventory variance leads to higher holding inventory and backorder costs (Disney & Lambrecht, 2008).

Figure 5-3 illustrates how the variance of inventory generates tholding and shortage costs.

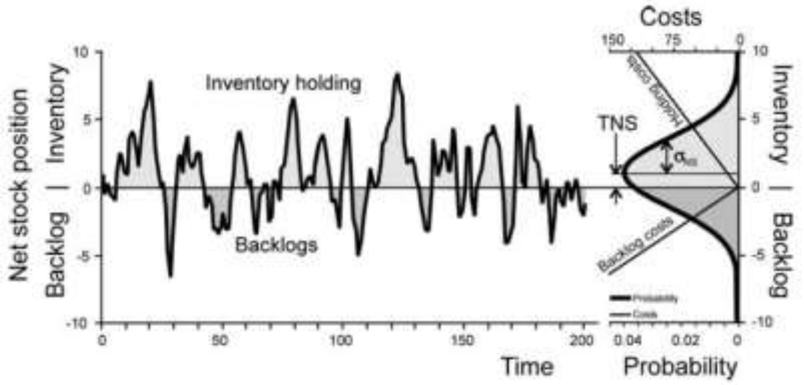

Figure 5-3: The generation of holding and shortage costs related to net stock variance

From Table 5-6 and Table 5-7, it is evident that the standard deviations of net stock are significantly higher under decentralized information sharing compared to centralized information sharing. Specifically, the standard deviation of net stock increases drastically from the retailer stage to the manufacturer stage in decentralized information sharing, reaching values as high as 25,491.16 (approximately 44 times larger) compared to 584.14 at the retailer stage. On the other hand, under centralized information sharing, the standard deviation of net stock fluctuates only slightly and remains relatively consistent from the retailer stage to the manufacturer stage, ranging from 241.47 to 283.17.

The results of the net stock amplification for the two information sharing strategies are presented in Table 5-8 and Table 5-9. Additionally, the figures illustrating net stock variance and net stock amplification ratios can be found in Figure 5-4 and Figure 5-5, respectively.

Standard deviation of net stock under decentralized information			
Replication	Retailer	Distributor	Manufacturer
10	793.93	1699.74	26,078.54
20	618.72	1067.06	23,167.45
30	230.75	493.92	29,913.74
40	622.24	1089.48	26,056.34
50	623.74	839.29	25,084.99
60	745.58	1390.19	27,602.02
Aggregation	584.14	1447.22	25,491.16

Table 5-6: Standard deviation of net stock under decentralized information

Standard deviation of net stock under centralized information			
Replication	Retailer	Distributor	Manufacturer
10	246.36	310.52	363.40
20	303.47	0.00	253.24
30	235.19	130.72	171.42
40	203.30	395.29	196.85
50	301.91	318.27	176.84
60	243.00	320.79	165.74
Aggregation	241.47	281.23	283.17

Table 5-7: Standard deviation of net stock under centralized information

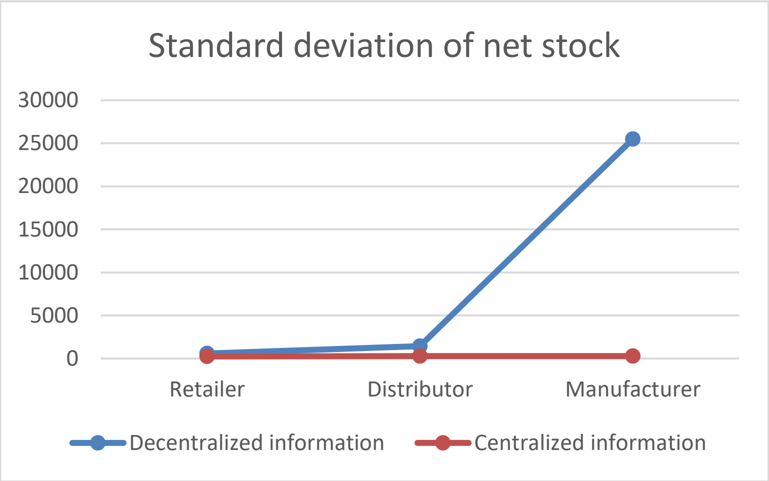

Figure 5-5: Standard deviation of net stock

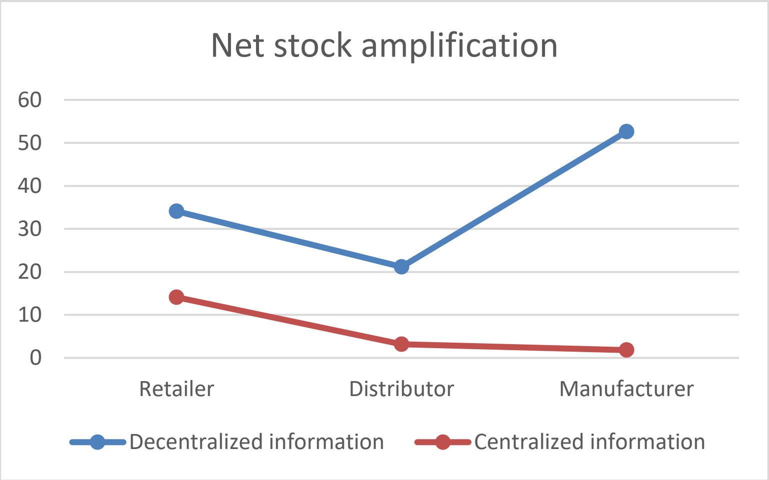

Figure 5-4: Net stock amplification ratio

Inventory amplification ratio under decentralized information			
Replication	Retailer	Distributor	Manufacturer
10	46.93	24.86	52.27
20	35.55	15.96	46.26
30	13.36	7.15	57.88
40	35.59	15.62	53.70
50	35.99	12.13	51.95
60	45.03	21.15	54.85
Aggregation	34.08	21.17	52.60

Table 5-8: Inventory amplification ratio under decentralized information

Inventory amplification ratio under centralized information			
Replication	Retailer	Distributor	Manufacturer
10	14.56	3.48	2.15
20	17.44	0.00	1.66
30	13.61	1.43	1.15
40	11.63	4.36	1.17
50	17.42	3.47	1.15
60	14.67	3.63	1.02
Aggregation	14.10	3.15	1.81

Table 5-9: Inventory amplification ratio under centralized information

Inventory cost, which includes inventory holding cost and backorder cost, as well as ordering cost, contribute to the total cost of each individual operating in the supply chain (Silver et al., 2017). The total cost can be calculated as the sum of ordering cost, holding cost, and backorder cost:

$$Total\ cost = Ordering\ cost + Holding\ cost + backorder\ cost \quad (5.5)$$

The ordering cost is determined by multiplying the number of orders during the time horizon by the fixed ordering cost. Holding cost is calculated by multiplying the value of inventory at the end of each period by the per-unit holding cost. Backorder cost is calculated by multiplying the shortage amount by the per-unit backorder cost.

Additionally, it is important to consider the overall supply chain cost to evaluate the performance of the supply chain from a cost perspective. The supply chain total cost is the sum of the total costs of each individual member:

$$Supply\ chain\ total\ cost = Retailer\ total\ cost + Distributor\ total\ cost + Manufacturer\ total\ cost \quad (5.6)$$

Based on the assumptions made earlier, with an ordering cost of 70 per order, holding cost of 20 per unit, and a backorder cost of 140 per unit shortage, the total cost of each echelon, as well as the supply chain total cost, can be calculated. The values obtained from the excel spreadsheets are presented in table 5-10 and table 5-11 (refer to appendix 5 for all 60 replications).

Analyzing the aggregated data of total cost, it can be observed that under the decentralized information sharing strategy, the total cost increases from retailer to distributor and then decreases at the manufacturer stage. On the other hand, under the centralized information sharing strategy, the total cost decreases from retailer to manufacturer. The behavior of total cost for each member of the supply chain under the two information sharing strategies is illustrated in Figure 5-6.

Implementing information sharing has resulted in lower total costs for each echelon in the supply chain compared to the costs incurred in the absence of information sharing. As a result, the supply chain total cost in the centralized information sharing strategy (approximately 71.3 million) is lower than that in the decentralized information sharing strategy (approximately 141.1 million). Furthermore, in the centralized information sharing strategy, the distributor and the manufacturer have lower total costs compared to the retailer. This further supports the findings of Lee et al. (2000) that upstream sites benefit the most from sharing end-customer demand data.

Total cost under decentralized information				
Replication	Retailer	Distributor	Manufacturer	Supply chain
10	72,242,790.74	83,343,724.02	3,718,683.67	159,305,198.43
20	80,311,862.78	52,576,917.13	3,840,469.87	136,729,49.79
30	69,046,857.59	83,293,901.14	4,401,706.23	156,742,464.96
40	34,469,460.92	82,617,251.25	3,908,373.47	120,995,085.63
50	22,120,277.82	82,483,830.24	3,887,870.03	108,491,978.09
60	81,010,479.74	83,534,554.47	4,179,375.31	168,724,409.53
Aggregation	59,584,441.81	77,215,012.25	4,333,973.73	141,133,427.79

Table 5-10: Total cost under decentralized information

Total cost under centralized information				
Replication	Retailer	Distributor	Manufacturer	Supply chain
10	37,536,586.05	34,666,684.98	3,956,689.11	76,159,960.14
20	63,098,235.55	79,138,642.13	1,897,097.47	144,133,975.15
30	9,414,452.47	2,595,200.71	636,162.95	12,645,816.13
40	13,209,948.97	1,420,333.70	663,794.11	15,294,076.78
50	83,406,859.59	83,002,542.23	725,810.25	167,135,212.07
60	1,819,645.71	617,074.62	600,440.90	3,037,161.24
Aggregation	42,881,937.39	26,039,183.78	2,371,589.34	71,292,710.52

Table 5-11: Total cost under centralized information

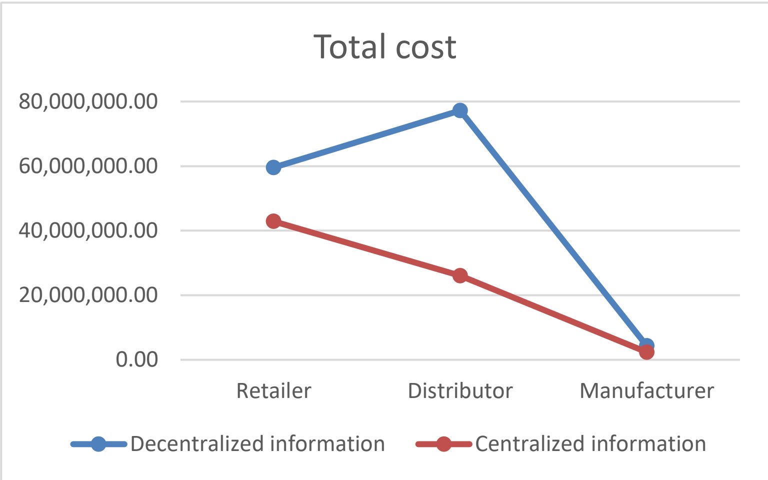

Figure 5-6: Total cost of each echelon in supply chain

In conclusion, the findings of this section demonstrate the significant value of information sharing in multi-echelon supply chains. By sharing demand information, both the bullwhip effect and inventory variance are reduced among the members of the supply chain. This reduction in variance leads to lower inventory management costs, as the on-hand inventory becomes more stable and predictable. Consequently, the ordering pattern becomes more streamlined, allowing for optimal inventory levels to be maintained. The result is a smoother supply flow throughout the chain, which contributes to lower total costs for each member.

Furthermore, the implementation of information sharing brings substantial benefits to the upstream sites in the supply chain. As the demand information is shared, the upstream sites can better align their operations with the actual customer demand. This alignment improves the overall performance of the supply chain, as the smooth supply from upstream to downstream minimizes disruptions and inefficiencies.

In summary, the value of information sharing in a multi-echelon supply chain is evident in the reduction of the bullwhip effect, inventory variance, and overall costs. The benefits are particularly pronounced for the upstream sites, highlighting the importance of effective information sharing practices in achieving a high-performing supply chain.

6 Discussion of simulation assumptions

The simulation results presented in the previous section demonstrate a notable decrease in the bullwhip effect through the implementation of information sharing in the supply chain. However, it is important to discuss the assumptions that were made in the simulation model, as these assumptions have an impact on the outcomes of the results. Considering these assumptions is crucial for a comprehensive understanding of the simulation findings. The key assumptions that were considered include the demand processing model, replenishment lead-time, forecasting technique, inventory policy, ordering policy, and information sharing. Each of these assumptions plays a role in shaping the simulation results. Additionally, it is essential to explore the managerial implications that are relevant to these assumptions, as they provide insights into the practical implications of the simulation findings. By examining these assumptions and their managerial implications, we can gain a deeper understanding of the dynamics and effectiveness of information sharing in the supply chain.

Discussion of demand processing model:
Since the emergence of the bullwhip effect topic, several authors have investigated it to provide insights into optimal operational practices under various settings and assumptions. Most authors assume a non-seasonal and stationary demand processing model, often using an autoregressive moving average (ARMA) process of the first order. Lee et al. (1997) adopted Kahn's (1987) demand model, an auto-regressive process of the first order with a non-negative autocorrelation parameter (AR(1)). Many subsequent studies followed this approach, using periodic review order-up-to level policies. However, this simple auto-regressive model does not capture the complexities of real-world supply chains (Gaur et al., 2005). Real-life demand patterns often exhibit higher-order autoregressive processes (ARMA) due to seasonality and business cycles, which naturally occur in multi-echelon supply chains.

When measuring the impact of the bullwhip effect under information sharing, Gaur et al. (2005) used higher-order autoregressive processes (AR(p), $p \geq 1$) or autoregressive moving-average processes (ARMA(p,q), $p \geq 1$, $q \geq 1$). Costantino et al. (2013) investigated the impact of demand seasonality on the bullwhip effect. This raises the question of whether the impact of the bullwhip effect remains the same under different demand processing models, such as higher-order autoregressive and seasonal models, compared to the AR(1) model used in this research.

Gaur et al. (2005) studied the time-series structure of the demand processing model in a two-echelon supply chain and found that the benefits of demand information are greater under ARMA(1,1) models compared to AR(1) models. Information sharing is especially valuable when the magnitude of autoregressive and moving average coefficients is high. The study also highlighted that sharing end-customer demand information facilitates better order and allocation decisions using downstream information, enabling manufacturers to reduce safety stock in production. Gaur et al. (2005) suggested that their findings on ARMA(1,1) models and information sharing can be applied to multi-echelon supply chains to examine the relationship between demand time-series structure, demand propagation, and the value of information sharing.

Costantino et al. (2013) investigated the impact of seasonal demand models on inventory variance and demand fill rate in a four-echelon supply chain using a base stock ordering policy with a moving average forecast. The results showed that information sharing significantly reduced the bullwhip effect, inventory variance, and increased the average demand fill rate in each supply chain member when facing high seasonal demand. The study concluded that for supply chains with external seasonal demand, order variance and inventory variance provide better estimates of the bullwhip effect in dynamic supply chains.

The bullwhip effect in the supply chain is attributed to demand uncertainty, as uncertainty leads to distorted perceptions of true demand. To mitigate demand uncertainty, companies rely on forecasts, which amplify the demand as it moves upstream. The larger the supply chain, the greater the amplification. Reducing demand uncertainty in processing customer demand can help mitigate the bullwhip effect in the supply chain.

Discussion of replenishment lead-time:

Both Lee et al. (1997, 2000) and Chen et al. (2000) agree that replenishment lead-time has a significant impact on the magnitude of the bullwhip effect in the supply chain. Lead-time is closely related to forecasting activity, as it is used to estimate safety stock and the order-up-to level. A longer lead-time requires higher safety stock and target inventory levels. Additionally, in periodic review systems like the simulation models used in this research, the review interval also influences safety stock requirements. Longer lead-times and review intervals contribute to higher safety stock levels and, consequently, higher target inventory.

The simulation model in this research assumes a fixed lead-time of two days for both the decentralized and centralized information sharing models. However, this fixed lead-time assumption does not accurately replicate real-world supply chains. In reality, replenishment lead-times are often stochastic. Lee et al. (1997), Chen et al. (2000), and Wang et al. (2008) mention that longer lead-times lead to increased order variability, and together with the review interval, they have a multiplicative impact on the bullwhip effect. Kim et al. (2006) highlight that whether lead-time is deterministic or stochastic, it significantly contributes to increasing the bullwhip effect in the supply chain.

Countermeasures for long replenishment lead-times are suggested, such as implementing the Quick Response manufacturer strategy (Lee et al., 1997) and using fixed lead-time contracts with suppliers (Chen et al., 2000). However, the simulation model in this research only uses a small fixed lead-time to minimize the presence of the bullwhip effect and compare it between decentralized and centralized information sharing. This choice of fixed lead-time aligns with the discrete-event simulation method used in this research. It would be beneficial to investigate the impact of the bullwhip effect under the Quick Response strategy and fixed lead-time contracts to explore their effectiveness in the simulation model.

Discussion of forecasting techniques:

Forecasting plays a crucial role in production planning across all echelons of the supply chain, as highlighted by Lee et al. (1997). The bullwhip effect occurs when the demand signal is transmitted along the chain. Chen et al. (1999) also supports the notion that forecasting the mean and standard deviation of demand contributes to the bullwhip effect. When an echelon follows an order-up-to level policy without updating the forecasted mean and standard deviation of demand, the target inventory level remains unchanged, resulting in no order variability and consequently, no bullwhip effect. However, this scenario applies only to deterministic demand, where the retailer has complete knowledge of end-customer demand and the associated mean and standard deviation. In most real-world supply chains, end-customer demand is probabilistic, necessitating the use of forecasting to estimate expected future demand and update the mean and standard deviation, as well as the order-up-to level.

Researchers such as Lee et al. (1997), Chen et al. (2000), and Hosoda & Disney (2006) have explored various forecasting methods, such as moving average, exponential smoothing, and minimum mean squared error, to quantify the bullwhip effect under the *AR(1)* demand processing model. It is important to note that these methods do not guarantee the lowest bullwhip effect, as they are based on different assumptions. However, they are commonly employed techniques to quantify the bullwhip effect in supply chains.

In this research, exponential smoothing forecasting is introduced in the simulation models to illustrate the bullwhip effect in a multi-echelon supply chain. The choice of using exponential smoothing with a low smoothing parameter aims to minimize order variation. Additionally, this forecasting technique offers advantages over moving average forecasting. Moving average forecasts, with a larger number of historical data, may reduce demand variability but cannot provide an expected demand forecast for the initial periods. In contrast, exponential smoothing can predict the expected demand in the first period. Considering that the simulation model in this research has a short lead-time of 2 days, the use of exponential smoothing aligns with Chen et al.'s (2000) recommendation that longer lead-times require more demand data to mitigate the bullwhip effect. Hence, there is no need to employ moving average forecasting in this research.

Overall, forecasting techniques play a significant role in understanding and managing the bullwhip effect, and the choice of a suitable method depends on the specific characteristics and requirements of the supply chain being studied. Discussion of inventory and ordering policy:

Most of the researches of the bullwhip effect implements the order-up-to level inventory policy, typically, Lee et al., 1997, Chen et al., 2000, Duc et al., 2008 and so on implement the order-up-to inventory policy (R, S) with the order-up-to level which is determined as $S_t = \widehat{D}_t^{L+R} + z\,\hat{\sigma}_t^{L+R}$ and therefore, the ordering policy associated with that order-up-to level S is estimated as $q_t = S_t - S_{t-1} + D_{t-1}$. This research studies the bullwhip effect in different way that the other previous may not study before. This research adopts (R, s, S) periodic review inventory system in which the order-up-to level is determined from re-order point and economic order quantity. At the review interval, a replenishment order is placed whether if the inventory position is lower than the re-order point. The order quantity is the gap between order-up-to level and the inventory position. Since the order-up-to level contributes to the increasing of the bullwhip effect, the choice of order-up-to (R, s, S) policy and the ordering policy in this research still reflects the increasing of the bullwhip effect in the supply chain, these choices are made to make a difference from previous research of bullwhip effect.

Discussion of information sharing:
The simulation model introduced earlier clearly demonstrates the value of sharing end-customer demand in a multi-echelon supply chain. The results confirm the findings of Lee et al. (1997) and Chen et al. (1999) that to significantly reduce the bullwhip effect, demand information from downstream sites should be made available to upstream sites. In addition to sharing demand information, Lee et al. (1997) and Croson et al. (2005) suggest that sharing inventory information is even more effective in reducing the bullwhip effect.

Lee et al. (2000) states that sharing information across the supply chain brings significant benefits to manufacturers, especially in highly correlated, highly variable demand situations with long lead times. Shared information allows all echelons of the supply chain to make accurate predictions based on real demand, enabling clear visibility for production planning. As bullwhip effect typically occurs in uncertain environments, information sharing among supply chain members reduces uncertainties and eliminates the negative impact on the bullwhip effect (Lofti et al., 2013). However, the incentive issue, lack of trust, and concerns about confidentiality pose obstacles to information sharing. Implementing technology for sharing information incurs costs and requires skilled personnel, making it a time-consuming and expensive investment. Moreover, inefficient system and unskilled personnel can hinder information sharing, resulting in less information and knowledge being shared among members.

To counteract the bullwhip effect in information sharing, Lee et al. (1997) and Chen et al. (1999) propose establishing strategic partnerships such as Vendor Managed Inventory (VMI). VMI changes the way information is shared and inventory is managed, reducing the bullwhip effect. In VMI, the manufacturer manages the retailer's inventory, eliminating the need to rely on the retailer's demand orders.

Disney & Towill (2003) suggest that implementing VMI in the supply chain can greatly improve its dynamic performance. By eliminating delays in information and material flows and reducing distorted information in the order waveform, VMI offers potential two-fold improvements. VMI serves as a practical way to establish strategic partnerships and achieve the benefits of echelon elimination without creating conflicts in the existing supply chain. Various terms have been coined for VMI in different industries, but they all share the same fundamental idea. Examples include Quick Response (QR), Synchronized Consumer Response (SCR), Continuous Replenishment (CR), Efficient Consumer Response (SCR), Rapid Replenishment (RR), Collaborative Planning, Forecasting, and Replenishment (CPFR), and Centralized Information (Disney & Towill, 2003). These terminologies differ based on sector application, ownership issues, and scope of implementation but are essentially specific applications of VMI.

In the simulation model of this research, one of the strategic partnerships implemented is centralized information sharing, which significantly reduces the bullwhip effect along the supply chain. This partnership provides incentives for downstream members to share end-customer demand with upstream stages. The results also demonstrate the possibility of avoiding two causes of the bullwhip effect: echelon elimination and demand processing signal.

The simulation models in this research are based on customized choices derived from previous studies to simulate the impact of information sharing on the bullwhip effect in the supply chain. Although the assumptions vary across different research studies, these assumptions have successfully mitigated the bullwhip effect by implementing information sharing. Furthermore, the findings from the simulation models can be applied to larger multi-echelon supply chains to study the impact of information sharing on the bullwhip effect in a broader network.

7 Conclusion

The Bullwhip effect has garnered significant attention from researchers over the past several decades. It is characterized by an increase in demand variability as one moves up the supply chain. This heightened variability negatively impacts supply chain performance and disrupts coordination among its participants.

The objective of this study was to examine how the Bullwhip effect can be mitigated through the implementation of information sharing, specifically focusing on decentralized information sharing (no information sharing) and centralized information sharing (information sharing).

By investigating the impact of information sharing on the Bullwhip effect, this study contributes to a deeper understanding of how supply chain dynamics can be improved. The findings highlight the importance of information sharing in mitigating the Bullwhip effect and offer insights into effective strategies for demand information sharing. Moreover, the simulation model results provide tangible evidence of the benefits derived from implementing centralized information sharing practices.

In conclusion, this study emphasizes the significance of addressing the Bullwhip effect and explores information sharing as a viable solution. By investigating the research questions and leveraging simulation models, we have gained valuable insights into the causes, countermeasures, and strategies associated with the Bullwhip effect. These findings can serve as a foundation for future research and provide practical guidance for supply chain practitioners aiming to enhance performance and coordination within their supply chains.

8 Limitations

This research investigates a four-echelon supply chain with specific assumptions, which limits its applicability to real-world supply chain situations. A more complex supply chain network with multiple retailers, wholesalers, distributors, manufacturers, and suppliers could provide a more comprehensive understanding of the bullwhip effect.

Another limitation is that the simulation models assume that every individual in the supply chain employs the same inventory review system, forecasting technique, ordering policy, service level, constant lead-time, and review interval throughout the entire time horizon. In reality, each echelon practices its own inventory review system, forecasting technique, and ordering policy based on what they perceive as most suitable for their organization. Service level estimation is also subject to various factors and tends to fluctuate over time, making it challenging to fix a specific service level. Additionally, replenishment lead-time is influenced by uncertainties in transportation and the performance of upstream stages. The reliance on fixed lead-times does not capture the dynamic nature of supply chain operations.

The third limitation arises from the constraints of the ARENA software used for simulation. The used version of ARENA limits the construction of entities to no more than 150, which restricted the design of the simulation model to only a four-echelon supply chain.

Lastly, the combination of ARENA software and Excel spreadsheets imposes a limitation on the number of automatic running replications. Generally, running replications more than 4 to 5 times leads to system crashes and errors. This constraint hinders the measurement of half-width statistics, which are crucial for verifying the precision of the simulation."

9 Future research

In future research, it is recommended to further explore the implementation of Vendor Managed Inventory (VMI) strategies and their impact on mitigating the bullwhip effect. Specifically, the focus should be on replicating more VMI strategies in a larger multi-echelon supply chain using simulation models such as ARENA. These models should incorporate various factors, including different forecasting techniques, inventory policies, ordering policies, stochastic replenishment lead-time, and varied service levels, to better understand the complexities of the bullwhip effect in a real-world supply chain context. By conducting such research, a deeper understanding of the bullwhip effect and the effectiveness of VMI strategies can be gained.

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Appendix 1: Standard normal probabilities

Table entry for *z* is the area under the standard normal curve to the left of *z*.

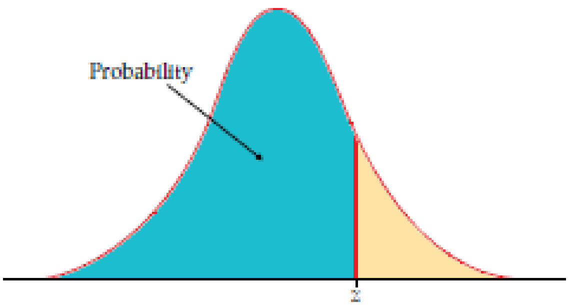


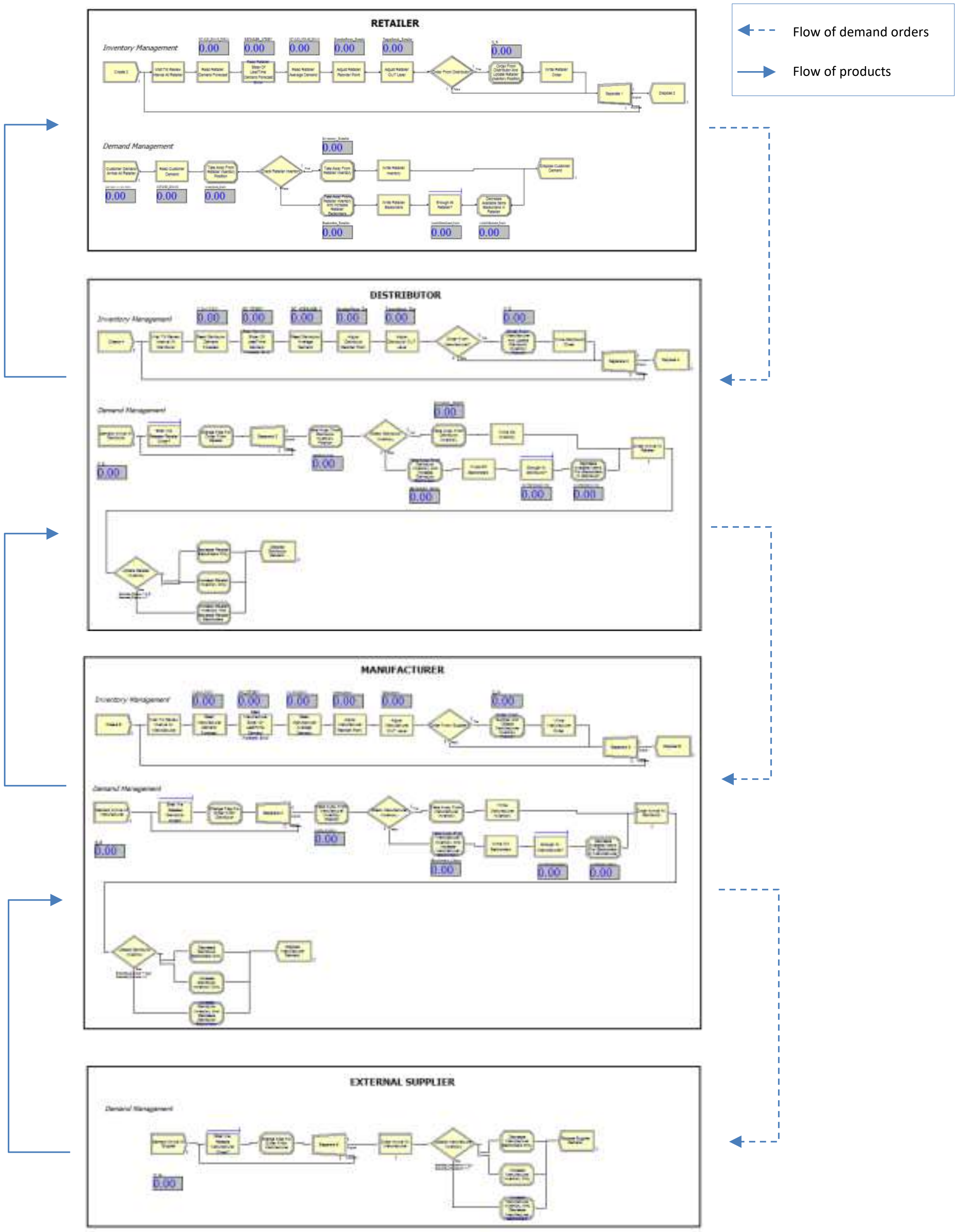
TABLE A

Standard normal probabilities

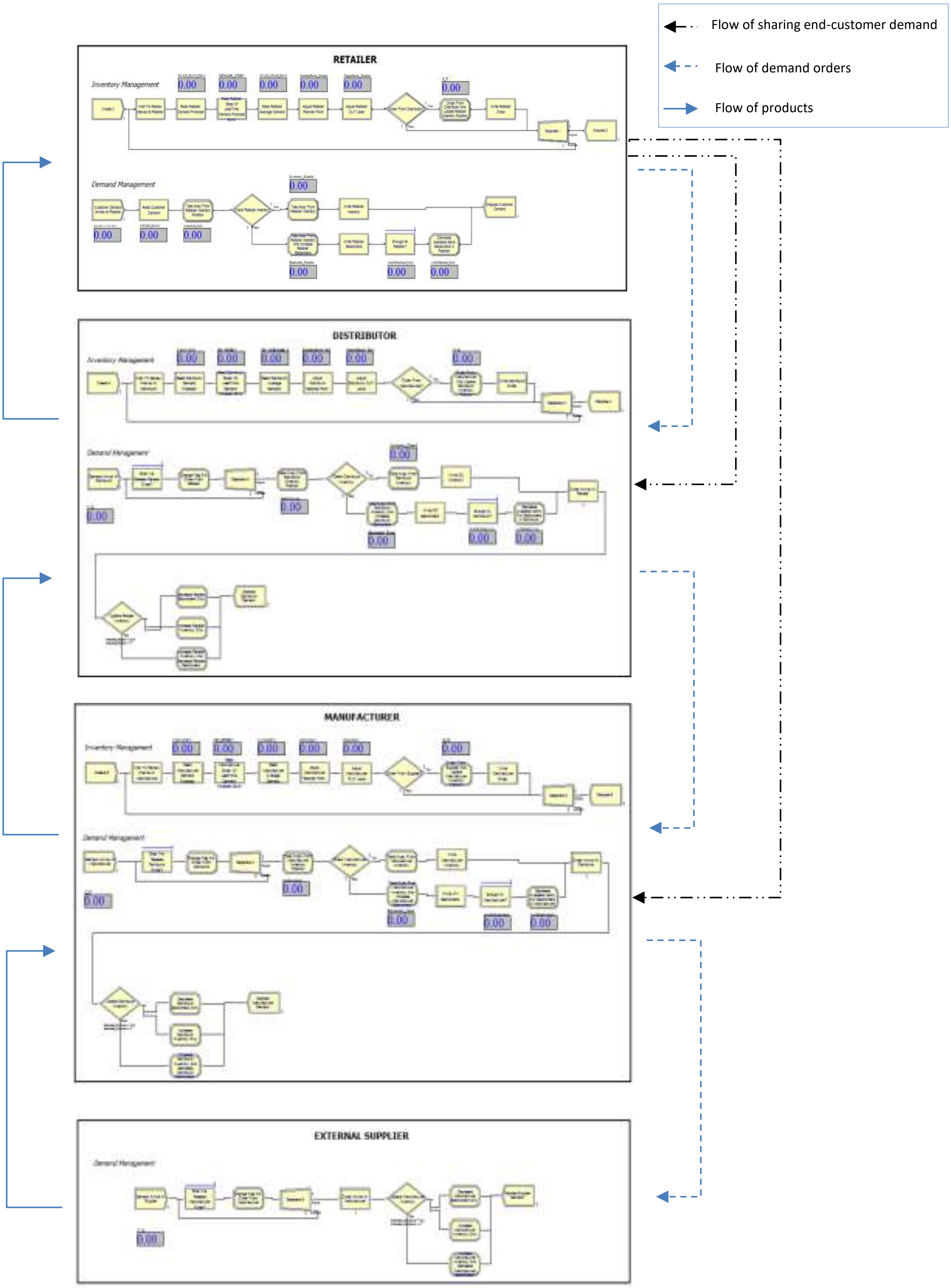
z	.00	.01	.02	.03	.04	.05	.06	.07	.08	.09
0.0	.5000	.5040	.5080	.5120	.5160	.5199	.5239	.5279	.5319	.5359
0.1	.5398	.5438	.5478	.5517	.5557	.5596	.5636	.5675	.5714	.5753
0.2	.5793	.5832	.5871	.5910	.5948	.5987	.6026	.6064	.6103	.6141
0.3	.6179	.6217	.6255	.6293	.6331	.6368	.6406	.6443	.6480	.6517
0.4	.6554	.6591	.6628	.6664	.6700	.6736	.6772	.6808	.6844	.6879
0.5	.6915	.6950	.6985	.7019	.7054	.7088	.7123	.7157	.7190	.7224
0.6	.7257	.7291	.7324	.7357	.7389	.7422	.7454	.7486	.7517	.7549
0.7	.7580	.7611	.7642	.7673	.7704	.7734	.7764	.7794	.7823	.7852
0.8	.7881	.7910	.7939	.7967	.7995	.8023	.8051	.8078	.8106	.8133
0.9	.8159	.8186	.8212	.8238	.8264	.8289	.8315	.8340	.8365	.8389
1.0	.8413	.8438	.8461	.8485	.8508	.8531	.8554	.8577	.8599	.8621
1.1	.8643	.8665	.8686	.8708	.8729	.8749	.8770	.8790	.8810	.8830
1.2	.8849	.8869	.8888	.8907	.8925	.8944	.8962	.8980	.8997	.9015
1.3	.9032	.9049	.9066	.9082	.9099	.9115	.9131	.9147	.9162	.9177
1.4	.9192	.9207	.9222	.9236	.9251	.9265	.9279	.9292	.9306	.9319
1.5	.9332	.9345	.9357	.9370	.9382	.9394	.9406	.9418	.9429	.9441
1.6	.9452	.9463	.9474	.9484	.9495	.9505	.9515	.9525	.9535	.9545
1.7	.9554	.9564	.9573	.9582	.9591	.9599	.9608	.9616	.9625	.9633
1.8	.9641	.9649	.9656	.9664	.9671	.9678	.9686	.9693	.9699	.9706
1.9	.9713	.9719	.9726	.9732	.9738	.9744	.9750	.9756	.9761	.9767
2.0	.9772	.9778	.9783	.9788	.9793	.9798	.9803	.9808	.9812	.9817
2.1	.9821	.9826	.9830	.9834	.9838	.9842	.9846	.9850	.9854	.9857
2.2	.9861	.9864	.9868	.9871	.9875	.9878	.9881	.9884	.9887	.9890
2.3	.9893	.9896	.9898	.9901	.9904	.9906	.9909	.9911	.9913	.9916
2.4	.9918	.9920	.9922	.9925	.9927	.9929	.9931	.9932	.9934	.9936
2.5	.9938	.9940	.9941	.9943	.9945	.9946	.9948	.9949	.9951	.9952
2.6	.9953	.9955	.9956	.9957	.9959	.9960	.9961	.9962	.9963	.9964
2.7	.9965	.9966	.9967	.9968	.9969	.9970	.9971	.9972	.9973	.9974
2.8	.9974	.9975	.9976	.9977	.9977	.9978	.9979	.9979	.9980	.9981
2.9	.9981	.9982	.9982	.9983	.9984	.9984	.9985	.9985	.9986	.9986
3.0	.9987	.9987	.9987	.9988	.9988	.9989	.9989	.9989	.9990	.9990
3.1	.9990	.9991	.9991	.9991	.9992	.9992	.9992	.9992	.9993	.9993
3.2	.9993	.9993	.9994	.9994	.9994	.9994	.9994	.9995	.9995	.9995
3.3	.9995	.9995	.9995	.9996	.9996	.9996	.9996	.9996	.9996	.9997
3.4	.9997	.9997	.9997	.9997	.9997	.9997	.9997	.9997	.9997	.9998

Appendix 2: Simulation of the supply chain in decentralized and centralized information

Simulation of the supply chain in decentralized information



Simulation of the supply chain in centralized information



Appendix 3: Standard deviation of demand and order, and the bullwhip effect ratio under decentralized information

Standard deviation of demand and order under decentralized information of 60 replications

Number of Replication	End-customer demand	Retailer	Distributor	Manufacturer
1	17.01	65.30	451.81	5333.71
2	17.01	62.87	387.91	4338.91
3	16.78	66.09	496.94	5225.32
4	17.29	66.11	445.75	4679.57
5	17.37	65.93	476.56	5098.17
6	17.25	62.75	426.65	4715.84
7	16.77	64.51	453.64	5227.11
8	17.43	67.50	492.30	5154.84
9	17.27	69.98	517.74	5645.15
10	16.92	68.38	498.90	5350.71
11	17.03	64.92	445.98	4943.95
12	17.70	68.12	449.72	5061.42
13	17.26	64.97	452.78	5145.87
14	17.44	68.03	472.48	4903.15
15	17.47	69.42	470.46	5028.91
16	16.86	65.11	520.39	5190.51
17	17.03	68.35	489.84	5744.82
18	18.19	74.26	506.18	5257.29
19	16.84	68.02	519.14	5893.27
20	17.41	66.87	500.78	5135.95
21	17.57	65.92	430.40	4969.25
22	16.99	73.01	550.42	6417.42
23	17.03	68.14	514.24	5514.38
24	16.51	66.58	501.51	5578.62
25	16.73	66.81	526.80	5310.77
26	17.82	69.58	432.46	5053.21
27	17.59	68.52	444.25	3575.49
28	16.88	65.41	500.23	5006.60
29	17.27	69.29	562.80	5519.80
30	17.28	69.04	516.81	5951.92
31	16.69	66.00	462.43	5308.54
32	17.00	66.06	461.50	5293.35
33	17.24	66.10	470.18	5433.96
34	17.26	68.82	495.67	5736.76
35	16.36	64.26	458.11	5500.94
36	16.83	70.35	550.73	6003.37
37	16.85	66.56	472.23	5229.89
38	16.99	61.46	401.87	4420.84
39	16.89	63.54	471.88	4961.41
40	17.48	69.73	485.25	5487.82
41	17.74	74.35	514.49	5887.93
42	16.69	65.50	533.40	5334.08
43	16.92	67.31	533.78	5481.77
44	16.85	67.96	533.80	5584.96
45	17.22	67.86	431.31	5084.11
46	16.98	72.09	502.87	6006.96
47	16.86	68.55	519.13	5911.67
48	17.01	66.42	568.47	5266.78
49	17.14	67.18	503.26	5134.90

50	17.33	69.17	482.85	5303.88
51	16.84	66.53	486.08	5389.06
52	16.82	65.94	411.98	4514.21
53	17.44	68.09	448.77	5083.16
54	17.21	65.77	426.39	4909.67
55	17.11	69.14	486.45	5576.89
56	17.62	73.89	519.81	6127.40
57	17.06	66.50	492.65	5412.94
58	16.42	68.83	546.93	6130.00
59	17.63	70.88	455.57	5466.05
60	16.56	65.72	503.27	5628.04
Aggregation	17.12	67.54	485.34	5309.31

Bullwhip effect ratio under decentralized information of 60 replications

Number of Replication	Retailer	Distributor	Manufacturer
1	3.84	6.92	11.81
2	3.70	6.17	11.19
3	3.94	7.52	10.52
4	3.82	6.74	10.50
5	3.80	7.23	10.70
6	3.64	6.80	11.05
7	3.85	7.03	11.52
8	3.87	7.29	10.47
9	4.05	7.40	10.90
10	4.04	7.30	10.73
11	3.81	6.87	11.09
12	3.85	6.60	11.25
13	3.76	6.97	11.37
14	3.90	6.95	10.38
15	3.97	6.78	10.69
16	3.86	7.99	9.97
17	4.01	7.17	11.73
18	4.08	6.82	10.39
19	4.04	7.63	11.35
20	3.84	7.49	10.26
21	3.75	6.53	11.55
22	4.30	7.54	11.66
23	4.00	7.55	10.72
24	4.03	7.53	11.12
25	3.99	7.89	10.08
26	3.91	6.22	11.68
27	3.90	6.48	8.05
28	3.87	7.65	10.01
29	4.01	8.12	9.81
30	4.00	7.49	11.52
31	3.95	7.01	11.48
32	3.88	6.99	11.47
33	3.83	7.11	11.56
34	3.99	7.20	11.57
35	3.93	7.13	12.01
36	4.18	7.83	10.90
37	3.95	7.09	11.07
38	3.62	6.54	11.00
39	3.76	7.43	10.51

40	3.99	6.96	11.31
41	4.19	6.92	11.44
42	3.92	8.14	10.00
43	3.98	7.93	10.27
44	4.03	7.85	10.46
45	3.94	6.36	11.79
46	4.25	6.98	11.95
47	4.07	7.57	11.39
48	3.91	8.56	9.26
49	3.92	7.49	10.20
50	3.99	6.98	10.98
51	3.95	7.31	11.09
52	3.92	6.25	10.96
53	3.91	6.59	11.33
54	3.82	6.48	11.51
55	4.04	7.04	11.46
56	4.19	7.03	11.79
57	3.90	7.41	10.99
58	4.19	7.95	11.21
59	4.02	6.43	12.00
60	3.97	7.66	11.18
Aggregation	3.95	7.19	10.96

Appendix 4: Standard deviation of demand and order, and the bullwhip effect ratio under centralized information

Standard deviation of demand and order under centralized information of 60 replications

Number of Replication	End-customer demand	Retailer	Distributor	Manufacturer
1	17.01	90.48	152.62	185.99
2	17.01	83.80	166.95	204.49
3	16.78	90.15	149.67	223.03
4	17.29	87.73	164.69	219.44
5	17.37	93.89	157.26	226.03
6	17.25	87.26	142.11	192.11
7	16.77	86.06	166.82	205.95
8	17.43	90.59	187.89	237.78
9	17.27	90.20	145.62	197.11
10	16.92	89.20	169.14	228.69
11	17.03	86.16	135.39	177.38
12	17.70	96.46	157.12	206.22
13	17.26	87.43	160.15	224.63
14	17.44	89.99	167.26	237.77
15	17.47	87.17	155.95	201.73
16	16.86	88.48	144.95	206.60
17	17.03	90.30	159.82	211.38
18	18.19	94.42	162.22	209.85
19	16.84	87.12	157.69	218.64
20	17.41	85.84	152.15	183.93
21	17.57	89.68	148.88	202.81
22	16.99	94.22	152.49	225.17
23	17.03	89.15	151.44	212.25
24	16.51	82.87	163.97	220.24
25	16.73	86.46	155.41	201.81
26	17.82	90.59	149.41	219.13
27	17.59	90.59	145.77	205.74
28	16.88	87.55	142.84	218.55
29	17.27	90.60	166.11	231.70
30	17.28	91.18	149.15	211.01
31	16.69	88.46	173.40	215.90
32	17.00	88.31	166.86	215.70
33	17.24	90.35	163.39	222.47
34	17.26	92.42	162.42	228.16
35	16.36	86.23	166.39	221.88
36	16.83	86.44	149.31	204.95
37	16.85	86.22	153.25	197.84
38	16.99	87.24	142.70	216.18
39	16.89	87.20	160.53	228.78
40	17.48	90.69	168.40	214.97
41	17.74	94.24	159.68	222.95
42	16.69	85.55	142.24	183.07
43	16.92	87.67	155.21	211.33
44	16.85	90.23	157.54	202.48
45	17.22	89.25	138.61	209.51
46	16.98	94.15	179.11	230.90
47	16.86	91.50	160.64	214.13
48	17.01	86.52	152.57	203.91
49	17.14	89.39	143.55	183.55

50	17.33	91.63	154.28	206.73
51	16.84	84.91	143.50	206.11
52	16.82	85.97	149.52	211.92
53	17.44	88.56	153.79	217.78
54	17.21	88.16	174.17	235.58
55	17.11	92.24	145.29	192.40
56	17.62	92.98	162.06	215.15
57	17.06	86.10	145.70	203.79
58	16.42	88.77	153.20	207.39
59	17.63	93.83	158.05	217.56
60	16.56	88.28	162.38	212.07
Aggregation	17.12	89.13	156.37	212.14

Bullwhip effect ratio under centralized information of 60 replications

Number of Replication	Retailer	Distributor	Manufacturer
1	5.32	1.69	1.22
2	4.93	1.99	1.22
3	5.37	1.66	1.49
4	5.07	1.88	1.33
5	5.41	1.67	1.44
6	5.06	1.63	1.35
7	5.13	1.94	1.23
8	5.20	2.07	1.27
9	5.22	1.61	1.35
10	5.27	1.90	1.35
11	5.06	1.57	1.31
12	5.45	1.63	1.31
13	5.07	1.83	1.40
14	5.16	1.86	1.42
15	4.99	1.79	1.29
16	5.25	1.64	1.43
17	5.30	1.77	1.32
18	5.19	1.72	1.29
19	5.17	1.81	1.39
20	4.93	1.77	1.21
21	5.10	1.66	1.36
22	5.55	1.62	1.48
23	5.24	1.70	1.40
24	5.02	1.98	1.34
25	5.17	1.80	1.30
26	5.08	1.65	1.47
27	5.15	1.61	1.41
28	5.19	1.63	1.53
29	5.25	1.83	1.39
30	5.28	1.64	1.41
31	5.30	1.96	1.25
32	5.19	1.89	1.29
33	5.24	1.81	1.36
34	5.35	1.76	1.40
35	5.27	1.93	1.33
36	5.14	1.73	1.37
37	5.12	1.78	1.29
38	5.13	1.64	1.51
39	5.16	1.84	1.43

40	5.19	1.86	1.28
41	5.31	1.69	1.40
42	5.13	1.66	1.29
43	5.18	1.77	1.36
44	5.36	1.75	1.29
45	5.18	1.55	1.51
46	5.55	1.90	1.29
47	5.43	1.76	1.33
48	5.09	1.76	1.34
49	5.22	1.61	1.28
50	5.29	1.68	1.34
51	5.04	1.69	1.44
52	5.11	1.74	1.42
53	5.08	1.74	1.42
54	5.12	1.98	1.35
55	5.39	1.58	1.32
56	5.28	1.74	1.33
57	5.05	1.69	1.40
58	5.41	1.73	1.35
59	5.32	1.68	1.38
60	5.33	1.84	1.31
Aggregation	5.21	1.76	1.36

Appendix 5: Total cost of each echelon and total cost of supply chain in decentralized and centralized information

Total cost of each echelon member and the supply chain total cost in decentralized information

No. of Replications	Retailer	Distributor	Manufacturer	Supply chain
1	72,242,790.74	83,343,724.02	3,718,683.67	159,305,198.43
2	70,627,217.45	84,226,158.03	3,197,510.28	158,050,885.76
3	60,200,514.77	80,889,058.34	3,973,999.33	145,063,572.44
4	59,143,147.31	51,793,180.26	3,459,393.05	114,395,720.62
5	66,660,233.00	83,147,493.79	3,827,221.12	153,634,947.90
6	82,853,447.88	83,098,088.69	3,450,742.49	169,402,279.07
7	74,694,822.36	83,331,104.12	3,797,267.24	161,823,193.72
8	57,455,944.42	72,562,767.58	3,844,726.58	133,863,438.58
9	33,106,262.24	82,414,346.11	4,219,030.66	119,739,639.01
10	16,379,438.16	82,197,093.40	4,016,279.50	102,592,811.06
11	65,476,080.41	83,321,122.66	3,629,313.92	152,426,516.98
12	26,644,486.16	84,208,768.33	3,750,119.18	114,603,373.67
13	48,837,665.74	83,255,713.79	3,809,280.95	135,902,660.48
14	81,706,056.88	55,802,095.80	3,639,181.74	141,147,334.41
15	34,297,094.64	77,897,618.58	4,142,080.12	116,336,793.34
16	76,097,861.32	49,393,371.73	3,893,927.38	129,385,160.43
17	32,183,510.24	83,727,805.12	4,164,408.85	120,075,724.21
18	60,317,508.94	65,577,715.91	3,868,991.50	129,764,216.35
19	36,322,308.92	82,993,503.85	4,309,973.77	123,625,786.54
20	80,311,862.78	52,576,917.13	3,840,469.87	136,729,249.79
21	55,816,459.11	83,406,617.64	3,719,605.14	142,942,681.89
22	82,572,915.08	83,595,474.81	4,995,981.24	171,164,371.13
23	79,756,635.32	80,600,955.29	4,032,034.06	164,389,624.67
24	57,038,262.88	82,422,479.37	4,141,300.51	143,602,042.76
25	81,231,229.39	56,943,284.86	3,956,475.99	142,130,990.24
26	42,406,272.23	83,769,533.27	3,575,481.70	129,751,287.20
27	45,260,534.53	69,595,192.69	17,937,169.89	132,792,897.11
28	52,655,094.39	56,667,780.57	3,656,850.15	112,979,725.10
29	81,914,783.90	23,890,720.06	4,116,411.64	109,921,915.60
30	69,046,857.59	83,293,901.14	4,401,706.23	156,742,464.96
31	51,113,610.44	83,779,668.84	3,900,220.93	138,793,500.21
32	80,452,664.07	83,630,058.37	3,719,358.99	167,802,081.44
33	79,531,962.06	83,807,885.34	4,009,767.29	167,349,614.69
34	79,493,723.67	83,994,671.02	4,225,727.54	167,714,122.24
35	66,967,582.43	83,404,474.44	3,848,422.81	154,220,479.68
36	80,459,423.76	86,615,294.27	14,337,814.61	181,412,532.64
37	34,137,049.89	83,021,044.83	3,753,524.59	120,911,619.31
38	42,870,040.28	83,076,218.66	3,147,782.31	129,094,041.25
39	74,987,624.49	80,768,895.05	3,718,409.71	159,474,929.25
40	34,469,460.92	82,617,251.25	3,908,373.47	120,995,085.63
41	57,509,200.12	83,257,943.27	4,233,954.54	145,001,097.93
42	62,095,567.20	54,194,730.05	3,858,772.33	120,149,069.59
43	34,665,018.36	64,488,719.16	4,006,126.17	103,159,863.68
44	75,866,522.60	78,477,377.46	4,148,540.06	158,492,440.13
45	65,890,351.71	83,383,759.06	3,695,644.25	152,969,755.02
46	75,793,939.54	83,680,339.51	4,389,534.54	163,863,813.60
47	81,873,317.37	83,266,461.03	4,280,290.02	169,420,068.42
48	74,078,262.27	80,483,618.43	4,000,669.93	158,562,550.63

49	9,464,265.59	67,530,021.40	3,826,532.25	80,820,819.24
50	22,120,277.82	82,483,830.24	3,887,870.03	108,491,978.09
51	45,472,180.78	82,754,627.01	3,878,275.63	132,105,083.41
52	26,982,224.58	82,809,810.85	3,223,772.30	113,015,807.74
53	62,182,830.61	83,438,736.01	3,718,474.47	149,340,041.09
54	60,779,548.24	83,587,919.30	3,465,077.41	147,832,544.95
55	77,138,057.01	83,012,734.89	4,145,908.87	164,296,700.77
56	76,390,267.03	83,751,338.17	4,466,297.74	164,607,902.94
57	80,706,782.12	83,111,329.21	3,861,499.41	167,679,610.74
58	52,961,587.51	83,404,591.58	4,582,164.85	140,948,343.94
59	57,003,736.39	83,717,956.45	3,919,333.68	144,641,026.52
60	81,010,479.74	83,534,554.47	4,179,375.31	168,724,409.53
Aggregation	59,584,441.81	77,215,012.25	4,333,973.73	141,133,427.79

Total cost of each echelon member and the supply chain total cost in centralized information

No. of Replications	Retailer	Distributor	Manufacturer	Supply chain
1	102,400,500.19	115,872,260.27	3,965,159.60	222,237,920.06
2	98,021,281.16	88,307,801.89	3,370,323.05	189,699,406.09
3	77,469,481.50	49,891,554.61	3,998,338.10	131,359,374.21
4	42,403,702.68	30,386,274.59	1,856,074.90	74,646,052.16
5	78,326,689.27	80,816,149.32	1,086,317.16	160,229,155.75
6	79,730,358.38	19,811,461.45	2,906,391.27	102,448,211.09
7	81,802,443.43	73,356,769.53	4,814,526.14	159,973,739.10
8	57,356,526.61	61,054,452.78	2,947,183.62	121,358,163.01
9	10,065,002.40	2,225,351.96	639,504.04	12,929,858.39
10	37,536,586.05	34,666,684.98	3,956,689.11	76,159,960.14
11	883,502.86	1,183,043.17	4,137,329.89	6,203,875.91
12	10,623,522.99	2,335,130.46	1,240,679.19	14,199,332.64
13	32,615,734.86	30,882,725.44	1,300,789.87	64,799,250.17
14	72,758,203.62	1,403,217.11	4,548,812.93	78,710,233.65
15	64,178,683.57	62,595,332.46	597,718.14	127,371,734.17
16	76,762,052.80	2,420,976.87	1,960,986.18	81,144,015.85
17	5,267,826.31	1,474,116.48	670,129.47	7,412,072.27
18	9,146,542.76	1,280,676.32	5,163,123.02	15,590,342.10
19	11,039,163.91	1,082,929.18	4,169,799.35	16,291,892.44
20	63,098,235.55	79,138,642.13	1,897,097.47	144,133,975.15
21	26,871,347.67	2,429,385.12	752,135.60	30,052,868.39
22	49,097,176.27	3,892,470.04	2,515,284.50	55,504,930.81
23	5,742,223.77	1,114,048.60	3,833,745.38	10,690,017.75
24	21,081,893.81	3,153,982.94	1,484,117.20	25,719,993.95
25	49,075,495.01	41,515,473.17	742,566.91	91,333,535.09
26	1,449,408.76	2,318,869.78	1,754,865.41	5,523,143.95
27	14,449,131.51	2,091,578.43	3,168,865.59	19,709,575.53
28	30,075,217.01	13,770,014.17	970,298.93	44,815,530.12
29	44,764,018.35	16,319,165.15	696,569.38	61,779,752.88
30	9,414,452.47	2,595,200.71	636,162.95	12,645,816.13
31	44,649,059.29	64,540,958.83	623,958.30	109,813,976.42
32	66,544,628.55	24,231,112.84	595,178.60	91,370,919.99
33	73,132,836.90	48,741,291.70	3,460,801.64	125,334,930.23
34	21,525,523.69	24,936,974.50	2,275,625.67	48,738,123.86
35	55,734,224.42	1,631,320.70	4,525,057.53	61,890,602.65

36	83,445,730.10	83,176,833.60	1,263,737.00	167,886,300.70
37	61,915,371.27	11,398,219.87	4,415,013.99	77,728,605.12
38	869,443.00	1,951,587.69	3,226,668.88	6,047,699.57
39	58,770,730.80	53,876,572.19	1,535,578.84	114,182,881.83
40	13,209,948.97	1,420,333.70	663,794.11	15,294,076.78
41	47,650,125.23	40,627,065.09	2,801,629.52	91,078,819.83
42	22,234,852.91	16,154,798.40	640,098.78	39,029,750.08
43	66,685,091.99	967,391.81	4,292,445.21	71,944,929.01
44	24,183,401.51	11,616,953.68	720,056.84	36,520,412.03
45	42,610,936.12	1,966,907.98	1,880,203.39	46,458,047.49
46	71,859,468.83	64,537,372.71	1,003,451.57	137,400,293.11
47	10,784,526.19	1,492,606.75	1,502,561.68	13,779,694.61
48	78,094,775.42	57,648,621.24	4,813,440.60	140,556,837.25
49	83,654,867.22	83,161,472.48	4,260,190.86	171,076,530.56
50	83,406,859.59	83,002,542.23	725,810.25	167,135,212.07
51	55,374,829.10	1,885,507.55	1,568,035.74	58,828,372.39
52	76,368,721.41	77,237,406.57	2,893,000.46	156,499,128.44
53	55,976,623.12	22,966,241.50	4,009,307.54	82,952,172.16
54	38,287,280.50	31,943,361.87	4,245,857.09	74,476,499.46
55	58,851,362.65	1,830,385.03	3,875,457.53	64,557,205.21
56	10,737,710.85	6,130,238.61	651,027.60	17,518,977.06
57	2,130,292.62	403,529.49	4,394,236.45	6,928,058.56
58	2,234,741.59	1,005,755.05	3,461,210.95	6,701,707.59
59	56,184,791.32	1,697,926.07	1,183,468.95	59,066,186.34
60	1,819,645.71	617,074.62	600,440.90	3,037,161.24
Aggregation	42,881,937.39	26,039,183.78	2,371,589.34	71,292,710.52