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UNIVERSIDADE D COIMBRA

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IMPACTO DA ESCOLHA DE ALGORITMOS DE REAPROVISIONAMENTO NO EFEITO DE CHICOTE

Dissertação no âmbito do Mestrado em Engenharia e Gestão Industrial orientada pelo Professor Doutor Luís Miguel D. F. Ferreira e pelo Professor Doutor Cristóvão Silva e apresentada ao Departamento de Engenharia Mecânica, da Faculdade de Ciências e Tecnologia da Universidade de Coimbra.

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Impacto da Escolha de Algoritmos de Reaprovisionamento no Efeito de Chicote

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The Impact of Replenishment Policies in the Bullwhip Effect

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Look up at the stars and not down at your feet. Try to make sense of what you see and wonder about what makes the universe exist. Be curious.

Stephen Hawking

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Resumo

O efeito de chicote descreve o fenómeno da amplificação da procura ao longo de uma cadeia de abastecimento. Esta amplificação gera grandes consequências para as empresas, tais como previsões incorretas da procura, grandes custos de inventário e falhas no nível de serviço prestado.

Tudo isto leva a que haja grande pressão sobre os gestores para que estejam cientes de quais os fatores que causam efeito de chicote, bem como para que minimizem os mesmos. Torna-se assim importante perceber se os algoritmos de reaprovisionamento utilizados estão a contribuir para este efeito e qual o seu impacto.

Esta dissertação aborda a lacuna de pesquisa existente sobre a avaliação do impacto de algoritmos de abastecimento no efeito de chicote através do uso da simulação de eventos discretos. Foi simulada uma cadeia de abastecimento com quatro elos, que fornece apenas um produto, tendo sido testados quatro algoritmos de reabastecimento.

Os resultados da simulação revelam alterações ao nível da média e desvio padrão da procura, assim como nos níveis de inventário, indicando assim a presença do efeito de chicote. Durante a avaliação de resultados foi ainda possível apoiar as teorias de Disney et al. (2005) e Pozzi et al. (2018), Potter & Disney's (2006, apud Bhattacharya & Bandyopadhyay, 2011) e Potter & Disney (2006) relacionadas com o impacto do lead time, do tamanho do lote e do tempo entre encomendas, respetivamente, na amplificação da procura.

Os resultados mostram que, nas condições testadas, a escolha do algoritmo de reabastecimento tem efeito sobre o efeito de chicote experienciado pela cadeia.

Investigação futura poderá ser feita no sentido de validar esta descoberta em diferentes estruturas de cadeias de abastecimento, bem como diferentes níveis de procura. Caso venha a ser validada, existe a possibilidade de se poder desenvolver uma ferramenta de apoio à tomada de decisão que guie os gestores na escolha do algoritmo mais adequado à sua cadeia.

Palavras-chave: Cadeia de Abastecimento, Efeito de Chicote, Reaprovisionamento, Simulação, Inventário.

Abstract

The Bullwhip Effect describes the phenomenon of amplification of demand throughout the supply chain and brings great consequences to a company such as failure to predict the real demand, large inventory costs and poor customer service.

As managers are urged to be aware of all the factors that contribute to this problem and minimize them as much possible, it's important to understand if the used replenish algorithms can be a cause of bullwhip and what is its impact.

This dissertation addresses the gap related to assessing the impact of replenishment algorithms in the bullwhip effect through the use of discrete-event simulation, by simulating a 4-echelon supply chain, serving a single product, under four different replenishment strategies.

It was possible to clearly identify changes in the average demand, demand standard deviation and inventory levels that confirmed the existence of bullwhip effect. During the data analysis, it was also possible to support the theories of Disney et al. (2005) and Pozzi et al. (2018), Potter & Disney's (2006, apud Bhattacharya & Bandyopadhyay, 2011) and Potter & Disney (2006) related to the impact of batch sizes, lead time and time between orders, respectively, in the bullwhip effect.

In the end, results found that, under the studied conditions, the choice of replenishment algorithm does influence the bullwhip experienced by the chain.

Further research is needed to validate these findings under a broader range of demand patterns and supply chain configurations. If these findings are proven to be valid there's a possibility to develop a managerial tool in order to help guide the decision of choosing replenishment algorithms in supply chains.

Keywords Supply Chain, Bullwhip Effect, Replenishment, Simulation, Inventory.

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1. INTRODUCTION

Logistic operations and decisions across a supply chain are of utmost importance, thereby all processes must be well coordinated within all members to ensure a smooth product flow. At each level, decisions regarding how much inventory to keep in stock, how should we replenish and how efficient is our transportation method, influence the remainder levels, since each echelon is mutually dependent from the others. These decisions can create a delay on the feedback received at each level, leading up to some instability in the product flow, which ultimately can cause a bullwhip effect. Despite being the target of many research articles, it's still a concern in the real world (Wangphanich et al. 2010, apud Hussain & Saber, 2012).

The bullwhip effect can be described as an increase of variance of the orders in comparison to the sales through the supply chain, generating inadequate forecasts which contribute to creating both stockout and over-capacity periods, leading to poor customer service which, ultimately increases inventory costs along the chain. This means that decreasing the bullwhip effect brings great cost advantages to the companies. (Hussain & Saber, 2012).

Replenishment decisions impact indirectly the subsequent echelons of the supply chain as they can increase the volatility of the demand in the supply chain (Disney et al., 2005), ultimately contributing to the bullwhip effect.

The study of the effect of the replenishment policies in the bullwhip effect is considered a research gap, but despite the importance of this topic, it hasn't been properly addressed by the literature (Derbel, Hachicha, & Masmoudi, 2014).

This dissertation pretends to address this gap by investigating whether the choice of the replenishment policy affects the experienced bullwhip effect and compare several classic algorithms, which brings us to our research question:

RQ1 – Can the choice of replenishment algorithm enhance the bullwhip effect experienced by a supply chain?

The thesis is organized in 5 chapters. The first chapter introduces the topic and its importance to both the scientific and managerial community. The second chapter provides the necessary definitions and the characterization of concepts in order to understand both the topic and the implemented methods. The third chapter describes the implementation of the proposed methodology. The fourth chapter presents and discusses the findings. The fifth, and final chapter, sums up the findings and presents concluding remarks, pointing out topics for further research.

2. LITERATURE REVIEW

This chapter presents the state of art of the research related to the topic of this dissertation and allows the reader to acquire the knowledge needed to fully comprehend all the steps taken, in order to answer the research question.

The bullwhip effect is discussed in order to understand its causes, consequences and how it can be measured within a supply chain. An overview of the concept of ordering policies is performed and a deeper look is taken into the 4 most commonly used algorithms within the industry. To end, the key factors to understand the bullwhip effect in a supply chain are presented, such as its structure, modeling approach and performance measures.

2.1. Bullwhip Effect

The bullwhip effect, also known as Forrester Effect, illustrates the phenomenon where the order variability increases as the orders move upstream within the supply chain. In other words, the consumer demand creates large fluctuations in production for the suppliers at the other end of the supply chain (Wang & Disney, 2016).

Typically, this will generate excessive inventory, poor forecasts, insufficient or excessive capacities, poor customer service due to product shortage or backlog, uncertainty during the production planning and high costs to correct problems, related, for example, to shipments and worker overtime (Lee, Padmanabhan, & Whang, 1997).

Wang and Disney (2016) argue that this effect becomes particularly important for a company when costs from fluctuations in production or ordering outweigh the cost of holding inventory.

2.1.1. Causes

In their research, (Lee et al., 1997) refer to four major operational causes for this effect: Demand forecast updating; Order Batching; Price Fluctuation; and the Rationing and shortage gaming.

With the advance of research, some authors have identified other operational causes for this effect. In the table below we can see a summary of the factors identified by Novitasari & Damayanti (2018) in their literature review and the authors who originally referenced them.

Table 1 - Operational Factors for the Bullwhip Effect (adapted from Novitasari & Damayanti (2018))

Factors	Authors
Demand Forecasting	Lee et al. (1997) a)
Order Batching	Lee et al. (1997) a)
Price Fluctuation	Lee et al. (1997) a)
Rationing and Shortage Gaming	Lee et al. (1997) a)
Lead Time	Heydari et al. (2009); Wang et al. (2008); Huang L, Liu Y. (2008)
Inventory Policy	Chandra C, Grabis J (2005) Aharon et al. (2009)
Replenishment Policy	Jakšič M, Rusjan B (2008) Su C-T, Wong J-T (2008) Zhang L, Zhang Q (2007)
Improper Control System	Geary et al. (2006)
Lack of transparency	Lee et al. (1997) b) Sohn SY, Lim M (2008) Lee et al. (2000) Zhao W, Wang D (2008) Agrawal et al. (2009)
Number of echelons	Alony I, Munoz A (2007)
Multiplier Effect	Geary et al. (2006)
Lack of Synchronization	Erkan et all (2008)
Misperception of feedback	Moyaux et all (2007)
Local optimization	Moyaux et all (2007)
Company Processes	Moyaux et all (2007)
Capacity restrains	Alony I, Munoz A (2007)
Interaction Between two rational supply chain members	Lee et al. (1997) b)

One can argue that the research appeal of these factors isn't equal, as authors tend to focus on particular topics as opposed to others. According to Derbel et al. (2014), the major interest lies in the study of the impact generated by forecasting methods, batch sizes, price fluctuations and lead time.

On another hand, it can't be factored out the human error out of this equation, as there are some behavioral causes to the bullwhip effect as well. In their research, Novitasari & Damayanti (2018) reference that ignoring time delays in the decision-making process, lack of experience and the fear to reach a stockout point are among the most important explanatory factors.

Research studies make it clear that there are many ways to increase the bullwhip effect in our supply chain, but it's a fool's errand to try and fight them all at once, thus there's a need to try and prioritize those that have the greatest impact. With this in mind, Khan & Ahmad (2018) used the Analytical Hierarchy Process[1] (AHP) technique in order to try and rank the operational causes of the bullwhip effect. The authors found that there are seven major contributors, of which 4 of them accounted for more than 80% of the contribution to the bullwhip effect (see Table 2).

Table 2 - Results obtained by Khan & Ahmad (2018)

Rank	Factors	Priority (in %)
1	Order Batching	29.28
2	Demand Signal Processing	25.38
3	Lead Time	16.58
4	Inventory Policy	14.93
5	Price Fluctuation	5.58
6	Lack of trust	4.27
7	Number of Echelons	4

In the following paragraphs, we will dive deeper into the 4 most contributing causes identified by the authors.

[1] The Analytical Hierarchy Process is a general theory of measurement used to obtain priorities in absolute scales (Saaty & Vargas, 2006).

2.1.1.1. Order Batching

Within the supply chain, typically, an order is placed to an upstream member using an inventory control or monitoring system. This means, that when the demand arrives an order, may not immediately be issued, because often, the demand is accumulated or batched before sending an order (Lee et al., 1997).

As a result, the placement of periodic orders amplifies the variability and contributes to the bullwhip effect since the ordering pattern from the clients is more unstable compared to its consumption pattern (Lee et al., 1997).

Later on, some authors kept investigating the topic and contributing to major findings to the field. In Table 3 we can find a summary of the major research contributions to the impact of batching in the bullwhip effect, based on the work done by Bhattacharya & Bandyopadhyay (2011).

Table 3 - Contributions of Major Research Studies on the effect of batching on the Bullwhip Effect (adapted from Bhattacharya & Bandyopadhyay (2011))

Authors	Contributions
Riddalls and Bennett (2001)	Bullwhip levels are related to the remainder of the ratio between the batch size and average demand.
Holland and Sodhi (2004)	The level of bullwhip across one echelon is proportional to the square of the batch size.
Gaalman and Disney (2006)	The bullwhip effect is basically caused by the covariance between the inventory level and the demand forecast.
Potter and Disney (2006)	Batch sizes should be reduced as much as possible, in order to reduce the negative impact of batching.

2.1.1.2. Demand Forecast Updating

Usually, companies within a supply chain base their expectations about future demand on orders they receive from the next link. This means that there's an increase in orders, which is then transferred to the next link, thus increasing order quantities. The next link will also see an increase in its demand and, consequentially update its forecasts and, once again, generate a distortion to the next link of the chain (Fransoo & Wouters, 2000).

This "double forecasting" creates a demand amplification every time there's a forecast on an upper stream member of the supply chain, increasing the bullwhip effect (Khan & Ahmad, 2018). Consequentially, the forecasting method used can be considered one of the main causes of the bullwhip effect as it has a direct impact on the inventory systems in the supply chain (Derbel et al., 2014).

2.1.1.3. Lead Time

The supply chain lead time can be defined as the time between the order placement and its actual reception. The longer the lead time, the more ambiguous the supply chain becomes, thus increasing the bullwhip effect (Khan & Ahmad, 2018).

The lead time is a key part in calculating the safety stock, reorder point and order-up-to levels, so an increased lead time variability is magnified into an increased order variability (Disney et al., 2005), thus contributing to the bullwhip effect, implying that a steady lead time is of extreme importance (Pozzi et al., 2018). Both Disney et al. (2005) and Pozzi et al. (2018) support that a reduction of the lead time is of utmost importance in order to reduce order variability, supporting the adoption of actions such as, adoption of investment in communication and production technology, strategic partnerships and removing unnecessary intermediaries in the supply chain.

In theory, reducing the lead time to zero would eliminate the bullwhip effect, but in practice, things are not quite that simple. Lead time can be generated from physical or information delays, which we do not differentiate when modeling the supply chain, therefore is practically impossible to attain a constant lead time (Michna, Nielsen, & Nielsen, 2018).

2.1.1.4. Inventory Policy

Inventory policies define the rules as of when a replenishment algorithm should send an order, as well as the amount to be ordered. Inventory and ordering policies are interrelated since, order amount and time of order depend on the inventory level (Khan & Ahmad, 2018)

The literature regarding the choice of the replenishment system as a cause of bullwhip is scarce (Derbel et al., 2014), and limited to some algorithms.

Periodic Revision

When dealing with a periodic review, fixed quantity (R, nQ) system, the bullwhip effect can be reduced by decreasing the review period (R) (Potter & Disney, 2006) and decreasing the batch size (Q), assuming that Q is a multiple of the average demand Cachon (1999, apud Noblesse, Boute, Lambrecht, & Van Houdt, 2013).

Chen and Lee (2012, apud Noblesse et al., 2013) discovered that the bullwhip ratio in the (R, nQ) is dependent on the batch amount, demand characteristics and capacity constraints, so when demand is independent and identically distributed and the supply chain doesn't present constraints, batch ordering generates bullwhip effect.

Continuous Revision

On a general note, Giard & Sali (2013) found that this type of policies contribute to the bullwhip effect in supply chains where management is decentralized.

On the particular case of the order-point, order-up-to-point (s, S) policy there's not much literature concerning it but Caplin (1985, apud Noblesse, Boute, Lambrecht, & Van Houdt, 2013) found that assuming single unit demands, the variance of the units ordered in a certain interval compared to the demand received in the same interval, increases linearly with the batching quantity. These results were later confirmed and extended by Noblesse et al. (2013) for randomly sized batches and generalized intervals.

2.1.2. Measures

Now that we fully understand the causes of the bullwhip effect, we need to be able to quantify it within our supply chain.

Considering a supply chain as a set of several subsequent echelons, in order to measure the bullwhip effect at a particular echelon or group of echelons Fransoo & Wouters (2000), Ponte, Ruano, Pino, & De Fuentela (2015) and Parra-pena, Mula, & Campuzano-bolarin (2012) use the following equation:

$$BE = \frac{\sigma_{POE}^2 / \mu_{POE}}{\sigma_{POR}^2 / \mu_{POR}} = \frac{\sigma_{POE}^2}{\sigma_{POR}^2} \tag{2.1}$$

Where BE corresponds to the bullwhip effect generated at a generic node of a linear supply chain, σ_{POE}^2 is the quotient of variance of the orders issued at the node, μ_{POE} is the expected value of the intensity of the flows at the node , σ_{POR}^2 is the quotient of variance of the orders received at the lower level and μ_{POR} is the expected value of the intensity of the flows at the lower level.

This calculation was adapted to spreadsheet use by Parra-pena et al. (2012), who adapted the general variance formula shown in Equation 2.2 to the calculation the order variance in the current period.

$$var(x) = \frac{\sum_{i=1}^{n}(x_i - \bar{x})^2}{n-1} \tag{2.2}$$

Where:

x_i – vector of n elements that represents the orders. The first (n-1) elements are equal to zero and the nth term contains the order for a given time period(t);

$\bar{x}$ – order average;

Assuming that orders are composed of (n-1) terms equal to zero, the calculus of the variance implies that we sum the (n-1) identical terms and the nth term. Therefore, the equation takes the following form:

$$var(x) = \frac{\left(\sum_{i=1}^{n}(x_i - \bar{x})^2\right) + (x_n - \bar{x})^2}{n-1} \tag{2.3}$$

Given that we have (n-1) terms with a value of zero, the equation can be transformed into:

$$var(x) = \frac{(n-1)(-\bar{x})^2 + (x_n - \bar{x})^2}{n-1} \tag{2.4}$$

Due to the previous assumption, we can also assume that the order average ($\bar{x}$) is equal to the orders received in the n periods (x_n), divided by n. When computing this in the previous equation, we obtain the following result:

$$var(x) = \frac{(n-1)\left(-\frac{x_n}{n}\right)^2 + \left(x_n - \frac{x_n}{n}\right)^2}{n-1} \tag{2.5}$$

This formula can be easily adapted to a spreadsheet, as it only depends on the order information and number of time periods (n).

The bullwhip effect can then be calculated as a cumulative expression of each cumulative distortion using the following expression:

$$BE_t = \begin{cases} BE_{t-1}, & orders_t - sales_t = 0 \\ BE_{t-1} + \frac{Var(order)}{Var(Sales)}, & other\ wise \end{cases} \tag{2.6}$$

Yet the BE metric only evaluates the output variance compared with the input variance, so in their work, Ponte et al. (2015) make use of another metric, the Alternative Bullwhip Effect (ABE), which measures the quotient of variance of the stock (${\sigma^2}_{STOCK}$) at a generic node and variance of the demand (σ^2_{POR}).

$$ABE = \frac{{\sigma^2}_{STOCK}}{\sigma^2_{POR}} \tag{2.7}$$

The ABE quantifies the inventory fluctuations and serves as a measure of stability within the supply chain, on the other hand, is associated with a possible increase and variation of holding costs per unit (Vicente, Relvas, & Barbosa-Póvoa, 2018). One value of ABE is computed per echelon (Cannella, Ciancimino, Canca Ortiz, & Setchi, 2010), a geometrical or exponential increase in the values represents inventory instability along the supply chain, caused by desynchronization and information distortion (Shaw, 2011). In order to quantify the distortion of information and make comparisons, we can use the inventory instability slope, which is calculated by computing the slope of the linear regression of the curves generated at the supply chain. A positive value for the slope indicates the propagation of information distortion (Cannella et al., 2010).

As a complementary measure, in order to keep track of the average holding cost, the average inventory level is often used (Vicente et al., 2018) and can be calculated through the following equation:

$$Average\ inventory = \frac{\sum_t^T Stock_t}{T} \tag{2.8}$$

Where:

$Average\ inventory$ = average inventory at a generic node;

$Stock_t$= Stock at the generic node at period t;

T=Total simulation time;

Another measure considered adequate by Vicente et al. (2018) was the average customer demand at the retailer, calculated as follows:

$$Average\ Customer\ Demand = \frac{\sum_t^T Demand_t}{T} \tag{2.9}$$

Where:

$Average\ Customer\ Demand$ = average customer demand at the retailer;

$Demand_t$ = Demand at the retailer at period t;

T = Total simulation time;

Given the fact that ordering policies play a major role in the creation of the Bullwhip Effect (Khan & Ahmad, 2018), they will be explained in the next chapter. First, we will be exploring the deterministic models, used for stable demand and supply, and then we move on to the stochastic models, which consider the occurrence of variability in these inputs.

2.2. Ordering Policies

A company needs to have, at the right time, all materials and products needed for its activities. To do that they need to fully understand when and order should be submitted and what's the right quantity of each component (Courtois, Martin-Bonnefous, & Pillet, 2003).

To answer these questions, we can use several ordering policies, each of them providing us a different answer. In order to choose the best one, first we must understand a critical aspect regarding both our offer and demand behaviors, are they steady and predictable or is there some randomness inherent to them? Thus, the ordering policies can be classified into two categories: Deterministic and Stochastic models (Carvalho, 2010).

2.2.1. Deterministic Models

In these models, both the supply and demand are considered steady throughout time. Which means that supplier delivery times are fixed and always met, the ordered amount is the supplied amount and the customer demand is always known (Carvalho, 2010).

Several models have been developed, but for the purpose of this thesis, we will be focusing only on the Economic Order Quantity Model.

2.2.1.1. Economic Order Quantity

This model's main objective is minimizing costs, which means we will be ordering the quantity that will bring the least costs to the company. The main costs to take into consideration are the stock holding costs and ordering costs. The stock holding costs represent the cost that company intakes by storing the products for a given period of time. The ordering costs correspond to the cost to create and process an order to a supplier.

As it was mentioned before, the main goal of this model is to minimize both ordering and stock holding costs, yet as we can see from Figure 1, as we increase the ordered quantity, despite our ordering costs diminish, we see an increase of the holding costs. This brings up the need to find the equilibrium point of the trade-off between the stock the company is willing to keep and the frequency they will place an order. This point will be the minimum value of the Total Cost function, which will then correspond to our Economical Order Quantity.

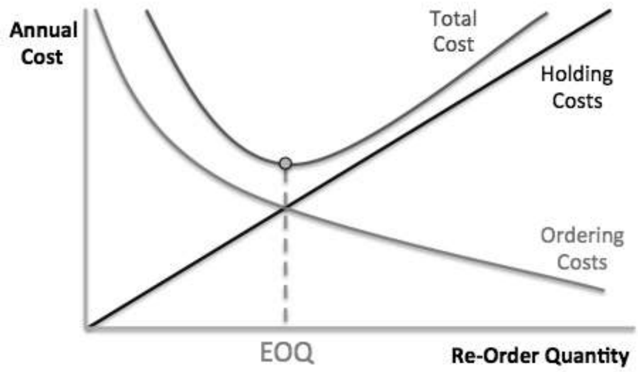

Figure 1 – Representation of the Total Cost, Holding Cost and Ordering Cost

The Total Cost can be calculated through the following equation:

$$CT = \frac{D}{Q} \times A + \frac{Q}{2} \times H \qquad (2.10)$$

Where CT corresponds to the Total Cost (€/unit of time), D is the demand (units/unit of time), Q is the quantity to order (units), A is the ordering cost (€/order) and H is the holding cost (€/unit/unit of time).

If we derive the previous equation in order to find its minimum value, we can easily find the quantity that will minimize the total costs.

$$CT' = -\frac{DA}{Q^2} + \frac{H}{2} = 0 \qquad (2.11)$$

Solving this equation in order to Q, we can find the economic order quantity.

$$EOQ = \sqrt{\frac{2DA}{H}} \tag{2.12}$$

Now that we know how much to order, we need to know when the right time is to place it. Since the demand is constant and known, this decision will depend only on the supplier delivery time, which in this case, will also be known and constant.

In this model, an order is placed when the stock level reaches a pre-defined quantity – order point, which depends on the supplier delivery time and product demand rate. We can calculate it using the following equation:

$$s = d \times L \tag{2.13}$$

Where s corresponds to the reorder point (units), d is the demand (units/ time units) and L is the supplier lead time (time units).

2.2.2. Stochastic Models

Stochastic models are applied when supply and/or demand have an uncertain behavior. This uncertainty turns the stock management into a more complex issue, as now managers must deal with the possibility of stock-outs. To deal with this random behavior we need to create a safety stock that can handle variations over the average values, yet as we are dealing with random variables, this safety stock will absorb some of those variations but not all of them. Of course, the higher we set our safety stock, the higher the probability of it being able to absorb an unpredictable variation, yet there's always a probability that there's a stockout. In this context, it becomes important to determine at which service level we wish to operate.

The service level is the probability that the company has the wanted quantity at the time of its request. Meaning that the higher the customer service level, the higher the safety stock that will be needed to be kept.

Another factor that contributes to the safety stock size is the variability of the supply and/or demand compared to the average values. If this variability is too high the company will need a larger safety stock to keep up with the promised serviced level.

Lastly, safety stock sizing depends on the implemented stock management model which, in the case of the stochastic models, can be fitted into two main categories: Continuous Revision and Periodic Revision models.

2.2.2.1. Introduction to Stock Terminology

When dealing with stochastic models it’s important to have present some basic definitions regarding inventories and stocks.

First, we need to understand that **On-Hand Stock** refers to the physical stock present on the shelf, therefore it can never be negative.

On the other hand, **Net Stock** is defined by the following equation:

$$Net\ stock = OnHand\ - Backorders \tag{2.14}$$

This equation shows us that the Net Stock, unlike the previous, can take a negative value when the backorders are superior to the on-hand stock. If an item is out of stock and there’s demand for it, an order will still be accepted, considering it backordered, and the demand will be fulfilled as soon as there’s available stock.

Despite the previous types of stock offering useful insights about the state of the system, the **inventory position** (IP) or available stock, is the main decision-maker on whether to replenish a company or not and can be computed by the following expression:

$$Inventory\ Position = On\ Hand + On\ Order - Backorders - Commited \tag{2.15}$$

The “On Order” quantity corresponds to the quantity that’s been ordered but hasn’t arrived yet at the considered point. The “Committed” quantity is necessary if some of the stock cannot be used in the short term. (Pyke, Silver, & Thomas, 2017).

2.2.2.2. Continuous Revision Models

Now that we are aware of the basic terminology, we can dive a bit further into the models per se. We will start with the continuous revision models.

These models are characterized by the constant monitorization of the inventory position. This is necessary because when the stock reaches the reorder position there's a need to make an order to the supplier. If the order isn't made at this point the stock-out risk increases (Carvalho, 2010).

The reorder point can be calculated as follows:

$$reorder\ point\ (s) = \widehat{x_L} + Safety\ Stock \tag{2.16}$$

Where $\widehat{x_L}$ corresponds to the expected demand during the replenishment time, in units and the safety stock, in units, is calculated by the following expression:

$$Safety\ Stock = z \times \sigma \tag{2.17}$$

Where z corresponds to the safety factor and σ, the standard deviation of the demand during replenishment time, is the defined in the equation below:

$$\sigma = \sqrt{\bar{L} \times {\sigma_d}^2 + \bar{d}^2 \times {\sigma_L}^2} \tag{2.18}$$

Where:

$\bar{L}$= average delivery time

$\bar{d}$=average demand during the delivery time

σ_d= demand standard deviation

σ_L= delivery time standard deviation

We can calculate $\widehat{x_L}$, the expected demand during replenishment time, through the following expression:

$$\widehat{x_L} = d \times L \tag{2.19}$$

Where d represents the average echelon demand, in unit/time, and L represents the supplier lead time in time units.

According to Pyke et al. (2017) companies adopt mainly two types of continuous review systems: Order Point, Order Quantity and Order-Point, Order-Up-to-Level.

2.2.2.2.1. Order Point, Order Quantity (s, Q) System

Based on continuous revisions, this system dictates that when the inventory position drops below the reorder point (s) an order of size Q, will be made, as shown in Figure 2.

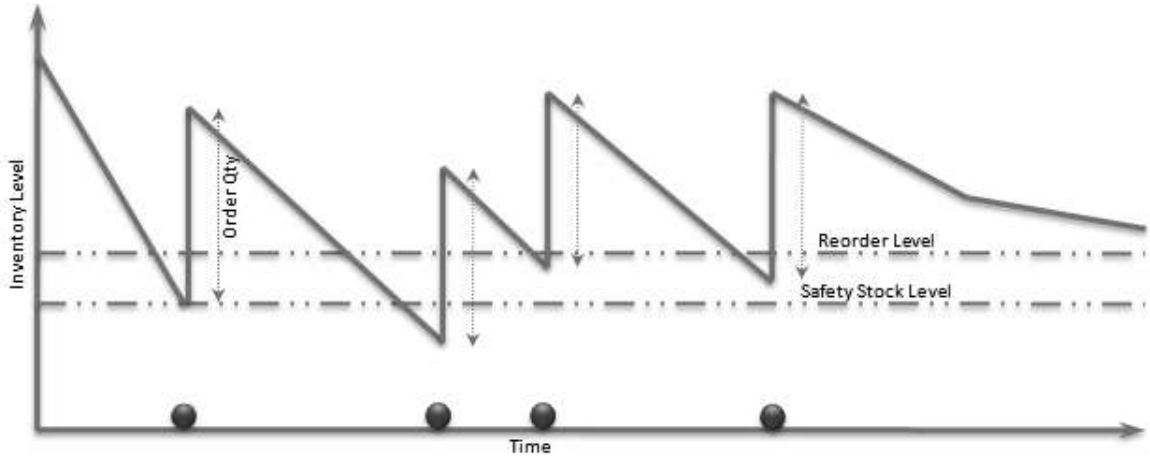

Figure 2 - Representation of the (s, Q) System

The reorder point (s) can be calculated as depicted in Equation 2.16 and the quantity Q is usually given by the Economic Order Quantity, as it minimizes the total costs, and can be calculated using Equation 2.12. Despite this equation being developed for deterministic models, it has been shown that the error of using this formula for a probabilistic demand approach is minimal compared to the optimal solution (Maddah & Noueihed, 2016).

Commonly, this algorithm is implemented with two storage bins. The items in the first bin will be used to satisfy the demand and the second bin corresponds to the order point. Primarily demand will be fulfilled with items from the first bin, when those are not enough and there's a need to resort to second bin, an order is then triggered. When replenishment arrives, first the second bin is filled and then the remainder is sent to replenish the first.

The main advantage of this policy is its simplicity, especially in its two-bin form, making it easier for the personnel to understand. It's also worth to note that there's less probability of error occurrence and the production requirements for the supplier are predictable since the orders are sent in fixed quantities.

Regarding the disadvantages, if the quantity Q is not adjusted properly, the system might not be able to cope effectively with a large individual order, particularly when Q is not enough to raise the inventory position above the reorder point (Pyke et al., 2017).

2.2.2.2.2. Order-Point, Order-Up-to-Level (s, S) System

Once again, we are before a continuous review policy that triggers an order when the inventory position drops to the order point s or lower. However, the replenished quantity is now variable, ordering just enough to bring the inventory level to its order-up-to-level (S), as shown in Figure 3.

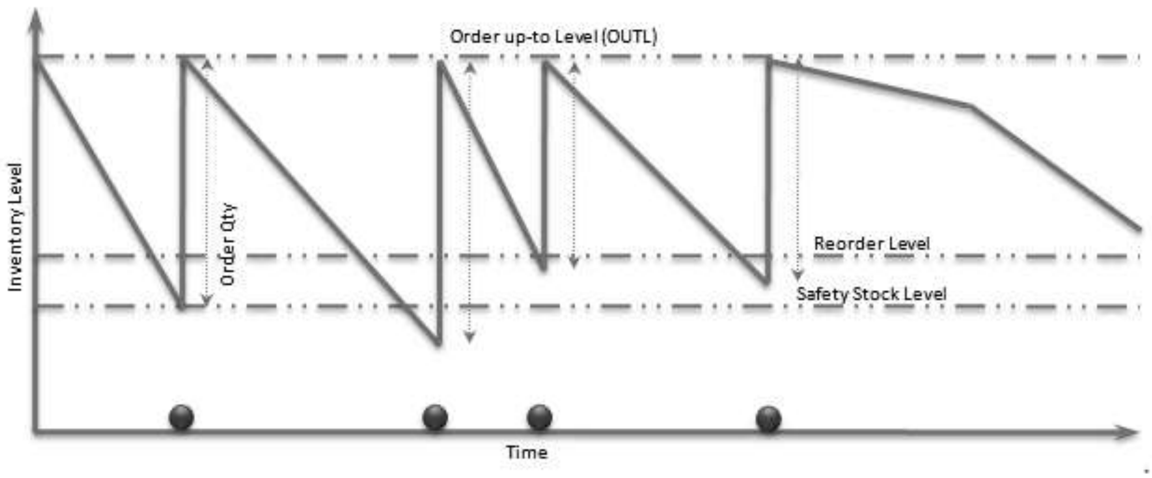

Figure 3 - Representation of the (s, S) system

Like the previous system, the reorder point (s) can be calculated as depicted in Equation 2.16. Going forward, we need to calculate the order-up-to-level (S), which is given by the following equation:

$$S = s + Q \tag{2.20}$$

Where, once again, Q is usually given by the Economic Order Quantity, calculated through Equation 2.12

The quantity to be ordered will be given by the following equation:

$$Order = S - IP \tag{2.21}$$

The best (s, S) systems can be shown to outperform the best (s, Q) in terms of replenishment costs, carrying inventory and shortage, but this comes with greater computational effort, making this approach particularly interesting for items that present great savings potential (Pyke et al., 2017). Despite this fact, the (s, S) policy is frequently encountered in practice, however, the values for the control parameters are usually set in an arbitrary fashion.

The main disadvantage of this system relates to the variable order quantity, as the suppliers could make errors more frequently and they also tend to prefer more predictable orders, especially if the size is convenient for both packaging and handling (Pyke et al., 2017).

To sum up the continuous revision algorithms, in the table below, the essential information regarding each algorithm is presented.

Table 4 - Summary of the continuous revision algorithms

Algorithm	Type of order	Order size
(s, Q)	Fixed	EOQ
(s, S)	Variable	(S - IP)

The (s, Q) algorithm is characterized by placing orders of fixed quantities, which usually correspond to the economic order quantity (EOQ). In the (s, S) system, we place orders of variable sizes, as the order amount is given by the difference between the order-up-to-level and the current inventory position.

2.2.2.3. Periodical Revision Models

In these models, all the orders are sent at a pre-defined date, agreed previously with the supplier, with a fixed periodicity. When the day arrives, we compare the inventory position with the order-up-to-level, the order will be the difference between the values.

To deal with the randomness associated with the demand it's important to allocate a safety stock to assure a certain service level, which can be calculated through the following expression:

$$Safety\ Stock = z\ \times \sigma_{R+L} \tag{2.22}$$

Where z corresponds to the safety factor and σ_{R+L}, the standard deviation of the demand during the R+L period, is the defined in the equation below:

$$\sigma_{R+L} = \sqrt{(T + \bar{L}) \times {\sigma_d}^2 + \bar{d}^2 \times {\sigma_L}^2} \tag{2.23}$$

Where:

R= time between deliveries

$\bar{L}$= average delivery time

$\bar{d}$=average demand during the delivery time

σ_d= demand standard deviation

σ_L= delivery time standard deviation

Once again, we will be following Pyke et al. (2017)'s recommendation on the most common periodic revision model: Periodic Review, Order-up-to-Level

2.2.2.3.1. Periodic Review, Order-up-to-Level (R, S) System

Also known as a replenishment cycle system, this is a model that's particularly common in companies without sophisticated computer control software. This algorithm is designed so that every R units of time an order will be made of just enough stock to raise the inventory position to the order-up-to-level(S), as shown in Figure 4.

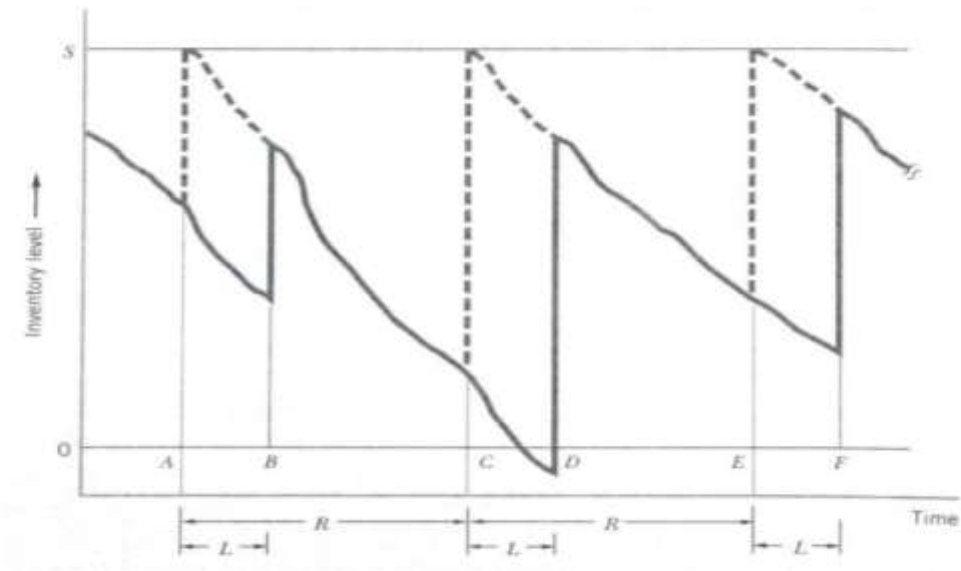

Figure 4 - Representation of the (R, S) system

A, C and E – Time of Order; B, D and F – Time when the order is received

Dashed Line – Inventory Position; Continuous Line – On-hand inventory

The order-up-to-level can be calculated using Equation 2.20. The time between revisions should be agreed with the suppliers but should be as close as possible to the Economic Order Interval, which is calculated as:

$$EOI = \frac{EOQ}{D} = \frac{\sqrt{\frac{2DA}{H}}}{D} = \sqrt{\frac{2A}{DH}} \tag{2.24}$$

Where:

EOQ= Economic Order Quantity, units

D = Demand, units/ unit of time

A = Ordering cot, €/unit

H = Holding cost, €/unit/ unit of time

This system is usually preferred when coordinating replenishment of related items or in cases where optimizing transported inventory is necessary to diminish costs (Pyke et al., 2017).

2.2.2.4. Hybrid Model – The (R, s, S) System

This structure combines both the (s, S) and (R, S) algorithms so that every R units of time the inventory position is assessed. If it is below the reorder point (s), one order is placed so that the level can be brought up again to its order-up-to-level (S). On the other hand, if the inventory position is above the reorder point, no order is made until the next audit (Pyke et al., 2017). An example of this algorithm is depicted in Figure 5.

Once again, the reorder point can be calculated by Equation 2.16, the order-up-to-level through Equation 2.20 and the revision period with Equation 2.24.

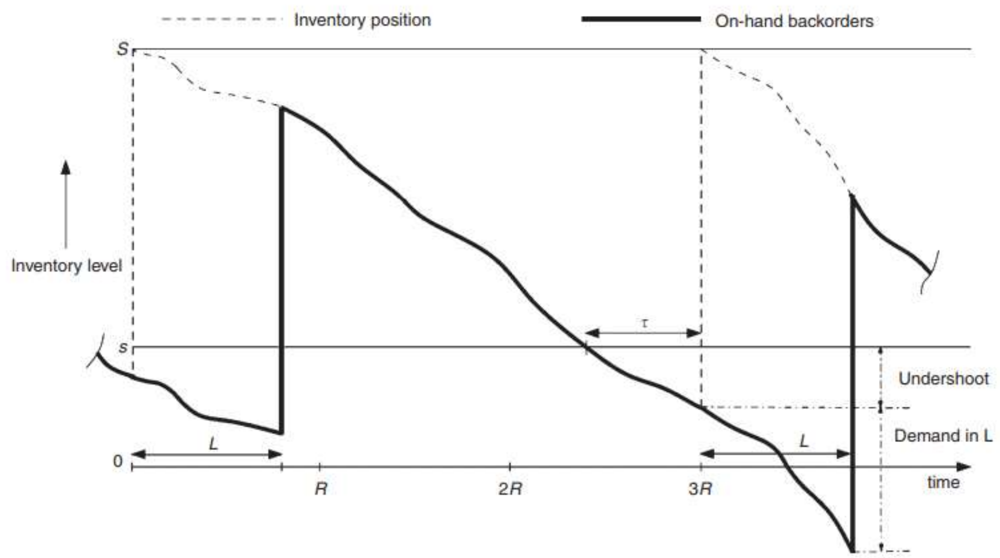

Figure 5 - Representation of the (R, s, S) system

After understanding the role played by the inventory policies in the bullwhip effect, learning what are the most common policies implemented in the industry and how do they work, it's important to start thinking about which factors are important to consider when studying the bullwhip effect in a supply chain.

2.3. The Bullwhip Effect analysis in Supply Chains

The challenge of studying and analyzing a complex system, such as supply chains, demands that we make several decisions, and those need to be taken seriously as they can affect our outcomes. When modeling the bullwhip effect, the main decisions include choosing the supply chain structure, the modeling strategy, inventory control policies and performance measures (Giard & Sali, 2013). We will now take a look at each one of these factors, in order to understand our options.

2.3.1. Structure

A supply chain (SC) can be defined, according to Thierry et al. (2008), as a network of organizations that are involved, through upstream and downstream links, in the different processes and activities that create value to the customer. These organizations can be organized in several forms, commonly represented by a graph connected by arrows. These representations show the different constraints of the SC, both on the information and physical level and indicate the modeling tools required and their complexity. Typically, there are 5 common structures used when representing a SC (Giard & Sali, 2013):

- Dyadic Structure – Connects a single customer with a single supplier;
- Serial Structure – A supply chain where a node can be connected to only one upstream node and only one downstream node;
- Divergent Structure – A supply chain where a node can be connected to only one upstream node, but several downstream nodes;
- Convergent Structure – A supply chain where a node can be connected to several upstream nodes, but only one downstream node;
- Network Structure – There is no restriction on the connections;

A great part of the literature reviewed by Giard & Sali (2013) considers SCs to be either dyadic or serial. The focus on the dyadic SC is due to the fact that they are the basic components of any configurations, yet they are only valid under certain assumptions. The serial structure becomes particularly relevant when the results from the dyadic structure are too complex and the customer demand is managed by only one supplier.

2.3.2. Modeling

The development of Supply Chain Management (SCM) created the need to carefully design approaches in order to investigate and assess the performance of the supply chain (Kersten & Saeed, 2014). There are 3 different ways to model and analyze a supply chain: Analytical Methods; Physical Experimentations; and Simulation;

Analytical methods can become impractical due to the complexity of solving the model of a real case, and as expected, there are huge limitations, both cost and technical, related to physical experimentations. (Thierry et al., 2008). In order to respond to these difficulties, the simulation models started to gain appeal, as they were able to model complex systems in real time that the analytical models were deemed too impractical to represent (Giard & Sali, 2013).

After reviewing articles published between 2010 and 2013, Derbel et al. (2014) concluded that researchers tend to prefer using simulation to study the bullwhip effect, so this dissertation will be focused on that topic.

2.3.2.1. Simulation

Simulation has been preferred in the domain of the SCM, as it is the better approach to model and analyzes performance measures, allowing to experiment with different scenarios in order to design better solutions and evaluate them before they are implemented in the real life (Kersten & Saeed, 2014). It becomes especially interesting when "theoretical focus is longitudinal, non-linear or processual", or empirical data is not easy to access, and can show how the different actors and supply chains interact throughout the time (Macdonald, Zobel, Melnyk, & Griffis, 2018).

One of the main benefits of simulation is the creation of models without limiting assumptions, these models can be created with as much precision as desired. Allied to this, simulation allows the user to either speed up or slow down time, providing an easier monitorization of the process. Last, but not least, another useful feature is the incorporation of random events, allowing an estimation of their effects (Wan & Evers, 2011). All these main features, along with others, enable the "what-if" analysis that guides us to a better decision and policy evaluations (Thierry et al., 2008).

Broadly speaking, we can distinguish 5 categories of simulation:

2.3.2.1.1. Spreadsheet Simulation

Spreadsheet simulation is the use of a spreadsheet to represent simulation models and perform experiments. Despite not being used as a formal analysis method, it has been widely used in the decision making context (Kersten & Saeed, 2014), a few examples are the performance evaluation of a manufacturing system developed by Koo et al. (1994 apud Kersten & Saeed, 2014) and the determination of a replenishment policy in a vendor managed inventory system, done by Sui et al. (2010 apud Kersten & Saeed, 2014).

2.3.2.1.2. System Dynamics

This type of simulation assumes that the state of the system varies continuously. Companies are considered complex systems comprised of different types of flows and stocks, where the individual elements can’t be differentiated, thus the managerial control is done by changing the rates of the variables, which impacts the flows and stocks (Kersten & Saeed, 2014).

2.3.2.1.3. Discrete-Event

In the discrete-event simulation, a state change happens at discrete stages in time, representing individual events. It is more detailed, compared to the previous types presented, and it’s an important method used in SCM providing support in several decision-making processes (Kersten & Saeed, 2014). According to Kersten & Saeed (2014), this is the most frequently used method by scholars when doing research.

Given the fact that the purpose of this dissertation is to study replenishment algorithms and their effect on the bullwhip effect, a small list of articles was chosen due to their use of discrete event simulation, data availability, easiness of comprehension and algorithms tested. The studies, along with respective authors, a brief description and algorithms used are summarized in Table 5.

Table 5 - Studies of inventory control models using simulation

Author	Algorithm tested	Description
Ponte et al. (2015)	(R, S)	Illustrates the generation of BE at a water supply network through simulation
Patil, Jin, & Li (2011)	(s, Q)	Simulates a multi-echelon supply chain in order to improve customer service
Saife, Seliaman, & Ahmad (2006)	(s, S)	Provides data to develop a simulation model that will be used by the authors in future research to optimize several parameters related to replenishment algorithms
Wan & Evers (2011)	(s, S)	Compares the bullwhip effect in a supply chain with a variable number of retailers

2.3.2.1.4. Agent-Based

This type of simulation considers an agent as a real or virtual entity that captures the behavior of several entities and acts independently in its surrounding world (Saberi et al., 2012; Ilie-Zudor and Monostori, 2009 apud Kersten & Saeed, 2014). The agents are autonomous, reactive, proactive and have social abilities among them (Julka et al., 2002 apud Kersten & Saeed, 2014), as systems with multi-agents collaborate and share information among their agents in order to improve their solutions.

2.3.2.1.5. Business Games

Business Games are usually used for education and research. They appeared due to the difficulty of modeling human performance and, a simple solution would be allowing managers to operate the supply chain in a simulated environment, such as a game (Campuzano & Mula, 2011). Some examples are the “Beer-Game” and the “Lean Leap Logistics Game”, but several games have been proposed recently (Kersten & Saeed, 2014). These games can be divided into 2 groups:

- Strategic Games – several teams compete between themselves;
- Operational Games – a unique team interacts with the model for several rounds;

2.3.3. Performance Measures

Performance measures (PMs) are important when we want to draw comparisons between presented alternatives, thus it's a must to include one or more key indicators (Giard & Sali, 2013).

There's a wide range of supply chain performance measures, but since we this thesis intends to evaluate the performance of a SC under different replenishment policies, we focused our research in understanding which PMs are used under these circumstances. In the table below, follows a summary of the literature review performed by Pamulety, George, & Pillai (2017) which analysis the work done by the several authors who studied replenishment systems, highlighting the PMs used.

Table 6 - Common PMs used in supply chains with replenishment systems based on Pamulety, George, & Pillai (2017)

Author	Performance measures used
Chatfield et al. (2004) Chen et al. (2000) Daniel and Rajendran (2005) Dominguez et al. (2014) Paul and Rajendran (2010) Pillai et al. (2013), Wadhwa et al. (2009)	Order variance ratio, cost, service level, inventory variance ratio
Chan and Prakash (2012) Kelle and Milne (1999) Monthatipkul and Yenrade (2008) Pillai et al. (2013) Wadhwa et al. (2009)	Order variance ratio, cost, service level
Andersson and Marklund (2000) Chan and Prakash (2012) Lee and Wu (2006) Pillai et al. (2013) Wadhwa et al. (2009)	Cost, average stock level, back order level, order variance ratio

3. CREATION OF SIMULATION STUDY MODEL

As stated before, the main objective of this dissertation is to study the impact of the several replenishment algorithms in the bullwhip effect experienced by a company. That study will be done by simulating a four-echelon supply chain under the several policies addressed in the previous chapter. In order to do that, we will be using discrete-event simulation through the use of the Simul8 software.

Later, a comparison study will be done in order to assess the impact each of the policies has on the several key performance indicators (KPIs) previously defined as critical to evaluate the results.

3.1. Model and Parameters

The model used in this dissertation is based on the work done by Wan & Evers (2011). The authors built their model on the well-studied Beer Game model introduced by Jay Wright Forrester in 1958.

The studied supply chain is, therefore, comprised of four echelons organized in a serial structure, a retailer, a wholesaler, a distributor, and a factory, with only one firm per echelon, as depicted in the figure below, and comprised of only one product.

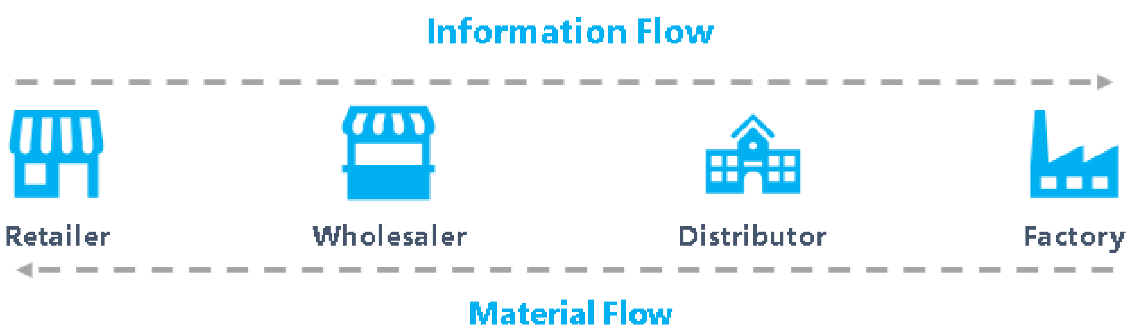

Figure 6 - Case study supply chain model

The process starts at the beginning of every shift, when each firm receives a shipment from its supplier, increasing its on-hand stock. If there are any backorders, they are shipped.

If an order from a customer arrives, the company checks whether it has available stock or not. If it has, the requested quantity is sent and deducted from the on-hand inventory. In the case of not having enough available on-hand inventory to fully satisfy the order, the company sends the available quantity, reduces the on-hand inventory and updates the backorder inventory. The inventory position is refreshed, and the firm checks whether it needs to make an order to its suppliers. In the case they do, the order is made at the end of the shift.

Despite being a simple process, some considerations are taken into account in order to diminish the number of factors that could cause noise to the measures.

First, we consider that each shift is comprised of 8 working hours and that each firm works 5 days a week.

Next, it should be pointed that an order is received by the supplier one day after its placement by the customer due to processing activities and the transportation time is set at 2 days, between any point within the supply chain, except the factory which has instantaneous replenishment.

As explained, orders arrive daily at the retailer and they come in lots sized according to a Poisson Distribution with a mean of 30 units.

Like the original Beer Game, there are no capacity constraints for production or transportation, and it’s assumed that there are no break downs, changeovers or additional delays.

For the sake of the reader, a simplified list of the simulation inputs is shown in Table 7.

Table 7 - Simulation Input Parameters

Parameter	Distribution
End Customer Inter-Arrival Time	1 [Day]
Customer Demand	Poisson (30) [units]
Transport Retailer-Wholesaler	2 [Days]
Transport Wholesaler-Distributor	2 [Days]
Transport Distributor-Factory	2 [Days]

3.2. Base Simulation model

In order to facilitate the simulation process, a base model was built and then previously adapted to the different algorithms.

The first step was to represent both the flow of information and materials within the supply chain. The division is shown in Figure 7.

We will now elaborate on each of the flows in order to understand how they were built.

3.2.1. Information flow

The information flow represents the process of ordering a product through the supply chain. It starts when a client arrives at the “Encomendas” Work Entry Point, after this, the request is sent to the “Retalhista” workstation. Here, the request is attached the labels “hora_chegada” and “hora_despacho”, and divided in two pieces of information, one that will follow through the information flow process and the other will be sent to the storage bin “PreDelieveryR” in order to be attached to the stock and assure that a particular stock is assigned to a customer.

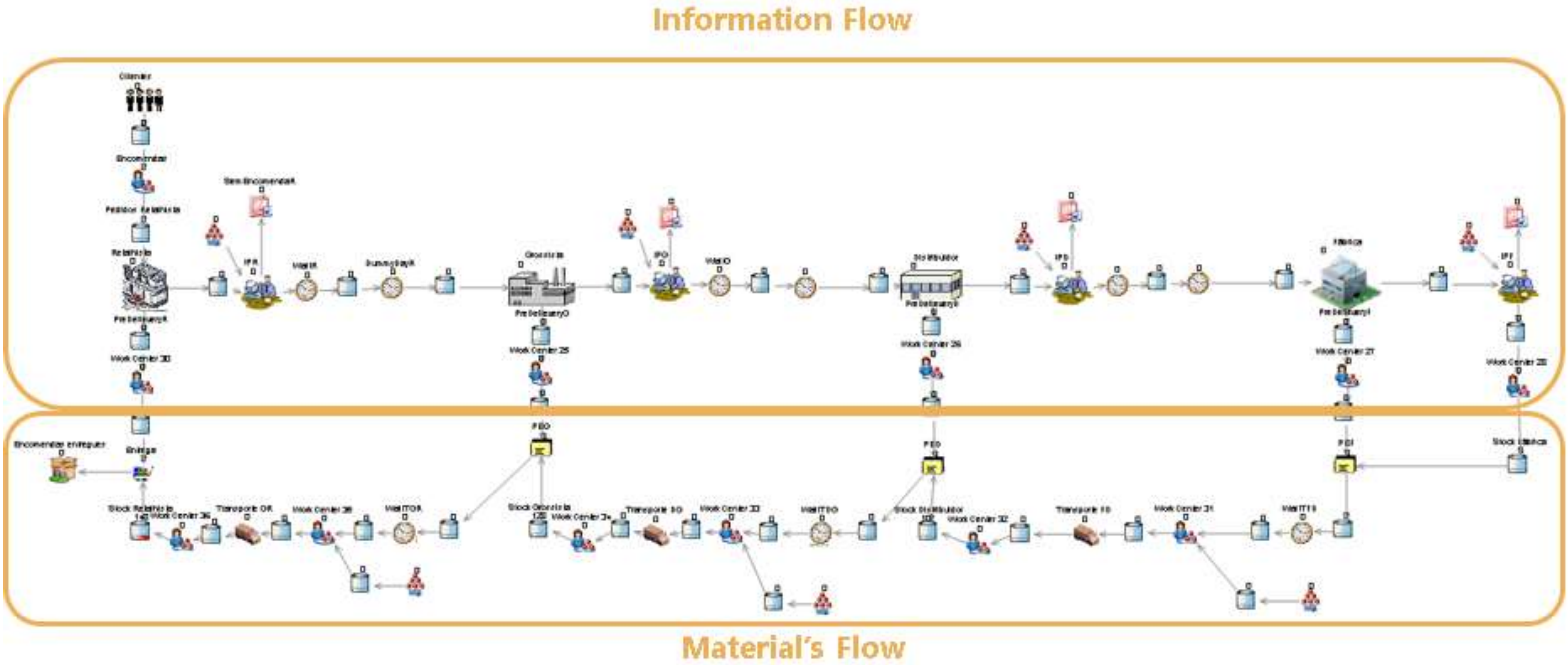

Figure 7 - Representation of the Information and Material Flow

Next, the request that follows the information flow path goes to the "IPR" workstation. Here, as well as on the "IPG", "IPD" and "IPF" workstations, through the help of Visual Logic we will be checking the need for the echelon to make an order to its supplier, or not, direct the request given this decision and, lastly, in the case where an order is made, save its value to an excel sheet.

The decision to order is made based on the inventory position, independently of which of the algorithms is chosen, which is calculated as depicted in Figure 8. The label "onHandR" accounts for the stock present at the retailer level at the time the work item passes through the "IPR" workstation, "BackOrdersR" gives the number of orders that are awaiting the arrival of stock in order to be fulfilled, and the "onOrderR" local variable[2] captures the value of the global variable "InTransportR" at the given time, showing the current number of orders being transported to the Retailer. Then, according to Equation 2.15, we calculate the Inventory Position.

```
SET onHandR = Stock Retalhista.Count Contents
SET BackOrdersR = BackR.Count Contents
SET onOrderR = InTransportR
SET InvPosR = [[onOrderR+onHandR]-BackOrdersR]-order
```

Figure 8 - Visual Logic to calculate Inventory position

After deciding whether an order should be filled or not according to each of the algorithms it must be routed accordingly. To do that, we use the "Routing out by label" option in the "Routing out" menu and choose the label "RotaEncomendaR" in the "Detail" button. We can see that if the label as the value 1 it will follow to the "SemEncomendaR" Work Exit Point and if it has the value of 2 it will go the "WaitR" work center as shown in Figure 9.

[2] The Simul8 software gives us the possibility to assign both local and global variables. Global Variables are accessible at any time by any point of the simulation. Local variables are attached to a particular work item and can only be accessed if said item is being handled by the workstation that is requesting the variable.

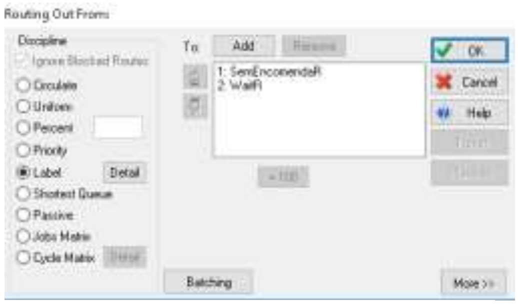

Figure 9 - Routing out of IPR, IPG and IPD

Given this, we can set the value of the label with the Visual Logic keeping in mind that if we want to place the order we should assign the label "RotaEncomendaR" the value of 2 and if the algorithm deems unnecessary an order placement this label should have the value of 1, as shown below.

```
SET RotaEncomendaR = 1    SET RotaEncomendaR = 2
```

Figure 10 - Visual Logic for order routing

Next, in the case an order is sent, the value of the inventory in transit is updated by adding the size of the order to the variable "InTransportR" as shown below.

```
SET InTransportR = InTransportR+encomendaR
```

Figure 11 - Update of in-transit inventory

In the end, in order for posterior data treatment to be possible, the information regarding all the order made is kept in a spreadsheet that can be exported to an excel file. The values of the order, as well as the time it was made, are stored with the help of the Visual Logic depicted in Figure 12.

```
SET LotesRetalhista[1,LinhaLotes] = Simulation Time
SET LotesRetalhista[2,LinhaLotes] = encomendaR
SET LinhaLotes = LinhaLotes+1
```

Figure 12 - Visual Logic for Spreadsheet creation

Given the need to work with independent values for each echelon, labels such as “encomenda”, “RotaEncomenda”, “InvPos”, “onHand”, “BackOrders”, “InTransport” and “OnOrder” are set at each of the mentioned workstations, we can differentiate each echelon by the end letter of the label, as an “R” pertains to the retailer, “G” to the Wholesaler, “D” to the Distributor and “F” to the Manufacturer.

If there’s no need for replenishment, the request is sent to the work exit point, “SemEncomenda”, though a label-based distribution built on the value set by the Visual Logic code, represented at the top of the respective workstations.

In the case where an order needs to be made, the workstation sends out a batch of requests and increases the number of units in transport. This batch is, for the case of the Retailer, based on the size of the “encomendaR” label. These requests will then follow to the next workstation, “WaitR”, where the values to the labels “hora_chegada” and “hora_despacho” will be attributed with the following Visual Logic code:

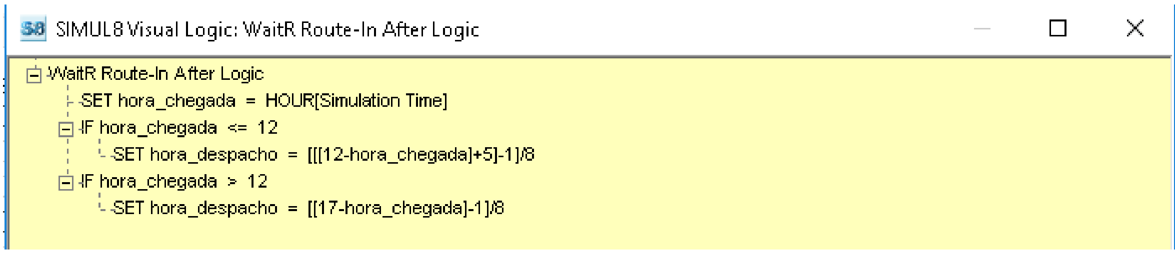

Figure 13 - Visual Logic code for "WaitR", “WaitG”, “WaitD” and “WaitF”

This code, along with label-based distributions, will guarantee that the orders will only be released at the end of each shift. At arrival, the code sets the variable “hora_chegada” to the current simulation time, representing the arrival time at the workstation.

In the case where an order arrives before or at noon, the time for it to leave the workstation is calculated by checking the remaining time until noon and adding the 5 hours until the end of shift. Then, because the software skips from 17h to 9h right away, an hour is subtracted so that the request can still be sent on that same day. In the end, since the simulation clock is pre-set to days, there’s the need to divide the previous result by 8 hours, duration of the shift, to get the result in days. If the order arrives afternoon, the process is similar to the previous, except that we only need to check how many hours are left until the end of shift (17h) before proceeding to all the adjustments.

The workstations “WaitG”, “WaitD” and “WaitF” work in a similar fashion, changing the values of the labels “hora_chegada” and “hora_despacho” each time a request arrives at any of these workstations.

Moving on, the orders arrive at the “DummyDayR” workstation, where they simply wait for 24 hours, to comply with the order processing time set by the authors. Once again, “DummyDayG”, “DummyDayD” and “DummyDayF” work in the same way.

At the end of the processing time, the requests will then follow to the next echelon, which works exactly like “Retalhista”, except at the factory level, as this echelon is considered to have infinite capacity. At the factory level it was considered that the production time was zero, so as soon as the request arrives, stock of that same amount is sent to the “StockFábrica” storage bin.

3.2.2. Material Flow

The material flow represents the path traveled by the stock ordered from its supplier to its customer.

Starting at the Manufacturer level, when an order arrives, in case there’s no backorder upon arrival, it goes straight to the “PEF” work center. Here, the order is attached to an item from “StockFábrica” storage bin and follow immediately to the “WaitTFD” work center. In this case, given the condition of the infinite capacity of this level, there’s always available stock to cover the demand. In the other echelons, its capacity is constrained by their stock level in “StockDistribuidor”, “StockGrossista” and “StockRetalhista”, whether we are at the Distributor, Wholesaler or Retailer echelon, respectively.

Given the case that there’s no stock available, the order is backordered and waits until there’s available stock to fulfill it, only then it can follow to the next workstation.

Upon arriving at “WaitTFD”, the stock is assigned the label “horaTransporte” and is kept waiting until the end of the shift before being shipped through the use of a distribution based on the label “horaTransporte”.

Through Visual Logic, the value of the label "hora_chegada" is reset to the current simulation time, and the time remaining until the end of the shift is calculated and assigned to the "horaTransporte" label, as shown in Figure 14. The work centers "WaitTFD", "WaitTDG" and "WaitTGR" work in the same manner.

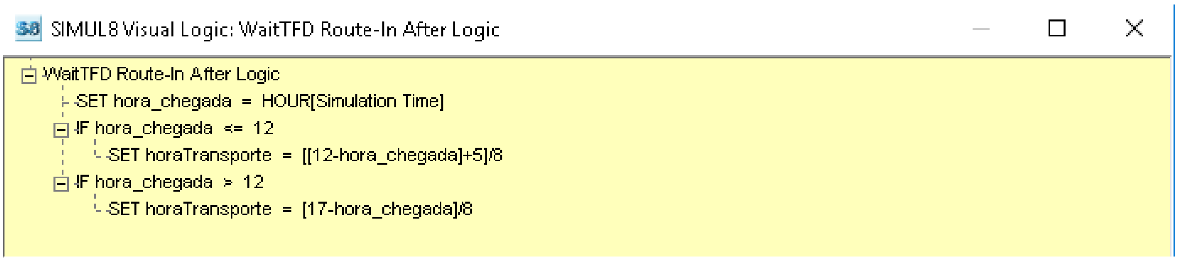

Figure 14 - Visual Logic code for "WaitTFD", "WaitTDG" and "WaitTGR"

At the end of the shift, the stock will be sent to "Work Center 31" where they will be shipped in lots.

In order to do this, a work item needs to be available at the "Storage Area 39". This storage bin is fed through "Work Entry Point 3", which delivers a work item daily since orders are at the beginning of every shift.

The lots are sent accordingly to the ordered amount if there's enough stock to fulfill the order, if not the available stock is sent, and the remainder is sent with the next lot. In order to control the size of the lots, there was a need to use Visual Logic, shown in Figure 15.

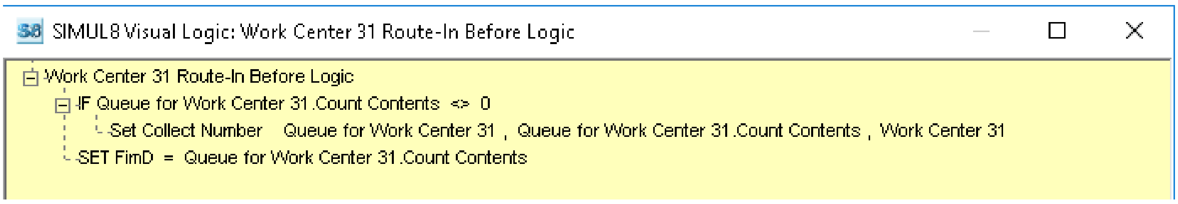

Figure 15 - Visual Logic for Work Center 31, 33 and 35.

Before entering the work center, the number of items to be collected is set to the number of items that are waiting for the "Queue for Work Center 31", and we also set the path of the lot to be the "Work Center 31".

Since the items were assembled into one lot, now we have the need to return the lot into individual items, in order to make this transformation, the number of items assembled is stored in the global variable "FimD".

Upon loading the work, we use visual logic to assign the number in “FimD” to the local variable “FinalD” that travels with each work item.

Next, the lot is sent to “TransporteFD”, where it will be kept for the assigned shipment time. At the end of this stage, it will be sent to “Work Center 32” where the lots will be converted into individual items and sent to the next echelon stock storage bin which, in this particular case, is the “StockDistribuidor”.

Upon exit it’s important to notice that each unit that leaves “Work Center 32” decreases the number of units in transports by one unit, making sure that each work item is only counted once.

After traveling through the whole chain, or partially, the stock arrives at the retailer level, where the order that the client sent to the Retailer is assigned stock from “Stock Retalhista” at the “Entrega” work center, it then follows to the work exit point “Encomendas Entregues”, which show us all the fulfilled client orders.

3.2.3. Results Collection and Warm-up Period

In order to only collect results that correspond to the system when it has reached its equilibrium, there was a need to set a warm-up period, and since we need enough data for the results to have some significance we also need to set an appropriate results collection period.

These times were chosen according to the recommendation of the authors Wan & Evers (2011), which defined the warm period to be 150 days and collected for 300 days.

3.3. Implementation of the algorithms

After developing the base model, we are ready to start the process of implementation of the algorithms that we wish to test. This process starts with the calculation of the initial parameters’ that define each algorithm and posterior implementation in the simulation.

3.3.1. Definition of starting parameters

In order to calculate the initial parameters, we need to take in account several data, such as average demand that the echelon needs to serve and its standard deviation, both average and standard deviation of the lead time, service level and costs related to holding, stockout and ordering.

The values for the demand average and standard deviation are computed after data collection from the simulation, calculated with Excel's "AVERAGE" and "STDEV.S" functions, respectively, and converted to daily demand[3]. The service level is set by default at 95% for all echelons. A summary of the obtained data is gathered in Table 8.

Table 8 - Values for demand and service level

Parameter	Values
Average Demand at the retailer	30.192 [units/day]
Standard Deviation of the Demand at the Retailer	5.735 [units/day]
Service Level	95%
Safety factor (z) for the required service level	1.645

The values for the costs were obtained from the work done by Saife, Seliaman, & Ahmad (2006), illustrated in Table 9, and the ordering costs were adapted in order to have an EOQ larger than the average demand.

Table 9 - Original cost values provided by (Saife et al., 2006)

	Retailer	Wholesaler	Distributor	Factory
Ordering Costs [€]	10	15	20	-
Holding Costs [€/unit/day]	5	6	10	12
Stockout Costs [€/unit]	7	10	15	12

[3] A more detailed explanation of this process can be found in section 4.3- Lot Size, Time Between Orders and Daily Customer Demand Calculation.

In order to do this, the original values were multiplied by a factor of 11, the first number that allowed the needed condition, the resulting values are summarized in Table 10. On another note, since the authors didn't provide an ordering cost for the factory, given the fact that the original values for these costs were increasing by 5€ per echelon, we considered a possible base value for the factory to be 25€.

Table 10 – Adapted cost values for Ordering, Holding and Stockout Costs

	Retailer	Wholesaler	Distributor	Factory
Ordering Costs [€]	110	165	220	275
Holding Costs [€/unit/day]	5	6	10	12
Stockout Costs [€/unit]	7	10	15	12

The values of the lead time depend on the algorithm used, so they are calculated with the help of the simulator and posteriorly treated in Excel.

3.3.2. Data gathering process

Given the fact that we only have data to calculate all the parameters for the retailer echelon, we will need to acquire the data for the remaining nodes through the simulation. To do this, after calculating the parameters of one node, we update the values in the simulation and then re-run it. After that, we are able to obtain the values of the demand for the following node and proceed with the calculations.

The lead time presents a special case for data gathering, as we can't immediately obtain it until we have all the parameters, this is due to the fact that despite we consider a fixed lead time of 3 days, every time there are backorders somewhere in the supply chain it affects all the nodes. This means that the lead time needs to be computed individually for each node in each algorithm.

In order to have a start point to begin the calculations, the initial lead time considered in all algorithms was the 3 days of lead time, considering 2 days for transportation and 1 day for processing, with no standard deviation, except the factory due to the instantaneous replenishment condition.

After all the parameters related to demand are calculated, verification for the lead time is run at each echelon.

Once again data is collected and with the help of the Excel's functions "AVERAGE" and "STDEVPAD.S" so that we are able to obtain the average and standard deviation of the lead times.

Then, all the parameters are once again adjusted to make sure that they reflect the real lead times. This process is repeated until the lead time variation is no longer verified or is so small that doesn't cause alteration in the parameters that are being calculated.

3.3.3. Calculation of the required inputs

Now that we are aware of how all the models work and we built a functioning base model, in order to start the process of implementation of the specific algorithms, we must calculate all the required parameters they need to set their conditions. The following sections present a guide on how to calculate said parameters, an explanation of the adaptations made to the base simulation model and tables with all the final values obtained.

3.3.3.1. Order Point, Order Quantity (s, Q)

This algorithm requires that we define the Economic Order Quantity (EOQ) and a Reorder Point (s), as defined in section 2.2.2.2.1, which means that these inputs will be used in our simulation process. This data is computed using Equations 2.12, 2.16, 2.17, 2.18

```
PR Route-In After Logic
    SET onHandR = Stock Retalhista.Count Contents
    SET BackOrdersR = BackR.Count Contents
    SET onOrderR = InTransportR
    SET InvPosR = [[onOrderR+onHandR]-BackOrdersR]-order
    IF InvPosR > 147
        SET RotaEncomendaR = 1
    IF InvPosR <= 147
        SET RotaEncomendaR = 2
        SET encomendaR = 36
        SET InTransportR = InTransportR+encomendaR
        SET LotesRetalhista[1,LinhaLotes] = Simulation Time
        SET LotesRetalhista[2,LinhaLotes] = encomendaR
        SET LinhaLotes = LinhaLotes+1
```

Figure 16 - Visual Logic code for the (s, Q) algorithm

and 2.19. Posteriorly, they are coded at the “IPR”, “IPG”, “IPD” and “IPF” workstations Visual Logic as shown in Figure 16.

From the above figure, we can see that if the inventory position reaches, or is below, the reorder point of 147 (see Retailer Reorder Point in Table 11), an order will be sent out. This order will be the economic order quantity defined for this echelon.

After obtaining all the values of EOQ and reorder points for each level, the parameters are adjusted by updating the lead times with the values generated by the simulator. The table below depicts all the values calculated for this system.

Table 11 - Final Values for the (s, Q) algorithm

	Retailer	Wholesaler	Distributor	Factory
Average Demand [units/day]	30.19	30.32	30.30	30.28
Demand Standard Deviation [Units/day]	5.74	0	0	0
Lead Time Standard Deviation [days]	0.20	0.37	0.29	0
Average Lead Time [days]	4.12	3.42	3.36	0
Safety Stock [units]	22	19	15	0
Economic Order Quantity (Q) [units]	36	41	36	37
Reorder Point (s) [units]	147	123	117	0

From Table 11 we notice that the order standard deviation becomes 0 after being batched in the retailer, this happens due to the fact that all orders will have the size of the Economic Order Quantity defined for each echelon, therefore there’s no variation within the echelon regarding the amount demanded.

3.3.3.2. Order Point, Order-Up-to-Level (s, S)

As previously seen in section 2.2.2.2.2, this algorithm requires the definition of an order point (s) and an order-up-to level (S).

After obtaining these parameters, using equations 2.12, 2.16, 2.17, 2.18, 2.19 and 2.20, they are set at the “IPR”, “IPG”, “IPD” and “IPF” workstations with the help of Visual Logic, as shown in Figure 17.

```
IPR Route-In After Logic
    SET onHandR = Stock Retalhista.Count Contents
    SET BackOrdersR = BackR.Count Contents
    SET onOrderR = InTransportR
    SET InvPosR = [[onOrderR+onHandR]-BackOrdersR]-order
    IF InvPosR > 148
        SET RotaEncomendaR = 1
    IF InvPosR <= 148
        SET RotaEncomendaR = 2
        SET encomendaR = 184-InvPosR
        SET InTransportR = InTransportR+encomendaR
        SET LotesRetalhista[1,LinhaLotes] = Simulation Time
        SET LotesRetalhista[2,LinhaLotes] = encomendaR
        SET LinhaLotes = LinhaLotes+1
```

Figure 17 - Example of the IPR Visual Logic code for the (s, S) algorithm

Here we can see that an order is only sent to the next echelon if the inventory position is equal or below the reorder point of 148. In that case, the order sent is equal to the order-up-to level minus the current value of the inventory position.

Upon having all the reorder points and order-up-to levels for all echelons it's time to adjust them by checking the lead time with the simulator. The final values are detailed in the following table:

Table 12 - Final values for the (s, S) algorithm

	Retailer	Wholesaler	Distributor	Factory
Average Demand [units/day]	30.19	30.26	30.33	30.31
Demand Standard Deviation [Units/day]	5.74	9.76	16.11	26.94
Lead Time Standard Deviation [days]	0.23	0.20	0.19	0.00
Average Lead Time [days]	4.14	3.22	3.20	0.00
Economic Order Quantity [units]	36	41	37	37
Safety Stock [units]	22	30	48	0
Reorder Point (s) [units]	148	128	146	0
Order-up-to Point (S) [units]	184	169	183	37

3.3.3.3. Periodic Review, Order-Up-to-Level (R, S)

From the information gathered at the section 2.2.2.3.1, this system is based on the definition of a Review Period (R) and an Order-Up-to-Level (S) in order to decide whether an order should be made or not.

These parameters are calculated using equations 2.12, 2.16, 2.19, 2.20, 2.22, 2.23 and 2.24 they are set at the “IPR”, “IPG”, “IPD” and “IPF” workstations through Visual Logic, as shown in Figure 18.

```
IPR Route-In After Logic
    SET onHandR = Stock Retalhista.Count Contents
    SET BackOrdersR = BackR.Count Contents
    SET onOrderR = InTransportR
    SET InvPosR = [[onOrderR+onHandR]-BackOrdersR]-order
    IF Simulation Time <> IntR
        SET RotaEncomendaR = 1
    IF Simulation Time = IntR
        SET encomendaR = 194-InvPosR
        IF encomendaR > 0
            SET InTransportR = InTransportR+encomendaR
            SET RotaEncomendaR = 2
            SET LotesRetalhista[1,LinhaLotes] = Simulation Time
            SET LotesRetalhista[2,LinhaLotes] = encomendaR
            SET LinhaLotes = LinhaLotes+1
        ELSE
            SET RotaEncomendaR = 1
```

Figure 18 - Visual Logic for (R, S) system

The fact that we are dealing with a periodic review system created the need to add an additional parameter to the Work Entry Point (WEP) before the “IPR”, “IPG”, “IPD” and “IPF” work centers as shown in Figure 19. This WEP makes sure that an order is issued every R units of time as demanded in the algorithm. This is done by assigning the global variable “IntR” the time at which an object leaves the WEP and comparing the time at which it enters the work center. Since the transportation and processing times are zero, this process is instantaneous, so if the time at which an object enters the work center is equal to the time it left the WEP there’s an order to be made.

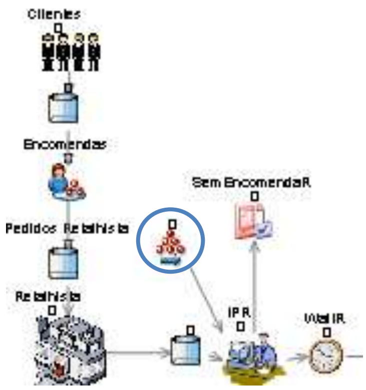

Figure 19 - Work Entry Point for Periodic Review system

The size of the order made is given by the difference between the Order-up-to-Point and the current inventory position. In the case this difference is greater than 0, the order follows through to the next step.

Finally, after obtaining all the values for R and S and perform the lead time adjustments, the final values obtained are represented in the table below.

Table 13 - Final Values for the (R, S) Algorithm

	Retailer	Wholesaler	Distributor	Factory
Average Demand [units/day]	30.19	30.27	30.83	31.77
Demand Standard Deviation [units/day]	5.74	13.24	16.69	19.70
Lead Time Standard Deviation [days]	0.34	0.43	0.49	0.00
Average Lead Time [days]	4.28	4.29	4.14	0.00
Economic Order Quantity	36	41	37	38
Safety Stock [units]	28	56	68	36
Reorder Point [units]	158	186	196	36
Order-up-to Point (S) [units]	194	227	233	74
Revision Period (R) [days]	1.207	1.348	1.195	1.201

3.3.3.4. Hybrid (R, s, S)

This system was presented in section 2.2.2.4, as the name states, it's a hybrid model that combines the (R, S) and the (s, S) systems. This implies that we will need all three parameters in order to succeed in its implementation.

These parameters are acquired using equations 2.12, 2.16, 2.19, 2.20, 2.22, 2.23 and 2.24 they are set, once again, at the “IPR”, “IPG”, “IPD” and “IPF” work centers by Visual Logic as shown in Figure 20.

```
IPR Route-In After Logic
  SET OrderR = order
  SET onHandR = Stock Retalhista.Count Contents
  SET BackOrdersR = BackR.Count Contents
  SET onOrderR = InTransportR
  SET InvPosR = [[onOrderR+onHandR]-BackOrdersR]-order
  IF Simulation Time <> IntR
    SET RotaEncomendaR = 1
  IF Simulation Time = IntR
    IF InvPosR <= 175
      SET encomendaR = 211-InvPosR
      IF encomendaR > 0
        SET InTransportR = InTransportR+encomendaR
        SET RotaEncomendaR = 2
        SET LotesRetalhista[1,LinhaLotes] = Simulation Time
        SET LotesRetalhista[2,LinhaLotes] = encomendaR
        SET LinhaLotes = LinhaLotes+1
      ELSE
        SET RotaEncomendaR = 1
    ELSE
      SET RotaEncomendaR = 1
```

Figure 20 - Visual Logic for the (R, s, S) Algorithm

Given the fact that this is a hybrid model, the decision of whether to order is divided into the two phases previously explained. First, we look through the periodic lens, and with the help of a structure like the one depicted in Figure 19, we will check if it’s time to make an order, i.e. if we are at the revision period (R).

If we are in the time frame we chose to make an order, we will look a bit through the continuous algorithm frame and check if we reached our reorder point (s). If any of these conditions are not met, either the work item didn’t arrive at the proper time to make an order or we are above the reorder point, this means that an order won’t go through to the next link and will be directed to its respective work exit point.

Assuming both conditions are met, we are able to make an order. The size will be determined by the difference between the Order-up-to-Point and the Inventory Position.

A table with the final values is presented below. These values are gathered after obtaining all the needed values and perform adjustments to the lead time.

Table 14 - Final Values for the (R, s, S) Algorithm

	Retailer	Wholesaler	Distributor	Factory
Average Demand [units/day]	30.19	30.32	30.33	30.16
Demand Standard Deviation [units/day]	5.74	10.48	12.23	13.59
Lead Time Standard Deviation [days]	0.72	0.74	0.74	0.00
Average Lead Time [days]	4.37	4.41	4.39	0.00
Economic Order Quantity	36	41	37	37
Safety Stock [units]	42	56	60	25
Reorder Point (s) [units]	175	190	194	25
Order-Up-to-Point (S) [units]	211	231	231	62
Revision Period (R) [days]	1.207	1.347	1.204	1.232

3.3.4. Validation

The simulation was validated by comparing the results obtained with the expected outcomes provided by the literature review.

4. RESULTS AND DISCUSSION

As previously mentioned, the main objective of this dissertation is to compare the impact of each replenishment policy in the bullwhip effect experienced in a determined supply chain.

In order to measure this impact at each echelon, as defined previously in section 2.1.2, four measures were selected: Bullwhip Effect, Alternative Bullwhip Effect, Average Stock Level, Average Customer Demand and Service Level. In order to fully comprehend the behavior of these metrics, complementary analysis were chosen: Average Lot Size, Average Lead Time, Average Time between Orders and Instability.

In the following sections, a detailed explanation for the computation of the bullwhip effect, alternative bullwhip effect, average customer demand, average lot size, the time between orders, average stock level and stockout percentage is presented.

4.1. Bullwhip effect Calculation

The calculation of the Bullwhip Effect follows the methodology proposed by Parra-pena et al. (2012), which adapts the calculation of the Bullwhip Effect to Excel.

In order to do this, both the customer demand and the demand for each echelon under each replenishment policy we obtained through the designated spreadsheets created in the simulation. We only took into consideration data beginning on the 150th day, as all the prior data was referent to the warm-up period, resulting in the evaluation of the supply chain in the remaining 300 working days.

The following table illustrates an example of the calculation of the Bullwhip effect using equations 2.5 and 2.6.

Table 15 – Spreadsheet for Calculation of the Bullwhip Effect using the method proposed by Parra-pena et al. (2012)) at the retailer echelon under an (s, S) replenishment system

A	B	C	D	E	F	G
Time (t) [days]	Customer Demand [units]	Retailer Demand [units]	Difference [units]	Variance at Retailer [units]	Variance at the Customer [units]	BE
150	18	0	-18	0	0	0
151	23	38	15	9.5	12.5	0.76
152	30	37	7	8.948	36.333	1.006
…	…	…	…	…	…	…
447	32	0	-32	0	34.297	48.417
448	37	71	34	11.227	34.337	48.744
449	32	0	-32	0	34.233	48.744
450	25	0	-25	0	34.209	48.744

First, we need to calculate the difference between customer demand and the retailer (or the echelon we wish to evaluate) demand.

$$Difference(150) = C150 - B150 \tag{4.1}$$

This formula is then applied as is until the end of the data.

Then, we compute the retailer variance using Equation 2.5, once again, the formula is applied as is until the end of data.

$$Var.Ret(t) = \left(IF \left(\begin{matrix} D_t <> 0;\ (A_t) * Power\left(\frac{C_t}{A_{t+1}}; 2\right) + \\ Power\left(C_t - \left(\frac{C_t}{A_{t+1}}\right) 2\right);\ 0 \end{matrix} \right) \right) / A_t \tag{4.2}$$

Next, we use Excel's "VAR" function which will compute the customer demand variance at time t, using the values since the 150th day, until t. This formula only applies after t=151 days, as the variance between only one value is assumed to be 0, therefore, E150=0.

$$Var.Customer(t) = Var(C\$150{:}\, C_t) \tag{4.3}$$

Finally, using Equation 2.6, we calculate the bullwhip effect starting on t=151 days. Due to the customer variance at the 150th day being equal to zero, its bullwhip will also be zero.

$$Bullwhip\ Effect(t) = G_{t-1} + IF\left(D_t = 0; 0; \left(\frac{E_t}{P_t}\right)\right) \tag{4.4}$$

4.2. Alternative Bullwhip effect Calculation

This calculation is very similar to the previous, except that instead of the demand at each echelon, we use the stock levels at each echelon. The following table shows an example of the spreadsheet used in the calculation of the alternative bullwhip effect.

Table 16 - Spreadsheet for Calculation of the Bullwhip Effect based on the method proposed by Parra-pena et al. (2012) at the retailer echelon under an (s, S) replenishment system.

Time (t) [days]	Customer Demand [units]	Retailer Stock [units]	Difference [units]	Variance at Retailer [units]	Variance at the Customer [units]	BE
150	18	72	54	34.331	0	0
151	23	72	49	34.105	12.5	2.728
152	30	50	20	16.340	36.333	3.178
…	…	…	…	…	…	…
448	37	52	15	6.022	34.337	89.782
449	32	16	-16	0.569	34.233	89.798
450	25	47	22	4.898	34.209	89.942

Just like the case of the Bullwhip effect, first, we need to calculate the difference between the customer demand and the retailer (or the echelon we wish to evaluate) demand, applying this formula to all the cells in the column.

$$Difference(150) = C150 - B150 \tag{4.5}$$

Then, we compute the stock variance at the retailer (or the echelon we wish to evaluate).

$$Var.Ret\ Stock(t)\ = \left(IF \left(\begin{array}{c} D_t <> 0;\ (A_t) * Power\left(\frac{C_t}{A_{t+1}}; 2\right) + \\ Power\left(\ C_t - \left(\frac{C_t}{A_{t+1}}\right)\ 2\right);\ 0 \end{array} \right) \right) / A_t \tag{4.6}$$

Next, we will compute the customer demand variance at time t.

$$Var.Customer(t) = Var(C\$150{:}\,Ct) \tag{4.7}$$

Finally, we calculate the alternative bullwhip effect starting on t=151 days. Due to the customer variance at the 150th day being equal to zero, its alternative bullwhip will also be zero.

$$Alternative\ Bullwhip\ Effect(t) = G_{t-1} + IF\left(D_t = 0; 0; \left(\frac{E_t}{P_t}\right) \right) \tag{4.8}$$

4.3. Lot Size, Time Between Orders and Daily Customer Demand Calculation

Next, follows a detailed explanation on how to calculate the average lot size, the lot size standard deviation, the average time between orders, average daily customer demand and the standard deviation the daily customer demand, using the retailer echelon following a (s, S) algorithm as an example. The table below shows an excerpt of the generated values for the orders received at the retailer.

Table 17 - Spreadsheet for Calculation of Lot Size (Average and Standard Deviation), Time Between Orders and Daily Demand (Average and Standard Deviation) at the Retailer echelon under an (s, S) replenishment system

A	B	C
Time	**Order**	**Time Between Orders**
151	38	
152	37	1
154	59	2
…	…	…
444	64	3
446	71	2
448	71	2

The Average Lot Size can be determined by calculating the average, using Excel's "AVERAGE" pre-set function, of all the issued ordered between the 150th and the 450th days at each echelon.

$$Average\ Lot\ Size = Average(B150{:}\,B450) \qquad (4.9)$$

The Lot Size Standard Deviation is determined using Excel's "STDEV.S" function, since we are working with a sample of the values, for all the values between the 150th and the 450th days at each echelon.

$$Lot\ Size\ Standard\ Deviation = STDEV.S(B150{:}\,B450) \qquad (4.10)$$

To obtain the time between orders we need to subtract the time at which the previous order was made to the time the current order is being made. Since the 151st day has the first order, we will only start to calculate after the 152nd day.

$$Time\ Between\ Orders(t) = A_t - A_{t-1} \qquad (4.11)$$

Now that we have both the average lot size and the time between issued orders, we can determine the average daily demand and its standard deviation.

$$Average\ Daily\ Customer\ Demand = \frac{Average\ Lot\ Size}{Time\ Between\ Orders} \tag{4.12}$$

Finally, the standard deviation of the daily customer demand can be computed as follows:

$$Standard\ Deviation\ of\ Daily\ Customer\ Demand = \frac{Lot\ Size\ Standard\ Deviation}{\sqrt{Time\ Between\ Orders}} \tag{4.13}$$

4.4. Average Stock Level Calculation

The average stock at each echelon is obtained using Excel's pre-set "AVERAGE" function between the 150th and 450th days.

4.5. Stockout Percentage Calculation

The stockout percentage will serve as a measure of the service level offered at each echelon under a certain policy.

In order to do this, we used Excel's "COUNTIF" to count all the values that were equal to zero, and "COUNT" to check how many inventory movements were made. The service level is then defined by:

$$Stockout\ Percentage = \frac{Number\ of\ Stockouts}{Total\ inventoy\ movements} \times 100\% \tag{4.14}$$

4.6. Final Results

After running trials on all the algorithms and performing the calculations for both the performance measures and complementary analysis, the following results were obtained:

Table 18 - Bullwhip Effect per Echelon

Algorithm/ Echelon	Maximum Bullwhip Effect experienced at each echelon			
	Retailer	Wholesaler	Distributor	Factory
(s, S)	48.744	71.397	103.038	159.001
(s, Q)	28.951	34.516	33.695	34.052
(R, S)	18.770	45.079	53.989	53.307
(R, s, S)	49.713	61.135	62.789	66.553

After observing Table 18 we can immediately observe that there's clearly a difference between the bullwhip generated by the replenishment algorithms and that, under the studied circumstances, the bullwhip effect it's minimized under an order-point, order quantity (s, Q) policy.

Taking a closer look to the same (s, Q) policy we can see that at first sight it has a somewhat odd behavior, as there's a decrease in the bullwhip effect between the wholesaler and distributor, but if we study the batch sizes, in Table 19~~Table 20~~, we can understand the reason behind this decrease.

Previously we saw that a smaller batch size contributes to a decrease in the bullwhip effect (Potter &Disney, 2006, apud Bhattacharya & Bandyopadhyay, 2011), if we look in Table 19 we can see that there's also a batch size decrease between the wholesaler and the retailer.

Table 19 - Average lot size ordered by each echelon

Algorithm/ Echelon	Average lot size ordered per echelon [units]			
	Retailer	Wholesaler	Distributor	Factory
(s, S)	54.470	78.319	104.151	144.182
(s, Q)	36	41	37	37
(R, S)	36.544	45.522	50.300	50.567
(R, s, S)	59.235	66.088	68.241	71.352

If we observe Table 20 we can see that also the lead time decreases between the wholesaler and the distributor when compared to the lead time between the retailer and the wholesaler. This decrease also contributes to the decrease in the experienced bullwhip effect, as previously explained by Disney et al. (2005) and Pozzi et al. (2018).

Table 20 - Average lead times experienced between the echelons

Algorithm/ Echelon	Average Lead Time [days]		
	Retailer-Wholesaler	Wholesaler-Distributor	Distributor - Factory
(s, S)	4.144	3.222	3.203
(s, Q)	4.119	3.419	3.356
(R, S)	4.284	4.290	4.146
(R, s, S)	4.373	4.414	4.389

In chapter 2.1.1.4 we introduced Potter & Disney's (2006) principle, stating that an increase in the time between orders generates an increase in the bullwhip effect, taking a look at the values in Table 21 we can see that there's an increase in time between orders, which translates into an increase in the bullwhip effect throughout the supply chain, in all the systems except for the (s, Q).

Table 21 - Time between orders at each echelon

Algorithm/ Echelon	Time between orders [days]			
	Retailer	Wholesaler	Distributor	Factory
(s, S)	1.800	2.583	3.440	4.600
(s, Q)	1.187	1.353	1.222	1.200
(R, S)	1.207	1.477	1.583	1.671
(R, s, S)	1.953	2.179	2.262	2.349

Taking into consideration the values observed for the time between orders, lead time and the batch sizes, they seem to predict the outcome obtained for the bullwhip effect.

Next, we will analyze the performance level since, at the end of the day, we need to attain a good performance level in order to maintain a business up and running, as we need to be able to give our customers what they want, when they want it. In the table below we can see the performance results, in terms of stockout percentage.

Table 22 - Stockout percentage at each echelon

Algorithm/ Echelon	Stockout percentage at each echelon [%]		
	Retailer	Wholesaler	Distributor
(s, S)	0.2%	2.5%	1.7%
(s, Q)	0.6%	11.0%	27.0%
(R, S)	6.6%	3.8%	4.4%
(R, s, S)	3.4%	7.4%	8.7%

From Table 22 we can gather some important information, despite previously setting our service level at 95%, accepting 5% stockouts, we can see that some values are quite far, some for better and others for worse. This means that we are either under-protecting or over-protecting our echelons, resulting in additional costs.

We can also see that, what up until now was the preferred algorithm, the (s, Q) model, is over-protecting its retailer and leaving its wholesaler and distributor largely unprotected, and as a manager, this is something we can't allow.

These deviations can be due to the fact that the lead time was assumed to be normally distributed in order to compute Equations 2.18 and 2.23, which require both the lead time' average and standard deviation. Since the actual distribution doesn't follow a normal distribution there will be deviations in terms of what would be the expected performance. Further research should be focused on using a computation of the safety stock that can handle other distributions besides the normal.

Another contributory factor, for the (s, Q) case, might be the fact that the Distributor's Economic Order Quantity is smaller compared to the Wholesaler's, which means that both of them will stock out, as the Distributor can't refill fast enough to deal with the Wholesaler's demand. As mentioned by Pyke et al. (2017), this system can have some troubles dealing effectively with large individual orders, especially if Q is not enough to raise the inventory position above the reorder point. It's advised the performance of a sensitivity analysis in order to understand how the system behaves under circumstances with increasing, decreasing or stable batch sizes between echelons, in order to understand if under the (s, Q) algorithm there are different types of responses in terms of both service level and the bullwhip effect, or if this example was an outlier.

Taking a look at the way inventories change over time in a supply chain is a good indicator of how much the information is being distorted by the replenishment algorithms, therefore indicating whether the bullwhip effect experienced is being enhanced or not.

First, by comparing Figure 21, Figure 22 and Figure 23, which represent the (s, Q) system, we can understand that there's a great increase in variability from the retailer to the wholesaler and that there's a smaller increase between the wholesaler and the distributor. We can also see that both the wholesaler and the distributor attain higher stock levels compared to the retailer, and both of them enter the stockout state multiple times, especially the distributor, as seen in Table 22. It's also noticeable that seems to be an increase from the average stock values from the Retailer to the Wholesaler and a small decrease between the Wholesaler and the Distributor. This decrease is probably due to the system's incapacity, to deal with the total Wholesaler's demand, generating a large number of stockouts, thus bringing down the average stock values.

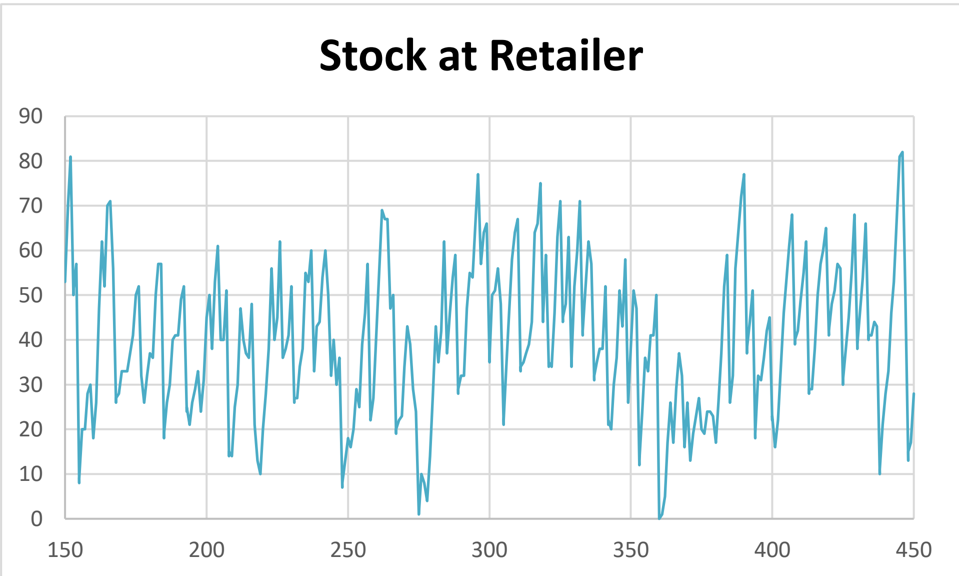

Figure 21 - Stock at the Retailer under (s, Q) replenishment

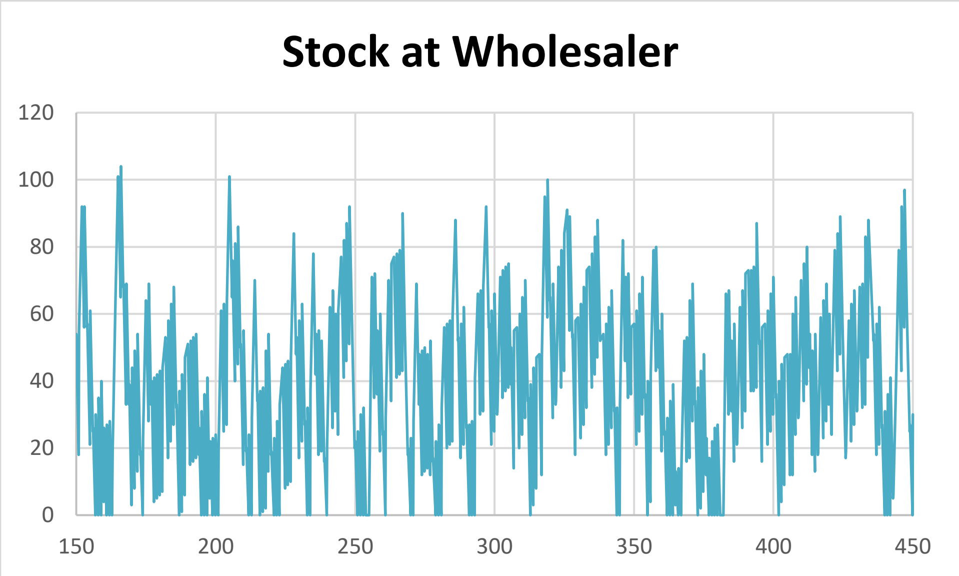

Figure 22 - Stock at the Wholesaler under (s, Q) replenishment

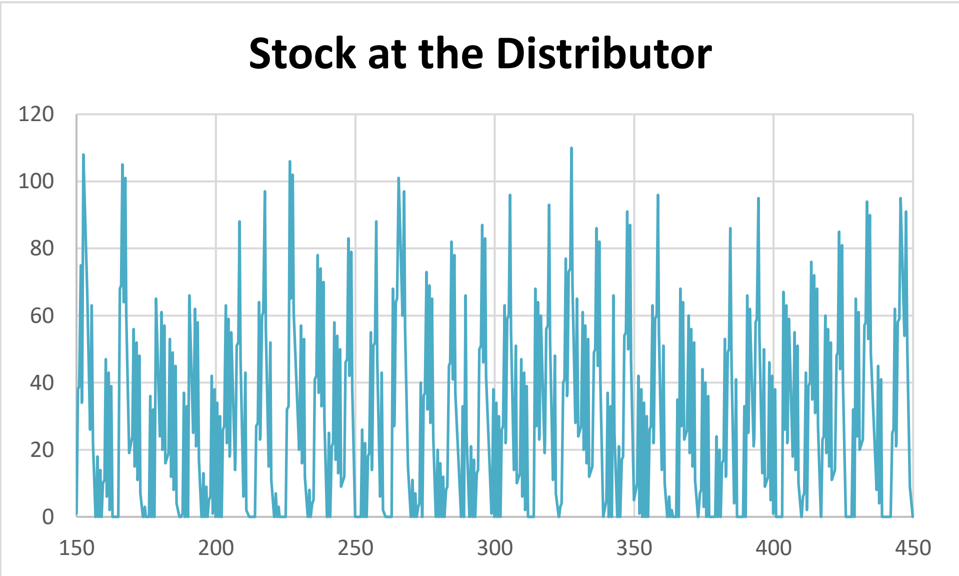

Figure 23 - Stock at the Distributor under (s, Q) replenishment

Next, comparing Figure 24, Figure 25 and Figure 26, that represent the (s, S) algorithm, we can see that the maximum inventory reached, as well as the average inventory levels, at echelon increases throughout the supply chain, supporting the existence of bullwhip effect. We can also see that there's an increase in the variability across the SC, manifesting itself in larger amplitudes and erratic stock behavior.

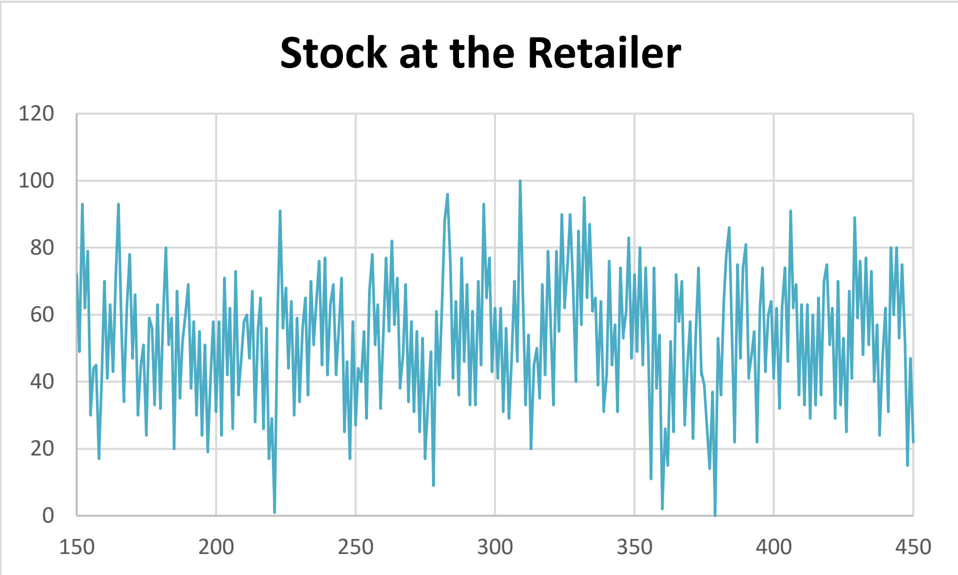

Figure 24 - Stock at the Retailer under (s, S) replenishment

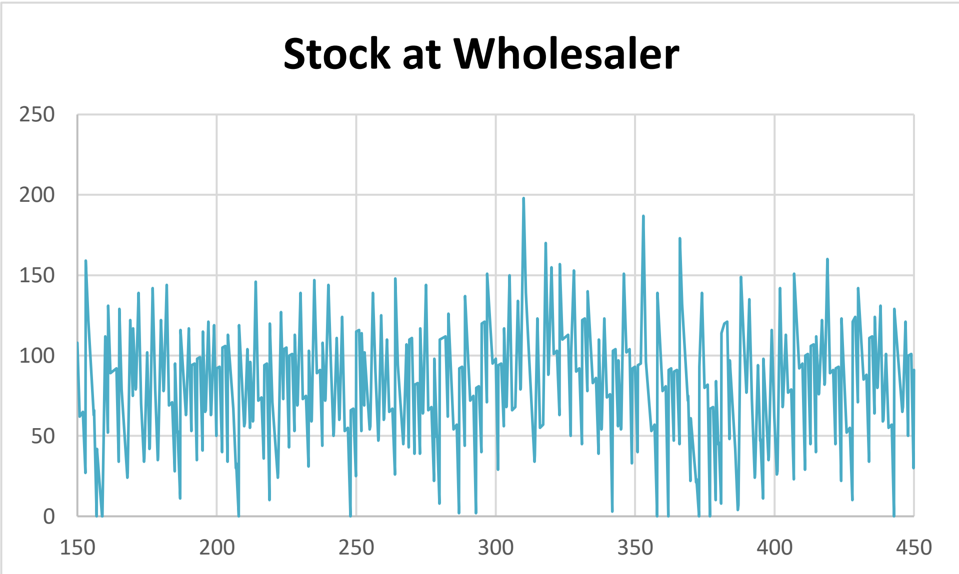

Figure 25 - Stock at the Wholesaler under (s, S) replenishment

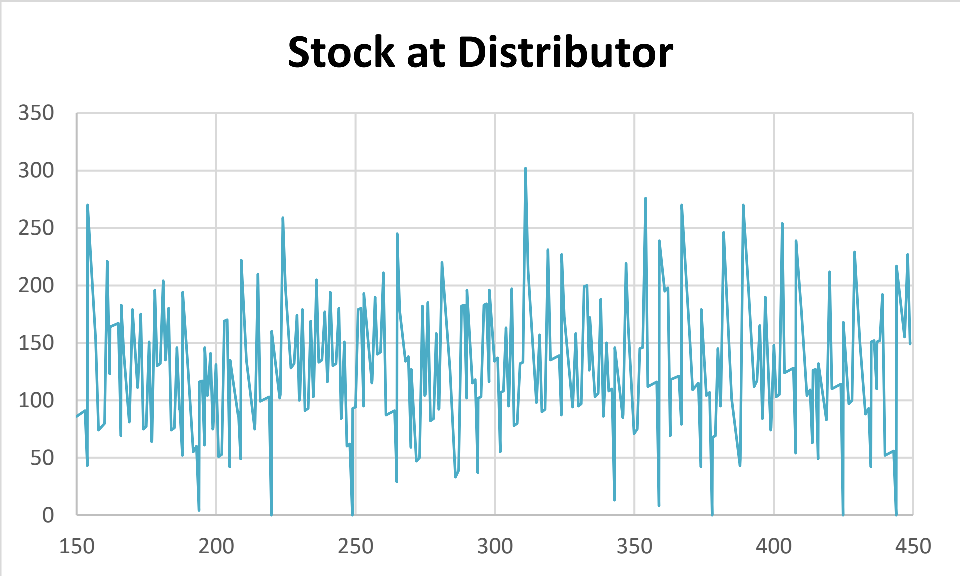

Figure 26 - Stock at the Distributor under (s, S) replenishment

Moving on to Figure 27, Figure 28 and Figure 29 for the (R, S) system and Figure 30, Figure 31 and Figure 32 for the (R, s, S) algorithm, we observe that similarly to the previous case, there are increases in the maximum stock held, average values and variability.

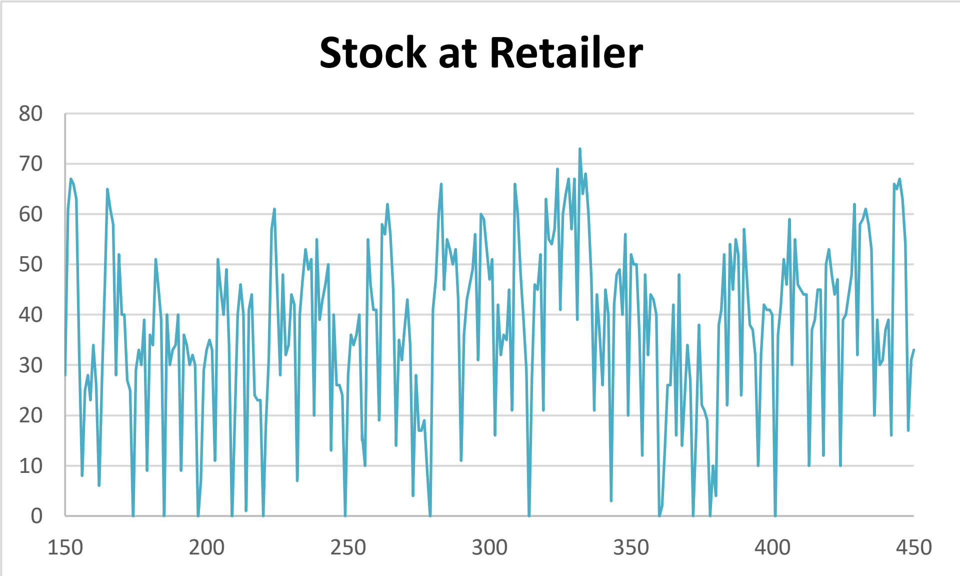

Figure 27 - Stock at the Retailer under (R, S) replenishment

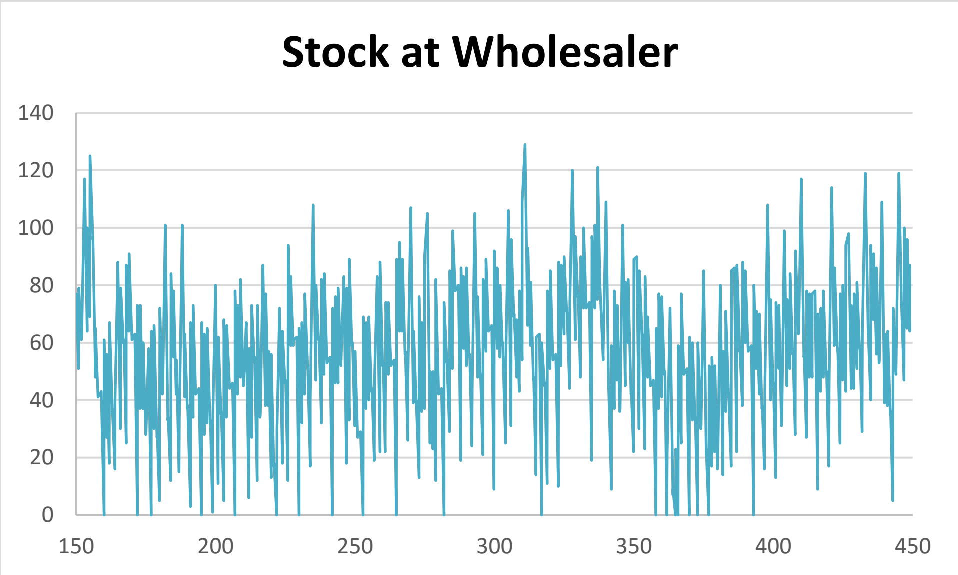

Figure 28 - Stock at the Wholesaler under (R, S) replenishment

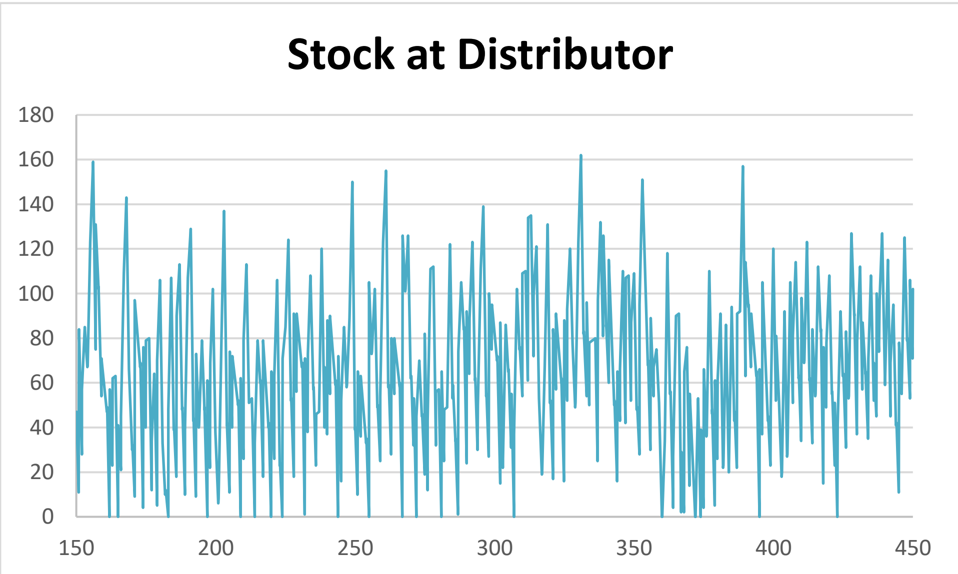

Figure 29 - Stock at the Distributor under (R, S) replenishment

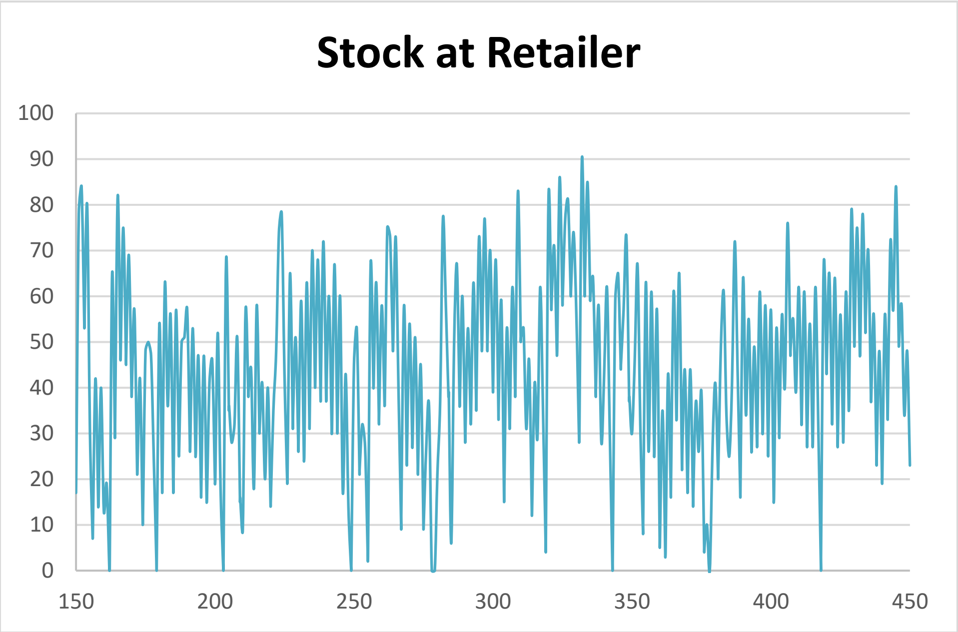

Figure 30 - Stock at the Retailer under a (R, s, S) Replenishment

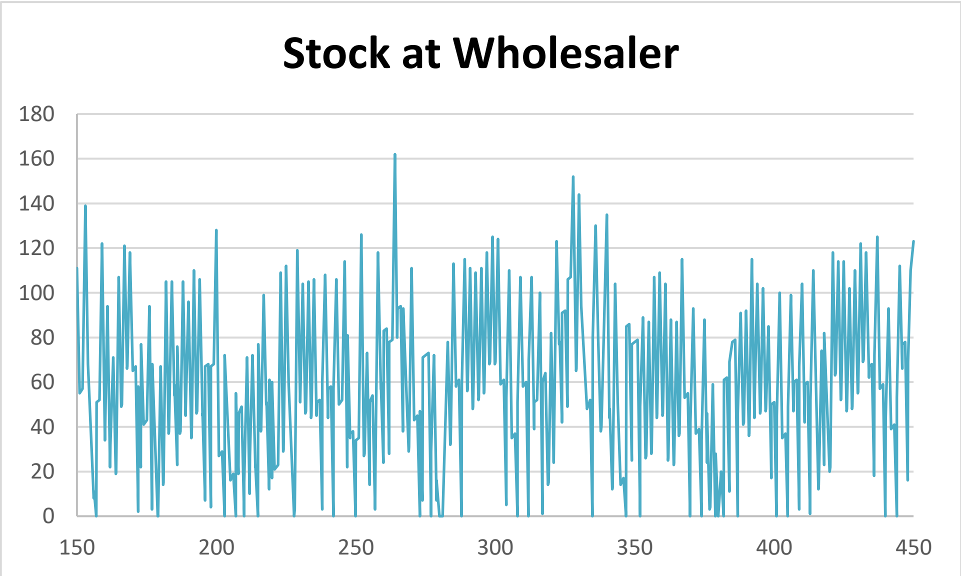

Figure 31 - Stock at the Wholesaler under a (R, s, S) Replenishment

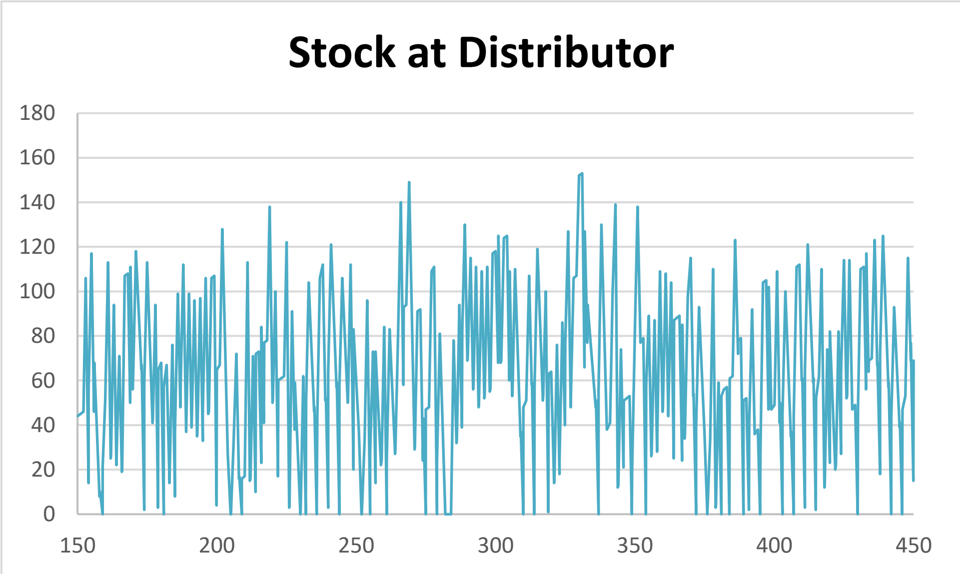

Figure 32 - Stock at the Distributor under a (R, s, S) Replenishment

When we compare our visual analysis to the values obtained for the standard deviation in Table 23 we confirm our suspicions, there's an increase of the inventory variance along the supply chain, independently of the used algorithm, confirming that some type of information distortion is occurring and generating the bullwhip effect.

Table 23 - Inventory Variance at each echelon

Algorithm/ Echelon	Standard deviation of the inventory at each echelon [units]		
	Retailer	Wholesaler	Distributor
(s, S)	19.401	38.508	57.032
(s, Q)	16.818	25.253	26.686
(R, S)	18.350	26.763	34.677
(R, s, S)	20.577	35.449	37.762

When analyzing the average stock at each echelon, in Table 24, we see that, except for the (s, Q) system, all the algorithms experience an increase in their inventory levels throughout the echelons, as expected due to the bullwhip effect, confirming the hypothesis formulated during the analysis of the inventory graphs. Despite higher levels of bullwhip generating higher stocks, it must be also taken in consideration that the performance levels also affect these values, hence the lack of true correspondence to what one would expect given the results obtained in terms of bullwhip effect, yet this effect is still perceptible, as the increases among the values for the average stock give strength to the idea that there's information distortion occurring in this supply chain, independently of the algorithm chosen.

Table 24 - Average Stock at each echelon

Algorithm/ Echelon	Average Stock at each echelon [units/day]			
	Retailer	Wholesaler	Distributor	Factory
(s, S)	51.888	61.663	109.055	150.644
(s, Q)	40.279	24.648	19.382	37.000
(R, S)	37.422	40.116	50.483	49.780
(R, s, S)	43.355	39.917	45.249	35.395

Next, we move on to the analysis of the demand variation graphs, available in Figure 33, Figure 34, Figure 35 and Figure 36. The first thing we notice is that in all of them, except for the (s, Q) algorithm, there's a general increase in the demand levels across all the echelons. We can also see how the different algorithms mask the original customer demand, generating information distortions along the supply chain.

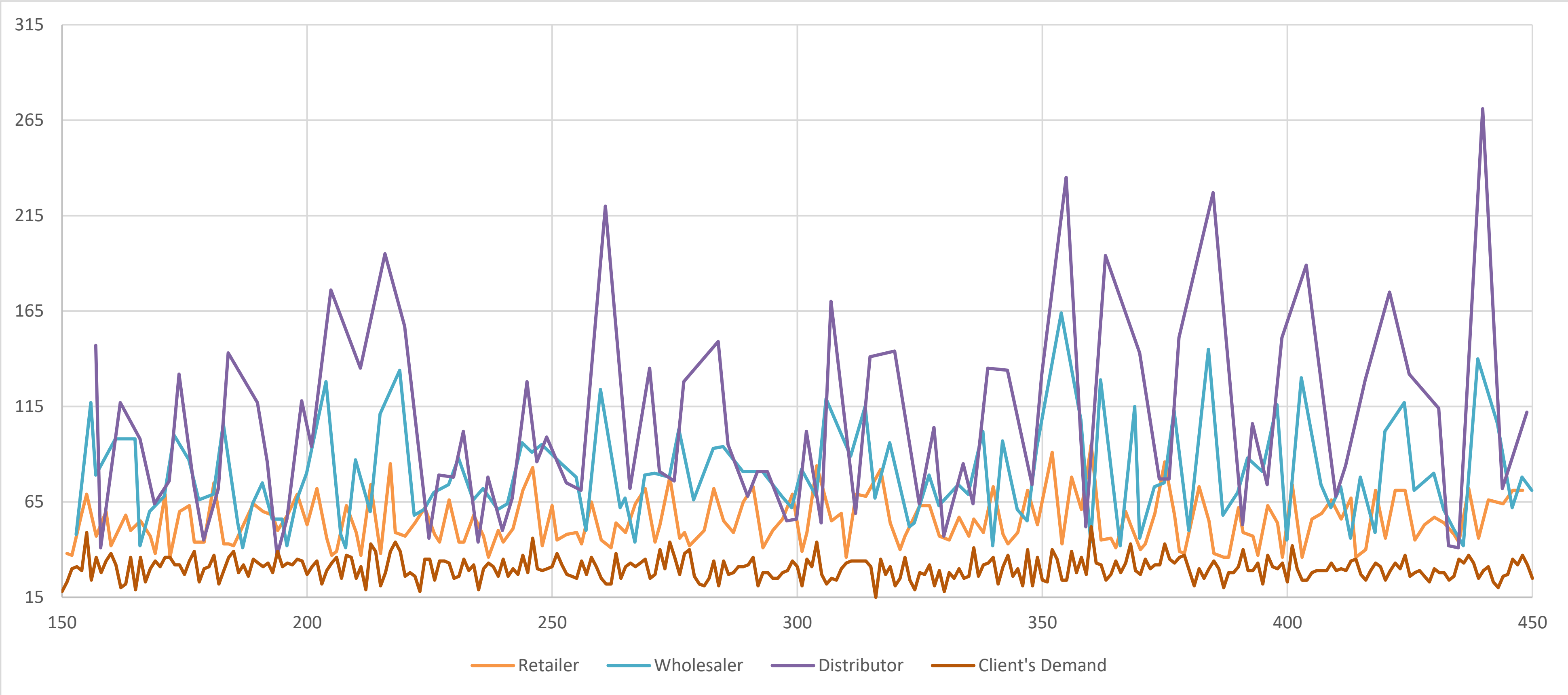

Figure 33 - Demand generated by the (s, S) system

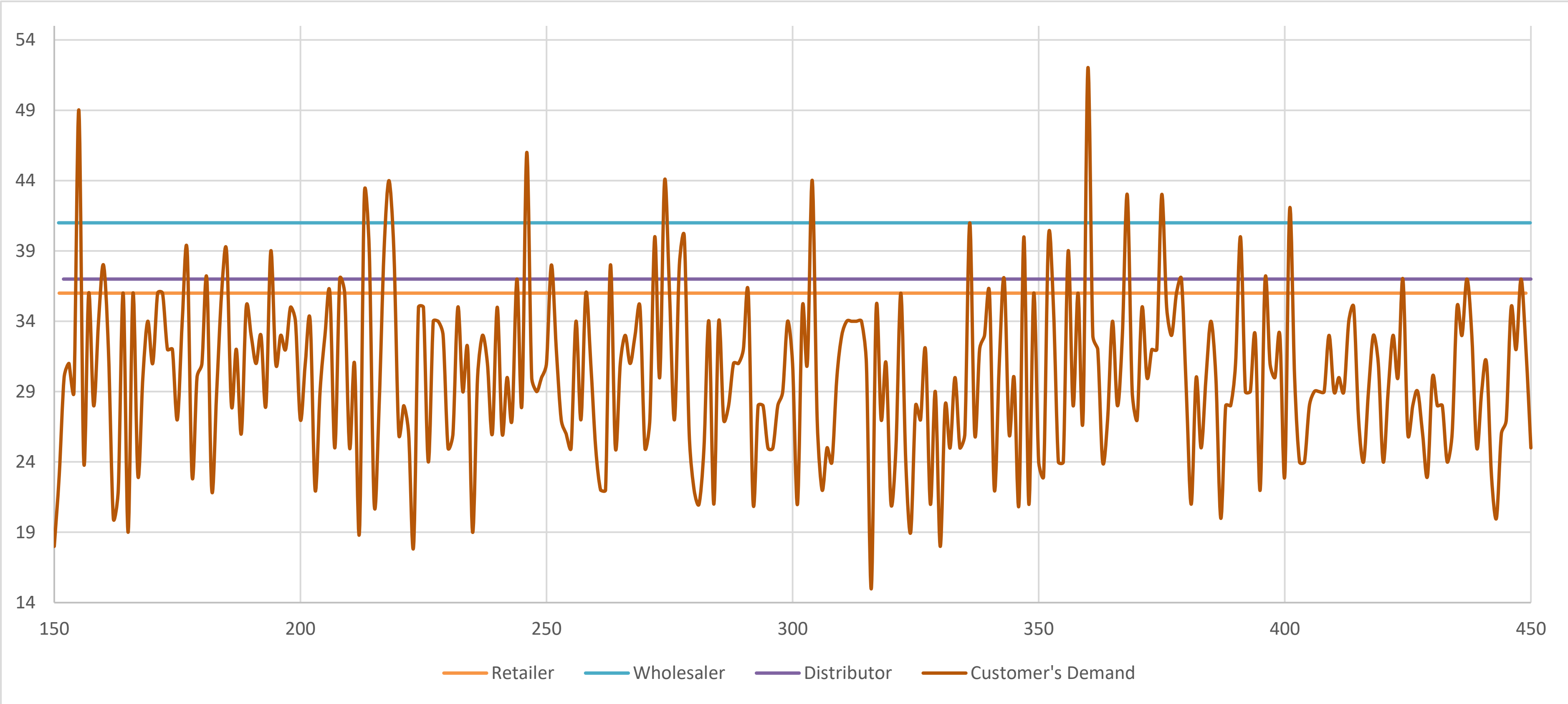

Figure 34 - Demand Generated by the (s, Q) system

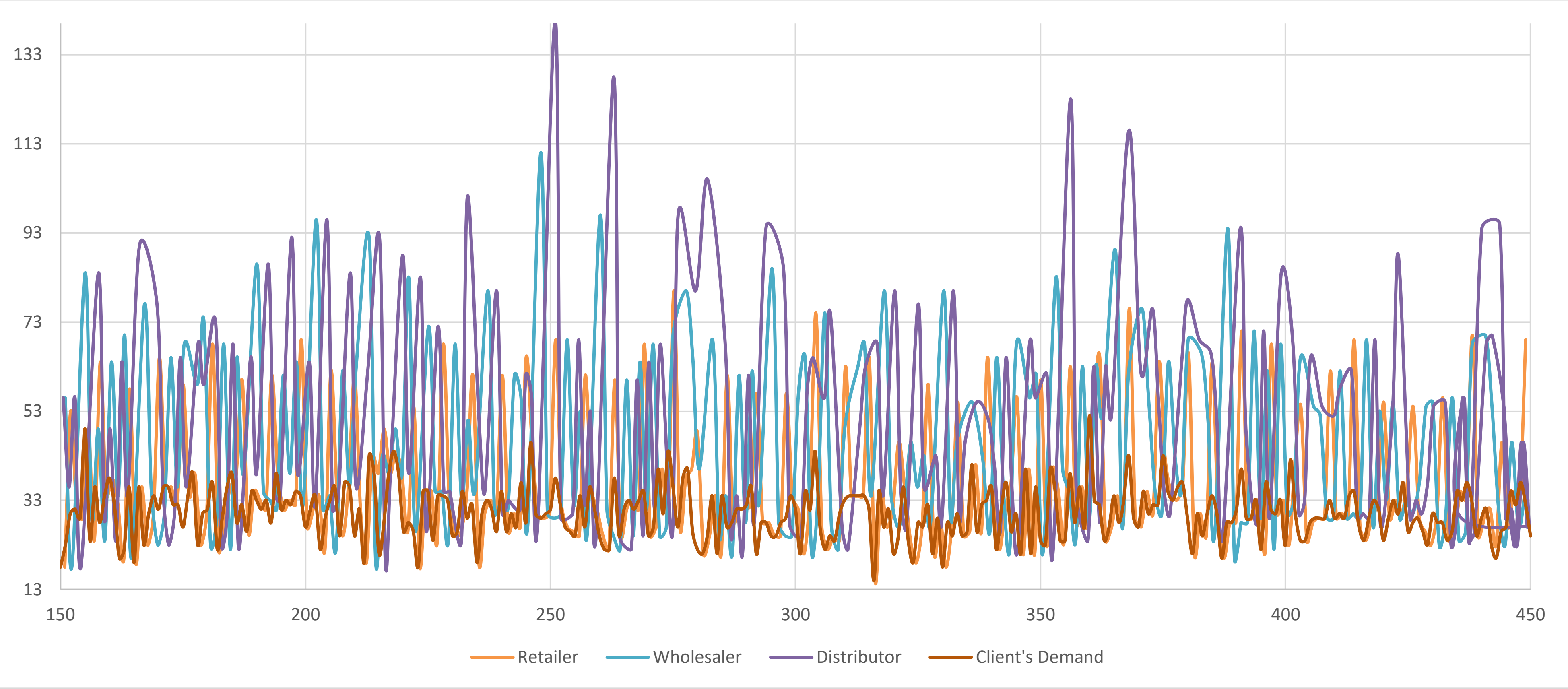

Figure 35 - Demand Generated by the (R, S) System

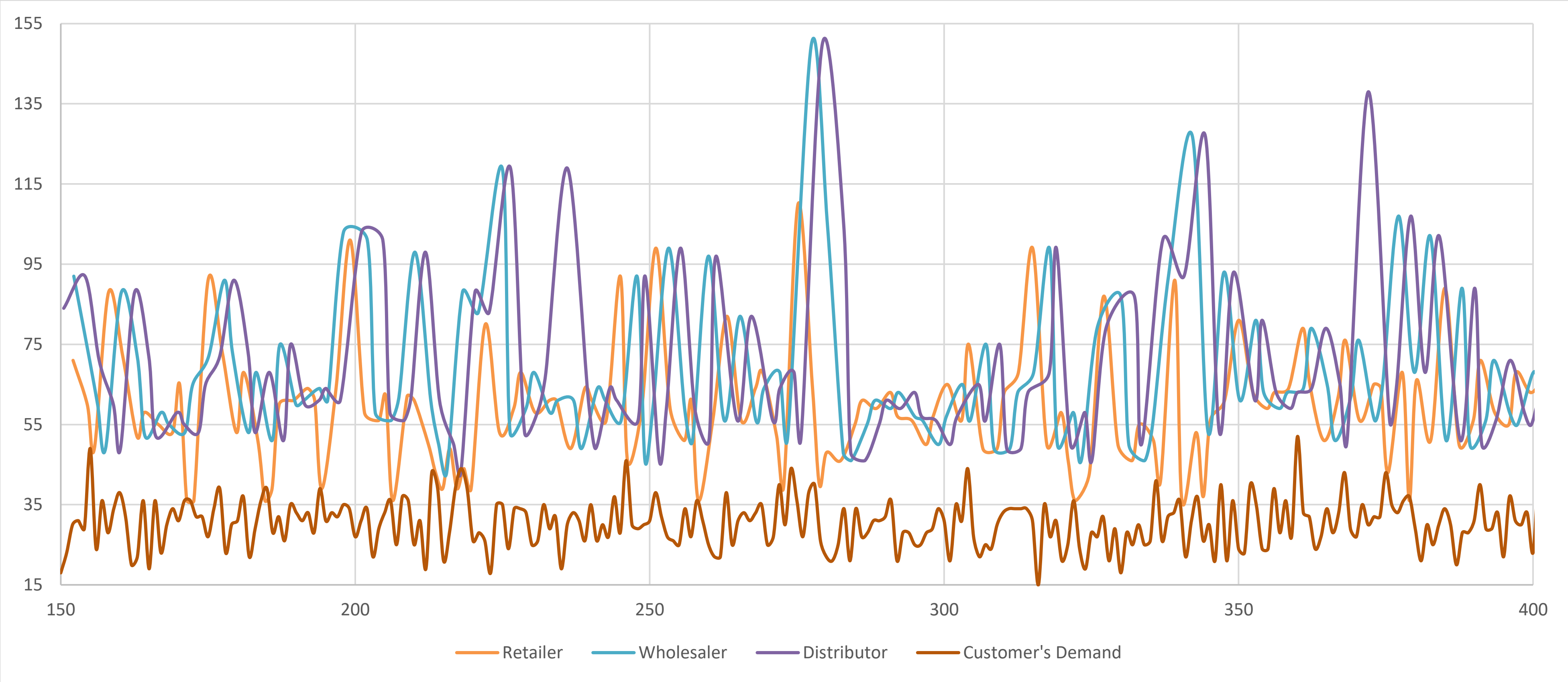

Figure 36 - Demand Generated by the (R, s, S) System

In order to better understand the demand behavior, let us take a look at both the average and standard deviation of the demand in Table 25and Table 26 where we can see that on a general term, they seem to increase along the supply chain.

Table 25 - Average demand experienced at each echelon

Algorithm/ Echelon	Average Demand experienced at each Echelon [units/day]			
	Retailer	Wholesaler	Distributor	Factory
(s, S)	30.193	30.261	30.326	30.318
(s, Q)	30.193	30.322	30.304	30.283
(R, S)	30.193	30.277	30.831	31.776
(R, s, S)	30.193	30.324	30.330	30.167

There are some interesting points to be made: 1) the average demand decreases from the distributor to the factory; 2) despite the (R, S) policy having greater order standard deviation along the supply chain compared to the (R, s, S) the bullwhip effect behaves in the reverse form; and 3) the (s, Q) policy has no standard deviation except on the retailer.

Table 26 - Standard Deviation of the orders received at each echelon

Algorithm/ Echelon	Average Standard Deviation of the received orders [units/day]			
	Retailer	Wholesaler	Distributor	Factory
(s, S)	5.735	9.764	16.115	26.940
(s, Q)	5.735	0.000	0.000	0.000
(R, S)	5.735	13.237	16.692	19.704
(R, s, S)	5.735	10.482	12.233	13.590

Looking at point 1), this decrease might be explained by the fact that the factory has instantaneous replenishment time, bring down the order-point and, consequentially, the order-up-to-levels, as the safety stock becomes smaller.

Next, one possible explanation for point 2) is that the (R, S) system has smaller times between orders,

We've been constantly presented with evidence that there's information distortion in this supply chain, independently of the chosen algorithm, in order to confirm it the alternative bullwhip was used to study this factor. Given the fact that the alternative bullwhip effect is closely related to the supply chain instability (Cannella et al., 2010), we can immediately acknowledge, by observing Table 27 that, given the circumstances, once again the (s, Q) algorithm has the best performance. On the other hand, the order-point, order-up-to-level (s, S) seems to create a great amount of instability, thus, apparently, we should avoid it.

Table 27 - Alternative Bullwhip Effect Experienced at each echelon

Algorithm/ Echelon	Maximum Alternative Bullwhip Effect experienced at each echelon			
	Retailer	Wholesaler	Distributor	Factory
(s, S)	89.942	149.508	422.344	819.178
(s, Q)	52.940	26.966	25.519	37.564
(R, S)	46.241	55.421	89.233	83.192
(R, s, S)	63.158	60.760	85.509	60.414

In order to quantify the distortion of information and make comparisons among the tested algorithms, we will use the method proposed by Cannella et al. (2010), previously mentioned in section 2.1.2. After graphing the curves for each algorithm, their linear regression curve is obtained and, in the end, its equation is computed. The results can be seen in Figure 37, Figure 38, and Table 28.

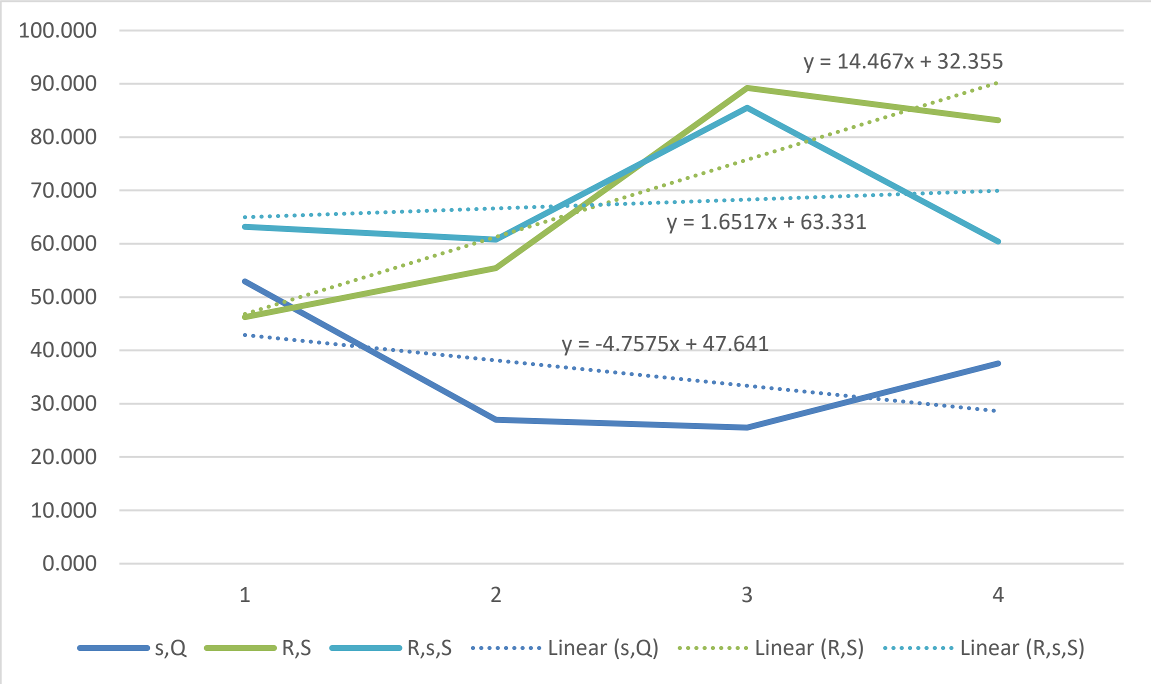

Figure 37 - Linear Regression Graphs for the (s, Q), (R, S) and (R, s, S)

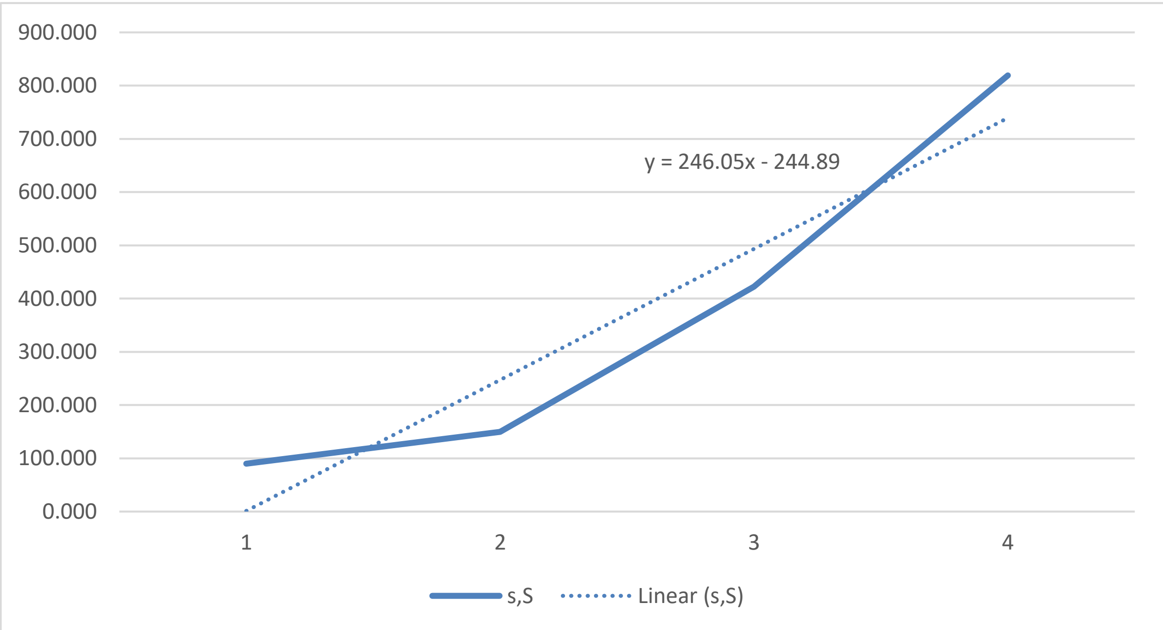

Figure 38 - Linear Regression Graph for the (s, S) algorithm

We can now confirm, by looking at Table 28, that the (s, S) propagates a great amount of instability throughout the supply chain and that the (s, Q) actually decreases the information distortion. Going back to Table 18, we can see that these represent algorithms with the highest and lowest bullwhip effect, respectively.

Table 28 - Instability Generated by each Algorithm

Algorithm/ Echelon	Instability
(s, S)	246.05
(s, Q)	-4.7575
(R, S)	1.6517
(R, s, S)	14.467

Now that we've gathered all the data and analyzed it, we are finally in conditions to address the proposed research question.

RQ1 – Can the choice of replenishment algorithm enhance the bullwhip effect experienced by a supply chain?

Based on the experimented data, it was found that there are significant differences on the bullwhip experienced, as well as the alternative bullwhip effect, translating into instability across the supply chain.

In the present conditions it's clear that the (s, Q) algorithm diminishes both the bullwhip effect and instability, only lacking in terms of service level, and on the reverse side, the (s, S) system extremely enhances these values while overprotecting the chain. The (R, S) system was the second best in terms of BE and instability while maintaining acceptable service levels in all echelons.

Further studies with a broader range of demand patterns and supply chain schemes are needed in order to validate that indeed, in a general level, the replenishment algorithms can influence the bullwhip experienced by a supply chain.

5. CONCLUSION AND FUTURE REMARKS

The major challenge addressed by this dissertation was to understand if the use of certain replenishment algorithms could be a contributive factor to the increase of the bullwhip effect experienced in the supply chain.

It became clear that, under the studied circumstances, there's a clear difference between the performance of the four replenishment algorithms tested. Simply looking at the values for the bullwhip effect, the best choice would be the order-point, order quantity (s, Q) system, as it carried the minimum values for this measure as well as the information distortion metric, yet we must not forget that that system had a poor service level. As managers, we need to take into consideration the fact that we must be able to attain a certain performance in order to satisfy our clients, or we incur the risk of losing them to our competitors. Therefore, taking this into account, and the fact that there are no restrictions to order sizes, my recommendation would be to implement the periodic review, order-up-to-point (R, S) system in this supply chain.

During this work was also possible to support Potter & Disney's (2006, apud Bhattacharya & Bandyopadhyay, 2011) affirmation that smaller batch sizes generate smaller bullwhip effect, Disney et al. (2005) and Pozzi et al.'s (2018) affirmations regarding that reduction of lead times also contributes to decreasing the bullwhip effect, and Potter & Disney's (2006) statements concerning that a smaller time between orders decreases the bullwhip effect experienced in the chain.

It's worth noting that this research is limited by the simplicity of the model used, as it is far from the supply chain reality in several factors, such as complexity, size, lack of constraints, lack of consideration of unpredictable events, the assumption of only one product, among others. Further research should be focused on testing this model's validity under more complex supply chains, closer to what is the reality of the industrial world.

Another limitation is the fact that the equations used consider that both the demand and the lead times follow a normal distribution, which is not the case, resulting in calculation errors that can cause over-protection or under-protection of the supply chain when dimensioning the safety stock. In the future, this model should be adapted taking into consideration the true characteristics of both the demand and lead times in order to produce more accurate results.

Due to time constriction, it wasn't possible to do a sensitivity analysis, as its common practice in studies like this, in the future it's advisable to this analysis and test if this hypothesis holds under various types of demand and lead time.

This study is also limited in the fact that doesn't take in consideration any kind of forecasting, a common practice in today's industry, thus it is important to extend this study by taking into account forecasts.

Also, only four types of replenishment policies were considered, narrowing these findings to a restrict set of algorithms. In the future, this hypothesis should be tested with a broader spectrum of algorithms in order to understand if the findings presented in this thesis can be applied to a broader set of policies or they only apply to tested ones.

It's clear that there's a big path to go through before we can be certain that the choice of the replenishment policies really does affect the bullwhip effect experienced at a supply chain, but this first step gives hope in proving this theory.

Given the case that, in the future, this hypothesis holds under several distributions of demands and it's applicable to more complex supply chains, a managerial tool could be developed in order to help guide the decision of replenishment policies in a company's supply chain, bringing them one step closer to taming their bullwhip effect.

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