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The effect of demand information sharing in a supply chain under demand uncertainty: a simulation study

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To my Parents, my sister Inês and my dearest Telma

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Abstract

The modern business environments are constantly subject to unpredictable events that can adversely influence the supply chain (SC) performance. In order to remain competitive, SCs are therefore striving to achieve greater coordination and collaboration among SC entities. The advances in technology in the area of information technology are enabling instantaneous information sharing amongst SC entities. Demand information sharing appears as a widely used tool to improve the SC performance. In this context, SC simulation appears as a fundamental tool to quantitatively analyze this management practice in a virtual system environment, enabling multiple scenario analysis.

This dissertation intends to verify through the use of discrete event simulation, the impact of the presence of demand information sharing on the performance of a SC and whether this practice can reduce the impact of an uncertain customer demand in terms of the total SC costs and the service level. Considering that the customer demand follows a Normal distribution with an unknown standard deviation, three different scenarios are simulated using three distinct standard deviations. Further, two information sharing scenarios are considered, namely the presence and absence of demand information sharing. This analysis is applied on a case study that is built for this purpose. The software used to develop the simulation model and reproduce the operational behavior of the SC is Arena.

The analysis of the simulation results indicates that an increase in the variability of the customer demand worsens all the studied performance measures. However, the introduction of demand information sharing improves the SC performance in terms of the SC costs.

Keywords: Supply Chain, Simulation, Uncertain demand, Information sharing

Resumo

Os ambientes empresariais atuais estão frequentemente sujeitos a eventos imprevisíveis que podem influenciar negativamente o desempenho das cadeias de abastecimento e colocar em causa a sua competitividade. Assim, de modo a permanecerem competitivas, as entidades da cadeia de abastecimento têm preconizado uma maior coordenação e colaboração entre elas. Os progressos na área das tecnologias de informação têm vindo a permitir a partilha de informação entre as várias entidades da cadeia de abastecimento. A partilha da informação relativamente à procura ao nível do cliente final surge como uma das práticas utilizadas para melhorar o desempenho da cadeia de abastecimento. A simulação é uma ferramenta que permite analisar quantitativamente esta prática de gestão num ambiente virtual, possibilitando a análise de diferentes cenários.

O principal objectivo desta dissertação é o desenvolvimento de um modelo de simulação discreta de uma cadeia de abastecimento, no qual se analisa o efeito da partilha de informação no desempenho da cadeia de abastecimento e se esta prática de gestão permite atenuar o efeito negativo da incerteza da procura ao nível do cliente final relativamente às medidas de desempenho, nível de serviço e custo total. Considera-se que a procura segue uma distribuição Normal com uma média conhecida e desvio padrão desconhecido, sendo simulados cenários para três desvios padrão distintos nos contextos, nomeadamente na presença e ausência de partilha de informação relativamente à procura. Esta análise é aplicada num caso de estudo construído para o efeito. O software utilizado para desenvolver o modelo de simulação e reproduzir o comportamento operacional da cadeia de abastecimento é o Arena.

A análise dos resultados da simulação mostra que um aumento da variabilidade ao nível da procura no cliente final provoca um agravamento das medidas de desempenho. No entanto, quando as entidades da cadeia de abastecimento partilham a informação relativamente à procura do cliente final o desempenho da cadeia de abastecimento é melhor, nomeadamente os custos totais.

Palavras-chave: Cadeia de abastecimento, Simulação, Incerteza da procura, Partilha de informação

Table of Contents

List of Figures

List of Tables

List of Abbreviations

BOM	Bill of materials
ERP	Enterprise resource planning
FDDM	Forecasted demand distributing method
MIP	Mixed integer programming
MU	Monetary units
PDTM	Planned demand transferring method
s	Reorder level
S	Maximum inventory level
SC	Supply chain
SCM	Supply chain management
SMDP	Simulation model development process
SKU	Stock keeping unit
T	Review period

Chapter 1 Introduction

1.1 Context of the dissertation

The current competitive business environment has forced organizations to minimize their costs, while still providing high quality products and services in great diversity to the customers. This challenge has compelled enterprises not only to optimize the existing operations, but also consider alternative solutions that may improve the general performance. The appearance of simulation to manage the supply chain (SC) of enterprises turns out to be an essential tool to satisfy the emergence of this need. The development witnessed in the information technology over the last decades accompanied by a growing number of people mastering high level programming languages are significantly contributing to a global acceptance of this tool, which allows managers to evaluate and compare virtual scenarios that might be adopted, at a high speed and a relatively low cost.

Another consequence of the current state of the market and the economic situation is an increase in the stimulation of inter-organizational collaboration within networks and the smoothening of the SC flows (Zhang and Zhang, 2007). This appearance is characterized as the information sharing techniques, which are becoming increasingly popular within the organization and between organizations. It is widely recognized from studies that the introduction of information sharing amongst the SC members appeared as an efficient practice against the present issues, while instantly improving the general SC performance. However, many enterprises still fear that the information sharing policy can damage their own benefits. Thus, in order to encourage enterprises to share information, the generated benefits need to be comprehensively recognized and evaluated through further studies (Chen et al., 2007). It should be noted that the benefits of the information sharing depend on the type of information as well as the demand patterns and capacity constraints that are imposed (Chan and Chan, 2009).

The use of information sharing is also one of the most common strategies to minimize the effects of uncertainties in SCs, which can have significant negative effects on the SC performance (Datta and Christopher, 2011). Although uncertainty is an inevitable factor within a SC that cannot be completely eliminated, many authors agree that demand uncertainty is the major source of SC uncertainty, making it therefore the most important element to manage within this field (Geunes and Pardalos, 2005; Acar et al., 2010; Hugos, 2011).

It is thus necessary to continue studying the effect and value of information sharing practices in SCs from a theoretical as well as practical point of view, by developing new strategies and evaluating new scenarios, in order to aid decision-making and maintain SCs globally competitive, even when facing an increase in SC uncertainties. This dissertation attempts to satisfy this need and be a motivation for future work in this research area.

1.2 Objectives

The objective of this dissertation lies on the verification if demand information sharing can increase the SC performance under an uncertain customer demand, in terms of the service level and the SC costs, within a four level SC that is consisted of one retailer, one distributor, one manufacturer and two suppliers, which produce and deliver a product to one final customer. Additionally, one verifies whether demand information sharing can reduce the impact of an uncertain customer demand on the studied SC's performance measures.

In the presence of demand information sharing, the customer demand that arrives at the retailer is instantly known by the manufacturer and the two suppliers. When there is no demand information sharing between the SC entities, the demand is exclusively acknowledged by the amount of units that are ordered by a downstream entity. The customer demand uncertainty is modeled by a variable that follows a Normal distribution with mean zero and an unknown standard deviation. Given the objectives of this dissertation, three distinct customer demand standard deviations are considered in the presence and absence of demand information sharing, generating six scenarios. Note that each considered customer demand standard deviation is used in the presence and absence of demand information sharing. A comparative study between the six possible scenarios intends to dictate the best scenario, regarding the SC performance.

In order to simulate and compare these scenarios, Rockwell Arena 9.0 software is used.

1.3 Research methodology

The research methodology employed to guide this research is summarized in Figure 1.1. In the first step of this methodology a literature review intends to provide an overview in this research field in order to develop a case study.

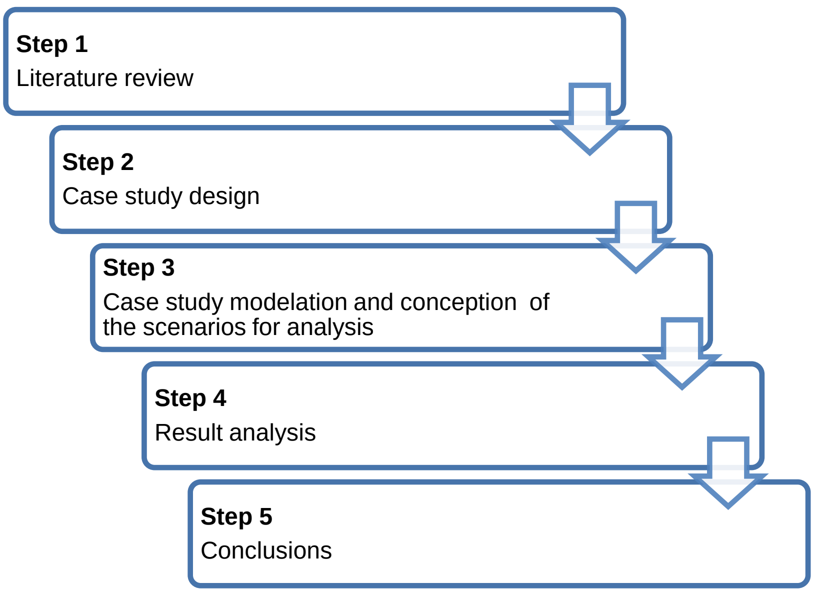


Figure 1.1 – Outline of the dissertation

The literature review is conducted using the B-on scientific database provided by *Faculdade de Ciências e Tecnologias* of the *Universidade Nova de Lisboa*. In fact, the used database is consisted of several scientific databases including, BioMed Central, Directory of Open Access Journals (DOAJ), Informa Taylor & Francis (CrossRef), OneFile (GALE), SciVerse ScienceDirect (Elsevier), Science Citation Index Expanded (Web of Science) and Social Sciences Citation Index (Web of Science). The key-words that are inserted in the topics of the database to obtain literature information are simultaneously “supply chain” and “simulation”, providing a total of 707 results. It should be noted that the key-words have to be introduced in the two available topics of the database, by choosing the subject option. Following this research, this dissertation is approximately based on 40 journal articles and 20 books. The main criteria considered for this selection, consists in reading the most appealing journal titles along with their abstract that have been written in the last five years. In case the abstract reveals to possess potential valuable information, the rest of the article is read, analyzed and the conclusions are drawn. The books are consulted to obtain complementary theoretical research information.

In the second step, the conceptual model for a case study is developed based on ideas and suggestions encountered in the conducted literature review, in which the objective is defined for a given SC.

The third step of the study consists in developing the simulation model of the case study, defined in the previous section, including the scenarios for analysis. This activity is accomplished with the help of a simulation software, namely Rockwell Arena 9.0 that uses a SIMAN programming language.

After the desired scenarios are completely formulated, one can advance to the next step, which consists in analyzing the results of different simulation scenarios. According to the objectives, the performance measures of the scenarios are carefully studied and compared in order to extract valid conclusions.

In the final step the conclusions are drawn regarding the purpose of the dissertation.

1.4 Dissertation structure

The dissertation is organized into six chapters. The first chapter provides a general introduction, regarding the scope of the study, the outlined objectives, the research methodology used and the encountered research contributions.

Since the study involves a specific knowledge in SC simulation, supply chain management (SCM) and demand information sharing, it is justifiable that each of these fields should firstly be presented in some detail before moving to the presentation of this dissertation. Chapter two is therefore dedicated to an overview of the relevant issues concerning these subjects.

In chapter three, the case study is presented along with the conceptual SC modeling and simulation propositions that are assumed in order to study the outlined objectives.

In the fourth chapter a simulation study is applied to the specifications of the conceptual model. The required simulation conditions have to be carefully identified and programmed in order to obey the theoretical assumptions of the previous chapter. The last part of this chapter is dedicated to the verification and validation procedures as well as the definition of the simulation environment under which the simulation model operates.

Chapter five provides the case study results followed by a critical analysis of the obtained results. The relevant comments and discussions are dispersed throughout this chapter.

In the final chapter, the main conclusions regarding this research are drawn from the results analysis and the proposed further research is presented based on the work developed so far.

The dissertation ends with the references used in the literature review and the annexes.

Chapter 2 Literature Review

This chapter intends to provide the necessary background that is required to comprehend the development of the dissertation, according to the established objectives. The three main issues that have to be studied to meet this goal are supply chain management (SCM), supply chain (SC) simulation and demand information sharing.

This chapter is therefore divided into three sections, namely SCM, SC simulation and demand information sharing. The SCM section addresses the background and the main characteristics of this scientific area. Ultimately, the definition of this concept is encountered with the help of the author's work developed so far, as well as the objectives are defined. The SC simulation section provides an overview of the characteristics that are present in the case study that can be seen later on in this dissertation. These sections include SC uncertainties, which can be divided into demand and supply uncertainties, demand forecasting and the verification and validation procedures The demand information sharing section describes when, how and where this practice is used.

2.1 Supply chain management

2.1.1 Introduction

A SC includes the companies and the business activities needed to design, produce, deliver and use a product or a service. Every business fits into one or more SCs and has a role to play in each of them (Hugos, 2011). The main objective of a SC is to provide the right products and services on time, with the required specifications, at the right place to the final customer (Carvalho et al., 2012).

A SC is characterized by possessing three types of flows, namely material, information and financial flows. It should be noted that all three flows are bidirectional, which means that they can flow both in a downstream way as in an upstream way. These network flows require therefore careful planning and close coordination in order to thrive in an operational SC (Jung et al., 2007).

The appearance of dynamic and segmented markets, in which the customer's requirements are constantly changing and highly unpredictable along with the presence of a fierce competition through globalization, is forcing the SCs to become faster, better and economically more efficient (Jespersen and Skjott-Larsen, 2005). Thus, organizations are becoming increasingly interested in improving their SC performance and are starting to research several areas over the last decades, that for example can improve the customer delivery performance, reduce inventory and increase both SC flexibility and responsiveness (Suwanruji and Enns, 2006). The ability to create trust-based and long-term business relationships with customers, suppliers and other strategic entities is becoming a crucial competitive parameter (Jespersen and Skjott-Larsen, 2005). Klemenčič (2006) measures the competitiveness between SCs based on how efficiently and effectively the customer preferences in terms of service, cost, quality and flexibility are met.

2.1.2 Definition

Before these facts, SCM appears as the ideal solution. The only question that remains is the actual meaning of this concept. In literature however, one witnesses that there is still a lack of consistency and clarity regarding the definition of SCM, making it particularly difficult to understand the essence of this activity. Table 2.1 provides some definitions that may clarify its meaning.

Table 2.1 – SCM definitions

Authors	SCM definition
Mentzer et al. (2001)	"Systemic, strategic coordination of the traditional business functions and the tactics across these business functions within a particular company and across businesses within the SC, for the purposes of improving the long-term performance of the individual companies and the SC as a whole."
Li (2007)	"A set of synchronized decisions and activities utilized to efficiently integrate suppliers, manufacturers, warehouses, transporters, retailers and customers so that the right product or service is distributed at the right quantities, to the right locations, and at the right time, in order to minimize system-wide costs while satisfying customer service level requirements."
Lambert (2008)	"Integration of key business processes from end-user through original suppliers that provides products, services, information that add value for customers and other stakeholders"
Supply Chain Council (2012)	"…the inclusion of the management of supply and demand, sourcing raw materials and parts, manufacturing and assembly, warehousing and inventory tracking, order entry and order management, distribution across all channels, and delivery to the customer."

Looking at the previous definitions, one can identify several mutual characteristics, including strategic collaboration and integration, production and inventory management and finally the added value that is being generated for the final customer (Cabral, 2011). It should be noted that the management of a SC along with the roles of the various entities involved, usually differ from industry to industry and company to company and depend vastly on the business strategy considered (Shukla et al., 2011).

2.1.3 Objective

The main objective of SCM is to simultaneously minimize the total SC cost and enhance a competitive advantage without compromising the desired customer service level (Mentzer et al., 2001). Hung et al. (2006) indicates that SCM is the most effective strategy to deal with external strategic changes, as for instance globalization, and operational uncertainties, such as demand fluctuations, in order to take advantage of eventual opportunities that may arise.

This innovative management approach is actually increasing the integration and cooperation within the SC and leading to a higher level of management complexity, which requires therefore an increasing coordination of resources and activities (Jespersen and Skjott-Larsen, 2005). With the growing changes in business strategies, operational policies and customer requirements, managers are increasingly seeking to minimize the risk of committing mistakes by quantitatively analyzing their SCs through the introduction of simulation models (Hung et al., 2006).

2.2 Supply chain simulation

2.2.1 Introduction

Simulation is one of the most frequently used tool to study the behavior of SCs, in order to quantify their efficiency and study the implementation of new management strategies in a relatively short period of time (Iannone et al., 2007).

The introduction of simulation in SCM brought several benefits to enterprises. Harrison et al. (2007) highlights the ability to provide accurate estimates of efficiency and effectiveness of systems and the possibility to perform detailed sensitivity analysis in a virtual system environment. Kelton et al. (2004) emphasizes the flexibility with which conceptual models can be solved, regardless of their complexity. Besides this factor, the constant improvement, in recent years, of the performance/price ratio of computer hardware has rendered simulation into one of the most important tools in the actual global business environment.

The literature regarding the SC simulation covers numerous areas, such as, inventory management, information sharing, uncertain scenarios and entity collaboration, among others, but usually possesses a common purpose that consists in initially studying a real-based or virtual SC, in which the main characteristics are identified. Afterwards, the author establishes an objective and introduces a unique feature to study the impact that it has on the desired performance measures.

In the studied literature, approximately 40% of the authors consider the total SC costs and the service level measured downstream, which is equal to the ratio between the quantity of filled customer demand and the total customer demand, as the chosen performance measures. Regarding the customer demand at the downstream level, almost 50% of the authors use a normal or a poisson probability distribution to represent this characteristic. Generally, the authors study multi-echelon SCs, allowing a more complex approach of a system. In fact, these virtual representations brings one closer to reality and enable the extraction of more extensive conclusions regarding the SC.

2.2.2 Supply chain uncertainties

With the current market experiencing a globalization of the enterprises, customers are becoming more demanding, urging improved customized products and expect their service level to be higher than before. This high competitive pressure, forces enterprises to decrease product life cycles, increase product variety and improve the ability to adapt to technological changes. These facts are consequently leading to an increase in uncertainties throughout the entire SC (Merschmann and Thonemann, 2011). Having identified this threat, one should characterize the meaning of uncertainty.

Walker et al. (2003) define uncertainty as “any deviation from the unachievable ideal of completely deterministic knowledge of the relevant system’”, while Ivanov and Sokolov (2009) characterize it as a system that represents the incompleteness of our knowledge about the system and the conditions of its development.

The systematic consideration of SC uncertainties can facilitate the determination of the expected return and the estimation of the associated risks based on the current status and future predictions (Papageorgiou, 2009).

Wangphanich et al. (2010) emphasize that one of the main aims in the SCM of an organization is to coordinate the upstream flow of incoming materials with the downstream services, in order to cope with uncertainties that may appear without generating excess inventories. The consequent danger regarding uncertainty, lies on the perturbation influences that may occur in the operational SC, leading to a change in the planned course of events (Ivanov and Sokolov, 2009). The main factors that contribute to SC uncertainty include, inaccurate forecasting, long order lead times, delivery delays, incomplete shipment, batch ordering and fluctuations in prices, among other factors (Wangphanich et al., 2010).

Within the SC uncertainties, one can identify two major groups that contribute for this undesired phenomenon: demand uncertainties and supply uncertainties (Chiang and Feng, 2007; Bidgoli, 2010).

2.2.3 Demand uncertainties

The fact that demand uncertainty reflects the uncertainty of a downstream demand for a product or service and being a constant factor present in the majority of the SCs, made many authors agree, that this source of uncertainty is the major source of SC uncertainty (Geunes and Pardalos, 2005; Acar et al., 2010; Hugos, 2011). This indicates that the demand uncertainties are the most important element to manage within the SC uncertainties.

Demand uncertainty tends to vary according to the type of manufacturing product. The functional products represent stable goods, such as food items and gas, tend to have a low demand uncertainty, while the innovative products, such as technological and fashion items are rapidly changing and are perceived as risky by the end customers, possessing a high demand uncertainty (Mohr et al., 2009).

Whenever a product or a service faces uncertain demand, there are generally three types of coordinated strategies that can suppress this threat. In first instance, one can reduce uncertainty by developing improved forecasting systems. Secondly, managers can reduce the lead times and provide an increase in the SCs' flexibility in order to produce only when needed. Finally, it can be dealt with the creation of buffers of inventory or the generation of excess in capacity (Mentzer, 2001). The centralization of demand information throughout the entire SC is also frequently used to reduce uncertainty, in which each level in the SC is updated with complete information regarding the actual customer demand (Simchi-Levi et al., 2004).

Throughout literature, demand uncertainty has been extensively studied by authors and can be represented in a variety of ways. Acar et al. (2010) developed a mixed integer programming (MIP) model to determine the impact of demand, supply and lead-time uncertainties on customer service performance and costs. With the help of the ANOVA concept, a comparison is made between the tree types of uncertainties, resulting with the identification of demand uncertainty as possessing the greatest negative impact on the SC performance (Acar et al., 2010). Generally, the authors used a simple probability distribution to represent the demand uncertainty. However, Chan and Chan (2010); Acar et al. (2010), represent demand uncertainty in the SC by varying the variance of the corresponding probability distribution, allowing the creation of multiple scenarios with distinctive characteristics with the possibility to perform sensitivity analysis. Reiner and Trcka (2004) use smooth and volatile demand to represent the customer demand, in which the difference lies in the standard deviation parameter, which was much higher for the volatile demand. Bottani and Montanari (2010) study the introduction of a demand peak in a fast moving consumer SC with the objective to obtain insights on how to optimize SC design. Whenever this feature occurs, the authors significantly increase the mean and the standard deviation of the demand probability distribution and compare the outputs with the initial original demand values without a demand peak. Wadhwa et al. (2009) use a similar approach to study different inventory control policies under the presence of impulsive demand disturbances. The imposed variability actually influences each SC node differently, depending on the inventory policy that is used.

Sari (2010); Lau et al. (2008); Chiang and Feng (2007) use expression 1 during simulation to represent the customer demand uncertainty,

$$D_t = base + season \times \sin\left(\frac{2\pi}{Season\ Cycle} \times t\right) + noise \times snormal, \quad (1)$$

where D_t represents the demand during period *t*. The sine function is used to capture the seasonality of customer demand, whereas *snormal* is a standard normal random variable. The *Base* and *Season Cycle* parameters are fixed parameters, while the *Season* and *Noise* parameters, characterize different magnitudes of demand uncertainties, generating different fluctuation levels and dynamic noise levels of demand.

Yan (2010); Zhu et al. (2011) use a different approach to represent demand uncertainty within the studied SCs. The authors adopt the following expression to define the customer's demand, $D = \overline{D} + \varepsilon$. $\overline{D}$ represents a deterministic mean demand that usually is derived from historic data and ε is a random variable, which follows a normal distribution, with a mean of zero and variance of V. In fact, the V can range from zero up to ∞, creating a higher demand uncertainty but a lower forecasting accuracy parameter. The customer demand D follows a normal distribution. The case study developed in the next chapter is going to adopt this characteristic to represent the presence of SC uncertainty.

2.2.4 Supply uncertainties

On the contrary of demand uncertainty, supply uncertainty has not received the same attention as it should have acquired in literature. The fact that an enterprise possesses greater control over supply than demand, lead to the thinking that supply uncertainty is thought to be managed by focusing exclusively on the selection of the indicated suppliers and their development, rather than on the management of the supply uncertainty (Shah, 2009).

Supply uncertainty can take a different number of forms, namely supply disruptions, yield uncertainty and lead time uncertainty. As the term indicates, supply disruptions refers to an interruption of the supply in goods at a certain stage in the SC, which generally occurs due to natural disasters, strikes or the fact that a supplier can go out of business. Yield uncertainty refers to the fact that occasionally the supplier delivers a quantity that falls short regarding the actual amount ordered. This phenomenon can be a result of product defects or of batch processes, in which only a certain percentage of a given batch, that represents the yield, can be used. Lead time uncertainty represents an uncertainty in the supply lead time that usually results of stock-outs at the supplier or of manufacturing and transit delays, among other factors (Snyder and Shen, 2011).

Chan and Chan (2010) represent supply uncertainty by comparing scenarios, in which the normal suppliers' capacity was increased up to 40% of its original value. Acar et al. (2010) illustrate supply uncertainty by generating uncertain machine breakdowns that follow a uniform distribution and by comparing an increase of 10% of the suppliers' capacity with their normal capacity.

Regarding the lead time uncertainties, Heydari et al. (2008) study the impact of lead time variation on SC performance, giving special emphasis to the following parameters, the ordering variance, the bullwhip effect and the inventory position. Initially, a structural model is developed to evaluate the impact of lead time uncertainty on the SC parameters. Afterwards, several hypotheses are tested using a covariance structure analysis based on the simulation results. The authors conclude that lead time variance significantly affects the inventory management, for it is responsible for changing the order variances and increasing both the holding quantity and the number of stock-outs. Acar et al. (2010) study the effect of transportation lead time uncertainty by comparing a scenario that possesses a fixed lead time with a 10% standard deviation of the expected lead time.

The constant threat of SC uncertainties, is forcing managers and researcher to develop effective methods that can minimize this danger. Common methods that address this issue include demand forecasting and sharing information regarding the demand.

2.2.5 Demand forecasting

The ability to accurately forecast short and long-term events remains one of the most crucial factors in the operational planning of any organization, regardless of the adopted production system or the dimension of a SC (Christou, 2011). Forecasting can be defined as an activity that uses the information at hand, including hunches, formal models and data, to make statements about the likelihood of future events (Elliott et al., 2006).

It should be noted that regardless of the forecasting method used to esteem demand, there are certain characteristics that always remain valid. A forecast is only an estimate of the future and therefore will always be wrong. The only question worth asking is the dimension of its error. An aggregate forecast is considered to be more accurate than a forecast of an individual item within the aggregation. Finally, a short-term forecast is generally more accurate than long-term forecasts, due to the presence of more uncertainty regarding the course of future events (Christou, 2011).

Within this research area, demand forecasting can be determined using quantitative or qualitative forecasting techniques. Quantitative forecasting can be defined as a statistical technique that applies mathematical models to existing and previous scenarios in order to predict future events. There are two primary groups within the quantitative methods. The time-series analysis uses historical data to predict future events based on cyclical, trend and seasonal influences, while causal analysis attempts to identify the linkage between two or more variables. Qualitative forecasting, on the other hand, focusses on subjective factors to draw conclusions, such as, estimates and opinions (Boyer and Verma, 2009).

In terms of the encountered literature review, Hussain et al. (2012) study the impact of two forecasting methods, exponential smoothing and minimum mean squared error, on the bullwhip effect and inventory variances in a SC under a periodic review policy. The bullwhip effect phenomenon describes a situation in which harmless demand variances incurred at the retailer are amplified through the SC, causing heavy demand fluctuations at the upstream entities. Inventory variances are greater for exponential smoothing than for minimum mean squared error and the difference between the two forecasting methods increases as the lead time increases. Simulation experiments show that depending on the structure of a demand process, the appropriate selection of forecasting technique can reduce or even eliminate the bullwhip effect. Crnkovic et al. (2008) use Monte Carlo simulation to develop a decision-support framework in order to study the tradeoffs in manufacturing short shelf life product quantities under different SC configurations and alternative forecasting options, given uncertain demand environments. It should be noted that the authors consider the difference between the actual forecast and the desired forecast, which represents the error in forecasting, to be characterized as a monotonically decreasing function. The forecast quality is modeled by assigning a specific half-width to the sampling interval. The half-width represents half of the range of a confidence interval for the sample mean. In this case a significance level of 5% is considered. A high quality forecast requires therefore a small half-width of the sampling interval but possesses a much higher forecasting cost. Besides demand forecasting, information sharing regarding the demand also appears as an efficient tool to address SC uncertainties . Mostard et al. (2011) study demand forecasting in a mail order apparel organization that lacks historic demand data. In order to forecast the demand, the authors compare an expert judgment method with a new approach namely forecasting based on advance information sharing. The judgments are obtained from purchase managers and other experts of the organization. The forecasting technique using advance information sharing starts by forecasting the total season demand in the upcoming season for a group of stock-keeping-units (SKU's), by scaling up to the registered advance (preview) demands for the respective SKU's. The results of this study indicate that the advance information sharing forecasting produces more robust estimates of the demand, in which high forecasting errors are avoided. However, the authors conclude that in most cases the forecasting using the expert judgment method outperforms the advance information sharing forecasting method. Combining these two forecasting methods may bring further benefits when forecasting demand.

2.2.6 Verification and validation

When constructing a SC simulation model, Tannock et al. (2007) emphasize the need to undertake the control processes of validation and verification, in order to be assured that the proposed model and its results, accurately represent the behavior of the studied system. Once this process is completed, the model can be run in order to extract the results regarding the SC behavior and performance of the desired study interests. In most situations, a simulation expert is required to be closely involved with the simulating process as a precaution. In fact, a SC can suffer frequent modifications over time, which can actually limit the practice of simulation by non-expert users.

The fact that there is no widely accepted standard to evaluate the rigor of discrete-event simulation studies in the area of SCM, has led to the development of a process that can address and manage these issues. A simulation model development process (SMDP) with an eight-step process is proposed to be a guideline for the general use in the design and execution of rigorous simulation actions, as can be seen in Figure 2.1. It is expected that such guidance may provide high quality simulation modeling research and be an optimal framework towards designing and presenting studies. The eight-step process of the SMDP encompasses the problem formulation, the specification of the independent and dependent variables, the development and validation of the conceptual model, the data collection, the development, verification and validation of the computer-based model, the performance of simulations and finally the analysis of the results (Manuj et al., 2009).

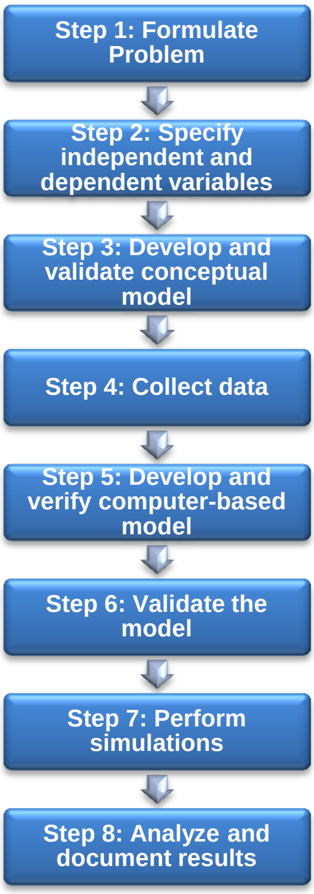


Figure 2.1 – Simulation model development process (SMDP) (Manuj et al., 2009)

In the first two stages of the SMDP, the problem should be entirely formulated, in which the objectives and the evolved variables, both dependent and independent, are clearly defined regarding the emphasis of the study. After the successful development of the conceptual model it requires an initial validation to verify if the main assumptions, algorithms and model components are accurately described. If desired, a structured walk-through can be performed to minimize any unforeseen errors. The next step consists in the collection of data that is necessary to specify the model parameters and the definition of the operating procedures required to perform the simulation study. Note that the SC modeling parameters and the operating procedures are determined based on the encountered literature within this research area. Once these operations are completed, the researcher can proceed with the verification of the computational model, followed by the model validation (Manuj et al., 2009).

Before entering the final two steps of the SMDP, it is necessary to reveal the main characteristics and the definition of validation and verification procedures that are vital in any simulation study.

In the validation process, the simulation model is verified whether it is providing an accurate representation of the system for the particular objectives of the study (Law and Kelton, 2000). The problems encountered during the validation phase are generally attributed to the model conceptualization or data collection, which can lead erroneous conclusion and decisions (De Sensi et al., 2008).

The model validation is composed of two distinct procedures, namely the conceptual and the results validation (Manuj et al., 2009). The conceptual model validation aims at determining whether the model specifies its features with sufficient clarity, precision and adequate detail, in order to meet the requirements of the study (Tannock et al., 2007). The undertaken techniques that are used in this simulation model for the conceptual validation consist in researching the existing theory and literature performed in similar simulation studies. Regarding the applied results validation techniques in this simulation study, a sensitivity analysis is undertaken after the generation of the six scenarios, in order to study and compare the results. Powers and Closs (1987) emphasize that sensitivity analyses applied to simulation models can identify the model factors that have the greatest impact on the performance measures as well as provide a good analysis model assumptions are modified.

During the verification of the SC model, one studies if the conceptual simulation model has been correctly translated into a computer program model (Law and Kelton, 2000). In order to reflect this translation correctly, the model verification is firstly applied to a SC consisted of a single entity. In case this SC is positively verified, another entity can be added to the SC. This process is repeated until the entire SC has been verified (Wan and Evers, 2011).

After this process is finished, one can answer the question related to the fact if the model is rightfully built and acknowledge that only the assumed specifications are taken into account in the model and nothing else. When the verification and validation procedures have taken place, the studied model can finally perform simulations. In the final step, the simulation results are documented and analyzed according to the pre-defined objectives (Manuj et al., 2009).

2.3 Demand information sharing

2.3.1 Introduction

An effective SC is not achievable by a single organization, but rather requires a virtual entity that can integrate all the involved entities. This virtual entity should share real-time information among SC entities regarding the SC characteristics, causing therefore a global collaborative management (Chen et al., 2007).

Prior to the 1980's, the majority of the information flows between operational areas within an organization and between organizations were paper based. These paper based transactions and communications turned out to be slow, unreliable and susceptible to errors, generating a decrease in a SC's effectiveness regarding the design, development, procurement, production and the distribution of their products or services. The advances in technology have driven many changes in the area of information technology, enabling the connection of organizations of a SC into a unified and coordinated system (Handfield and Nichols, 1999). The constant progress in SCM is actually making the managers realize that in order to remain globally competitive, one must invest in improved information sharing techniques (Byrne and Heavey, 2006). The lean manufacturers have particularly benefited with the introduction of information sharing between SC entities, providing greater collaboration and simplify the elimination of waste (Iida, 2012). Demand information sharing appears in literature as one of the most used information sharing techniques to study SCs.

2.3.2 Characteristics

A SC is considered to be fully coordinated when all decisions are aligned to fulfill the global system objectives. The absence of coordination occurs whenever the decision makers have incomplete information or incentives that are not compatible with the global SC objectives. In fact this feature is indicated as one of the most crucial factors that influences the SC performance (Yu et al., 2010). The absence of information sharing can cause excessive inventory and shortage levels, increasing lead times and demand variability, as well as, reducing service levels (Byrne and Heavey, 2006).

The main threat of information sharing within a SC, lies on the fact that SC entities often pursue their own objectives, causing a misalignment in the internal operations and force entities to make decisions that can deviate from the optimal SC solution (Iida, 2012). Chen et al. (2007) emphasize that the lack of trust and suspicions that arise can harm a cooperative development between organizations. Therefore, the benefits generated by demand information sharing need to be comprehensively studied and evaluated in order to encourage organizations to share information.

2.3.3 Demand information sharing applied in supply chains

Regarding the literature review on demand information sharing, Byrne and Heavey (2006) study the impact of information sharing and forecasting on the SC performance of an industrial SC of a small to medium-sized organization that produces multiple products using an ERP system. Assuming that customer demand was based on historic data, the outcome of this paper reveals that the involved distributors and the production entities experience cost savings of 9,7% and 6,3%, respectively, when compared with the scenario of no information sharing. Ryu et al. (2009) study the SC performance in terms of throughput, inventory level and service level, with two types of information sharing methods, namely planned demand transferring method (PDTM) and forecasted demand distributing method (FDDM). Within the PDTM, the retailer obtains the forecast information based on the market demand. After a procurement plan is created, it is transferred to the downstream entities. Consequently, the downstream entity generates its own production plan based on the information received by the retailer. The FDDM assumes that a third party organization is responsible for forecasting the demand. Given the inventory level and the lead time of each entity, the forecasted demand is distributed to each entity. The simulation results demonstrate that FDDM has a better performance than PDTM in terms of throughput. Whenever a high forecasting error occurs or there is high demand variability, FDDM still maintains lower inventory levels than PDTM. However, if the demand variability is low, PDTM outperforms FDDM. Yu et al. (2010); Chen et al. (2007) use a cross efficiency data envelopment analysis approach to study the impact of different information sharing scenarios on the SC performance, which include total costs, fulfillment rate and the customer service level. The possible information sharing scenarios include none, partial and full information sharing between the SC entities of their capacity level, inventory level and the customer demand. After performing a sensitivity analysis between these factors, a non-parametric data envelopment analysis approach is used to rank the scenarios according to the best performance measures. Curiously, the most efficient scenario turned out to be the partial demand information scenario, rather than full information sharing. It should be noted that a scenario which shares the capacity and/or inventory level without sharing demand information, actually interferes with production and causes internal misunderstandings. Zhao et al. (2002) investigate the impact of various forecasting models on the value of information sharing by using simulation. Information sharing is categorized into three different levels, namely non-information sharing, demand information sharing and demand and order information sharing. During non-information sharing, the suppliers can merely proceed with production according to the downstream orders. When demand information sharing is considered the retailers share demand forecast to the suppliers. In case of the order information sharing, the retailers share demand forecasts and order planning information to the suppliers. The simulation results indicate that the selection of a forecasting model significantly influences the SC performance and the value of information sharing (Zhao et al., 2002). Iida (2012) studies the alignment of the entities' incentives in order to stimulate cooperative cost reduction activities. Two cost reduction effort agreements are considered to improve the SC coordination, namely effort sharing agreements and effort compensation agreements. The effort sharing agreements benefit a cooperative cost reduction, while the effort compensation agreements compensate the entities for the cost of their efforts. Numerical results show that collaborative cost reduction efforts reduce the production costs and strengthen competitive advantages. Ding et al. (2011) analyze the value created of information sharing when reducing the inventory levels and introducing a collaborative mechanism that encourages upstream profit sharing in a three echelon SC. The results indicate that the retailer cannot obtain extra profit from information sharing. However, the bullwhip effect of the market demand is lowered, reducing the downstream entities' holding costs. Further it is shown that providing incentive together with a profit allocation mechanism can benefit the entire SC. Datta and Christopher (2011) use agent based simulation to study the efficiency of different methods of information sharing and coordination mechanisms in order to reduce the uncertainty in a SC. After performing a sensitivity analysis, regarding the centralization of the decision making, the frequency of the information flow for production planning and the presence of information sharing between entities, the authors conclude that under uncertainty, a decentralized decision making and centrally coordinated material flow along with daily local stock and global inventory information based production planning, and increased shared-information based ordering decisions, improves the performance of a make-to-stock SC in all aspects.

The literature review regarding information sharing indicates that the use of demand information sharing and other collaborative techniques generally benefits all the SC entities. However, if the information sharing techniques are not effectively introduced in the SC, it can actually cause misunderstandings and worsen the SC performance.

Chapter 3 Case Study: Supply Chain Model

In this chapter a case study is presented in order to achieve the proposed objectives. This chapter is divided into eight sections. The proposed supply chain (SC) is initially described under the following sections: physical model, customer demand, demand forecasting, inventory management, SC entities and the operations scheduling. Afterwards, a section is dedicated to the performance measures, in which they are carefully identified and characterized. The final section is devoted to the implementation of the SC scenarios that are defined to study the SC performance under the established conditions.

3.1. Physical model

The modeled SC consists of a single retailer, one distributor, one manufacturer and two suppliers that are producing and delivering a product to the final customer. This indicates that the modeled SC features four echelons, as can be seen in Figure 3.1.

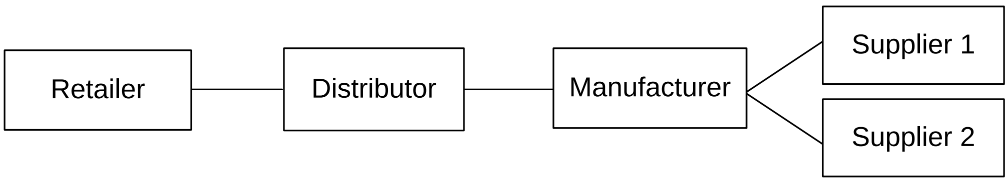


Figure 3.1 – Supply chain constitution

The product is going to be produced at the manufacturer, according to a Bill of Materials (BOM) as can be seen in Figure 3.2. In fact, one unit of the final product requires two raw materials, raw material 1 and raw material 2, with distinct quantities, namely one unit of raw material 1 and two units of raw material 2.

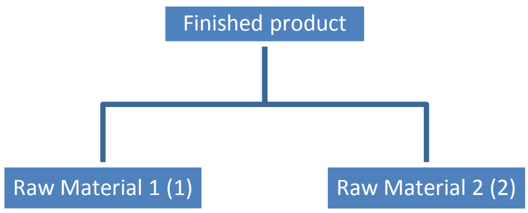


Figure 3.2 – Bill of Materials

During the production phase at the manufacturer, the two raw materials suffer a value added transformation, in which the product is produced with the help of a single machine. The production quantity is determined whenever the finished product inventory at the manufacturer places an order to refill its inventory. Further, the production quantity has to comply with a production capacity constraint that limits the production to 250 units per day. The raw materials are supplied by two distinct suppliers. Raw material 1 is exclusively supplied by supplier 1 and raw material 2 by supplier 2. After the production has taken place, the product is shipped to the distributor. Afterwards the distributor ships the product to the retailer, who satisfies the stochastic customer's demand.

The retailer and the distributor operate according to the received downstream orders and can hold stocks. The manufacturer and the two suppliers operate on the same basis. Besides this factor, these last three entities also perform demand forecasts based on historical data.

It is assumed that the SC entities are located in mainland Portugal, more specifically, the retailer in Lisbon, the distributor in Carregado, manufacturer in Leiria, supplier 1 in Porto and supplier 2 in Coimbra, as can be seen in Table 3.1.

Table 3.1 – Geographical locations of the SC entities

Entity	Retailer	Distributor	Manufacturer	Supplier 1	Supplier 2
Location	Lisbon	Carregado	Leiria	Porto	Coimbra

The shipment of product and raw materials between the SC entities are performed by road mode. The duration of the transportation is stochastic and depends on the distance that separates the involved entities.

Further, it is assumed that the SC operates 5 days a week and 8 hours a day. An overview of the SC regarding the entity's locations, the used transportation mode as well as the information and material flows between the entities can be seen in Figure 3.3.

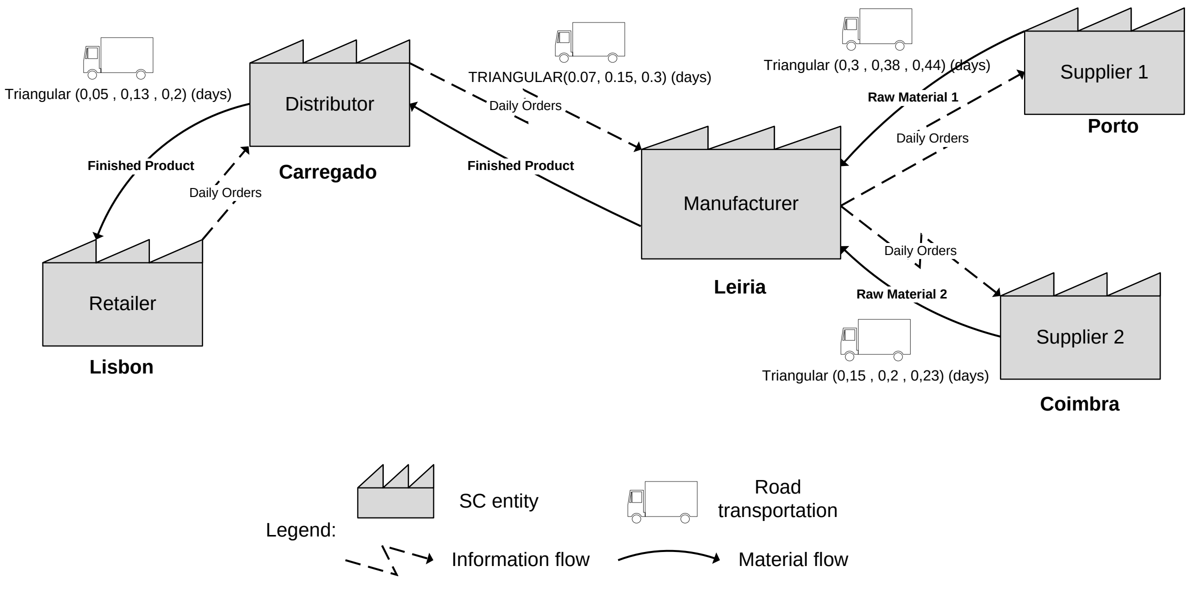


Figure 3.3 – Supply chain model

3.2 Customer demand

The customer demand is assumed to be the sum of a constant value 100 with an uncertainty that is modeled using a random variable following a Normal distribution with mean zero and an unknown standard deviation. Besides this factor, the customer demand has a weekly seasonal component. The seasonal factors illustrated in Table 3.2 indicate that the customer demand on Mondays and Fridays are 10% and 20% higher than expected, respectively. During the remaining weekdays, the customer demand is 10% lower than expected.

Table 3.2 – Seasonal factors

Weekday	Monday	Tuesday	Wednesday	Thursday	Friday
Seasonal Factor	1,1	0,9	0,9	0,9	1,2

Whenever an entity is unable to meet a downstream demand, it incurs lost sales with an associated lost sales cost. Actually, the downstream demand can be partially satisfied, as long as the inventory level of the upstream entity is higher than zero. Suppose that the downstream demand is 10 units and the inventory level of the upstream entity is equal to 6 units, then the downstream entity is going to be partially satisfied with 6 units. In fact, the lost sales cost is proportional to the number of units that remain unsatisfied.

Further, it is assumed that the inter-demand time is equal to one day, meaning that every day there is a customer demand arrival at the retailer. In order to perform SC simulation, a value has to be given to the unknown standard deviation. Therefore, three scenarios are studied, namely when the standard deviation of the customer demand of each order arrival is equal to 10, 40 and 90 units. Under these circumstances, the daily customer demand pattern is given by Table 3.3.

Table 3.3 – Daily customer demand pattern

Daily customer demand	100 + Normal(0, *i*) , $i \in \{10, 40, 90\}$

Figure 3.4 illustrates the values that the daily customer demand can obtain using the three standard deviations given the weekly seasonal factors for a simulation of 100 days. As expected, a higher standard deviation of the daily customer demand, implies that the customer demand takes values further away from the daily mean, which is equal to 100 units. Note that the negative values of the daily customer demand given a standard deviation equal to 40 and 90 units are assumed to be equal to zero within the simulation model.

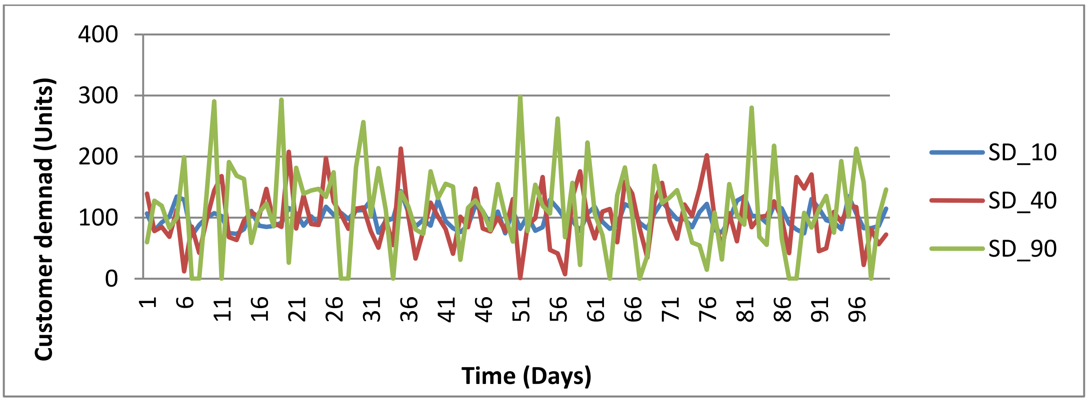


Figure 3.4 – Daily customer demand using a standard deviation of 10, 40 and 90 units for a simulation of 100 days

3.3 Demand forecasting

The forecasting technique used for the SC entities is going to be the simple moving average based on three homologous weekdays. The simple moving average is determined this way, since the customer demand suffers a daily seasonality. The reason for choosing this forecasting technique lies on the fact that the customer demand does not follow any trend combined with the fact that, according to Mahadevan (2009), it is easy to set up. The forecast for a weekday *t* is given by expression 2.

$$F_t = \frac{R_{t-5}+R_{t-10}+R_{t-15}}{3} \tag{2}$$

Thus, a forecast for Monday, F_{Monday}, is given by the arithmetic mean of the last three real values of Monday, $R_{Monday-5}$, $R_{Monday-10}$ and $R_{\mathrm{Monday-15}}$ divided by 3. According to the chosen forecasting method, the simple moving average, the demand forecast F_t needs to be made during the time period of *t-4* and *t-1*, in order to assure that the homologous real values are considered. Since it is not advisable to perform demand forecasts immediately prior to production, it is assumed that the forecasts are made four days previously, *t-4*, to the actual production, generating enough time to prepare the resources needed for the process. It is assumed that the forecasts are made every day by the manufacturer and the two suppliers.

If it is Monday, for example, the manufacturer or the suppliers predict the demand for Friday. It should be noted that the demand forecasts are constantly being rounded to the upper integer, preventing the appearance of non-integer values within the simulation model and ensuring that the actual forecast is entirely satisfied.

Note that the demand forecasts performed by the manufacturer and the two suppliers depend on the presence or absence of demand information sharing. In case there is demand information sharing the real values are equal to the customer demand at the retailer. Otherwise, the real values used to determine the forecast, are the order quantities of the downstream entities.

In order to initialize the forecasting procedure in the simulation model, the values of the first three variables regarding the real values for every weekday, R_{t-5}, R_{t-10} and R_{t-15}, have to be assigned and are assumed to be equal to the mean of the daily customer demand. Theoretically, this assumption can affect the simulation results but due to the introduction of a warm-up period these initial considerations are not influencing the performance measures.

3.4 Inventory management

The SC entities use a common inventory management model, namely a (*T, s, S*) model, in which *T* represents the review period between two consecutive reviews, *s* stands for the reorder level and *S* represents the maximum inventory level. Whenever the inventory level is equal or lower than *s* at *T* days, an order is immediately made in order to fill the inventory up to *S*. The entities that perform forecasts within the SC manage their inventory according to a (*T, s, S*) model and their demand forecasts. Whenever their inventory minus the forecast lies below *s*, an order is made to fill the inventory up to *S*. Otherwise, no order needs to be placed.

Persson and Araldi (2009) emphasize the flexibility of an (T*, s, S)* inventory management model in a push environment, whenever the user can set these three parameters. For instance, if *s* is equal to *S*, a fixed-order period system is obtained, while in case *T* is close to zero, the inventory is going to be continuously reviewed. Note that the combination of the last two suppositions is also a possible scenario. Therefore, the parameters of this inventory management model have to be carefully chosen, in order to not compromise the purpose of this study. In the first instance the safety stock needs to be determined for all the SC entities. Given that the adopted inventory management model operates under a periodic review and possesses uncertain demand and lead-time patterns, the safety stock (Q_{safety}) for a given entity *i* is determined using expression 3. Note that a maximum stock-out probability of 10% is considered, representing the probability of the demand during the lead time exceed the safety stock in a Normal distribution. This indicates that the service level of all the SC entities can never fall beneath 90%. In expression 3, *Z* stands for the Z-score and $\sigma_{D(L+T)}$ for the standard deviation of the customer demand during delivery time and the period between two consecutive inventory reviews.

$$Q_{safety_i} = Z * \ \sigma_{D(L+T)} \tag{3}$$

The Z-score value depends on the desired service level as can be seen in Table 3.4. A 90% desired service level is equivalent to a Z-score of 1,29. This means that in order to satisfy demand with a 90 percent of confidence level, it is necessary to carry an extra inventory equal to 1,29 standard deviations of the demand variability.

Table 3.4 – Relationship between the desired service level and the Z-score

Desired service level (%)	Z-score
90,0	1,29
95,0	1,65
99,0	2,33
99,9	3,10

In turn, $\sigma_{D(L+T)}$ is determined using expression 4, where $\bar{D}$ stands for the mean demand, $\bar{L}$ for the mean lead-time, *T* for the review period, σ_D^2 for the demand variance and σ_L^2 for the lead-time variance.

$$\sigma_{D(L+T)_i} = \sqrt{(\bar{L} + T) * \sigma_D^2 + (\bar{D}^2 * \sigma_L^2)} \tag{4}$$

Once the safety stock is determined, one defines the *s* of each entity by adding the units that are necessary to satisfy the average daily customer demand to the safety stock of each entity. The *S* that best suits each entity *i*, is determined using expression 5. Further it is assumed that the review period for all the SC entities is equal to one day and that the initial inventory is equal to the *S* of each SC entity.

$$S_i = (\bar{L} + T) * \bar{D} + Q_{safety} \quad (5)$$

It should be noted that three different customer demand standard deviations are considered to study the objectives, meaning that each scenario involves a different safety stock and a consequent distinct *s* and *S*. An example is given regarding the determination of the inventory management parameters of the retailer, considering a standard deviation of the customer demand equal to 10 units. Assuming that for the retailer $\bar{D}$ is equal to 100 units, σ_D is equal to 10 units, *T* is 1 day, $\bar{L}$ is equal to 0,48 days and σ_L is equal 0,031 days, then $\sigma_{D(L+T)} = \sqrt{(0{,}48 + 1) * 10^2 + (100^2 * 0{,}031^2)} \Leftrightarrow \sigma_{D(L+T)} =$ 12,55 units. The way in which the lead time and the respective standard deviation for the retailer and the other entities are determined, is accurately explained in the operations scheduling section. The safety stock for the retailer is obtained multiplying this value with 1,29, which equals 16,2 units. Assuming that the safety stock can only possess an integer value, it is therefore equal to 17 units. The *s* for the retailer is obtained by adding the mean daily customer demand, which is equal to 100 units. Therefore, *s* is equal to 117 units. Finally, $S = (0{,}48 + 1) * 100 + 17 \Leftrightarrow S = 165$ units.

Note that the inventory management parameters of the suppliers are defined distinctly in order to ensure that the downstream demand of the manufacturer is permanently satisfied. These parameters are also adjusted with an increase in variability of the customer demand.

Tables 3.5, 3.6 and.3.7 provide an overview of the inventory parameters considered for the SC entities with a customer demand standard deviation of 10 and 40 and 90 units respectively.

Table 3.5 – Inventory management parameters with a customer demand standard deviation of 10 units

Entity	Type of Product	Safety stock (units)	*s* (units)	*S* (units)	*T* (days)
Retailer	Finished Product	17	117	165	1
Distributor	Finished Product	18	118	180	1
Manufacturer	Finished Product	31	131	181	1
	Raw Material 1	18	118	200	1
	Raw Material 2	18	218	346	1
Supplier 1	Raw Material 1	50	150	250	1
Supplier 2	Raw Material 2	50	250	400	1

Table 3.6 – Inventory management parameters with a customer demand standard deviation of 40 units

Entity	Type of Product	Safety stock (units)	*s* (units)	*S* (units)	*T* (days)
Retailer	Finished Product	63	163	211	1
Distributor	Finished Product	66	166	228	1
Manufacturer	Finished Product	69	169	219	1
	Raw Material 1	70	170	252	1
	Raw Material 2	67	267	395	1
Supplier 1	Raw Material 1	100	200	300	1
Supplier 2	Raw Material 2	100	300	450	1

Table 3.7 – Inventory management parameters with a customer demand standard deviation of 90 units

Entity	Type of Product	Safety stock (units)	*s* (units)	*S* (units)	*T* (days)
Retailer	Finished Product	142	242	290	1
Distributor	Finished Product	148	248	310	1
Manufacturer	Finished Product	145	245	295	1
	Raw Material 1	156	256	338	1
	Raw Material 2	149	349	477	1
Supplier 1	Raw Material 1	150	250	400	1
Supplier 2	Raw Material 2	150	350	500	1

3.5 Supply chain entities

The retailer is responsible for receiving the daily customer orders, which dictates the SC operations. The first daily activity consists in verifying if the retailer has sufficient products in inventory to satisfy the customer demand. Whenever this condition is true, the customer is fully satisfied, otherwise lost sales are incurred. Afterwards, the retailer manages its inventory by verifying if the retailer's inventory is equal or lies below the reorder level (*s*) at the review period (*T*). In case this condition is true an order has to be placed to the distributor in order to refill the inventory up to the maximum inventory level (*S*) of the retailer. The final daily activity of the retailer is the reception of the placed orders to the distributor and the consequent update of the inventory levels, whenever the customer's orders are fully or partially satisfied. The fact that *T* is equal to one day for all the SC entities implies that every entity verifies on a daily basis if they need to place orders to refill their inventories.

The distributor starts its daily routine by receiving the retailer's orders and verifying if they can satisfy them with their current inventory. In case this condition is false, the remaining inventory is used to partially satisfy this order and lost sales are incurred. The other two activities are similar to the retailer's, namely the inventory review and the order reception from the upstream entity.

The manufacturer is assumed to hold three different types of inventories, namely the finished product inventory, the raw material 1 inventory and the raw material 2 inventory. As the name implies, the finished product inventory exclusively retains the products that are ready to be delivered to the distributor, while the raw materials inventories hold the raw materials necessary to produce the actual product. Note that the raw materials suffer a value added operation using a machine, in which they are transformed into the product. In the studied SC, the demand derives from the downstream entity, which in this case is the distributor. Whenever an issued order by the distributor can be satisfied, the product is shipped and the inventory level of the manufacturer is updated. In case the finished product inventory is unable to satisfy this demand, lost sales are incurred based on the quantity that is unable to be satisfied.

After having defined the daily demand forecasts at the manufacturer with four days in advance using the simple moving average based on three homologous weekdays, the inventory review of the finished product can be performed. The finished product inventory verifies at the review period if an internal order needs to be placed to the production based on the (*T, s, S*) model and the daily demand forecasts in order to refill the inventory level up to *S*. An internal order is therefore made to the production whenever the inventory level of the finished products minus the demand forecast is equal or lies beneath *s*. This action triggers the production process within the manufacturer.

Before initiating the production process, one needs to verify whether the current inventory levels of the two raw materials can satisfy the internal order made by the finished product inventory. Whenever the inventory levels of the two raw materials are sufficient to meet the internal order, the required raw materials are withdrawn from their inventories and transformed into the product using the machine in the SC. In case the raw material inventories are not sufficient, only the minimum level between the inventory level of raw material 1 and the inventory level of raw material 2 divided by two (rounded down) can be produced. It should be noted that the product quantity that is unable to be produced due to the lack of raw materials available does not generate directly any kind of penalty to the SC. After the desired production quantity has been produced, the inventory level of the finished product is assumed to be directly supplied with this quantity, disregarding a supply time. In case a single raw material or both being unavailable in stock for the production of a product, the system does not produce. Further, a production capacity constraint is considered, in order to represent the daily maximum production quantity that the machine can process during one day, which is considered to be equal to 250 products. Note that the inventory management adopted by the raw material inventories operates the same way as the finished product inventory, namely a (*T, s, S*) model combined with the daily demand forecasts.

The supplier's activities are practically identical to the ones adopted by the manufacturer. The two suppliers start by receiving the manufacturer's orders of raw materials and verify if they can be satisfied. Whenever this condition is false, lost sales are incurred. The inventory review and the demand forecasting procedure adopted are managed the same way as at the manufacturer, except for the fact that the suppliers do not produce. The main difference lies on the fact that they are the first entities within the SC. Therefore their inventories need to be supplied by virtual entities.

3.6 Operational scheduling

In this section, the chronological operations that are undertaken by the SC entities are described, with the aim of providing a detailed overview on how the SC operates during the course of time.

Whenever an order is placed by an entity to an upstream entity, a delay is considered. This delay represents the time spent on preparing and sending the order and is denominated the order placement delay. It lasts 0,05 days per order for all SC entities. Additionally, the orders received at the upstream entities suffer an order processing delay, representing the time spent on preparing the available resources in order to face the incoming orders. The order processing delay has a duration of 0,30 or 0,4 days per order depending on the SC entity. Table 3.8 provides an overview regarding the order delays suffered by the SC entities.

Table 3.8 – Order delays suffered by SC entities

Entity	Type of Product	Order placement delay (days/order)	Order processing delay (days/order)
Retailer	Finished Product	0,05	-
Distributor	Finished Product	0,05	0,30
Manufacturer	Finished Product	-	0,40
	Raw Material 1	0,05	-
	Raw Material 2	0,05	-
Supplier 1	Raw Material 1	-	0,40
Supplier 2	Raw Material 2	-	0,40

Looking at Table 3.8, one verifies that not all entities suffer the delays induced in this simulation model. In fact, the order placement delay is only incurred by entities that perform orders to upstream entities. Since the finished product inventory of the manufacturer issues internal orders to the raw materials, no order placement delay is considered. The orders performed by the suppliers are also assumed to possess no order placement delay, since they are supplied by virtual entities. It should be noted that the only operational delay between the suppliers and the virtual entities is a transportation delay. The order processing delay is only incurred by entities that receive and process downstream orders and deliver them back to the original entity. This is the case of the distributor, the manufacturer of the finished products and the two suppliers. The retailer is assumed to immediately process the orders of the customers, without incurring such delay. The raw material inventories of the manufacturer also lack this delay, since it processes internal orders emitted by the finished product inventory.

Whenever an order is shipped from an upstream to a downstream entity a delivery delay is considered, representing the associated transportation time. This delay is stochastic and is modeled by a triangular distribution, which requires three parameters, a minimum, a modal and a maximum value. These parameters are determined based on the distance between the geographical locations of the SC entities. Table 3.9 provides an overview of the transportation times incurred between the SC entities.

Table 3.9 – Transportation time between SC entities (triangular distribution, in days)

From → to	Retailer	Distributor	Manufacturer
Distributor	(0,05 ; 0,13 ; 0,2)	-	-
Manufacturer	-	(0.07 ; 0,15 ; 0,3)	-
Supplier 1	-	-	(0,3 ; 0,38 ; 0,44)
Supplier 2	-	-	(0,15 ; 0,2 ; 0,23)

Note that the products shipped from the virtual entity to the suppliers also incur a transportation time delay that follows a triangular distribution with parameters, (0,01 ; 0,015 ; 0,02) days, preventing an immediate update of this phenomenon.

During production at the manufacturer, a production delay is incurred representing the time spent on producing the final product, which is given by expression 6. Note that the production delay is proportional to the production quantity, since the higher the production quantity, the higher the production delay. In case the production quantity is equal to the daily production capacity, the production delay is equivalent to one day.

$$Production\ delay = \frac{Production\ quantity}{Daily\ production\ capacity} \tag{6}$$

Having defined the major delays incurred in the SC it is possible to determine the lead times and the respective standard deviations for each entity. Since the only stochastic parameter of the lead time is the transportation delay that follows a triangular distribution, the standard deviation of the lead time for entity *i* is determined based on the triangular distribution, which is given by expression 7. The lead times and the respective standard deviations of each entity can be seen in Table 3.10. The lead time of the retailer, for example, is equal to the sum of the order placement delay of the retailer, the order processing delay of the distributor and the transportation delay between the distributor and the retailer, which is equal to 0,48 days.

$$\sigma_{L_i} = \sqrt{\frac{a^2+b^2+c^2-ab-ac-bc}{18}} \tag{7}$$

Table 3.10 – Lead time and the standard deviation of the lead of each entity

Entity	Type of Product	Lead time (Days)	σ_L (Days)
Retailer	Finished Product	0,48	0,031
Distributor	Finished Product	0,62	0,048
Manufacturer	Finished Product	0,46	0,205
	Raw Material 1	0,82	0,029
	Raw Material 2	0,64	0,016
Supplier 1	Raw Material 1	0,015	0,002
Supplier 2	Raw Material 2	0,015	0,019

Note that the delay incurred by the finished product inventory of the manufacturer is only given by the production delay. Thus, this lead time is equal to the average production delay with a standard deviation of the lead time equal to standard deviation of the production delay. Since the production delay is exclusively influenced by the production quantity and the fact that it follows no distribution, it becomes necessary to approach the average and the standard deviation of the production delay by a an average and a standard deviation of a known distribution. Knowing that the production delay has an approximate average value of $\frac{100}{250}$= 0,4 days and the fact that the minimum and maximum value of the production delay are one and zero respectively, a triangular distribution with parameters, (0 ; 0,4 ; 1) days is chosen.

After having defined the major delays as well as the main activities, including the customer demand, the demand forecasts and the inventory management, occurring in the SC, one can generate the operations scheduling adopted by each entity. This provides a simple chronological order of the daily operations that take place at each entity in the SC, as can be seen in Figure 3.5. It should be noted that the chronological operations adopted by each entity repeats the same pattern every day. The customer demand arrival, the inventory review and the forecasting activity are the only operations that occur on a daily repetition basis, without any exception. The production at the manufacturer only occurs in case there are sufficient raw materials in inventory to produce at least one unit. Further, the order processing and the order placement operation only occur whenever an order is emitted by a SC entity, while the transportation delay is only incurred when an order is satisfied.

Figure 3.5 also depicts the instant in which the downstream orders are satisfied and the chronological order arrival to their destination. Note that the inventory reviews are not performed simultaneously by all SC entities. The retailer performs its inventory review later on the day, when compared with the other entities, namely at the instance 0,7 of that day. This ensures that there have been sufficient customer arrivals to justify an inventory review.

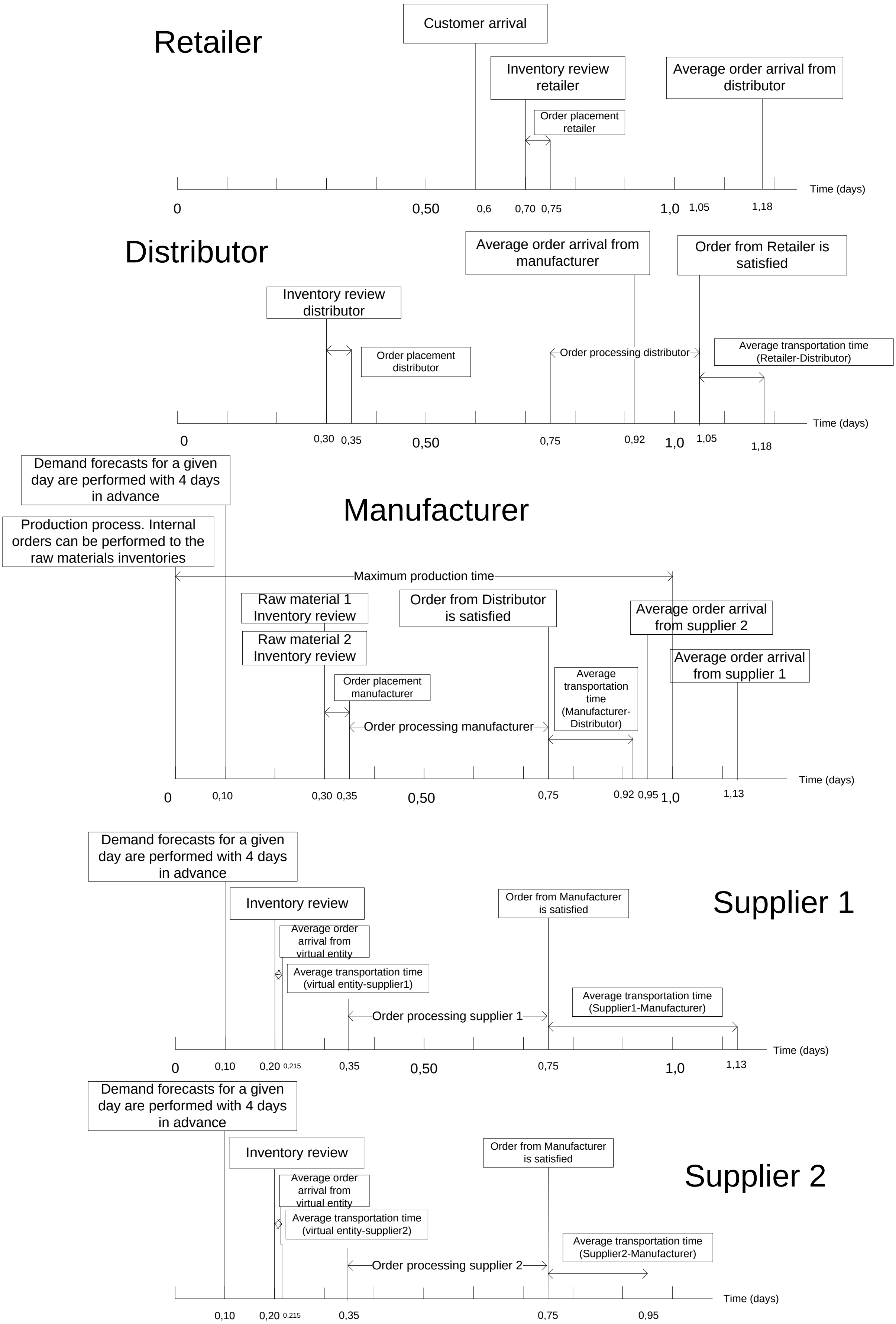


Figure 3.5 – Daily chronological operations performed by each SC entity

3.7 Performance measures

Based on these assumptions, the performance measures studied in the SC include the service level, and the SC costs. The service level for a given entity is measured using expression 8.

$$Service\ level_i = \frac{Number\ of\ satisfied\ units_i}{Total\ ordered\ units}, \tag{8}$$

$$i \in \{retailer, distributor, manufacturer, supplier\ 1, supplier\ 2\}$$

The service level of the retailer, for example, is given by the ratio between the number of satisfied units by the retailer and the total ordered amount of units by the customer. Note that the service level of the SC is given by the service level of the entity that satisfies the customer demand, which is the retailer.

The total SC costs are the sum of the holding costs, the lost sales costs, the transportation costs and the ordering costs incurred at each entity *i*, expression 9.

$$\begin{aligned} Total\ SC\ costs = \textstyle\sum_i (&Holding\ costs_i + Lost\ Sales\ costs_i \\ &+ Transportation\ costs_i + Ordering\ costs_i\ ) \end{aligned} \tag{9}$$

$$i \in \{retailer, distributor, manufacturer, supplier\ 1, supplier\ 2\}$$

The holding cost is a unitary cost that is incurred every time an entity possesses units in stock. This cost is quantified every time an entity performs its inventory review at the review period.

The lost sales cost is also a unitary cost and is incurred every time an entity's inventory is unable to fully meet a downstream demand. So, this cost is equal to the entity's unitary lost sales cost times the unfulfilled downstream demand.

The transportation costs are associated with the shipment of products and raw materials to downstream entities. The transportation cost are a unitary cost and is equal to the amount of products or raw materials that are satisfied times the transportation cost that is incurred between the two involved entities. Further, it is assumed that the virtual entity that supplies the suppliers does not incur any transportation cost.

The ordering cost are incurred every time orders are placed to upstream entities and are assumed to be an order based cost. Whenever an order is made, a fixed ordering cost is incurred regardless of the units the order possesses. Additionally it is assumed that the suppliers incur an ordering cost when placing orders to the virtual entity.

Note that the transportation and the ordering costs are updated in different instances. The transportation costs are only incurred when the product ordered is received at a downstream entity, while the ordering costs are immediately taken into account whenever an entity performs an order to an upstream entity.

Table 3.11 provides an overview of the costs incurred by the SC entities that are represented in monetary units (MU).

Table 3.11 – SC costs of the entities

Entity	Type of Product	Holding Cost (MU/product)	Lost Sales Cost (MU/product)	Transportation Cost (MU/product)	Ordering Cost (MU/order)
Retailer	Finished Product	0,5	10	-	2
Distributor	Finished Product	0,5	5	0,5	2
Manufacturer	Finished Product	0,5	2	1,1	-
	Raw Material 1	0,2	-	-	2
	Raw Material 2	0,2	-	-	2
Supplier 1	Raw Material 1	0,2	1	1,9	2
Supplier 2	Raw Material 2	0,2	1	0,8	2

Looking at Table 3.11, one can verify that the retailer does not possess a transportation cost, since it is assumed that the product at the retailer is directly delivered to the final customer. The raw material inventories at the manufacturer do not incur any lost sales or transportation costs since they only receive and ship internal orders within the manufacturer. In turn, the finished product inventory does not incur ordering costs since they are placing internal orders.

3.8 Scenarios

Initially two scenarios are analyzed in this SC, in which the presence of demand information sharing is faced against the absence of this management practice for the same customer demand standard deviation. It should be noted that the main differentiating factor between the two scenarios lies on the way the demand forecasting is performed.

Additionally, three different standard deviations are considered for the customer demand in the presence and absence of demand information sharing, namely 10, 40 and 90 units. In this case, one attempts to verify whether the presence and absence of demand information sharing influence the performance measures when there is an uncertain demand.

3.8.1 Demand information sharing

When demand information sharing is considered, the customer demand that arrives at the retailer is assumed to be instantly known by the manufacturer and the two suppliers, generating visibility throughout the SC.

In order to perform the demand forecasts at the manufacturer and at the two suppliers, the real values of the customer demand at the retailer are required.

3.8.2 No demand information sharing

The absence of demand information sharing between the SC entities indicates that the demand is exclusively acknowledged by the amount of products that are ordered by a downstream entity. This scenario allows no visibility within the SC.

Note that the demand forecasts made at both the manufacturer and the two suppliers require the real values of the downstream order quantities. Hereby, the SC entities retain historic records of downstream orders that can support the forecasting of the next orders.

3.8.3 Customer demand variability

In the final scenario the standard deviation of the customer demand is going to be altered, in order to verify if demand information sharing can reduce the impact of an uncertain customer demand in terms of the performance measures. Both the information sharing scenarios are going to be tested for three different customer demand standard deviation scenarios, namely for 10, 40 and 90 units. From now on, the presence and absence of demand information sharing scenarios generate 3 scenarios with different customer demand standard deviations that are given by the following abbreviations that can be seen in Table 3.12.

Table 3.12 – Scenario abbreviations

	Standard deviation of the customer demand (units)		
Used information sharing practice	10	40	90
With demand information sharing	W_sd10	W_sd40	W_sd90
No demand information sharing	N_sd10	N_sd40	N_varsd90

Having theoretically described the SC and identified the scenarios that are going to be tested in order to meet the objectives, it becomes necessary to translate the conceptual model into a computational model. This issue is fully addressed in the next chapter.

Chapter 4 Case Study: Simulation Model

In this chapter, a simulation study is going to be applied to the case study that has been characterized in the previous chapter. This chapter is divided into three sections, namely the supply chain entities, the verification and validation of the simulation model and finally the simulation environment. In the first section the simulating conditions are described under which the entities operate. In the next section the verification and validation procedures that the supply chain (SC) model undertakes are carefully studied. In the final section the adequate warm-up period and the number of replications are estimated.

4.1 Supply chain entities

Before analyzing the SC as a whole, it is advisable to study the individual entities that establish the operations within the SC. The use of flowcharts provides a simulation overview that can aid understanding the global functioning and operations of the SC in terms of simulation. The flowchart represented in Figure 4.1 depicts the actions undertaken by the retailer and distributor, while Figure 4.2 and Figure 4.3 reflect the operations at the manufacturer and the two suppliers, respectively.

4.1.1 Retailer

Looking at Figure 4.1, one can verify that the retailer firstly, receives a downstream demand from the customer for a given weekday. In case the retailer has enough products in inventory to satisfy the customer demand, it is fully met and the retailer's inventory is updated to the previous inventory level minus the customer demand. Otherwise, another condition has to be verified, namely whether the retailer's inventory is equal to zero. If this condition turns out to be true, then the retailer does not satisfy the customer and the respective lost sales are quantified. In case the retailer's inventory is higher than zero, the retailer can partially satisfy the customer and also incurs lost sales costs. Note that the retailer's inventory level needs to be updated to zero, since it spends its remaining inventory to partially satisfy the customer's order. During the inventory review at the retailer, the (T, s, S) model is applied, in which the retailer's inventory is daily (T=1) verified whether its current inventory level is lower or equal to the reorder level (s). If this condition is true, an order is placed to the distributor, with a consequent order placement delay, in order to refill the inventory up to the maximum inventory level (S). If the retailer's inventory is bigger than (s), it is assumed that it possesses enough inventory to meet the downstream demand. The final activity consists in receiving the ordered products from the upstream entity, which in this case is the distributor. Note that the retailer needs to update its inventory level by adding the received products to its current inventory level.

Additionally, the customer demand that is being generated through a normal distribution and multiplied with the daily seasonal factors is constantly being rounded to the nearest integer, in order to only assure integer demand within the simulation model. In order to introduce this daily characteristic in the simulation model, a condition is required to specify the weekday in which the variable TNOW, which depicts the actual simulation time, is currently in. For example, the model assumes that the weekday is Monday whenever the condition *MOD(AINT(TNOW), 5) == 0* is true. The *MOD(a, b)* function in

Arena 9.0 returns the integer remainder between the division of *a* and *b,* while the *AINT(a)* function truncates *a* to the lower integer. So, the first condition is valid whenever 0 ≤ TNOW < 1, or 5 ≤ TNOW < 6 or when 10 ≤ TNOW < 11 and so on. An overview of the simulation model in Arena regarding the retailer can be seen in Annex 4.

4.1.2 Distributor

The distributor starts by receiving the retailer's order and verify if it can be satisfied with the current inventory. In case this condition turns out to be true, the order is fully satisfied and shipped to the retailer with a given transportation time. Note, that if the distributor's inventory level is merely enough to partially satisfy an order, it is also shipped to the retailer with the same transportation time. In this case, the distributor's inventory level is going to be equal to zero, until an order is made during the inventory review to refill the inventory level up to the maximum inventory level (*S*). The other two activities are similar to the retailer's, namely the inventory evaluation and the order reception from the downstream entity. The simulation model built in Arena representing the distributor can be seen in Annex 4.

4.1.3 Manufacturer

Looking at Figure 4.2 one can verify that the only activity that differs from the retailer and the distributor is the production activity, which takes place at the manufacturer. In case the inventory review of the finished products verifies that the actual inventory level minus the forecast is equivalent or lower than the reorder level (*s*), a production quantity is emitted equal to the difference between the maximum inventory level (*S)* and the maximum level between the inventory level less the forecasts and zero, which corresponds to filling the inventory up to *S*. Note that if the difference between the inventory level and the forecasts is lower than zero, the production quantity is equal to *S*. Otherwise no production is needed and the production quantity is assigned to 0.

The production at the manufacturer starts with processing the production quantity assigned by the inventory review. Within the production activity, the production quantity is constantly verified whether it follows the model restrictions, namely if there are sufficient raw materials and complies with the maximum production capacity. So, the first condition that needs to be verified is whether there are sufficient raw materials in inventory to satisfy the downstream order. In case the downstream order cannot be fully satisfied, the production quantity is updated according to the available raw materials. If there are sufficient raw materials to satisfy the internal order, the production quantity remains unmodified. Additionally, another condition needs to be verified before starting the production, namely whether the production quantity exceeds the daily production capacity. In case this is true, the production quantity is updated to the model restrictions. Finally, the production quantity is verified whether it is bigger than zero. In case this condition is false, there is no production. Otherwise, the required raw materials are withdrawn from their inventories and the production process takes place. The products that have been created are finally added to the finished product inventory. It should be noted that the production activity embraces a quantitative delay action that represents the time necessary to produce a desired quantity. Whenever the maximum allowed number of products is produced, the production delay is virtually equal to 1 day. In fact, the production delay has a duration of 0,998 days, in order to update the finished product inventory still in the same day. Note that the machine used to produce the products follows a seize-delay-release action. In first instance the machine seizes the necessary raw materials, which is followed by a production delay that represents the value added operation. When the delay comes to an end, the finished product is released from the machine.

The inventory management of the raw materials at the manufacturer operates in a similar way to the inventory management of the finished products. The only difference lies on the fact that the forecast used to verify if an order needs to be placed to the suppliers is based on the forecast of the demand of the following day. For example, in case the current time corresponds to the weekday Monday, the raw material inventories only place an upstream order, whenever the actual inventory minus the forecast for Tuesday is equal or lower than the reorder level (*s*). This precocious measure tries to ensure that at the beginning of the day of Tuesday the requirements of the finished product inventory can be satisfied. The simulation model in Arena representing the manufacturer can be seen in Annex 5. Note that the only difference between the presence and the absence of demand information sharing within the simulation model lies on the forecasting activity.

4.1.4 Suppliers

The suppliers' activities in Figure 4.3 are very similar to the manufacturer, except for the absence of the production activity that does not occur at the suppliers. The suppliers start with the reception of the manufacturer's orders and verifying if these can be satisfied. Like in the previous entities, the unitary lost sales are incurred every time a unit remains unsatisfied. The inventory review dictates the point at which orders have to be made to the virtual entities, namely when the inventory level minus the forecasts are equal or lower than the reorder level (*s*). The inventories are refilled by virtual entities that incur a transportation time delay.

It should be noted that the data used for the forecasting procedure at the manufacturer and the two suppliers are totally different for the two studied scenarios. In the presence of demand information sharing, one uses the last three homologous real values of the customer demand at the retailer to determine the simple moving average for a given weekday. In the absence of demand information sharing, the last three values of the downstream order quantities are used to forecast the demand for the same weekday. Additionally, the forecasts are constantly being rounded to the upper integer. An overview of the supplier's simulation model is displayed in Annex 6. Like at the manufacturer, the only difference between the presence and absence of demand information sharing lies on the forecasting activity.

4.1.5 Other characteristics

Note that the different types of SC costs incurred at each entity are quantified in different simulation instances. For instance, the holding costs of each entity are determined whenever an inventory review is performed at each entity. The lost sales costs are quantified every time an order at an upstream entity is unable to be partially or totally satisfied. The ordering costs are taken into account whenever an entity performs an order to an upstream entity, while the transportation costs are incurred whenever a product or raw material is received at a downstream entity. The average inventory levels of each entity are determined at the end of the simulation length. Thus, a variable is created to accumulate the inventory level of each entity at the review period until the end of the simulation length. At this instance, the value of the accumulator is divided by the simulation length, giving the average inventory level for a given entity. The number of orders performed by each entity is recorded by a variable that is incremented by one every time an order is made.

Note that the performance measures are not quantified during the warm-up period. This action is represented within the simulation model by assigning a decision module that verifies if the actual simulation time is bigger than the warm-up period before the performance measures are determined. Whenever the actual simulation time is lower than the warm-up period, the performance measures are not collected.

The probability distributions used in Arena are based on default random numbers uniformly distributed between 0 and 1 that are generated by a multiplicative congruential generator. The fact that the generator is recursive means it requires an initial value that is defined as a seed. Arena uses by default a value that allows one to reproduce a sequence of 10 random numbers, which are used in the generation of the random variables involved in the modulation. In order to decrease the variability of the simulation results, it becomes advisable to use different sequences for each type of random input in the model. This way, one can integrally reproduce the behavior of the SC entities when the simulation model is executed for a given period of time, decreasing at the same time the variability of the outputs. Therefore it is assumed that all the probability distributions used in the simulation model possess different random stream numbers that ensure the generation of the same data within the studied scenarios, as can be seen in Table 4.1. This way, the results comparison acquires a higher degree of certainty.

Table 4.1 – Random stream numbers assigned to the different probability distributions

Activity	Probability distribution	Random stream number
Customer Demand	Normal	11
Transportation time between distributor and retailer	Triangular	20
Transportation time between manufacturer and distributor	Triangular	15
Transportation time between supplier 1 and manufacturer	Triangular	35
Transportation time between supplier 2 and manufacturer	Triangular	18

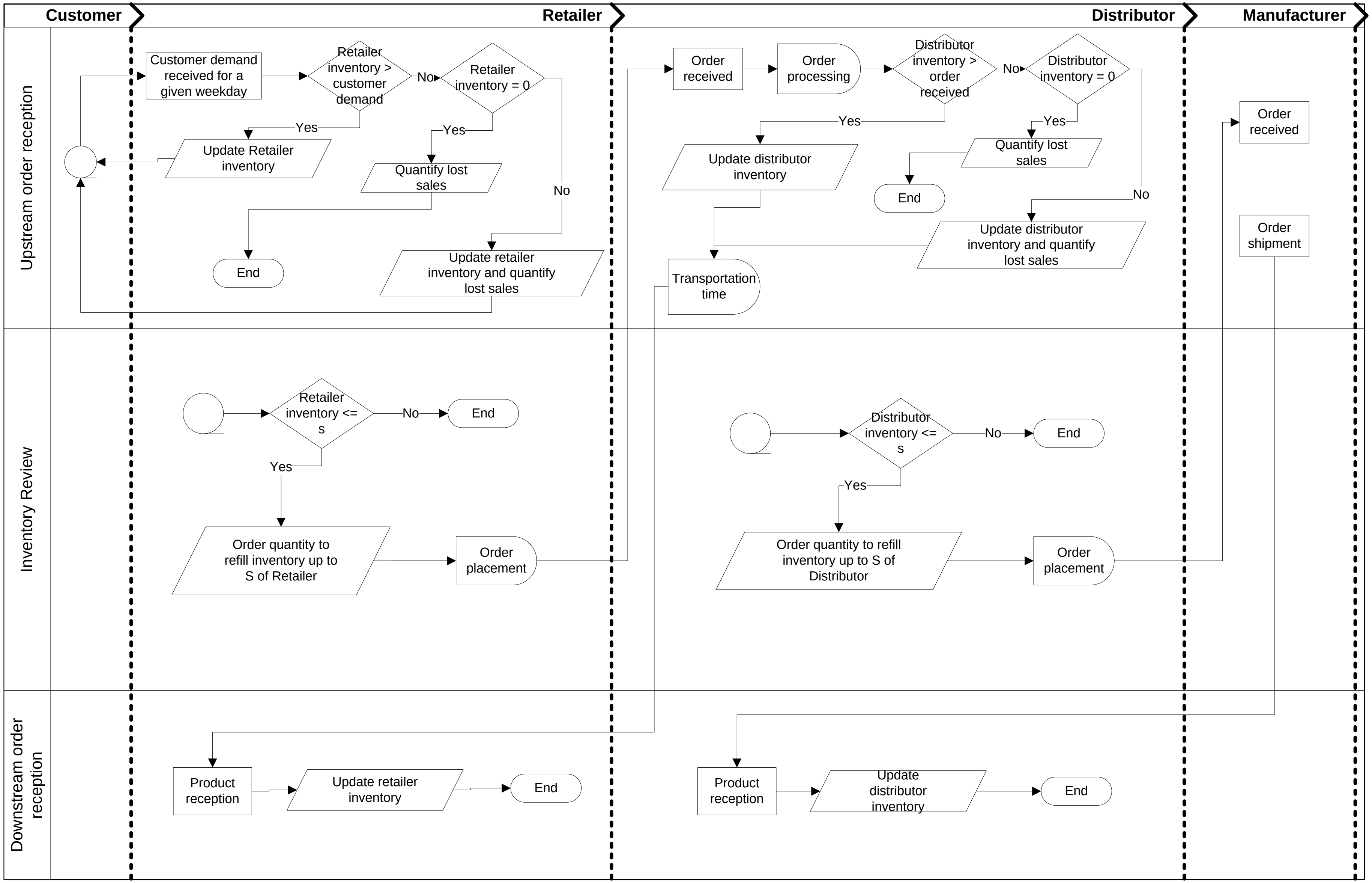


Figure 4.1 – Retailer's and distributor's flowchart

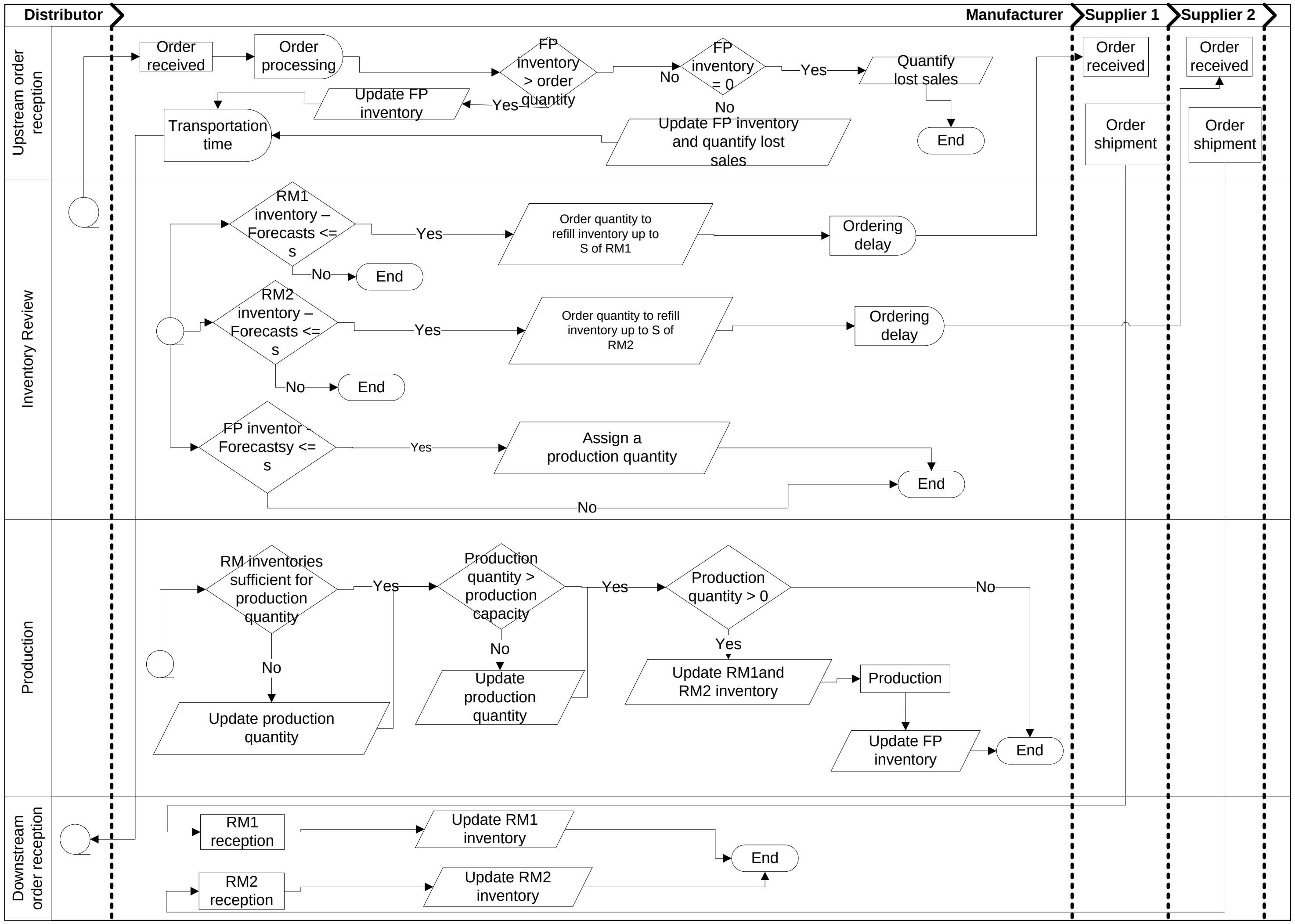


Figure 4.2 – Manufacturer's flowchart

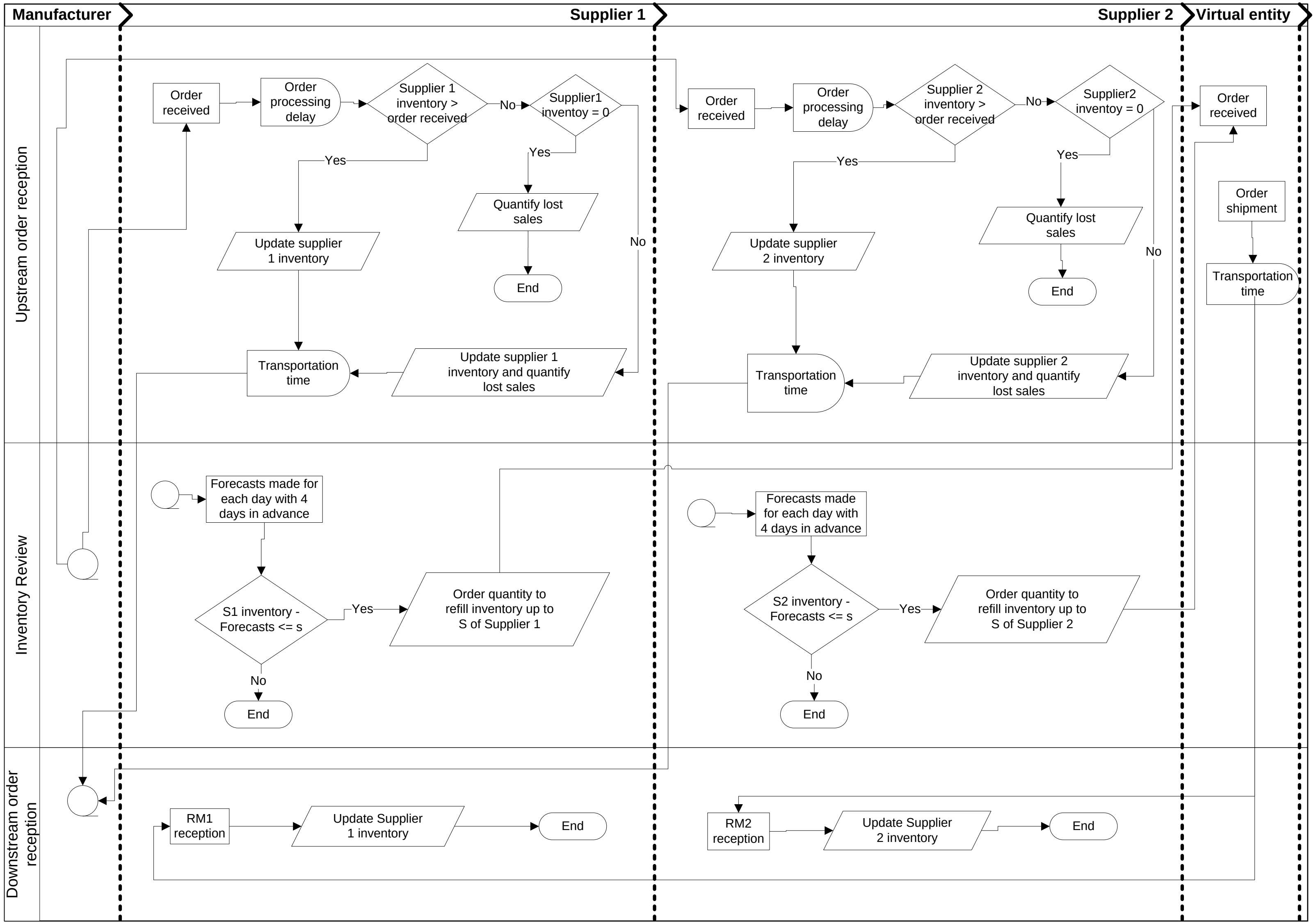


Figure 4.3 – Supplier's flowchart

4.2 Verification and validation of the simulation model

The verification and validation procedures adopted in the simulation model are based on the model developed by Manuj et al. (2009). The verification procedures adopted to verify whether the conceptual model has been correctly translated into the computational model include a detailed code checking in order to identify premature errors. For example, the simulation model is initially run under specific conditions, in which the outputs can easily be predicted. Note that this analysis is initially applied to the SC consisted of only one entity. In case the SC is positively verified, the following entity is introduced, until the SC of the case study is obtained.

The main validation procedure adopted to verify whether the simulation model is providing an accurate representation of the system for the objectives of the study, consists in researching the existing theory and literature performed in similar simulation studies.

Further analyzes that are applied in the simulation model to detect simulation errors include the use of read-write modules. In fact, the read-write modules appear in Arena as one of the most efficient tools to detect simulation errors. This module displays the evolution of a chosen attribute or variable during the simulation length, allowing a more custom error detection. Note that the read-write module is very flexible since it can be placed anywhere in the simulation model. Additionally a comparative analysis is undertaken regarding the outputs of the studied scenarios, in order to detect any awkward values. In case aberrant values are detected, one knows where to search for the error within the simulation model. Ultimately, the creation and analysis of flowcharts provide an effective method to identify errors both for the validation and verification procedures.

4.3 Simulation environment

Kelton et al. (2004) emphasize the need to choose an adequate simulation length that can mitigate the effects of random or stochastic input parameters that will consequently lead to random outputs. In this simulation model, the simulation length is considered to be approximately equal to one working year, 260 days, which is believed to be long enough to mitigate the effect of the variability on the outputs. In order to determine the adequate warm-up period and the number of replications, two external studies are performed with the help of the SC simulation outputs.

4.3.1 Warm-up period

During the warm-up period in simulation, a model does not gather any statistical data. Within this period, the model outputs suffer several variations until they adapt themselves to the model parameters. The end of the warm-up period usually coincides with the verification of a repeated pattern in the model outputs, which is denominated by the steady-state period.

In order to determine the adequate warm-up period for the SC model, the *Ouput Analyzer* application of Arena 9.0 is used. This application is particularly useful to analyze some outputs of the SC model with more precision. Using this application, the outputs of the service levels are carefully analyzed, providing a graphical acknowledgment of the required warm-up period for this simulation model. The

SC costs are not studied to determine this parameter, since these performance measures possesses additive characteristics. When choosing the ultimate warm-up period for the SC model, one should consider the worst scenario in terms of the time required to stabilize the output data. Initially, 5 replications are considered to study this phenomenon with a simulation length equal to 260 days.

Figures 4.4 and 4.5 are an example of this analysis for supplier 2 in the presence and absence of demand information sharing with a customer demand standard deviation equal to 90 units. Examining these figures, one verifies that supplier 2 in the presence and absence of demand information sharing requires a warm-up period of 100 days.

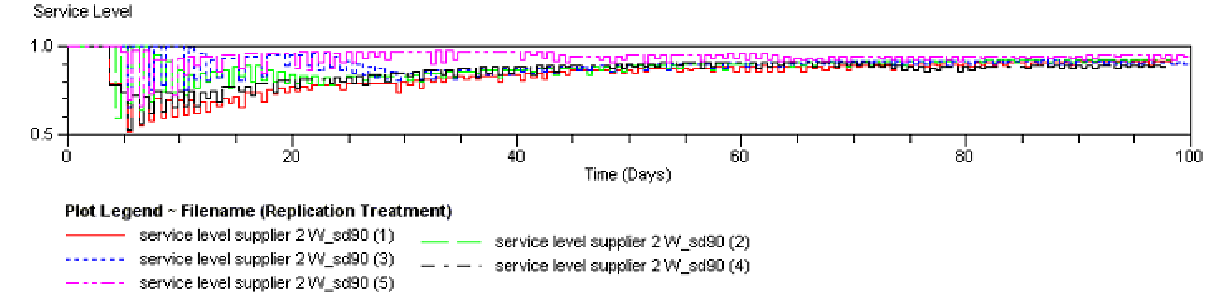


Figure 4.4 – Warm-up period estimate using the service level of supplier 2 W_sd90

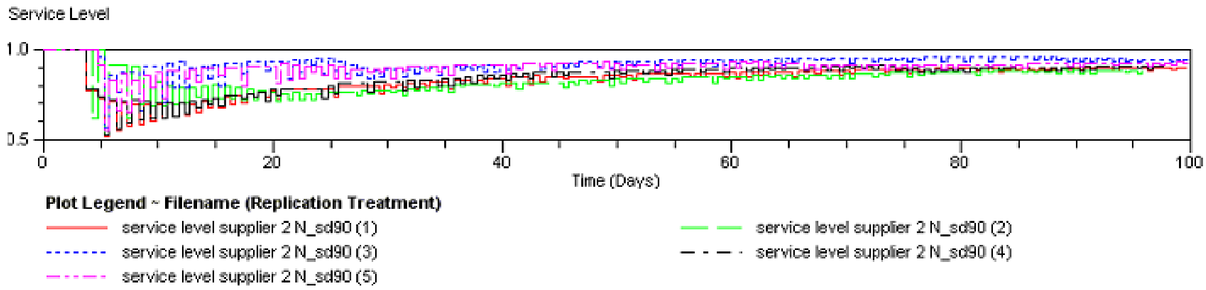


Figure 4.5 – Warm-up period estimate using the service level of supplier 2 N_sd90

The graphical development of the remaining service levels to verify the required warm-up period to reach the steady-state period of each entity can be verified from Annex 1.1 up to 1.14, in case there is demand information sharing and from Annex 2.1 up to 2.14, if there is no demand information sharing.

Analyzing the development of remaining service levels during the considered simulation length, one verifies that the service level of supplier 2 with demand information sharing and a standard deviation of the customer demand equal to 40 and 90 units, possesses the longest variation period that lasts 100 days. Note that the service level of supplier 2 in the absence of demand information sharing, with a standard deviation of 90 units also requires 100 days to stabilize this performance measure. The required warm-up period for the service levels of each entity can be seen in Table.4.2.

Analyzing Table 4.2, one verifies that the warm-up period that is required to reach the steady-state period for this SC model is going to be 100 days (4,6 months), with a simulation length equal to 360 days. This simulation length is obtained by adding the warm-up period with the desired simulation length.

Table 4.2 – Warm-up period required to reach the steady-state period for the service levels (days)

	With demand information sharing			No demand information sharing		
	Customer demand standard deviation (units)			Customer demand standard deviation (units)		
Entity	**10**	**40**	**90**	**10**	**40**	**90**
Retailer	0	0	0	0	0	0
Distributor	30	30	40	30	30	30
Manufacturer	30	40	50	30	30	50
Supplier 1	70	60	40	80	50	40
Supplier 2	90	100	100	80	90	100

4.3.2 Number of replications

The number of replications dictates the amount of times a simulation model is repeated. Each replication provides an observation of an output. This function becomes particularly convenient in the presence of stochastic data within a simulation model. Note that the replication of a model with stochastic data provides different outputs on every replication.

In order to determine the accurate number of replications for this SC model a study is performed using half-width. The half-width represents half of the range of a confidence interval associated with the mean value. In the simulation model the mean value corresponds to each performance measure.

The number of replications that are adequate for this simulation model is given by expression 10, in which h_0 stands for the half-width of the mean value for n_o replications and h for the desired half-width of the mean value. In fact the half-width can be reduced by increasing the number of replications. It should be noted that the obtained number of replications n are always rounded up to the nearest integer, since one can only perform an integer number of replications.

$$n = n_0 * \frac{h_0^2}{h^2} \tag{10}$$

This study is performed for the six scenarios with a warm-up period equal to 100 days and a simulation length of 360 days, defined previously, for five replications. The determination of the ultimate number of replications should be performed similarly to the warm-up period, in which the worst number of replications are required to stabilize all the output data of the performance measures. Table 4.3 provides an overview regarding the estimation of the required number of replications to stabilize the output data of the service levels for W_sd40, based on five replications.

Table 4.3 – Determination of the number of replications for the service levels for W_sd40

Performance measure	Value	Half-width	Desired half-width	n
Average service level retailer	0,99	0	0,05	0
Average service level distributor	0,98	0	0,05	0
Average service level manufacturer	0,96	0,01	0,05	1
Average service level supplier 1	0,99	0,01	0,05	1
Average service level supplier 2	0,93	0,02	0,05	1

Table 4.4 provides an overview regarding the estimation of the required number of replications to stabilize the output data of the SC cots for W_sd40, based on five replications. The estimation of the required number of replications to stabilize the performance measures for the remaining scenarios can

be visualized from Annex 3.1 up to Annex 3.10. Examining these annexes as well as Tables 4.3 and 4.4, one verifies that the highest number of replications necessary to obtain the desired precision of the performance measures is equivalent to 111 replications. This consideration is obtained when there is demand information sharing and a customer demand standard deviation equal to 40 units. According to this study, the simulation model requires therefore 111 replications.

Table 4.4 – Determination of the number of replications for the SC costs for W_sd40

Performance measure	Value (MU)	Half-width	Desired half-width	n
Average total holding costs	102756	2131	5138	1
Average total lost sales cost	39084	9170	1954	111
Average total ordering costs	2608	53	130	1
Average total transportation costs	134740	3749	6737	2

Chapter 5 Case Study: Results

This chapter is dedicated to the presentation of the case study results and the respective results analysis. Therefore, a section is dedicated to the results analysis, in which the six proposed scenarios of the case study are compared in terms of the studied performance measures, namely the supply chain (SC) costs and the service level.

5.1 Result analysis

The aim of this section is to provide an extensive and detailed result analysis in order to extract valid conclusions that can effectively answer the objective of this study. In first instance, the presence and absence of demand information sharing scenarios are compared with the same standard deviation of the customer demand. Thus, it is possible to exclusively compare the impact of the demand information sharing practice on the supply chain management (SCM). Afterwards, this study intends to verify whether the impact of demand information sharing can reduce the negative effect of an increase in the customer demand uncertainty on the SCM. In this case it is necessary to compare the presence and the absence of the demand information sharing scenarios with different standard deviations of the customer demand. The results analysis is divided into two sub-sections, which study the analysis of each performance measure, namely the SC costs and the service levels.

5.1.1 Supply chain costs analysis

In first instance, the total SC costs are compared between the presence and absence of demand information sharing under the three standard deviations of the customer demand scenarios. This analysis is shown in Table 5.1.

Table 5.1 – Total SC costs comparison between the scenarios in the presence and absence of demand information sharing

Scenario	Total SC costs (MU)	Difference (MU)	Difference (%)
W_sd10	244 649	2 737	1,1
N_sd10	247 386		
W_sd40	282 964	9 246	3,2
N_sd40	292 210		
W_sd90	357 528	17 960	4,8
N_sd90	375 488		

Table 5.1 demonstrates that the W_sd10 scenario possesses 1,1% lower total SC costs than in the N_sd10 scenario. In the same way, W_sd40 incurs 3,2 % less total SC costs than N_sd40 and W_sd90 less 4,8% total SC costs than N_sd90. This analysis demonstrates that in terms of the total SC costs, the presence of demand information sharing outperforms the absence of this practice. Curiously, the difference in terms of percentage of the total SC costs between the presence and absence of demand information sharing appears to be proportional with an increase in the standard deviation of the customer demand.

The impact of the customer demand variability in the presence and absence of demand information sharing regarding the SC costs is another study that can help answering the initial objective. The total SC costs obtained under the presence and absence of demand information sharing for the three customer standard deviations are shown in Table 5.2. As expected, a higher customer demand variability yields higher total SC costs in both the presence and absence of demand information sharing. In fact, W_sd40 possesses 13,5% more total SC costs than W_sd10. Further, W_sd90 possesses 20,9% more total SC costs than W_sd40 and 31,5% more total SC costs than W_sd10. Performing the same analysis in the absence of demand information sharing, N_sd40 possesses 15,3% more total SC costs than N_sd10. N_sd90 possess 22,2% more total SC costs than N_sd40 and 34,1% more total SC costs than N_var1. Note that as the customer demand variability increases in the presence of demand information sharing, the evolution of the total SC costs is slightly lower than in the absence of demand information sharing. The reason for such occurrence has to do with the fact that the entities who are directly influenced by the presence of demand information sharing, namely the manufacturer and the two suppliers, base their operations on demand forecasts of the actual demand. In fact, under the presence of demand information sharing, the obtained demand forecasts are a better representation of the actual customer demand than in the absence of this management practice.

Table 5.2 – Comparison of the total SC costs between scenarios with the same information sharing practice

Scenario	Total SC costs (MU)
W_sd10	244 649
W_sd40	282 964
W_sd90	357 528
N_sd10	247 386
N_sd40	292 210
N_sd90	375 488

It should be noted that in this simulation model, some of the inventory management parameters, namely the safety stock, the reorder level (*s*) and the maximum inventory level (*S*), are adjusted according to the variability of the customer demand. In case this adjustment is not performed, one should obtain bigger differences in terms of the total SC costs, with an increase in the customer demand variability.

The fact that the total SC costs are composed of four types of costs, namely the holding, lost sales, ordering and transportation costs, makes it interesting to study the proportion that these acquire in terms of the total SC costs. An overview of the incurred types of SC costs in the presence of demand information sharing can be seen in terms of percentage in Figure 5.1 and in terms of their values in Table 5.3.

Figure 5.1 – Proportion of the types of SC costs in terms of percentage in the presence of demand information sharing

Analyzing Figure 5.1, one verifies that the majority of the total SC costs are composed by the holding costs and the transportation costs. In fact, these costs can represent from 87% to 96% of the total SC costs, depending on the applied customer demand standard deviation. The remaining SC costs are composed of lost sales and ordering costs. Note that an increase in the standard deviation of the customer demand significantly modifies the SC costs proportion regarding the presence of demand information. In terms of costs proportion, the transportation costs decrease at the expense of the holding costs and the lost sales costs which encounter a significant increase. Within W_sd10, the transportation costs represent 55%, the holding costs 41% and the lost sales 3% of the total SC costs, while in the W_sd90 scenario the transportation costs represent 39%, the holding costs 48% and the lost sales costs 12% of the total SC costs. The evolution of the ordering costs is not mentioned, since they are insignificant regarding the total SC costs.

Table 5.3 – Incurred types of costs in the presence of demand information sharing

Type of cost	W_sd10	W_sd40	W_sd90
	Value (MU)		
Holding costs	101 288	127 554	173 316
Lost sales costs	6 993	19 796	41 413
Ordering costs	2 671	2 263	1 906
Transportation costs	133 696	133 351	140 893

It should be noted that the adjustments made regarding some of the inventory management parameters, namely the safety stock, the reorder level (*s*) and the maximum inventory level (*S*), are the reason why the holding costs suffer such an increase in terms of the proportion of the total SC costs, when there is an increase in the customer demand variability. In fact, a higher standard deviation of the customer demand provides higher inventory management parameters, which directly affect the incurrence of holding costs by the SC entities. The lost sales costs also increase in terms of their actual values and in terms of proportion of the total SC costs. This depicts that in general there is a greater difficulty in satisfying upstream orders. The transportation costs suffer a decrease in terms of the percentage of the total SC costs when the customer demand variability is increased. Examining Table 5.3, one verifies that the actual increase in the transportation costs is insignificant regarding the increases in the holding and lost sales costs, with an increase of the standard deviation of the customer demand. This is the reason why in terms of the percentage proportion the transportation costs decrease.

The same overview regarding the incurred types of costs in the absence of demand information sharing can be seen in Figure 5.2 and in Table 5.4. Likewise, in the absence of demand information, the evolution of the SC costs proportions follows the same trend with an increase in the customer demand variability. In fact, in the N_sd10 scenario, the transportation costs are equal to 54%, the holding costs 42% and the lost sales costs 3% of the total SC costs, while in the N_sd90 scenario, the transportation are only 38%, the holding costs 51% and the lost sales costs 10% of the total SC costs.

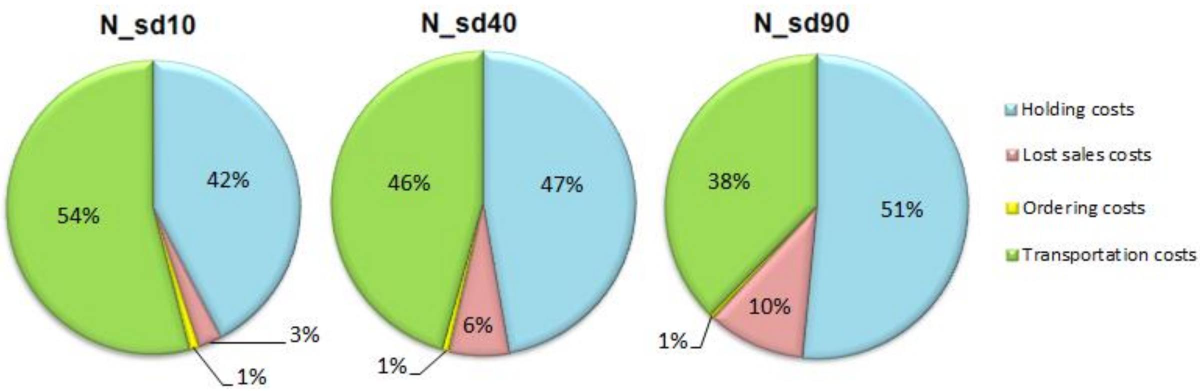


Figure 5.2 – Proportion of the types of SC costs in terms of percentage in the absence of demand information sharing

When comparing the composition of the types of costs in terms of their values, as can be seen in Tables 5.3 and 5.4, one verifies that the SC always incurs more holding costs when there is no demand information sharing. The fact that in the presence of demand information sharing, the manufacturer and the two suppliers possess more certainty regarding the real value of the downstream demand is the explanation for this verification. Examining the lost sales costs, one verifies that for a standard deviation of the customer demand equal to 40 and 90 units, the absence of demand information sharing incurs more lost sales costs than in the presence of this practice. The SC cost analysis regarding each entity may help answer this phenomenon. Further, one verifies that the difference in terms of the ordering and transportation costs between the presence and absence of demand information sharing is insignificant.

Table 5.4 – Incured types of costs in the absence of demand information sharing

Type of cost	N_sd10	N_sd40	N_sd90
	Value (MU)		
Holding costs	104 786	137 960	193 436
Lost sales costs	6 507	18 619	38 911
Ordering costs	2 515	2 178	1 875
Transportation costs	133 578	133 454	141 266

The average total SC costs proportion per entity in terms of percentage in the presence and absence of demand information sharing are depicted in Figure 5.3. It should be noted that the average total SC costs in terms of percentage is considered for each information sharing scenario, since there is no significant modification when the standard deviation of the customer demand is increased. Analyzing Figure 5.3, one verifies that the manufacturer is an entity responsible for incurring more than half of the total SC costs, namely 56% or 55% depending on the considered information sharing practice. The remaining percentage of the total SC costs are approximately incurred with 18% or 17% by the distributor, 14% by the retailer, 8% by supplier 2 and 5% by supplier 1. The main reason why the manufacturer incurs such high costs lies on the fact that this entity possesses three types of inventory, namely the finished product and the two raw materials inventory, which all acquire holding costs. Additionally, the two raw material inventories incur two ordering and two transportation costs. The fact that the suppliers feature rather low SC costs in terms of percentage derives from the absence of transportation costs when these are supplied by virtual entities. The exact values in monetary units of these costs are discussed further in this section. Note that the comparison of the average total SC costs composition in terms of percentage in the presence and absence of demand information sharing are practically identical.

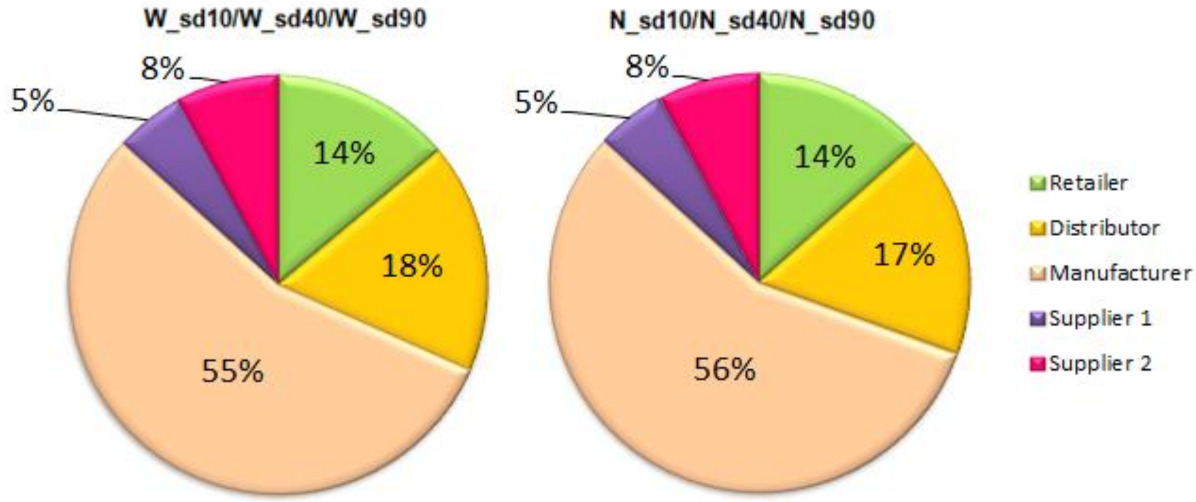


Figure 5.3 – Average total SC costs composition in percentage per entity in the presence and absence of demand information sharing

Within the total SC costs analysis, it also seems of interest to analyze the total costs incurred by each entity under the presence and absence of demand information sharing. An analysis is therefore performed, in which the total costs incurred at each entity are compared between the scenarios with the same standard deviation of the customer demand. This analysis is shown in Table 5.5, considering a standard deviation of the customer demand equal to 10 units. Note that the percentage difference column in Table 5.5 provides the cost difference between the presence and absence of the demand information sharing management practice.

Table 5.5 –Total costs comparison per entity between the W_sd10 and N_sd10

Entity	Total costs (MU) W_sd10	Total costs (MU) N_sd10	Difference (%)
Retailer	24 762	24 688	-0,30
Distributor	41 928	41 928	0
Manufacturer	144 948	147 094	1,46
Supplier 1	12 348	12 634	2,27
Supplier 2	20 664	21 041	1,79

Examining Table 5.5, one verifies that there is practically no difference between the total retailer and distributor costs in the presence and absence of demand information sharing. The reason for such verification lies on the fact that these entities are indifferent before the presence and absence of demand information sharing. In fact, the retailer and the distributor are identically modeled and perform the same activities, disregarding the presence or absence of demand information sharing. The absence of demand information sharing causes the manufacturer to incur 1,46% more costs than in the presence of demand information sharing. The entities that most benefit with the introduction of demand information sharing are supplier 1 and supplier 2, which incur 2,27% and 1,79% less costs when compared with the absence of demand information sharing. The same analysis is shown in Tables 5.6 and 5.7, considering a standard deviation for the customer demand equal to 40 and 90 units, respectively.

Table 5.6 –Total costs comparison per entity between the W_sd40 and N_sd40

Entity	Total costs (MU) W_sd40	Total costs (MU) N_sd40	Difference (%)
Retailer	37 010	36 720	-0,79
Distributor	50 760	50 142	-1,23
Manufacturer	157 070	165 743	5,23
Supplier 1	15 302	15 607	1,95
Supplier 2	22 821	23 997	4,90

Table 5.7 –Total costs comparison per entity between the W_sd90 and N_sd90

Entity	Total costs (MU) W_sd90	Total costs (MU) N_sd90	Difference (%)
Retailer	61 410	61 167	-0,40
Distributor	64 452	64 609	0,24
Manufacturer	185 531	202 319	8,30
Supplier 1	203 33	20 472	0,68
Supplier 2	25 802	26 922	4,16

Examining Tables 5.6 and 5.7, one verifies that an increase in the customer demand variability in both information sharing scenarios have practically no effect on the total costs incurred by the retailer and the distributor. The manufacturer, on the other hand, verifies a significant increase regarding the percentage difference in terms of the incurred costs, when there is demand information sharing and an increase in the customer demand variability. The difference between the presence and absence of demand information sharing in terms of the incurred costs at the manufacturer, actually increases from

1,46% to 8,30% with a standard deviation of the customer demand equal 10 and 90 units, respectively. The reason why the manufacturer benefits with the introduction of demand information sharing, when compared to the distributor and retailer, has to do with the fact that his inventory management, namely a (*T, s, S*) model aided by forecasts, is directly affected by the introduction of this policy. Regarding the incurred costs at the suppliers, one verifies that the percentage difference between the presence and absence of demand information sharing for supplier 1 decreases from 1,95% to 0,68%, considering a standard deviation of 40 and 90 units, respectively. Comparing these values with the percentage difference considering a standard deviation of 10 units, which is equal to 2,27%, one verifies that an increase in the variability of the customer demand decreases the percentage difference between the presence and absence of demand information sharing costs of the costs of supplier 1. Performing the same analysis for supplier 2, one verifies that the percentage difference drops from 4,90% to 4,16%, when considering a standard deviation of 40 and 90 units, respectively. Knowing that the percentage difference is 1,79% given a standard deviation of the customer demand equal to 10 units, one still verifies a significant increase of this difference with an increase in the variability of the customer demand.

The fact that the conclusions drawn regarding the behavior of the supplier's costs with an increase in the customer demand variability are distinct, makes one believe that the inventory management parameters of the suppliers are inaccurately defined. However, one verifies that the supplier's costs under the presence of demand information sharing are always higher, in every scenario, than in the absence of this management practice. The fact that the supplier's costs represent 14% of the total SC costs, means that these variations significantly affect the total SC costs. Finally, one verifies that an increase in the customer demand variability increases the SC costs for all the entities in both information sharing practices, as was proven earlier in Table 5.2.

Further it is interesting to verify the ordering pattern that every entity acquires as well as the incurred ordering costs. This analysis is shown in Tables 5.8, 5.9 and 5.10 for a standard deviation of the customer demand equal to 10, 40 and 90 units, respectively.

Table 5.8 – Average number of orders and ordering costs incured by each entity for W_sd10 and N_sd10

Entity	Type of product	W_sd10		N_sd10	
		Average number of orders	Average ordering costs (MU)	Average number of orders	Average ordering costs (MU)
Retailer	FP	259	518	259	518
Distributor	FP	260	520	260	520
Manufacturer	RM1	210	421	199	397
	RM2	227	455	219	437
Supplier 1	RM1	173	345	159	318
Supplier 2	RM2	207	413	163	326

Table 5.9 – Average number of orders and ordering costs incured by each entity for W_sd40 and N_sd40

Entity	Type of product	W_sd40		N_sd40	
		Average number of orders	Average ordering costs (MU)	Average number of orders	Average ordering costs (MU)
Retailer	FP	235	469	235	469
Distributor	FP	218	435	217	434
Manufacturer	RM1	175	351	162	325
	RM2	194	389	180	360
Supplier 1	RM1	142	284	138	277
Supplier 2	RM2	168	336	156	313

Table 5.10 – Average number of orders and ordering costs incured by each entity for W_sd90 and N_sd90

c	Type of product	W_sd90		N_sd90	
		Average number of orders	Average ordering costs (MU)	Average number of orders	Average ordering costs (MU)
Retailer	FP	190	379	190	379
Distributor	FP	180	360	178	356
Manufacturer	RM1	156	313	147	294
	RM2	172	344	163	326
Supplier 1	RM1	105	210	109	219
Supplier 2	RM2	149	298	151	302

Analyzing these tables, one verifies that an increase in the customer demand variability causes the SC entities to perform less upstream orders and incur consequently lower ordering costs, independent of the considered information sharing practice. The fact that the average number of orders is proportional to the average ordering costs explains why the average ordering costs follow this same pattern. Examining the entities, one verifies that the retailer and the distributor make the same amount of orders, independently on the presence of demand information sharing. The reason for such verification has to do with the fact that these entities operate indifferently regarding the presence or absence of demand information sharing. The manufacturer and supplier 2 perform a higher amount of orders in the presence of demand information sharing when compared with the absence of this practice.

A consequent difference between the presence and absence of demand information sharing lies on the average inventory levels and the holding costs that are incurred at each entity. Therefore, Table 5.11 provides an overview regarding the average inventory levels at each entity depending on the studied scenario, while Table 5.12, displays the holding costs incurred at each entity.

Table 5.11 – Average inventory levels of the SC entities

Entity	Type of product	Average inventory level					
		W_sd10	N_sd10	W_sd40	N_sd40	W_sd90	N_sd90
Retailer	FP	47	46	77	77	129	129
Distributor	FP	58	58	88	88	141	143
Manufacturer	FP	130	140	156	185	211	267
	RM1	136	140	174	195	240	285
	RM2	239	247	274	304	335	408
Supplier 1	RM1	167	171	209	213	279	281
Supplier 2	RM2	281	288	312	328	352	366

Table 5.11 demonstrates that the average inventory levels of the retailer and the distributor possess approximately the same average inventory levels in the presence and absence of demand information sharing, since they are not directly influenced by the information sharing practice. On the other hand, the three types of inventories of the manufacturer and the two suppliers possess lower inventory levels when there is demand information sharing. This confirms that the demand forecasts generated in the presence of demand information sharing are more representative of the real customer demand, resulting in lower average inventory levels. Additionally, one verifies that an increase in the variability of the customer demand increases the average inventory levels for both information sharing scenarios. The reason for such occurrence lies on the fact that the inventory management parameters are adjusted with an increase in the variability of the customer demand, generating an higher inventory levels throughout the SC. Examining, Table 5.12, one verifies that the drawn conclusion are similar to those of Table 5.11, since that the average inventory levels are proportional to the holding costs. The manufacturer and the suppliers incur higher holding costs in the absence of demand information sharing for the same standard deviation of the customer demand. The retailer and the distributor incur approximately the same holding costs for the same standard deviation of the customer demand. The analysis of Table 5.12 is therefore consistent with Table 5.1, which confirms that the total SC costs incurred in the presence of demand information are lower than in the absence of demand information sharing.

Table 5.12 – Holding costs incured by the SC entities

		Holding costs (MU)					
Entity	**Type of product**	**W_sd10**	**N_sd10**	**W_sd40**	**N_sd40**	**W_sd90**	**N_sd90**
Retailer	FP	8 361	8 363	13 879	13 902	23 245	23 265
Distributor	FP	10 358	10 388	15 752	15 892	25 306	25 679
Manufacturer	FP	23 320	25 129	28 157	33 341	37 981	48 123
	RM1	9 799	10 112	12 536	14 011	17 280	20 485
	RM2	17 197	17 763	19 726	21 891	24 094	29 338
Supplier 1	RM1	12 003	12 317	15 019	15 323	20 074	20 217
Supplier 2	RM2	20 251	20 715	22 485	23 601	25 336	26 328

The following study that is performed, intends to compare the average order quantity of units that are made at each entity with the respective average satisfied order quantities under the presence and absence of demand information sharing for the same standard deviation of the customer demand. The quotient between these two quantifications dictates the incurred lost sales costs at each entity. An overview of these characteristics is shown in Tables 5.13, 5.14, 5.15 for a standard deviation of the customer demand equal to 10, 40 and 90 units.

Analyzing these tables, one verifies initially that an increase in the customer demand variability, forces all SC entities to perform higher order quantities. The reason for this lies on the fact that there is on average a higher demand within the simulation model and the inventory management parameters possess higher values with an increase in the customer demand variability.

Table 5.13 – Average satisfied order quantities and the lost sales cost for W_sd10 and N_sd10

Entity	Type of product	W_sd10			N_sd10		
		Average order quantity	Average satisfied order quantity	Average lost sales cost (MU)	Average order quantity	Average satisfied order quantity	Average lost sales cost (MU)
Retailer	FP	101	-	3 003	101	-	2 928
Distributor	FP	101	99	2 524	101	99	2 493
Manufacturer	FP	-	100	1 466	-	100	1 086
	RM1	126	-	-	133	-	-
	RM2	233	-	-	242	-	-
Supplier 1	RM1	-	126	0	-	133	0
Supplier 2	RM2	-	233	0	-	242	0

Table 5.14 – Average satisfied order quantities and the lost sales cost for W_sd40 and N_sd40

Entity	Type of product	W_sd40			N_sd40		
		Average order quantity	Average satisfied order quanty	Average lost sales cost (MU)	Average order quantity	Average satisfied order quanty	Average lost sales cost (MU)
Retailer	FP	112	-	9 851	112	-	9 533
Distributor	FP	124	109	6 148	123	109	5 383
Manufacturer	FP	-	119	3 797	-	119	3 611
	RM1	150	-	-	163	-	-
	RM2	272	-	-	294	-	-
Supplier 1	RM1	-	150	0	-	294	7
Supplier 2	RM2	-	272	0	-	163	84

Table 5.15 – Average satisfied order quantities and the lost sales cost for W_sd90 and N_sd90

Entity	Type of product	W_sd90			N_sd90		
		Average order quantity	Average satisfied order quanty	Average lost sales cost (MU)	Average order quantity	Average satisfied order quanty	Average lost sales cost (MU)
Retailer	FP	146	-	24 308	146	-	24 040
Distributor	FP	162	142	8 804	160	142	8 582
Manufacturer	FP	-	151	8 084	-	153	5 960
	RM1	178	-	-	191	-	-
	RM2	325	-	-	344	-	-
Supplier 1	RM1	-	178	49	-	191	36
Supplier 2	RM2	-	325	168	-	344	293

Combining this finding with the analysis of Tables 5.8, 5.9 and 5.10, one concludes that an increase in the customer demand variability forces entities to make a lower amount of orders but higher order quantities. Another finding indicates that in the presence of demand information sharing, the average order quantities are lower in the case of the manufacturer and the suppliers independent of the considered standard deviation of the customer demand. This means that in the presence of demand information sharing the entities who forecast their demand are more benefited, since their order quantities are more representative of the real requirements. The retailer and the distributor order the same product quantity, since the presence of demand information sharing is irrelevant regarding their operations.

The average satisfied order quantity provides the number of satisfied order quantities regarding the placed order quantities, which depicts the lost sales costs. When comparing the evolution of the lost sales costs, with an increase in the customer demand variability for both information sharing scenarios, one verifies that in most cases there is an increase in the lost sales costs. Note that the lost sales incurred at each entity are actually inversely proportional to the obtained service level, meaning that the higher the lost sales cost, the lower the service level is. A more detailed analysis is given in the next section, in which the service levels are extensively studied.

Regarding the incurred transportation costs in the SC, one verifies that these costs are proportional with the average satisfied order quantities in both information sharing scenarios. Analyzing Tables 5.13, 5.14 and 5.15, one verifies that an increase in the variability of the customer demand increases the transportation costs, since there are more units being satisfied. For the same reason, one verifies that the absence of demand information sharing brings more transportation costs in comparison with the presence of the studied management practice. This occurs due to the fact that in the absence of demand information sharing, the SC entities place a lower amount of orders with greater quantities. Note that this statement is accurate, since the transportation costs are a unitary based cost.

5.1.2 Service level analysis

After having discussed the supply chain costs, it is necessary to study the remaining performance measure of the case study, which is the service level. The obtained service level of each entity is initially analyzed in the presence and absence of demand information sharing. Afterwards, one verifies the impact of demand information sharing given an uncertain customer demand in terms of the service levels.

An overview of the entity's service levels in the presence and absence of demand information sharing are illustrated in Figures 5.4, 5.5 and 5.6, given a standard deviation of 10, 40 and 90 units respectively.

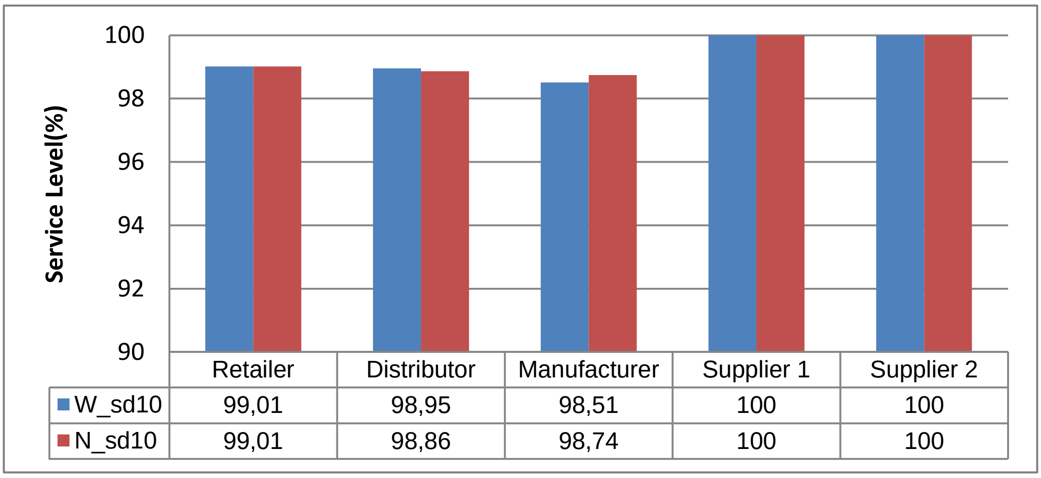


Figure 5.4 – Overview of the entities' service levels under W_sd10 and N_sd10

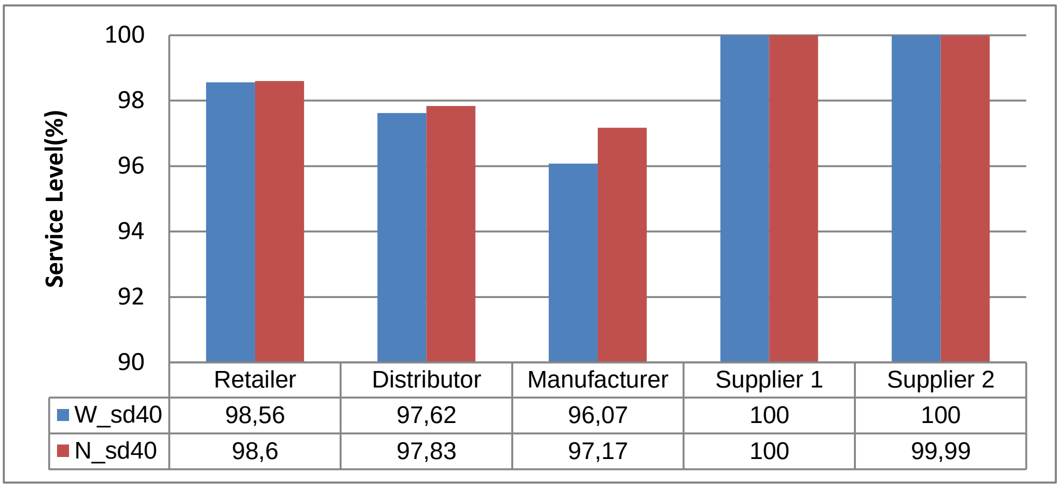


Figure 5.5 – Overview of the entities' service levels under W_sd40 and N_sd40

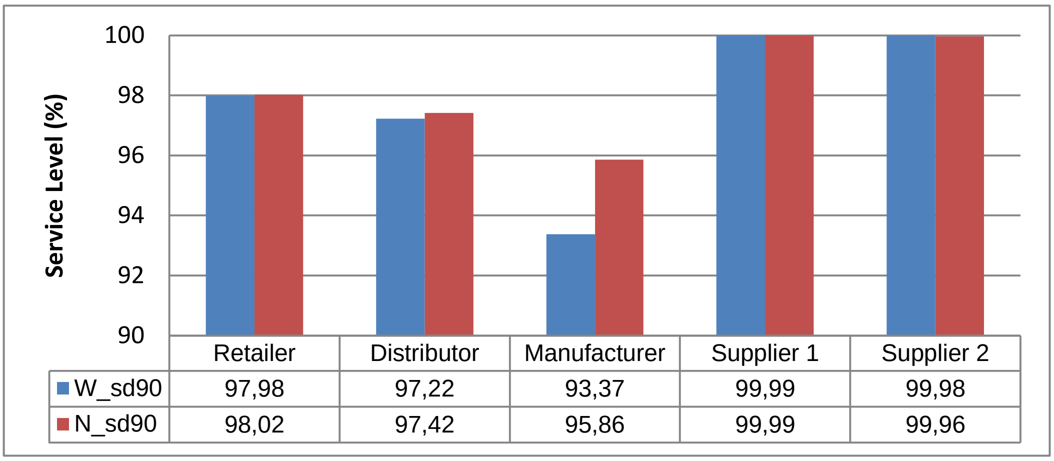
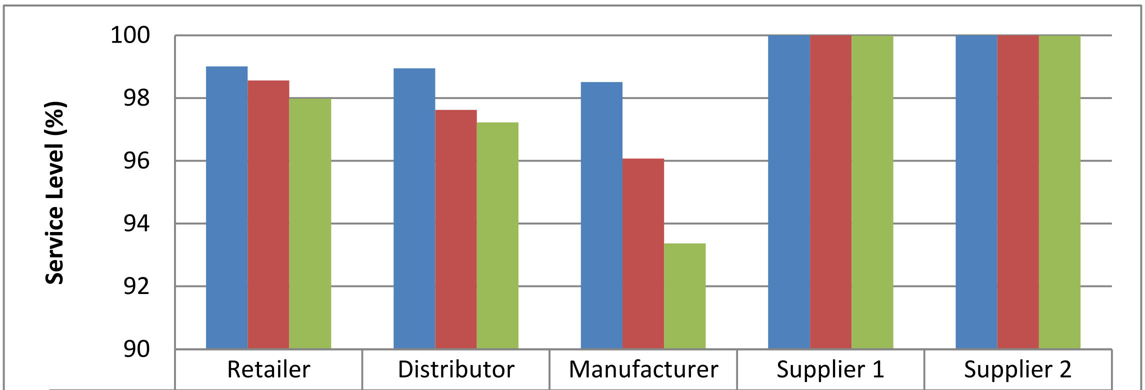


Figure 5.6 – Overview of the entities' service levels under W_sd90 and N_sd90

In first instance, one notices that Tables, 5.13, 5.14, and 5.15, which depict the service level of the SC entities in terms of the ratio between the satisfied order quantities and the order quantities made by each entity, are consistent with the obtained service levels. Examining Figures 5.4, 5.5 and 5.6, one verifies that the service levels of the retailer and the distributor remain practically the same independent of the adopted information sharing practice. The reason for this occurrence is that the operations of the retailer and the distributor are indifferent regarding the presence of demand information sharing. Regarding the service level of the manufacturer, one verifies that it is slightly more benefited when there is no demand information sharing, especially with higher customer demand variability. The main reason for such occurrence lies on a significant decrease of the demand forecasting quality in the presence of demand information sharing, especially with high customer demand variability. In fact, these forecasts depend directly on the variability of the customer demand, which indicates that a standard deviation of the customer demand equal 90 units greatly affects the forecasting quality. On the contrary, the forecasts made under the absence of demand information sharing depend on the orders from the distributor, which smoothen the forecasting quality. In this case, the variability of the customer demand is damped by the retailer and the distributor that appear as a buffer regarding the forecasting quality. Examining the service levels of the two suppliers, one verifies that this performance measure is hardly affected by the presence of demand information sharing. In fact, these service levels remain in all scenarios practically equal to 100%, which means that the suppliers can always satisfy the orders of the manufacturer. These results are therefore in agreement with Tables 5.13, 5.14 and 5.15. The reason for such occurrence lies on the definition of the inventory management parameters of the two suppliers. In fact these parameters are defined in order to ensure that the orders from the manufacturer are always satisfied.

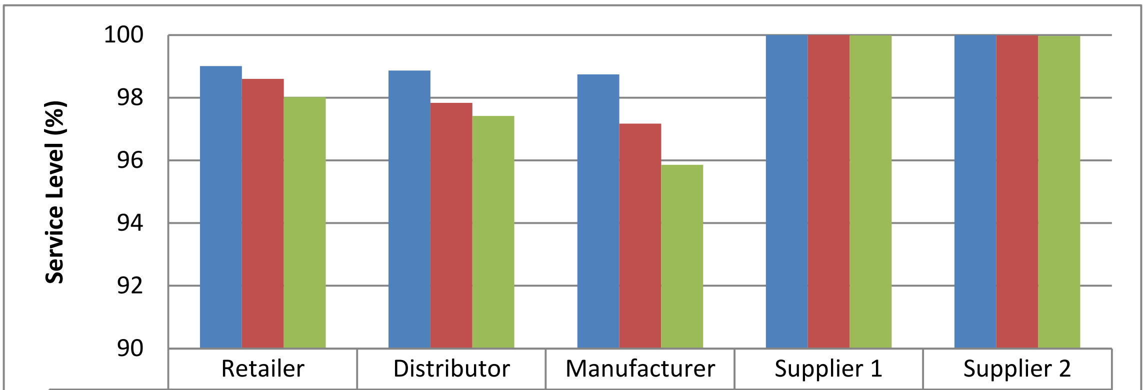
It should be noted that the service level of the entire SC is given by the service level of the retailer, which satisfies the customer demand. In both information sharing scenarios the service level ranges from 99% to 98% depending on the considered customer demand variability. This indicates that the presence of demand information sharing has no effect on the service level of the entire SC. Thus, the difference between the performance of the presence and absence of the demand information sharing scenarios depend exclusively on the incurred SC costs. Finally, the worst service level occurs with a standard deviation of the customer demand equal to 90 units, which corresponds to the customer demand with the biggest variability.

Finally, it is necessary to study the impact of the presence of demand information sharing on the customer demand variability, regarding the service levels of the SC entities. Hereby, Figures 5.7 and 5.8 provide an overview regarding the entity's service levels under the presence and absence of demand information sharing respectively, given the three standard deviations of the customer demand.



	Retailer	Distributor	Manufacturer	Supplier 1	Supplier 2
W_sd10	99,01	98,95	98,51	100	100
W_sd40	98,56	97,62	96,07	100	100
W_sd90	97,98	97,22	93,37	99,99	99,98

Figure 5.7 – Overview of the entity's service levels under W_sd10, W_sd40 and W_sd90



	Retailer	Distributor	Manufacturer	Supplier 1	Supplier 2
N_sd10	99,01	98,86	98,74	100	100
N_sd40	98,6	97,83	97,17	100	99,99
N_sd90	98,02	97,42	95,86	99,99	99,96

Figure 5.8 – Overview of the entity's service levels under N_sd10, N_sd40 and N_sd90

Examining Figures 5.7 and 5.8, one verifies that the service level of the retailer and the distributor are not very affected entity by an increase in the variability of the customer demand. The service level of the retailer drops from 99% to 98, while the service level of the distributor drops from 99% to 97%, with a standard deviation of the customer demand of 10 and 90 units respectively. The reason why these service levels are hardly affected is due to the fact that their inventory management parameters are adjusted with an increase in the customer demand variability. The service level of the manufacturer drops from 99% to 96% or 93% depending on the considered information sharing practice, with an increase in the standard deviation of the customer demand from 10 to 90 units. Examining the evolution of the service levels of the suppliers for both information sharing scenarios, with an increase in the customer demand variability, one verifies this performance measure is hardly affected. Like in the previous analysis, the service levels remain in all scenarios practically equal to 100%, which means that the suppliers can always satisfy the orders of the manufacturer, disregarding the variability of the customer demand. The reason for such lies once again on the definition of the inventory management parameters of the two suppliers, which are defined to ensure that the orders from the manufacturer are always satisfied.

It should be noted that the cost for implementing the demand information sharing policy within the SC is not considered in this case study. In reality, one should examine the incurred expenditure with introducing such policy, before drawing final conclusions.

Having analyzed the impact of demand information sharing given the assumptions of the studied SC, one concludes that the introduction of demand information sharing improves the SC performance by reducing the total SC costs from 1,1% to 4,8%, depending on the considered standard deviation of the customer demand. This finding agrees with literature, regarding the fact that the introduction of information sharing practices reduces the total SC costs (Byrne and Heavey, 2006; Datta and Christopher, 2011). Further, one acknowledges that the presence of demand information has no impact on the obtained service level of the SC, when considering distinct customer demand variability.

Thus, the difference between the performance of the presence and absence of the demand information sharing scenarios depends exclusively on the incurred SC costs.

When analyzing the impact of an increase in the customer demand variability, one verifies that all the studied performance measures worsen for both the information sharing scenarios. In terms of the total incurred SC costs, the W_sd90 scenario possesses 31,5% more total SC costs than W_var1, while N_var15 incurs 34,1% more total SC costs than N_var1. Note that the holding cost is the type of cost that increases the most with an increase in the customer demand variability for both information sharing practices. This verification has to do with the adjustments performed on the inventory management parameters, which depend on the variability of the customer demand. Regarding the service level of the entire SC, one verifies that it drops in both information sharing scenarios from 99% to 98% with an increase in the customer demand variability.

Note that that the retailer and the distributor remain indifferent regarding the presence or absence of demand information sharing, both in terms of the service level and the costs incurred at these entities. The fact that these entities are identically modeled, disregarding the presence of demand information sharing confirm this statement.

The manufacturer appears as the entity responsible for incurring more than half of the total SC costs both in the presence and absence of demand information sharing. One of the reasons why the difference in terms of the total SC costs increases between the presence and the absence of demand information sharing has to do with the fact that the difference between the costs of the manufacturer also increases between the presence and absence of demand information sharing with an increase in the customer demand variability.

It should be noted that under a high customer demand variability and the presence of demand information sharing, the quality of the demand forecasts decreases, when compared with the absence of this management practice. In fact, the demand forecasts under the presence of demand information sharing depend directly on the variability of the customer demand. On the contrary, the forecasts made under the absence of demand information sharing depend on the downstream orders, which smoothens the forecasting quality. When there is no demand information sharing, the variability of the customer demand is damped by the retailer and the distributor that appear as a buffer regarding the forecasting quality. This statement assumes that the forecasting technique used is a simple moving average based on three homologous periods.

Chapter 6 Conclusions

6.1 Conclusions

The absence of a reliable information sharing technique is frequently the reason for an increasingly volatile and turbulent supply chain (SC) performance. The technological progress is actually forcing SCs to permanently question the introduction of an information sharing policy that can bring several benefits, as can be seen in literature. However, one still fears that the use of information sharing between organizations can damage their personal benefits. Thus, in order to encourage organizations to share information, the generated benefits need to be comprehensively recognized and evaluated through further studies in this research area.

Simulation appears as an ideal tool to study the implementation of this practice in a relatively short period of time. Additionally, the constant improvement in recent years of the performance/price ratio of computer hardware is turning simulation into one of the most used tools in the actual global business environment that can more specifically be applied to the study of SCs and aid supply chain management (SCM).

This research attempts to proceed the study regarding the effect and the value of information sharing practices in SCs when facing uncertainties, more specifically under an uncertain customer demand variability. Hereby, one studies the impact of the presence of demand information sharing and whether this practice can reduce the impact of an uncertain customer demand in terms of the total SC costs and the service level. A simulation model is developed in Arena to study this research. This dissertation contributes to the SC literature by providing analytical support regarding how information sharing strategies can boost SC performance and be a motivation for future work within this research area.

The simulation results show that the introduction of demand information sharing among the considered SC entities improves the SC performance by reducing the total SC costs from 1,1% up to 4,8%, depending on the variability of the customer demand. These results inspire the confidence that they are in agreement with literature, regarding the benefit of the presence of information sharing in SCs. On the other hand, the service level of the SC is not influenced by the presence of demand information sharing.

Analyzing the impact of an increase in the variability of the customer demand, one concludes that all the studied performance measures worsen for both the information sharing scenarios. Regarding the total SC costs, the W_sd90 scenario possesses 31,5% more total SC costs than W_sd10, while N_sd90 incurs 34,1% more total SC costs than N_sd10. This indicates that in the presence of demand information sharing, the incurred SC costs are slightly lower, when compared with the absence of this management practice. In terms of the service level of the entire SC, one concludes that in both information sharing scenarios it drops from 99% to 98% for a standard deviation of the customer demand equal to 10 and 90 units, respectively. Further, one verifies that the best scenario regarding the SC performance occurs when there is demand information sharing with a standard deviation of the customer demand equal to 10 units.

The fact that the retailer and the distributor operate regardless of the demand information sharing practice brought no direct benefits to them, regarding the incurred SC costs and the service level. The fact that the operations of the retailer and the distributor are indifferent regarding the presence of demand information sharing is the reason for this occurrence. On the contrary, the manufacturer and the suppliers are directly affected by the introduction of this management practice.

6.2 Future work

Regarding future work, it is interesting to continue studying SCs under different forms of uncertainty. The introduction of a stochastic supply uncertainty or machine breakdowns, for example, can bring additional contributions to this dissertation, regarding the presence of uncertainties in SCs. Further, one can introduce an inter-demand time that follows a probability distribution, in order to depict a more realistic demand pattern. The present simulation model, assumes that a customer arrives with a fixed time interval equal to one day.

In order to generate a uniformly demand information sharing throughout the SC, it seems interesting to also introduce this policy at the distributor. In this case, the entire SC is affected by the presence of demand information sharing, rather than the actual simulation model, in which only the manufacturer and the two suppliers use this management practice. Additionally, the retailer and the distributor can also perform demand forecasts.

The way the inventory management parameters of the suppliers are determined and the way the adjustments are made with an increase in the customer demand variability need to be reviewed. The inventory management parameters of the remaining entities are assumed to be adequate, since they are not the first entities of the SC.

An additional extension of this study may be the performance of a sensitivity analysis regarding the simulation model in which, for example, the review period (*T*) and the daily production capacity are altered in order to verify their impact on the studied outputs. It should be noted that an alteration in these parameters forces one to make amendments regarding the simulation model, namely at the level of the inventory management parameters.

The introduction of multiple entities per level in the SC is also a possible extension of the work developed so far that can depict further benefits of the introduction of demand information sharing. Finally, it would be interesting to apply this study to an actual enterprise, in which the drawn conclusions can actually benefit and improve the existing operations, rather than performing a virtual study.

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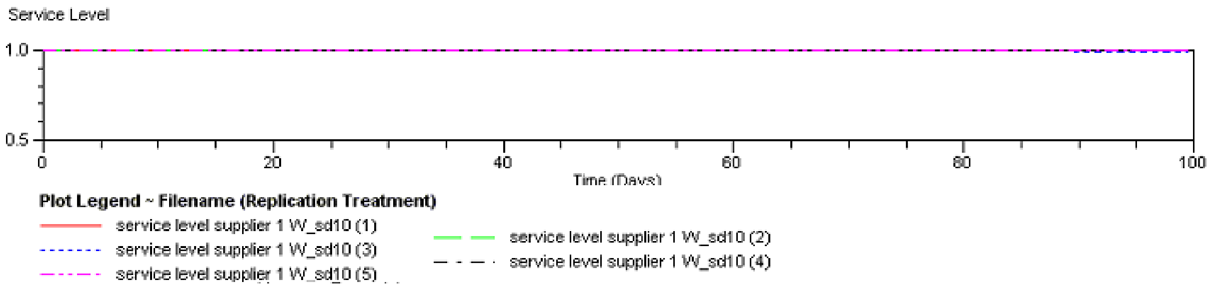
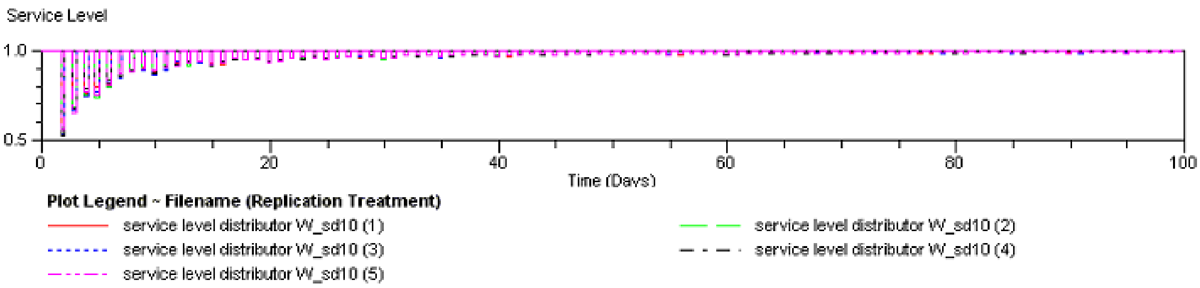
Annexes

Annex 1 Development of the service levels when choosing the warm-up period with demand information sharing

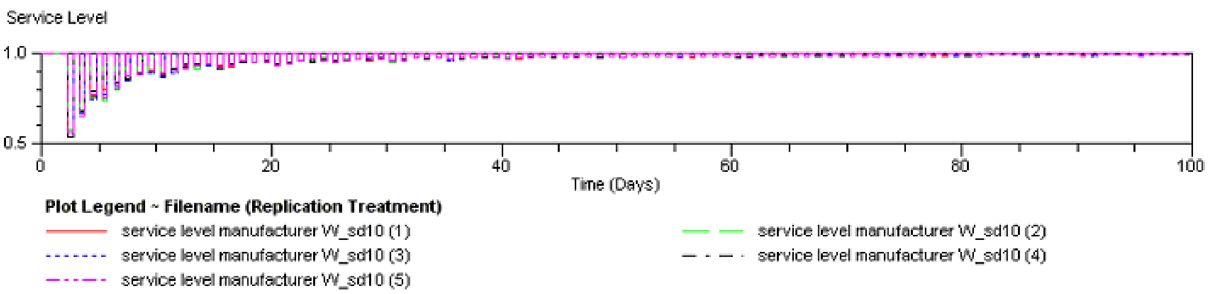
Annex 1.1 – Service level of the retailer for W_sd10



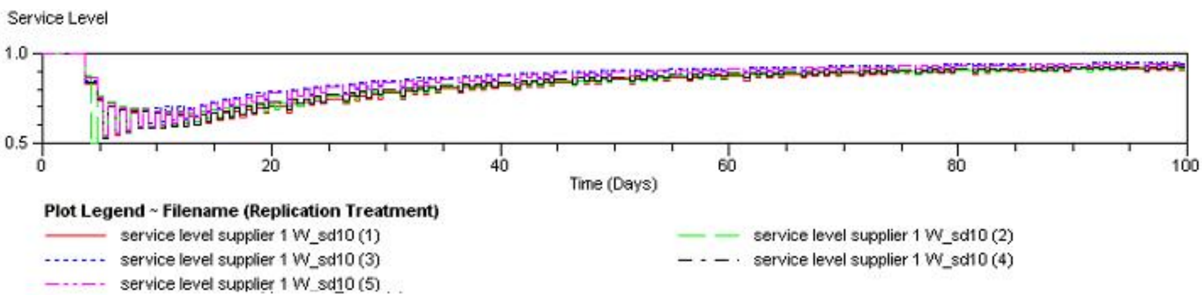
Annex 1.2 – Service level of the distributor for W_sd10



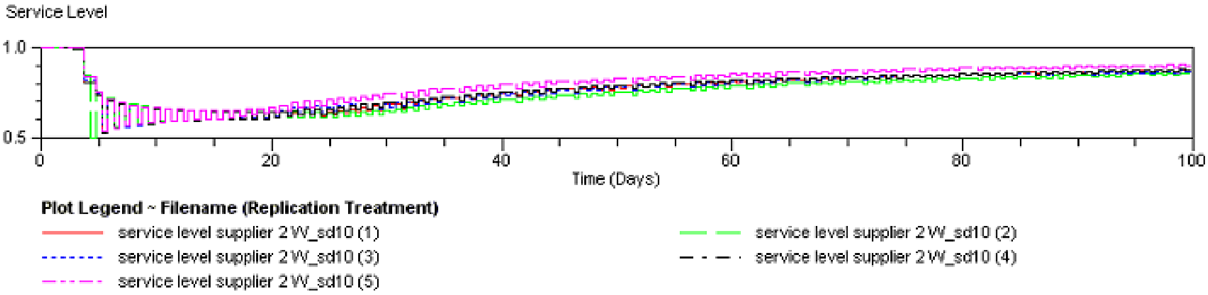
Annex 1.3 – Service level of the manufacturer for W_sd10



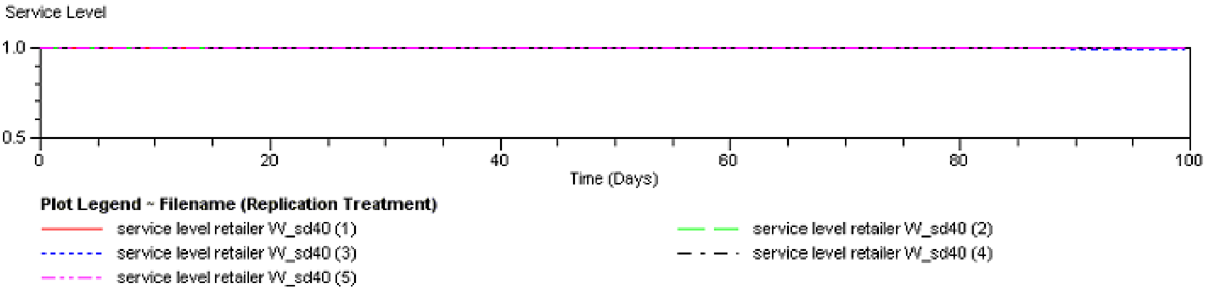
Annex 1.4 – Service level of supplier 1 for W_sd10



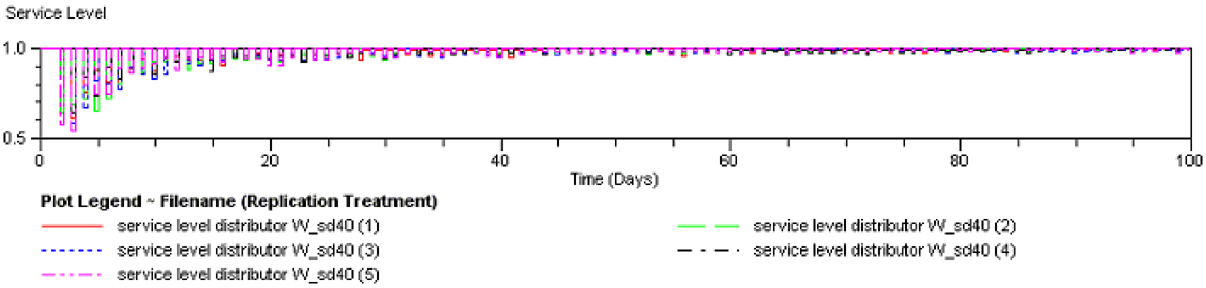
Annex 1.5 – Service level of supplier 2 for W_sd10



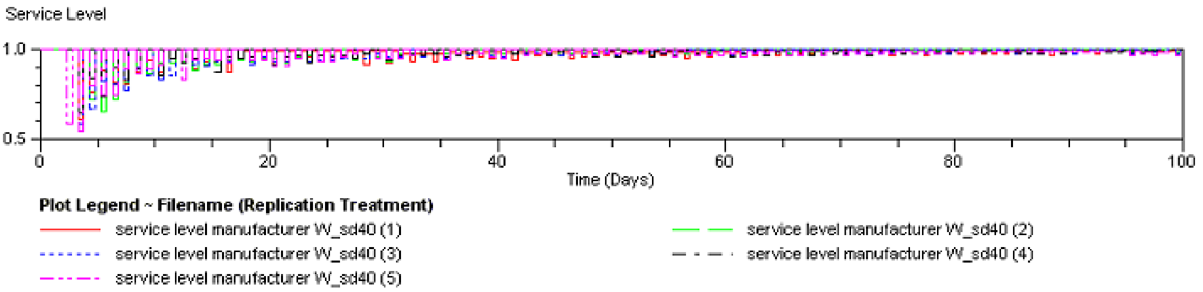
Annex 1.6 – Service level of the retailer for W_sd40



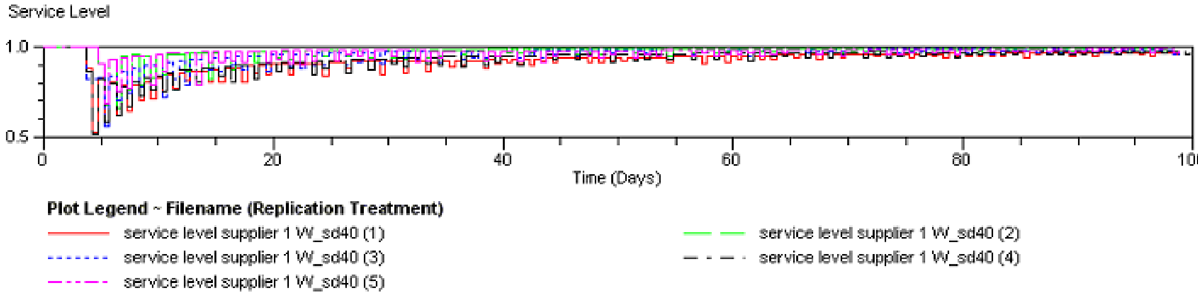
Annex 1.7 – Service level of the distributor for W_sd40



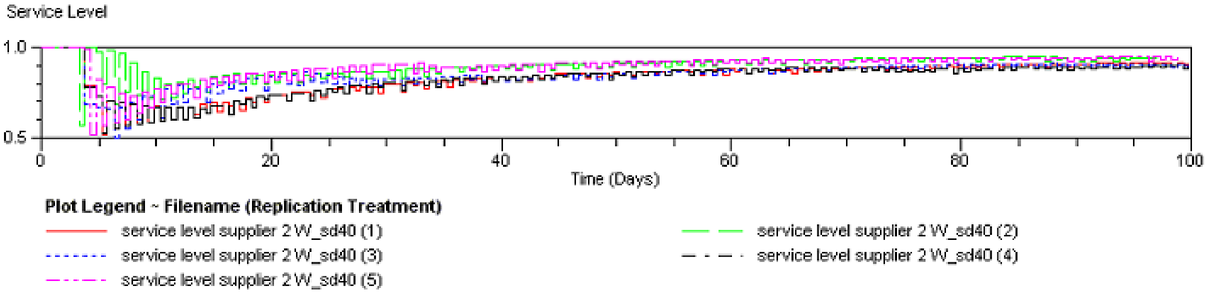
Annex 1.8 – Service level of manufacturer for W_sd40



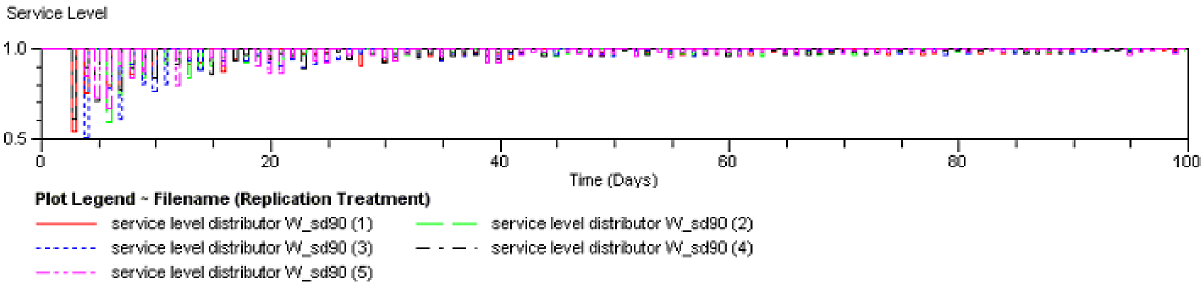
Annex 1.9 – Service level of supplier 1 for W_sd40



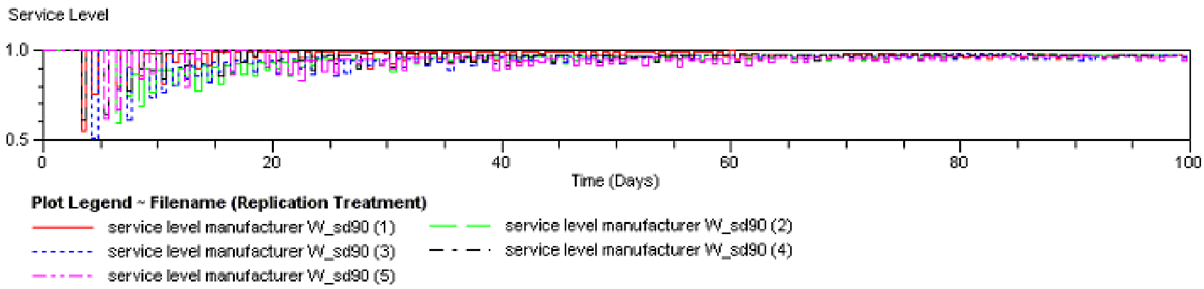
Annex 1.10 – Service level of supplier 2 for W_sd40



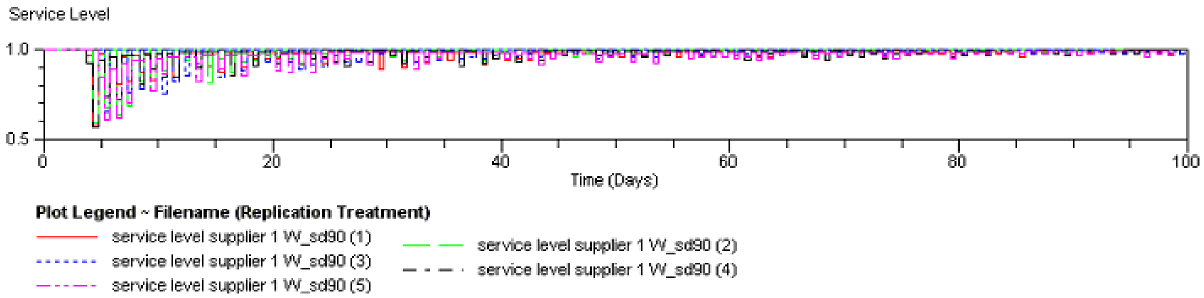
Annex 1.11 – Service level of the distributor for W_sd90



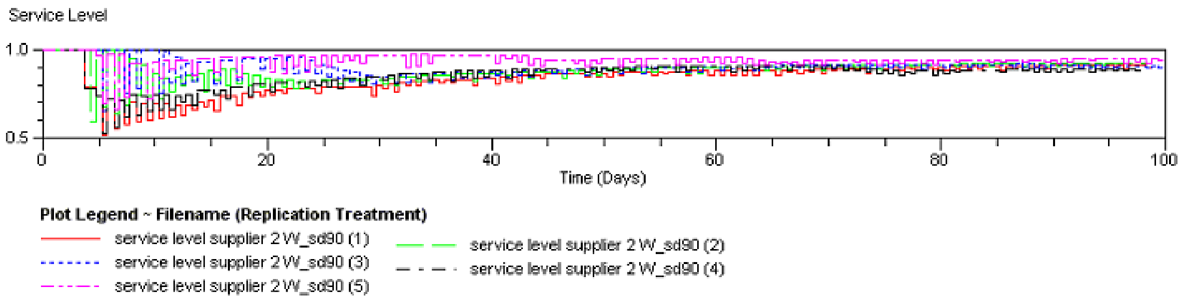
Annex 1.12 – Service level of the manufacturer for W_sd90



Annex 1.13 – Service level of supplier 1 for W_sd90

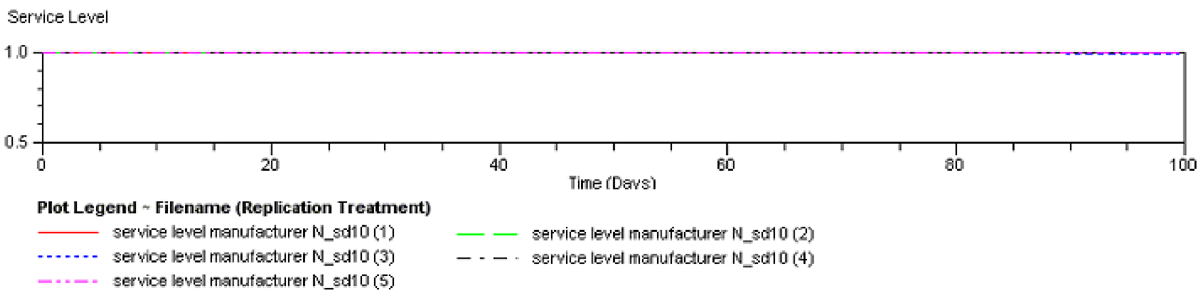


Annex 1.14 – Service level of supplier 2 for W_sd90

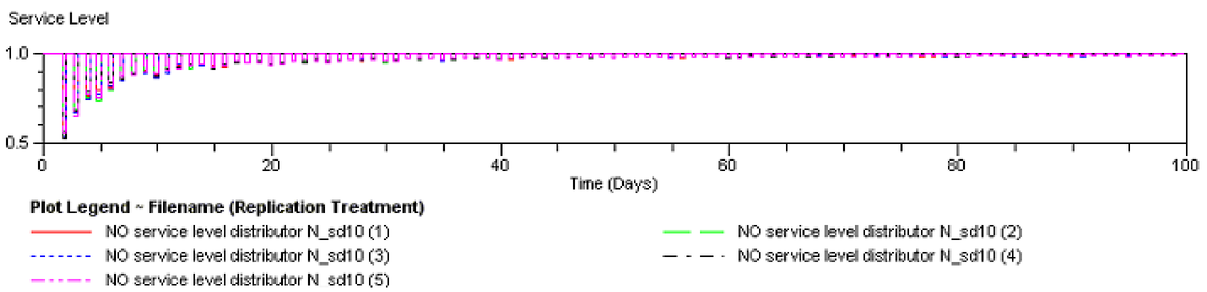


Annex 2 Development of the service levels when choosing the warm-up period with no demand information sharing

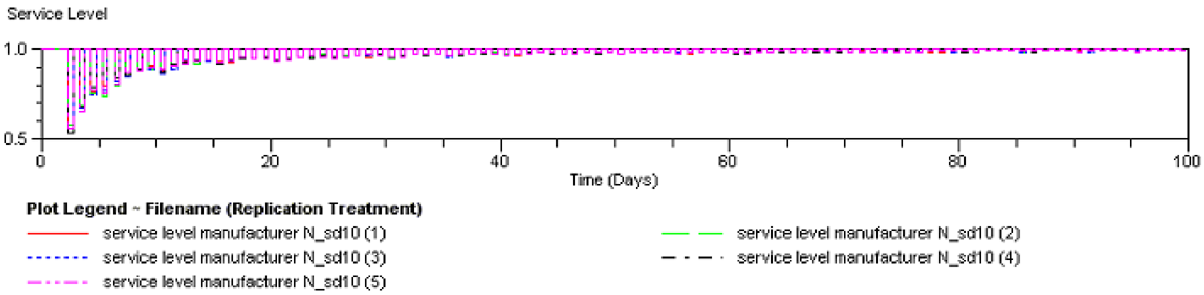
Annex 2.1 – Service level of the retailer for N_sd10



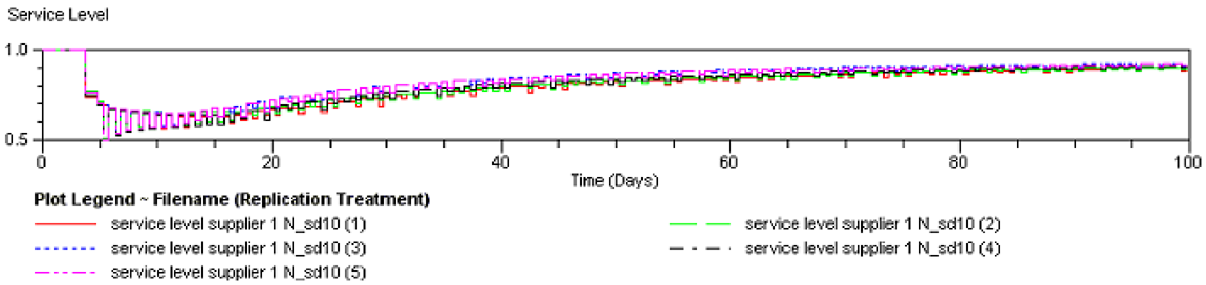
Annex 2.2 – Service level of the distributor for N_sd10



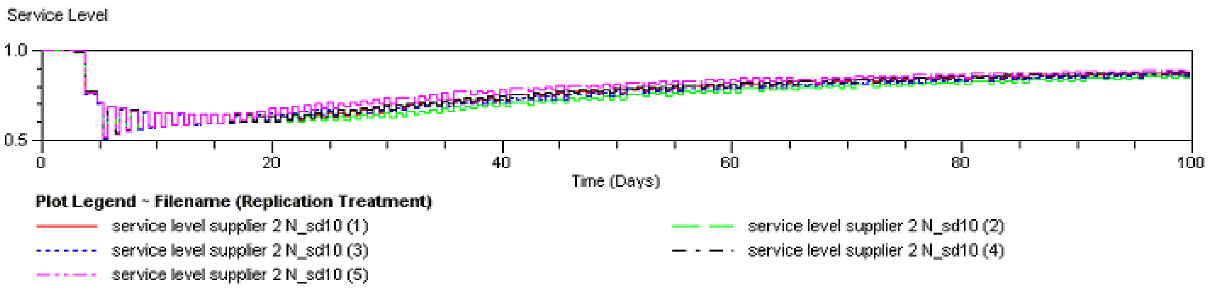
Annex 2.3 – Service level of the manufacturer for N_sd10



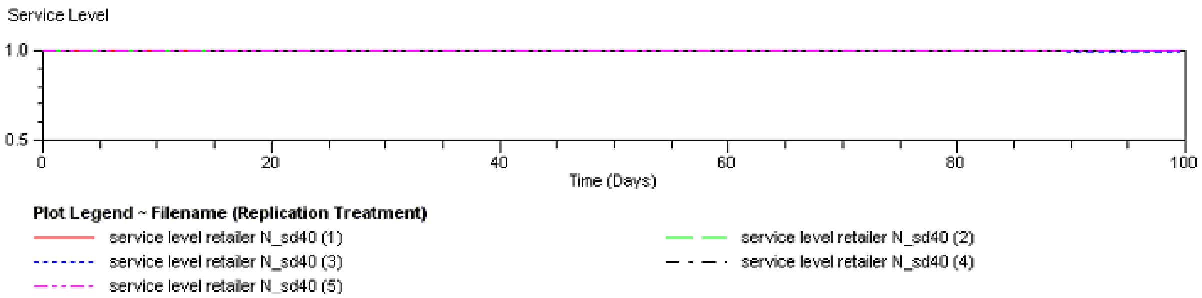
Annex 2.4 – Service level supplier 1 for N_sd10



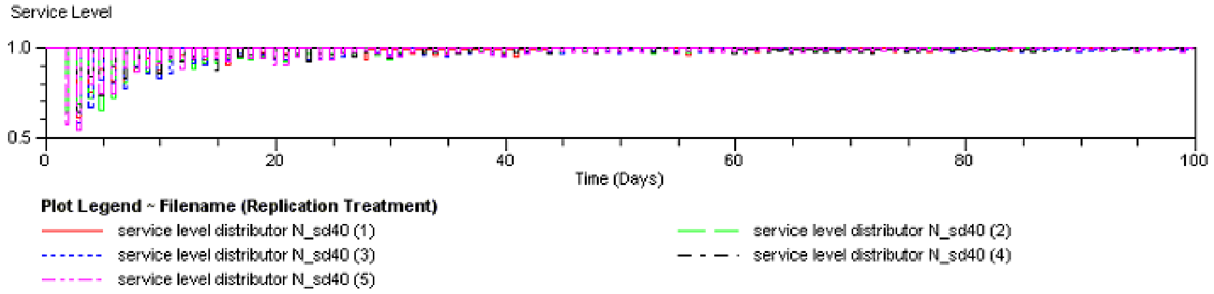
Annex 2.5 – Service level of supplier 2 for N_sd10



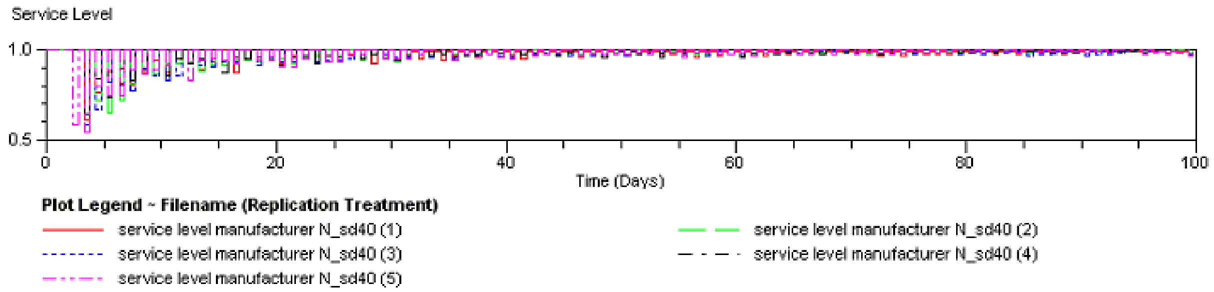
Annex 2.6 – Service level of the retailer for N_sd40



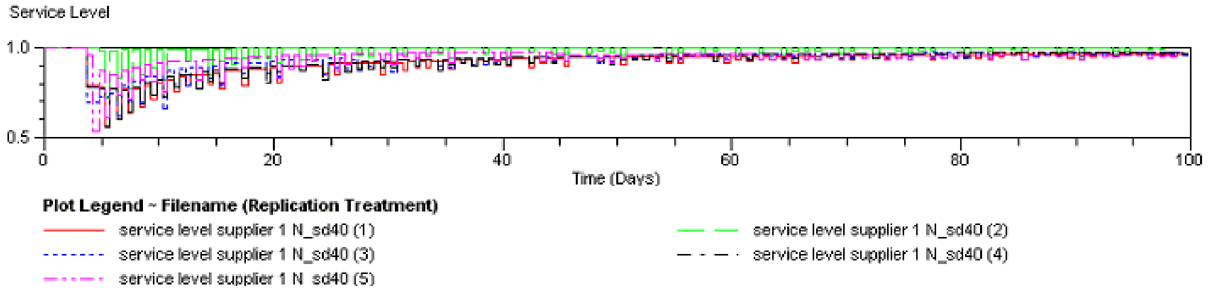
Annex 2.7 – Service level of the distributor for N_sd40



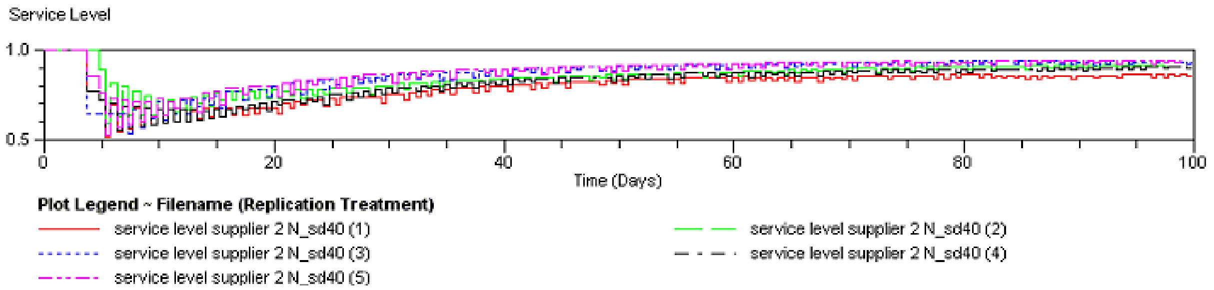
Annex 2.8 – Service level of the manufacturer for N_sd40



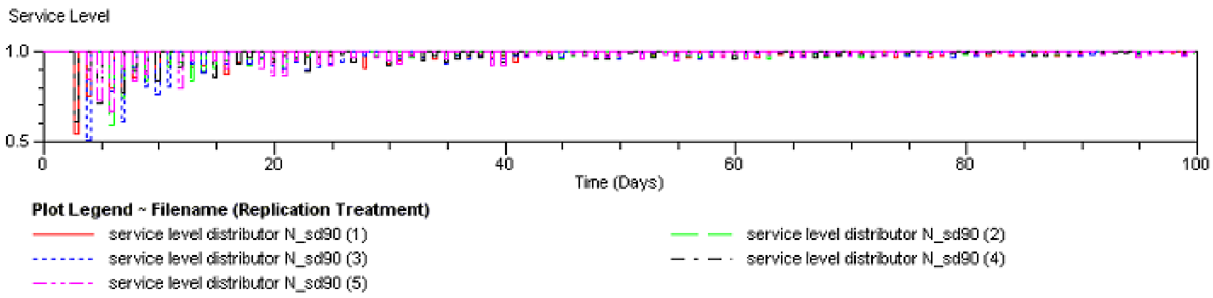
Annex 2.9 – Service level of supplier 1 for N_sd40



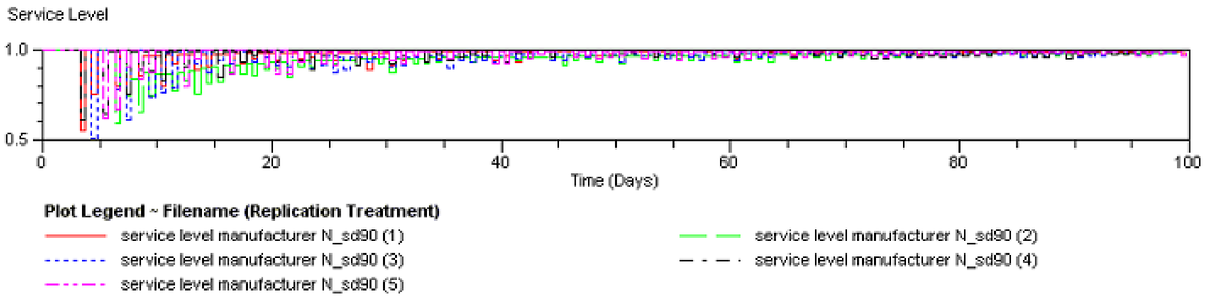
Annex 2.10 – Service level of supplier 2 for N_sd40



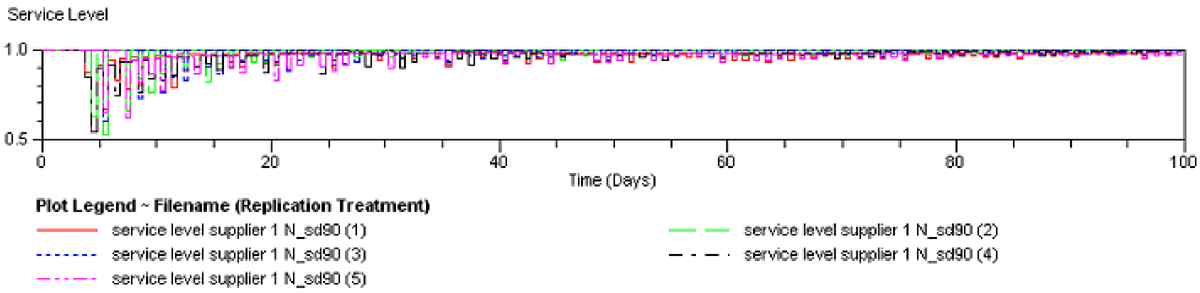
Annex 2.11 – Service level of the distributor for N_sd90



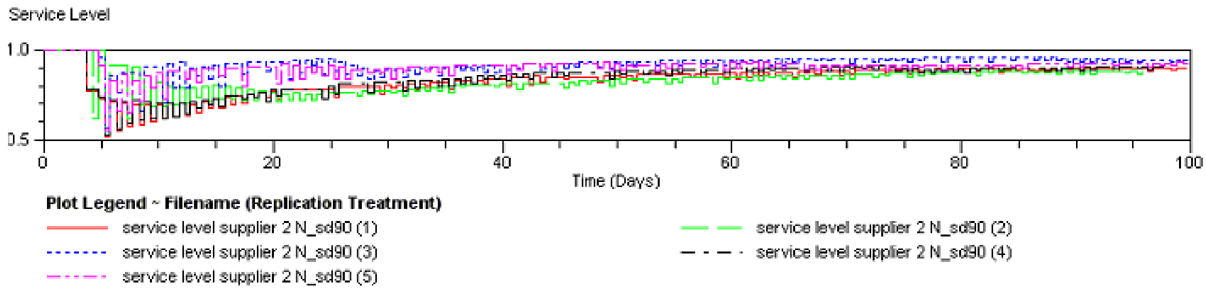
Annex 2.12 – Service level of the manufacturer for N_sd90



Annex 2.13 – Service level of supplier 1 for N_sd90



Annex 2.14 – Service level of supplier 2 for N_sd90



Annex 3 Determination of the number of replications of the performance measures

Annex 3.1 – Determination of the number of replications for the service levels for W_sd10

Performance measure	Value	Half-width	Desired half-width	n
Average service level retailer	0,99	0	0,05	0
Average service level distributor	0,98	0	0,05	0
Average service level manufacturer	0,97	0	0,05	0
Average service level supplier 1	0,95	0	0,05	0
Average service level supplier 2	0,91	0,01	0,05	1

Annex 3.2 – Determination of the number of replications for the SC costs for W_sd10

Performance measure	Value (MU)	Half-width	Desired half-width	n
Average total holding costs	74386	1319	3719	1
Average total lost sales cost	32334	4486	1617	39
Average total ordering costs	2966	10	148	1
Average total transportation costs	133957	862	6698	1

Annex 3.3 – Determination of the number of replications for the service levels for W_sd90

Performance measure	Value	Half-width	Desired half-width	n
Average service level retailer	0,98	0	0,05	0
Average service level distributor	0,98	0	0,05	0
Average service level manufacturer	0,94	0,01	0,05	1
Average service level supplier 1	0,99	0,01	0,05	1
Average service level supplier 2	0,90	0,02	0,05	1

Annex 3.4 – Determination of the number of replications for the SC costs for W_sd90

Performance measure	Value (MU)	Half-width	Desired half-width	n
Average total holding costs	147718	2210	7384	0
Average total lost sales cost	69369	8903	3468	33
Average total ordering costs	2268	107	114	5
Average total transportation costs	142836	8230	7142	7

Annex 3.5 – Determination of the number of replications for the service levels for N_sd10

Performance measure	Value	Half-width	Desired half width	n
Average service level retailer	0,99	0	0,05	0
Average service level distributor	0,98	0	0,05	0
Average service level manufacturer	0,97	0	0,05	0
Average service level supplier 1	0,93	0	0,05	0
Average service level supplier 2	0,90	0,02	0,05	1

Annex 3.6 – Determination of the number of replications for the SC costs for N_sd10

Performance measure	Value (MU)	Half-width	Desired half-width	n
Average total holding costs	77395	1685	3870	1
Average total lost sales cost	36108	5640	1805	49
Average total ordering costs	2946	9	147	1
Average total transportation costs	133819	875	6691	1

Annex 3.7 – Determination of the number of replications for the service levels for N_sd40

Performance measure	Value	Half-width	Desired half-width	n
Average service level retailer	0,99	0	0,05	0
Average service level distributor	0,98	0	0,05	0
Average service level manufacturer	0,96	0,01	0,05	1
Average service level supplier 1	0,96	0	0,05	0
Average service level supplier 2	0,92	0,01	0,05	1

Annex 3.8 – Determination of the number of replications for the SC costs for N_sd40

Performance measure	Value (MU)	Half-width	Desired half-width	n
Average total holding costs	111956	2686	5598	2
Average total lost sales cost	43620	8349	2181	74
Average total ordering costs	2555	66	127	2
Average total transportation costs	134943	3902	6747	2

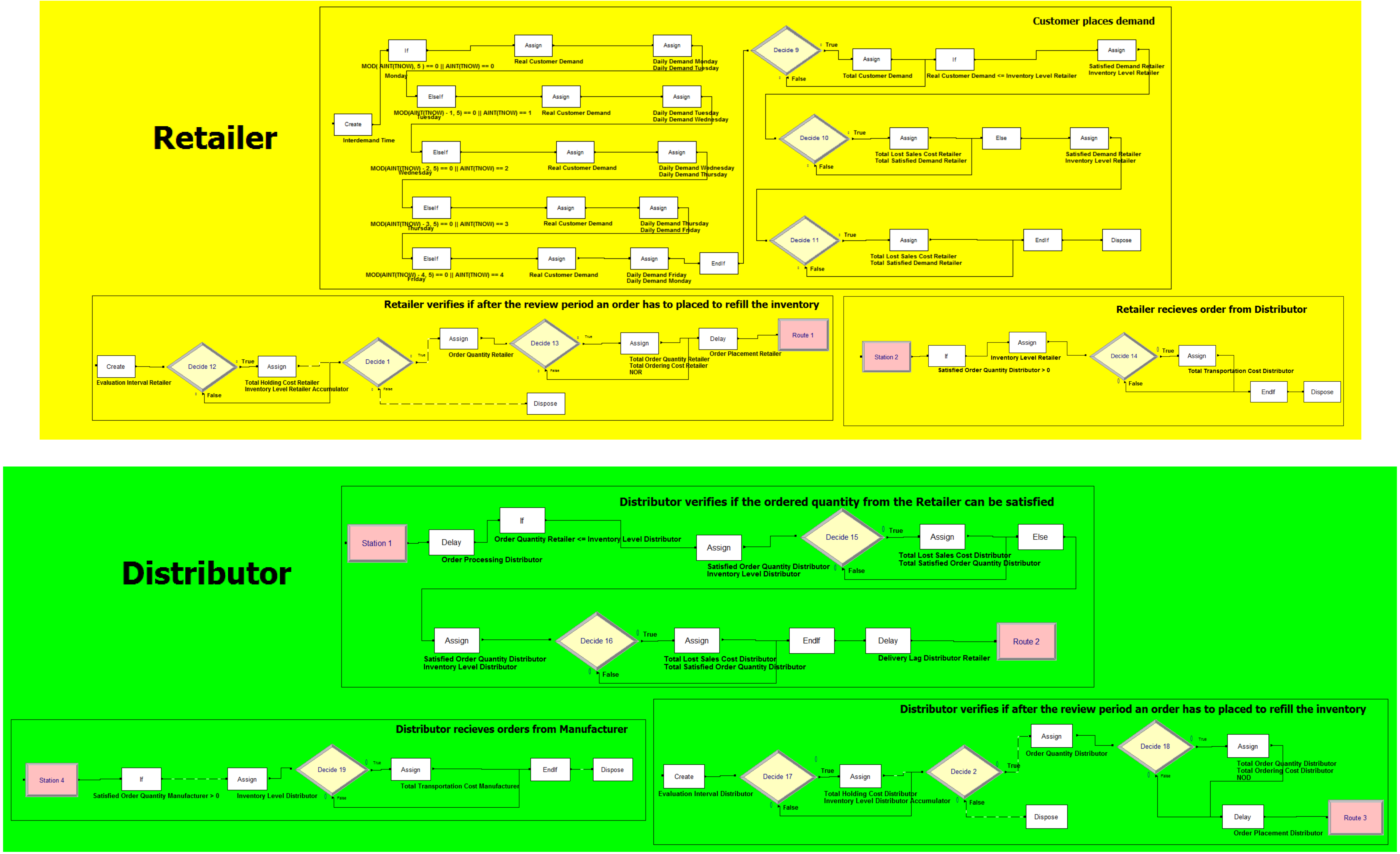
Annex 3.9 – Determination of the number of replications for the service levels for N_sd90

Performance measure	Value	Half-width	Desired half-width	n
Average service level retailer	0,98	0	0,05	0
Average service level distributor	0,98	0	0,05	0
Average service level manufacturer	0,95	0,01	0,05	1
Average service level supplier 1	0,98	0	0,05	0
Average service level supplier 2	0,92	0,02	0,05	1

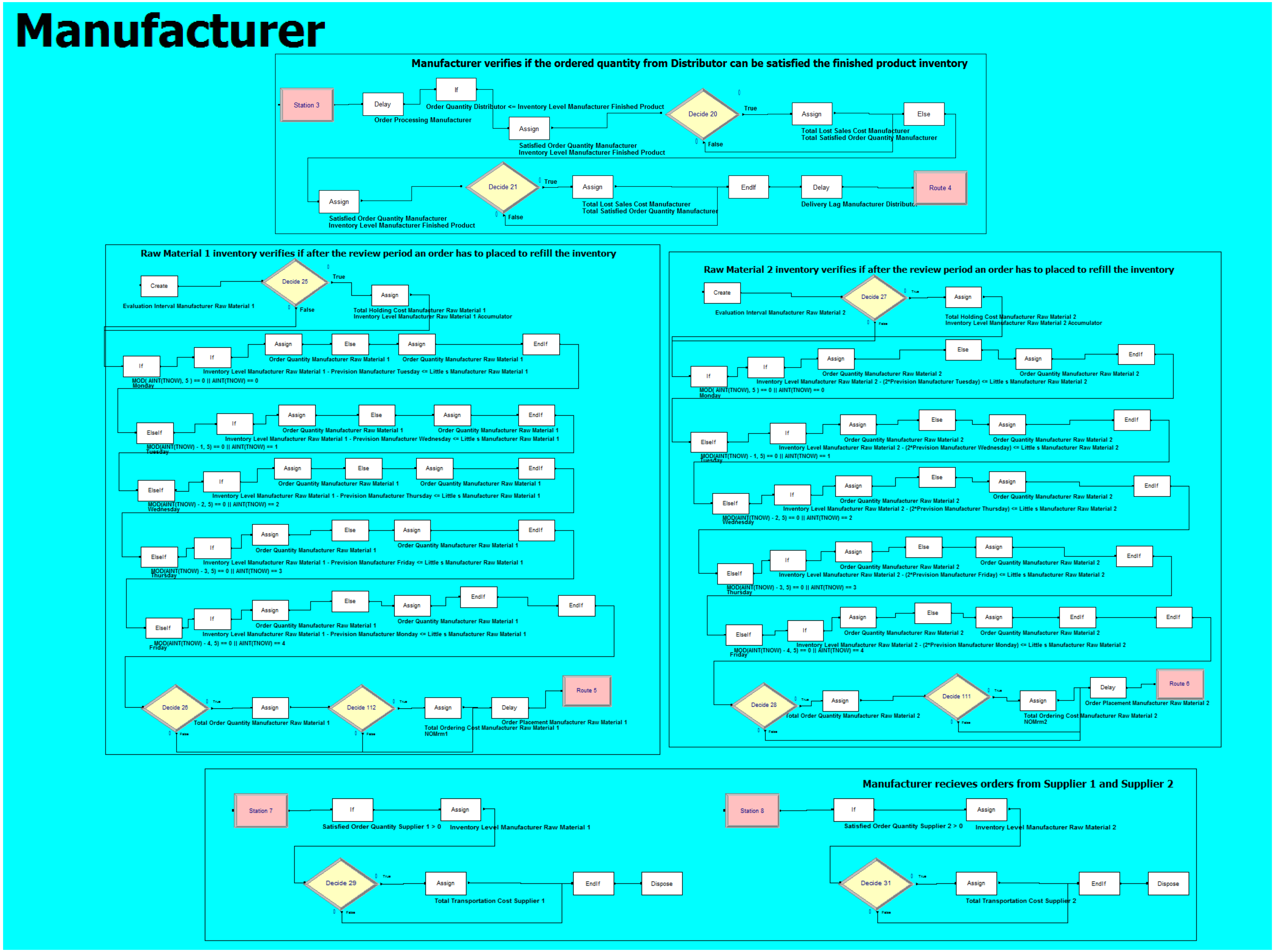
Annex 3.10 – Determination of the number of replications for the SC costs for N_sd90

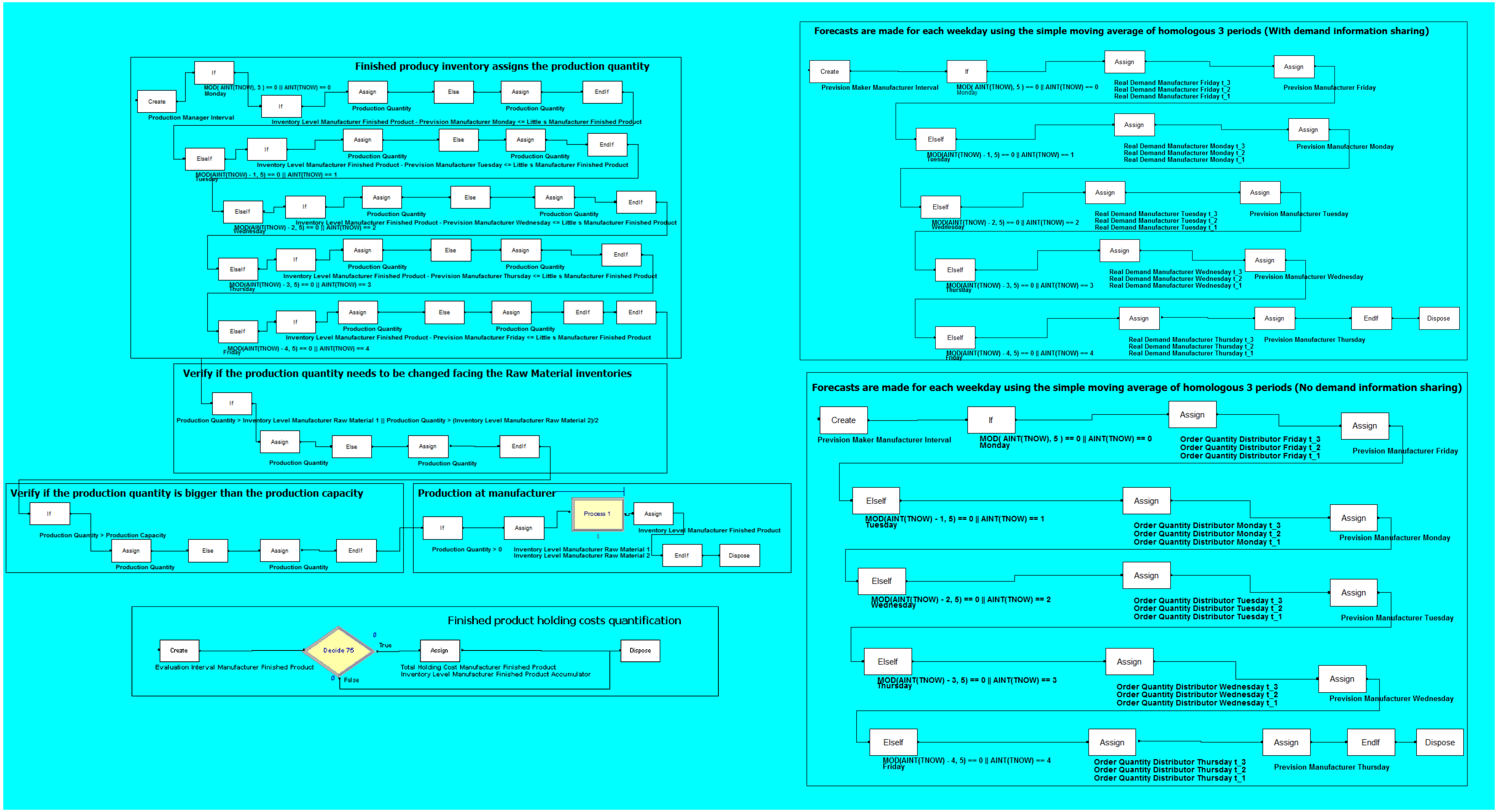
Performance measure	Value (MU)	Half-width	Desired half-width	n
Average total holding costs	168490	5193	8425	2
Average total lost sales cost	64520	10889	3226	57
Average total ordering costs	2249	78	112	3
Average total transportation costs	143052	8187	7153	7

Annex 4 – Retailer's and distributor's simulation model in arena

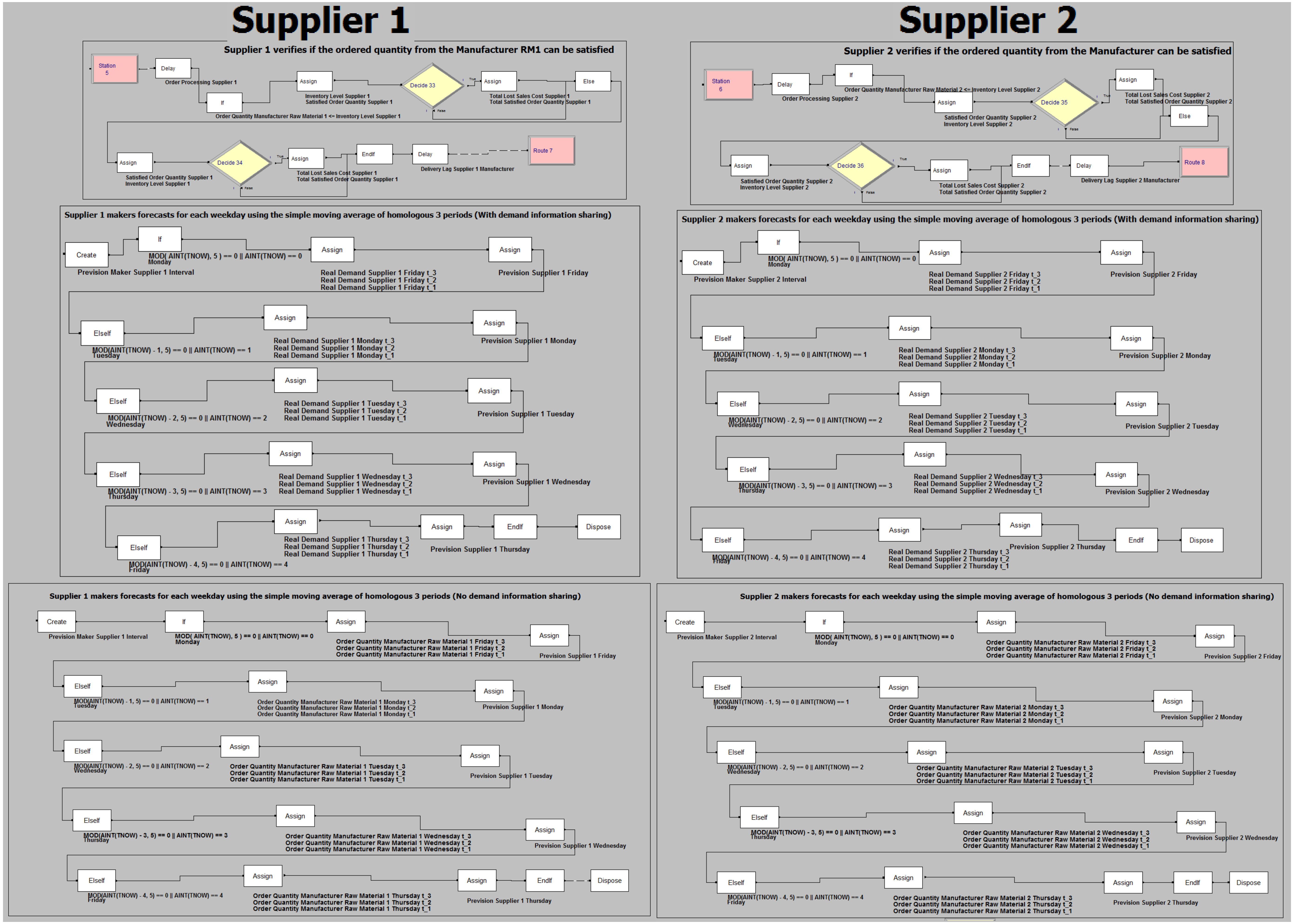


Annex 5 – Manufacturer's simulation model in arena




Finished producy inventory assigns the production quantity
Create
Production Manager Interval
If
MOD(AINT(TNOW), 5) == 0 || AINT(TNOW) == 0
Monday
Assign
Production Quantity
Else
EndIf
Inventory Level Manufacturer Finished Product - Prevision Manufacturer Monday <= Little s Manufacturer Finished Product
ElseIf
MOD(AINT(TNOW) - 1, 5) == 0 || AINT(TNOW) == 1
Tuesday
Inventory Level Manufacturer Finished Product - Prevision Manufacturer Tuesday <= Little s Manufacturer Finished Product
MOD(AINT(TNOW) - 2, 5) == 0 || AINT(TNOW) == 2
Wednesday
Inventory Level Manufacturer Finished Product - Prevision Manufacturer Wednesday <= Little s Manufacturer Finished Product
MOD(AINT(TNOW) - 3, 5) == 0 || AINT(TNOW) == 3
Thursday
Inventory Level Manufacturer Finished Product - Prevision Manufacturer Thursday <= Little s Manufacturer Finished Product
MOD(AINT(TNOW) - 4, 5) == 0 || AINT(TNOW) == 4
Friday
Inventory Level Manufacturer Finished Product - Prevision Manufacturer Friday <= Little s Manufacturer Finished Product
Verify if the production quantity needs to be changed facing the Raw Material inventories
Production Quantity > Inventory Level Manufacturer Raw Material 1 || Production Quantity > (Inventory Level Manufacturer Raw Material 2)/2
Verify if the production quantity is bigger than the production capacity
Production Quantity > Production Capacity
Production at manufacturer
Production Quantity > 0
Inventory Level Manufacturer Raw Material 1
Inventory Level Manufacturer Raw Material 2
Process 1
Inventory Level Manufacturer Finished Product
Dispose
Finished product holding costs quantification
Evaluation Interval Manufacturer Finished Product
Decide 75
True
False
Total Holding Cost Manufacturer Finished Product
Inventory Level Manufacturer Finished Product Accumulator
Forecasts are made for each weekday using the simple moving average of homologous 3 periods (With demand information sharing)
Prevision Maker Manufacturer Interval
MOD(AINT(TNOW), 5) == 0 || AINT(TNOW) == 0
Real Demand Manufacturer Friday t_3
Real Demand Manufacturer Friday t_2
Real Demand Manufacturer Friday t_1
Prevision Manufacturer Friday
Real Demand Manufacturer Monday t_3
Real Demand Manufacturer Monday t_2
Real Demand Manufacturer Monday t_1
Prevision Manufacturer Monday
Real Demand Manufacturer Tuesday t_3
Real Demand Manufacturer Tuesday t_2
Real Demand Manufacturer Tuesday t_1
Prevision Manufacturer Tuesday
Real Demand Manufacturer Wednesday t_3
Real Demand Manufacturer Wednesday t_2
Real Demand Manufacturer Wednesday t_1
Prevision Manufacturer Wednesday
Real Demand Manufacturer Thursday t_3
Real Demand Manufacturer Thursday t_2
Real Demand Manufacturer Thursday t_1
Prevision Manufacturer Thursday
Forecasts are made for each weekday using the simple moving average of homologous 3 periods (No demand information sharing)
Order Quantity Distributor Friday t_3
Order Quantity Distributor Friday t_2
Order Quantity Distributor Friday t_1
Order Quantity Distributor Monday t_3
Order Quantity Distributor Monday t_2
Order Quantity Distributor Monday t_1
Order Quantity Distributor Tuesday t_3
Order Quantity Distributor Tuesday t_2
Order Quantity Distributor Tuesday t_1
Order Quantity Distributor Wednesday t_3
Order Quantity Distributor Wednesday t_2
Order Quantity Distributor Wednesday t_1
Order Quantity Distributor Thursday t_3
Order Quantity Distributor Thursday t_2
Order Quantity Distributor Thursday t_1

Annex 6 – Supplier's simulation model in arena




Supplier 1 inventory verifies if after the review period an order has to placed to refill the inventory
Supplier 2 inventory verifies if after the review period an order has to placed to refill the inventory