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# A qualitative and quantitative analysis of the impact of the Auto ID technology on supply chains

Evren Sahin

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**ÉCOLE CENTRALE DES ARTS  
ET MANUFACTURES  
« ÉCOLE CENTRALE PARIS »**

## **THÈSE**

**présentée par**

**Evren SAHIN**

**pour l'obtention du**

## **GRADE DE DOCTEUR**

**Spécialité : Génie Industriel**

**Laboratoire d'accueil : Laboratoire Génie Industriel, Ecole Centrale Paris**

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**A qualitative and quantitative analysis of the impact of the Auto ID  
technology on the performance of supply chains**

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**devant un jury composé de :**

**Besoa RABENASOLO**

Professeur à l'Ecole Nationale Supérieure des Arts et Industries Textiles

**Président**

**John BUZACOTT**

Professeur à York University, Schulich School of Business

**Rapporteur**

**Yannick FREIN**

Professeur à l'Ecole Nationale Supérieure de Génie Industriel

**Rapporteur**

**André THOMAS**

Maître de conférences, HDR à l'Ecole Nationale Supérieure des Technologies et  
Industries du Bois

**Rapporteur**

**Yves DALLERY**

Professeur à l'Ecole Centrale Paris

**Directeur**

**No. 2004 - 25**

Pour mon Cher Papa qui a toujours cru en moi.

Et qui, du haut du Ciel,  
ne cesse de m'encourager chaque jour.

Sevgili Babacığım,  
sayende « küçüğün » bir adım daha attı.

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# GENERAL INTRODUCTION

The need to present more valuable service to customers and, at the same time, cut the cost of logistic processes are among the main objectives of supply chain management [1]. Many research have alluded to the compelling benefits and tremendous payoff that is associated with an effective management of operations ([2], [3], [4]). For instance, an interesting analysis on the relationship between supply chain glitches and the shareholder value is developed in [5]. Companies adopting innovative supply chain management solutions that enhance the value added to customers at a lower cost will quickly be able to improve their competitive advantage. Today, Radio Frequency Identification (RFID) technology, which is one type of Automatic Identification and Data Capture (AIDC) system used to monitor items within a supply chain, combined with other systems is becoming the basis for such new solutions contributing to a better management of supply chains, in terms of cost reduction and improvement of the customer service level. Examining the impact of this technology on improving the reliability of inventory record data, this thesis highlights the savings that enterprises would achieve by having more accurate information concerning their inventory levels.

In most industries, Automatic Identification and Data Capture systems originated with the development of barcode readers, barcodes and the Universal Product Code. In a significant evolutionary step forward from today's technology, new technologies that extend an enterprise's ability to capture accurate information about the location and status of physical entities across the supply chain are being developed.

Our work is motivated by the development of the EPCglobal Network system -the Auto ID technology for short- developed by the Auto ID Center of M.I.T. whose aim is to create a technology that can potentially perform even better than the bar code system and replace it in the long term. This technology which uses Electronic Product Codes carried by RFID tags is expected to generate significant savings by identifying items automatically and enabling item level product data management.

Current supply chains are facing several challenges. In globally dispersed supply chains consisting in several enterprises located in many different countries or continents, the increasing demand for a higher number of product variants as well as the necessity to deliver products to individual end consumers led to a vastly great number of delivery addresses. This results, for many industries, in an important number of differentiated material and information flows [6]. Within this context, in order to remain competitive, enterprises have to move to shorter delivery lead times in response to the lead times proposed by the other enterprises.

Secondly, actually, supply chain networks are more and more complex as multiple companies participate in processing individualized products. The tendency for outsourcing activities has also led to a significant increase in the number of partners. Furthermore, companies that are involved in the design, production and distribution of products in the network do not remain the same over the product life-cycle [7], depending, for example, on fluctuations of the currency rates or changes in the product design [8]. As highlighted in [9], managing the information flow pertaining to entities flowing through the pipeline (e.g. pallets, cases, individual products) in such complex and dynamic supply chains is one of the biggest challenges facing supply chain management practices.

The third challenge is the ability of companies involved in a supply chain to satisfy strict governmental and end consumers' requirements on traceability, after-sales support and product lifecycle management. For instance, [10] reports that, in the European Union, all consumer electronics have to be recycled and their minimum warranty time has been set to two years. On the other hand, there is an increasing customer pressure to be able to track and trace human consumed products, from pharmaceuticals to grocery. The consequence of these requirements is the necessity to store and process a large volume of information concerning products in order to be able to monitor the activities that take place within a supply chain, including the after sales service or recycling activities.

From a product identification and data capture technology point of view, to overcome the challenges described above, the system used to monitor entities should be able satisfy the following main functions:

- To be able to support a fast and efficient handling of differentiated material flows in order to improve lead times.
- To be able to support the control of activities and products flowing through the supply chain network accurately.

When items are moved across organizational boundaries, there might be severe problems in matching the information flow to the physical flow to synchronize both flows. Even within the four walls of an enterprise, if an appropriate product monitoring system is not used, the level of inventory physically available may vary without any change being recorded in the information system, creating a mismatch between the physical and information flows.

In some situations, an accurate control of processes may require the individual identification of entities. In environments where products are subject to counterfeiting, recall or regulatory control (e.g. pharmaceuticals) or if there is a need to monitor their physical properties (e.g. temperature), product type level information would not be enough to streamline the physical flow of materials since one has to distinguish one product from the other. This implies that the item identification and data capture

technology being used within the supply chain should be able to monitor entities individually.

Secondly, being able to control processes and products necessitates also the possibility of sharing information concerning the physical flow and the associated activities across dynamic, multiple actors supply chain networks. For this purpose, product specific information should be available anywhere, whether in an assembly line or a store in order to ensure that decisions are based on accurate and timely data.

The current practices for identifying products and capturing data are that companies use the Bar Code system or a paper based system. In such cases, since data is gathered manually, inaccuracies that result in mismatches between the information and physical flows can occur. The problem is intensified by the fact that companies rarely have common product codes for specific products or parts [11]. Also, the increasing quantity and variety of information to be managed makes the definition of standard transactions for exchanging the gathered data difficult [9]. There is, therefore, a need for the development of new data capture and product identification approaches.

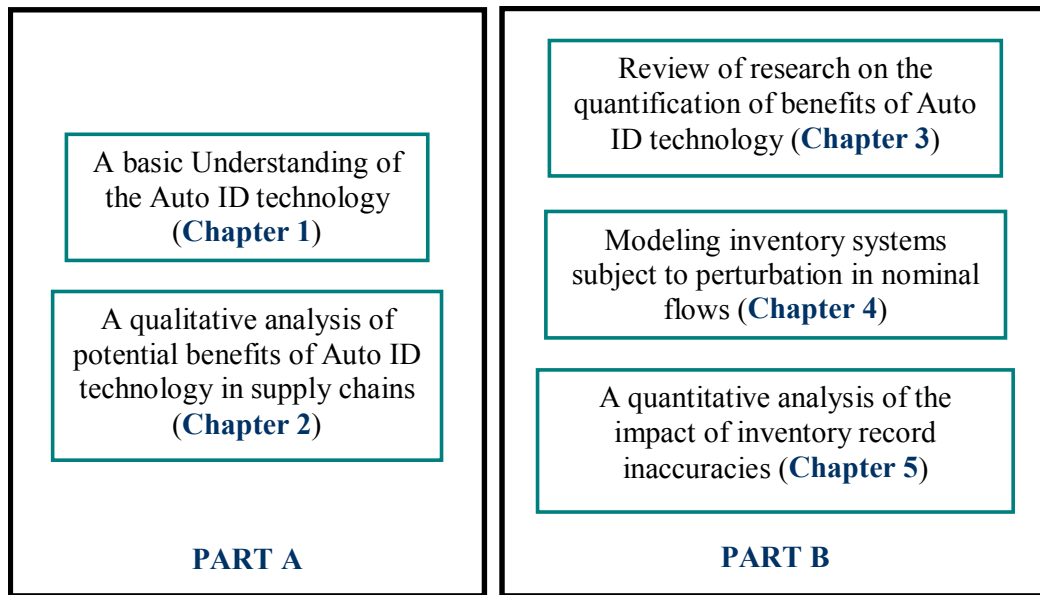
The Auto ID system is an answer to challenges presented above and it can be used to satisfy the expected functionalities since: (1) the automatic identification property of this system enables to deal with both the product handling and data accuracy problems (2) due to the item level product monitoring property, it is possible to individually control items everywhere in a supply chain, e.g. in manufacturing or distribution processes, (3) effective information sharing is achieved with the creation of an infrastructure in which databases store and communicate information on product characteristics and their movements to relevant supply chain members.

## **Organization of the report**

The aim of our research is to characterize the main benefits of using this new technology in a supply chain and to quantify one of the concrete improvements stemming from its use, namely the benefit of having more accurate inventory data records. Our dissertation report is thus organized in two parts. The first part includes a qualitative research on how the Auto ID technology will impact existing supply chain practices. The second part is a quantitative study on benefits companies may expect from the improvement in inventory data accuracy enabled by Auto ID. In an attempt to find an answer to the question: “How does the elimination of inventory data inaccuracies improve supply chain performance?” we analyze the supply chain interactions of a wholesaler and its supplier within a Newsboy modeling framework.

The structure of the dissertation is as represented in the figure below:





## Part A

In the first part of our research which includes Chapter 1 and 2, we are interested in identifying the main benefits of Auto ID in supply chains. For this purpose, first of all, we introduce a new concept: the “Automatic Identification, Data Capture and Sharing (AIDCS) System” which can be defined as an integrated system including an Automatic Identification and Data Capture (AIDC) component and a Data Sharing component. Examples of such systems include the bar code or the more recent Auto ID technology. This basic understanding is extremely helpful to analyze the potential benefits and implications of the Auto ID technology which are outlined later. In the first part of Chapter 1, characteristics, strengths and weaknesses of each technology are described. Then, at the end of this chapter, some issues and barriers that the widespread cross-industry deployment of the Auto ID technology may face are considered.

In chapter 2, our aim is to highlight the benefits (in terms of reduction in inventory holding costs and improvement of the customer service level) of using the Auto ID technology, and to present an overview of the current state of Auto ID applications in industry. We first characterize the main sources of uncertainties in decision-making processes that hinder optimal supply chain performance. In order to analyze how the use of Auto ID technology can reduce these uncertainties, we follow a two-step approach. First, we identify two criteria, namely the degree of automation of the data capture process and the level at which data is monitored and managed by the system, as being the main factors that permit to compare the performances of different AIDC systems. Using this framework, we then compare two sets of AIDC technologies: (the bar code system and UPC) versus (the RFID system and EPC-two components of the Auto ID technology). It should be noted here that the comparison between these systems has been done at the AIDC level and does not include the data sharing ability. In other words, the ability of Auto ID to share data among supply chain members has not been

compared with the (potential) reciprocal property of the bar code system since as explained in Chapter 1, up to now, such an industry wide use of bar code system does not exist. We would thus assume that this functionality is an innovative perspective enabled by the Auto ID technology.

The second step consists of delineating how the identified properties of the Auto ID technology can reduce or eliminate sources of supply chain uncertainties presented previously to improve the operational performance. This gives a clue to the question of how companies may benefit from using the Auto ID technology.

In the last section of this chapter, some of the current applications of the Auto ID technology in industry are presented.

## **Part B**

As described in the previous part, Auto ID yields different types of benefits and many investigations have been developed in order to evaluate them at a macro level. One question can now be asked: What should our efforts to measure Auto ID benefits focus on?

The qualitative analysis conducted in the first part identifies the elimination of discrepancies between the quantity of products a company has in its inventory system and the on hand quantity recorded in information system as a major improvement that is achieved due to the automatic continuous monitoring property of the Auto ID technology. The second part of the dissertation analyses this benefit in a quantitative way. For this purpose, we have developed a mathematical model built upon the well known Newsboy Problem framework that gives insights to managers in evaluating impacts of Auto ID on inventory inaccuracies.

Supply chain actors seek to fulfill customer demand by ensuring that inventory is at the right place at the right time and in the right quantity. In order to do that, most enterprises use inventory management systems that track and trace the physical flow and manage inventory levels. Deploying the capability to have an accurate information on goods (identity, precise location, physical condition, ...) stored within an inventory system is thus crucial for supply chain actors.

We have observed that the literature on the application of new methods and/or technologies to improve inventory visibility within a supply chain is quite extensive and that most of the existing research gives qualitative information on ways in which inventory inaccuracy can be tackled rather than quantifying its impacts. The consequence is that managers may know that by reducing errors occurring in their processes they could improve their inventory system but they still do not have appropriate decision support tools to help them. Management science based models can contribute to the design of such tools that would aid practitioners for justifying (or not) the acquisition of a new identification and data capture technology.

The aim of our research is to fill this gap and provide managerial insights on benefits companies may expect from a more accurate inventory data enabled by Auto ID. We are seeking an answer to the question: “How does the elimination of inventory inaccuracies improve supply chain performance?” Our focus is on fashion products, which are characterized by a short product lifecycle and a short selling season.

This second part is organized as follows: In chapter 3, we first present an overview of the research pertaining to the quantification of benefits of Auto ID. We then make a special focus on the review of research related to the inventory inaccuracy issue in supply chains. Our research reveals that although supply chain scholars very often assume the availability of error free inventory data to define and implement a specific inventory policy, accurate data should not be taken for granted in the supply chain and without this, the performance of such policies will be compromised.

According to various researches, the performance of supply chains can be improved by better coordinating the physical and information flows between suppliers, wholesalers, retailers and consumers. We show in Chapter 4 that a facility, even though using an advanced identification technology like the bar code system, may not know the exact quantity of products stored in a facility. This is mainly due to factors that lead to perturbations impacting the physical flow of products, in the one hand, and to errors polluting data capture errors on the other hand. We separate these two types of factors and present in a structured way the root causes, magnitudes and characteristics of errors causing deviations in supply chain flows. A detailed analysis that describes these inefficiencies highlights the major sources of inventory inaccuracies, provides a better understanding of the issue of inaccuracies and suggests a way to model the different industrial practices.

Chapter 5 addresses our main research question in a quantitative manner. The model we developed investigates the consequences of inaccurate inventory records on the performance of an inventory system to assess the benefit of the Auto ID technology. We conducted several analyses in order to address issues such as: What is the optimal policy in presence of inventory inaccuracies? How much the system performance is degraded as a result of inaccuracies? Is the implementation of Auto ID technology justified, if yes under what conditions?

## **Main contributions**

This research was motivated by the potential ability of an automatic identification under development at the Auto ID Center to address the potential obstacles in managing effectively supply chains. The investigation carried out extends the existing literature in several respects:

- Our qualitative study presents the main benefits of Auto ID in a structured manner. The existing literature on benefits of Auto ID technology discusses its impacts on either reducing cost or increasing revenue. However, it is unclear how this is realized, i.e. what kind of

uncertainty is reduced by Auto ID? Does the use of Auto ID have a direct or an indirect impact in improving supply chain performance? Our aim was to fill this gap by answering these questions. Therefore, we integrate the existing literature on supply chain uncertainties and extend it by establishing a relationship between the reduction or the elimination of uncertainties and the use of Auto ID technology.

Secondly, we classify the nature of benefits enterprises can achieve by identifying two main criteria to evaluate the performance of an item identification and data capture system: automatic identification and item level identification properties. This provides further insights for managers who want to compare the performances of the well known Bar Code type of identification systems and the Auto ID technology. We then provide a quite exhaustive list of potential benefits of the technology.

- Among the benefits, we identified the elimination of inventory record inaccuracies as a point that merits further attention. Thus, in Chapter 4, we examine the problem of inventory inaccuracies by identifying some of its drivers and their magnitudes. This issue has so far only been in a limited number of researches.

The contribution of this chapter is to propose a general framework to represent an inventory system subject to defects that affect supply chain flows. Most of the existing literature on the inventory inaccuracy issue recognizes that inaccuracies stem from several factors presented in this chapter. Nevertheless, there has been limited effort on a better understanding of the relationship between the use of identification and data capture technology and its impact on reducing the different types of defects. Our detailed analysis clarifies the main sources of inventory inaccuracies, shows that managers should have a thorough knowledge of their operational processes to understand why, despite the use of an advanced data capture system such as the Bar Code System, inventory records fail to match the physical quantities of products stored within the facility.

We propose several models to represent an inventory system depending on the type of errors considered. This framework will also enable us to assess the impacts of the Auto ID technology on improving the performance of an inventory system in Chapter 5.

- The quantitative study we conducted in Chapter 5 provides valuable insights to managers seeking to evaluate the economic impact of inventory inaccuracies. Many enterprises are still unaware of how errors occurring in their data capture process can influence their performance. We quantify the cost of having errors and conduct several analyses to identify conditions in which this cost is important. Our study reveals that even a small rate of errors can disrupt the replenishment process and generate either additional inventory costs or penalties stemming from shortage situations. Furthermore, we show that companies have much to gain not only from deploying new technologies such as Auto ID but also from identifying ways to improve the existing operational processes such as optimizing the system

in presence of inventory record errors. We also take into account the cost of the technology and determine conditions in which the implementation of Auto ID is economically feasible.

# **PART A**

# Chapter 1

## A BASIC UNDERSTANDING OF AUTOMATIC IDENTIFICATION, DATA CAPTURE AND SHARING SYSTEMS

### Introduction

The aim of this chapter is to provide a basic understanding of Automatic Identification, Data Capture and Sharing (AIDCS) Systems which will later be defined as an integrated system including an Automatic Identification and Data Capture (AIDC) component and a Data Sharing component. Examples of such systems include the bar code or the more recent Auto ID technologies. The characteristics, strengths and weaknesses of each technology are first discussed. Then, some issues and barriers that the widespread cross-industry deployment of the Auto ID technology may face are considered.

### 1 General Trends in Supply Chains

In response to intensified global competition and the emergence of new markets, consumers are demanding products and services that specifically fit their needs more than ever, while companies are striving to attain process efficiencies that would enable them to drive down costs and provide competitive advantage. The need to present high quality service to customers and, at the same time, cut the cost of the delivery process is the most difficult problem in supply chain management [1]. As a result, during the past decade, companies have developed new supply chain management solutions to achieve these objectives.

There has been a significant change in the nature of the relationship between supply chain actors. Traditionally, relationships between supply chain players have been confrontational and adversarial. The competitive environment was often dominated by individual companies seeking local optimization of their internal processes [12]. Organizations have for many years strived to improve the efficiency of their internal supply chain activities, e.g. purchasing, manufacturing and logistics. Even within walls of the same company, division managers were working for the local optimization of their processes without paying attention to constraints generated by other departments. Each supply chain actor, having its own incentives and state of information, was searching ways to improve individual firm performances. In addition, due to the predominant functional focus of such activities, demand was disconnected from supply in the form of stockpiles of inventory both within and between organizations and their trading partners [13]. As a result, the supply chain was operating at a sub optimal level.

In the best of all possible worlds, total supply chain profits would be maximized if all decisions were made by a single decision-maker having access to globally available information. More and more companies now begin to understand that with a local optimization way of thinking, it would be impossible to reach the desired customer service level and efficiency in supply chain operations. Firms are becoming increasingly cognizant of the interdependencies that naturally exist between their internal operational processes and those of their suppliers and customers. In sharp contrast to the adversarial between buyer and vendor characteristic of the past, the notion of contemporary supply chain management emphasizes the development of close working partnership and collaboration among channel members [14]. Companies, more aware of the complexity and the increasing uncertainty of business operations, try to adopt this new approach that gives way not only to a continuous search for local company optimization but also to new areas of collaboration.

Cooperation between supply chain partners, not restricted to the closest partner but extended in many cases to the second- or third- supplier or customer, is already in practice across a number of sectors in industry. The involvement of suppliers and customers in product design activities or Vendor Managed Inventory (VMI) practices is already common in the automotive sector. In the fast moving consumer goods sector, retailers initiated projects in order to share their inventory status and/or point of sales (POS) data and built jointly replenishment orders with manufacturers. Some other retailers and manufacturers deploy the Collaborative Planning Forecasting and Replenishment (CPFR) process which is a 9-steps approach that aims at building concerted demand forecasts by collecting all relevant information from the buyer and the vendor.

Moreover, the use of advanced information and communication technologies to transfer and share data among internal departments of an enterprise or between supply chain vendors and buyers enables actors to make their decisions on up to date information. In fact, the management of almost all of the operations – the networking of geographically dispersed structures, the connectivity between companies, the processing of huge amount of data needed for planning and executing activities across the supply chain, etc... would be impossible without the use of efficient and effective information and communication technologies in automating existing processes and decreasing labor intensive activities.

In the past, the velocity of the business environment was inhibited by limitations in information processing. Actors were forced to take decisions in an environment where the only information they had was not real time updated but was transferred in batch at different intervals of time. The explosion of computerized tools in the 1990's has empowered the enterprise not only to search for cost and productivity drivers through activity automation but also to integrate and network information [15].

Nowadays, companies use enterprise databases capable of handling information in volumes and speeds previously unimaginable. The heavy information processing constraints of the past



were lifted, revealing new horizons of information and rendering obsolete many of the older methods and organizational process and structures. The development of Enterprise Resource Planning (ERP) solves one of the fundamental problems that had long plagued the effective transfer of information in the enterprise: how to establish a single source of data that could be easily accessed by a community of users to facilitate meaningful decision making and operations execution. The objective of these ERP packages is to provide accurate and real time information to enable intra-enterprise and inter-enterprise networking across functional boundaries.

The use of Electronic Data Interchange (EDI) between suppliers, manufacturers and retailers has been a key element in building transparency in the supply chain. It facilitates faster ordering /delivery cycle and lowers the administrative costs. The rate of development of information technology has opened up the possibility of market access through the Internet. Today's company has found it increasingly easier to coordinate procurement, design, product marketing, fulfillment and distribution processes with other partners to form "virtual" marketplaces capable to respond easier, faster and with less cost to any customer opportunity.

However, further supply chain improvements have been limited by the item identification and data capture technology used to monitor goods through processes. Bar codes, representing a significant step forward when first introduced decades ago, have significant shortfalls. In addition to being prone to damage, they require human intervention to be read and provide limited information since they only represent a product number. To achieve the next leap forward in supply chain efficiency, many organizations are turning to Radio Frequency Identification (RFID) Tags. The use of Radio Frequency ID wireless technology provides organizations with an opportunity to enhance supply chain processes significantly and deliver improvements in customer service.

Unlike bar codes, RFID tags are robust and do not need line of sight identification, removing the need for human intervention. RFID tags enable automation throughout the supply chain, including optimization of store space, reduced shrinkage and improved goods tracking. This provides a platform for cost reduction and improved customer service. Innovative companies already use RFID technology with great benefits in specific functional areas, e.g. manufacturing and warehousing. However, the biggest potential is in supply chain wide solutions. That is why, the Auto ID Center at MIT has developed a new automatic identification and data capture system, the EPCglobal network system, combining RFID technology with other technologies to track items within a supply chain and share information over the Internet.

In our dissertation, we will consider the impacts of the use of this new system in supply chains. In order to identify the real benefits of this system and dissociate them from benefits stemming from other supply chain management practices described above, we will use the notions of hard and soft benefits since in some cases, improvements (stemming mainly from

enhanced collaboration or improved data exchange between actors) are not solely attributable to the use of this system which should rather be viewed in this situation as a means of facilitating the implementation of other actions.

## **2 An Introduction to Automatic Identification, Data Capture and Sharing Systems**

We define an Automatic Identification, Data Capture and Sharing (AIDCS) System as a system consisting of two complementary sub systems:

The first component is an automatic identification and data capture (AIDC) system being characterized by two functionalities:

- the ability to identify products at a certain level of granularity (e.g. is product identified by the system as being a 'Diet Coke 330 ml can, Coca-Cola Company, US version, Serial Number 23657, expiration date 01/05/2006' or as a 'Diet Coke 330 ml can Coca-Cola Company'?)
- the ability to capture product data with a certain level of accuracy and automation (e.g. manual vs. automatic capture, at what frequency data is updated?)

The second component concerns the ability to share the data collected by the AIDC system among supply chain actors.

The aim of this section is to introduce these concepts and to consider two examples of such systems including the bar code technology and the EPCglobal network technology developed by the Auto-ID Center in which identifiers communicate with readers using radio waves.

### **2.1 Concepts**

#### **2.1.1 Automatic Identification and Data Capture Systems**

Automatic identification is the broad term given to a host of technologies that are used to help machines identify objects. Automatic identification is often coupled with automatic data capture. That is, companies want to identify items, capture information about them and somehow get the data into a computer without having employees type it in. From barcodes to smart cards, Automatic Identification and Data Capture technologies (including Bar Code, Optical Character Recognition, Biometric Identification, Vision Recognition, Smart Card, Contact Memory, Bluetooth, Global Positioning Systems, GSM cell location systems and Radio Frequency Identification technologies) are widely used by most industries ([16], [17], [18]). Their applications range from access and security systems to systems for item tracking, inventory management and checkout process in retail stores.

In the consumer packaged goods industry, AIDC originated with the development of barcode readers, barcodes (1966) and the Universal Product Code (UPC) (1973). Today's developing

AIDC technologies, in particular electronic product codes (EPCs) and radio frequency identification (RFID) tags are expected to perform even better and generate savings. These new technologies upgrade the ability to identify automatically objects through UPCs and barcodes, providing more accurate data and enabling item level product data management.

In the following, the bar code and RFID technologies will be discussed in greater detail since these are the most applicable identification technologies used for supply chain management purposes. Strengths and weaknesses of each system will also be briefly described. Details on the other above mentioned automatic identification technologies can be found in ([19], [18],[20]).

### **2.1.2 Existing Approaches to Data Sharing**

In contrast to the new EPCglobal network system, an industry wide standard data sharing approach and system associated with the Bar Code AIDC system has not been developed. Applications using the bar code technology until now have been mostly at individual company levels. Supply chain wide solutions and models using global standards have not been developed. The main reasons are a lack of industry wide standard for identifying products (there are over 200 bar code symbologies and companies rarely have common product codes for specific products [8]) and a lack of an infrastructure necessary to manage and share all data captured.

These findings are confirmed by a recent study [21]. This analysis states that efforts deployed for managing and sharing (bar coded) product information are basically based on two approaches: (1) developing proprietary solutions or (2) developing standards for creating compatible solutions.

One type of proprietary solutions are systems developed by a single company to track and trace its individual products in a centralized database, where the information concerning a certain product can be accessed using its identity code. The main weaknesses of this kind of systems are that they use their own item coding and are functional only with codes and reading points that are connected to their systems.

The other type of proprietary solutions are systems developed by service providers (such as Airclick Inc.) utilizing an existing (bar) code base, most often the EAN13 or UPC code. The advantage of these systems is that these are ready-made solutions and can be taken into use quickly. The main weaknesses are that: (a) codes used do not always give the possibility to manage item level information, i.e. they work only at the product type level. This is because the codes used only distinguish different types of products, not individual entities (b) a company gets the information only through the server of a particular service provider. All companies in the supply network should then use the same service provider. This is not feasible for companies belonging to several supply networks, and thus the solution is not scalable in an environment with complex, interlinked supply networks.

In contrast to proprietary solutions, the EPCglobal network system takes a cross company perspective for monitoring supply chain entities. If the standardization of product coding is successful, the system has been designed to be able to make attributes of tagged supply chain entities globally available over the Internet. That is why, in the remaining of the dissertation, we will assume that the inter enterprise data sharing ability, that is not really available for the Bar Code system, is a new perspective enabled by this technology.

A product data management and sharing system entitled Dialog that uses an approach conceptually similar to that of Auto-ID Center has also been proposed by the Helsinki University of Technology. A technical comparison between the EPCglobal network system and the Dialog system can be found in [21].

## **2.2 Examples of Automatic Identification, Data Capture and Sharing Systems**

### **2.2.1 The Bar Code System**

Bar codes are identifiers in which the information is encoded in a series of printed areas (bars) and spaces. The Bar code technology encompasses these printed symbologies that encode data to be optically read, the printing technologies that produce machine readable symbols, the scanners and decoders that capture visual images of the symbologies and convert them to computer-compatible digital data, and the verifiers that validate symbol quality. Bar coding is a quite mature technology [18]. Far exceeding initial expectations, five billion codes are scanned every day in 140 countries [22].

The bar code system requires line of sight, i.e. bar codes have to be oriented towards the reader in order to be scanned. Furthermore, multiple bar codes can not be read at the same time, which causes extra handling in many applications [23].

One dimensional codes are most commonly used and two dimensional codes are used in applications where it is difficult to apply the one dimensional code (due to the size and place of the marking). Some development is ongoing in the field of bar code printers, readers, and two-dimensional symbologies and global standards exist in the field on bar coding. Bar codes are cheap and relatively easy to produce. The price of bar code readers ranges from \$200 to \$1500 depending on their functionality [18].

### **2.2.2 The EPCglobal Network System**

More advanced systems of AIDCS offer the potential for increased functionality and an opportunity to obtain automatic and item level information concerning supply chain entities. The Auto ID Center, an academic research project headquartered at the Massachusetts Institute of Technology with labs at five leading research universities around the globe, has developed one such system: the EPCglobal Network system. The EPCglobal Network uses RFID technology to monitor entities in the supply chain. The main idea of researchers of the Auto-ID Center is that supply chains may be better managed if companies were being able to identify unique products using a technology that does not require line of sight. They thus

developed the elements that will enable RFID technology, which is one type of AIDC technology using radio waves to identify items automatically, to track them and share information over the Internet. This system, namely, the EPCglobal Network is described in greater depth<sup>1</sup> in this section.

The RFID technology is not new; it has been around for about 50 years and has been used in many areas. A detailed analysis of the history of the technology is provided in Appendix 2. RFID has become a hot topic today due to the announcement made in June 2003 by Wal-Mart that they would require their top 100 suppliers to provide RFID tags on pallets and cases by January 1, 2005, and extend this requirement to all suppliers by 2006 [24]. This has motivated many consumer packaged goods companies scurrying for information on what RFID is and what it might mean for their organizations. The Department of Defense (DoD) has also mandated that new contracts with its suppliers include RFID tracking of all sustainment cargo, unit movement equipment and cargo, ammunition shipments, and pre-positioned material and supplies by January of 2005 [25]. For compliance by January 2005 for Wal-Mart and the DoD alone, the number of manufacturers that must be ready to attach “one-way” tags to cases and pallets is 250 or more and represents approximately 1,000 sites during 2004. [26] expects this number to escalate in 2005 to 25,000 vendors at 50,000 sites, given the current plans of Wal-Mart, the DoD, the FDA, Target, and others.

Wal-Mart had a similar impact when they began using barcodes in the 1980s [27]. Again, Wal-Mart is driving the market towards the new technology. A number of these suppliers are tempted to do more than just affix chips to the goods they ship to Wal-Mart; they are also looking to implement RFID technology more broadly in their organizations in hopes of cutting their own supply chain costs. Retailers and consumer products manufacturers, aware of Wal-Mart’s interest in RFID, have also begun eyeing it as the next supply chain technology to invest in [28].

### **2.3 Components of the EPCglobal Network System**

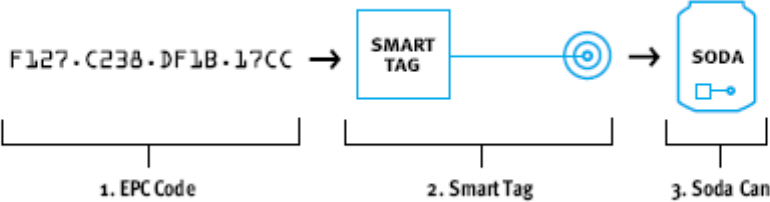
This system is comprised of five fundamental elements: the Electronic Product Code (EPC), the RFID System (RFID Tags carrying EPCs and RFID Readers), Object Name Service (ONS), Physical Markup Language (PML) and Savant.

In this system, individual physical objects are identified with a 96-bit electronic product code (EPC), a number designed to uniquely identify a specific item in the supply chain, stored in memory chips known as “smart tags.” The EPC can uniquely identify more than 268 million manufacturers, each with more than one million products, with enough numbers left over to tag all the individual consumer products manufactured for the foreseeable future. Under the

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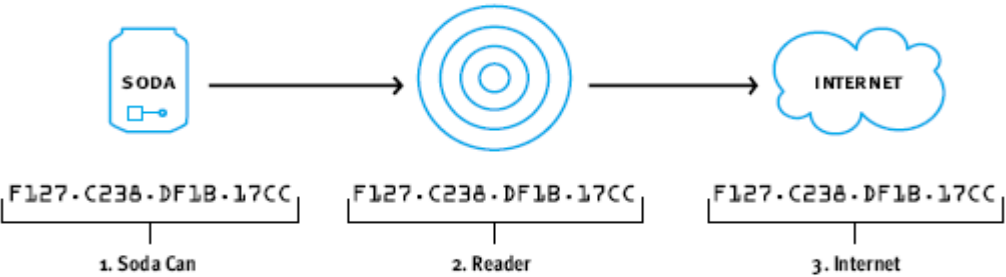
<sup>1</sup> The text in this section is adapted primarily from information contained in the web pages of Auto ID Center ([www.autoidcenter.org](http://www.autoidcenter.org)). We shortened and paraphrased the web content for this paper, but the ideas that inform the explanation remain the Auto-ID Center’s.

Auto-ID Center’s scheme, the Electronic Product Code will be the only information stored on the chip in an RFID tag. That is because chips with less memory cost less money (cf. Appendix 1). The smart tags – which are attached to, or embedded in each object – have antennae that allow them to communicate wirelessly to other devices.



**Figure 1. Components of the EPCglobal Network System <sup>2</sup> (1)**

Tags communicate with readers using radio waves; strategically placed wireless radio frequency “readers” scan the smart tags and transmit an object’s embedded identity code to the Internet, where more detailed information on the object is stored. That information can then be communicated back from the Internet to provide manufacturers, suppliers, logistics service providers or retailers whenever information is needed about that object. Scanners on store shelves, for instance, could alert managers to perishable items that have passed their freshness dates.



**Figure 2. Components of the EPCglobal Network System (2)**

On the Internet, the EPC works together with the Savant system, an Object Naming Service (ONS) and a Product Markup Language (PML).

The Savant system (a distributed architecture software storing and managing data) sends a query over the internet to an Object Name Service (ONS) database. The ONS server matches the EPC number to the address of a server which has extensive information about the product and tells computer systems where to find information about the object. The ONS is similar to the Internet’s existing Domain Name System (DNS), which routes information to appropriate web sites, but it will likely be many times larger, locating data for every one of the trillions of

<sup>2</sup> Figures in this section are reproduced from Auto ID Center archives.

objects carrying an EPC code. The PML is a new standard “language” for describing physical objects in the same way that HyperText Markup Language (HTML) is the common language that tells web browsers how to display most Internet web pages. In addition to product information that does not change (e.g. material composition), PML data might include the temperature of a shipment of fruit, vibration levels from a machine, an object's location, the date of manufacture, the name of the last person to handle the item and the warranty period.

It should be noted that, so far, in order to simplify the explanation, we have considered a local application; in other words, we have considered a unique savant system. In the Auto ID Center’s scheme, there will be Savants running in stores, distribution centers, regional offices, factories, perhaps even on trucks and in cargo planes within a supply chain. Savants at each level will gather, store and act on information and interact with other Savants. For instance, a Savant at a store might inform a distribution center that more products are needed. A Savant at the distribution center might inform the store Savant that a shipment was dispatched at a specific time. At each level, the Savant has to decide what information needs to be forwarded up or down the chain. For instance, a Savant in a cold storage facility might forward only changes in the temperature of stored items. Furthermore, all Savants, regardless of their level in the hierarchy, feature a Task Management System (TMS), which enables them to perform data management and data monitoring using customizable tasks. For example, a Savant running in a store might be programmed to alert the stockroom manager when product on the shelves drops below a certain level.

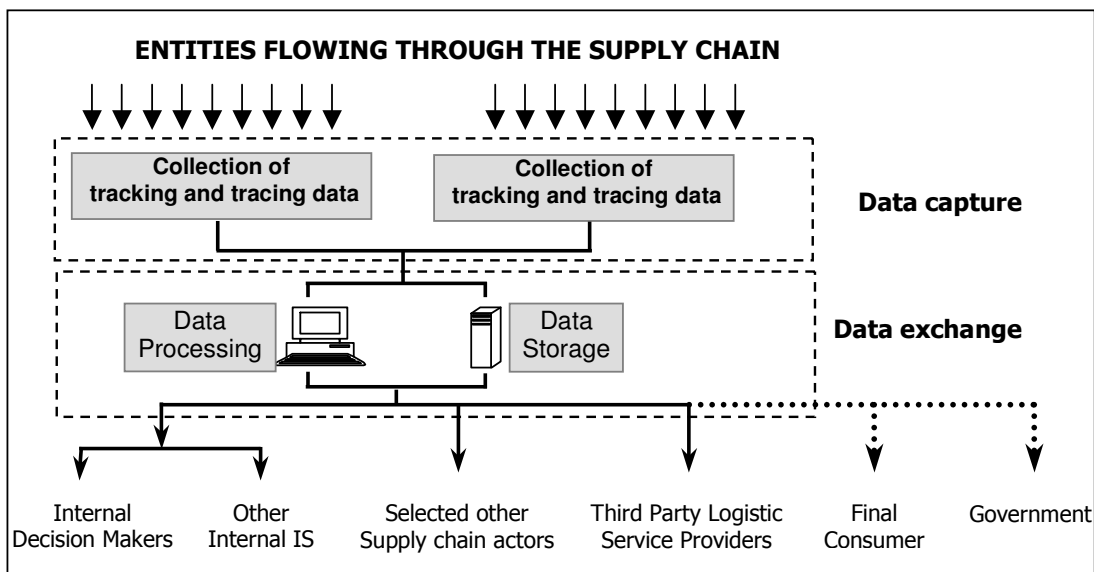
### **RFID tag types and specifications of the Auto ID Center**

There are different kinds of RFID tags for different applications, as is explained in more detail in Appendix 1. The Auto ID Center is not concerned with creating RFID tags or even telling vendors what types of tags to make since RFID technology has been in commercial use for over twenty years [24], they explain this by “Our only concern is that tags carry an EPC, communicate in an open standard way, and meet some minimum performance requirements so they can be read by readers anywhere. However, because very low-cost tags are a key component of our system, we have been working on designs for chips that will cost around 5 cents when produced in bulk and can be read from at least four feet. The first tags are ultra-high frequency; that is, they operate at 915 MHz. They use EEPROM (electrically erasable programmable read-only memory), so companies can write an EPC to the tag when the item is produced and packaged, but other memory technologies could also be used.”

In summary, the properties of the EPCglobal network system developed by the Auto ID Center can be recapitulated in two main points (cf. figure below):

- **An improved AIDC functionality:** RFID tags carrying a unique EPC enable to perform an item level product monitoring as well as an automatic data gathering.
- **An enhanced data sharing across the supply chain:** Attributes of products are made globally accessible for supply chain members over the Internet. The widespread

adoption of EPC and component technologies in data acquisition and management, applications and integration software depend on the development of standards supporting it. In [29], the importance of standards is compared to similar maturation cycles for barcodes and wireless LANs: “The developments that ushered bar codes and WLAN from niche to mainstream technologies are quite clear. In each case, it was the development of open, internationally recognized standards”. As with the hardware infrastructure for RFID, the Auto-ID Center is working with sponsor companies and organizations (Code Council and EAN International, the two main bodies that oversee international bar code standards) to define how the EPC will be implemented in the RFID technology [30] and how the associated software and information services should operate [31]. For this purpose, EPCglobal which is a joint venture between EAN International and the Uniform Code Council (UCC) entrusted by industry to establish and support the Electronic Product Code as the global standard in any industry and anywhere in the world has been created. The objective is to drive global adoption of the EPCglobal Network.



**Figure 3. Functionalities of the EPCglobal Network System**

**Remark**

For the remainder of the dissertation, the term Auto ID technology will be used to refer to the set of technologies enabling to achieve the Auto ID Center vision, i.e. “a word where all high volume/low-value items consumer goods will be tagged with mass produced RFID tags, which will be extremely cheap due to the vast number being produced. The tags would hold items’ Electronic Product Code (EPC) which could then be matched to information about the item which would be stored on Internet. The required information could then be forwarded to wherever it was required”. In other words, it would refer to the set of technologies that includes RFID tags with integrated EPC codes, mechanisms for reading from the tags and sharing the data over the Internet.



## **2.4 Challenges in Information Sharing When Deploying the Auto ID Technology**

In today's competitive business environment, it is difficult for a company to survive in isolation of its suppliers and other business partners in the network of value chain which encompasses the entire production activities of a product lifecycle [32]. Recent research on supply management has focused on a debate regarding the need for closer relationships between businesses in the search for a better coordination to optimize the chain-wide performance. [32] reports that this interest increased significantly when companies saw the benefits of business partnerships within and beyond their own organization. A basic enabler for tight coordination is information sharing among multiple functions and independent companies engaged in the delivery of a product or a service to end consumers, which has been greatly facilitated by the advances in information technology [33].

Various information sharing practices have been observed so far in many industries. For instance, Procter & Gamble routinely receives sell-through data from its major customers' distribution centers and point-of-sales (POS) data from some retail stores, IBM and Hewlett-Packard ask for sell through data as part of their agreement with computer resellers [34]. Although one may think that within a supply chain, decisions based on global information on products would be more effective in coordinating supply chain activities than decisions based on partial visibility, the goals and interconnected needs of manufacturers, logistics providers and retailers being different, some core issues need further investigations.

The difficulties in information sharing will not disappear by the implementation of Auto-ID technology or any particular technology [35] and the widespread adoption of Auto-ID will require all actors to arrive at consensus on ways to face a variety of technical, economic and organizational issues that may impede effective deployment [16]. Some of the issues and barriers that the widespread cross-industry Auto ID deployment will be faced are described in the following points:

### **What type of data should be associated with the EPC code?**

Companies will have to decide what type of data they are willing to share with outside organizations and whether data will be proprietary or be shared only with the designated external organizations. Supply chain partners, by exchanging data may be worried of the possibility of other partners abusing information [34]. While it seems natural to think that certain types of information should be shared among all partners involved in the supply chain, companies may want to hide some confidential information pertaining to their activity. Examples of such information would concern cost data (e.g. purchase price of parts), production data (e.g. which machine has been used by the manufacturer to produce the quantity of products ordered by a specific retailer), product quality data (e.g. is the product sold by the manufacturer produced from recycled material?) or data pertaining to shelf assortment in a given store (e.g. how does the store display products of the different manufacturers?). Furthermore, sharing the data captured continuously at various stages of a

supply chain may enable an enterprise to deduce indirectly its partners' performance (such as lead times, queuing delays at workstations, etc), even if this data is not explicitly exchanged. This, in turn, may have consequences on the way partners are working together.

### **Who owns the data?**

Does data become automatically shared among supply chain actors? Do manufacturers for instance suddenly get their own POS data or do they buy it back off retailers? Such critical considerations concern the ownership of data. Types and amounts of information an enterprise may want to share with its partners would depend on the individual relationships it has with each of them. Rules and profiles for access to total or partial information need to be well defined.

### **The data accessibility and security issue**

[34] highlights this issue through an example: suppose, for example, that a supplier supplies a critical part to two manufacturers who compete in the final product market. Either manufacturer would not share information (like sales data) with the supplier unless it is guaranteed that the information is not leaked to the other manufacturer. But the situation becomes tricky if the supplier and one of the two manufacturers are the same company.

### **Need for investments in the infrastructure**

The introduction of Auto ID will require modifications to existing back office systems, development of new back office and analytical systems, integration with other systems, facility reconfiguration, and training/transition costs; thus, companies implementing Auto ID will have to face technical, organizational and process challenges. Furthermore, there can be disagreements about the sharing of investments in the technology and benefits obtained. This is, as always, a difficult issue to resolve for investments where other companies benefit as much as, or more, than the company making the investment. For instance, [16] points that, even if retailers see relatively few benefits from case-level tags, manufacturers will want to track cases of their products into stores. And given the large number of retail outlets, it does not make sense for manufacturers to deploy proprietary readers that can scan only their own Auto ID tags. Unlike manufacturers, retailers are primarily interested in item level Auto-ID applications – especially those relevant to store operations. Given that manufacturers expect only marginal benefits from item-level EPCs, who should support the costs of deploying EPC tags, readers and related software when benefits may be greater for retailers versus manufacturers or vice-versa? Cooperative game theory [36] offers a starting point to the resolution of such conflicts, but reality may be much more complicated.

The current solutions consist of service providers such as Savi and Chep, making the initial investments. Companies using these services pay to the service providers for the benefits enjoyed [37].

## **Need for standards**

The development of standards to support the widespread adoption of EPC and component technologies in data acquisition and management, applications and integration software is another constraint. There are various things that need to be standard [38]. Firstly, the information on the tags needs to be standardized. The tags, readers and other infrastructure need to be standard. Finally standard frequencies are required. The frequency and power that the US is allowed to use is different from Europe or Japan.

Companies will not get the full value of shared benefits from Auto-ID unless and until their industries develop a consensus on an appropriate business model for deploying Auto-ID systems [16]. Creating one, open global network for Auto ID means that companies can invest in systems and have confidence that the tags they put on their products can be read by retailers and other business partners.

If Auto ID is deployed in systems such as military defense systems or highway toll reading systems, standards are not an issue because the actor has total control of the technology. These are commonly referred to as “closed loop” systems. This is not true in open commercial systems where there are a number of competing technologies and vendors to choose from. Generally accepted standards are necessary to ensure that the tags applied by ABC company can be read by the readers at X, Y and Z companies. A responsive information system technology should accordingly require compatibility and interactivity which can cope with the increasingly complex settings of organizations and markets. [16] reports that at present, most vendors’ Auto ID technologies are incompatible with other vendors’ software and hardware offerings.

Generally accepted standards are being developed for passive tag encoding protocols and content, transmission protocols and frequencies, application usage, hardware conformance, and many other related areas. As with the hardware infrastructure for RFID, The Auto-ID Center began this standards development process, which is now being guided under the auspices of the Uniform Code Council (UCC) and EPCglobal. The most visible results of these efforts will be the electronic product code (EPC) that will be at the heart of the Wal-Mart initiative. The good news is that the mandates (Wal-Mart, Target, DoD, and FDA) agree on the same EPC standard. The bad news is that the exact content to be on the tag, including its format, is still being negotiated. The possible result could be a change in the amount of data on the tag, driving a change in the memory requirements for the tag, impacting the unit cost of each tag [26].

## **Technical barriers**

There are still a number of technical barriers which need to be overcome, before Auto ID can be rolled out successfully. First the companies producing tags will need to be ready for mass production on a scale unknown to them so far, and the tags will need to be completely reliable [38].

Second, the effective scanning distance of an RFID tag is affected, often dramatically, by the material to which it is attached. The latter issue underscores one of the most significant reasons why manufacturers must comprehend their own RFID environments now. For example, high-moisture material or metal will reduce scanning distance by as much as 50% [26]. Radio waves are absorbed by moisture (on pallets for instance) and reflected by metal, which may make the use of tags something of a challenge in a store environment. Pallet manufacturers have solved this issue by fitting the tag into the center of the pallet, where it is most protected, and using a special antenna which can cope with the still slightly damp environment [38].

Furthermore, the widespread Auto-ID deployment will require a new breed of data management and network services. As Auto ID readers interrogate numerous tags at multiple points in the value chain, they will generate substantial volumes of item-level EPC data that needs to be processed and communicated across the value chain. Today, data management services that scale to simultaneously track millions or hundreds of millions of items in real time are still in their infancy and the scalability of these services remains unproven [16].

These are real problems but all those working on Auto ID implementation perceive them as challenges rather than barriers and expect them to be totally resolved in the near future.

## **Chapter 2**

# **A QUALITATIVE ANALYSIS OF POTENTIAL BENEFITS OF THE AUTO ID TECHNOLOGY ON SUPPLY CHAIN PROCESSES**

### **Introduction**

The aim of this chapter is to highlight the benefits of using the Auto ID technology in supply chains and to present an overview of the current state of Auto ID applications in industry. In section 2, we characterize the main sources of uncertainties in decision-making processes that hinder optimal supply chain performance. In order to analyze how the use of the Auto ID technology can reduce these uncertainties, we follow a two-step approach.

First, in section 3, we identify two criteria, namely the degree of automation of the data capture process and the level at which data is monitored and managed by the system, as being the main factors that permit to compare the performance of different AIDC systems. Using this framework, we compare two sets of AIDC technologies: (the Bar Code system + UPC) versus (the RFID system + EPC two of the components of the Auto ID technology).

The second step developed in section 4 consists of identifying how the identified properties of the Auto ID technology can reduce or eliminate the sources of supply chain uncertainties previously analyzed to improve the performance of operations. In this section, we provide an exhaustive list of benefits of building supply chain level Auto ID applications. This demonstrates today's potential for Auto ID technology. A variety of applications are possible and financially justifiable for certain product types and market requirements.

In the last section of this chapter, some current applications of the Auto ID technology are presented.

# **1 Notions of Complexity, Variety, Uncertainty and Supply Chain Management**

Before moving on to discussing how the use of the new Auto ID technology can contribute to a better management of supply chains, let us dwell into the challenges companies are facing today. Several factors lead to difficulty in managing today's supply chains. Product/process complexity, product proliferation combined with globally dispersed structures, distribution channels and uncertainty are among factors that create considerable complexity and inefficiencies increasing the cost of operations.

## **Product and Process Complexity**

According to [39], complex systems are made up by single elements which have intimate connections, counterintuitive and non-linear links: as a consequence, complex systems present self emerging, often chaotic behaviors. Within operations management, product complexity refers to the number of parts needed to produce a good [40] or a service [41]. Industries such as computer, consumer electronics and automobile are examples which support the production of multiple end products where each end product has a complex multi level bill of material consisting of thousands of components and subassemblies [42]. For instance, on average, a car is made from around 13,000 parts [43]. The larger is this number, the higher would be the risk to have inefficiencies occurring in production and distribution processes.

The second major aspect of complexity is related to the production process: i.e. the number of elementary operations needed to manufacture a product. If each operation has a probability to be performed in a way that does not satisfy quality requirements, the probability to have a defective end product may be considerable. If we consider for instance, a car production process consisting in 10 000 operations and if we suppose that an operator makes an error in 1 operation over 10 000, the probability to produce a car without defects would be  $(0,9999)^{10000} = 0.37$ , which signifies that 63% of cars need to be remanufactured [44].

## **Product Variety**

Product variety or product proliferation is defined as the breath and the depth of product lines by researchers in the area of operations management [45]. In recent decades, product variety has increased dramatically in almost all industries including automotive, computer hardware, software, and telecommunication. Diversifying products has become the strategy of a large number of enterprises. The term customization is used to refer to an extreme differentiation of a product or a service for a precise customer. The Dell company case constitutes a good example illustrating customization: customers specify through a dozen of parameters the computer they want to buy. For each characteristic, they have the choice between an average of three or four options. The number of possible PC configurations they may built is as large

as 10<sup>5</sup>. In the packaged-goods industry, the number of new products introduced doubled from 12,000 in 1986 to 24,000 in 1996 [46]. The number of products available in large supermarkets has increased from on the order of 1000 in the 1950s to 30,000 in a modern supermarket [47]. Home depot, for example, had 12 000 different products in 1979 while in 1998 it had 48 000.

Today's operational context of most enterprises is worth exploring: more and more supply chains have an extended structure meaning that the different value-adding activities are strategically dispersed among various countries and coordinated to produce the competitive advantage -as is the case of most multi-company, multi-site European supply chains ([48], [49],[50])- in order to increase market share and reduce costs [51]. As said in [34], modern businesses attempt to deploy global resources to maximize the potential opportunities in the global community. Factories produce millions of individual items per year with thousands of SKUs in dozens of product categories. Products flow from factories to manufacturers' own distribution centers and to wholesalers' distribution centers, moving eventually directly to specific retail stores and store shelves. A global supply chain can thus be viewed as a network of factories and material sourcing on a worldwide basis [52]. And to make matters even more interdependent, many product categories vary in overall demand, have a certain seasonality, and events such as new product introductions or promotions create demand spikes or out-of-stock positions on retail shelves [16]. All this adds to the complexity on informational, physical and service transactions and inter enterprise interactions [53].

Therefore, the choice of putting on the global market a very rich variety of finished products requires for a supply chain to master a wide amount of different and equally demanding processes and technologies; to control and exploit many different distribution and sales channels; to deliver products to a large amount of customers; to manage a large variety of different subgroups, components and final products' inventory; to handle mixed loads and multiple products pallets; to perform more complex forecasting [54], purchasing [55] and production scheduling processes [56]. In turn, upstream supply chain actors have to manufacture a wide mix of components, subgroups, raw materials and packaging material, together with the need to interact with different logistics service providers, manage multiple order-processing processes or the need to manufacture in different locations, and in smaller batches. Non-repetitive manufacturing in small lots could turn out to be a constraint when it comes to process automation, while the wide variety of components to procure could require interacting with a large amount of different upper tier suppliers, globally located.

A considerable amount of research has been devoted to discuss how the variety of products or components, the multiplicity of actors, the complexity of distribution channels and the interdependency of decision processes can enhance the competitive strength on the one hand, but increase coordination and management costs on the other hand and how supply chains cope with this ([57], [58],[59]).

Product identification, data capture and sharing systems can help to tackle with the increasing complexity of supply networks by means of reducing costs and improving the service level. Among these are the ability to handle efficiently a large number of differentiated material flows, to track and trace them effectively in a complex multi-company, multi-site network, to control activities within an enterprise or across the boundaries of enterprises from different continents as well as outsourced activities, to name but a few. For a given product type flowing through a defined supply chain configuration, these expected functionalities become even more critical and issues are intensified in presence of uncertainties creating perturbations in existing flows and leading to additional inefficiencies such as non value adding activities.

### **Uncertainty**

Uncertainty, as described in ([60],[61]), refers to decision making situations in which the decision maker does not know exactly what to decide as he is indistinct about the objectives; or lacks information about the supply chain; or lacks information processing capacities; or is unable to predict accurately the impact of possible control actions on the supply; or does not have effective control actions (non controllability). It is widely recognized that the uncertainties in supply processes and demand have major impacts on operations ([62],[63],[64]). Hence, [65] states that those companies which cope best with uncertainty are most likely to produce internationally competitive bottom-line performances. While [62] focuses on the impact of uncertainties on the manufacturing function, other investigations such as ([63], [66], [67], [68]) stress on uncertainties in other processes such as transportation. [69] reviews the sources of uncertainty encountered in the literature and point out the level of decision (strategic, tactical, operational) at which each of them should be resolved.

([60], [61]) provide an excellent review of the notion of uncertainty in supply chains as well as a framework enabling to identify the main sources of uncertainty. They then discuss several supply chain redesign actions/strategies that can be used to reduce and/or eliminate uncertainty and, as a result, improve performance based on an extended multi-disciplinary, multi-industry literature review and come up with a list of potential actions.

In order to identify the potential benefits stemming from the application of the Auto ID technology in supply chains, we built upon the methodology developed by ([60],[61]): we first identify the sources of uncertainties in decision-making processes that hinder optimal chain performance and then highlight how the introduction of the Auto ID technology can reduce or eliminate certain types of uncertainty and improve operations. The following section on the sources of uncertainties has been adapted from the investigation developed by [60].

#### **1.1 The Major Sources of Uncertainty Within a Supply Chain**

There are several sources of uncertainties leading to inefficiencies within a supply chain. We will distinguish four major sources of uncertainty. In each case, the uncertainty should be



interpreted as a factor that generates variability in quantity, in quality, in delay or in physical locations.

## **1.2 Inherent factors causing fluctuations**

Inherent factors may cause more or less predictable fluctuations in:

- Processes (production/distribution/reverse logistic processes): e.g. fluctuations in process outcomes (quality and quantity) and delays due to variable process yield, machine breakdowns, errors, scrap, unavailable resources or execution problems that prevent products to be available when needed. This uncertainty is expressed in questions such as: will the supplier deliver the requested goods on time? is the total amount of products requested delivered? according to demanded quality specifications, how much time will it take to perform manufacturing operations? will there be any deviations from the expected delays?
- Products (and more generally components, semi finished or end products): certain types of products have shelf life constraints (e.g. perishable products) or may be easily imitated (e.g. pharmaceutical products)
- Demand: Even if you know average customer demand, there are always variations due to changing customer preferences.

## **1.3 Uncertainty on data captured from physical transactions**

Data captured from physical transactions is used either directly by decision makers or indirectly by other supply chain information systems that support decision making (e.g. inventory management systems, Advanced Planning and Scheduling systems, store management systems, etc.)

The uncertainty may concern one of the four dimensions of data quality:

- Data accuracy: does data reflect exactly the physical system which it is associated with, i.e. is it error free and up to date?
- Data capture delays: what is in average the delay needed to capture data? is it subject to variability?
- Data granularity: at which level data is monitored and managed? (e.g. at product type level or at individual product level)
- Data availability: can supply chain members have an easy access to data and is data provided in the right format?

## **1.4 Uncertainty on the configuration of the supply chain and the deployment of resources**

This concerns structures, facilities, parties involved and the roles they perform in the supply chain. Uncertainty (in the form of complex networks, distances between suppliers and

customers, number of actors) would render difficult the monitoring of entities across the supply chain and the activities performed by each actor.

### **1.5 Uncertainty on supply chain control structure**

Decision processes govern the execution of operational activities aimed at achieving the objectives within the constraints set by the chain configuration (e.g. delivery frequency, order quantity, production planning structure, etc.). Uncertainty may be associated with decision processes' delays or the quality of decisions (e.g. wrong decision rules applied resulting in bad performance).

## **2 Identifying the Properties of the Auto ID Technology**

In the following two sections, we are mainly interested in identifying the relationship between the sources of supply chain uncertainty and how Auto ID technology can be used to tackle them. The existing literature on benefits of Auto ID technology discusses its impacts in either reducing cost or increasing revenue. However, it is unclear how this is realized, i.e. what kind of uncertainty is reduced by Auto ID? Does the use of Auto ID have a direct or an indirect impact in improving supply chain performance? Our aim is to fill this gap by answering these questions. To do that, we first characterize the properties of the Auto ID technology, the main question being what makes Auto ID an improved AIDC system compared with the barcode technology. Then, we classify the nature of benefits enterprises can achieve by using it. Finally, by answering the question “how Auto ID can reduce or eliminate a certain type of uncertainty?”, we report a quite exhaustive list of potential benefits of the technology.

### **2.1 Criteria for the Evaluation of Performances of an Automatic Identification and Data Capture System**

When investing an identification and data capture system, an enterprise must have a good understanding of specific constraints coming from its products and process characteristics. Depending on expected functionalities, the application environment and the characteristics of products monitored, different AIDC systems would satisfy the requirements.

We have identified two main criteria enabling us to evaluate the performance of an item identification and data capture system:

- The degree of automation of the data capture process
- The degree of detail of data monitored and managed by the system (SKU level or individual item level information)

#### **2.1.1 The Degree of Automation of the Data Capture Process**

The first criterion concerns to what extent items are identified and data is captured efficiently. Depending on the level of human intervention needed to capture data (manual, semi

automatic, automatic), this process may be time consuming or prone to error. The degree of automation of this activity would also impact the frequency at which the data monitored is updated.

### **2.1.2 The Degree of Detail of Data Monitored and Managed by the System**

The second criterion evaluates the granularity of data captured and monitored by the system.

Product type level (or SKU level) information management can be used when different products of the same type contain basically the same product characteristics and are interchangeable. One weakness of these kinds of systems is that identifiers used to recognize entities do not give the possibility to manage item level product information. This is because codes used only distinguish different types of products, not individual entities.

If products flowing through a supply chain are subject to counterfeiting, theft, recall, or regulatory control (e.g. the pharmaceutical distribution), product type level information would not be sufficient to streamline the physical flows. Strict governmental requirements on product lifecycle management, traceability, and after sales support are also applications demanding item level information management [18]. For example, in the European Union, all consumer electronics have to be recycled with a minimum warranty time set to 2 years [10]. There is also increasing consumer pressure for individual item level traceability systems for many product groups ranging from pharmaceuticals to grocery products.

## **2.2 Comparison Between the Bar code Technology and the Auto ID Technology**

Based on these two criteria, we shall now compare the performances of two AIDC technologies: (the Bar Code system + UPC) versus (the RFID system + EPC).

Note that we elaborated the comparison of the Auto ID technology over the Bar Code technology at the AIDC system level since an industry wide standard data sharing system associated with the Bar Code AIDC system has not been developed, we assume that the inter enterprise data sharing ability of Auto ID is a new perspective enabled by this new technology (cf. Chapter 1).

### **2.2.1 Properties of the Bar Code Technology**

In most industries, especially in the retail sector, Bar Codes are used as a principal mean to identify items [17]. In a Bar Code System, each time items are moved from one point to another, labels must be precisely positioned to be detected and identified by the reader. This characteristic called line of sight positioning requirement necessitates human intervention (thus effort and time) for the scanning process and leaves room for errors and inefficiencies.

Furthermore, the fact that identification is performed manually hinders decision makers (e.g. inventory managers, forecasters) to have an up to date data concerning supply chain entities unless a continuous scan is realized by operators.

The second particularity of this system is that it identifies only classes of products, thus, information obtained from scanning labels is relative to SKU properties of an item -some generic information on characteristics such as price, color, weight, length, volume, etc... This means that we know we are seeing a certain type of product but we do not know which individual product it is: hence, the Bar Code on one milk box is the same as every other, making it impossible to identify which one might pass its expiration date first.

Note that the above mentioned properties are associated with the most common use of the Bar Code system in industry. Theoretically, it is possible to overcome these drawbacks (cf. examples in section “Intermediate Cases”) but these specific applications being too costly would not reflect the most common applications in industry.

### **2.2.2 Properties of the Auto ID Technology**

As described previously, the Auto ID technology uses RFID system and Electronic Product Codes to capture data from items. Tags do not need a particular positioning or physical contact with the reader, i.e. they can scan themselves as long as they are in the field of the reader. This particularity of Auto ID allows tags to be read with no human effort and multiple tags in the reading field to be considered simultaneously.

The implications stemming from the automatic identification property of Auto ID are its ability to:

- Reduce identification and data capture process delays
- Provide accurate (exhaustive and up to date) information about the entities

The second property of Auto ID is that there is an assignment of a unique identification number to individual logistical entities (be it an individual consumer unit, a box or a pallet) which allows a monitoring at unique item level. Thus, one can track and trace a particular entity through all supply chain operations, from design to recycling activities. The implications of this particularity are quite interesting: a feature that directly results from this, is that simply by reading the tag, one can distinguish a consumer unit from a similar one and obtain information about which plant the item came from, where and when it was packaged, its best before date, how long it has been waiting at a particular point of the supply chain. This unique code prevents also to double-count entities, whereas with Bar Codes, as all entities of the same SKU have the same Universal Product Code, there is never a guarantee that an employee would not accidentally scan an entity twice.

#### **Remark**

##### **1. Auto ID’s Item Level Identification Property**

In the previous sections, the granularity of data has been described as the level (SKU or item level) at which data concerning logistical entities is monitored. A second point concerns

whether the entities are monitored at individual or a more aggregated level (e.g. consumer units monitored individually or in batches). Benefits resulting from the assignment of a unique identifier to individual entities will vary significantly and therefore, the level of granularity at which entities are tracked will be governed by the category which they belong to:

- High value items such as cosmetics, jewellery, apparel, white goods and consumer electronics or short lifecycle products that require very careful management may justify carrying an individual identifier whereas low value products (such as dry grocery) will not support an economic model for tagging individual products. It would make sense for this second category of products to assign an identifier to a batch, or a lot of items, and to use the identifier to describe a particular type of common component.

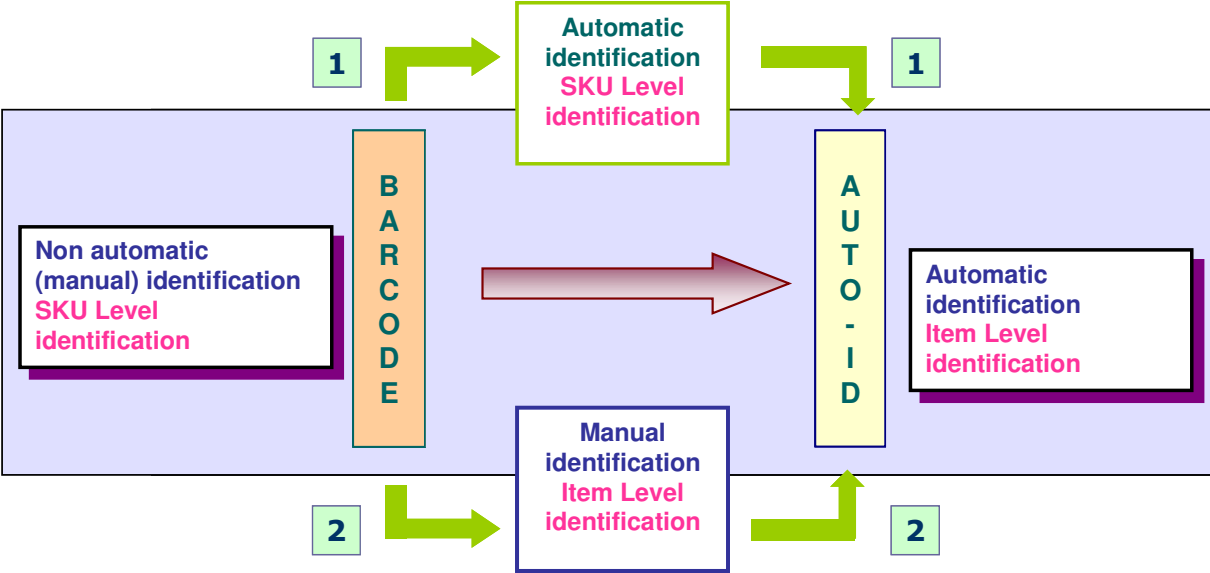
- A single EPC embedded in a monolithic object (a box of soap), does not necessarily make sense for small assemblies, such as integrated circuits, nor to common parts in manufactured products, such as standard bolts and rivets [70]. Batches of small, uniform parts, such as ball bearings and electronic resistors may not benefit from individual serialization. It would make sense, however, to assign an EPC to a batch, or lot of items, and in this case, the EPC is used to describe a particular type of common component. The advantages of automatic identification continue under this expanded definition, but the concept of a single EPC for a single object does not (the individual object traceability and benefits of serialization are lost for these items) [71].

- Temporary arrangements of objects, such as shipments, pallet configurations and assemblies, may also require an identification number. This number, however, comes into existence with the configuration of the components, such as a shipment, and is eliminated (except for historical records) once the configuration is removed. An EPC applied to this case is truly a virtual EPC, since the EPC does not describe any physical object, but simply the configuration of physical objects. The electronic tag and the corresponding EPC number, in these cases, will be attached to the container – whether bin, box or bag.

Individual product level information management would generally be demanded when attributes of individual products are of importance. Among factors influencing the need for individual product level information management are: the value of the item, the criticality of the item, the length of the item's lifetime, the complexity of the system the item is attached to, and external requirements (authentication, ..) [18]. Examples of such items are clothing, CDs, bottles of spirits, razor blades and video cassettes. For instance, Gillette has been involved in a number of Auto ID tagging trials for razor blades, in an effort to prevent shrinkage by tracking units at item level.

**2. Characteristics of the Application Environment and Product Attributes**

Beyond the two properties of Auto ID outlined in section 2.2.2., exogenous conditions such as the characteristics of the operating environment within which the identification and data capture process is realized may have an impact on the performance of the system, one may thus take advantage of another property of the RFID system based Auto ID technology: unlike most other technologies (including Bar Codes) that are stressed under extreme thermal conditions or wet environments rendering illegible damaged paper labels, RFID has the ability to withstand extreme environments [72]. As Bar Codes are read with a ray of light, they also have to be located at the surface of the product or packaging, which leads to a serious readability problem in difficult environments or under several handling times due to dirt and bending ([73], [74]). Industrial strength RFID applications have proven that it is possible to collect information with a greater degree of precision than any previous generation of technology. Tags are durable, with some able to survive temperature ranges from minus 40 degrees Centigrade to 200 degrees Centigrade [75].



**Figure 1. A framework to compare the Bar Code and Auto ID technologies**

**2.2.3 Intermediate Cases**

Within an enterprise, the transition from a Bar Code technology based system -the initial situation- to an Auto ID technology based traceability system -the final situation- can be realized in two different ways (cf. the figure above).

The **first intermediate case** is a situation where the enterprise uses an item identification and data capture system operating automatically but providing SKU level information. This case is similar to the level of detail of information given by Bar Codes and the automated identification property eliminates human intervention, thus, opportunity for errors and scan

delays. If SKU level information provided by this system is not sufficient to track and trace items, other data carriers such as human and/or machine readable labels containing item specific data (sell by date, batch number, specific instructions) need to be used.

The **second intermediate solution** is a system where items are identified manually, as in the case of the Bar Code System, but information captured contains individual items' attributes, like in RFID tags. Due to this item level identification capability of the system, individual items can be better tracked, sources (location and date) of problems (non quality, defects, delays, etc.) can be better detected, and situations such as returns or recalls where individual product characteristics need to be used can be better managed. The drawback of this system is the need for human intervention for product identification, the probability of having inaccurate records due to this intervention, i.e. the potential drawbacks associated with a manual scanning process.

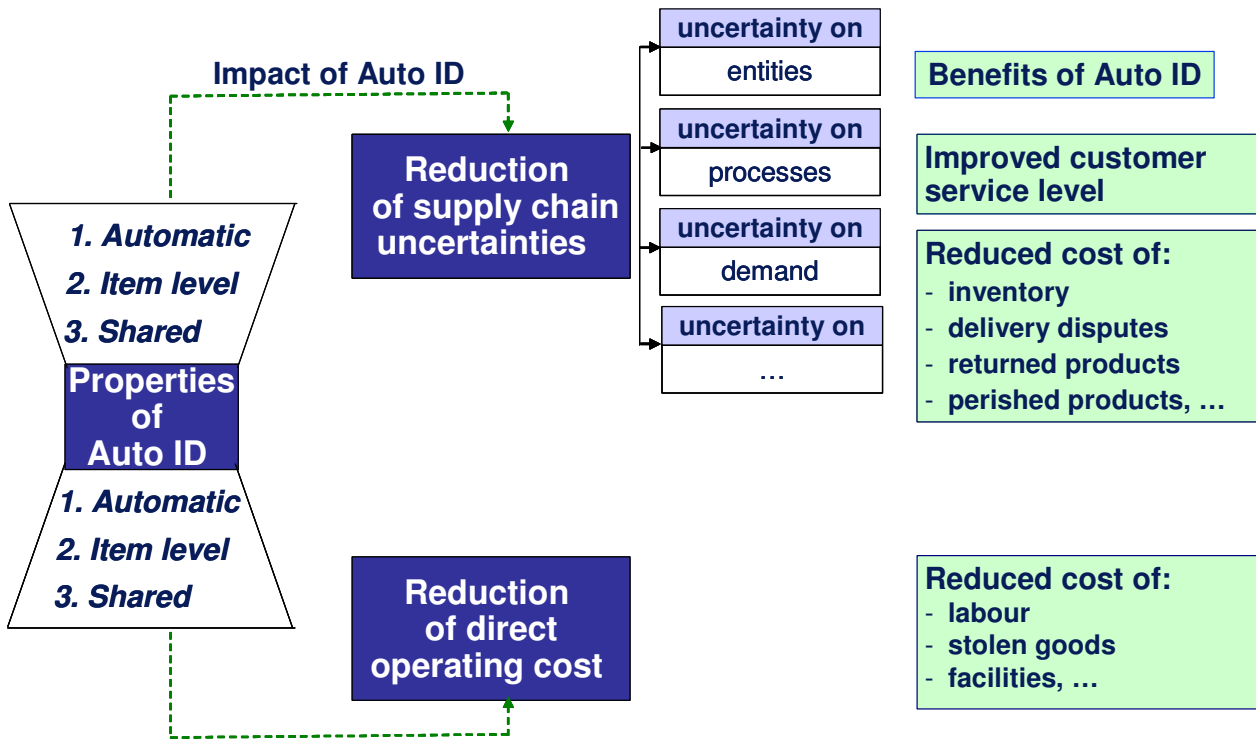
### **3 Potential Impacts of Auto ID Technology on Supply Chain Processes**

Before identifying and characterising the potential benefits stemming from the use of the Auto ID technology in supply chains, we have developed the following two sections which first present a typology of the impacts of Auto ID and then classify the nature of benefits, i.e. identify which of the improvements can be considered to be totally related to Auto ID and which ones stem partially from its use.

#### **Typology of the impacts of Auto ID**

Due to the properties presented earlier, the use of the Auto ID technology would affect supply chain processes basically in two ways:

- On the one hand, the Auto ID technology reduces directly certain types of operating costs
- On the other hand, using Auto ID contributes to the reduction or the elimination of supply chain uncertainties



**Figure 2. Classification of benefit types**

While the remaining of the chapter focuses more on the second type of benefits, i.e. situations in which the use of Auto ID enables to reduce or eliminate a certain type of supply chain uncertainty, the following examples illustrate the first type of benefits, i.e. cases where using Auto ID reduces directly the cost of performing activities:

### 1. Reduction of labor cost due to an easier data capture

Bar code labels are optical, in other words, if the scanner can not see the symbol, it can not read it. The fact that the product identification and scanning process is manual generates an additional labor cost which can be considerable for most distribution centers' operations (e.g. according to [76], for manufacturers and retailers, labor costs represents from 50–80% of overall distribution centers' costs).

The **automatic identification property** of Auto ID makes it possible to synchronize the physical flow of goods and the associated information flow without the need for human intervention since if supply chain entities are tagged, operators do not need to manually scan them.

Similarly, according to a study realized in Finland, checkout costs represent approximately 3% of retail revenue in supermarkets and the magnitude of this cost is quite similar in other industrialized countries [77]. Tagging products in stores will contribute to decrease the number of check out counter employees required.



## **2. Acceleration of the physical flows of products**

An Auto ID reader can scan numerous tags that are in his field at the same time (and even tags that are in movement). This reduces considerably product identification delays and speeds transactions during receiving, cross-docking, shipping, sorting and store checkout processes. The Auto ID system can process as many as 50 tags per second – 40 times faster than bar-code scanning [78]. Results are faster material flow -it is possible for example to scan an entire load of pallets coming to a warehouse and avoid products to sit too long in receiving area and remain unavailable for shipping.

This in turn, improves for instance the service provided to end consumers who often report great dislike for waiting in grocery checkout lines [79]. Although the average checkout time has declined from 6.5 minutes in 1975 to 4.38 minutes in 1991 [80], the checkout wait has remained a long-standing necessary irritant. The Auto ID system scheme in which the consumer simply collects products (with embedded Auto ID tags) he wishes to purchase and proceeds to leave the store without having to wait in a checkout line or produce a signature gives the opportunity to define a new organization for stores.

## **3. Reduction of theft issues**

The National Retail Security Survey conducted annually by the University of Florida, concluded that nearly 2 % of total sales in United States is lost each year due to "shrinkage" - employee and customer theft, vendor fraud and administrative error [22]. As the Bar Code system cannot address the pilferage problem, Electronic Article Surveillance (EAS) systems are used in applications such as electronics, CDs and clothing. While this technology performed well in the early stages of adoption, its effectiveness has decreased over time due to three primary reasons:

- Employee turnover in the store is such that as training procedures slip, the compliance in working with the technology also slips.
- EAS “pollution” can arise, where tags that have not been deactivated cause alarms to be triggered in other stores using the same technology.
- EAS systems operate only at the checkout or exit, not continuously throughout the environment.

**Automatic identification property of the technology:** With Auto ID, readers placed at facility egresses prevent the casual theft of product tagged at the unit product level. Systems can be set up to alert security when an item is moved by unauthorized personnel and deny unauthorized access to facilities.

**Item level identification property of the technology:** Tags permit to identify which particular item has been moved thus, render the tracking of stolen goods easier. Similarly, Auto ID technology can be used in giving additional theft prevention functionality to

products. An application in the automotive industry already exists; today many vehicles are equipped with remote entry and access control systems. The key typically employs an encrypted transponder and controller chip. The transponder is verified when the key is put into the ignition lock. The car will start only if the correct code is read. According to Gartner, in 1999 more than 50 % of sub-128 kHz Auto ID chips were used for this application. In 2001, 60 million transponders were sold for this application by Philips Semiconductors, Sokymat and Texas Instruments [81].

#### **4. Savings in space**

When Bar Codes are used in stores, approximately 1% of the sales area is allocated to check out counters. This space could be used as sales space giving an opportunity to stores to better organize the layout if Auto ID tags and readers are used to automate the sales process.

Similarly, in warehouses, the elimination of product verification process on the receiving/shipping dock would reduce the need for staging (and the space necessary for this operation). This, in turn, enables to simplify structures and optimize processes. Within the warehouse, Auto ID has the potential to contribute to change the warehousing, because products can be stored almost anywhere, moved as needed and found in a moment's notice. Goods do not need to be stored according to product type for manual location, and can be stored in a more efficient manner based on size and shape. For instance, [82] estimates that the possibility to change the way in which warehouse space is allocated can save between 10 to 20 % of warehouse space.

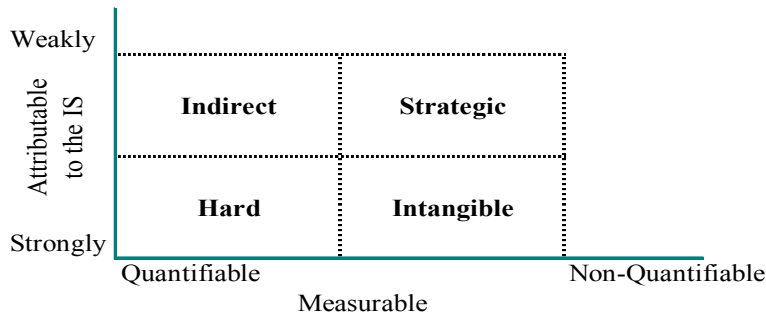
#### **Nature of Auto ID Benefits**

Before getting in detail on how the properties of Auto ID enable to reduce or eliminate potential supply chain uncertainties, we will classify the nature of benefits, i.e. clarify which of the improvements can be considered to be totally related to Auto ID and which ones stem partially from its use.

This section is built upon the typology initially suggested in [83] and revisited later in [84]. Examples considered in this section are mainly those developed in [84].

First of all, the benefits stemming from the implementation of a new information system technology can be split in two parts: hard and soft benefits.

Hard benefits are a direct result of the introduction of the technology and can therefore be easily measured. According to [83], soft benefits include at least intangible, indirect and strategic benefits. The figure below builds upon this classification to surface the importance of both the extent to which benefits are directly attributable to the introduction of the information system and the extent to which they can be readily quantified.



**Figure 3. Nature of benefits**

The horizontal axis distinguishes between quantifiable and non quantifiable benefits, while the vertical axis distinguishes between those benefits that are realized solely as a result of the introduction of the new system, and those that depend, to a greater or lesser extent, on other organizational factors as well.

Hard benefits are usually related to cost reduction or revenue generation, such as the reduction in data-entry staff made possible by the introduction of an electronic ordering system, the increased through-put as a result of a new production control system [84]; the reduced cycle-time thanks to the use of automated materials handling, automatic data capture and electronic data interchange, computer-aided design and engineering/computer-aided manufacturing (CAD/CAE and CAM) and computerized production-planning systems [85].

Intangible benefits can be attributed to particular applications but they can not be easily expressed in quantitative terms. Benefits of this type are observed, for example, with the introduction of a decision support system. Such systems are primarily expected to improve the quality of decision making as well as the job structure of their users. First, it is difficult to define “quality of decision making” and “job structure”. Second, even if this is achieved, it may still be difficult to assign a quantitative (monetary) measure of improvement in advance.

Indirect benefits are potentially easy to measure but can not be fully attributable to the proposed investment and can only be realized as a result of further investments, enabled by the new system. For example, the implementation of a local area network (LAN) across an organization provides the infrastructure on which valuable shared applications can later be implemented. Although this is a potential benefit made possible by the LAN, it can not be realized unless these shared applications are also successfully introduced. Such complementary investments may be in IT or in any other organizational resource, such as a change in business processes enabled by the introduction of IT.

Strategic benefits refer to positive impacts that are realized in the long run and usually result from the synergistic interaction among a number of contributing factors. They are the outcome of, for example, a new business strategy or a better market positioning of the organization, which can only be partially attributed to a given system. Such benefits are

notoriously difficult to quantify in advance due to their very nature and the risk associated with their realization.

Based on this typology, we classified the benefits stemming from the use of Auto ID (cf. table page 49). In some cases, the use of Auto ID has a hard (direct) impact on the reduction of a type of uncertainty (for instance, the reduction of labor costs due to the elimination of manual inspections), whereas in others, its implementation is only a factor among others contributing to an improvement by providing a more reliable information. In the second case, the Auto ID technology should rather be viewed as a facilitator enabling (indirectly) the deployment of other actions/strategies by supporting them through a “better data capture and exchange”. In such applications, since the “output” of Auto ID is used as an “input” by other supply chain decision support systems (such ERP, APS, ..), the benefit achieved is indirectly associated with the use of Auto ID. For instance, for applications used in the manufacturing area, Auto ID can provide the enabling data at a much greater level of accuracy, timeliness and detail than other data capture system alternatives. [86] supports that idea by reporting that Auto ID technology may close the link between a manufacturer’s Enterprise Resource Planning (ERP) system and Manufacturing Execution Systems (MES): today, the MES application does not have easy access to detailed information; and therefore, the ERP has no idea of what is really happening on the shop floor (e.g., subcomponents not being where they were expected, trained people not showing up when they should and machines going down). Auto ID can provide those systems with the accurate, timely and detailed information they require to operate effectively.

In the following we present with greater detail the benefits of Auto ID technology in supply chains.

## **Benefits of Using Auto ID technology in Supply Chain Processes**

### **3.1 Reduce uncertainties on inherent factors causing fluctuations in processes**

The use of Auto ID technology has a direct impact on the elimination of certain types of uncertainties pertaining to supply chain processes (e.g. production, distribution, store, and reverse logistics). Each benefit is either due to the automatic or item level identification properties of the technology. Some of the benefits stem from the ability of Auto ID to provide an infrastructure to share information across the supply chain. Finally, in some cases, the benefit of using Auto ID results from the combined impact of these three characteristics. In the following, while describing each benefit, we will precise the main property from which it results.

### **3.1.1 Reduction of labor cost due to the elimination of non value adding control activities**

As explained before, the fact that the bar code scanning process is often performed manually creates opportunities for human errors that represent a source of uncertainty in the exact quantity of products identified during the process. Furthermore, the accuracy of data concerning the locations of entities within a facility may deteriorate when products are handled without their movements being recorded in the information system and placed in another location.

Therefore, when the Bar Code technology is used, non value adding activities such as manual inspection when receiving/shipping products (counting and verification processes) and cycle/physical counting activities are to be performed in order to control whether the quantity, quality and location of entities flowing through the facilities are accurate. Although it can be assumed that the verification process is relatively easy for the upstream supply chain actors (mostly dealing with bulk pallets), this can be more challenging in the downstream supply chain where pallets usually contain multiple products coming from multiple vendors.

If Auto ID tags are put on supply chain entities, operators do not need to manually scan them; due to the **automatic identification property** of this technology, they can have an up-to-date information concerning the locations of entities eliminating the actual delay necessary to find items.

### **3.1.2 Reduction of delivery disputes**

Delivery errors or misdirected items often stem from inefficiencies in control points or from the organization of working procedures. In most actual practices, the fact that invoices do not match up with what was delivered is difficult to notice simply because, in order to save time and accelerate the material flows in warehouses and/or stores -especially in receiving process where hundreds of cases move through- operators do not systematically separate and analyze the individual entities, resulting in an uncertainty on the identity and quantity stored within the inventory system. The possibility of shipping the wrong unit or incorrect quantity of goods to customers remains even if shipped products are controlled. The Auto ID technology lessens this possibility, due to its **automatic data capture property**.

Furthermore, the **information sharing** infrastructure associated with Auto ID technology enables the exchange of data in between the shipping and receiving enterprises, it reduces potential discrepancies between what a supply chain stage says he has sent and what the following stage says he has received and shortens payment delays of shipped products since errors are eliminated and originally misdirected products are redirected. As a consequence, the number of claims and invoice adjustments are reduced and additional transactions required to fix them are eliminated.

### 3.1.3 Reduction of losses pertaining to returns

Returned goods represent an important part of the physical flow and include goods returned due to a quality problem (damage, defects, outdated products,...), a shipment problem (products not shipped to the right customer, products not shipped on time, items that are not identified by the customer,...) as well as the flow of containers and pallets returned by customers after use.

At the simplest level, the disposition of returned goods consists of junking them or giving them away. But with a better organization, returned goods can be put back into inventory, sold at liquidation centers, or may pass through either the demanufacturing or remanufacturing processes<sup>3</sup>. The efficient identification of returned goods enables a better control of returns and a better accuracy of invoicing data.

By having the possibility to **identify products at item level**, stores would know exactly when an item was sold (or if, in fact, it was sold at all) and for what price. This will reduce shrinkage by allowing them to better enforce return policies for discount purchases, returns beyond time limits, items purchased from another supermarket and stolen items.

Furthermore, in industries such as consumer electronics and office supplies, due to the high risk of product obsolescence, when products are launched (i.e. at the beginning of the selling season), return contracts are established between producers and retailers. The cost of reverse logistics may lower profits for the computer and electronics industries by as much as 25%. This represents potential savings for some product categories such as CD-ROM and DVD drives that have had return rates in the past of 25-40% [87]. Having an item level information on product identity, manufacturing date, price, etc. would help to better manage such agreements.

An efficient handling of returns is also necessary for maintaining inventory data accuracy. For instance, in the apparel industry, inventory errors arise essentially because of improper management of commercial returns. When a customer buys a medium size sweater and then wants to exchange it for a small, the returned garment should be scanned into the register as a return, and the requested garment should be scanned as a new purchase. In reality, the salesperson trying not to inconvenience the customer, exchanges the medium for the small one without scanning both items [9].

**Automatic identification property:** Another type of return flow concerns reusable pallets, tote boxes, containers, barrels, and shipping cases. Especially for logistics service providers including asset aggregators who provide these components, the accuracy of data concerning

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<sup>3</sup> Demanufacturing characterizes the entire process involved in recycling, reuse, incineration, and/or disposal of a product after it has been taken back by a company. Remanufacturing deals with the refurbishment of partly worn products for their subsequent reuse.

the locations of individual entities within or in between facilities (e.g. pallet movements) plays a significant role in managing flows, improving asset utilization, reducing delays and increasing responsiveness. Most of time, when these Bar Coded entities are handled without their movements being recorded, the quality of data pertaining to their locations deteriorates. At the macro level, a network of Auto ID readers employed across the supply chain may make products visible whether they are in store, in transit or in a distribution center while at the micro level, specific product occurrences can be automatically located within a facility [16].

### **3.1.4 Reduction of profit losses due to a faster detection of out of stock situations**

Retailers and suppliers have long struggled with how to make sure an item is always on the shelf when a customer wants to buy it. Most of today's inventory systems records only show what is being sold. Furthermore, there is an uncertainty on what is (and is not) on shelves. For instance, in the apparel industry where items have to be stocked in a specific order, current inventory information systems provide no information about what is in stock but not in the right place. As a result, sales are lost even when goods are in store because their location is not known.

The Procter Gamble company alone figured that out-of-stock products were costing \$3 billion a year in lost revenue and that on 10 % of shopping trips, the consumer can not find what he wants, and so tends to buy something else or nothing at all [17]. According to a recent research by the GMA into the out-of-stock situation in North America, 20% of the promoted products are out-of-stock at the shelf, meaning that the shopper faces a 1 in 5 chance of coming to the store to seek a particular product that is advertised but unavailable [7]. Accenture's research for the Coca-Cola Retailing Research Council also indicates a potential for lost sales of 3% annually to CPG manufacturers due to out-of-stocks – equating to a \$12 billion revenue opportunity [88]. According to the same study, out of stocks are not “democratic” in their impact; they do not affect all product lines equally. In grocery stores, the fastest moving 25% of items account for 66% of lost sales, with promotional lines typically the most adversely affected, averaging an out of stock rate on advertised items of 15%. An analysis carried out by IBM on purchasing intentions vs. product availability estimated that some retailers they loose an amount up to \$5,000 a month at each store from having the stock but not having it available for the customer when they wanted it, because of poor visibility of on hand quantities in the back room, fitting room and returns areas [87].

**Automatic identification property:** Auto ID tags can provide accurate data on shelf and backroom product availability without human intervention and help to reduce out of stock situations. This automatic continuous monitoring capability can also reduce potential reasons of out of stocks before they occur. By analyzing data given by Auto ID tags, actors can evaluate the delay each order spends at each company, the lead times, etc...

Warehouses would also prevent out of stock situations through a continuous monitoring of items and thus eliminate unexpected shortage situations arising at the time trucks have to be loaded.

Besides these hard benefits, the use of Auto ID technology can play a role in facilitating the management and/or reengineering of other processes. These soft (indirect) benefits are:

### **3.1.5 Improved reliability of the quantity and quality of goods produced**

#### **Better production monitoring, faster identification of bottlenecks**

**Item level identification property:** Tagging individual parts may enable a more reliable assembly process. Furthermore, this would permit to track if the sequence and timing of the manufacturing steps are correct.

**Automatic identification property:** A continuous tracking of products as they move through the manufacturing process would help to identify and resolve bottlenecks, plan better parts routing and redirect products during assembly if needed in order to optimize the flow of work in process. This in turn, would increase production yields.

#### **Better tracking and tracing of quality problems in production**

**Item level identification property:** In industries such as aeronautics or electronics where products are composed of expensive parts, manufacturers need to be able to detect the faulty component and go through a process of not just finding and replacing the part but also determining whether it was from a bad batch of parts [2]. As stated in the previous section, Bar Codes identify only classes of products, not items. With item level product codes, the Auto ID system is providing means to exactly find only defective part(s) and help to react against any quality problem (block items if necessary, process them when they do not meet the standards required, remove them from distribution) at a lower cost than the Bar Code system can do.

#### **Improved compliance to legal/safety requirements**

**Item level identification property:** Companies that transport or process hazardous materials, food, pharmaceuticals and other regulated materials can record the time they received and transferred material on a Auto ID tag that travels with the material; updating the tag with the timing of handling operations creates a chain of custody record that could be used to satisfy FDA (Food and Drug Administration), DOT (Department of Transportation) and other regulatory reporting requirements.

### **3.1.6 More efficient product recalls and enhanced consumer safety**

Consumer safety has become one of the most critical and priority issues for the food supply chain. Traceability is particularly important in this sector where food safety incidents could have significant impacts on consumer buying patterns, companies and commodity groups. The traceability system being in use should be able to enhance consumer safety by giving



them detailed information about where an individual item comes from, what are its components and their origins, what is the processing history in a routine basis and be able to find effectively all items condemned in case of critical situations. In the BSE infected beef or foot-and-mouth diseases, the European meat and livestock industries were financially devastated due to ineffective tracking systems [14]. The ability to trace the origins of products throughout the supply chain can secure efficient product recall procedures and help producers, distributors, packers and logistic providers minimize damage.

Recall systems can be established on a minimum of traceability information (e.g. production date) however, the more sub-descriptors that are included (e.g. production time, batch number, production conditions) the more focused the product recall can be. This will minimize the loss of money and protecting enterprise reputation [18].

**Item level identification property:** The item level product monitoring property and the information exchange infrastructure enabled by Auto ID technology permits to target recalls and improve safety for human consumed products. When tags are used, if there is a problem with a particular batch of products, one could exactly know where that batch went, rather than having to recall every product on every shelf in every country.

Similarly, the traceability of products that directly impact consumer safety (e.g. vehicle tires) can be enhanced with the use of Auto ID tags (giving information on when and where the tire was manufactured, its size and components) placed on the inside of vehicle tires to provide information when a tire recall becomes necessary. Further, every tire can be matched to the vehicle on which it is installed. The history of the vehicle then can be tracked, including the manufacturer and the eventual owner, so that if a recall occurs, tires can be associated with an individual vehicle.

### **3.1.7 Better management of the after sales service**

**Item level identification property:** Products returned to a facility for after sales service/repair can be tracked with Auto ID tags providing information (about sales dates and locations, manufacturing/maintenance dates and locations, original manufacturing lot, performed inspections) which ensure an improved compliance with warranties, post-sales service programs and if shared with manufacturers, permit them to improve product quality.

For instance, during maintenance processes, if all major parts are previously tagged, the technician can see what parts were used (original parts, replacements, etc.) without disassembly. Additional information on the parts can help in providing the appropriate maintenance. Parts approaching end-of-life can be more easily identified and proactively replaced.

### **3.1.8 Improved efficiency in recycling products**

**Item level identification property:** If information on materials that products contain and instructions of how to disassemble and handle them is provided by tags attached to products, they can be more efficiently sorted and recycled. An area which may have interesting applications is white and brown goods- washing machines, televisions, etc.

### **3.2 Reduce uncertainties on inherent characteristics of products**

The use of Auto ID would indirectly contribute to actions that aim to reduce uncertainties pertaining to products. These indirect benefits include:

#### **3.2.1 Better management of perishable items**

The sell by date information is used to evaluate item freshness. Because this information is not integrated in most of Bar Codes, it must be traced on an additional label affixed to products. Data on this second label must be read by operators to become a relevant information. But generally, the effort to read the sell by date label may be time consuming, especially for pallets containing different batches of the same product or completely different products which necessitate differentiating accurately multiple sell by dates on the pallet.

Although the introduction of new bar coding standards that enable adding the sell-by dates to the codes helps in retaining the integrity of stock rotation and to solve the spoilage problem [89], the reading of barcodes invariably requires manual handling, creating unawareness of where the oldest stock is located in short shelf life products' warehouses. As operators could not keep track of product locations, it results in trouble in the application of inventory policy and generation of waste. Effective stock rotation ensures that short shelf life products are taken from the storage in the correct order, as determined by their sell-by dates. The magnitude of the problem is alarming. For example, in one Nordic retailer, the spoilage costs are in excess of 10 % of total sales for all short shelf-life products [90].

Correct rotation and the minimization of supply chain inventory are keys for reducing spoilage.

**Automatic identification property:** the continuous monitoring of perishable items performed by sensors added to Auto ID tags throughout supply chain processes gives a complete visibility of the location of the oldest stock and permits to track items' sell by date;

**Item level identification property:** an automatic comparison between this information and the actual date permits the system to detect products that need to be processed first and the ones outdated. By monitoring the use-by date, operators can analyze what they have in stock and compare it against what they expect to sell and make decisions early about what to do with the inventory. This allows a more efficient management of perishable items, monitor FIFO compliance, thus a reduction of waste and improvement of service level.

### **3.2.2 Enhanced control of counterfeited items**

The amount of money involved in 2.608 reported fraud cases over the last ten years, studied by the USA's Association of Certified Fraud Examiners (ACFE), totaled US\$15 billion [91]. Counterfeiting has a large impact on the automotive spare parts business, a segment that contributes significantly to manufacturers' overall profit. According to DaimlerChrysler, 10% of all car parts sold are counterfeits. This equals a loss of \$12 billion every year [43]. Recently, Boeing and Airbus starting to use RFID, estimated that as much as 10% of parts are "unapproved", meaning the part is counterfeit or someone took an old part, reconditioned it and sold it as new. This, in turn has a direct great impact on the airplane makers, their suppliers and the safety of the industry [92].

**Item level identification property:** Authentication applications will be used in situations in which exact identification of an object is needed. The identification can be done either automatically or by human beings. Losses from counterfeiting can be reduced by assigning a unique identification number to every produced item. During audit and inspection processes, counterfeited items can be easily identified by the fact that their EPCs are either missing, illegitimate or duplicate EPCs on known authentic products. Any item without a code can then be immediately spotted as a fake. Even if a counterfeiter managed to produce phony Auto ID tags for counterfeit goods, retailers and customs officials could refer to item information stored in traceability system's database to find that the electronic product code in question is a duplicate of an existing code [22].

Unlike traditional barcodes, RFID tags are difficult and expensive to reverse engineer and reproduce. Thus, this substantially reduces the possibility of counterfeit tags being used ([93], [94]).

### **3.3 Reduce uncertainties on demand**

Auto ID indirectly contributes to improving the accuracy of demand forecasts by better tracking consumers' habits:

#### **Improved knowledge of consumer buying patterns due to a continuous monitoring of items**

**Automatic identification property:** If scanners are integrated into shelves, store managers can continuously monitor products' movements and get information about when items have been bought or when consumers attempted to buy them but gave up for some reason. This knowledge may have a great importance for analyzing consumer buying patterns especially for new or promoted items. Marketing can use this information to make better decisions and forecasts when defining stores' product assortments, pricing and advertising policies.

Furthermore, Auto ID based location information can reveal which areas of the store drive the highest sales for a particular product. Armed with this information, store planners can better determine where products need to be placed to maximize sales.

### **3.4 Reduce uncertainties on data used by other information systems and applications**

Auto ID technology is an interface between the physical world of items monitored, and the world of information systems using this data to support decision making and to perform operations (e.g. systems used to manage inventory, to control production, Enterprise Resource Planning systems, forecasting systems, etc..).

Uncertainty in this case is related to the lack of accurate and/or item specific information. As described previously, the automatic property of the Auto ID technology enables to capture data in an accurate way, within a short delay. Furthermore, in case item level data is required by other systems, queries on Electronic Product Codes can be made in order to reach to the desired data. Data collected enables, in turn, a better management of the supply chain. For instance, according to [95], by using Auto ID, supply chain costs have been reduced by 3-5% and sales have increased 2-7% as a result of improved inventory control.

### **3.5 Some other soft benefits of Auto ID**

In many other applications, Auto ID contributes, like any other means, to reduce uncertainties pertaining to existing processes in order to better organize or reengineer them. We qualify these benefits as being soft, i.e. indirect or intangible.

#### **3.5.1 Reduce uncertainties pertaining to supply chain configuration**

##### **Increased visibility over the supply chain network**

A critical success factor for strategies such as product cross sourcing or transshipment is to know precisely the location of products over the entire supply chain network by sharing information with the trading partners as if they were part of a single organization [96]. Up to date location information pertaining to shipping units and trucks moving across organizational boundaries, allowed by the automatic identification propriety of Auto ID and the associated sharing information infrastructure, would enable a dynamic routing of products so that they arrive where they will best serve customer needs.

##### **More precise measurement of supply chain performance metrics**

As companies nowadays focus on their core activities and tend to outsource a part of their operations to other business partners, it is important for them to monitor effectively the activities outside their boundaries. One of the critical success factors in working with outsourced service activities (e.g. transportation) is managing service levels.

**Automatic identification property:** Auto ID products continuous monitoring can provide both the outsourcer and the client enterprise with accurate status on how a given shipment is

being processed. This data can be cross-referenced with vendor invoices and carrier manifests along with appropriate service-level agreements. In this context, Auto ID provides data to support compliance to contracts and helps in deciding to change or reduce the number of parties involved or change the location of facilities.

### **Re-allocation of the roles employees perform**

By facilitating activity tracking and labor reporting (e.g. time and attendance), Auto ID can help human resources management practices in redefining labor resource priorities and setting new measures of performance. Furthermore, due to its ability to monitor continuously supply chain entities, it gives information to organizations on how and where to deploy resources (e.g. define new challenges for loss prevention personnel), thus supports the reallocation of tasks performed by supply chain actors.

### **3.5.2 Reduce uncertainties pertaining to supply chain control structure**

#### **Enhanced coordination and opportunity to redefine policies for improved effectiveness**

Uncertainty in decision results in part from whether a chosen policy or process organization yields a good performance. Visibility enabled by Auto ID may help in measuring this and if needed, in supporting the redesign of control policies used if they observe that the chosen solution does not fit. For instance, in a warehouse storing perishable items, data captured by Auto ID could be used in deciding how to design the facility or in decisions concerning investments in new equipment enabling compliance to temperature. Furthermore, in a store environment, the use of Auto ID can enable new practices such as yield management

#### **Remark**

Besides its automatic and item level properties, the Auto ID technology enables also to share information across the supply chain. In situations where several actors are concerned, this last property plays a considerable role for exchanging data. For instance, the traceability of products concerns all supply chain actors, situations where products have to be recalled can be more effectively managed if there is an infrastructure that enables to share item level information.

Using Auto ID reduces the uncertainty on		Nature of Benefit	Benefit Description	The benefit is enabled by		
				automatic identification	item level identification	an infrastructure to share information across the SC
Inherent characteristics of processes, products, demand	production/ distribution/ store/reverse logistics processes	hard	A reduction of labor cost due to the elimination of non value added control activities	+		
		hard	A reduction of the cost of delivery disputes	+		+
		hard	A reduction of losses pertaining to returns	+	+	+
		hard	A reduction of profit losses due to a faster detection of oos situations	+		
		soft	Improved reliability of production quantity and quality	+	+	
		soft	Improved efficiency of product recalls and enhanced consumer safety		+	+
		soft	A better management of after sales service		+	
	products (components, semi finished and end products)	soft	A better management of perishable items	+	+	
		soft	An enhanced control of counterfeited items		+	+
	demand	soft	An improved knowledge of consumer behavior	+		
Data (pertaining to supply chain entities) used for decision making	hard	An accurate data concerning supply chain entities (semi finished or end products, containers, pallets, tools, spare parts, other means, employees)	+		+	
	hard	Reduced data capture delays	+			
	hard	An item level product data		+		
	soft	A better management of the SC (cost reduction-especially inventory holding cost- and improvement of service level)	+	+	+	
Supply chain configuration	soft	An increased visibility over the supply chain network	+		+	
	soft	Measurement of supply chain performance metrics	+		+	
	soft	Potential re-allocation of the roles employees perform	+	+		
Supply chain control structure	soft	An enhanced coordination and opportunity to redesign policies (eliminate or reallocate processes) for improved effectiveness	+	+	+	

**Table: Summary of the benefits of Auto ID technology**

## 4 Industry Trials and Pilot Projects

Today a number of companies are using RFID business applications or piloting the technology to evaluate the benefits. At present, these efforts do not rely on EPCs, but rather enterprises are employing proprietary RFID technologies to obtain company-specific operational benefits. Wal Mart, Woolworth, Marks & Spencer, Procter & Gamble, Metro, Carrefour and Gillette are some of the best known. All these projects are similar in that they involved closed loop applications, i.e. tags and readers are being used within one company or a small group. Things become more complicated once tagging moves out of that closed loop.

The practitioner literature is full of references on industrial trials of RFID (see, for example, articles in publications such as RFID Journal, Frontline Solutions, Logistics Management, Modern Materials Handling, Supply Chain Systems, Computerworld, Information Week, Wired News, InternetWeek -to name but a few). Other sources of reference are the websites of solution providers such as Hi Point Technology, Zebra Technology, Texas Instruments, Philips Semiconductor, Hitachi, Dallas Semiconductor, Intermec Technologies, TagSys (formerly Gemplus), Savi Technology, Alien Technologies, SAP, Symbol Technologies. Of interest here are the various white papers that are available from these websites as well as the literature that describe their applications. Publications more specifically focused on RFID include RFID Newsletter from AIM (a global trade organization for the automatic identification and data capture industry) and Global ID magazine, newsletters from the RFID group at Texas Instruments. Consultancy groups such as AMR Research, Forrester Research, Red Prairie, RFID Consultancy, Accenture, IBM Business Consulting Services, Aberdeen Group, Venture Development Corporation are also producing a significant amount of white papers, reports and benchmark studies on potential applications and results observed in many industrial RFID trials.

A few of them are the following:

- Wal Mart together with Procter & Gamble and SAP have conducted trials of smart shelves and item level RFID for cosmetics. In this trial, item level RFID would be used in the form of smart shelves that constantly monitor stock and send out of stock and replenishment alerts to store personnel and the store management system. New mandates from Wal-Mart and the U.S. Department of Defense require leading manufacturers to be RFID enabled by 2005. Initially, Wal-Mart is planning to implement RFID technology in its warehouses by January 2005. Wal-Mart has also “heavily encouraged” its top 100 suppliers to begin using wireless inventory tracking equipment by the same date; this primarily consists of using RFID tags on shipping pallets, which would certainly increase productivity in the warehouses [97]. The total cost of Wal-Mart’s June announcement to its top 100 suppliers to adopt RFID is an

estimated \$2 billion. This includes not only the cost of tags and readers, estimated at \$5 to \$10 million per manufacturer, but also system integration, changes to current supply chain applications, and storage system upgrades, which may amount to \$13 million per manufacturer [98]. The Department of Defense (DoD) has also mandated that new contracts with its suppliers include RFID tracking of all sustainment cargo, unit movement equipment and cargo, ammunition shipments, and pre-positioned material and supplies by January of 2005 [25].

- Among manufacturers, Gillette has been involved in tagging trials in the UK, US and Germany, Kraft Foods plans to improve its container handling in the US and Procter & Gamble is tagging shampoos at Metro's "store of the future"- to name but a few. Gillette has reportedly ordered 500 million passive tags to be attached to their razors [99]. The company estimates that \$30 billion is lost per year by retailers because shelves stand empty. By including RFID tags which signal empty shelves, these losses, as well as losses from petty theft, could be drastically reduced.

According to [26], the manufacturer's principal focus is retention of the mandating customers and the associated costs. Mandates aside, manufacturers are looking for improved customer service; improvements in asset management or return on invested capital; and improved operational efficiencies. They expect operational improvements to come from reduced leakage/ theft, reduced labor costs and faster processing time. Improvements in customer service are expected from improvements in inventory availability and reduced stock outs, as well as streamlined shipping and advanced shipment notification (ASN) processes and improved responsiveness to customer needs. The classic examples are the tagging of bins used to move parts from a manufacturer to an assembler (parts bins from OEMs to assembly lines in the auto industry), tracking containers in a transportation environment (rail cars in North America, overseas shipping containers), or tagging containers that are reused (beer kegs, spare parts/components containers). The survey realized by [26] indicates that 6.1% of the respondents have RFID systems and that 53% of those implementations are asset management focused.

- Ford Motor Company used RFID to track parts to improve the manufacturing process control. Examples of data stored on a tag include unique tag ID, part type, plant location, and a time-date stamp. Pilot studies have indicated 100% data accuracy. One difficulty, however, is attaching the tags to metal parts such as engines [78].
- Goldwin Sportswear Europe, the European branch of one of the largest branded sportswear companies in Japan, has piloted the use of RFID tags on individual clothing items to track shipments, prevent unauthorized out-of-area distribution and authenticate products [100].



- An oil and gas refinery in the UK is using an RFID system to assist with monitoring and maintaining pressure safety relief valves in vessels, pipe work and process equipment, reducing the re-certification and repair cycle time by up to 64% as compared to manual methods [101].
- When Figleaves.com, an online lingerie company, discovered that too many customers were receiving items different from their orders, it turned to RFID to help improve its fulfillment process [102].
- One step of the manufacturing process of Pierrel-Ospedali, an Italian pharmaceutical company, whose medical solution products are highly regulated by the government required that these products be sterilized for a period of time at over 120 degrees C. This process must be carefully controlled and documented. RFID has been used for this purpose since tags can withstand the harsh environment and high temperature of the autoclave, whereas a Bar Code label never could [103].
- A major consumer goods company (Accenture's study, client name is confidential) uses RFID tags to track materials through the production process, ensuring that the sequence and timing of manufacturing steps are correct and that better quality products result from existing manufacturing processes [16].
- QSC-Audio Products has built a smart conveyerised assembly system using RFID technology. This system enables the company to build to order with mass production efficiency. RFID tags are used to identify the products on the assembly line, and the configuration of a particular product to be assembled is attached to its identity [104].
- Meanwhile, retail companies are beginning to follow Wal-Mart's trends and are establishing their own internal RFID inventory systems. In January 2003, British retailer Tesco began a controversial six-month test using the Gillette Mach3 razors (among which theft was a common problem) and have extended the trial to include DVD products in collaboration with Entertainment UK [105]. The trial with Gillette was mainly associated with theft prevention and CCTV cameras were triggered when the tagged razor blades were picked up [38].
- Marks & Spencer have plans to tag all their food containers (3.5 million food trays) in the near future. The company also plans to put RFID tags on all individual garments across all clothing ranges. The retailer hopes that the initiative will speed up point of sale, prevent theft and in the future they predict that intelligent washing machines will recognize the tags and prevent washing at the wrong temperature [106].
- Sainsbury was a pioneer as far as RFID is concerned, doing extensive work in this area some years ago. Three years ago, they decided to proceed with investigating RFID, and conduct a trial to establish the benefits that it could achieve with the technology.

Subsequently, two more practical goals were set to the trial: reducing labor associated with stock counting and rotation monitoring in stores and reduce spoilage in the supply chain [90] The total benefits achievable for Sainsbury with a full-scale implementation without supplier participation were estimated to be £8.5 million a year. Only straightforward benefits resulting from more efficient stock rotation and control are accounted for in the figure, possible new operations models are not included. The investment needed for the system was calculated to be between £18 million to £24 million. The reader and tag costs used in calculating the capital investment were £6,000 and £8,000 for readers, and 30p and 65p for a tag [90]. On the basis of the estimated savings and the investment needed we conclude that the payback period of the RFID system would have been between two and three years.

- Asda recently took part in a large item level RFID trial, tagging CDs in two of their stores. Over 7000 CDs from EMI were fitted with tags that uniquely identified each one, and enabled them to be tracked through the supply chain. The technology was also used to track returns [25]
- Container providers such as Chep and a Finnish provider Transbox, have been considering tagging their transport containers ([107], [108]). Tagging would help in managing the containers more efficiently and the costs of the tags could also be partly offset by collecting a premium on the rental charges of the tagged containers [109]. Chep, in the USA, has engaged in a large scale trial to test RFID in tracking its equipment, and argues that it has a good business case if the technology proves functional [108].

Besides this, RFID technology is used in every industry, commerce and service where data needs to be collected, including animal tagging, waste management, time and attendance, postal tracking, road toll management, enterprise valuable asset tagging (tools, computers,..), laundry/textile identification, fare collection, document tracking.

- The transportation industry is among examples of fields that will benefit through the implementation of RFID tracking [97]. Both the United States Postal Service and the United Parcel Service view RFID technology as an inevitable upgrade in their infrastructure from the traditional Bar Code. In fact, the United States Postal Service has explored the idea of putting RFID semiconductors inside of envelopes and has recently signed a deal with Savi Technology Inc. to conduct further research into the development of a mail-tracing and routing RFID system [110].
- Airlines are developing methods of implementing RFID onto luggage tags, so that the luggage can be better tracked; the possible benefits are huge as the amount of lost luggage could be greatly reduced [111].

- An RFID based system exists at the Tyne Tunnel in the United Kingdom [112]. Located to the north of England, the Tyne Tunnel is a 1.7 kilometers tunnel running under the River Tyne that currently sees over 35,000 vehicles of traffic per day, leading to heavy congestion and delays. Previously cash, credit or tickets could be used for payment. However, manual payment involves delays and automatic cash collection is expensive to install; tickets are open to fraud and thus cause a delay while being inspected, and using a credit card results in waiting for authentication and in a 5% transaction fee. Thankfully, a Texas-Instruments engineered passive-RFID system has been created where the wireless chips are attached to windshields using suction cups and are automatically authenticated and billed while cars pull up to the sensor, resulting in minimal delays.
- There are plans in Singapore to tag all public library books. Some economic facts that help justify installing the RFID system are that a lost book typically costs the library around \$45.00; an average library can have as many as 22 million items circulating each year; with RFID labels on items, check in and check out saves 1 1/2 minutes per transaction.
- RFID is also used as a way to improve the management of important document files in industries like insurance and legal where the loss of such files can cause severe problems. RFID improves the tracking of documents so that files can be more quickly located and legal document workflow more easily tracked [103]. The European Central Bank's idea to incorporate tags in bank notes [38] is another illustration of the use of RFID.
- The healthcare and pharmaceuticals industry is beginning to use RFID labels and tags to track supplies, patients and pharmaceuticals, including their expiration dates, as well as portable diagnostic equipment shared between departments. This enables healthcare institutions to better control inventory and maximize their equipment to keep costs down, while delivering the highest level of patient care ([113], [114]).

# **PART B**

## Chapter 3

# LITERATURE REVIEW

### Introduction

More and more companies use enterprise resource planning, supply chain execution or warehouse management systems in order to plan and control their material flow effectively [115]. Many of these systems have, however, yielded poor results due to the unavailability of accurate information. It is thus critical to the success of these companies to have an accurate information on the status and location of entities (items, cases or pallets) during the various transactions occurring within their operations [116].

In Chapter 2 we have identified potential benefits of Auto ID in a qualitative manner. We will now focus on investigations quantifying these benefits. One of the questions managers and researchers face today is how to justify costly supply chain management investments. A lot of effort is deployed by practitioners to answer this question. The scientific literature that may help managers is still scarce and needs to be developed.

The literature review of work related to our research has been organized into 2 sections:

The first section concerns the research on the general benefits of Auto ID technology. This section begins with a brief part presenting some examples of investigation modeling the business value derived from the different technologies used in supply chains. Next, research pertaining to the quantification of benefits stemming from the Bar Code technology is described. This is followed by an overview of the existing literature on the quantification of supply chain improvements due to Auto ID.

The second section of this chapter has a more specific focus on the inventory inaccuracy issue, which is one of the previously identified benefits of Auto ID that would be quantified in Chapter 5.

### **1 Quantifying Benefits of Automatic Identification and Data Capture Technologies**

Before moving on to discussing how benefits of the Auto ID technology are quantified, let us give some examples of research modeling the business value derived from the different technologies used in a supply chain.

## 1.1 Assessing the Business Value of Technologies Used in Supply Chains

Enterprise managers, seeking evidence that technology investment efforts produce better firm performance ([117],[118]) have faced the following questions [119]: (1) What are the operational gains accrued by supply chain members? Does the technology pay off? (2) How can we quantify it?

As global competition intensifies in response to tougher trading conditions, supply chain members from manufacturer to retailer are striving to attain process efficiencies that will enable them to drive down costs and provide competitive advantage. [120] states that technology has the potential to support the information flow and affect many of the dimensions of supply chain management such as cost, quality, delivery, flexibility and ultimately profits of the firm. It supports the communication and coordination of the economic activities between separate units of an organization and collaboration along the supply chain by enabling better information processing, sharing [121] and faster responsiveness by making available online, real-time information networked around the organization and giving full supply chain visibility [122]. Therefore, since 1998, companies have spent \$14.9 billion on supply chain software [76]; for instance, automotive manufacturers spend roughly 60% of their IT budgets for the improvement of their supply chain management systems [123].

The term logistics IT/IS is used in the literature for the hardware, software, network investment and design to facilitate the processing and exchange of data. It thus includes not only computer hardware and application systems, but also the related components such as satellite transmission, electronic data interchange, bar coding, etc. When we use the term supply chain technology in this part, we refer not only to IT/IS but include all systems that support decision making or are required to perform operations (technologies such as WMS (warehouse management systems), replenishment systems and computer aided ordering [124], ERP (enterprise resource planning), EDI (electronic data interchange) ([125],[126]), CIM (computer-integrated manufacturing), CAD (computer-aided design), CAM (computer-aided manufacturing), CAPP (computer-aided process planning), APS (advanced planning and scheduling) [127], Internet, Internet-based transaction processing systems such as electronic marketplaces, extranet, ([128], [129]) and automatic identification technologies [122], such as barcode and radio frequency technologies.

From an academic standpoint, the interest on the impact of information technology on enterprise performance has intensified since Roach introduced the concept of “productivity paradox” [130]. He stated that although business is investing huge sums of money in IT, positive results could not be observed. Studies have then evaluated empirically IT’s relationship to overall business performance with no relationship ([131],[132]), a slight relationship [133] or a positive relationship ([134],[135]). Based on a more recent extensive

literature review, [136] states that enough evidence has been gathered on the positive effects of IT in recent years that the productivity paradox can be labeled as a myth of the past.

The investigation methodologies used to quantify the benefits of a technology are either case oriented empirical studies or quantitative models including financial models, simulation, stochastic models or heuristics. For instance, some researchers have examined the positive effect of IT/IS investments on firm productivity ([137], [138]) by proposing a general modeling framework or by conducting empirical studies ([135], [139]). Several quantitative methods using traditional financial approaches such as payback period, return on assets, return on investment, discounted cash flow methods ([140], [141], [142]), return on equity [143], net present value (NPV) analysis [144] have also been used for selecting IT/IS systems. One of the main problems when trying to apply any of these financial techniques for assessing a particular investment seems to be the difficulty in identifying and measuring the expected benefits of a proposed technology [145]. Business process modeling and simulation are mechanisms used by several authors for experimenting with alternative investments, assessing the benefits introduced by particular system and process configurations, and helping the management to take decisions concerning investments ([146], [147],[148]).

Other authors have formulated the investment decision as a mathematical model built upon well known operations management problems. For instance, [149] develops a model for the justification of the acquisition of a new technology by evaluating its effect on the inventory setup costs in a lot size reorder point (r,Q) model. [127] proposes a multi-objective mathematical model for the effective acquisition and justification of IT/IS for supply chain management, the main contribution of this paper being the development of a multi-objective mathematical model that effectively incorporates cost, quality, flexibility and time goals. [143] presents an approach to investigating the effects of IT on technical efficiency in a firm's production process through a two-stage analytical study with a firm-level data set.

In addition to these investigations, other research methodologies have also been used. For instance, authors such as [150] have applied system dynamics. According to [84], this technique is relatively easy to apply, accommodates subjective judgment and change, and leads to improved system specifications. However, it is not rigorous enough to support low level analysis and assessment. Moreover, detailed modeling is difficult or impossible given the existing formalism and software tools [150]. In [151], the recent developments in the application of fuzzy concepts to IT/IS justification process are also addressed while [152] proposes interpretative approaches, which include exploratory methods and meta-methodologies.

## **1.2 Assessing the benefits of the Bar Code Technology**

The Bar Code system is among technologies that have been widely used in almost every industry. By leveraging the barcode technology, the grocery industry, for instance, was able to

realize hard and soft savings (as percentages of revenue) of 2.76% and 2.89% respectively [16]. By 1997, the industry estimates that these hard and soft cost reductions added up to approximately \$17.0 billion in total annual savings taken from every area of its end-to-end value chain – starting at production and ending on the store shelf [153].

Typical goals in implementing a Bar Code system (and more generally Automatic Identification and Data Capture systems) are reduction of data capture errors, timely data for inventory control, buyer's and seller's communication enhancement and improvement of customer service ([154], [155], [156]). [157] adds that contemporary Automatic Identification and Data Capture systems must provide discipline and control that is based not only upon plans and performance goals, but also upon the dynamics of actual operations: these systems are the major source of real-time feedback, they allow businesses to monitor operations, manage resources, and flag anomalies before they impact throughput.

Bar codes originated in the food sector as the cornerstone technology to automate the check out process and in that way, reduce labor costs as well as cash register errors. It was not until the 1983-1987 period that Bar Code usage spread to sectors served by mass retailers like Kmart and Wal Mart [158].

Several investigations have been conducted on how supply chains can benefit from Bar Code applications. This includes non quantitative research that explains the concept of the Bar Code technology and develops conceptual methods in an effort to better understand it. Most of the time, results developed are validated within the context of case studies within enterprises. An example of such study would include [159] who, based on ten case studies carried out in distribution and manufacturing companies, show how the Bar Code system can enhance inventory management performance. In all cases, the system, mostly used for work in process tracking and shipment control (which ensures that the right product is shipped to the right customer) has enhanced the performance of the company, but quantitative results are not available. Among results achieved are less capital tied up in inventory, enhanced inventory control, enhanced customers' service and empowered employees. [160] develops a conceptual framework for the integration of a Bar Code system in inventory and marketing information systems using the barcode technology as an enabler for effective supply chain management. Problems, benefits and solutions regarding the integration of the Bar Code technology are examined in the context of a case study. [116] shows how batch processing is currently a major drawback in industrial applications and emphasizes the role of Radio Frequency systems integrated to technologies of automatic identification, bar-coding, and automatic data capture in increased inventory accuracy and timeliness of real-time data pertaining to internal and external logistics transactions. Main results obtained in a very large Distribution Centre are increased productivity, higher accuracy of the amount and pallet location, reduced cost of material handling.



More sophisticated investigations on the impact of Bar Code technology have been realized with a specific interest on the inventory inaccuracy issue. For instance, [161] discusses on mechanisms used in Bar Code equipped facilities to track and correct errors creating mismatches in inventory records. He argues that these activities should be realized in order to investigate and correct the cause of the error rather than simply correcting a number in the system.

### **1.3 Assessing the benefits of the Auto ID Technology**

To our knowledge, almost all papers that aim to quantify the impacts of Auto ID in supply chains have mainly been developed by the Auto ID Centre community. Within this community, besides research related to technical aspects of the Auto ID technology (hardware, software, languages, etc..) several investigations have been conducted on how companies can benefit from the use of Auto ID as an enabling technology to support more intelligent automation and control (for instance, [162] discusses how flow shops can be adapted by intelligent software agents making distributed decisions; meanwhile [163] highlights the impact Auto ID technology will have in Materials Handling Systems) and improved supply chain management. As our investigation is related to supply chain management, we will present an overview of studies developed within this area.

Up to date, the major part of research considers the evaluation of hard benefits (e.g. [76]). Indirect impacts in the form of organizational change, consequences due to the redesign of processes, impacts on competitive advantage, and so on have caught less attention.

Case study type investigations on hard benefits developed in collaboration with partners of the Auto ID Centre<sup>4</sup> are either considering a particular industry, CPG industry ([16], [35]), automotive [43], retail ([164], [124], [165]) and healthcare [113], in order to point out pain points of today's supply chains and evaluate several benefits simultaneously [76], or are focused on benefits resulting from a particular application, e.g. benefits of Auto ID on product obsolescence [87], on shrinkage or theft [166].

These reports provide insights on how Auto ID technology would be adopted in industry; price points, product characteristics, current business performance, current infrastructure and physical attributes of products are among factors that will determine the time and scope of the adoption [166]. According to [16], despite the larger benefits of multiple supply chain actor implementations, companies will initially develop focused applications that offer proprietary benefits and are easier to justify internally.

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<sup>4</sup> including enterprises such as Alien Technology, Best Buy, Checkpoint Systems, ConnecTerra, Display Edge Systems, Escort Memory Systems, Gemplus, Gillette, Graviton, Identec, Intel, Lyngsoe, Manhattan Associates, Matrics, Microsoft, Omron, Philip Morris, Philips Semiconductors, Procter & Gamble, RF Code, Rafsec, Red Prairie, Retek, SCS, SAMsys, SAP, Sara Lee Corporation, Savi Technology, Sensormatic Electronics, Snyder Electronics, Symbol Technologies, Target Corporation, TEKsystems, Texas Instruments, The Home Depot, The Limited, Unilever, Wallace, Wal-Mart Stores and WhereNet

As far as the roll out is concerned, ([166], [16]) report that it will follow a two step scenario. First, Auto ID will be used in Distribution Centers. In the second stage, as tag costs will diminish, value will migrate from tagging shipping pallets to tagging cases to tagging individual items and stores would be converted to Auto ID. But stores would incur the greatest tagging cost (every item with SKU-level identification), and substantial modification of systems and facilities [96]. Most analyses suggest that stores offer the largest potential gains ([96], [167]). Auto ID is immediately appropriate, even at current cost levels, for an important set of products – those that require very careful management. These include high value/high margin goods [166], products with volatile demand or supply [96], and short lifecycle products (promotions, electronics, apparel and expensive consumer durables) . These products carry the highest risk of revenue loss due to out-of-stock or product obsolescence. High-profile products subject to recall, such as certain types of electronics, toys, pharmacy and safety items, also would have a high payoff from Auto ID. Products such as razor blades that are especially susceptible to theft need the tight management that Auto ID offers.

Manufacturers' benefits will not be uniform. Companies selling low values of expensive goods and experiencing significant out of stock and shrinkage (drug, video games, electronics, high fashion and cosmetics) are more likely to benefit from RFID than manufacturers selling high volumes of less expensive goods (dry grocery, frozen goods) [167].

[86] reports that benefits coming from the activity within the four walls of a manufacturer (production efficiency, quality control, lot tracking and visibility, asset utilization, inventory reduction and labor productivity) are obtained from tagging the assets and equipment used to hold, move and process the raw materials and work-in-process being manufactured since if the models used to quantify benefits were using item-level tagging hypothesis, a positive ROI would be difficult to calculate based on today's tag price points looking solely at the benefits obtained within the manufacturer's operations. The exception to this is a manufacturer in the Consumer Electronics product category – most of the items in this category are not packed into cases – i.e., they are stacked individually onto pallets (e.g., VCRs, DVDs, TV sets).

[16] also argues that CPG manufacturers can realize proprietary benefits from Auto-ID applications for production processes, but leading manufacturers tend to have sophisticated process control systems already in place, making the marginal benefits of new Auto-ID based systems less attractive for them.

All these studies mostly use simple accounting techniques, notably cost-benefit analysis to examine the feasibility of Auto-ID. The evaluation is made through simulations based on some assumptions which generate estimates of the gains achieved. Results obtained depend on the specific conditions considered. For instance, results presented in [164] include a decreased cost of goods sold of 1 to 5% from improved overall equipment effectiveness; a reduced working capital ranging from 2 to 8% from reducing raw materials; reduced fixed

assets of 1 to 5% from better maintenance; 35% improvement in direct labor productivity; 88% improvement in vendor and paperwork shrink (shrink caused only by vendor and paperwork errors). Another example reports that a manufacturer could expect to boost sales by 1 to 2% by reducing out-of-stock items; decrease inventory by 10 to 30% by cutting the amount of safety stock kept on hand in case demand suddenly rises; and reduce shrinkage by 10%. These are addition to less tangible benefits such as gaining more insights into why goods get returned [168].

At this point, it must be noted that Auto ID yields different types of benefits and investigations have been developed in order to evaluate them at a macro level. One question can now be asked: **What should our efforts to measure Auto ID benefits focus on?**

([169], [170], [84]) suggest that the benefits evaluation exercise should start with those benefits which are realized as a direct outcome of the technology under examination and are quantifiable, namely hard benefits. As we presented in the section above, most of investigations on the quantification of hard Auto ID benefits consider the cost reduction stemming from the reduction of waiting times, the elimination of non value adding activities or the prevention of theft. There are other types of benefits for which a simple modeling approach may not be enough, meaning that a more sophisticated analysis is necessary. Measuring benefits that stem from having more accurate data is an example of such benefits. The focus of our research is on this specific point, namely, we are seeking an answer to the question “how can we measure the value of automatic item level information provided by this new technology in managing inventory systems?”

In the following, we provide an overview of literature focusing on this issue. Our research integrates and extends this literature.

## **2 The Inventory Inaccuracy Issue**

In a more general context, the data inaccuracy problem has been encountered and studied in many different areas such as bank applications, statistics and econometric database applications, airline reservation systems or health maintenance organizations. For instance, [171] states that most databases are not error free, and some contain a surprisingly large number of errors; [172] affirms that the records of many of those involved with the criminal justice system contain potentially damaging errors. While [173] cites the example of an airline for which physical and book inventory do not match, [174] illustrates the issue through an example on incorrect customer billing due to poor database information quality. [175] also reports that the lag from the time a production event occurs until the time it is entered into the system results in the proliferation of bad data and the creation of a blank spot in production visibility on the shop floor.

Some of these investigations focus on data quality: how to define and characterize it, how to achieve it and the consequences of inadequate data ([176], [177], [178]). An important part of research concentrates on reasons why deviations from real values occur in large databases and which actions should be implemented in order to tackle with this issue; others work on defining the optimal frequency of updates ([179], [180]); some authors are interested in the design and implementation of internal and external error detection mechanisms improving the accuracy; other research is on probabilistic databases deal with whether a database should store the estimates of real values or just store the information about probabilistic distributions of such values [181].

Similarly, the quality of product related information is one of the biggest problems currently faced by supply chain management ([77], [182]). For example, according to [183], an average of 30% of information in retailer systems is incorrect, and studies have shown that as much as 63% of product descriptions can diverge in supplier and wholesaler systems [184]. In a study conducted for the Grocery Manufacturers of America, A.T. Kearney Inc. estimates that retailers and manufacturers each lose \$2 million for every \$1 billion in sales due to bad data. They predict that eliminating bad data could save \$10 billion per year [185]. All these examples illustrate the magnitude of data inaccuracy problems present in managing supply chains.

The literature in the field of inventory management is vast. However, the common assumption underlying most research is that data gathered from physical transactions are accurate. There is a scarcity of works that address inventory record errors. Among exceptions that consider the problem of inventory inaccuracy are the following:

[186] states that responsiveness to customer demand and overall customer satisfaction can not be achieved without a proper management of the movement of goods and the associated information flow throughout the supply chain. [187] also identifies information as a main driver of supply chain performance: no system or method which has been designed to plan and control inventory will work properly if the input of inventory status is inaccurate or late.

Several studies in the practitioner literature reveal that accurate inventory data should not be taken for granted in supply chains and emphasize the importance of maintaining high levels of inventory accuracy ([188], [189]). [190] and [191] discuss managerial behaviors that make the cycle counts more effective and to improve the inventory record accuracy in multi item production environment. Authors such as [192] and [193] suggest sampling techniques that could be used to choose and count only a portion of inventory in multi SKUs inventory environments where counting the entire inventory is too costly.

While [194] claims that achieving inventory accuracy should be the number one priority in implementing a manufacturing resource planning system, [195] focuses on how inaccurate work in process counts can distort the effectiveness of a MRP system. He explains reasons

why to maintain accurate work in process inventory system records and develops a framework to describe the different sources of inaccuracies: errors usually stem from system structure problems, system discipline problems, process variability problems, measurement problems and quality related problems.

Other examples illustrating the magnitude of the problem are provided by ([196], [197], [198]). For instance, [198] reports that the Naval Supply Depot using the Master Stock Record history of a sample of 714 items from the 20 000 line item types stocked there, found that 25% of the item types had accumulated discrepancies that exceeded 24 units after one year. It also found the distribution of accumulated errors to be closely approximated by a normal distribution.

The study of [199] reveals that a large retailer with annual sales of roughly \$ 11 billion from more than 1500 stores worldwide estimates a profit loss of \$ 32 million annually due to its inventory record inaccuracy problem. According to a store level analysis, 65% of nearly 370 000 inventory records from 37 stores of a large retail chain are inaccurate at the time of the physical inventory audit. Moreover, for 15% of these records, the absolute difference between system inventory and actual inventory quantity per SKU was eight or greater. This study identifies the magnitude and drivers of poor inventory records and provides an empirical study of inaccurate inventory records in a retail store at both record and store levels. It is reported that the probability of an inventory record being accurate can be predicted by product's characteristics such as item cost or whether the item is risky or not, annual units sold, the entity delivering this item or material flow characteristics such as the complexity of pallets received / to be prepared (multiple product pallets or homogeneous pallets), etc..

[196] develops a similar analysis: he finds that 36% of 200 000 inventory records sampled from several distribution centers of an organization with a large logistical operation were inaccurate.

[200] suggests that differences between accurate and inaccurate inventory records are associated with item cost, use of weight counting for inventory tracking and the number of different storage locations for a particular item. According to their analysis, low value, high volume items are most likely to be in error.

Various definitions and measures of inventory accuracy are presented in several works [201, 202] For example, it is defined as: (1) the total dollar deviation between the actual dollar value of inventory and recorded dollar value of the inventory ([193], [203]), (2) the percentage error in the inventory records [204], (3) the proportion of SKUs with agreement between recorded and actual levels [205]. (1) and (2) allow positive and negative values to balance each other so any aggregate measure may appear to be small even though inventory records have a lot of error. (3) does not recognize that small levels of error may be tolerable. The measure developed by [206] considers the proportion of errors in every record while

recognizing the difference between positive and negative balances. A quality control chart mechanism is then used for monitoring the changes in the inventory accuracy.

The relationship between supply chain management and inventory inaccuracy is also stressed by investigations analyzing the impacts on supply chain performance. While some of these papers are interested in evaluating the effect of inventory inaccuracies (rather than optimizing), others develop models based on established inventory control methods that aid to tackle with inaccuracies. Models consider this issue either within a production environment or are related to distribution/store processes.

[207] study the impact of errors in inventory perturbing the material requirement planning systems. They use simulation as research method to compare the effect of inaccuracy on MRP based factory performance with those of other variables. The authors conclude that the frequency of error has a dominant impact on the percentage of late units and inventory costs. [208] also study this issue and suppose that inventory inaccuracy is introduced by incoming and outgoing deliveries (a certain percentage of deliveries is assumed to be inaccurate). They conclude that inaccuracies have less impact than anticipated. Of the factors considered, a reduction in batch sizes combined with shorter set up times had the single most impact on performance.

In presence of inventory miscounts, when the lead time is variable, the realized service level, measuring parts availability from shelf, is much lower than the prescribed service level.[209] develops quantitative measures for the evaluation of the degradation in service level in a continuous review  $(r,Q)$  setting as a function of the level of inventory miscount and the lead time variability.

[198] also evaluates the poorer service level resulting from inaccuracies and performs a sensitivity analysis of this measure to several actions (faced with the inaccuracy issue, managers may act in different ways; i.e. increase the safety stock; increase the frequency of inventory counts or initiate efforts to pinpoint the sources of the errors and reduce them) that improves it.

Rather than optimizing a system,[210] focuses on the individual impacts of different types of inaccuracies (e.g. theft, unsaleables, poor process quality) on the performances of a supply chain (monetary or non-monetary measures). They use simulation and variance analysis (Anova) as research method. They consider two settings; in the base case, they set up a supply chain where information on end consumer demand is available to all echelons in real time, and the physical flow is perturbed by several factors. Then they modify the model so that physical inventory and information system records are aligned in each time period and compare the two models.

[211] proposes a mathematical model which determines an optimal frequency for periodical inventory taking processes within a supermarket or a convenience store. Deviations in

inventory records tend to decrease with increasing frequency of a periodical inventory taking and thus the total loss incurred also decreases as the frequency of a periodical inventory taking becomes large. However, when the inventory taking frequency increases, the total cost for periodical inventory taking activities increases. The expected cost per unit time is formulated, considering the cost for inventory taking activities and the investigation cost for the causes of deviations.

A less recent study carried out by [212] develops an analytical tool to aid in controlling inventory record errors, the objective being to select the type and frequency of counts and to modify the predetermined stocking policy by adding a buffer to cover for errors so as to minimize the total cost (inventory holding + inventory counting cost) per unit time subject to the probability of errors not depleting this buffer between inventory counts does not exceed a prescribed level. In setting the error buffer stock, their principal tool is a limit theorem for the maximum of partial sums that has nothing to do with inventory theory.

[213] use analytical and simulation based modeling to demonstrate that even a small rate of stock loss undetected by the information system can lead to inventory inaccuracy that disrupts the replenishment process and creates severe out of stocks. Various methods of compensating for the inaccuracy are also presented.

Finally, [214] is interested in analyzing how, in decentralized supply chain with two actors, costs that stem from Auto ID should be distributed among supply chain partners: while manufacturers are generally most interested in tracking cases or pallets of their products, retailers are expected to gain the most benefit from individual product tracking on their shelves. [214] derive contract mechanisms which ensure that net profits for all supply chain members are possible.





## Chapter 4

# MODELING INVENTORY SYSTEMS SUBJECT TO PERTURBATIONS IN NOMINAL FLOWS

### Introduction

The objective of our research is to investigate the impact of inaccuracies on the performance of an inventory system. We conducted this analysis in several steps which are developed in chapters 4 and 5. These steps are to:

- Identify the factors and the root causes that impact the nominal physical flow of materials
- Identify the major drawbacks of a manual data capture system (such as the Bar Code technology) and reasons why mismatches occur between the physical flow and the information flow representing it
- Build a general framework to model errors occurring in supply chain flows (physical and information flows)
- Assess the benefit of Auto ID technology as a lever of performance improvement
- Develop and analyze a quantitative model to evaluate the impact of mismatches between the physical and recorded inventory levels

While the first four steps are mainly dealt with in this chapter, chapter 5 is entirely devoted to the last study.

This chapter is divided largely into 2 parts. The first part describes the basic components of an inventory system as well as potential factors generating a difference between the effective and expected physical and information flows. The second part proposes a general framework enabling to represent the different models that can be developed to evaluate the impact of errors on the performance of an inventory system. This chapter ends with some conclusions.

In the following section, we present the basic components of an inventory system as well as potential factors generating a difference between the effective and expected flows.

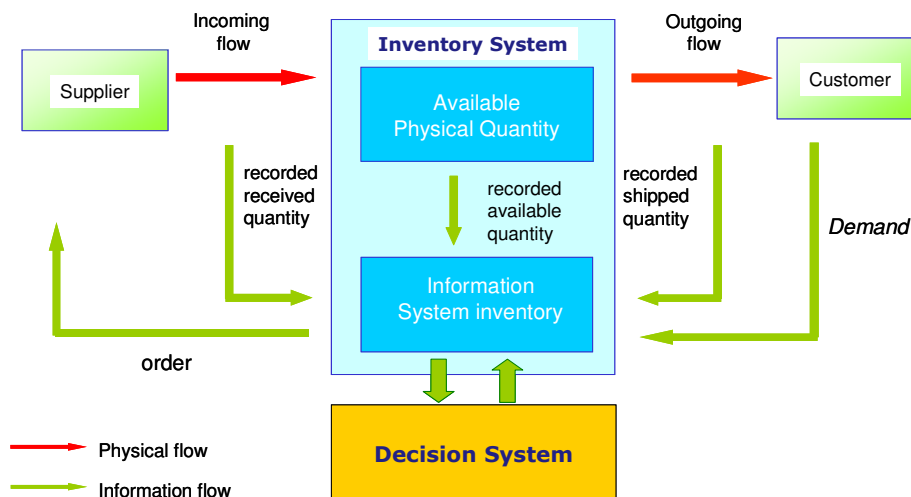
## Part 1: Perturbations in Inventory Systems

### 1 Components of an inventory system

For many companies that have automated their inventory management processes, an inventory system (whether a warehouse or a store) can be described by the following components:

- The physical flow of materials
- The information flow
- The decision system

A schematic representation of this system is as follows:



**Figure 1. Components of an inventory system**

#### 1.1 The physical flow

Items stored in an inventory system are handled in various processes which are the receiving, storage, order picking and shipping processes [144]. Most of the literature on inventory management assumes that during these processes, goods remain in perfect condition and are free from defects until they are used to satisfy customers.

In real practices, due to defects arising at different points, the real physical flow can diverge from the expected nominal flow. Defects stem either from the supply process or from events occurring during the storage period, which corresponds to the delay products remain in inventory from the moment they are received until they are used to fill demand. It would be useful to indicate that we use the term defect not only to describe quality related issues but also any quantitative type of deviations from the expected flow of products.

## 1.2 The information flow

According to [12], the modern logistics manager faces three main problems: allocation, communication and control.

- The allocation of expensive facilities and means of transport plays a crucial role in reducing costs. The use of IT offers significant levers to improve the allocation and the utilization of resources.
- Complex supply chains with several production, retail and logistics companies being involved often suffer from breaks in the information flow. They need to use communication structures enabling seamless information flow.
- In order to achieve a high service level, a thorough quality management extracting data from operational processes and using it to control the fulfillment of service levels has to be implemented.

[14] states that, in order to perform these activities efficiently, logistics information management needs to be based on the following principles: availability, timeliness and accuracy of data, exception based management, standardization and flexibility. Built upon these principles, the author defines the main functionalities of a logistics information management system:

- At the transaction level, individual logistics activities are represented in the information systems that process data associated with physical operations.
- Data gathered and treated by the transaction system is then used by management control systems to measure the performance of the logistics system in terms of utilization, customer service, productivity and financial profitability.
- Based on operational data and performance control indicators, decision analysis systems (such as transport routing and warehouse management system) are used to improve the performance of the logistics system.
- The highest level of information functionality is reached in the strategic planning systems, where problems such as network planning are addressed.

The general principles presented above are also valid for inventory systems: items and their physical movements are represented in the information system by capturing data with an item identification and data capture tool such as Bar Code or Auto ID system; then, data updates permit to track with more or less accuracy and continuity, the flow of goods received from the suppliers, shipped to the customers, the actual on hand inventory level, items which are no longer available, the identity and quantity of items which are back-ordered, as well as in stock items' physical conditions, locations and age.

There are two concerns regarding the follow up of an inventory system: the **data continuity** and the **data accuracy**.

- The continuity of data depends on **data update procedures** implement within the inventory system
- The accuracy of data depends on the performance of the **data collection processes**

Data update procedures define the modulation of data to be collected to perform the tracking and tracing of the physical flow, in other words, procedures give answers to the following main questions:

- At which specific points data should be collected within the inventory system?
- What should be the frequency to update data?

Different practices exist in industry for data update procedures:

### **1.2.1 Data update procedures pertaining to flows of materials coming in and going out the system**

#### **a) Data update based on measurement**

If warehouse managers expect that flows will be perturbed by several factors, data concerning the incoming flow (and the flow going out) will be gathered manually or by the means of a data collection tool. Although goods are identified and counted systematically at receiving and shipment, the accuracy of the data collection processes may be an issue. Two cases are possible: a) the measurement is accurate, i.e. whether perturbations impact or not the physical flow, the associated data recorded in the information system corresponds to it precisely or b) the data collected associated with the physical flow is polluted by errors presented in section 2.2.

#### **b) Automatic update of data based on order data**

If warehouse managers are not aware of the likelihood of potential deviations or if verification processes are too costly, they may decide to increase (or decrease) automatically the on hand inventory level, without measuring it, based solely on information (such as order data, shipment notification, etc.) exchanged with the other supply chain actors.

#### **c) Adjusted data update**

Another variant of the measurement based data update would take into account the probability for errors in the verification process. Data that will ultimately be recorded in the information system would thus be obtained by adjusting the measured value by a factor which compensates for errors arising in the verification process. Similarly, one could consider the

probability for errors while updating automatically the information system: data recorded in the information system will correspond to an adjusted ordered quantity.

A pragmatic and realistic view would suggest that this data update strategy would not be adopted in industry since the cultural barriers to its implementation may be significant.

### **1.2.2 Internal data update procedures**

In the same manner, the verification of the on hand inventory level is envisaged either if inventory is perturbed by factors outlined in section 2.1. or if there is a probability that measurements concerning the incoming (or outgoing) flow contain errors.

#### **a) Planned data update**

A planned data update corresponds either to:

**A periodic inventory counting:** this usually means a complete count of more or less all items over a short time period. For most organizations, this process is undertaken once or twice per year [215]. It is common that the stock of each item is counted twice by different persons.

**A cycle inventory counting:** it has become more and more common, to replace the periodic counting by cycle counting. Each day, a limited number of items are checked. In other words, a continuous counting of stock is performed throughout the year. Items are randomly counted, based upon some type of predefined parameters. Several methods can be used to decide what to count during cycle counts. For example, inventory is broken down by ABC classification and frequencies assigned such as A items counted 10 times/year, B items 5 times/year, and so on [216]. The frequency may depend on various elements, such as the availability of the labor and product characteristics, including the profit margin, sales velocity, and whether the products are highly prone to errors that will be described in section 2. Other methods consist in taking mini physical inventories (an area is selected and everything in this area is counted) or in building a control group that is a good representation of the overall inventory.

The cost pertaining to each of these policies varies. [217] reports that cycle counting is, in general, more costly than the periodic counting. The accuracy of these manual counting processes is another concern since in environments where hundreds of thousands of products are handled, items cannot be found in the designated locations during counting processes, human errors can occur, etc. Therefore, as reported by several practitioners, counting activities have not achieved the objective of improving accuracy since often, there is not a focus on finding and fixing the causes of errors.

## **b) Exceptional data update**

The on hand inventory data recorded in the information system may be updated to be aligned with the physical inventory in other circumstances, i.e. by observing patterns that are indicative of inventory errors such as:

- The detection of a shortage situation: a picking operator may remark that the inventory is less than the recorded on hand inventory or less than the amount of products to be prepared. For instance, [197] notes that retailers often use stock outs to detect anomalies.
- At the other extreme, because of lacking space, an operator replenishing shelves may remark that the physical on hand inventory is more than the recorded inventory level.

### **1.3 The decision system**

The last component of this system, namely the decision system, is in charge of taking decisions concerning the two basic inventory management related questions which are:

- When to replenish inventory?
- How much to replenish?

The decisions are based on information regarding the quantity of products available and other type of information such as demand forecasts, cost parameters such as ordering costs (administrative, transportation, handling costs), inventory holding costs, shortage penalties or the desired service level. There are many inventory management systems, some being widely used in industry and implemented in major ERP systems [15, 218].

## **2 Potential defects causing perturbations in flows**

Without any anomalies in the expected physical flows of an inventory system, the amount of goods available would increase each time an expected replenishment is made and decrease each time a demand is satisfied. These movements of stock can be qualified as known inputs and known outputs. But, because of the existence of varying unknown outputs and inputs, the real flow differs from the nominal one.

Unknown factors can be discovered and appropriate action can be taken if and only if data pertaining to the physical flow (items' identity, physical status, precise locations) is captured accurately and updated continuously. The Bar Code technology as well as the Auto ID system are examples of two technologies enabling to gather data concerning the physical flow of materials with different levels of performance.

## 2.1 Deviations occurring in the physical flow

Defects stem either from the supply process and the shipment process, or from events occurring during storage.

### 2.1.1 Defects generated by the supply process

The term "supply system" is used to describe:

- Replenishments from suppliers
- Intra company transfers, i.e. items that are transferred from one warehouse to another warehouse of the same company also known as transshipments,
- Customer returns

A supply system is said to be reliable when the quantity of goods effectively entering into an inventory system corresponds exactly to the expected (ordered) quantity. According to [76], deliveries that are on time, free from damage, and that contain the correct quantities, products and shipping documentation arrive to customers only 40 to 60 % of the time. The unreliability of this system stems from:

- **Delivery errors** (e.g. wrong products being delivered to the wrong place) or **supplier frauds**, defined as losses due to suppliers deliberately delivering fewer goods than companies are invoiced for or suppliers delivering unsaleable and/or damaged items. These frauds may arise in a replenishment process as well as in a customer return process where the customer returns fewer goods than he announced (because of wrong products returned and/or goods stolen in transit) or he claims to have returned goods when he has not.

In an extreme case, it has been observed in many stores that the people in charge of delivering the products claim that products ordered were “left” in the backroom although some of the products were not delivered. These are known as phantom deliveries in industry.

- **Theft during transportation** between the supplier and the customer, [166] reports hijacked trucks, pilferage, “grey market” diversion and 3PL drivers bartering with delivery personnel at retail destinations as main contributors to losses.
- **Over deliveries** caused by time-pressured or cautious shipping personnel overaging shipments to ensure customers are kept happy. [166] reports that in many cases, while the retailer is not acknowledging receipt of the additional products, and simply readjusts its inventory level accordingly, the cost to the manufacturer can be considerable.

### 2.1.2 Defects arising during storage

#### a) Theft

Organizations can be victims of theft carried out either by the staff they employ, called the internal theft, or by outsiders (contractors, carriers, consumers within the stores) targeting their assets, called the external theft. In a store environment, a well-known type of external theft concerns fraudulent returns since in many cases, a receipt showing proof of purchase is not required. [166] reports that retailers have tried to tighten controls to reduce fraudulent returns, but the problem persists, mainly because there is no proven proof of purchase link between the receipt and the product.

Concerning the internal theft, the National Retail Security Survey (NRSS) reports that it accounts in the US for \$15.23 billion of annual retail sales or 45.9 % of annual shrinkage for 2001. Some specific types of internal theft include [219]:

- Theft of stock, i.e. staff stealing goods from the premises by either hiding them in their bags or intentionally placing the item outside the building for later collection.
- Collusion occurring when a member of the staff works with customers to steal products. During this incident, the staff may not scan the item or the security person may intentionally ignore the offence as it occurs. Collusion may also occur when stolen items are being returned to the store.
- Grazing, i.e. items stored in the warehouse are consumed by the warehouse staff.

#### **b) Perished/obsolete products**

Products stored in a warehouse and/or a store are unsaleable at the end of their life (the date code shown on the packaging) and unsaleable at full retail price within their date code, when the quality of the product has deteriorated. Typically, these product categories reside within the grocery and related retail sectors and include dairy, produce, meat and pharmacy products. Items going out of date are not being sold in time due to:

- Errors in forecasting although more and more reduced due to manufacturers' investments in integrated planning solutions, improved ERP capability, and the development of more sophisticated collaborative forecasting capabilities between suppliers and retailers.
- The inability to track accurately the location, condition and age of products stored within a facility. This risk increases when items with different expiry dates are held together. Receiving operators may easily assume that all delivered products have the same expiry date and they will update information system data accordingly. This creates inaccurate data, which may be hard to correct until the unsaleable product is discovered during cycle counts or visual checks.

Within a supply chain, the length of time a perishable product is left on loading docks, in a store backroom or on the sales floor can vary significantly on a day-to-day basis. With the use



of the Bar Code system, these delays and their impact on products' condition is almost impossible to track. For instance, one retailer estimated that 50% of his perishable markdowns and wastage were due to temperature abuse. Nor is it easy to solve, as he put it – “It is very hard to find out when the abuse occurred and who was responsible for it.” [166]

### **c) Damaged products**

A key contributor to the issue of wastage is that products are moved and handled several times through different production processes, transportation modes and storage conditions. Product handling is affected by physical considerations such as the quality of the packaging or the conditions of storage (i.e. the safety of the palletized product, space constraints imposed by differing loading/unloading bay entrances, sorting units, internal truck dimensions...). Additionally, if a Bar Code System is used to monitor movements of products, the handling activities that are carried out to check temperatures, scan product codes and check sell by dates may increase the risk of creating damaged and unsaleable product.

### **d) Non recorded item movements (misplaced items)**

Misplaced items stem from execution problems that prevent products which have been delivered to the facility from being stored at the right location. Items that are temporarily moved in a different location than where they normally should be without their movements being recorded may get forgotten during these unplanned movements and inventory visibility may be lost.

The risk to have these execution problems is particularly important for products that are stored in several locations within a facility. For instance, warehouse managers often divide the storage area into a forward area and a reserve area in order to reduce the labor associated with the order picking process -which accounts for more than half of the costs [220]. The former is used for efficient picking; the later holds the bulk storage and is used for the replenishment of the forward area. The capacity of storage is limited in a forward area, either because a larger system would become too expensive or because enlarging the forward area would increase the travel times of the picking process. Execution errors arising while transferring products from one area to the other may result in products moved and misplaced in wrong locations.

Stores are also faced with the issue of shelving errors that occur when products are transferred from the backroom to shelves. A product that is placed on the wrong shelf at the other end of the store will not be available to satisfy customer demand.

Although regular inventory counts are performed, it has been observed that the issue of misplaced products are often not well handled in warehouses [221]: even though a physical count tells that products are missing, often nothing is done for locating lost products mainly because during this process, counters are faced with a choice between completing their audits

in the time allotted and spending time to search and correct on hand discrepancies. In this situation, counters simply adjust the inventory back to the amount visible on shelf [124].

In facilities where the information system does not permit to have an accurate information on the movements of goods, such as the Bar Code system, a special attention must be accorded to procedures that permit to keep track of the location of items in order to reach them rapidly. For a particular SKU, the probability of the information system inventory level equaling its actual value is not only associated with the characteristics of the recorded item<sup>5</sup> (the number of units sold annually, the total number of orders, the value of the product, etc.) but also with the definition of working procedures within a facility and whether operators adhere to predefined business rules. Procedures should be established to follow products in their life cycle, i.e. space should be allocated, labels containing products ID should be clearly affixed to shelves in order to allow the replenishment, discontinued products should be identified and the labels containing their ID affixed to shelves should be removed to avoid further replenishment and if the same item is stored in different locations (e.g., reserve area, bulk storage, back up storage area, shelves/racks, etc.) patterns linking locations must be updated regularly.

### **2.1.3 Defects generated by the shipment process**

In a similar way as for material flows coming in, the flow of products going out of the inventory system is also subject to errors: when preparing and shipping orders to customers, defects such as underage or overage errors, mistakes when loading pallets, delivery errors (for instance, pallets mistakenly unloaded at one store from a truck that contains multiple store deliveries on a given day) or theft during transportation may cause perturbations in the expected outgoing flow.

### **2.1.4 Magnitude of defects**

Typical inventory systems, be it a warehouse or a store, are the merge point of thousands of product categories that have different shapes, sizes and colors. Tens of thousands of items may come in and go out the system in a working day [213]. That is why, keeping track of the errors outlined in section 2.1. may be a difficult task. While performing our literature review, we found some empirical evidence on the magnitude of these factors. Based on a survey of supermarkets; internal and external theft, administrative errors and fraud made by vendor accounted for 1.8% of sales in US retail industry in 2001, assuming an annual sales base of \$1.8 trillion, this costs US retailers \$ 33 billion [222], European retailers €14.4 billion, Australasian retailers \$A 942 million [166]. Furthermore, Canadian retailers lose approximately \$4.5 million every single day. For US supermarkets, the National Supermarket

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<sup>5</sup> For further details, cf. [7].

Research Group estimates that internal and external theft, receiving errors, damage and retail pricing errors amount to 2.3% of sales [223]. These figures only take into account the item value, but not any process related costs (e.g. for handling of damaged items).

Factors that cause inventory inaccuracy arise from time to time with varying degrees of magnitude. As stated by [166], research in this area is viewed as a data desert, this contributing to the difficulty practitioners experience when getting their issues reviewed at a strategic level. Organizations and universities performing this kind of analysis only have the survey method at their disposal. For today's consumer goods and retail organizations to collect accurate information on defects, they would have to embark upon unsustainable work-studies that would suffer from inaccuracies due to the scale of the required activity (i.e. labor monitoring plus counting all inventories at every point in the supply chain from finished good to the point of sale).

To our knowledge, analyses on the state of these factors including estimates of values can be found in industry oriented research such as [224], [222] and [223]. According to this research:

- 0.25% of items are incorrect in deliveries
- 1.5% of items are stolen in storage
- 0.2% of inventory gets unsaleable

The surveys do not contain a comprehensive figure for misplaced items. The only information we found was in [199] who uses data from the annual physical audits of a company and finds that on average, over 6 000 SKUs in a store (or 3.4% of an average store's assortment) are misplaced in storages areas within the store where consumers cannot find or purchase them.

## **2.2 Deviations in the information flow**

In practice, most of enterprises rely on their information system in taking decisions pertaining to the management of their inventory. If information recorded in the system is incorrect, this would have severe impacts on the performance. In other words, the information system inventory records should reflect the physical inventory level accurately. Even though this point may seem trivial, a few typical industry quotes reported by [124] illustrate that it is still an issue in many industrial practices:

“ I am not always sure if I have actually got the product I ordered or where it is in the store.”

“ Our store managers do not believe the distribution centers always send the right products or quantities but they have to accept the transfer anyway.”

“ I use automated ordering, but the cycle counts I do to keep the on-hand position up to date often make the situation worse.”

Inventory accuracy can be defined by the degree to which physical and information system inventories are matched [12]. In practice, different measures are used to evaluate inventory accuracy:

- At the end of a physical count carried manually, the information system inventory record is compared to the actual stock. Then the percentage of SKUs whose inventory records matches the actual stock perfectly is calculated.
- Another way to measure accuracy is to consider that an inventory record is accurate if it matches with the physical inventory within  $\pm x$  items (or  $\pm y\%$  of items).

For instance, [199] reports that out of 370 000 SKUs investigated in a store environment, more than 65% of the inventory records did not match the physical inventory; 20% of the inventory records differs from the physical inventory by 6 or more items.

A perfect synchronization between the physical flow and the related data recorded in information system enables to verify if events happened as planned (without any product losses, overages or delays) and to identify the reasons of deviations. This synchronization is possible only if all transactions (i.e. known transactions as well as unknown transactions) are detected by the information system.

For any system, [225] emphasizes the importance of exploring the deviations from the expected behavior during the system requirements analysis process in order to identify the potential factors that can contribute to human errors once the system is implemented. We built on this study to pinpoint the potential failures that may occur in a warehouse where a Bar Code system is used to capture data.

A major factor undermining the identification of defects presented in section 2.1. is the lack of relevant, timely and accurate inventory data, creating a blurring of transparency in knowing the inventory quantities, their physical status and where they are. This is mainly due to:

- The technical limitations of the Bar Code system: this technology is not able to detect events accurately and continuously, i.e. without a time lag between the moment at which events occur and the moment they are detected.
- The potential failures that may occur when operators collect data from Bar Coded entities.

### **2.2.1 Failures stemming from the technical constraints of the Bar Code system**

Among sources of failures associated with the technical limitations of the Bar Code system are the following:

#### **a) Bar coding quality**

For a particular item to be identified (e.g. control at receiving/shipment, check-out registers), its Bar Code symbol must perform as intended. Several industry oriented research report that scanners cannot identify products due to poor symbology specification and bar coding quality, poor contrast, codes obscured by sealing tape and incorrect check digits. For instance, [226] reports that during the 1980s, first-read rates for barcodes were high – around 95 % scanned first time. However, as barcode print quality gradually declined, manufacturers of scanners increased the capability of the scanners to accept poor quality barcodes instead of tackling the problem at source. The same paper reports that a scanning exercise carried out by Sainsbury’s revealed that some 4% of traded units which were bar-coded by manufacturers of proprietary brands did not scan at all, while a massive 95 % did not comply with ANA (Article Numbering Association) standards. Only 27 % of the sample of 3,300 traded unit codes tested scanned first time. It also states that in most of supermarkets, a huge amount of products’ data is manually key-entered because of the inability of bar code labels to scan, though this is not published. However, according to the head of a supermarket, the results showed an “alarming rate of failure” of products to scan at the checkout.

During pipeline transactions, even initially well-printed Bar Code labels may become damaged and illegible. Furthermore, in various material handling processes across the supply chain, especially for returned goods, labels can be lost so that products arrive at their final destination without labels [86]. Such events create potential situations for data recorded in information system to deviate from the physical flow of materials.

#### **b) Line of sight technology**

Even if standardization committees such as EAN International and the UCC have defined rules for positioning labels on trade items and logistics units, the line of sight positioning requirement for Bar Code labels may leave room for errors and inefficiencies:

- When automated resources such as fixed position readers on conveyor belts capture data on items’ labels, it is likely to have a certain rate of no scans.
- The second consequence of the line of sight requirement is that it does not permit a continuous monitoring of items unless a perpetual scanning is being done. As outlined previously, the consequence is that events cannot be detected and recorded instantaneously – they are discovered after the fact. Thus, depending on the scanning frequency, employee or customer theft, damages occurred in a preparation process or spoilage during storage and non recorded and/or perished items disposed of without inventory corrections being made may continue to diminish products’ physical inventory levels while their recorded inventory values remain unchanged.

#### **c) Data content and management**

This point is related to the amount of information carried by Bar Codes. Generally, as manufacturers do not need to track consumer units as separate entities, they Bar Code items at case or pallet level. For downstream supply chain actors willing to get individual item level information or desiring to add more information in Bar Codes, in house repackaging and coding may be necessary. This manual code creation, the matching of this internal code to the initial code and the affixation of new labels to products may create opportunities for error.

The last point is associated with the management of data associated with items. Factors such as irregular updates of product information, the creation and use of various identification numbers for the same product within the different departments of a facility, too many and not well linked data sources would lead to inaccuracies. Especially in industries where changes in product portfolio are important (introduction of new products, substitutions, discontinued products, and change in bill of materials...) troubles in product data management may occur. Data recorded from movements of SKUs would not match real values if changes concerning product and packaging information are not rapidly taken into consideration or if there is a time lag between the moment changes occur and that of their updates in the product database.

### **2.2.2 Failures stemming from the interaction between human resources and the Bar Code system**

For a given order, the number of different products demanded may be large, while quantities per order line may be small, which often results in complex and costly order receiving, preparation and shipment processes. Therefore, when products flow from the manufacturer to consumers, the update of the information system data representing this flow is as accurate as operators handling items.

Furthermore, as operators often wary that detailed error reporting will lead to punitive actions [225], it is hard to anticipate the ways in which the above factors jeopardize errors, but common mistakes encountered in most of warehouses are identification (scanning), counting and keypunching errors occurring during processes such as receiving, put away or shipment. Among the common causes for errors are untrained personnel, carelessness, lack of transaction discipline, etc...

#### **a) Errors made when identifying entities**

Below are some examples illustrating typical identification errors:

- Operators not distinguishing the variants of a product of similar appearances, e.g. in a store, when a shopper brings similar products with identical prices, the cashier may scan only one of the products and thus treat them as identical items

- Operators forgetting to scan entities' ID (consumer units, cases or pallets), e.g. as multiple Bar Codes cannot be read at the same time, a last check before loading the truck done manually is often prone to errors
- To save time, operators deliberately not scanning entities' ID codes
- Wrong labels placed on products by both suppliers and retailers
- Items put in/picked from the wrong shelf location -during put away/picking processes or when finding locations for returned goods
- As the sell by date information is not carried by Bar Codes, a manual check of this label is performed by operators. During this activity, misreading and/or faulty identification of the oldest stock resulting in fresher products to be picked ahead of older stock may occur.

#### **b) Errors made when counting**

A second type of error occurs when counting items (consumer units, cases or pallets) during daily processes or in physical/cycle inventory activities. As all products of the same SKU have the same Bar Code number, there is not a real guarantee that an employee will not count accidentally more or less products than expected. For instance, when preparing an order that contains multiple units of the same product, the order picker may simply scan the item he first picked and count the rest as opposed to scanning each item individually.

#### **c) Errors made when keypunching data**

Even if operators do not make errors in item identification or counting process, if a mistake is made when keypunching an item code, a quantity or a location number in warehouse's master files or a portable data carrier, inventory records will deviate from physical values. For instance, when battery failures arise (e.g. scanners or transfer equipment), the manual key entering back up process which is subject to potential keypunching errors would degrade the quality of the recorded data.

As a conclusion, for reasons outlined above, the Bar Code system does not provide the capability to monitor accurately the real physical flow. There is a lot of guesswork, assumption and projection since the control and visibility on products can vary significantly among many manual hand off steps between manufacturing plants, distribution centers and retail stores. This has a significant knock on effect on the quality of decisions regarding inventory management. Thus, cycle/physical counting processes giving a feedback on the reliability of the data collection process constitutes a control mechanism. But, this manual practice is also vulnerable to counting, scanning or recording errors.

## **2.3 Consequences of not having an accurate inventory data**

By identifying how much value is lost due to inventory mismatches, companies can estimate savings they could achieve by better coping with inaccuracies. Inventory data inaccuracy can affect enterprises' performance in a number of ways.

### **2.3.1 Direct costs stemming from inventory inaccuracies**

#### **a) Inefficiencies in operations**

When detected by customers, errors made during receiving or shipment processes result in claims and/or product returns. This, in turn, generates labor costs associated with additional transactions (time spent in searching, verifying and administrating disputes and fixing inaccuracies, transportation, materials handling cost to detect missing or unsaleable items, etc). This issue is also valid for assets: whether company owned, leased or provided by a third party, assets are very often difficult to track. The time spent in looking again for the missing items, verifying and administrating disputes and fixing inaccuracies would result in poor asset utilization rates.

Furthermore, the risk to have inaccurate inventory levels force companies to spend additional, unproductive time cycle counting and performing wall-to-wall inventories to detect and correct on hand inventory discrepancies that can erode inventory data integrity. This generates additional labor costs and lost opportunity cost stemming from the fact that companies are shut down during these operations [161].

#### **b) Undetected losses of products**

Not having an accurate up to date knowledge of movements of the physical flow leads to undetected losses due to undetected overages in shipment, undetected underages in receiving, stolen or obsolete items.

Product obsolescence has two dimensions: perishability (e.g. dairy, produce, meat and pharmacy products) and short life cycle (e.g. apparel, toys, office supplies, consumer electronics). Factors increasing the risk for obsolescence include inventory inaccuracies due to human errors resulting in missed pallets of products which are found too late; inaccurate recording of perishable products' date codes which results in fresher product being picked ahead of older stock; manual errors on cycle counts where incorrect product identity and date information leads to wrong data being entered into warehouse management systems. This creates inaccurate data, which is hard to correct until the unsaleable product is discovered during cycle counts or visual checks.

For short shelf life products, not having products on shelf not only generates potential out of stocks but also as products' saleability expires rapidly as a result of the introduction of new



products or changes in season, the risk to have obsolete goods increases and generates money losses due to markdowns or inventory write-offs [87].

### **c) Additional inventory related costs**

#### **▪ Additional inventory holding cost**

Due to execution errors, there may be more items in inventory than what is observed in the information system. If sufficient effort is not deployed to find the misplaced products and to correct divergences between the information system inventory and the real inventory, a warehouse may continue to be charged for an additional inventory holding cost. Meanwhile, because decisions are based on values in information system and because the missing quantity is deducted from the information system inventory level, a new order would be generated when not really needed.

Furthermore, undetected overages in shipments leading to losses associated with late payments and additional inventory cost associated with products that have a limited shelf live have also an adverse financial impact on enterprises' performance.

#### **▪ Unexpected shortage situations**

At the other extreme, when the information system inventory record shows a higher quantity than the real inventory, there is a likelihood for out of stock situations. Since the decision to satisfy demand is based on information system data, a facility which has committed itself to ship a certain quantity of products may discover that the real quantity available is less than the committed quantity. In this case, the picking operator may wait for replenishment to complete the order. He may also report that the quantity requested is not available causing the product to be backordered or recorded as a lost sale even though the reserve area may have enough units to fill the demand. The time losses relevant to workers and material handling equipment include the time spent for going to the location and looking for the product, the time spent for looking in adjacent locations, the time spent to report errors and the time spent for the supervisor to verify the apparent error.

Similarly, undetected underages in shipments, either because products are not delivered to the correct point of request or are delivered partially, would also lead to shortage costs.

## **2.3.2 Indirect costs stemming from inventory inaccuracies**

### **a) Indirect impacts**

Data pertaining to inventory may be used for different purposes and applications within an enterprise. As illustrated in [160, 227], the interactions of the other processes with the inventory management system are various and there exists several processes that rely on data integrity and a high level of inventory visibility to be truly effective.

Retailers using automatic replenishment systems to manage inventory rely on the accuracy of on hand inventory; an accurate forecasting of demand and supply quantities also depends on accurate on hand data capture. The efficiency of other processes such as lean manufacturing, Kaizen, Six Sigma manufacturing strategies and applications such as Manufacturing Execution Systems (MES) or Computerized Maintenance Management Systems (CMMS), Statistical Process Control (SPC) for statistical and root-cause analysis [86] in store price optimization applications focusing on tracking prices and sales information over time in order to make recommendations for setting retail prices; markdown optimization applications depend on accurate, timely and detailed data to operate effectively.

### **b) Intangible impacts**

Inventory mismatches adversely affect the reputation and credibility of the firm in the mind of investors. Investors may turn out to be skeptical of the firm's future prospects and may value it at a discount when compared to similar firms [5].

### **2.4 Main benefits of Auto ID technology in supply chains**

The deployment of Auto ID technology at case and item level contributes to the elimination of defects throughout the supply chain. For instance,

- Concerning defects resulting from the unreliability of the supply system, the Auto ID technology can detect identification/counting errors immediately and reduce the cost of administering/ billing disputes and fixing inaccuracies
- Concerning the logistics of perishable items, the use of the Auto ID technology can:
  - Facilitate better FIFO and promotions management by improving data integrity and visibility with real time data to permit staff to select the oldest product first in all cases, therefore reducing perishable product waste
  - Facilitate the tracking and maintenance of temperature conditions supporting the integrity of the cold chain for meats and produce
  - Enable an increased visibility to stock on hand and to sales at each location, improving the accuracy of demand and supply forecasts
- Concerning theft issues, the Auto ID technology can:
  - Discourage thieves
  - Facilitate to locate sources, quantities and timings of theft losses across the supply chain
  - Determine the status of the product (purchased or not purchased) at customer service desk and thus help to eliminate fraudulent store returns

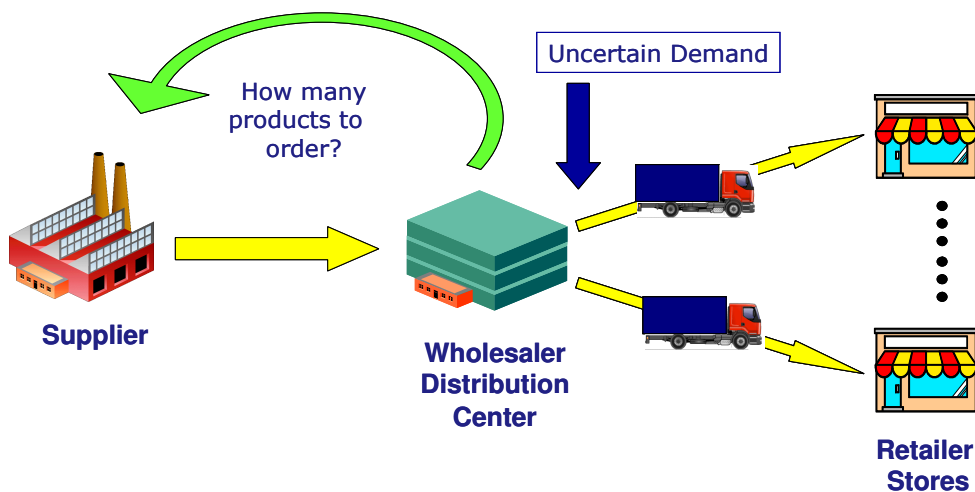
- Concerning misplaced items, the Auto ID technology based readers integrated into the shelves of warehouses and stores can permit to locate moved and misplaced products and thus eliminate non value adding activities such as cycle counting.

## Part 2: Quantitative Models of Inventory Systems Subject to Perturbations

### 1 The general framework

In this section, we present a general framework that will allow us to evaluate the economic impact of errors perturbing the physical flow and/or the information flow within an inventory system and show the potential benefits of the Auto-ID technology. Our framework is based on the classical single-period Newsvendor (or Newsboy) model [15, 218, 228, 229].

The supply chain under study includes three stages: the supplier, the wholesaler and the retailers (stores), where each actor plays a specific role. The supplier is the actor manufacturing the products, the retailers are the actors selling the products to the final consumer, and the wholesaler is the intermediate actor that buys products from the supplier and resells them to the retailers.



**Figure 2. The supply chain under study**

As in the classical Newsvendor model, we are concerned with seasonal (or “fashion”) type products, characterized by a short product lifecycle and a short selling season. Typical products that fall into this category are clothes (apparel industry). However, there are many other such products: toys, skis, etc... These products are usually manufactured before the beginning of the season because of long production (or distribution) lead time constraints. We focus on a single product.

Long before the season starts, the wholesaler will have to place a single order to the supplier. At this time, the retailers have not yet committed themselves to the wholesaler. Therefore, the decision of the wholesaler, i.e. the quantity he orders from the supplier, will not be based on retailers' firm orders, but rather on forecast type information available to the wholesaler regarding retailers' future demand. At that time, the wholesaler only needs to have information on the future aggregate retailers' demand. As in the Newsvendor model, we will assume that this information is given under the form of a distribution that represents in a probabilistic way the future demand  $D$ . Let  $Q$  be the quantity that the wholesaler orders from the supplier. When all the products have been produced, the supplier will deliver them to the wholesaler. The wholesaler will receive the goods and store them in his warehouse. Because of errors occurring in the physical flow and in the information flow, the amount of products available at the beginning of the season (the physical inventory) and/or the corresponding recorded data (the information system inventory) may differ from the quantity ordered.

Just before the start of the season, the wholesaler will receive orders from the retailers. The wholesaler will compare the cumulative order from all the retailers to the quantity of products he has in his warehouse based on the inventory system inventory data. If the cumulative order is less than the information system data (the information system inventory), the wholesaler will accept all the orders. If not, the wholesaler will only accept orders summing up to the information system inventory.

Later on, the products will be shipped from the wholesaler warehouse and delivered to the retailers. All the orders that the wholesaler has committed himself to should in principle be satisfied. However, this may not always be the case due to inventory systems inaccuracies. Such a situation occurs for instance when the information system inventory is larger than the physical quantity available (the physical inventory), and the demand is larger than the information system quantity.

Note that there is no opportunity for replenishment during the season either because the replenishment lead times are too long or the cost of acquisition of products during the season is too high.

The wholesaler will be facing three different costs:

- The overage cost due to products unsold at the end of the season, if any.
- The underage (or shortage) cost due to orders rejected by the wholesaler, if any.
- The underage cost due to orders initially accepted by the wholesaler but finally not delivered to the retailers

The first two costs are the costs already appearing in the classical Newsvendor model. On the other hand, the third cost is specific to our study and is capturing the impact of inventory system inaccuracies.

Let  $h$ ,  $u_1$  and  $u_2$  be the parameters characterizing these three costs, namely:

- $h$  : the overage cost per unit of product not sold at the end of the season
- $u_1$  : the underage cost per unit of demand rejected by the wholesaler
- $u_2$  : the underage cost per unit of demand initially accepted by the wholesaler but not delivered to the retailers

As in the classical Newsvendor model, these parameters can easily be related to the basic costs parameters of the underlying supply chain. Indeed, let:

- $P_A$  be the unit product purchasing cost
- $P_V$  be the unit product selling price
- $P_S$  be the unit product salvage value at the end of the season

In addition let:

- $C_{u_2}$  be the unit penalty cost, i.e. the penalty associated with the non delivery of an earlier committed unit of product

Then, the parameters  $h$ ,  $u_1$  and  $u_2$  can be related to these basic cost parameters as follows:

- $h = P_A - P_S$
- $u_1 = P_V - P_A$
- $u_2 = u_1 + C_{u_2}$

This will be further discussed in the different models.

The wholesaler's decision is to determine the quantity of products to order from the supplier before the season to satisfy retailers' aggregate demand. His decision is based on the evaluation of three potential risks: risk of shortage situation; risk of having unsold products at the end of the season; risk of not being able to deliver the quantity that he has made a commitment for.

Let us now discuss in more details the behavior of the inventory system regarding errors and their impact on the physical and information flows.

- **The physical flow:** The physical quantity available within the wholesaler's distribution center to satisfy retailers' demand, i.e.  $Q_{PH}$ , may be different from the quantity ordered. This takes into account the likelihood of defects perturbing the nominal physical flow, e.g. the supplier not delivering the right amount of products.

We thus have:  $Q_{PH} = Q_A$ , where  $Q_A$  is a random variable function of  $Q$ .

- **The information flow:** In presence of defects that perturb the nominal physical flow of materials, there are basically two ways to update the inventory data recorded in the information system:
  - The first way is to measure the effective physical flow, i.e. gather data by performing product identification and data capture processes. Because the data capture process may not be totally reliable, the available quantity appearing in the information system of the wholesaler's distribution center to satisfy retailers' demand, i.e.  $Q_{IS}$ , may be different from the physical quantity available,  $Q_{PH}$ .

In this case, we have:  $Q_{IS} = Q_B$ , where  $Q_B$  is a random variable function of  $Q_{PH}$ .

- The second way to update inventory on hand data is to assume that there are no anomalies occurring in the physical flow and set the inventory data record equal to the quantity requested from the supplier automatically, once the order is placed.

In this case, we have:  $Q_{IS} = Q$ .

The generic model can be represented by the following scheme:

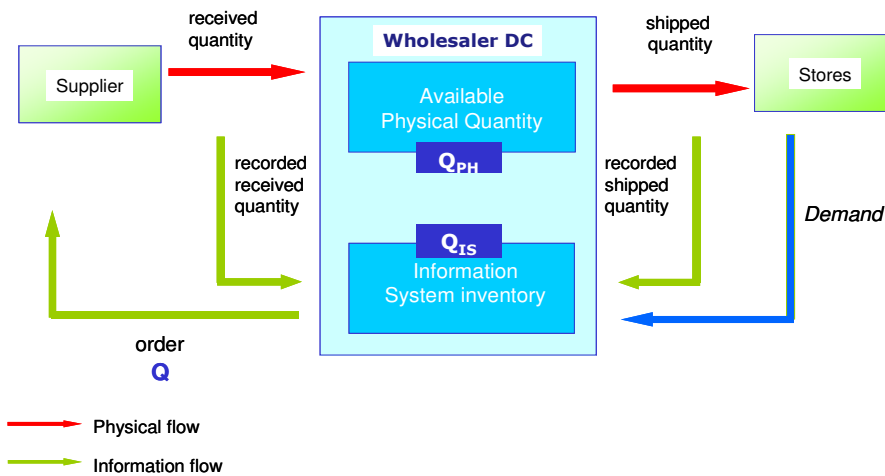


Figure 3. The generic model

## 2 Various models of interest

In this section, we discuss various models that belong to the general framework presented in the previous section. Hence, we distinguish several models:

- The model without errors, which corresponds to the classical newsvendor model. This model corresponds to a perfect situation in which there are no errors occurring throughout the supply chain, neither regarding the physical flow nor regarding the information flow. (*Model 0*)

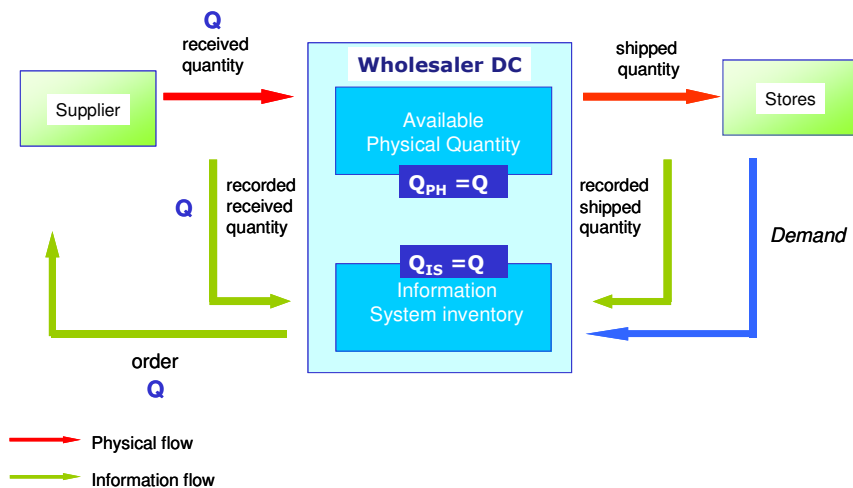
- Models with errors which take into account quantitative defects perturbing either the physical flow and/or the information flow. These models fall into two categories, depending on whether the measurement of the physical flow is performed or not.
- The first type of models with errors assumes that perturbations may impact the physical flow of products and that the information system inventory record is updated based on data collected from the physical flow. (*Model 3*)
- In the second type of model with errors, although defects perturb the physical flow, the information system inventory record is set equal to the quantity requested from the supplier when the order is placed. (*Model 4*)

The notations that will be used in this chapter (and in Chapter 5) are as follows:

- $C_0(Q)$  : The expected total cost in the model without errors
- $Q_0^*$  : The optimal order quantity in the model without errors
- $C_0(Q_0^*)$  : The corresponding total optimal cost
- $C_j(Q)$  : The expected total cost in the model j with errors
- $Q_j^*$  : The optimal order quantity in the model j with errors
- $C_j(Q_j^*)$  : The corresponding total optimal cost

## 2.1 Model 0: The model without errors

Model 0 corresponds to the classical Newsvendor model. In this model, it is assumed that no errors, in terms of inventory inaccuracies, are taking place in the supply chain processes.



**Figure 4. Inventory model associated with Model 0**

The detailed assumptions corresponding to Model 0 are as follows:

a) **Physical quantity:** The physical inventory available to satisfy demand when the selling season starts is equal to the quantity ordered  $Q$ .

$$Q_{PH} = Q.$$

b) **IS inventory data:** The IS inventory is obtained by measuring the physical flow using a perfect data capture system, that is, there are no errors involved in this process, or by setting the IS inventory equal to the quantity ordered. In this case, the two approaches are equivalent and lead to:

$$Q_{IS} = Q.$$

The behavior of Model 0 is as follows: at the beginning of the season, the wholesaler receives a total demand of  $D$  products from the retailers. This demand is addressed in two steps:

- An initial commitment is made by the wholesaler to the retailers based on the IS inventory information. The commitment corresponds to a quantity equal to  $Min(D, Q)$ . The corresponding shortage quantity is thus given by  $Max(0, D - Min(D, Q))$ .
- Some time after, products are shipped to the retailers. Because the physical inventory and the IS inventory are identical, the initial commitment is always fulfilled.
- If the physical inventory exceeds the shipped quantity, there would be some leftover inventory at the end of the selling period.  
The corresponding overage quantity is thus given by  $Max(0, Q - Min(D, Q))$ .

The corresponding costs are then given by:

- Overage cost:  $h \cdot Max(0, Q - Min(D, Q))$
- Underage cost:  $u_1 \cdot Max(0, D - Min(D, Q))$

The parameters  $h$  and  $u_1$  can be related to the basic cost parameters  $P_A, P_V$  and  $P_S$  (cf. App 1) as follows:

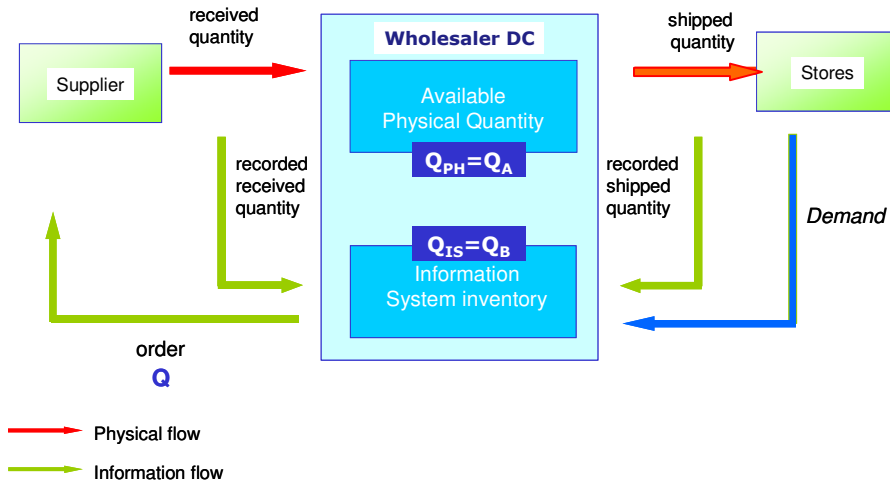
- $h = P_A - P_S$
- $u_1 = P_V - P_A$

The optimization of the system consists in determining the quantity which minimizes the expected total cost, which is the sum of the costs pertaining to these 2 situations.

## 2.2 Model 3 : A model with errors

Model 3 takes into account errors occurring in the physical flow as well as errors perturbing the data capture process of the physical flow.





**Figure 5. Inventory model associated with Model 3**

The detailed assumptions corresponding to Model 3 are as follows:

- a) **Physical quantity:** The physical inventory available to satisfy demand when the selling season starts is different from the quantity ordered  $Q$ . This is due to errors occurring in the physical flow.

$Q_{PH} = Q_A$ , where  $Q_A$  is a random variable function of the quantity ordered to the supplier,  $Q$ .

- b) **IS inventory data:** The IS inventory is obtained by measuring the physical flow. However, due to errors occurring in the data collection process, the quantity measured (and recorded in information system) is different from the real quantity available to satisfy demand.

$Q_{IS} = Q_B$ , where  $Q_B$  is a random variable function of the physical quantity available,  $Q_{PH}$ .

The behavior of Model 3 is as follows: at the beginning of the season, the wholesaler receives a total demand of  $D$  products from the retailers. This demand is addressed in two steps:

- An initial commitment is made by the wholesaler to the retailers based on the IS inventory information. The commitment corresponds to a quantity equal to  $Min(D, Q_{IS})$ .

The corresponding shortage quantity is thus given by  $Max(0, D - Min(D, Q_{IS}))$ .

- Some time after, products are shipped to the retailers. However, it may happen that it is not possible to fulfill the whole commitment because there are not enough physical products available in the warehouse. This second shortage situation arises if  $Min(D, Q_{IS}) \geq Q_{PH}$ .

The corresponding shortage quantity is thus given by  $Max(0, Min(D, Q_{IS}) - Q_{PH})$ .

- If the physical inventory exceeds the shipped quantity, there would be some leftover inventory at the end of the selling period.

The corresponding overage quantity is thus given by  $Max(0, Q_{PH} - Min(D, Q_{IS}))$ .

The corresponding costs are then given by:

- Overage cost:  $h.Max(0, Q_{PH} - Min(D, Q_{IS}))$
- First underage (shortage type 1) cost:  $u_1.Max(0, D - Min(D, Q_{IS}))$
- Second underage (shortage type 2) cost:  $u_2.Max(0, Min(D, Q_{IS}) - Q_{PH})$

The optimization of the system consists in determining the quantity which minimizes the expected total cost, which is the sum of the costs pertaining to these 3 situations.

Remark: although we assume that, in order to update the information system inventory data, a product identification process is performed, our model does not take into consideration the cost pertaining to this process explicitly. This point will be further developed in chapter 5.

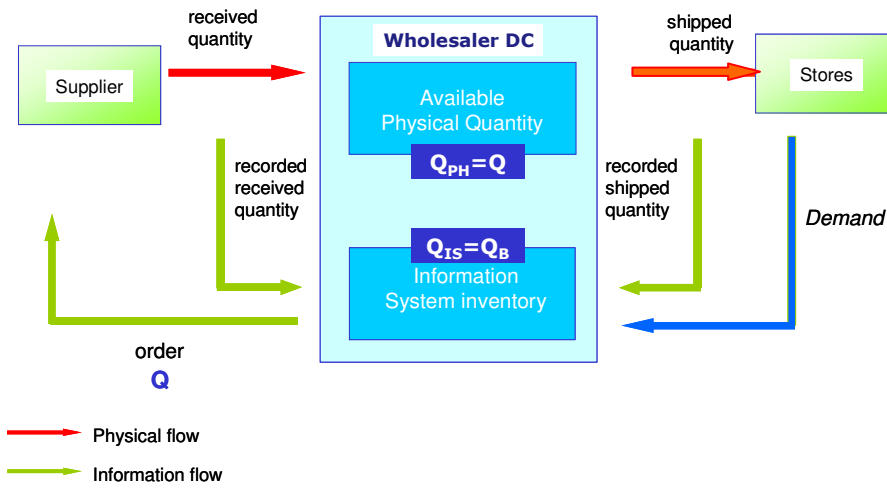
### **2.3 Variants of Model 3: Model 1 and Model 2**

Model 3 takes into account the two types of errors identified so far: errors on the physical flow and errors on the information flow. However, the simultaneous consideration of defects perturbing the physical flow and the information flow creates several problems. Firstly, the analysis of such a model is very tedious, if not impossible. Secondly, even if this model could be solved, it would probably be very difficult to interpret the results and get some interesting insights.

As a result, we will be considering two different variants of Model 3, each one corresponding to a special case: Model 1 and Model 2.

- Model 1 assumes that there are no errors on the physical flow but only errors in the information flow due to defects in the data capture process.
- Model 2 on the other hand assumes that the physical flow involves errors but that the data capture process is perfectly reliable.

### 2.3.1 Model 1



**Figure 6. Inventory model associated with Model 1**

Model 1 is as follows:

- a) **Physical quantity:** The physical inventory available to satisfy demand when the selling season starts is equal to the quantity ordered  $Q$ .

$$Q_{PH} = Q.$$

- b) **IS inventory data:** The IS inventory is obtained by measuring the physical flow. However, due to errors occurring in the data collection process, the quantity measured (and recorded in information system) is different from the real quantity available to satisfy demand.

$$Q_{IS} = Q_B, \text{ where } Q_B \text{ is a random variable function of the physical quantity available } Q.$$

The behavior of Model 1 is as follows: at the beginning of the season, the wholesaler receives a total demand of  $D$  products from the retailers. This demand is addressed in two steps:

- An initial commitment is made by the wholesaler to the retailers based on the IS inventory data. The commitment corresponds to a quantity equal to  $\text{Min}(D, Q_{IS})$ . The corresponding shortage quantity is thus given by  $\text{Max}(0, D - \text{Min}(D, Q_{IS}))$ .
- Some time after, products are shipped to the retailers. However, it may happen that it is not possible to fulfill the whole commitment because there are not enough products physically available in the warehouse. This second shortage situation arises if  $\text{Min}(D, Q_{IS}) \geq Q$ . The corresponding shortage quantity is thus given by  $\text{Max}(0, \text{Min}(D, Q_{IS}) - Q)$ .

- If the physical inventory exceeds the shipped quantity, there would be some leftover inventory at the end of the selling period.

The corresponding overage quantity is thus given by  $Max(0, Q - Min(D, Q_{IS}))$ .

The corresponding costs are then given by:

- Overage cost:  $h \cdot Max(0, Q - Min(D, Q_{IS}))$
- First underage cost:  $u_1 \cdot Max(0, D - Min(D, Q_{IS}))$
- Second underage cost:  $u_2 \cdot Max(0, Min(D, Q_{IS}) - Q)$

Then, the parameters  $h$ ,  $u_1$  and  $u_2$  can be related to these basic cost parameters as follows (cf. App 3):

- $h = P_A - P_S$
- $u_1 = P_V - P_A$
- $u_2 = u_1 + C_{u_2}$

The optimization of the system consists in determining the quantity which minimizes the expected total cost, which is the sum of the costs pertaining to these 3 situations.

**Remark:** It should be pointed out that this model of interest should be interpreted as a special case of Model 3. Indeed, if we were sure that the physical quantity available was always equal to the quantity ordered, there would be no need for a data capture process and therefore no errors would be involved in setting the IS inventory quantity. Thus, Model 1 will be used to get insights that should then be thought of as being relevant for the more general Model 3.

### 2.3.2 Model 2

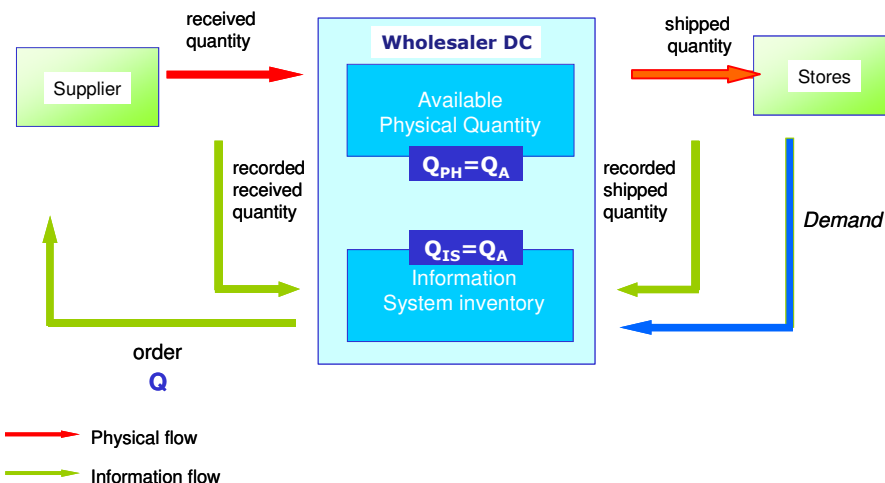


Figure 7. Inventory model associated with Model 2

Model 2 is as follows:

a) **Physical quantity:** The physical inventory available to satisfy demand when the selling season starts is different from the quantity ordered  $Q$ . This is due to errors occurring in the physical flow.

$Q_{PH} = Q_A$ , where  $Q_A$  is a random variable function of the quantity ordered  $Q$ .

b) **IS inventory data:** The IS inventory is obtained by measuring the physical flow using a perfect data capture system, that is, there are no errors involved in this process.

$Q_{IS} = Q_{PH} = Q_A$ .

The behavior of Model 2 is as follows: at the beginning of the season, the wholesaler receives a total demand of  $D$  products from the retailers. This demand is addressed in two steps:

- A commitment is made by the wholesaler to the retailers based on the IS inventory information. The commitment corresponds to a quantity equal to  $Min(D, Q_{IS})$ . The corresponding shortage quantity is thus given by  $Max(0, D - Min(D, Q_{IS}))$ .
- Some time after, products are shipped to the retailers. Because the physical inventory and the IS inventory are identical, the initial commitment is always fulfilled.
- If the physical inventory exceeds the shipped quantity, there would be some leftover inventory at the end of the selling period. The corresponding overage quantity is thus given by  $Max(0, Q_{IS} - Min(D, Q_{IS}))$ .

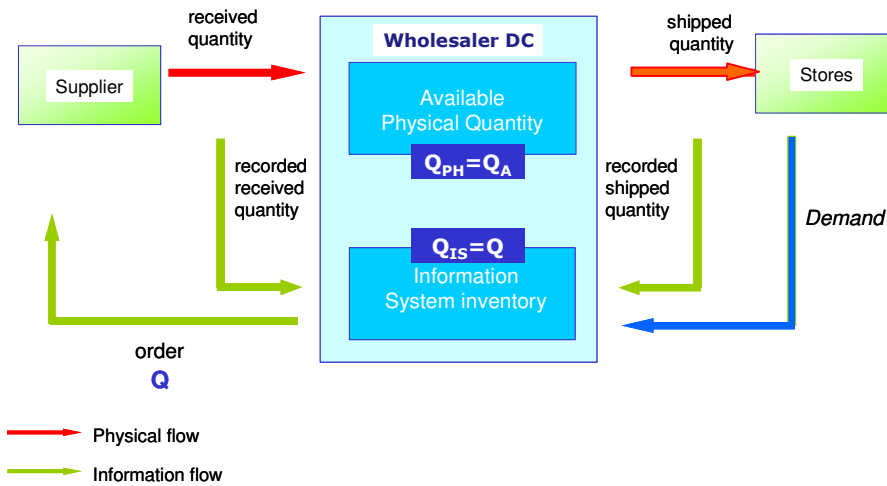
The corresponding costs are then given by:

- Overage cost:  $h \cdot Max(0, Q_{IS} - Min(D, Q_{IS}))$
- First underage cost:  $u_1 \cdot Max(0, D - Min(D, Q_{IS}))$

The parameters  $h$  and  $u_1$  can be related to the basic cost parameters  $P_A, P_V$  and  $P_S$  (cf. App 4)

The optimization of the system consists in determining the quantity which minimizes the expected total cost, which is the sum of the costs pertaining to these 2 situations.

### 2.3.3 Model 4



**Figure 8. Inventory model associated with Model 4**

The detailed assumptions corresponding to Model 4 are as follows:

- **Physical quantity:** The physical inventory available to satisfy demand when the selling season starts is different from the quantity ordered  $Q$ . This is due to errors occurring in the physical flow.

$Q_{PH} = Q_A$ , where  $Q_A$  is a random variable function of the quantity ordered to the supplier,  $Q$ .

- **IS inventory data:** Although defects perturb the physical flow, the IS inventory record is set equal to the quantity requested from the supplier when the order is placed

$$Q_{IS} = Q.$$

The behavior of Model 4 is as follows: at the beginning of the season, the wholesaler receives a total demand of  $D$  products from the retailers. This demand is addressed in two steps:

- An initial commitment is made by the wholesaler to the retailers based on the IS inventory information. The commitment corresponds to a quantity equal to  $Min(D, Q)$ . The corresponding shortage quantity is thus given by  $Max(0, D - Min(D, Q))$ .
- Some time after, products are shipped to the retailers. However, it may happen that it is not possible to fulfill the whole commitment because there are not enough physical products available in the warehouse. This second shortage situation arises if  $Min(D, Q) \geq Q_{PH}$ . The corresponding shortage quantity is thus given by  $Max(0, Min(D, Q) - Q_{PH})$ .

- If the physical inventory exceeds the shipped quantity, there would be some leftover inventory at the end of the selling period.

The corresponding overage quantity is thus given by  $Max(0, Q_{PH} - Min(D, Q))$ .

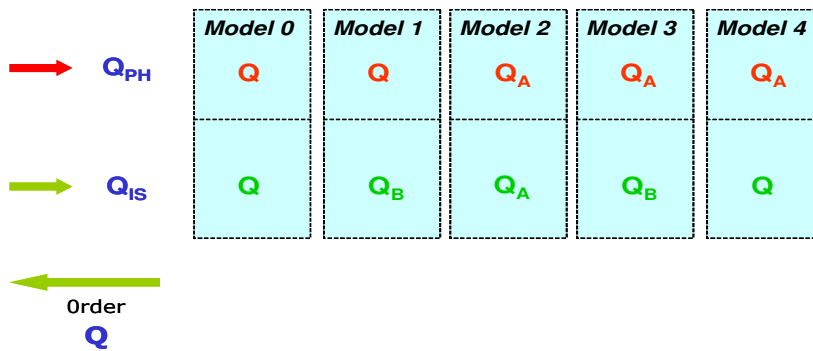
The corresponding costs are then given by:

- Overage cost:  $h.Max(0, Q_{PH} - Min(D, Q))$
- First underage cost:  $u_1.Max(0, D - Min(D, Q))$
- Second underage cost:  $u_2.Max(0, Min(D, Q) - Q_{PH})$

The optimization of the system consists in determining the quantity which minimizes the expected total cost, which is the sum of the costs pertaining to these 3 situations.

## 2.4 Synthesis of models

The synthesis of the different models discussed is represented in the figure below:



**Figure 9. Synthesis of the different models**

The analysis pertaining to the optimization of the Model 0, known as the classical Newsboy problem, is already done and can be found in various studies. The optimal policy, i.e. the expression of  $Q_0^*$  and  $C_0(Q_0^*)$ , in the case of normally and uniformly distributed demand assumption is provided in App. 2.

The analysis pertaining to the Model 2 is developed in [230]. This investigation derives the optimal policy in cases where demand and errors are either uniformly or normally distributed. For uniform distributions, closed form analytical solutions are obtained whereas when distributions considered are normal, numerical analyses are conducted.

In Chapter 5, our investigation concerns the analysis of Model 1 which is significantly more complex than that of Model 2. Indeed, under Model 2, the second type of shortage situation is never encountered.

To see how errors, by creating a discrepancy between the physical and recorded inventory, can affect the performance of an inventory system, we consider a single period Newsboy

problem which has the general framework presented earlier. The following additional assumptions on demand, errors and cost parameters are also adopted:

The parameters pertaining to Model 1 are given by the vector  $\vec{v} = (h, k, m, \mu_D, \sigma_D, \mu_e, \sigma_e)$  where:

### Cost parameters

$u_1 = k.h$  (i.e.  $k$  is the ratio between the unit shortage type 1 cost and the unit overage cost)

$u_2 = m.u_1$  (i.e.  $m$  is the ratio between unit shortage type 2 cost and unit shortage type 1 cost)

Depending on the specific industry and the product category considered,  $u_1$  and  $u_2$  would have different values. In our analyses, without loss of generality, we will set  $h=1$  and assume  $0.5 \leq k \leq 15$  and  $m \geq 1$ . Note that, the choice concerning the maximum values that cost parameters  $k$  and  $m$  take will vary depending on the nature of the analysis conducted; i.e., in part 2 of chapter 5, when optimizing the system with errors, in order to characterize the qualitative behavior of our model, in some cases, we have voluntarily given very high values to these parameters while, in analyses performed in part 3 of chapter 5, in order to reflect real industrial practices, the maximum value that these cost parameters take is lower.

### Demand

Demand is assumed to be uniformly or normally distributed with parameters  $(\mu_D, \sigma_D)$  where  $\mu_D$  and  $\sigma_D$  are the mean and standard variation of the distribution, respectively. We will assume  $\mu_D=10$  and  $\sigma_D \in [1, 3]$ .

### Errors

Parameters pertaining to errors are  $\mu_e$  and  $\sigma_e$ . This point is further developed in the following section.

### Notations

The additional notations used are as follows:

$x$ : the random variable representing demand

$f(x)$ : the probability density function of demand

$U_x$ : the upper bound of  $x$ , if  $x$  is bounded

$L_x$ : the lower bound of  $x$ , if  $x$  is bounded

$\mu_D$ : the mean of demand

$\sigma_D$ : the standard deviation of demand

$Q_A$ : the random variable representing the physical inventory available

$Q_B$ : the random variable representing the inventory recorded in the information system

$p$ : the random variable associated with errors (cf. multiplicative errors)

$g(p)$ : the probability density function of  $p$



$\mu_p$  : the mean of the random variable  $p$   
 $\sigma_p$  : the standard deviation of the random variable  $p$   
 $U_p$  : the upper bound of  $p$ , if  $p$  is bounded  
 $L_p$  : the lower bound of  $p$ , if  $p$  is bounded  
 $\varepsilon$  : the random variable associated with errors (cf. additive errors)  
 $g(\varepsilon)$  : the probability density function of  $\varepsilon$   
 $\mu_\varepsilon$  : the mean of the random variable  $\varepsilon$   
 $\sigma_\varepsilon$  : the standard deviation of the random variable  $\varepsilon$   
 $U_\varepsilon$  : the upper bound of  $\varepsilon$ , if  $\varepsilon$  is bounded  
 $L_\varepsilon$  : the lower bound of  $\varepsilon$ , if  $\varepsilon$  is bounded

## 2.5 Characterizing errors

Whether defects perturb the physical flow or the data collection process is prone to errors, the random variables representing  $Q_{IS}$  and  $Q_{PH}$  will respectively have the following expressions:  $Q_B = p_1 \cdot Q_A + \varepsilon_1$  and  $Q_A = p_2 \cdot Q + \varepsilon_2$  where  $p_j$  and  $\varepsilon_i$  are random variables with parameters  $(\mu_j, \sigma_j)$  and  $(\mu_i, \sigma_i)$ .

Several special cases of these general expressions can be considered. In this section, we will develop the case associated with Model 1 and use  $Q_B$  to illustrate our examples but, the principles presented here are general and can also be applied for  $Q_A$ .

Thus, in a general setting,  $Q_B$  will be expressed as:  $Q_B = p \cdot Q_A + \varepsilon$  where  $p$  and  $\varepsilon$  are random variables with mean and standard deviation parameters  $(\mu_p, \sigma_p)$  and  $(\mu_\varepsilon, \sigma_\varepsilon)$  respectively.

The way to determine the parameters pertaining to errors would consist in collecting data and comparing values of  $Q_{PH}$  and  $Q_{IS}$  observed in various selling seasons to characterize the types and magnitudes of errors. Since we did not have empirical results pertaining to this comparison, in our model, we will consider that estimates of these parameters come from prior experience and take them as exogenous.

In our model, the random variables representing errors will follow either a uniform or a normal distribution. Assuming that errors are normally distributed is a more realistic hypothesis. But since with this hypothesis, it is difficult to derive a closed form expression of the optimal policy, we have also considered the case of uniformly distributed errors.

3 special cases can be derived from the general expression presented above:

## 1. Errors are multiplicative

$Q_B = p \cdot Q$  where  $p$  is a non negative random variable with parameters  $(\mu_p, \sigma_p)$ . This leads to  $Q_B = p \cdot Q$  with  $E[Q_B] = \mu_p \cdot Q$  and  $\sigma[Q_B] = \sigma_p \cdot Q$ , dependent of  $Q$ .

The absolute discrepancy  $Q_{IS} - Q_{PH} = (p-1) \cdot Q$  is proportional to  $Q$ , and thus large orders tend to be associated with large discrepancies. Errors made by human beings can probably be modeled in this way since one can expect that the probability to make a mistake when identifying or counting items would increase as the order batch size increases.

### a) Interval of variation of $\mu_p$

$0.7 \leq \mu_p \leq 1.3$  would be assumed among values for  $\mu_p$  ( $\mu_p=1$  being the most likely value)

### b) Interval of variation of $\sigma_p$

- **If  $p$  is normally distributed:** Especially for small values of  $Q$ , the ignored negative tail of the distribution of  $Q_{IS}$  might create inaccuracies in the calculation of the expected cost. There are two ways to deal with this issue: **1)** one can chose appropriate parameters for the distribution of  $Q_B$  in order to limit the probability for such cases (cf. multiplicative errors) **2)** the other approach is to assume that the cost function is valid only for values of  $Q$  superior to a critical value (cf. additive or mixte errors).

For a given value of  $\mu_p$ , we will thus limit the maximum value that  $\sigma_p$  can take s.t.

$\sigma_p \leq \mu_p / 3$ . This assumption guaranties values of  $Q_{IS}$  to be positive with a probability  $P = 0.9987$ . (this is an arbitrary choice, we have observed that other authors set the condition  $\sigma_p \leq \mu_p / 2$  [231])

- **If  $p$  is uniformly distributed:** Theoretically, the minimum value that  $Q_{IS}$  can take is equal to  $Q \cdot L_p = Q \cdot (\mu_p - \sigma_p \cdot \sqrt{3})$ . The positivity constraint for this value implies:  $\sigma_p \leq \mu_p / \sqrt{3}$ . Note that constraints above permit us to calculate the maximum theoretical value of  $\sigma_e$  although in reality, the range of values for  $\sigma_e$  will be expected to vary between 0 and 0.2.

## 2. Errors are additive

$Q_B = Q + \varepsilon$  where  $\varepsilon$  is a random variable with parameters  $(\mu_\varepsilon, \sigma_\varepsilon)$ . This leads to  $Q_B = Q + \varepsilon$  with  $E[Q_B] = \mu_\varepsilon + Q$  and  $\sigma[Q_B] = \sigma_\varepsilon$ , independent of  $Q$ .

The absolute discrepancy  $Q_{IS} - Q_{PH} = \varepsilon$  is the same for all values of  $Q$ . This type of errors is particularly plausible for environments where batch sizes are relatively large. Errors occurring in a data collection process realized by a reader which has a scan rate following a stochastic

distribution, as well as human errors -for instance, one individual recording a 7 on an order form with a second person interpreting it as a 9- can also be modeled in this way.

**a) Interval of variation of  $\mu_\varepsilon$**

$-3 \leq \mu_\varepsilon \leq 3$  are among values of  $\mu_\varepsilon$  ( $\mu_\varepsilon = 0$  being the most likely value)

**b) Interval of variation of  $\sigma_\varepsilon$**

- **If  $\varepsilon$  is normally distributed:** In order to prevent assigning negative values to  $Q_{IS}$ , we shall limit the maximum value that  $\sigma_\varepsilon$  can take for a given value of  $\mu_\varepsilon$ . In contrast to the multiplicative model, an inequality between  $\mu_\varepsilon$  and  $\sigma_\varepsilon$  cannot be established since the lower bound of  $Q_{IS}$  depends on  $Q$ . We will set:  $Q + (\mu_\varepsilon - 3 \cdot \sigma_\varepsilon) \geq 0 \Rightarrow Q \geq 3 \cdot \sigma_\varepsilon - \mu_\varepsilon$  which guaranties values of  $Q_{IS}$  to be positive with a probability  $P = 0.9987$ .

- **If  $\varepsilon$  is uniformly distributed:** The same logic presented above leads to:  
 $Q + (\mu_\varepsilon - \sqrt{3} \cdot \sigma_\varepsilon) \geq 0 \Rightarrow Q \geq \sqrt{3} \cdot \sigma_\varepsilon - \mu_\varepsilon$

**3. Errors are mixte**

In between these two models, the third alternative for modeling errors is to set:

$$Q_B = p \cdot Q + \varepsilon \text{ where } \sigma_p = 0 \text{ and } \mu_\varepsilon = 0 \text{ which leads to } E[Q_B] = \mu_p \cdot Q \text{ and } \sigma[Q_B] = \sigma_\varepsilon$$

An approach similar to the previous cases gives:

- **If  $\varepsilon$  is normally distributed:**  $\mu_p \cdot Q + (0 - 3 \cdot \sigma_\varepsilon) \geq 0 \Rightarrow Q \geq 3 \cdot \sigma_\varepsilon / \mu_p$
- **If  $\varepsilon$  is uniformly distributed:**  $Q \geq (\sqrt{3} \cdot \sigma_\varepsilon) / \mu_p$

Thus, depending on the variant of model considered (multiplicative, additive or mixte errors model),  $\mu_e = \mu_p$  (or  $\mu_\varepsilon$ ) and  $\sigma_e = \sigma_p$  (or  $\sigma_\varepsilon$ ).

**3 Sources of errors and location of measurement points**

So far, in order to facilitate the general understanding of the different models we elaborated, the following two points have not been considered:

- Errors modeled by the random variable  $Q_A$  depend on the sources of errors causing variations in the physical flow
- Errors modeled by the random variable  $Q_B$  depend on the locations of points where the measurement(s) is (are) performed

In this part, our aim is to underline the fact that industrial practices may be various, meaning that a more profound definition of what is represented by random variables  $Q_A$  and  $Q_B$  is necessary.

### 3.1 The general framework of industrial practices

#### 3.1.1 The origins of errors perturbing the physical flow

The following scheme is a general representation of perturbations which may affect the physical flow associated with an order placed to the supplier from the moment in which the order is prepared by the supplier to the moment in which products are used by the wholesaler to satisfy demand.

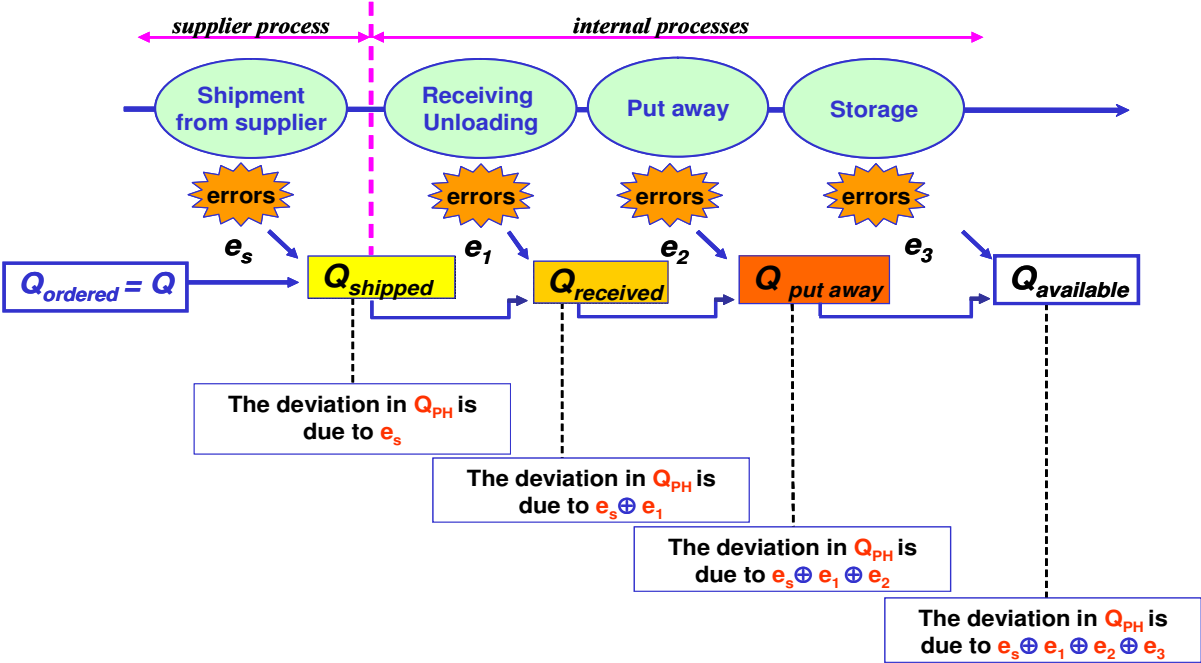


Figure 10. Potential errors perturbing the physical flow

The impact of a perturbation occurring during a process  $i$  is represented by the random variable  $e_i$ .

- $e_s$  represents the aggregate errors in provenance of the supplier (including underages, overages, theft during transportation, etc..),
- $e_1$  represents errors that might create a difference between the effective quantity sent by the supplier and the quantity going into the wholesaler warehouse (this may be, for instance, unreported product movements or theft between the moment in which products are unloaded and the moment in which they are entered within the warehouse),
- $e_2$  represents errors which may arise from the moment in which products are received by the warehouse to the moment in which they are put away on the warehouse shelves,

- $e_3$  represents the impact of factors that may perturb inventory during storage (e.g. theft, damage, misplacement,...)

The amount of products available to satisfy demand is thus the quantity ordered  $Q$  perturbed by the combined effect of all errors.

### 3.1.2 The impact of the location of the measurement point

Depending on the strategy of the warehouse, the collection of data pertaining to the physical flow may be performed at different points. The choice of the location of each measurement point (represented by  $M_i$  in the figure below) is important, since the measurement enables with more or less precision to capture information on errors that may have created deviations in the physical flow in the downstream part of this point.

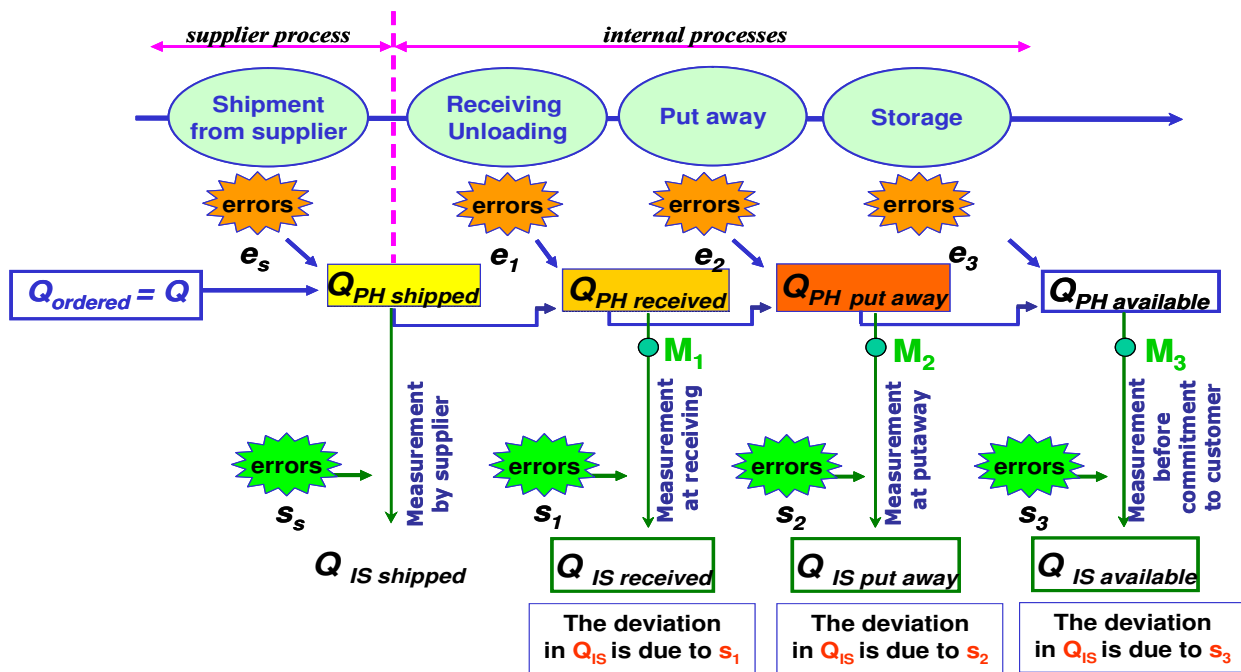


Figure 11. Locations of measurement points

If multiple measurements are made, the ultimate value to be recorded in IS should be clearly defined by warehouse managers.

Information pertaining to the physical flow may also be updated based on order information, without realizing any measurement.

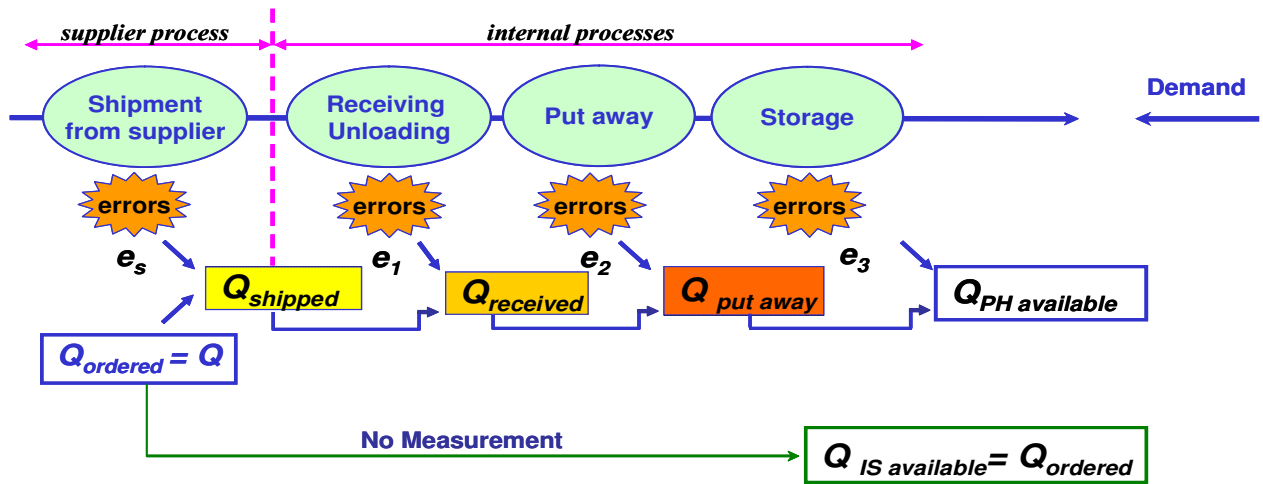


Figure 12. IS inventory data updated based on order data

Examples presented in section 3.1.1. and 3.1.2. enable to understand that the nature and type of errors perturbing the physical flow combined with the potential location of the measurement point(s) would lead to various practices in industry. The following section considers three particular practices to show that, despite the diversity of business cases, each of them can be represented by either one of the models we propose in section 2 or correspond to variants of these models. In an attempt to establish the relationship between the random variables  $Q_A$  and  $Q_B$  we presented previously and real business practices, we consider the following cases:

### 3.2 Some special cases

In practice, it may be difficult to evaluate the individual impact of errors occurring during the different supply chain processes. A more simple representation of the evolution of the physical flow seems thus to be necessary. By aggregating the factors having an influence on the physical flow, we consider two types of errors:

- Aggregated errors stemming from the supply system
- Aggregated internal errors

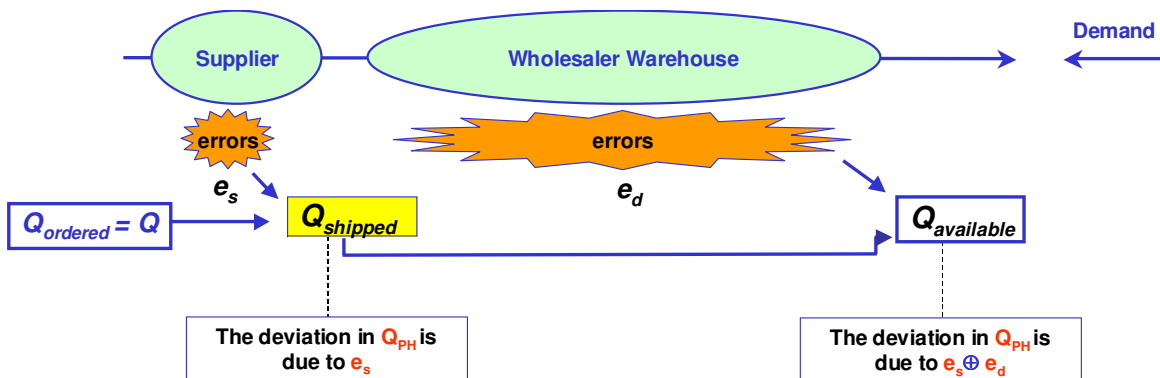


Figure 13. Aggregating errors perturbing the physical flow

### 3.2.1 Case 1 : errors that create variations in the physical flow stem only from the supply system

In this case, we assume that the organization of the wholesaler enables him to detect and eliminate potential errors that may occur internally.

Since errors perturbing the physical flow are done by the supply system, the measurement would be realized at receiving.

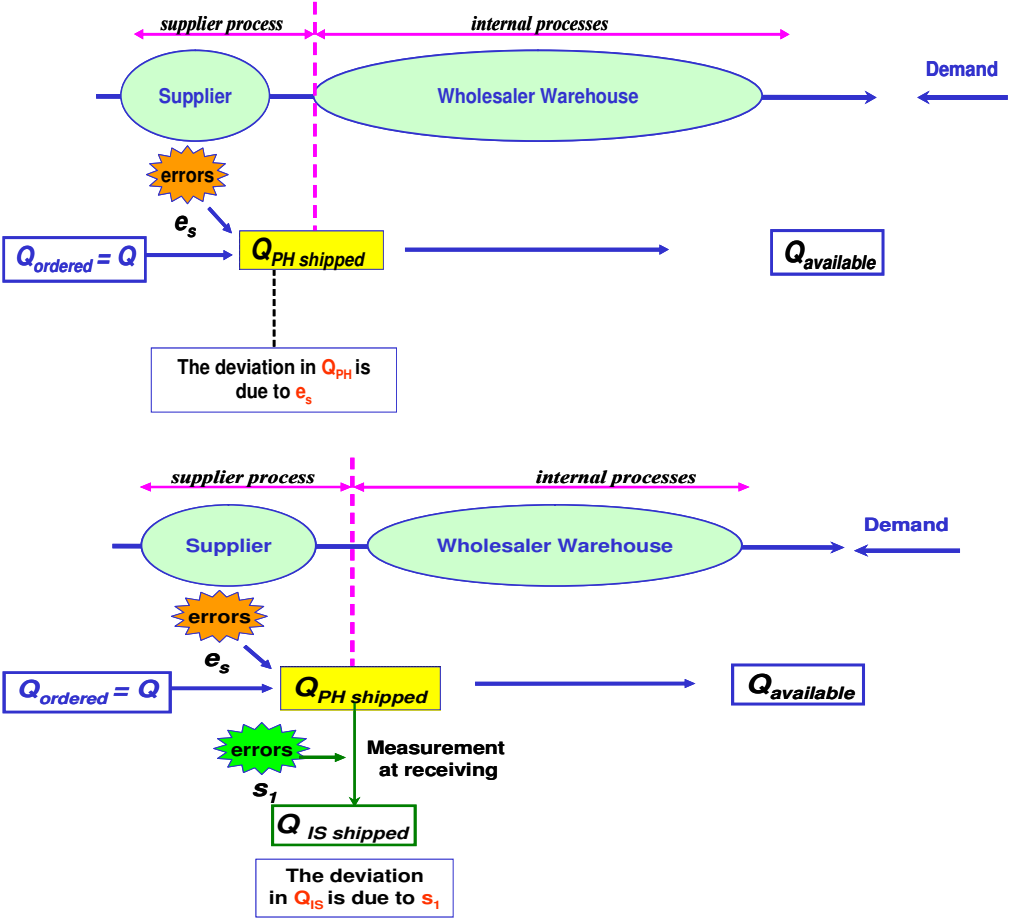


Figure 14. Physical and information flows associated with case 1

In this practical case, the random variables  $Q_A$  and  $Q_B$  can be characterized as follows:

- $Q_A$  represents  $Q$  perturbed by the combined effect of errors stemming from the supply system

$$Q \xrightarrow{+\Delta} Q_{PH} = Q_A$$

where  $\Delta$  represents the impact of deviations from the expected material flow.

- If the measurement is perfect, we have  $Q_B = Q_A$

Depending on the assumption pertaining to  $Q_{invoiced}$ , the amount of products invoiced by the supplier, there are two ways enabling to model this industrial practice:

- If  $Q_{invoiced} = Q_B$ , i.e. situations where the wholesaler pays to the supplier the amount of products physically received, Model 2 presented in section 2.3.2. enables to represent this industrial practice.
- If  $Q_{invoiced} = Q$ , i.e. situations where the amount paid to the supplier is based on the order data, besides the overage and underage cost components associated with Model 2, an additional cost stemming from the quantity  $\Delta$  should be taken into consideration while modeling this case.

This additional cost that will can be expressed by:

$P_A \cdot \max(0, Q_{invoiced} - Q_A) - P_A \cdot \max(0, Q_A - Q_{invoiced})$ , considers the fact that:

- a. If  $Q_{invoiced} > Q_A$ , defects occurring in the physical flow (such as theft, damages, ..) lead to a direct loss of money for the wholesaler
  - b. If  $Q_{invoiced} < Q_A$ , defects occurring in the physical flow (such as overages in the quantity shipped by the supplier) generate a profit for the wholesaler thanks to the received but non paid products
- If the measurement is imperfect,  $Q_B$  represents the impact on  $Q_A$  of errors arising during the data capture process performed at receiving.

Again, two cases should be distinguished depending on the amount invoiced by the supplier:

- If  $Q_{invoiced} = Q$ , a logic similar to the previous case necessitates to take into account an additional cost  $P_A \cdot \max(0, Q_{invoiced} - Q_A) - P_A \cdot \max(0, Q_A - Q_{invoiced})$  besides costs associated with Model 3 while modeling this industrial case.

- Depending on the existing rules to treat litigations and the relative powers of the wholesaler and the supplier,  $Q_{invoiced}$  may be different than  $Q$ . For instance, the amount paid by the wholesaler may be based on  $Q_{invoiced} = Q_B$ , which results in a situation where the wholesaler either incurs a loss of money or makes a profit on non paid products. Over time, since such situations will degrade the relationship between the supplier and the wholesaler (leading to the interruption of the business between the actors), this assumption seems to be not realistic.

- If any measurement is made,  $Q_B = Q$ . Since  $Q_{invoiced} = Q$ , besides overage and underage cost components associated with Model 4, the additional cost stemming from the quantity  $\Delta$  should be taken into consideration to model this industrial practice.



### 3.2.2 Case 2 : errors impacting the physical flow are internal

This case is observed if the organization of the supplier enables him to identify and eliminate entirely errors until products are received by the wholesaler, whereas the internal organization of the wholesaler does not permit him to track accurately the physical flow of goods stored within the warehouse.

Errors perturbing the physical flow being made internally, if the wholesaler knows that the supplier is reliable, he may decide to perform a unique scan process just before the moment at which he commits himself to satisfy stores' demand. Perfect measurement is achieved when the data collection process is reliable, while in the case of imperfect measurement, errors create perturbations.

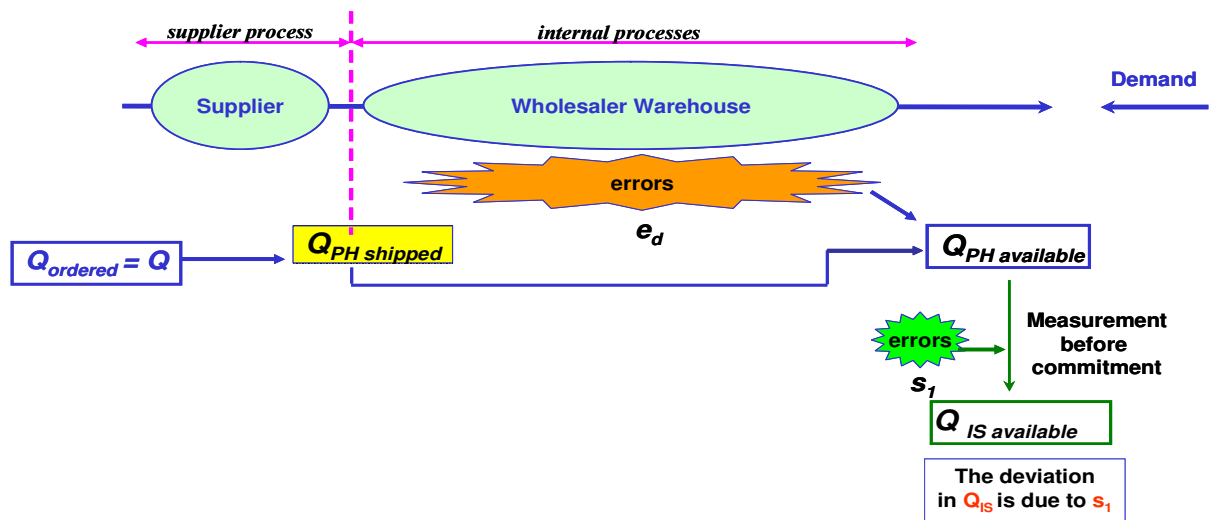


Figure 15. Physical and information flows associated with case 2

In this practical case, the random variables  $Q_A$  and  $Q_B$  can be characterized as follows:

- $Q_A$  represents  $Q$  perturbed with the combined effect of internal errors (theft, damaged, perished or obsolete products) arising until the moment at which stores' orders are prepared by the wholesaler
- If the measurement is perfect, we have  $Q_B = Q_A$

In this case, since the supplier is able to proof that the quantity sent is equal to  $Q$ , one will probably have  $Q_{invoiced} = Q$ . In order to model this practice, besides overage and underage cost components associated with Model 2, an additional cost stemming from the quantity  $\Delta$  should be taken into consideration. This additional cost, given by  $P_A \cdot \max(0, Q_{invoiced} - Q_A)$ , considers the fact that due to defects occurring during storage, the wholesaler incurs a direct loss of money.

- If the measurement is imperfect,  $Q_B$  represents the impact on  $Q_A$  of errors arising during the data capture process performed within the wholesaler's warehouse. (cf. Model 3)
- If any measurement is made,  $Q_B = Q$ . Since  $Q_{invoiced} = Q$ , besides overage and underage cost components associated with Model 4, the additional cost stemming from the quantity  $\Delta$  should be taken into consideration to model this industrial practice.

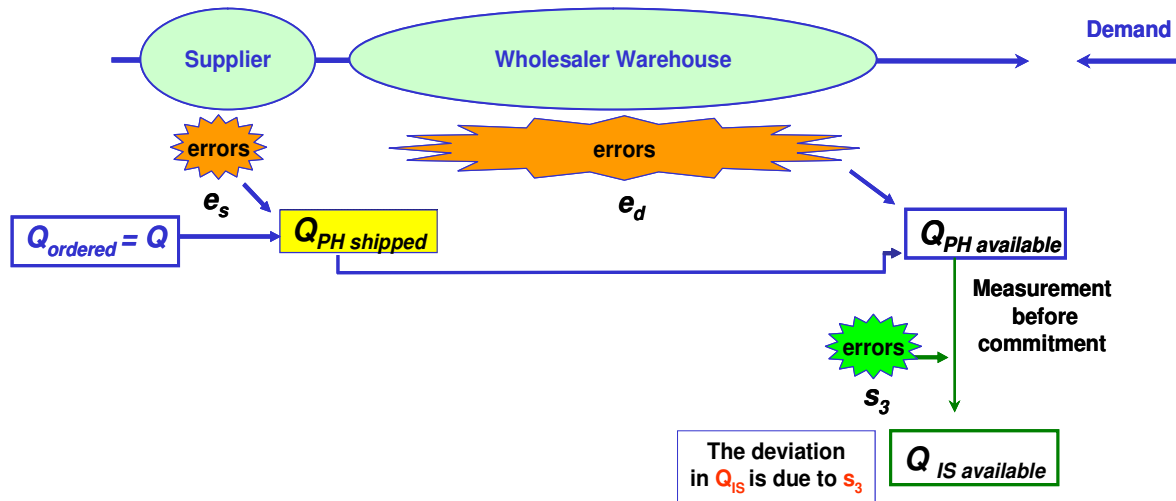
### **Remark**

If products stored within the wholesaler warehouse are subject to other execution errors such as misplacement, one part of the quantity of products will not be accessible since items will not be at their exact locations. In this case,  $Q_A$  integrates the effect of misplacement errors, i.e.  $Q_A = Q_{shelf}$  where  $Q_{shelf}$  is the physical quantity of products available on shelf, i.e. at the right location. To model this type of errors, beside the underage and overage costs associated with Model 3 (if the data capture process is not reliable) or Model 2 (if the data capture process is entirely reliable), one should also consider the additional cost  $h.(Q - Q_A)$ , expressing the fact that misplaced products, which are assumed to be found once stores' orders are satisfied, generate an additional inventory cost.

### **3.2.3 Case 3 : errors impacting the physical flow stem from the supplier and internal defects**

This case corresponds to the combination of errors presented previously: neither the supplier nor the wholesaler is able to detect and eliminate errors impacting the physical flow.

If the wholesaler is expecting to have an unreliable incoming flow as well as internal defects, he may, for instance, choose to make a measurement before commitment to customers in order to take into consideration the combined impact of errors.



**Figure 16. Physical and information flows associated with case 3**

In this case, the characterization of random variables  $Q_A$  and  $Q_B$  depend on the nature and type of errors perturbing the physical flow and the location of the measurement point(s). The model that represents each situation can be identified by conducting an analysis similar to the previous cases.

### Remark

It should be noted that in real cases, managers may encounter difficulties in defining the data update strategy to implement since they may not have enough data enabling them a whole visibility on the evolution of the physical flow (and the associated potential errors). For instance, cases where a unique measurement is performed during the receiving process of a warehouse within which internal defects continue to cause variations in inventory may be observed. Such situations in which, even if a measurement is made, the fact that the physical quantity changes after the measurement renders independent the initial measurement from the final physical quantity. This is not modeled by our models since we assume implicitly that the physical quantity does not vary once the measurement is realized.

## 4 Assessing the impact of errors

Whether defects perturb the physical flow or the data collection process is prone to errors, the result is the occurrence of additional inventory related costs. If we consider an initial situation where errors are made and if the decision system does not consider the likelihood for errors creating divergences from the expected nominal flows, it would act as if there were no defects and decide to order  $Q_0^*$ . The cost incurred will be  $C_j(Q_0^*)$  where  $C_j(Q)$  is referring to the cost associated with a model with errors.

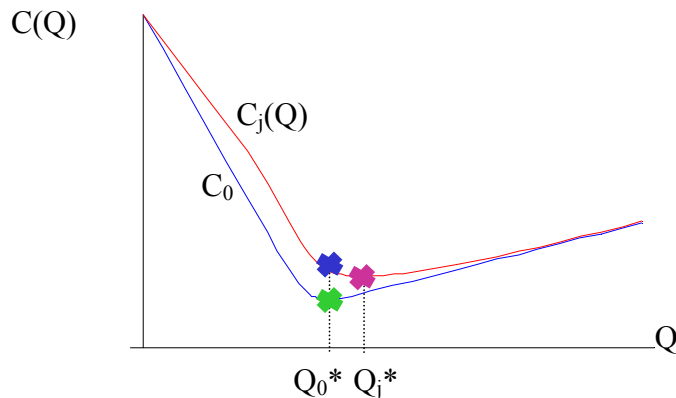
The cost penalty of ordering  $Q_0^*$  in this system can be measured by the following indicator:

$$R_3 = \frac{C_j(Q_0^*) - C_0(Q_0^*)}{C_j(Q_0^*)}$$

It can be equivalently interpreted as the benefits of moving from an imperfect situation (Model j) to a perfect situation (error free) captured by Model 0.

We chose this indicator since we believe that, most of companies, ignore the existence of errors and operate actually at  $C_j(Q_0^*)$ .  $C_0(Q_0^*)$  being the baseline to assess savings resulting from eliminating errors,  $R_3$  takes into account the additional cost generated by defects in information and/or physical flow within a facility.

While the ratio above represents the total gain stemming from improving an inventory system prone to errors, it is also possible to split the total gain in two parts. As represented in the figure below, there are two ways to improve such an inventory system:



**Figure 17. Costs associated with the Model with Errors and a Model without Errors**

#### **4.1 Improving the performance by taking into account the probability for errors when ordering**

If managers know that flows are prone to errors and if it is possible to estimate the parameters pertaining to errors, inventory related costs could be reduced by optimizing the system, i.e. by ordering  $Q_j^*$  instead of  $Q_0^*$ . The cost incurred will be  $C_j(Q_j^*)$ .

Therefore, the penalty due to an inappropriate order quantity resulting from a poor knowledge of the inventory system can be estimated by  $C_j(Q_0^*) - C_j(Q_j^*)$ . In our analyses, we will use

the ratio  $R_1 = \frac{C_j(Q_0^*) - C_j(Q_j^*)}{C_j(Q_0^*) - C_0(Q_0^*)}$  to evaluate the part of the total gain which is achieved

thanks to the optimization of the system by considering the probability for errors when ordering.

#### 4.2 Improving the performance by taking other actions

Once the optimization in presence of errors is realized, the cost can further be reduced by deploying appropriate action plans eliminating errors. Examples of such actions using a range of people, process and technologies are listed below:

- Re-engineer the physical organization of the warehouse
- Use a new product identification technology that reduces scanning errors
- Use a technology that enables to reduce theft in the warehouse
- Use a technology to effectively track products' sell by dates
- Double verify receiving and shipment processes
- Improve the actual processes (by defining new working procedures for operators, labor resource priorities and more appropriate indicators to evaluate their performance)
- Do benchmarking analysis and develop personnel awareness building actions that focus on the operational weaknesses

The performance of each action plan, i.e. its contribution to eliminate a certain type of error, as well as the cost associated with its implementation would vary. For instance, different means could be used to reduce (or even eliminate) the issue of theft: the use of EAS tags coupled with processes supporting them or better defined operators' working procedures coupled with more frequent verification processes or the use of Auto ID technology coupled with processes supporting it, etc... Similarly, within a warehouse using the Bar Code system, continuous improvement actions which sensitize operators to the consequences of misplaced items could help to reduce the frequently observed unreported product movements.

Since the impact of actions eliminating errors on the total cost can be evaluated by  $C_j(Q_j^*) - C_0(Q_0^*)$ , we will use a ratio complementary to  $R_1$ , namely:

$R_2 = \frac{C_j(Q_j^*) - C_0(Q_0^*)}{C_j(Q_0^*) - C_0(Q_0^*)}$  to evaluate the percentage of the total gain that is achieved if

appropriate actions are deployed to eliminate errors.

## 5 The Auto ID technology as a lever of performance improvement

The use of the Auto ID technology that is becoming available offers companies an opportunity to eliminate errors perturbing the physical and information flows at the same time. This technology has two major impacts on improving performance:

1. **Impact on the information flow:** the technology allows an accurate capture of data associated with the physical flow.

Depending on the initial situation considered, this impact can be quantified by comparing:

- the cost pertaining to Model 4 to the cost pertaining to Model 2
- the cost pertaining to Model 3 to the cost pertaining to Model 2
- the cost pertaining to Model 1 to the cost pertaining to Model 0

These comparisons enable to quantify the improvements resulting from a more accurate IS inventory data given the existing physical flow of products.

2. **Impact on the physical flow:** coupled with other processes supporting it, the Auto ID technology contributes to the elimination of errors that cause perturbations in the physical flow. The elimination of theft and a faster detection of perished items can be cited among such contributions.

The impact of Auto ID on the physical flow can be quantified by comparing the cost pertaining to Model 2 to the cost of Model 0.

In situations where errors impacting the physical flow stem from the supplier, the impact of the use of Auto ID by the supplier can be evaluated by comparing the cost pertaining to Model 3 to the cost pertaining to Model 1.

The scheme below represents these two impacts:

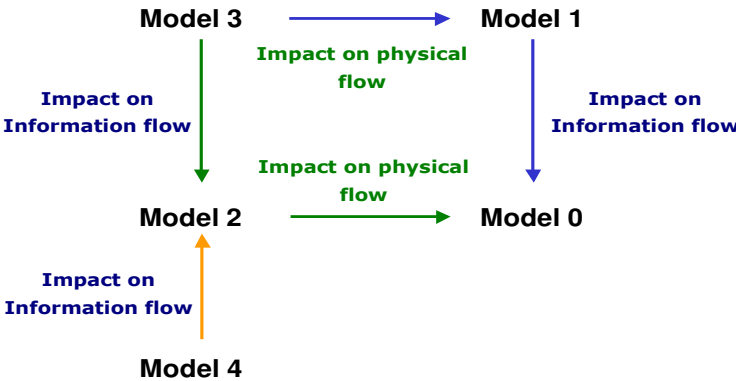


Figure 18. Impacts of the Auto ID technology

## 6 Quantifying savings associated with the use of Auto ID

As reported by [203], for managers having the responsibility to cost justify an investment in a new data collection application, estimating the initial and ongoing costs of the new system (including maintenance, technical support, change management,..) is relatively easy. The difficulty resides in estimating the savings to be derived from the investment.

For an enterprise that uses initially a Bar Code type identification and data capture system, the decision to invest in a new technology would depend on the trade off between the cost of acquisition and implementation of the new system and savings resulting from the investment:

- Data relative to the cost associated with the use of Auto ID can be found in several studies (cf. Chapter 1).
- The benefit of Auto ID may be evaluated by comparing the cost of the System with Errors where defects perturb both the physical and information flows, i.e. Model 3, with the cost of the System without Errors, i.e. Model 0. This comparison will help to answer our initial question which was « what is the cost reduction stemming from eliminating errors that perturb the physical flow **and** the information flow within an inventory system? »

Model 3 considers the simultaneous impact of both types of error. As stated before, the analysis of such a model is very tedious, if not impossible. Secondly, even if this model could be solved, it would probably be very difficult to interpret the results and get some interesting insights. Therefore, the comparison between Model 3 and Model 0 can be made in two steps :

- Comparing the optimal cost associated with Model 2 with the optimal cost of Model 0 answers the question « what is the cost reduction stemming from eliminating errors that perturb the physical flow? » (cf. Figure 19)
- Comparing the optimal cost associated with Model 1 with the optimal cost of Model 0 answers the question « what is the cost reduction stemming from eliminating errors that perturb the item identification and inventory data gathering process? » (cf. Figure 19)

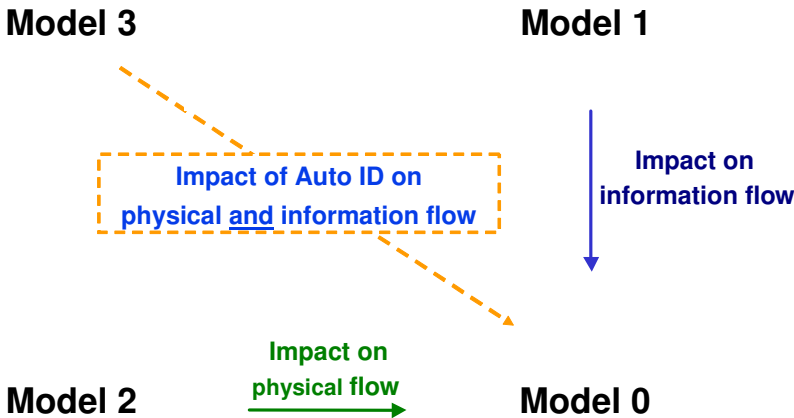


Figure 19. Decomposition of the problem

Indeed, if  $G_{ij}$  represents the reduction of cost due to the transition from Model  $i$  to Model  $j$ , we have:

- $G_{30} = G_{31} + G_{10} \leq G_{20} + G_{10}$
- $\max(G_{20}, G_{10}) \leq G_{30}$

which leads to:  $\max(G_{20}, G_{10}) \leq G_{30} \leq G_{20} + G_{10}$

## **Conclusion**

Our research reveals that although supply chain scholars very often assume the availability of error free inventory data to determine and implement a specific inventory policy, accurate data should not be taken for granted and without this, the performance of an inventory system will be compromised. We have shown that, even by using an advanced identification technology like the Bar Code system, a company may not know the exact quantity of products stored within a facility. This mainly results from factors that lead to perturbations impacting the physical flow of products, on the one hand, and errors polluting the data capture, on the other hand. We separated these two factors and presented in a structured way the root causes, magnitudes and characteristics of each of them.

Most of the existing literature on inventory inaccuracy recognizes that inventory inaccuracies stem from several factors presented in this chapter. Nevertheless, there has been limited effort on a better understanding of the relationship between the use of identification and data capture technology and its impact on physical and information flows. Our detailed analysis clarifies the main sources of inefficiencies that cause perturbations in physical flow and information flow, shows how the different industrial practices can be modelled and pinpoints the improvements that will result from the use of Auto ID.



## Chapter 5

# A QUANTITATIVE ANALYSIS OF THE IMPACT OF INVENTORY RECORD INACCURACIES

### Introduction

In Model 1, our aim is to evaluate the economical impact of potential mismatches between the physical and recorded inventory levels. Remember that this model does not correspond to a particular industrial practice. The reason why we are highly motivated to analyze and get insights from this (fictive) model is that it represents a particular case of a more general Model with errors, i.e. Model 3. The assumptions pertaining to this model are developed in sections 2.4. and 2.5. of Chapter 4. Among them, the following ones characterize this model:

- **Hypothesis concerning  $Q_A$ :** there is no divergence between the quantity ordered  $Q$  and the physical quantity  $\Rightarrow Q_A = Q_{PH} = Q$
- **Hypothesis concerning  $Q_B$ :** the data collection process is prone to errors which affect the information flow and therefore, the warehouse does not know exactly the quantity of products available physically  $\Rightarrow Q_B = Q_{IS} \neq Q$ .

Chapter 5 is divided into 3 parts: In the first part, we present the general principles to formulate the expected total cost and then, formulate the Newsboy problem for different models: in each model, demand and errors are either uniformly or normally distributed and errors are considered to be either multiplicative, additive or mixte. The second part derives the optimal policy in presence of inventory inaccuracies for each model presented in Part 1. Part 3 assesses the impact of inaccuracies by conducting several analyses; we first investigate by how much the performance of an inventory system is degraded when managers ignore inventory inaccuracies and errors are left uncorrected; then, we evaluate the relative cost reduction that stems from optimizing the system in presence of errors and finally, discuss the use of the Auto ID technology as a response to the inventory inaccuracy problem.

## Part 1: Formulation and analysis of the expected total cost

Steps to follow to formulate the expected cost function depend on whether the distributions considered are bounded or not. Since, if the distributions of demand and errors are bounded, the formulation of the expected cost function necessitates further development. In the following section, we present the main principles of this formulation and then express the expected cost when errors are multiplicative, in order to illustrate these principles. Our approach is generic and can be adapted to other models where demand and errors are uniformly distributed (e.g. additive or mixte errors).

Then, in section 2, we derive the expected cost function when demand and errors are normally distributed.

### 1. Uniformly distributed demand and errors

The methodology presented here can be used when the distributions of demand and errors are bounded, if distributions are uniform for instance.

#### 1.1. The relative positions of demand and error distributions: notion of configuration

If distributions of demand and errors are bounded, different configurations have to be considered to correctly formulate the expected cost function. A configuration corresponds to a specific position between the distribution of demand and the distribution of errors. Each configuration can also be assimilated to an interval of variation of  $Q$ .

#### 1.2. Elementary costs associated with a configuration

For each configuration,  $Q_{IS}$  and  $D$  being random variables, different relationships exist between  $Q_{PH}$  (which is equal to  $Q$ ),  $Q_{IS}$  and  $D$ . Remember that the cost associated with Model 1 was expressed by: (cf. section 2.3.1. in Chapter 4)

$$C_1(Q) = h \cdot \text{Max}(0, Q_{PH} - \text{Min}(D, Q_{IS})) + u_1 \cdot \text{Max}(0, D - \text{Min}(D, Q_{IS})) + u_2 \cdot \text{Max}(0, \text{Min}(D, Q_{IS}) - Q_{PH})$$

The table below develops exhaustively the individual cases that generate the elementary costs which correspond to an overage and/or an underage penalty. The expected cost pertaining to a configuration will be obtained by summing the elementary costs.

Case	Relationship between $Q_{PH}$ , $Q_{IS}$ and $D$	Type of cost associated
1	$Q_{IS} \leq Q_{PH} \leq D$	$u_1, h$
2	$Q_{PH} \leq Q_{IS} \leq D$	$u_1, u_2$
3	$Q_{IS} \leq D \leq Q_{PH}$	$u_1, h$
4	$Q_{PH} \leq D \leq Q_{IS}$	$u_2$
5	$D \leq Q_{PH} \leq Q_{IS}$	$h$
6	$D \leq Q_{IS} \leq Q_{PH}$	$h$

**Table 1. Potential elementary costs associated with a configuration**

### 1.3. The expected total cost

The expected total cost is the juxtaposition of a set of sub functions where each sub function expresses the cost associated with a specific configuration. The continuity of the expected total cost function for all values of  $Q$  should be verified.

To illustrate the concepts introduced above, the following section develops the formulation of  $C_1(Q)$  when errors are multiplicative and when they follow a uniform distribution.

### 1.4. Multiplicative errors

#### 1.4.1. Example Case

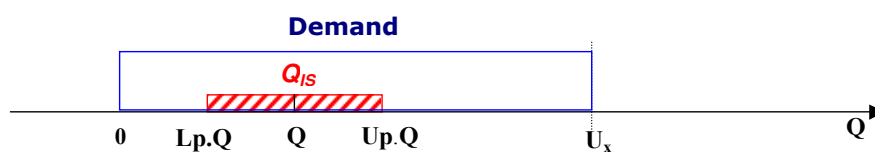
In the example treated below, we assume that  $L_x = 0$  and  $\mu_p = 1$  in order to limit the number of different configurations to consider.

#### a) The relative positions of the distributions of demand and errors

One can consider 4 potential positions between the distributions of errors and demand:

##### ▪ Configuration 1

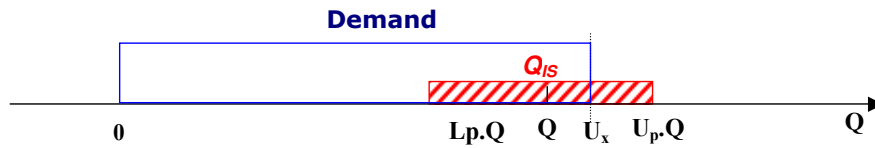
In this configuration, values that  $Q_{IS}$  can take are assumed to be smaller than the maximum value of demand.



Configuration	Relation between the distributions of demand and errors	Interval of variation of $Q$
Configuration 1	$\text{Max } Q_{IS} \leq \text{Max } D$	$0 \leq Q \leq U_x / U_p$

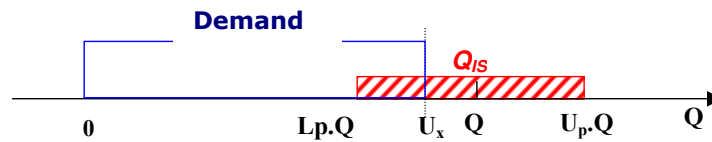
▪ **Configuration 2a**

In configuration 2, values that  $Q_{IS}$  can take might be superior to the maximum value of demand. In contrast to configuration 2.b., in configuration 2.a.,  $Q$  is inferior to  $U_x$ .



Configuration	Relation between the distributions of demand and errors	Interval of variation of $Q$
Configuration 2a	$\text{Max } Q_{IS} \geq \text{Max } D \text{ and } Q \leq \text{Max } D$	$U_x / U_p \leq Q \leq U_x$

▪ **Configuration 2b**



Configuration	Relation between the distributions of demand and error	Interval of variation of $Q$
Configuration 2b	$\text{Max } Q_{IS} \geq \text{Max } D \text{ and } Q \geq \text{Max } D$	$U_x \leq Q \leq U_x / L_p$

The last configuration corresponds to the situation where values of  $Q_{IS}$  are superior to the maximum value of demand. We did not consider it since the optimal quantity to order will never be found within this configuration.

**b) Expression of the elementary costs**

The following table represents the calculation of the expected cost associated with configuration 1, i.e.  $C_1^{config1}(Q)$ :

Case i		Cost Type	Elementary cost $C_i(Q)$ associated with case i
1	$Q_{IS} \leq Q_{PH} \leq D$	$u_1, h$	$u_1 \int_{p=L_p}^1 \int_{x=Q}^{\infty} (x - pQ)f(x)dxg(p)dp + h \int_{p=L_p}^1 \int_{x=Q}^{\infty} (Q - pQ)f(x)dxg(p)dp$
2	$Q_{PH} \leq Q_{IS} \leq D$	$u_1, u_2$	$u_1 \int_{p=1}^{U_p} \int_{x=p^*Q}^{\infty} (x - pQ)f(x)dxg(p)dp + u_2 \int_{p=1}^{U_p} \int_{x=p^*Q}^{\infty} (pQ - Q)f(x)dxg(p)dp$
3	$Q_{IS} \leq D \leq Q_{PH}$	$u_1, h$	$u_1 \int_{p=L_p}^1 \int_{x=p^*Q}^Q (x - pQ)f(x)dxg(p)dp + h \int_{p=L_p}^1 \int_{x=p^*Q}^Q (Q - pQ)f(x)dxg(p)dp$
4	$Q_{PH} \leq D \leq Q_{IS}$	$u_2$	$u_2 \int_{p=1}^{U_p} \int_{x=Q}^{p^*Q} (x - Q)f(x)dxg(p)dp$
5	$D \leq Q_{PH} \leq Q_{IS}$	$h$	$h \int_{p=1}^{U_p} \int_{x=0}^Q (Q - x)f(x)dxg(p)dp$
6	$D \leq Q_{IS} \leq Q_{PH}$	$h$	$h \int_{p=L_p}^1 \int_{x=0}^{p^*Q} (Q - x)f(x)dxg(p)dp$
<b>Total cost</b>			$= C_1^{config1}(Q) = \sum_{i=1}^6 C_i(Q)$

**Table 2. Elementary cost associated with configuration 1**

### Observation

The expected costs associated with the other configurations are obtained in a similar way (cf. App 1). The expression of the expected cost may be particularly complex for certain configurations. To illustrate this, we consider the expression of the expected shortage type 2 cost associated with the case  $Q_{PH} < D < Q_{IS}$  for  $Q$  within the interval  $U_x/U_p \leq Q \leq U_x$ , i.e. configuration 2.a. This cost would have two components: **a)** the first component is associated with values of  $Q_{IS}$  that may be between  $Q_{PH}$  and  $U_x$  **b)** the second component is associated with values of  $Q_{IS}$  that may be between  $U_x$  and  $U_p$

Therefore, the total cost will be given by:

$$\begin{aligned}
& u_2 \cdot \int_{x=Q}^{p \cdot Q} \int_{p=1}^{\frac{U_x}{Q}} (x - Q)f(x)g(p) + u_2 \cdot \int_{x=Q}^{U_x} \int_{p=\frac{U_x}{Q}}^{U_p} (x - Q)f(x)g(p) \\
& = \frac{u_2 \cdot (U_x - Q)^3}{12 \cdot \sqrt{3} \cdot Q \cdot U_x \cdot \sigma_e} + \frac{u_2 \cdot (Q - U_x)^2 \cdot (Q - U_x + \sqrt{3} \cdot Q \cdot \sigma_e)}{4 \cdot \sqrt{3} \cdot Q \cdot U_x \cdot \sigma_e}
\end{aligned}$$

### c) The expected total cost

The sequence of configurations to consider in order to formulate the expected total cost is therefore given by;  $Q \in [0, U_x/U_p]$ ,  $Q \in [U_x/U_p, U_x]$ ,  $Q \in [U_x, U_x/L_p]$ ,  $Q > U_x/L_p$ . The expected total cost is the juxtaposition of the sub functions associated with each of these intervals.

#### **d) Optimization of the expected total cost**

In certain intervals of variation of  $Q$ , a closed form analytical solution can be found for the optimal policy whereas for other configurations, the expected total cost is in the form of a rational function (cf. example above). In this case, several methods<sup>1</sup> can be used to derive the optimal policy. The results obtained by this way are hard to exploit for further insights since their expressions are too complex. Our approach is therefore to evaluate the optimal policy by conducting numerical analyses; by using numerical integration techniques, for each interval of variation of  $Q$ , we determine  $(Q_{\min})_{\text{int}_i}$ , i.e. the value of  $Q$  minimizing the cost function associated with a given interval  $i$ . This value is a potential candidate for the optimal quantity if **(a)**  $(Q_{\min})_{\text{int}_i} \in R^+$  and **(b)**  $(Q_{\min})_{\text{int}_i}$  is within the interval considered. The convexity analyses of the different sub functions lead to two situations: **1)** there is a unique quantity  $(Q_{\min})_{\text{int}_j}$  that satisfies simultaneously these two conditions, in other words, the expected total cost is minimized for  $Q_1^* = (Q_{\min})_{\text{int}_j}$  **2)** there are two local minima - one at  $Q=0$ , one at  $Q = (Q_{\min})_{\text{int}_j}$ . In this case, the global minimum is the quantity for which the expected total cost is at its minimum.

#### **1.4.2. Generalization of the formulation of the expected cost function**

##### **▪ Relaxing the constraint on $L_x$**

###### **a) Expressing the expected total cost**

In the example developed above, there was only one sequence of configuration to consider (cf. part **c)** of the previous section). Depending on values of system parameters, in contrast to this example, there may be potentially more than one sequence of configurations to consider. Therefore, the expected total cost would be expressed by more than one cost function. This adds another dimension of complexity to the analysis of the model.

For instance, if  $L_x \neq 0$ , depending on the particular sequence of configurations,  $C_1(Q)$  will be expressed by one of the cost functions  $Cost_{ij}(Q)$  which are each, associated with a particular sequence of configurations. The formulation of these cost functions is developed in App 2 for multiplicative errors. For additive and mixte errors, these general principles are also valid.

After having verified the properties of each  $Cost_{ij}(Q)$  ensuring that there is a unique value of  $Q$  minimizing it, we identify the interval of variation of  $Q$  (equivalently the configuration) in

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<sup>1</sup> Methods for solving a third degree polynomial function; cf. <http://villemmin.gerard.free.fr>, <http://www.spiderhog.com/Math/3rd.htm>, <http://www.cnice.mecd.es>

which the optimal quantity to order is, by evaluating the optimality condition  $\frac{dCost_{ij}(Q)}{dQ} = 0$ .

(cf. part **d**) of the previous section)

### **b) Tracking the evolution of the optimal policy**

In order to track the evolution of  $Q_1^*$  for increasing values of a chosen parameter pertaining to errors (mean or variance), one should evaluate the location of  $Q_1^*$  (equivalently the configuration within which it is) for each value of this parameter. For this purpose, we have developed an algorithm which is built upon the following general principles:

- For given values of system parameters, i.e.  $(L_x, U_x, L_p, U_p, k, m)$ , we first identify the cost function  $Cost_{ij}(Q)$  to consider and determine the optimal quantity to order.
- If the parameter pertaining to errors increases,  $Q_1^*$  remains in this configuration until the errors' parameter achieves a critical value. This critical value separates one configuration from another. If the parameter is higher than the critical value, two cases are observed: either  $Q_1^*$  is found in another configuration of the same cost function  $Cost_{ij}(Q)$  or  $Q_1^*$  switches from this cost function to another.

The transition occurs when system parameters satisfy the condition associated with one of these two cases. Steps to follow to determine the optimal policy and the new critical value are again the same.

An example case that considers the evolution of  $Q_1^*$  for varying values of  $\sigma_e$  (for multiplicative errors) is developed in App 3 to facilitate the understanding.

- **Relaxing the constraint on  $\mu_p$**

Similarly, assuming  $\mu_p \neq 1$  increases the number of configurations to consider (cf. example provided in App 4). An approach similar to the section 1.4.1. will permit to formulate the expected cost function when there is a relaxation on potential values that  $\mu_p$  can take.

In the remaining of the dissertation, when we talk about uniformly distributed multiplicative errors, our focus will be on the specific case of  $(\mu_p = 1; L_x = 0)$ .

### **1.4.3. The general properties of the expected total cost**

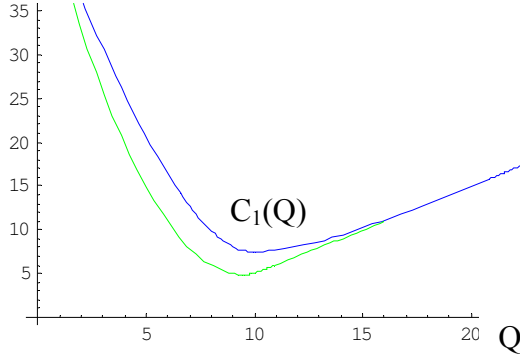
The shape of the expected cost function may be of two types: the cost function is either totally convex for  $Q$  in  $[0, \infty[$  or it is concave for  $Q$  in  $[0, U_x]$  and convex for  $Q$  in  $[U_x, \infty[$ . This mainly depends on the convexity of  $C_1^{config1}(Q)$ :

- If  $C_1^{config1}(Q)$  is convex, there is a unique global minimum

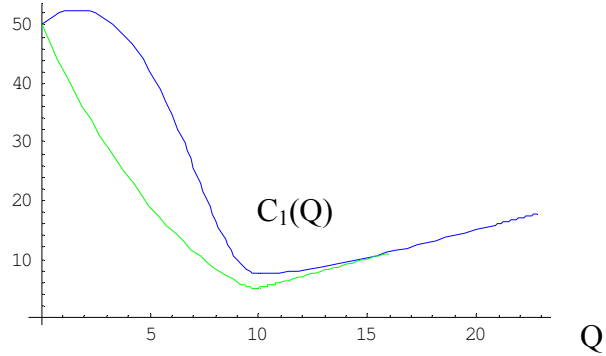
- If  $C_1^{config1}(Q)$  is concave, there might be two local minima - one at  $Q=0$ , one at  $Q>0$ .

In graphs below, the green curve is drawn for  $\sigma_e = 0.05$ , while the blue one is for  $\sigma_e = 0.3$ .

$U_x=10, m=2, k=10, h=1$



$U_x=10, m=10, k=10, h=1$



**Figure 1. Shape of the cost function**

It is possible to evaluate the convexity of the cost function for varying values of system parameters. For instance, in the example developed in App 5, by giving constant values to the other parameters, we have determined the critical values of  $m$  for which the convexity of the cost function varies. Similar analyses can be done for varying values of other parameters such as  $\sigma_e$  or  $k$ .

### Cost Components

Analyzing the different components of the expected total cost contributes to a better understanding of the model when system parameters vary, especially those pertaining to errors. By splitting the total cost, we obtain the following individual cost components:

1. Shortage type 1 cost, i.e.  $B_1(Q)$ , incurred if  $D \geq Q_{IS}$
2. Overage cost, i.e.  $H(Q)$ , incurred if  $\min(D, Q_{IS}) \leq Q_{PH}$
3. Shortage type 2 cost, i.e.  $B_2(Q)$ , incurred if  $\min(D, Q_{IS}) \geq Q_{PH}$

**$B_1(Q)$** : Due to errors, this penalty is higher (than the system without errors) mainly because when  $Q_{IS} = Q_{PH} = Q$ , it is incurred if  $D \geq Q_{PH}$ . Whereas, in presence of errors, it is incurred not only if  $D \geq Q_{PH}$  but also if  $D \leq Q_{PH}$ .

$B_1(Q)$  can be divided into two parts: in comparison with the system without errors, the impact of errors is either to modify the shortage type 1 cost incurred (i.e. cases  $Q_{IS} \leq Q_{PH} \leq D$  and  $Q_{PH} \leq Q_{IS} \leq D$  associated with  $B_1^1(Q)$  which is defined in the interval  $0 \leq Q \leq U_x$ ) or to generate an additional cost that is not incurred in the system without errors (i.e. the case  $Q_{IS} \leq D \leq Q_{PH}$  associated with  $B_1^2(Q)$  which is defined in the interval  $0 \leq Q \leq U_x/L_p$ ). Further information on  $B_1(Q)$  and its components is provided in App 6.



**$H(Q)$** : In model 0, there is an inventory leftover at the end of the period if  $Q_{PH} = Q \geq D$ . In presence of errors, an overage cost is incurred not only if  $Q_{PH} = Q \geq D$  but also if  $Q_{PH} = Q \leq D$  (e.g. the case  $Q_{IS} \leq Q_{PH} \leq D$ ). Furthermore, the quantity in excess in model 0 is equal to  $(Q_{PH}-D)$  whereas in model 1, due to errors, it may be more than  $(Q_{PH}-D)$ .

We decomposed the overage cost into two parts:

1)  $H^1(Q)$  defined for  $0 \leq Q \leq U_x/L_p$  is the overage penalty incurred if  $\min(D, Q_{IS}) = Q_{IS}$ , it is calculated based on the difference  $(Q_{PH} - Q_{IS})$  and 2)  $H^2(Q)$  defined for  $\forall Q \geq 0$  is the overage penalty incurred if  $\min(D, Q_{IS}) = D$  and is calculated based on the difference  $(Q_{PH} - D)$ .

The impact of errors is to increase the overage cost (i.e.  $Q_{IS} \leq D \leq Q_{PH}$ ) or to generate an additional overage cost that is not incurred in the system without errors (i.e.  $Q_{IS} \leq Q_{PH} \leq D$ ). This is due to the fact that, since the inventory recorded in IS may be smaller than the physical quantity, one part of inventory (which is within the warehouse) is not considered to satisfy demand since not recorded in IS. Further information on this cost and its components is provided in App 7.

**$B_2(Q)$** : For a given value of  $\sigma_e$ , this component, defined for  $0 \leq Q \leq U_x$ , achieves a maximum value since:

- it is increasing in  $Q$  because: a) the quantity in shortage associated with the case  $Q_{PH} \leq Q_{IS} \leq D$  increases and b) the interval of potential values for demand generating the case  $Q_{PH} \leq D \leq Q_{IS}$  becomes wider
- and it is decreasing for higher values of  $Q$  since the probability  $P(Q_{PH} \leq D)$  decreases.

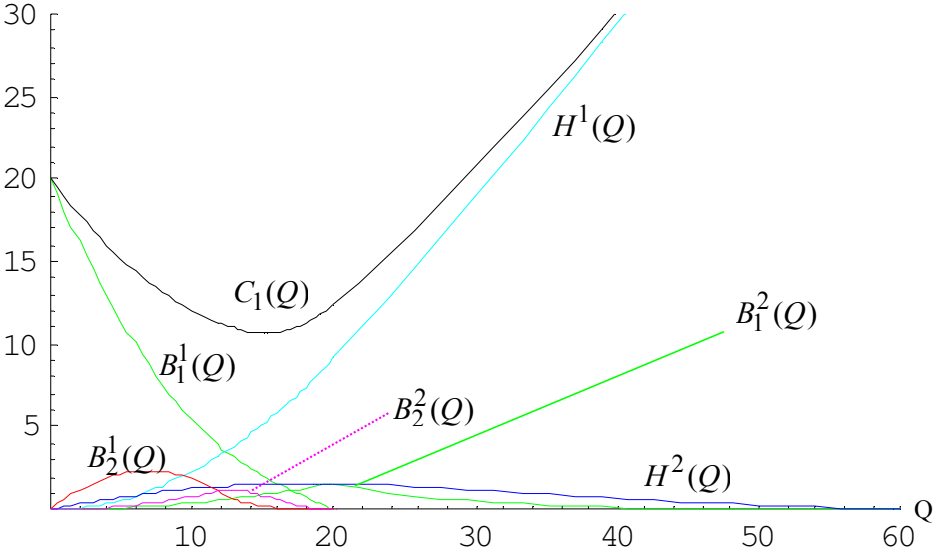
Further information on this cost and its components is provided in App 8.

**Observation 1:** The cost of the system in presence of errors is always higher than the cost of the system without errors and the difference increases as  $\sigma_e$  increases (cf. App 6.1., App 7.1., App 8.1.)

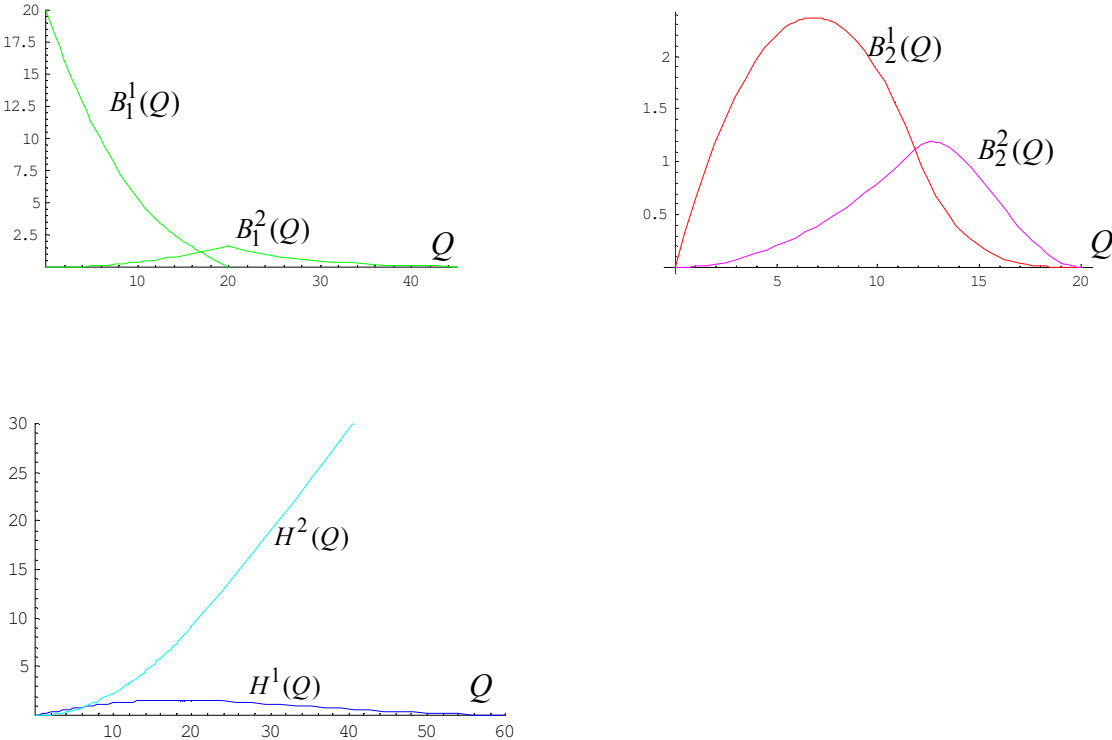
**Observation 2:** In most of inventory models, the cost associated with a shortage situation is decreasing in  $Q$  while the overage cost increases if  $Q$  increases. This general rule is not verified in our model. For instance, shortage cost components associated with several cases (i.e.  $Q_{IS} \leq D \leq Q_{PH}$ ,  $Q_{PH} \leq D \leq Q_{IS}$  or  $Q_{PH} \leq Q_{IS} \leq D$ ) would be increasing in  $Q$  in certain intervals. This behaviour is mainly due to the fact that: **a)** errors are multiplicative: consider for instance the case  $Q_{IS} \leq D \leq Q_{PH}$ , if  $Q$  increases, the interval which  $D$  is in as

well as the difference  $(Q_{PH}-Q_{IS})$  increases **b)** distributions considered are bounded. For instance, for the case  $Q_{IS} \leq D \leq Q_{PH}$ : in the interval  $Q \leq U_x$ ,  $P(Q_{IS} \leq D \leq Q_{PH})$  increases as  $Q$  increases, whereas for  $Q > U_x$ , the same probability decreases.

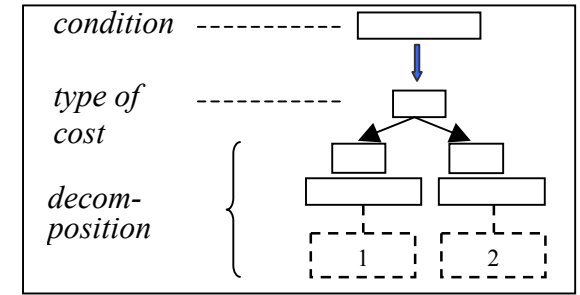
As an example, we represented graphically cost components for the following parameters:  
 $h = 1$ ;  $k = 2$ ;  $m = 2$ ;  $U_x = 20$ ;  $L_x = 0$ ;  $\sigma_e = 0.4$



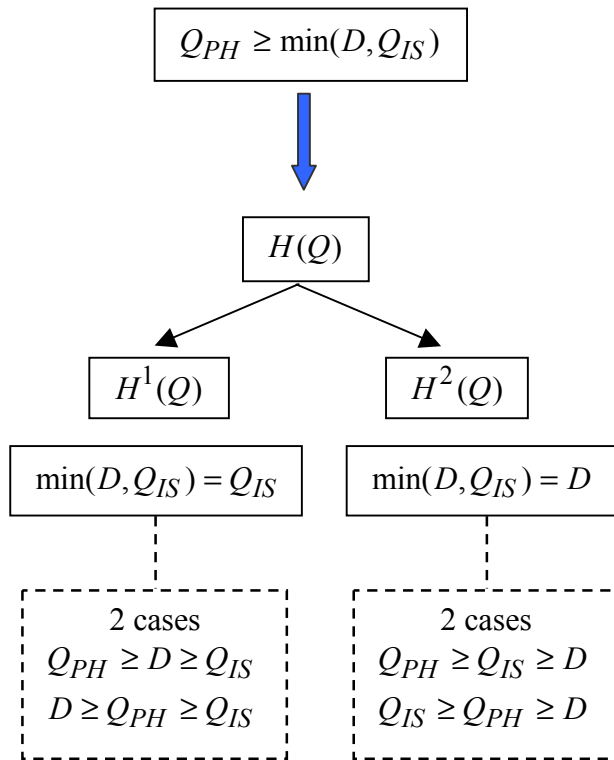
**Figure 2. Individual cost components for uniformly distributed multiplicative errors**



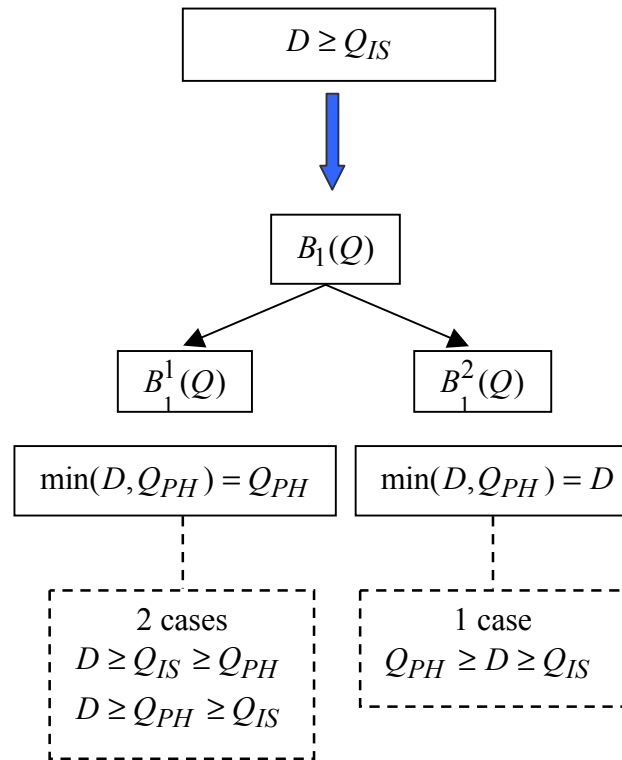
Legend



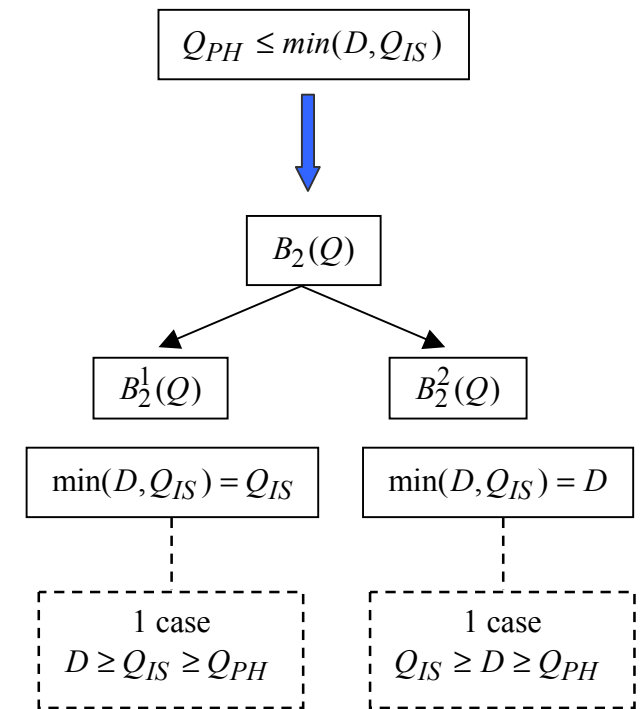
**Overage cost**



**Shortage type 1 cost**



**Shortage type 2 cost**

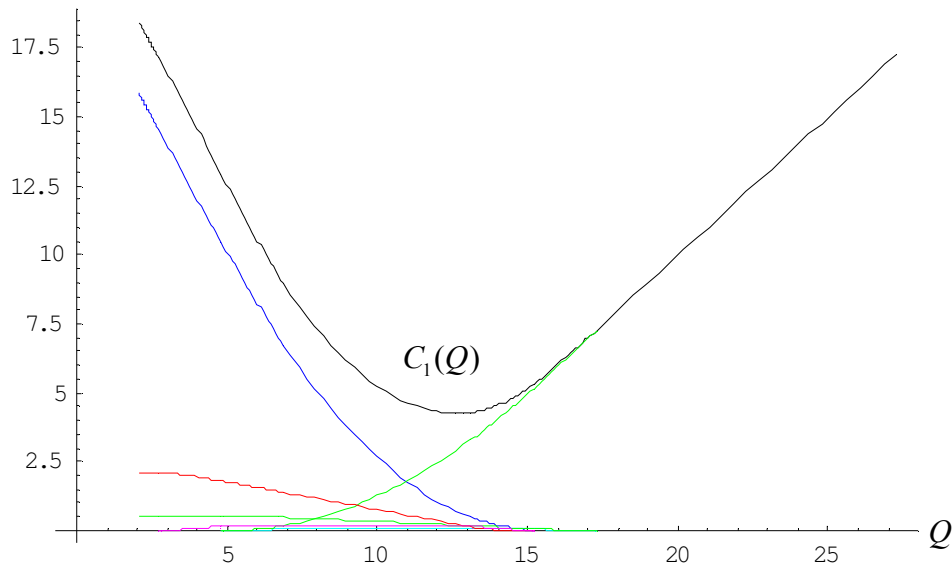


Elementary cost components resulting from the decomposition of the total cost

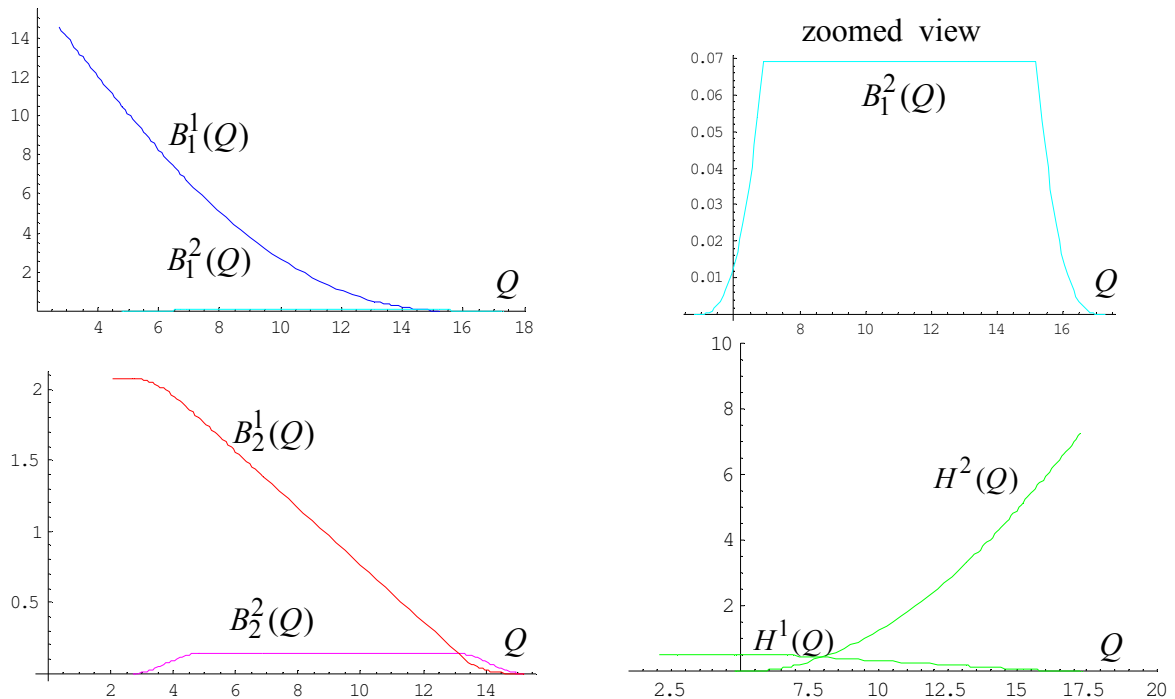
### 1.5. Additive errors

When errors are additive, one can follow the method described in sections 1.1.; 1.2. and illustrated in section 1.4. to formulate the expected total cost. Results pertaining to this analysis are presented in section 1.2. of Part 2. This section provides information on the components of the expected total cost.

As an example, the graph below represents the cost components for the following parameters:  
 $h = 1; k = 2; m = 2; \mu_D = 10; \sigma_D = 3; \sigma_e = 1.2$



**Figure 3. Individual cost components for uniformly distributed additive errors**



## Cost components

As in the case of multiplicative error, the cost components are  $B_1(Q)$ ,  $H(Q)$  and  $B_2(Q)$ .

### $B_1(Q)$ , the expected shortage type 1 cost

We decomposed this cost into two parts:  $B_1^1(Q)$  defined in the interval  $\sigma_e \cdot \sqrt{3} \leq Q \leq U_x$ , and  $B_1^2(Q)$  defined in the interval  $L_x \leq Q \leq U_x + \sigma_e \cdot \sqrt{3}$ .

- Within the interval  $L_x + \sigma_e \cdot \sqrt{3} \leq Q \leq U_x$ ,  $B_1^1(Q)$  is decreasing in  $Q$  since both  $P(Q_{IS} \leq D)$  and  $P(Q_{PH} \leq D)$  decrease as  $Q$  increases. If  $L_x \neq 0$ , for the same reason, it will be decreasing in  $Q$  within the interval  $\sigma_e \cdot \sqrt{3} \leq Q \leq L_x - \sigma_e \cdot \sqrt{3}$ .
- In contrast to the multiplicative errors model, the interval of values that  $Q_{IS}$  may take does not vary with  $Q$  and depends on  $\sigma_e$ . Therefore,  $B_1^2(Q)$  has a constant value within the interval  $L_x + \sigma_e \cdot \sqrt{3} \leq Q \leq U_x$ . For  $U_x \leq Q \leq U_x + \sigma_e \cdot \sqrt{3}$ ,  $B_1^2(Q)$  is decreasing in  $Q$  since the probability  $P(Q_{IS} \leq D \leq Q_{PH})$  decreases. Furthermore, if  $L_x \neq 0$ , this cost component is increasing in  $Q$  in the interval  $L_x \leq Q \leq L_x + \sigma_e \cdot \sqrt{3}$ .

### $H(Q)$ , the expected overage cost

The overage cost has 2 components:  $H^1(Q)$  defined in the interval  $\sigma_e \cdot \sqrt{3} \leq Q \leq U_x + \sigma_e \cdot \sqrt{3}$  and  $H^2(Q)$  defined in the interval  $L_x - \sigma_e \cdot \sqrt{3} \leq Q \leq U_x + \sigma_e \cdot \sqrt{3}$ .

- For  $L_x \leq Q \leq U_x + \sigma_e \cdot \sqrt{3}$ , the main cost component associated with  $H^1(Q)$ , i.e. the cost pertaining to the case  $Q_{IS} \leq Q_{PH} \leq D$ , is decreasing in  $Q$  (since the difference  $(Q_{PH} - Q_{IS})$  does not change but the probability  $P(Q_{PH} \leq D)$  decreases). If  $L_x \neq 0$ , for  $\sigma_e \cdot \sqrt{3} \leq Q \leq L_x$ ,  $H^1(Q)$  has a constant value.
- $H^2(Q)$ , generated by cases  $D \leq Q_{IS} \leq Q_{PH}$  and  $D \leq Q_{PH} \leq Q_{IS}$  (which does not depend on errors), is increasing in  $Q$  within the interval  $L_x - \sigma_e \cdot \sqrt{3} \leq Q \leq U_x$ . For the interval  $U_x \leq Q \leq U_x + \sigma_e \cdot \sqrt{3}$ , the cost associated with the case  $D \leq Q_{IS} \leq Q_{PH}$  has 2 components (one increasing and the other decreasing in  $Q$ ). The total  $H^2(Q)$  type cost would be increasing in  $Q$  (cf. App 9).

## **$B_2(Q)$ , the expected shortage type 2 cost**

The components of the shortage type 2 cost are  $B_2^1(Q)$  defined for  $\sigma_e \cdot \sqrt{3} \leq Q \leq U_x$  and  $B_2^2(Q)$  defined for  $L_x - \sigma_e \cdot \sqrt{3} \leq Q \leq U_x$ .

- For  $L_x \leq Q \leq U_x$ ,  $B_2^1(Q)$  is decreasing in  $Q$  (since  $P(Q_{IS} \leq D)$  decreases). If  $L_x \neq 0$ , for  $\sigma_e \cdot \sqrt{3} \leq Q \leq L_x - \sigma_e \cdot \sqrt{3}$ , this cost component does not vary with  $Q$ , while for  $L_x - \sigma_e \cdot \sqrt{3} \leq Q \leq L_x$ , it is decreasing in  $Q$ .
- For  $L_x \leq Q \leq U_x - \sigma_e \cdot \sqrt{3}$ ,  $B_2^2(Q)$  does not vary with  $Q$  since the probability to observe this case as well as the average quantity in shortage do not change as  $Q$  increases. Within the interval  $U_x - \sigma_e \cdot \sqrt{3} \leq Q \leq U_x$ , this cost is decreasing in  $Q$  (since the probability  $P(Q_{PH} \leq D \leq Q_{IS})$  decreases).

If  $L_x \neq 0$ , for  $L_x - \sigma_e \cdot \sqrt{3} \leq Q \leq L_x$ , this cost component is increasing in  $Q$  since the interval of values of demand that generates it becomes larger.

**Observation:** As in the case of multiplicative errors, the cost of the system in presence of errors is always higher than the cost of the system without errors and the difference increases as  $\sigma_e$  increases. This point will be developed with further details in section 1.1. of Part 2.

## **2. Normally distributed demand and errors**

When errors and demand are assumed to follow normal distributions, the expression of the expected cost does not depend on specific configurations.

### **2.1. Multiplicative errors**

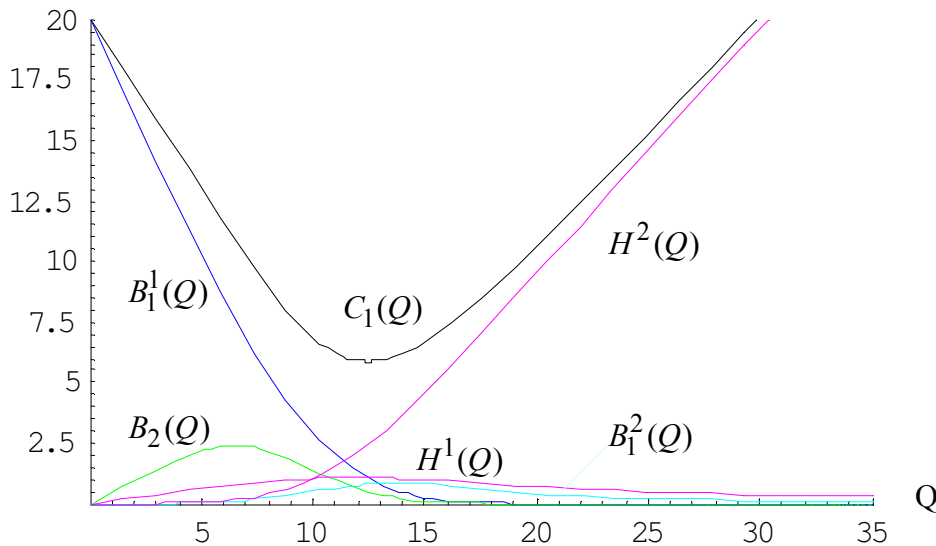
The expected total cost function can be expressed as follows:

$$\begin{aligned}
C_1(Q) &= \int_{p=1}^{\infty} \int_{x=p.Q}^{\infty} (u_1.(x-p.Q) + u_2.(p.Q-Q))f(x)g(p)dx dp && Q_{PH} \leq Q_{IS} \leq D \\
&+ \int_{p=-\infty}^1 \int_{x=Q}^{\infty} (u_1.(x-p.Q) + h.(Q-p.Q))f(x)g(p)dx dp && Q_{IS} \leq Q_{PH} \leq D \\
&+ \int_{p=-\infty}^1 \int_{x=p.Q}^Q (u_1.(x-p.Q) + h.(Q-p.Q))f(x)g(p)dx dp && Q_{IS} \leq D \leq Q_{PH} \\
&+ \int_{p=1}^{\infty} \int_{x=Q}^{p.Q} u_2.(x-Q)f(x)g(p)dx dp && Q_{PH} \leq D \leq Q_{IS} \\
&+ \int_{p=-\infty}^1 \int_{x=-\infty}^{p.Q} h.(Q-x)f(x)g(p)dx dp && D \leq Q_{IS} \leq Q_{PH} \\
&+ \int_{p=1}^{\infty} \int_{x=0}^Q h.(Q-x)f(x)g(p)dx dp && D \leq Q_{PH} \leq Q_{IS}
\end{aligned}$$

where  $f(x) = \frac{e^{-\frac{(x-\mu_D)^2}{2\sigma_D^2}}}{\sqrt{2\pi}\sigma_D}$  and  $g(p) = \frac{e^{-\frac{(p-\mu_p)^2}{2\sigma_p^2}}}{\sqrt{2\pi}\sigma_p}$ . The convexity of the cost function has been

verified through various numerical analyses. The shape of the expected total cost function as well as its components are similar to the case of uniform distributions. Differentiating  $C_1(Q)$  with respect to  $Q$  and setting it equal to zero lead to the optimal policy.

$$h = 1; \quad k = 2; \quad m = 2; \quad \mu_D = 10; \quad \sigma_D = 3; \quad \mu_e = 1; \quad \sigma_e = 0.3$$



**Figure 4. Individual cost components for normally distributed multiplicative errors**

## 2.2. Additive errors

**General expression of the expected total cost:** If the standard deviation of the recorded inventory is independent of the quantity ordered, the expected total cost is given by:

$$\begin{aligned}
C_1(Q) &= \int_{Q_{IS}=Q}^{\infty} \int_{x=Q_{IS}}^{\infty} (u_1 \cdot (x - Q_{IS}) + u_2 \cdot (Q_{IS} - Q)) f(x) g(\varepsilon) dx d\varepsilon \\
&+ \int_{Q_{IS}=0}^Q \int_{x=Q}^{\infty} (u_1 \cdot (x - Q_{IS}) + h \cdot (Q - Q_{IS})) f(x) g(\varepsilon) dx d\varepsilon \\
&+ \int_{Q_{IS}=0}^Q \int_{x=Q_{IS}}^Q (u_1 \cdot (x - Q_{IS}) + h \cdot (Q - Q_{IS})) f(x) g(\varepsilon) dx d\varepsilon \\
&+ \int_{Q_{IS}=Q}^{\infty} \int_{x=Q}^{Q_{IS}} u_2 \cdot (x - Q) f(x) g(\varepsilon) dx d\varepsilon \\
&+ \int_{Q_{IS}=0}^Q \int_{x=0}^{Q_{IS}} h \cdot (Q - x) f(x) g(\varepsilon) dx d\varepsilon \\
&+ \int_{Q_{IS}=Q}^{\infty} \int_{x=0}^Q h \cdot (Q - x) f(x) g(\varepsilon) dx d\varepsilon
\end{aligned}$$

$$Q_{PH} \leq Q_{IS} \leq D$$

$$Q_{IS} \leq Q_{PH} \leq D$$

$$Q_{IS} \leq D \leq Q_{PH}$$

$$Q_{PH} \leq D \leq Q_{IS}$$

$$D \leq Q_{IS} \leq Q_{PH}$$

$$D \leq Q_{PH} \leq Q_{IS}$$

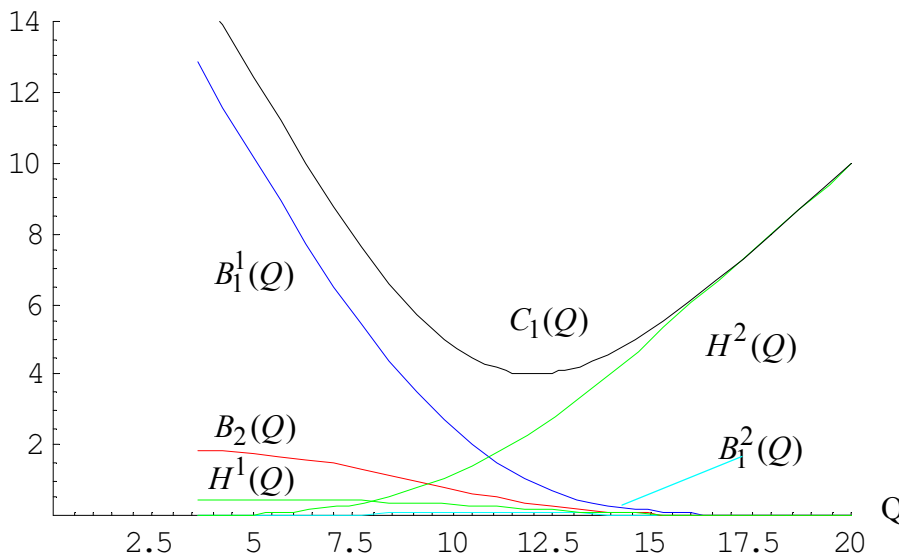
where  $Q_{IS} = \mu_p \cdot Q + \varepsilon$  and  $f(x) = \frac{e^{-\frac{(x-\mu_D)^2}{2\sigma_D^2}}}{\sqrt{2\pi} \cdot \sigma_D}$

### Additive Errors

The additive errors model is obtained by setting  $\mu_p = 1$  and  $g(\varepsilon) = \frac{e^{-\frac{(\varepsilon-\mu_\varepsilon)^2}{2\sigma_\varepsilon^2}}}{\sqrt{2\pi} \cdot \sigma_\varepsilon}$  in this general

formulation. The shape of the expected cost function as well as cost components are similar to the case of uniform distributions. Again, the convexity of the cost function has been verified through various numerical analyses. Differentiating  $C_1(Q)$  with respect to  $Q$  and setting it equal to zero lead to the optimal policy.

$$h = 1; \quad k = 2; \quad m = 2; \quad \mu_D = 10; \quad \sigma_D = 3; \quad \mu_\varepsilon = 0; \quad \sigma_\varepsilon = 1.2$$

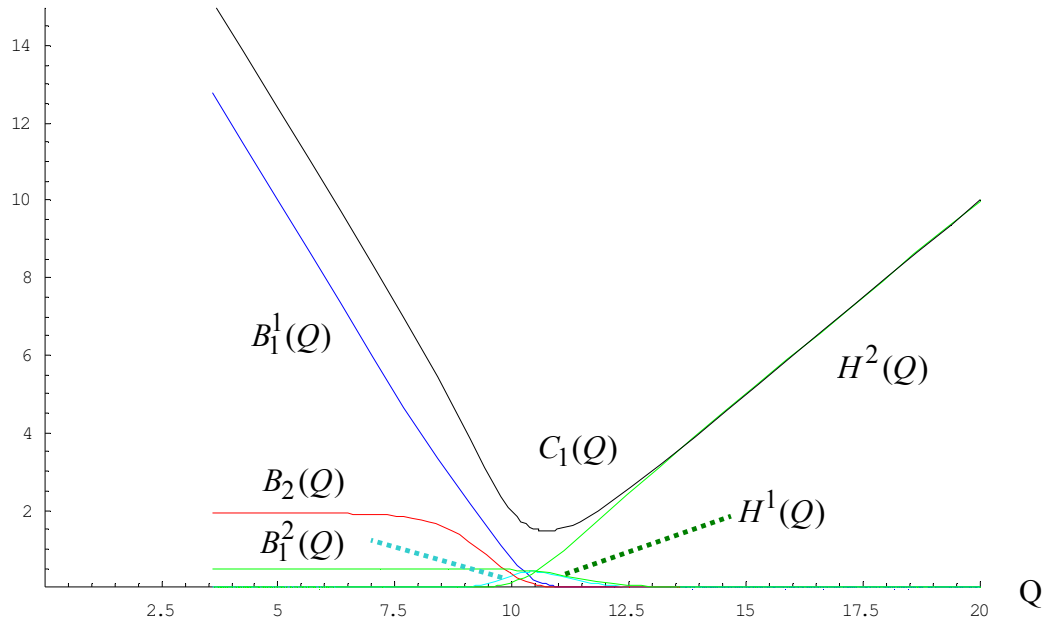


**Figure 5. Individual cost components for normally distributed additive errors (1)**



Note that for the same error rate, if the variability of demand is small, the interval of values of  $Q$  for which  $B_2(Q)$  and  $H^1(Q)$  are constant is larger (cf. figure below) since in this case, for small values of  $Q$ ,  $P(Q_{PH} \leq D)$  is smaller.

$$h = 1; k = 2; m = 2; \mu_D = 10; \sigma_D = 0.5; \mu_\varepsilon = 0; \sigma_\varepsilon = 1.2$$

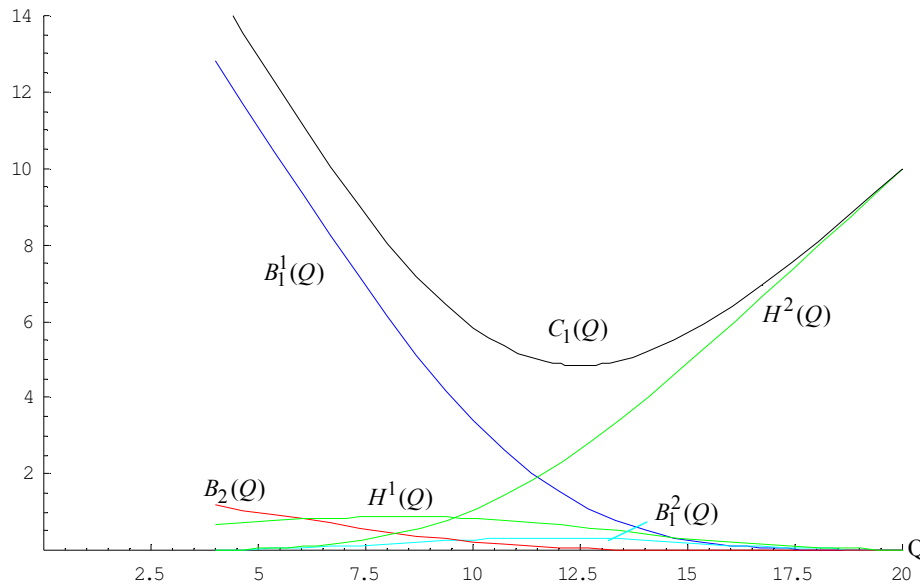


**Figure 6. Individual cost components for normally distributed additive errors (2)**

### 2.3. Mixte errors

The mixte errors model is obtained by setting  $\mu_\varepsilon = 0$  and  $g(\varepsilon) = \frac{e^{-\frac{\varepsilon^2}{2\sigma_\varepsilon^2}}}{\sqrt{2\pi}\sigma_\varepsilon}$  in the general formulation of the expected total cost given in section 2.2.

As an example, the graph below presents the cost components for the following parameters:  $h = 1; k = 2; m = 2; \mu_D = 10; \sigma_D = 3; \mu_p = 0.9; \sigma_\varepsilon = 1.2$



**Figure 7. Individual cost components for normally distributed mixte errors**

When errors are mixte, the following observations pertaining to the behavior of cost components can be done:

- $B_2(Q)$  is first increasing in  $Q$  since the difference  $(Q_{IS}-Q_{PH})$  increases and then decreases since the probability for demand to be higher than  $Q_{IS}$  or to be in between  $Q_{PH}$  and  $Q_{IS}$  decreases. This cost component is higher for  $\mu_p \geq 1$ .
- $H^1(Q)$  is first increasing in  $Q$  since the difference  $(Q_{PH}-Q_{IS})$  increases and then decreases since the probability for demand to be higher than  $Q_{PH}$  or to be in between  $Q_{PH}$  and  $Q_{IS}$  decreases. This cost component is higher for  $\mu_p < 1$ .

Note that in the figure above (with  $\mu_p < 1$ ), the probability  $P(Q_{PH} \leq Q_{IS})$  is so small that  $B_2(Q)$  is totally decreasing in  $Q$ .

[1]

1. *Where to Look for Incremental Sales Gains: The Retail Problem of Out-of-Stock Merchandise- A Study conducted by Andersen Consulting for the Coca-Cola Retailing Research Council; Accenture; 1996 Jan.*

## Part 2: Optimization of the model and insights on the behavior of the optimal solution

In this part, we examine how the expected total cost can be minimized in presence of inventory inaccuracies and derive the optimal policy for three models of errors. Hence, in section 1, errors are assumed to be additive while sections 2 and 3 discuss the case of multiplicative and mixte errors respectively. Each section presents the main results pertaining to the optimization of the system and investigates the evolution of the optimal policy for varying values of system parameters.

### 1. Additive errors

In this section, prior to the stochastic demand assumption, we have considered the case of deterministic demand and uniformly distributed errors. By assuming that demand is deterministic, we want to isolate the uncertainty on inventory as being the unique random factor in the model. This would permit us to derive insights on the optimization mechanism of the model in presence of errors perturbing  $Q_{IS}$ .

#### 1.1. Deterministic demand case

The formulation of the expected cost when demand is deterministic is provided in App 1. The main results pertaining to the evolution of  $Q_1^*$  are as follows:

##### 1.1.1. Uniformly distributed errors with $\mu_e = 0$

**Expression of  $Q_1^*$ :** The expression of the optimal quantity to order is given either by:

$$Q_1^* = D \text{ or } Q_1^* = D + \sqrt{3} \cdot \sigma_e \cdot \frac{k-1}{k+1}.$$

**Evolution of  $Q_1^*$  for varying values of  $\sigma_e$**

- If  $\sigma_e = 0$ , one will order  $Q_1^* = D$ .
- If  $\sigma_e$  increases;

For **small values of  $k$**  (i.e.  $k \leq 1$ ),  $Q_1^* = D$  since, ordering less than  $D$  **(a)** increases the probability  $P(Q_{IS} \leq D)$  resulting in an increased shortage type 1 cost, **(b)** generates an additional shortage type 2 cost, whereas, ordering more than  $D$  generates an additional overage cost that would be relatively important since  $k \leq 1$ .

For **higher values of k** (i.e.  $k > 1$ ), the optimal quantity is obtained for  $Q \geq D$ . Ordering more than the known value of  $D$  ensures that a shortage type 2 cost is not incurred. The quantity ordered results from the trade off between the shortage type 1 cost and the overage cost: if  $\sigma_e$  increases, the interval of values of  $Q_{IS}$  s.t.<sup>1</sup>  $Q_{IS} \leq D$  becomes larger, in order to reduce it, one increases  $Q_1^*$  which is given by  $Q_1^* = D + \sqrt{3} \cdot \sigma_e \cdot \frac{k-1}{k+1}$ .

### 1.1.2. Uniformly distributed errors with $\mu_\varepsilon \neq 0$

#### Expression of $Q_1^*$

- The expression of the optimal quantity to order is given either by:

$$Q_1^* = D \text{ or } Q_1^* = D + \frac{k-1}{k+1} \cdot \sigma_e \cdot \sqrt{3} - \mu_\varepsilon.$$

- If  $\sigma_e = 0$ ,  $Q_1^* = D - \mu_\varepsilon$  for  $\mu_\varepsilon \leq 0$  and  $Q_1^* = D$  for  $\mu_\varepsilon > 0$ .
- For higher values of  $\sigma_e$  and **small values of k** (i.e.  $k \leq 1$ ); k being small, as an approximation, we can assume that the shortage type 1 cost has a weak impact on the optimization problem.

If  $\mu_\varepsilon < 0$ : The optimal quantity results from the trade off between  $H^1(Q)$ , i.e. the overage cost associated with the case ( $Q_{IS} \leq D \leq Q_{PH}$ ), and  $H^2(Q)$ , i.e. the overage cost associated with cases  $D \leq Q_{IS} \leq Q_{PH}$  and  $D \leq Q_{PH} \leq Q_{IS}$  (the first case being the most important component of  $H^2(Q)$ ).

Remark that whatever the quantity observed in IS, an additional overage cost that stems from having products that are in the warehouse but are not used to satisfy demand (since not observed in IS) is incurred. If one orders more than  $D - \mu_\varepsilon$ ,  $H^1(Q)$  would decrease (since  $P(Q_{IS} \leq D)$  decreases) whereas  $H^2(Q)$  increases. As a result, the total cost increases since the increase in  $H^2(Q)$  is higher than the reduction in  $H^1(Q)$ , this being due to the fact that D is constant. The optimal quantity to order will thus be obtained for a configuration s.t.  $P(Q_{IS} \leq D) > P(Q_{IS} > D)$ , i.e.  $Q_1^* < D - \mu_\varepsilon$ . Its exact expression is given by:  $Q_1^* = D + \frac{k-1}{k+1} \cdot \sigma_e \cdot \sqrt{3} - \mu_\varepsilon$ . Note that there are some constraints on values of  $\sigma_e$  to ensure the validity of this expression (cf. App 2).

If  $\mu_\varepsilon \geq 0$ , the arguments presented in section  $\mu_\varepsilon = 0$  lead to ordering  $Q_1^* = D$ .

---

<sup>1</sup> Abbreviation used for: such that.

**Sensitivity of  $Q_1^*$  to varying values of  $\sigma_e$ :** For  $k \leq 1$  and  $\mu_e < 0$ ,  $Q_1^*$  is decreasing in  $\sigma_e$ ; if  $\sigma_e$  increases, the probability  $P(Q_{IS} > D)$  generating the dominant  $H^2(Q)$  type cost increases; to reduce it, one decreases  $Q_1^*$ .

For **higher values of k** (i.e.  $k > 1$ ); k being higher, one should also integrate the impact of the shortage type 1 cost to the optimization problem.

If  $\mu_e < 0$ , one orders  $Q_1^* = D + \frac{k-1}{k+1} \cdot \sigma_e \cdot \sqrt{3} - \mu_e$  which results from the trade off between  $B_1(Q)$ ,  $H^1(Q)$ ,  $H^2(Q)$  type costs associated with cases  $Q_{IS} \leq D \leq Q_{PH}$ ,  $D \leq Q_{PH} \leq Q_{IS}$  and  $D \leq Q_{IS} \leq Q_{PH}$ .

If  $\mu_e \geq 0$ , one first orders  $Q_1^* = D$  until the value that  $\sigma_e$  takes is s.t. the interval of  $Q_{IS}$  values becomes significantly large to represent an incentive to order  $Q_1^* = D + \frac{k-1}{k+1} \cdot \sigma_e \cdot \sqrt{3} - \mu_e$  which is higher than D.

**Sensitivity of  $Q_1^*$  to varying values of  $\sigma_e$ :** For  $k > 1$  and  $\mu_e < 0$ ,  $Q_1^*$  is increasing in  $\sigma_e$  to reduce the relatively more important  $B_1(Q)$  and  $H^1(Q)$  type costs.

### Evolution of $Q_1^*$ for varying values of $\mu_e$

For **small values of k** (i.e.  $k \leq 1$ ),

- If  $\mu_e < 0$ : for a given value of  $\sigma_e$ ,  $Q_1^* < D - \mu_e$ . If one continues to order the same quantity as  $\mu_e$  increases, the interval of values  $Q_{IS} < D$  becomes smaller and thus,  $H^2(Q)$  becomes relatively more important. To achieve a new equilibrium, one should decrease  $Q_1^*$ . If values that  $\mu_e$  takes are higher, i.e.  $\mu_e \geq \frac{\sqrt{3} \cdot (k-1) \cdot \sigma_e}{(1+k)}$ , in other words if the ratio  $\left| \frac{\sigma_e}{\mu_e} \right|$  increases, the overage cost is relatively less important and therefore, one orders  $Q_1^* = D$ . (cf. figure 1)

As  $\mu_e$  increases more, the interval of values of  $Q_{IS}$  s.t.  $Q_{IS} > D$  for which there is no cost that is incurred becomes larger, the cost incurred is thus reduced.

- If  $\mu_e > 0$ : Since k is small, on the one hand, ordering a quantity higher than D would increase the relatively important  $H^2(Q)$  type cost generated by  $Q_{IS}$  values s.t.  $Q_{IS} > D$ , and on the other hand, one does not have an enough incentive to order  $Q_1^* < D$  to reduce the

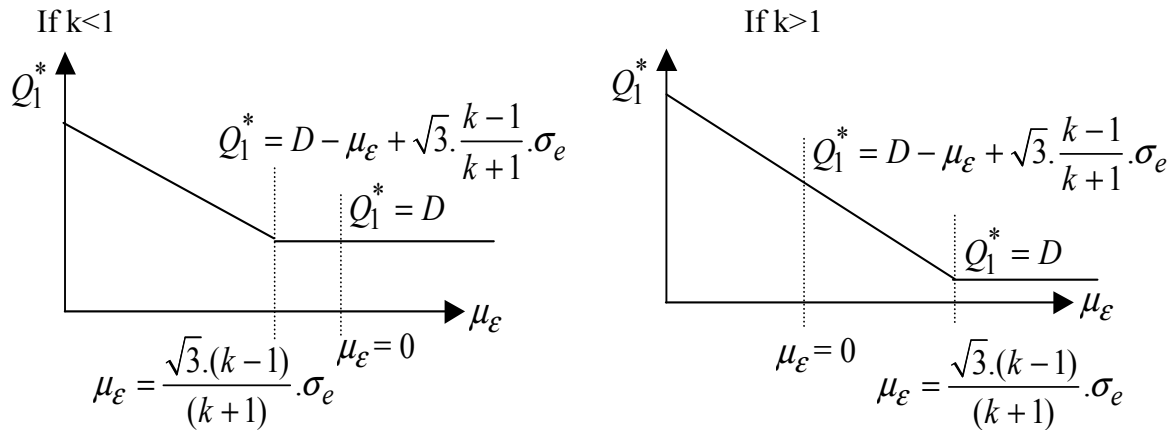
shortage type 1 cost. Furthermore, ordering less than  $D$  would generate a shortage type 2 cost. Thus,  $Q_1^* = D$ .

For **higher values of  $k$**  (i.e.  $k > 1$ ),

- If  $\mu_\varepsilon < 0$ : due to the combined impact of shortage and overage costs pertaining to the case  $Q_{IS} \leq D \leq Q_{PH}$ , for a given value of  $\sigma_e$ ,  $Q_1^* > D - \mu_\varepsilon$ . If  $\mu_\varepsilon$  increases, as in the case of  $k < 1$ ,  $Q_1^*$  decreases.

For  $\mu_\varepsilon$  smaller than  $\frac{\sqrt{3} \cdot (k-1) \cdot \sigma_e}{(1+k)}$  (which is positive), since  $k$  is higher, the penalty associated with the interval of  $Q_{IS}$  values s.t.  $Q_{IS} \leq D \leq Q_{PH}$  is relatively important, in order to reduce the likelihood to have a shortage situation, one orders more than  $D$ .

If  $\mu_\varepsilon \geq \frac{\sqrt{3} \cdot (k-1) \cdot \sigma_e}{(1+k)}$ , one orders  $Q_1^* = D$ . Since this interval of  $Q_{IS}$  values is smaller, one does not have an enough incentive to reduce it by ordering more; thus  $Q_1^* = D$ .



**Figure 1.  $Q_1^*$  for varying  $\mu_\varepsilon$  for deterministic demand and uniformly distributed errors**

## 1.2. Stochastic demand case

The analysis of the optimal policy is first conducted for uniformly distributed demand and errors with  $\mu_\varepsilon = 0$ . Then, in section 1.2.2., results obtained are extended to the case of normally distributed demand and errors for  $\mu_\varepsilon \neq 0$ .

### 1.2.1. Evolution of the optimal policy for varying values of $\sigma_e$

By applying the general principles of formulation of the expected total cost presented in Part 1, the following section reminds the potential configurations to consider in order to derive the

optimal policy. Then, part **b)** provides the closed form analytical expressions of the optimal policy associated with each configuration. And finally, the evolution of the optimal policy for varying values of  $\sigma_e$  is discussed in part **c)**.

#### **a) Potential configurations and the cost stemming from errors**

As in the case of multiplicative errors (cf. section 1.4.2. of Part 1), we have formulated the different cost functions  $Cost_{ij}(Q)$ , identified the potential configurations which  $Q_1^*$  may be in and tracked its evolution for increasing values of  $\sigma_e$ .

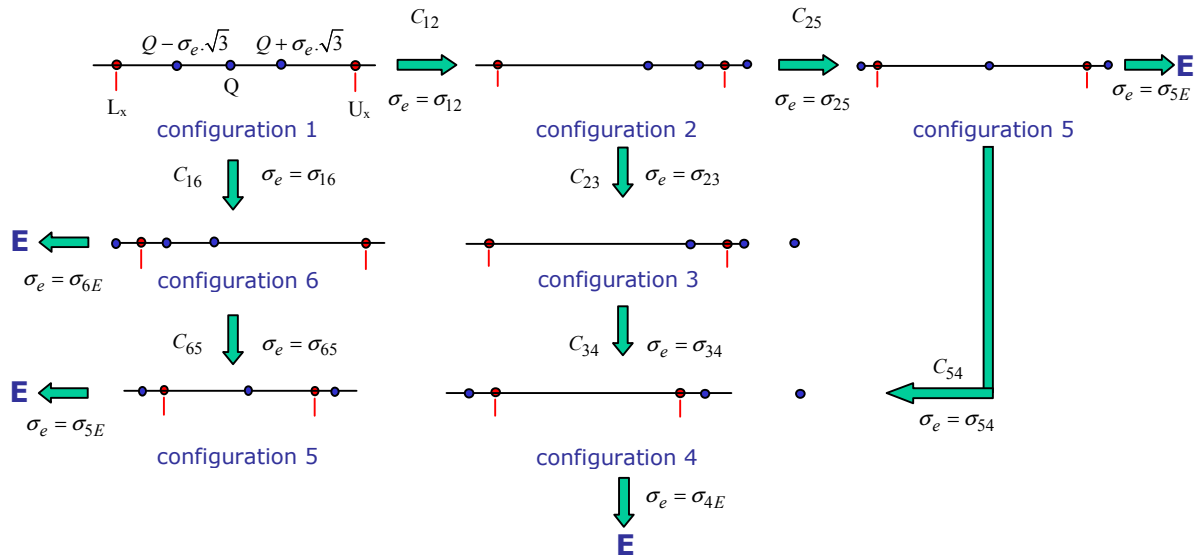
**Observation:** In comparison with the multiplicative errors model, the expected total cost functions associated with the different configurations have less complex expressions. This mainly stems from the fact that in the multiplicative errors model, in certain intervals of variation of  $Q$ , the integration bounds of cost components are such that the total expected cost is in the form of a rational function  $\frac{c_1.Q^3 + c_2.Q^2 + c_3.Q + c_4}{Q}$  (cf. the example concerning the calculation of cost components treated in part **b)** of section 1.4.1.) whereas in the additive model, for the analogue intervals of variation of  $Q$ , the integration bounds of cost components being proportional to  $Q$ , the expression of the total expected cost function is in the form of a third degree polynomial  $c_1.Q^3 + c_2.Q^2 + c_3.Q + c_4$ . Therefore, exploitable analytical solutions are obtained from the analysis of the additive errors model.

The figure below is a synthesis of results obtained from the analysis described above. The following observations can be made:

- If  $L_x = 0$ , depending on the values of the other parameters, there are three potential configurations in which the optimal quantity can be. These are configurations 1, 2 and 3 represented in figure 2. The expected cost associated with each configuration is provided in App 3.
- If  $L_x \neq 0$ , one should consider three other configurations, namely configurations 4, 5 and 6.
- The expression of the optimal policy associated with a given configuration is valid only if it satisfies the constraints resulting from the positions of distributions of demand and  $Q_{IS}$ .
- For given values of system parameters ( $k, m, \mu_D, \sigma_D$ ) and increasing values of  $\sigma_e$ , the transition from a configuration  $i$  to a configuration  $j$  occurs when  $\sigma_e$  achieves a critical value  $\sigma_{ij}$  under a condition  $C_{ij}$ . Expressions of conditions of transitions in between configurations as well as the critical values of  $\sigma_e$  are provided in App 4.

- Configurations 3 and 4 allow a unique transition: if  $\sigma_e$  achieves a critical value, either  $Q_1^*$  is in another configuration (e.g. transition from configuration 3 to 4) or the lower bound  $Q_{IS}$  achieves 0 (represented by the letter “E” in the figure).

There are 2 potential transitions from configurations 1, 2, 5 and 6 to the other configurations.

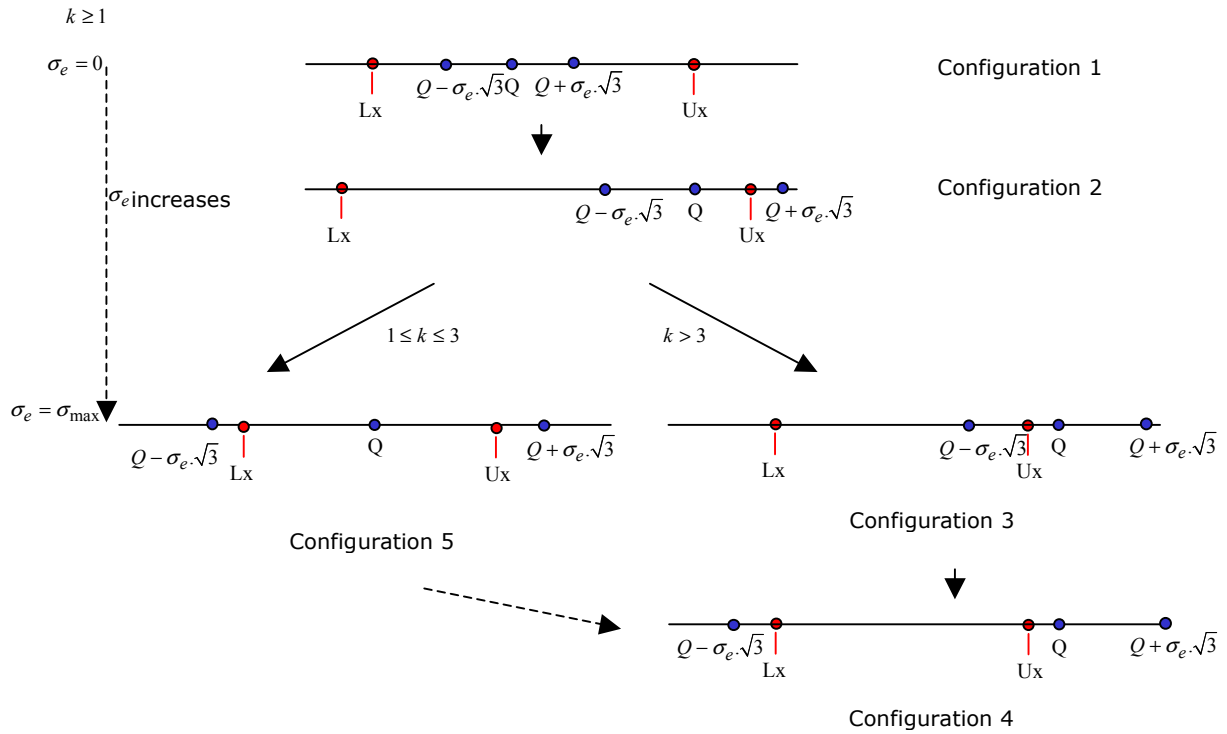


**Figure 2. Potential configurations for uniformly distributed additive errors**

### Example

We have considered the evolution of  $Q_1^*$  for increasing values of  $\sigma_e$  for  $k \geq 1$  and have obtained the following sequence of transitions between configurations:





**Figure 3. Sequence of configurations for additive errors ( $k > 1$ )**

A similar analysis conducted for  $k < 1$  is provided in App 5.

Note that configurations 1 and 2 are the most likely configurations that correspond to realistic values of  $\sigma_e$ . The other configurations are interesting to study from a theoretical standpoint. In the analysis of the optimal quantity, in order to be exhaustive, we consider all possible values for  $\sigma_e$ , but when deriving the managerial insights pertaining to the penalty of having errors (cf. Part 3), we will be interested in values of  $\sigma_e$  not higher than, say  $\sigma_D$ .

### The cost stemming from errors

**Observation:** The cost of the system in presence of errors is always higher than the cost of the system without errors and the difference increases as  $\sigma_e$  increases. (cf. App 6)

### b) Analytical expressions of the optimal policy

The table below summarizes the closed form expressions of  $Q_1^*$  for all configurations. The derivation of each expression is provided in App 3. An example illustrating the evolution of  $Q_1^*$  for  $k > 1$  where the critical values of  $\sigma_e$  are calculated is provided in App 7.

<b>Optimal quantity to order</b>	
Config. 1	$\mu_D + \frac{\sqrt{3} (\sigma_e + k m \sigma_e + 4 (-1 + k) \sigma_D)}{4 (1 + k)}$
Config. 2	$\frac{k (-1 + m) \mu_D + \sqrt{3} \sqrt{\sigma_e (4 \sigma_e + k (3 + m (5 + k (3 + m)))) \sigma_e - 8 k (-1 + m) \sigma_D} + \sqrt{3} (- (2 + k + k m) \sigma_e + k (-1 + m) \sigma_D)}{k (-1 + m)}$
Config. 3	$\mu_D + \sqrt{3} \left( \sigma_e + \sigma_D - \frac{2 \sqrt{2} \sigma_e \sigma_D}{\sqrt{(1 + k) \sigma_e \sigma_D}} \right)$
Config. 4	$\mu_D + \frac{\sqrt{3} (-1 + k) \sigma_e}{1 + k}$
Config. 5	$\frac{\mu_D + k m \mu_D + \sqrt{3} \left( - (1 + k m) \sigma_e + (-1 + k (-2 + m)) \sigma_D + \sqrt{(\sigma_e + k m \sigma_e)^2 + 8 k (1 + k m) \sigma_e \sigma_D - 4 k (1 + k) (-1 + m) \sigma_D^2} \right)}{1 + k m}$
Config. 6	$\mu_D + \frac{\sqrt{3} \left( - (1 + k) (\sigma_D + \sigma_e) + \sqrt{(1 + k) \sigma_e (8 k \sigma_D + \sigma_e + k m \sigma_e)} \right)}{1 + k}$

**Table 1. Optimal quantities to order for uniformly distributed additive errors**

The expressions of the optimal costs associated with these quantities are as follows:

<b>Optimal cost</b>	
Config. 1	$\frac{h (192 k \sigma_D^2 + 48 (1 + k m) \sigma_D \sigma_e - (5 + k (4 + m)) (-1 + k (-4 + 3 m)) \sigma_e^2)}{64 \sqrt{3} (1 + k) \sigma_D}$
Config. 2	Expression in the form of $c_1 \cdot \sigma_e^2 + c_2 \cdot \sigma_e + c_3 \cdot \sqrt{\sigma_e}$ provided in App 8.
Config. 3	$\frac{h \left( 3 \sigma_D + \sigma_e \left( 3 - \frac{4 \sqrt{2} \sigma_D}{\sqrt{(1 + k) \sigma_D \sigma_e}} \right) \right)}{\sqrt{3}}$
Config. 4	$\frac{h (12 k \sigma_e^2 + (1 + k)^2 \sigma_D^2)}{4 \sqrt{3} (1 + k) \sigma_e}$
Config. 5	Expression provided in App 8.
Config. 6	$\frac{-h (\sigma_e + k m \sigma_e + 8 k \sigma_D) \sqrt{(1 + k) \sigma_e (\sigma_e + k m \sigma_e + 8 k \sigma_D)} + h (1 + k) ((1 + k m) \sigma_e^2 + 3 (1 + k (4 + m)) \sigma_e \sigma_D + 12 k \sigma_D^2)}{4 \sqrt{3} (1 + k) \sigma_D}$

**Table 2. Optimal costs for uniformly distributed additive errors**

### c) Impact of $\sigma_e$ on the optimal policy

This section evaluates the impact of errors by considering the difference  $C_1(Q) - C_0(Q)$ :

1. When distributions of demand and errors are positioned such as in **configuration 1**, the major part of the additional cost stemming from errors is incurred if demand takes values that are higher than  $Q_{IS}$  (i.e.  $D \geq U_\epsilon$ ); having errors generates additional overage and shortage type 2 costs (associated with cases  $Q_{IS} \leq Q_{PH} \leq D$  and  $Q_{PH} \leq Q_{IS} \leq D$ ) which are decreasing in  $Q$ .

The second component of the “cost of errors”, which is due to values of demand within the distribution of  $Q_{IS}$  (i.e.  $L_\epsilon \leq D \leq U_\epsilon$ ), does not vary with  $Q$ .

If  $\sigma_e$  increases, the total additional cost stemming from errors would increase (cf. App 9). To reduce the additional cost, one orders more. The higher are  $k$ ,  $m$  or  $\sigma_e$ , the higher would  $Q_1^*$  be. Furthermore,  $C_1(Q_1^*)$  increases as  $\sigma_e$  increases since penalties associated with errors increase.

2. In **configuration 2**, the major part of the additional cost stemming from errors is incurred if demand takes a value higher than  $Q_{PH}$ , i.e.  $Q_{PH} \leq D \leq U_x$ . The cost of errors has two components:  $\Delta_1$ , i.e. the difference of overage and shortage type 1 costs pertaining to Model 0 and Model 1 (which decreases if  $Q$  increases) and  $\Delta_2$ , i.e. the additional shortage type 2 cost (which is also decreasing in  $Q$ ). Thus, for a given value of  $\sigma_e$ , to reduce the penalty of having errors, one should order more than  $Q_0^*$ .

If  $\sigma_e$  increases, both  $\Delta_1$  and  $\Delta_2$  would increase (cf. App 9). To reduce them, one orders more. Note that the expression of the optimal policy is more complex since distributions considered being bounded, the expected cost of certain elementary costs is fragmented and this renders their expressions less simple.

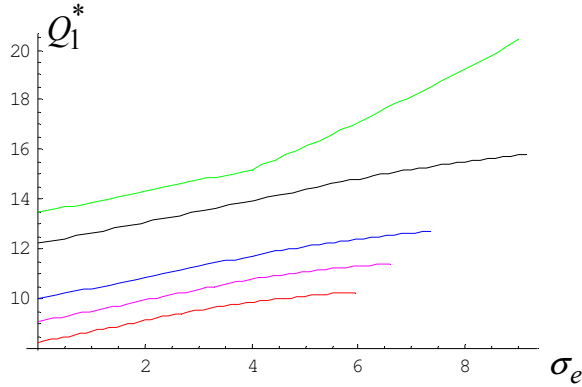
In the other configurations, the optimal quantity to order also increases as  $\sigma_e$  increases since:

3. In **configuration 3**, cases generating the total cost are  $D \leq Q_{PH} \leq Q_{IS}$ ,  $D \leq Q_{IS} \leq Q_{PH}$  and  $Q_{IS} \leq D \leq Q_{PH}$ .  $Q_1^*$  increases as  $\sigma_e$  increases to reduce the interval of values of  $Q_{IS}$  such that  $Q_{IS} < D$ .
4. In **configuration 4**, the optimal quantity to order has a fairly simple expression that does not depend on the variability of demand since an increase in  $\sigma_D$  would generate additional overage and shortage costs which compensate for themselves. The cost pertaining to **configuration 5** differs from configuration 4 mainly because there is a probability to have a shortage type 2 cost stemming from values of demand that are smaller than  $Q_{PH}$ .  $Q_1^*$  increases if  $\sigma_e$  increases in both configurations in order to reduce the interval of values of  $Q_{IS} < D$ .

5. In **configuration 6**, in order to reduce shortage and overage costs stemming from cases  $Q_{IS} \leq Q_{PH} \leq D$  and  $Q_{IS} \leq D \leq Q_{PH}$ , one orders more when  $\sigma_e$  increases.

Graphically, the evolution of  $Q_1^*$  vs.  $\sigma_e$  is as follows:

$$\mu_D = 10; \sigma_D = 3; m = 1; k = 0.5; k = 0.7; k = 1; k = 2.5; k = 5$$



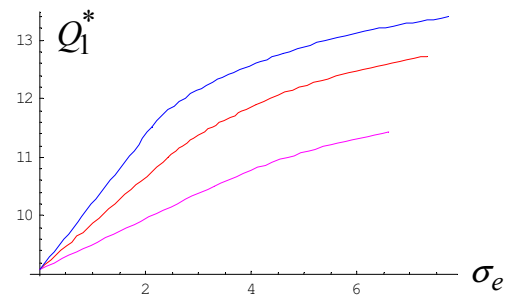
**Figure 4.  $Q_1^*$  with respect to  $\sigma_e$  for uniform distributions ( $m=1$ )**

For instance, if  $k=5$ , the optimal quantity to order is defined over 3 configurations, or equivalently 3 intervals of variation of  $\sigma_e$ : if  $0 \leq \sigma_e \leq 4$ ,  $Q_1^* = 10 + \frac{\sqrt{3}}{4} \cdot (8 + \sigma_e)$  is in configuration 1. If  $4 \leq \sigma_e \leq 9$ ,  $Q_1^* = 10 + \sqrt{3} \cdot (3 - 2 \cdot \sqrt{\sigma_e} + \sigma_e)$  is in configuration 3 and if  $9 \leq \sigma_e \leq 17.32$ ,  $Q_1^* = 10 + \frac{2 \cdot \sigma_e}{\sqrt{3}}$  is in configuration 4. The sequence of configuration to consider in the case  $m=1$  is provided in App 10.

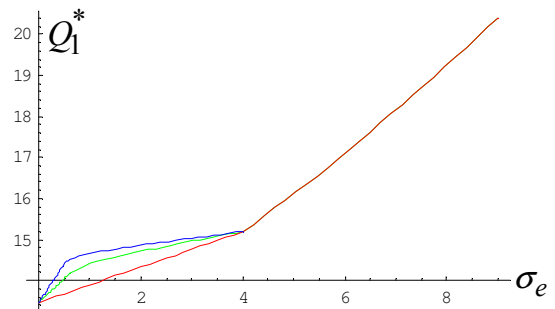
**The impact of higher values of  $m$  (i.e.  $m > 1$ )**

To minimize the cost of the system with errors, one should order more than in the system without errors. The difference  $Q_1^* - Q_0^*$  increases as  $m$  increases.

$$\mu_D = 10; \sigma_D = 3; k = 0.7; m = 1; m = 3; m = 5$$



$$\mu_D = 10; \sigma_D = 3; k = 5; m = 1; m = 3; m = 5$$

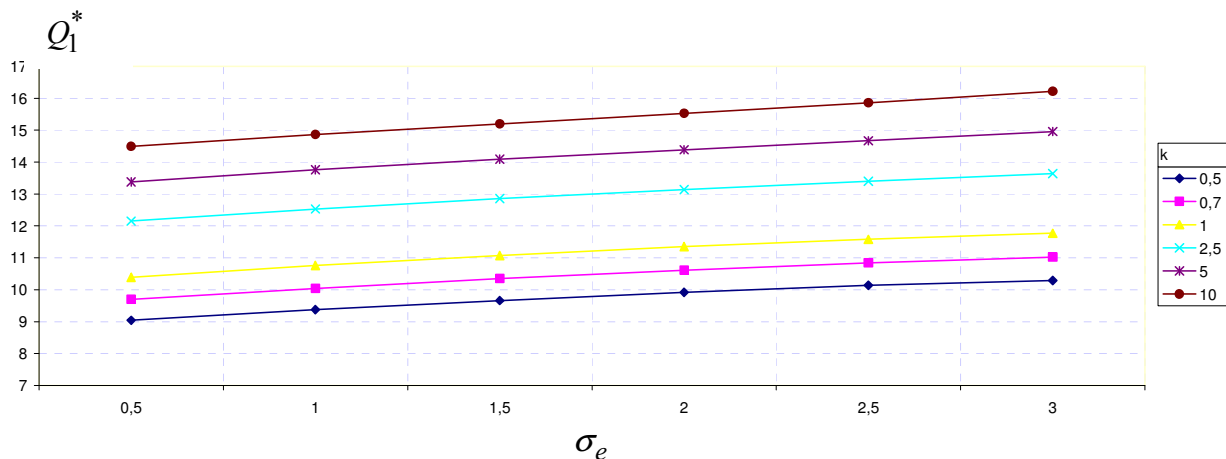


**Figure 5.  $Q_1^*$  with respect to  $\sigma_e$  for uniform distributions and varying values of  $m$**

Results presented in this section for uniform distributions are also valid in the case of normally distributed demand and errors. Since analytical solutions are not available, in order to get further insights, we conducted numerical analyses. Note that the examples developed to illustrate the behavior of the model represent a limited part of numerical studies we carried out.

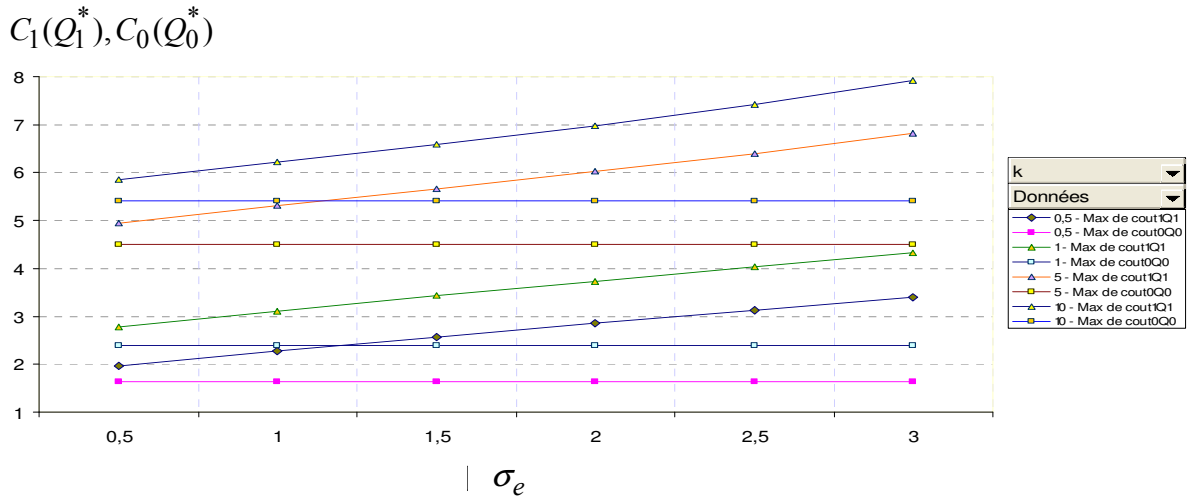
For instance, if  $\mu_D = 10; \sigma_D = 3; m = 3$ , the close agreement of normally distributed demand and errors with uniform distributions confirms the finding that the system performance is highly sensitive to inventory inaccuracies. Initially, for  $\sigma_e = 0$ , the optimal policies pertaining to Model 0 and Model 1 are equal. However, because of scan errors,  $C_1(Q_1^*)$  starts to diverge from  $C_0(Q_0^*)$ . As the error rate rises, the gap between the two curves widens.

One can also remark how severe are the economic consequences of having errors especially when the unit shortage type 2 penalty and  $\sigma_e$  are important (cf. figure 7). For instance, if we consider a product for which a first shortage situation results in a lost revenue which is 5 times the product cost<sup>2</sup>, i.e.  $k=5$ , and, if the economical impact of non satisfying an earlier commitment is 3 times the first shortage penalty, i.e.  $m=3$ , for  $\sigma_e = 2$ , by optimizing the system in presence of errors, one will incur  $C_1(Q_1^*) = 6.02$ , which means that, in comparison with  $C_0(Q_0^*)$ , a relative additional cost of 34% is incurred. Therefore, even if an adjustment is made when designing the inventory policy to integrate the likelihood for errors, the additional cost due to mismatches is substantial in competitive retail environments.



**Figure 6.**  $Q_1^*$  with respect to  $\sigma_e$  for normally distributed demand and errors and varying values of  $k$

<sup>2</sup> It is assumed in this example that  $P_S = 0$ .



**Figure 7.**  $C_1(Q_1^*)$  and  $C_0(Q_0^*)$  with respect to  $\sigma_e$  for normally distributed demand and errors and varying values of  $k$

### 1.2.2. Extension of results

If  $\mu_\varepsilon \neq 0$ , a qualitative equivalency between the cases  $\mu_\varepsilon = 0$  and  $\mu_\varepsilon \neq 0$  cannot be established: even if  $\sigma_e = 0$ , having errors generates an additional overage or shortage cost. The aim of this section is to extend the results presented above to the case of  $\mu_\varepsilon \neq 0$  for normally distributed demand and errors.

#### a) Evolution of the optimal policy for varying values of $\sigma_e$

In order to observe how the optimal policy is affected when  $\sigma_e$  is varied, we first suppose that  $\mathbf{m}=1$  (note that results obtained for the case  $\mathbf{m}=1$  are not specific, i.e. they are also valid for values of  $\mathbf{m} \approx 1$ ).

#### 1. Analysis of $Q_1^*$

If  $\sigma_e = 0$ ,  $Q_1^* = Q_0^* - \mu_\varepsilon$  for  $\mu_\varepsilon < 0$ . If  $\mu_\varepsilon \geq 0$ , one orders  $Q_1^* = Q_0^*$  since by having  $Q_{PH} = Q_0^*$  and observing a higher quantity in IS, one incurs the same cost than the system without errors.

For a given higher value of  $\sigma_e$ ,

- If  $\mu_\varepsilon < 0$ , the evolution of  $Q_1^*$  depends on the ratio  $\left| \frac{\sigma_e}{\mu_\varepsilon} \right|$  and the value of  $k$ : the impact of  $\mu_\varepsilon$  is to push  $Q_1^*$  to take lower values in order to reduce  $H^2(Q)$  and  $H^1(Q)$  type costs, whereas  $\sigma_e$  counteracts by pushing  $Q_1^*$  to take higher values to reduce potential shortage situations stemming from values of  $Q_{IS} \leq Q_0^*$ , i.e. it acts in the same direction than  $k$ .

Therefore, if  $k$  takes **small values** (i.e.  $k < 1$ ) and  $\mu_\varepsilon < 0$ ;

- For small values of  $\mu_{\mathcal{E}}$ , i.e. small values of  $\left| \frac{\sigma_e}{\mu_{\mathcal{E}}} \right|$ , since the impact of  $\mu_{\mathcal{E}}$  will be dominant, an optimization mechanism similar to the deterministic demand case leads to reduce  $Q_1^*$  as  $\sigma_e$  increases.
- If  $\left| \frac{\sigma_e}{\mu_{\mathcal{E}}} \right|$  is higher,
  1.  $Q_1^*$  increases as  $\sigma_e$  increases until  $\sigma_e$  achieves a critical value since :
    - (a) For  $\sigma_e=0$ ,  $Q_1^*$  takes a lower value than the previous case with a smaller  $\mu_{\mathcal{E}}$ . Therefore, the probability  $P(D \geq Q_{PH})$  is high, meaning that  $H^2(Q)$  is relatively less important.
    - (b) For increasing values of  $\sigma_e$ , the interval of values of  $Q_{IS}$  s.t.  $Q_{IS} < Q_0^*$  becomes wider and the risk to incur a  $B_2(Q)$  type cost increases. To reduce it, as well as  $H^1(Q)$  and  $B_1(Q)$  type costs associated with cases  $Q_{IS} \leq Q_{PH} \leq D$  and  $Q_{IS} \leq D \leq Q_{PH}$ , one increases  $Q_1^*$  as  $\sigma_e$  increases.
  2. For values of  $\sigma_e$  higher than this critical value,  $Q_1^*$  is decreasing in  $\sigma_e$  since  $H^2(Q)$  becomes again the dominant cost (cf.  $\mu_{\mathcal{E}}=-2$ ,  $\sigma_e=3$  in the example below).

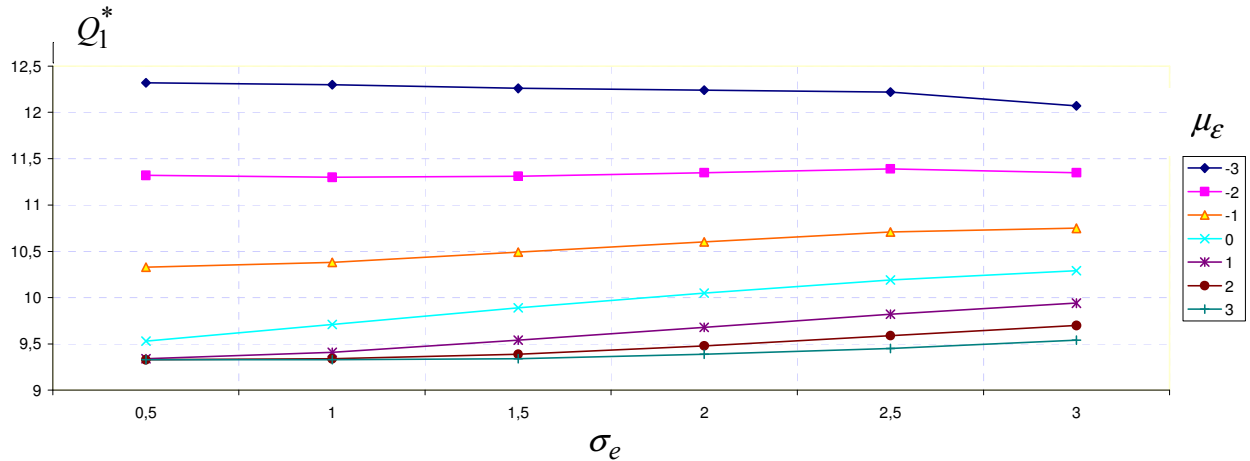
If values that  $\mu_{\mathcal{E}}$  takes are even higher, since the relative impact of the overage cost would decrease,  $Q_1^*$  will be totally increasing in  $\sigma_e$ .

- For  $\mu_{\mathcal{E}} \geq 0$ , if  $\sigma_e$  is small,  $Q_1^*$  is almost constant and equal to  $Q_0^*$  since almost all values of  $Q_{IS}$  are higher than  $Q_0^*$ . For higher values of  $\sigma_e$ , to reduce the risk to have  $Q_{IS} < Q_0^*$ , one orders more as  $\sigma_e$  increases.

### Observations

1. In contrast to the deterministic demand case,  $H^1(Q)$  and  $B_1(Q)$  type costs are relatively more important when demand is stochastic. That is why,  $Q_1^*$  may be increasing in  $\sigma_e$  even for  $k < 1$ .
2. The higher are values of  $\sigma_D$  and  $k$ , the more likely that  $Q_1^*$  will be totally increasing in  $\sigma_e$  (even for small values  $\mu_{\mathcal{E}}$ ).
3. For very small values of  $k$ , if  $\mu_{\mathcal{E}}$  is small ( $< 0$ ) and  $\sigma_e$  is high, one will order  $Q_1^* = -\mu_{\mathcal{E}} + 3\sigma_e$  since the truncated cost function will be convex increasing in  $Q$  (cf.  $\mu_{\mathcal{E}}=-3$ ,  $\sigma_e=3$  in the example below)

$$\mu_D = 10; \sigma_D = 3; m = 1; k = 0.7$$



**Figure 8.**  $Q_1^*$  with respect to  $\sigma_e$  for normally distributed demand and errors and varying  $\mu_\epsilon$  ( $k < 1$ )

For **higher values of k**, (i.e.  $k \geq 1$ )

- If  $\mu_\epsilon \leq 0$ , k being higher, observing  $Q_{IS} < Q_0^*$  is more costly: to reduce the risk of having a shortage situation, one increases  $Q_1^*$  as  $\sigma_e$  increases.
- If  $\mu_\epsilon > 0$ , the evolution of  $Q_1^*$  is the same as for small values of k.

## 2. Analysis of $C_1(Q_1^*)$

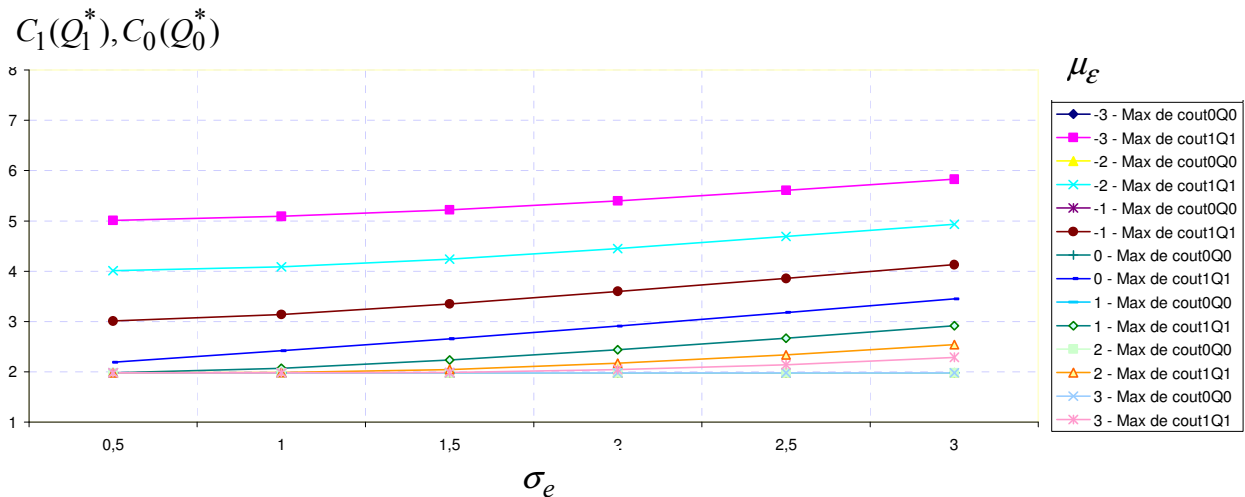
As expected and demonstrated previously, one incurs a higher cost in presence of inventory record errors. For a given value of  $\mu_\epsilon$ ,  $C_1(Q_1^*)$  increases as  $\sigma_e$  increases for all values of k:

- if  $Q_1^*$  is decreasing in  $\sigma_e$ ,  $H^2(Q)$  type cost decreases but the increase in  $H^1(Q)$  and  $B_1(Q)$  not only compensates this but also increases the expected total cost.
- if  $Q_1^*$  is increasing in  $\sigma_e$ ,  $H^1(Q)$  and  $B_1(Q)$  would decrease, while  $H^2(Q)$  increases. As a result, the total cost would increase since the impact of  $\mu_\epsilon$  is still important.

The difference  $C_1(Q_1^*) - C_0(Q_0^*)$  depends on the value of  $\mu_\epsilon$ : the smaller is  $\mu_\epsilon$ , the more important would  $H^2(Q)$  be, increasing the difference  $C_1(Q_1^*) - C_0(Q_0^*)$ . In other words, the average quantity of “non recorded phantom products” increasing, the additional overage cost would increase and therefore augment the expected total cost incurred.



$\mu_D = 10; \sigma_D = 3; m = 1; k = 0.7$



**Figure 9.**  $C_0(Q_0^*)$  and  $C_1(Q_1^*)$  with respect to  $\sigma_e$  for normal distributions and varying  $\mu_\epsilon$

### The impact of higher values of $m$ on the optimal policy

- If  $\sigma_e = 0$ ,  $Q_1^* = Q_0^* - \mu_\epsilon$  for all values of  $\mu_\epsilon \leq 0$ . For  $\mu_\epsilon > 0$ , in contrast to the deterministic case, even if  $\sigma_e = 0$ , there is a risk to have a shortage type 2 penalty since  $Q_{IS}$  is higher than  $Q_{PH}$ . Therefore, for  $\sigma_e = 0$ , one would order more than  $Q_0^*$ . The higher is  $m$ , the higher would be the difference  $Q_1^* - Q_0^*$ .

For all values of  $k$ ,

- For small values of  $\mu_\epsilon$  ( $< 0$ ), if  $\sigma_e$  is small, almost all values of  $Q_{IS}$  would be lower than  $Q_{PH}$ ,  $m$  has thus almost no impact on  $Q_1^*$ .

If  $\sigma_e$  takes a higher value, the risk to have a shortage type 2 cost increases, therefore, one orders more for increasing values of  $m$ .

As in the case  $m=1$ , if  $k$  is very small ( $k < 1$ ) and  $\sigma_e$  takes high values,  $Q_1^* = -\mu_\epsilon + 3\sigma_e$  since the truncated cost function is convex increasing in  $Q$ .

- For intermediate (negative and positive) values of  $\mu_\epsilon$ , for all values of  $m$ ,  $Q_1^*$  increases as  $\sigma_e$  increases to avoid a (costly) shortage type 2 cost. For the same reason, for a given value of  $\sigma_e$ , one orders more as  $m$  increases.
- If values that  $\mu_\epsilon$  takes are high (positive), for high values of  $m$ ,  $Q_1^*$  decreases as  $\sigma_e$  increases (for small values of  $\sigma_e$ ) and it increases as  $\sigma_e$  increases (for higher values of  $\sigma_e$ ) since:

For  $\sigma_e = 0$ , due to the impact of  $m$ , one orders more than  $Q_0^*$  to reduce the probability

$P(D \geq Q_{PH})$  that generates  $B_2(Q)$  type cost. For small values of  $\sigma_e$ , almost all values of  $Q_{IS}$  are higher than  $Q_{PH}$ : the relative importance of the shortage type 1 cost is therefore weak. In other words, the dominant cost is associated with the case  $D \leq Q_{PH} \leq Q_{IS}$ . To reduce it, one decreases  $Q_1^*$ . This action would reduce the dominant overage cost, thus  $C_1(Q_1^*)$  decreases.

For higher values of  $\sigma_e$ , the probability  $P(D \geq Q_{PH})$  becomes more important. Furthermore, the interval of values of  $Q_{IS}$  s.t.  $Q_{IS} < Q_{PH}$  becomes larger. In other words, costs associated with cases  $Q_{IS} \leq Q_{PH} \leq D$  and  $Q_{IS} \leq D \leq Q_{PH}$  are dominant. To reduce them, one increases  $Q_1^*$ .  $C_1(Q_1^*)$  would also increase since the (still) important overage cost increases.

If values that  $\mu_\epsilon$  takes increase more,  $Q_1^*$  is totally decreasing in  $\sigma_e$ . The associated cost would also decrease as  $\sigma_e$  increases.

For instance, if demand is  $N(10, 3)$ , for  $k=0.7$ , the evolution of  $Q_1^*$  with respect to  $\sigma_e$  (for varying values of  $m$  and  $\mu_\epsilon$ ) is as follows:

$Q_1^*$	mu epsilon														
	-2			-1			0			1			2		
sigma e	1	10	25	1	10	25	1	10	25	1	10	25	1	10	25
0,5	11,32	11,32	11,32	10,33	10,34	10,37	9,53	10,26	11,27	9,34	12,01	13,68	9,33	12,89	14,44
1	11,3	11,33	11,38	10,38	10,68	11,13	9,71	11,01	12,32	9,41	12,05	13,65	9,34	12,81	14,34
1,5	11,31	11,52	11,82	10,49	11,21	12,06	9,89	11,54	12,89	9,54	12,18	13,7	9,39	12,74	14,25
2	11,35	11,83	12,41	10,6	11,68	12,7	10,05	11,92	13,24	9,68	12,33	13,78	9,48	12,73	14,2
2,5	11,39	12,15	12,91	10,71	12,05	13,13	10,19	12,2	13,49	9,82	12,46	13,86	9,59	12,75	14,18

Figures below represent the evolution of  $C_1(Q_1^*)$  and  $C_0(Q_0^*)$  versus  $\sigma_e$  for various values of  $m$  (with  $k=0.7$ ). For high values of  $m$ , e.g.  $m=25$ , in the first example where  $\mu_\epsilon = -2$ ,  $C_1(Q_1^*)$  is increasing in  $\sigma_e$  whereas for  $\mu_\epsilon = 2$ ,  $C_1(Q_1^*)$  decreases as  $\sigma_e$  increases: when parameters pertaining to errors are such that  $\mu_\epsilon \neq 0$ , a general rule such as *the optimal cost incurred in an inventory system subject to inventory inaccuracies increases as the error rate grows* cannot be established.

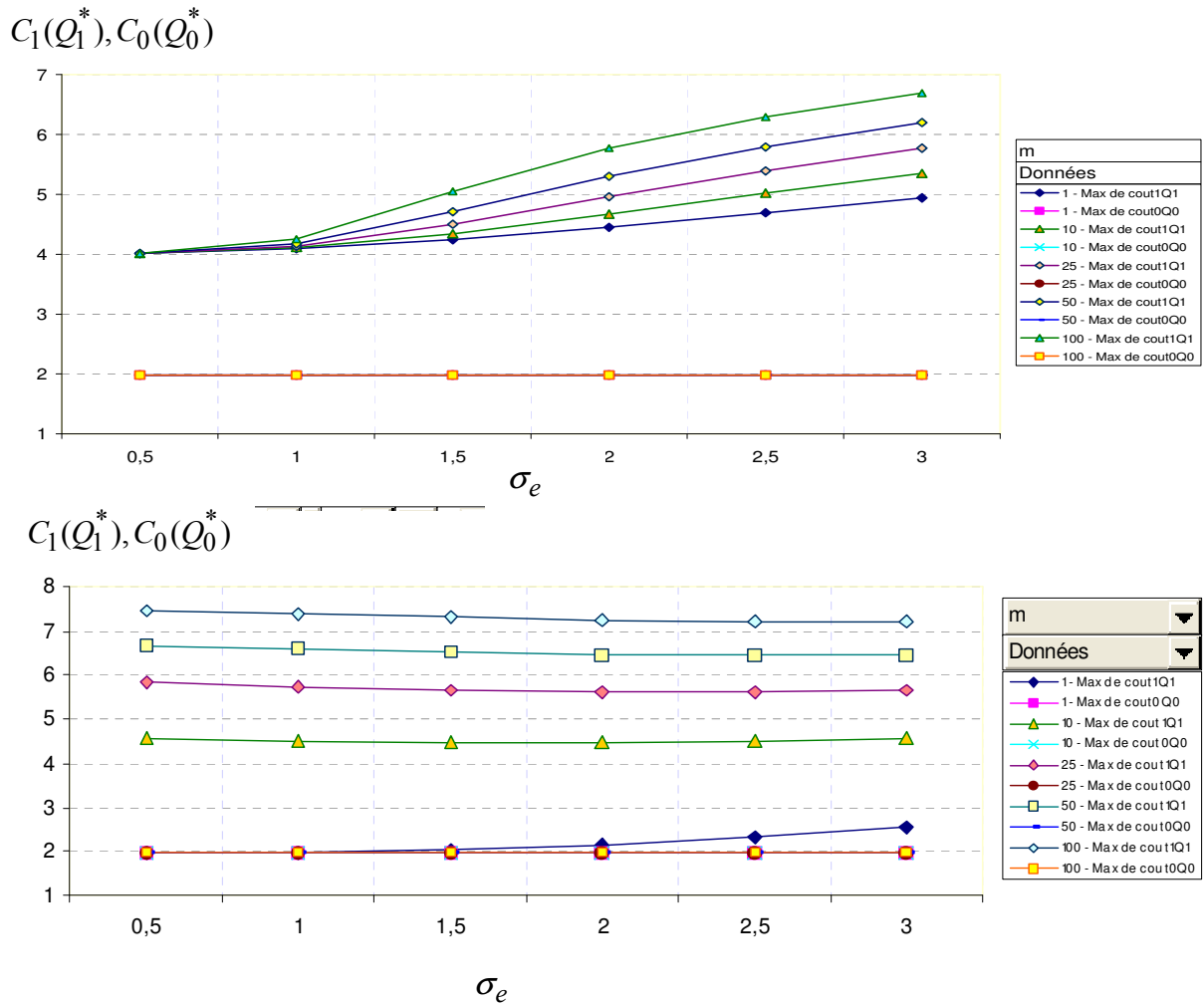


Figure 10.  $C_0(Q_0^*)$  and  $C_1(Q_1^*)$  with respect to  $\sigma_e$  for varying values of  $m$

Some of the insights resulting from our analysis are as follows:

- Parameters pertaining to errors, namely  $\mu_e$  and  $\sigma_e$ , have different effects on the optimal quantity to order
- The difference between  $Q_1^*$  and  $Q_0^*$  depends on the relative importance of  $\mu_e$  in comparison with  $\sigma_e$  and the relative importance of cost parameters  $k$  and  $m$
- Having a negative average error rate, i.e. observing on average a lower quantity in IS than the real quantity, results in lower performance, in terms of cost. Indeed, having a large amount of non recorded phantom products within the inventory system generates an important overage cost.
- In certain situations where  $m$  is relatively important,  $C_1(Q_1^*)$  may decrease as the error rate  $\sigma_e$  is varied.

**b) Evolution of the optimal policy for varying values of  $\mu_\varepsilon$**

If we suppose that  $m=1$ , the evolution of the optimal policy is similar to the deterministic demand case, i.e. one first decreases  $Q_1^*$  as  $\mu_\varepsilon$  increases and for values of  $\mu_\varepsilon$  higher than a certain value,  $Q_1^* = Q_0^*$  and  $C_1(Q_1^*) = C_0(Q_0^*)$ .

For **higher values of m**: In contrast to the case  $m=1$ , for values of  $\mu_\varepsilon$  higher than a critical value,  $Q_1^*$  increases as  $\mu_\varepsilon$  increases in order to reduce the likelihood to observe a costly shortage type 2 penalty.

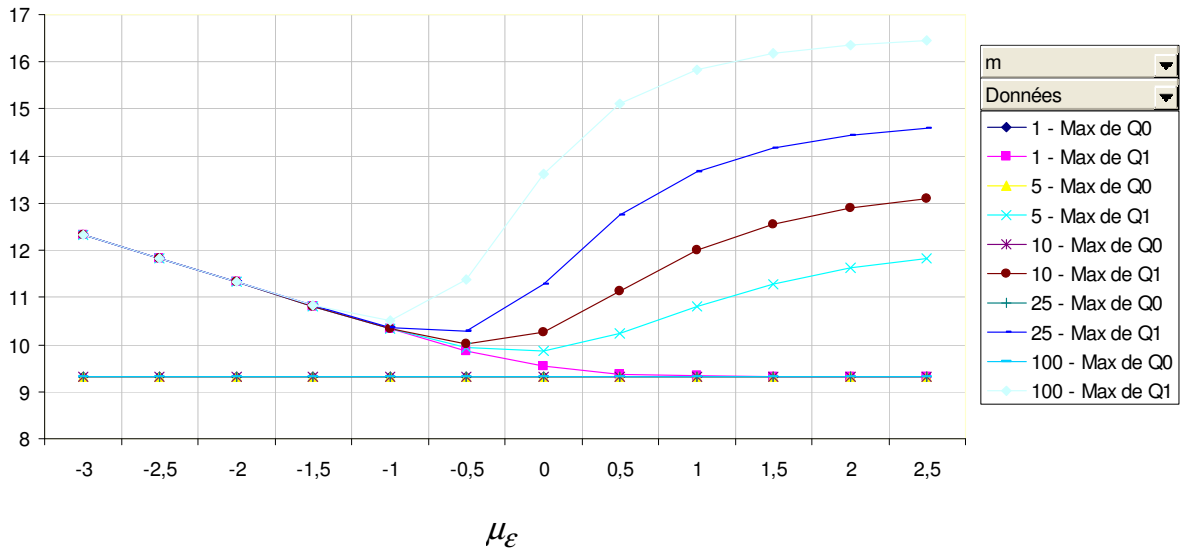
Since  $m$  is high, the quantity ordered is higher (than the case  $m=1$ ), meaning that, the overage cost incurred is important. On the other hand, the shortage type 2 cost increases as  $\mu_\varepsilon$  increases. As a result,  $C_1(Q_1^*)$  is increasing in  $\mu_\varepsilon$ .

Finally, by considering the whole interval of variation of  $\mu_\varepsilon$ , one would observe that  $C_1(Q_1^*)$  is decreasing in  $\mu_\varepsilon$  until a critical value  $\mu_\varepsilon^*$  is achieved, and then becomes to augment for  $\mu_\varepsilon \geq \mu_\varepsilon^*$ . This result conveys an interesting managerial insight: when the stochastic behavior of factors introducing uncertainty on  $Q_{IS}$  is known (especially  $\mu_\varepsilon$ ), a way to compensate for errors is to adjust the recorded inventory level by setting  $Q_{IS} = Q + \mu_\varepsilon^*$  (where  $Q$  is the quantity ordered). This corrective action can be expected to perform even better (in terms of cost) than merely optimizing the system with errors.

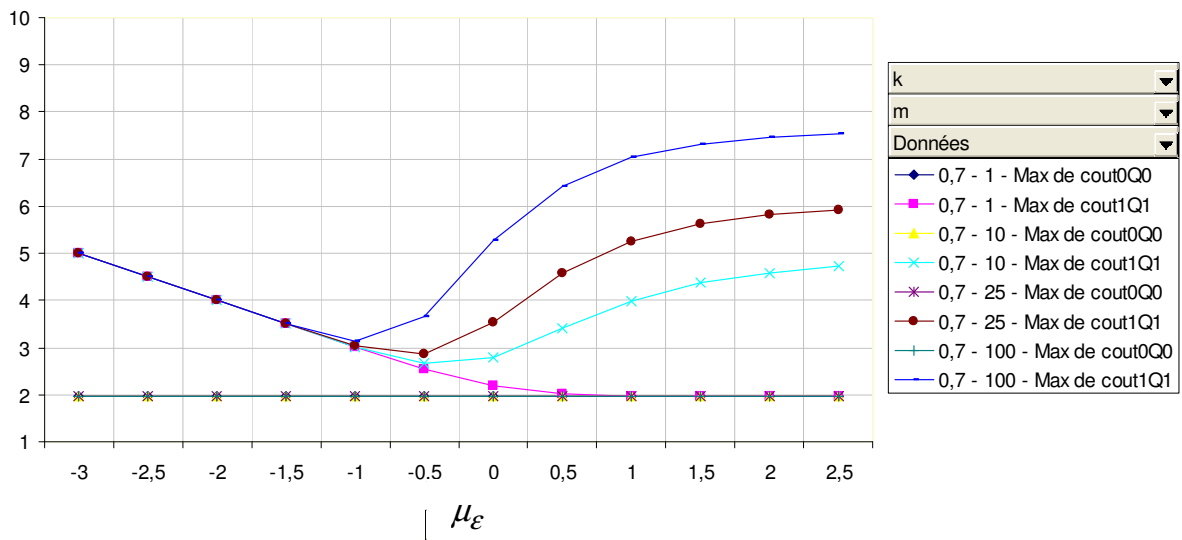
For instance, in the example below, for  $m=25$ , initially if we suppose that  $\mu_\varepsilon = 0$ , one will incur  $C_1(Q_1^*) = 3.53$ ; applying the strategy of decrementing the inventory record by  $\mu_\varepsilon^* = -0.5$  leads to  $C_1(Q_1^*) = 2.86$ , in other words, this results in a 19% relative cost reduction.

$$\mu_D = 10; \sigma_D = 3; k = 0.7; \sigma_\varepsilon = 0.5$$

$$Q_0^*, Q_1^*$$



$$C_1(Q_1^*)$$



**Figure 11. The optimal policies pertaining to Model 0 and Model 1 with respect to  $\mu_\epsilon$  for varying values of  $m$**

**Remark**

Although we do not have an analytical expression of  $\mu_\epsilon^*$ , one can characterize it by making the following observations:

1. The value of  $\mu_\epsilon^*$  decreases as  $m$  increases. If  $m$  is important, in order to reduce the risk to have a costly shortage type 2 cost, one would increase  $Q_1^*$  even for  $\mu_\epsilon < 0$  (one has  $\mu_\epsilon^* = -0.5$  for  $m=10$  in the example above)

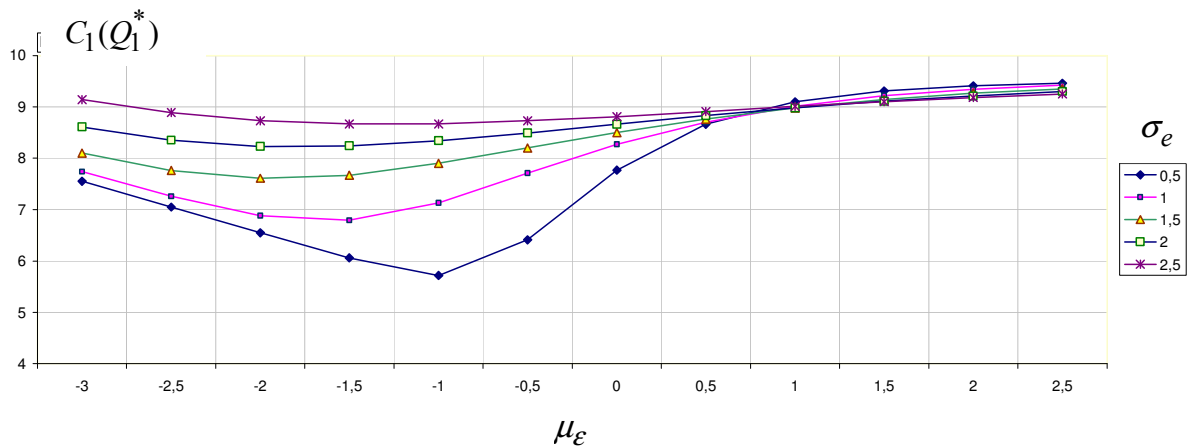
2. The evolution of  $\mu_\varepsilon^*$  for varying values of  $\sigma_\varepsilon$  depends also on values of that parameters  $k$  and  $m$  take.

Both  $B_1(Q)$  and  $B_2(Q)$  increase as  $\sigma_\varepsilon$  increases. Furthermore, while for small values of  $\mu_\varepsilon$ ,  $B_1(Q)$  type cost is relatively more important than  $B_2(Q)$  type cost; if  $\mu_\varepsilon$  increases,  $B_2(Q)$  becomes higher than  $B_1(Q)$ .

Therefore, if the ratio  $k/m$  is small, in order to reduce the dominant  $B_2(Q)$  type cost,  $\mu_\varepsilon^*$  will be decreasing in  $\sigma_\varepsilon$  unless  $\sigma_\varepsilon$  takes large values to create a potential for excessive shortage type 1 situations. Decreasing the quantity observed in IS would enable to avoid a costly shortage type 2 cost.

Whereas, if  $k/m$  is higher, to reduce the dominant  $B_1(Q)$  type cost,  $\mu_\varepsilon^*$  will be increasing in  $\sigma_\varepsilon$ . Since  $m$  is small, the total cost is reduced by increasing the quantity observed in IS. By doing so, the total shortage (type 1 and 2) cost of the system decreases.

$$\mu_D = 10; \sigma_D = 3; k = 5; m = 100$$



$$\mu_D = 10; \sigma_D = 3; k = 15; m = 3$$

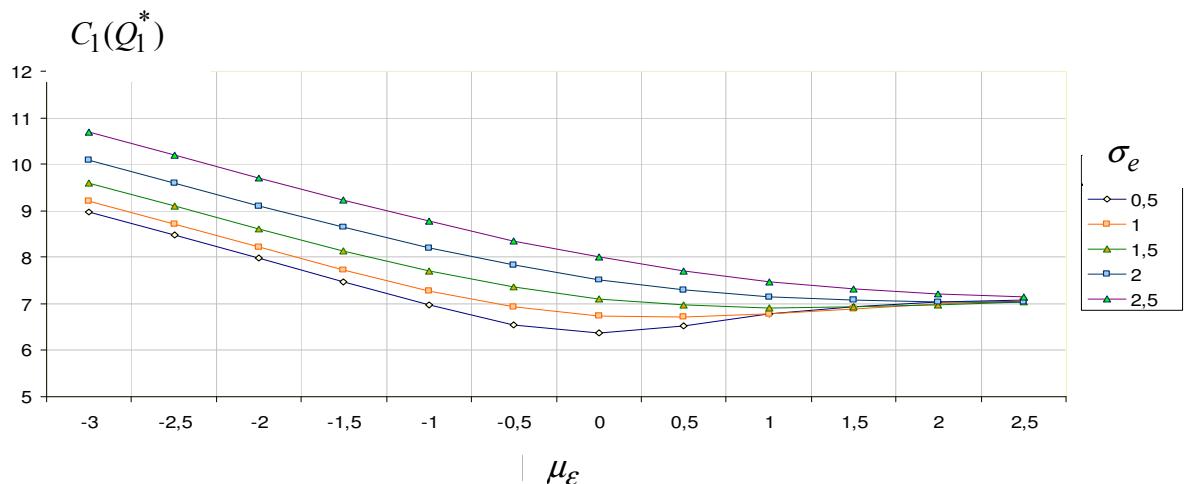


Figure 12. Using  $\mu_\varepsilon$  as a decision variable to minimize cost

## 2. Multiplicative errors

In this section, we examine the evolution of the optimal policy when errors impacting  $Q_{IS}$  are multiplicative. As in the previous section, the cases of uniformly and normally distributed random variables are investigated. Before assuming that demand is stochastic, on the first base, we consider the case of deterministic demand and uniformly distributed errors. This analysis leads to the following main results:

### 2.1. Deterministic demand case

#### a) Evolution of $Q_1^*$ for varying values of $\sigma_e$

**Expression of  $Q_1^*$**  : The expression of the optimal quantity to order is given by:

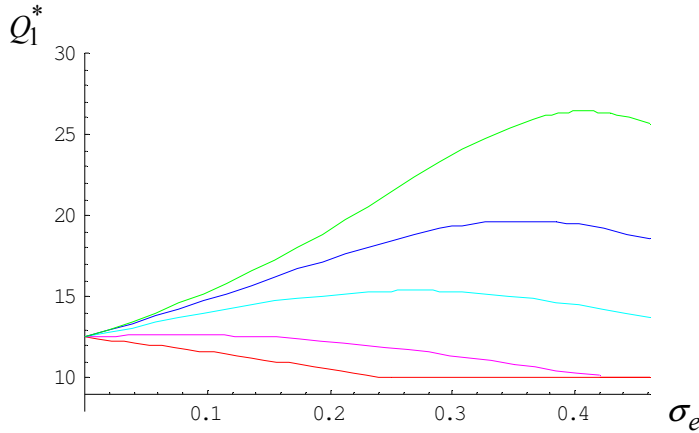
$$\begin{cases} Q_1^* = D \cdot \sqrt{\frac{(1+k)}{-6 \cdot (-2 + \mu_p + k \cdot \mu_p) \cdot \sigma_e + \sqrt{3} \cdot (1+k) \cdot (\mu_p^2 + 3 \cdot \sigma_e^2)}}, & \text{if } D \leq D \cdot \sqrt{\frac{(1+k)}{-6 \cdot (-2 + \mu_p + k \cdot \mu_p) \cdot \sigma_e + \sqrt{3} \cdot (1+k) \cdot (\mu_p^2 + 3 \cdot \sigma_e^2)}} \leq \frac{D}{L_p} \\ Q_1^* = D, & \text{otherwise} \end{cases}$$

Several configurations resulting from the different positions of the distribution of  $Q_{IS}$  and demand have been considered to correctly formulate the expected cost function. To illustrate this, App 1 formulates the expected cost for a distribution of  $Q_{IS}$  such that  $\mu_p = 1$ . The same approach has been adapted to the case of  $\mu_p \neq 1$  in App 2. In the following, we concentrate on the second case which is more general.

- If  $\sigma_e = 0$ , ordering  $Q_1^* = D/\mu_p$  generates an overage cost while ordering less than  $D/\mu_p$  reduces this penalty while generating an additional shortage cost. Therefore, the optimal policy is to order  $Q_1^* = 0$  if having a shortage is relatively less costly than having an overage, i.e. if  $\mu_p < \frac{1}{1+k}$ ; and order  $Q_1^* = \frac{D}{\mu_p}$  if  $\mu_p \geq \frac{1}{1+k}$ .
- For higher values of  $\sigma_e$ , the expression of the optimal quantity to order is provided above. Furthermore, if  $\mu_p < \frac{1}{1+k}$ , the decision would consist in  $Q_1^* = 0$  all for all values of  $\sigma_e$ . Note that for all values of  $\mu_p$ , the quantity minimizing the total cost is higher than  $D$ : ordering more than the known value of  $D$  ensures that a shortage type 2 cost is not incurred.

### Sensitivity of $Q_1^*$ to varying values of $\sigma_e$

$\mu_p = 0.8; D = 10; k = 1; k = 2; k = 5; k = 10; k = 20$



**Figure 13.**  $Q_1^*$  with respect to  $\sigma_e$  for deterministic demand and uniformly distributed errors

- For values of  $\mu_p \leq 1$ ,

For **small values of k**, if  $\mu_p$  is relatively small (cf. conditions expressed in App 2),  $Q_1^*$  decreases as  $\sigma_e$  increases. Decreasing  $Q_1^*$  reduces the overage cost stemming from the difference between  $Q_{PH}$  and  $D$  but increases  $H^1(Q)$  type cost, i.e. the cost associated with the case  $Q_{IS} \leq D \leq Q_{PH}$ . Since the first cost is incurred for all values of  $Q_{IS}$ , the decision is to order less.

For **higher values of k**, if values that  $\sigma_e$  takes are small,  $Q_1^*$  is increasing in  $\sigma_e$  in order to reduce  $H^1(Q)$  and  $B_1(Q)$  type costs. Meanwhile, the  $H^2(Q)$  type cost increases since both  $\sigma_e$  and  $Q_1^*$  increase.

**Complementary information on the behavior of  $H^1(Q)$  type cost:** When demand is deterministic and errors are multiplicative, the shape of the overage cost associated with the case  $Q_{IS} \leq D \leq Q_{PH}$  is similar to the stochastic demand case (cf. section 1.4.3 of Part 1) : this cost component is first increasing in  $Q$  (since the dominant factor is the augmentation of the average quantity in excess) and then, it is decreasing in  $Q$  (since the dominant factor is the reduction of the probability  $P(Q_{IS} \leq D)$ ).

If  $\sigma_e$  increases, the value of  $Q$  for which this cost achieves its peak value would increase since for a given value of  $Q$  that is in the interval  $[D, D/L_p]$ , the probability  $P(Q_{IS} \leq D)$  will increase (and therefore be less critical) as  $\sigma_e$  increases.



Therefore, the higher is  $\sigma_e$ , the more likely that  $H^1(Q)$  will be increasing in Q for values of Q higher than D.

That is why, for values of  $\sigma_e$  higher than a critical value, to reduce both  $H^1(Q)$  and  $H^2(Q)$  type costs, one will decrease  $Q_1^*$ .

- For  $\mu_p > 1$ ,

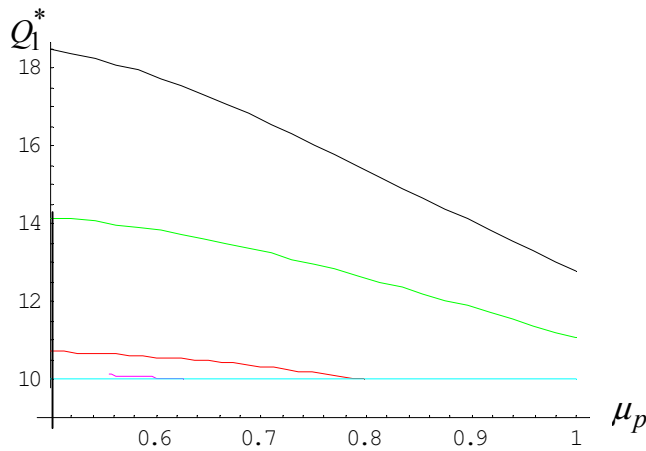
If  $\sigma_e = 0, Q_1^* = D$ . As long as values of  $\mu_p$  and  $\sigma_e$  are s.t. costs associated with the interval of  $Q_{IS}$  values that satisfies  $Q_{IS} < D$  are low, one orders  $Q_1^* = D$ . Otherwise, one orders

$$Q_1^* = D \cdot \sqrt{\frac{\sqrt{3} \cdot (1+k)}{-6 \cdot (-2 + \mu_p + k \cdot \mu_p) \cdot \sigma_e + \sqrt{3} \cdot (1+k) \cdot (\mu_p^2 + 3 \cdot \sigma_e^2)}} \quad (\text{which is } > D).$$

### b) Evolution of $Q_1^*$ for varying values of $\mu_p$

For  $\mu_p < 1$ , as  $\mu_p$  increases,  $H^2(Q)$  type cost becomes relatively more important. To counterbalance this, one decreases  $Q_1^*$  (cf. App 3 for technical proof).

$\sigma_e = 0.25; D = 10; k = 0.8; k = 1; k = 2.5; k = 5$



**Figure 14.**  $Q_1^*$  with respect to  $\mu_p$  for deterministic demand and uniformly distributed errors

For instance, for  $k=0.8$ ;

- if  $\mu_p \leq 0.55, Q_1^* = 0$ ;
- if  $0.55 \leq \mu_p \leq 0.627, Q_1^* = D \cdot \sqrt{\frac{\sqrt{3} \cdot (1+k)}{-6 \cdot (-2 + \mu_p + k \cdot \mu_p) \cdot \sigma_e + \sqrt{3} \cdot (1+k) \cdot (\mu_p^2 + 3 \cdot \sigma_e^2)}}$ ;
- if  $\mu_p > 0.627, Q_1^* = D$ .

## 2.2. Stochastic demand case

This section is beginning with the examination of the optimal policy for uniformly distributed demand and errors with  $\mu_p = 1$  and  $L_x = 0$ . Results obtained in this analysis are then extended to the case of normal distributions for  $\mu_p = 1$  as well as for  $\mu_p \neq 1$ .

### 2.2.1. Evolution of the optimal policy for varying values of $\sigma_e$

The analysis pertaining to the formulation of the expected cost associated with this model where inventory record errors are multiplicative is conducted in section 1.4. of Part 1. The following two sections show how  $Q_1^*$  and  $C_1(Q_1^*)$  are impacted by inaccuracies as the standard deviation of the distribution of  $Q_{IS}$  is varied.

#### a) Analysis of the optimal quantity to order

For reasons exposed earlier (cf. section 1.4.1. of Part 1), closed form analytical solutions being obtained for only certain intervals of variation of Q, the optimal policy has been characterized by means of numerical studies.

Beginning with the case  $m=1$ , results observed in these analyses are as follows<sup>3</sup>:

If  $m=1$ , for  $\sigma_e = 0$ ,  $Q_1^* = Q_0^*$ . For other values of  $\sigma_e$ :

- If  $k \leq 29/3$ , for all values of  $\sigma_e$ , the expression of  $Q_1^*$  is given by:

$$Q_1^* = \frac{U_x \cdot (-4k + \sqrt{3} \cdot (1+k) \cdot \sigma_e)}{2 \cdot (1+k) \cdot (-2 + (\sqrt{3} - \sigma_e) \cdot \sigma_e)}$$

Note that this is a particular case (where  $m=1$ ) of the more general expression given by:

$$Q_1^* = \frac{U_x \cdot (-4k + \sqrt{3} \cdot (1+k \cdot m) \cdot \sigma_e)}{2 \cdot (-2 + (\sqrt{3} - \sigma_e) \cdot \sigma_e + k \cdot (m \cdot \sigma_e \cdot (\sqrt{3} + \sigma_e) - 2 \cdot (1 + \sigma_e^2)))}$$

- For small values of k (i.e.  $k \leq 1$ ),  $Q_1^* < Q_0^*$  for all values of  $\sigma_e$
- If k is higher (i.e.  $k > 1$ ),  $Q_1^* > Q_0^*$  (and is increasing in  $\sigma_e$ ) for

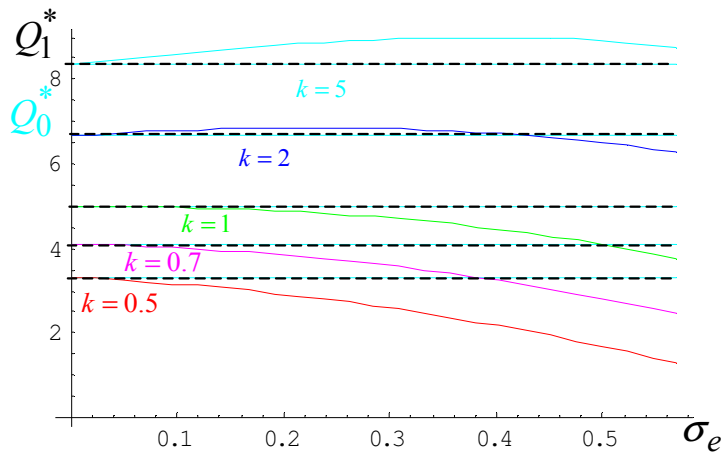
$$\sigma_e \leq \frac{4k - \sqrt{6 + 10k^2}}{\sqrt{3} \cdot (1+k)} \text{ while it is decreasing for higher values of } \sigma_e$$

- For higher values of k (i.e.  $k > 29/3$ ),  $Q_1^*$  is evaluated by conducting numerical analyses.

---

<sup>3</sup> cf. App 4 for further details.

$k = 0.5; k = 0.7; k = 1; k = 2; k = 5$



**Figure 15.**  $Q_1^*$  with respect to  $\sigma_e$  for uniformly distributed demand and errors (small values of  $k$ )

The explanation pertaining to the evolution of  $Q_1^*$  is as follows:

- If  $k$  takes **small values** (i.e.  $k \leq 1$ ), for small values of  $\sigma_e$ , costs associated with cases  $Q_{IS} \leq Q_{PH} \leq D$  and  $Q_{PH} \leq Q_{IS} \leq D$  are dominant: due to errors, values of  $Q_{IS}$  smaller than  $Q_0^*$  generate additional  $B_1(Q)$  and  $H^1(Q)$  type costs, while values of  $Q_{IS}$  higher than  $Q_0^*$  create a potential risk for  $B_2(Q)$  type cost, which is relatively small since  $u_2$  is small. Furthermore, if  $\sigma_e$  increases, the interval of potential values for  $Q_{IS}$  increases; the probability for demand to be in between  $Q_{PH}$  and  $Q_{IS}$  increases, thus, costs associated with cases  $Q_{IS} \leq D \leq Q_{PH}$  and  $Q_{PH} \leq D \leq Q_{IS}$  increase (since  $m = 1$ , the second case has less impact).

**Complementary information on the behavior of  $H^1(Q)$  type cost:** The  $H^1(Q)$  type cost (associated with cases  $Q_{IS} \leq D \leq Q_{PH}$  and  $Q_{IS} \leq Q_{PH} \leq D$ ) is first increasing in  $Q$  (since the dominant factor is the augmentation of the average quantity in excess) and decreases for higher values of  $Q$  (the reduction of the probability to observe these cases is the dominant factor). If  $\sigma_e$  increases, the value of  $Q$  for which this cost achieves its maximum value increases since the second effect becomes dominant for higher values of  $Q$ .

Since  $k$  is small,  $Q_0^*$  is also small. The probability  $P(D > Q_0^*)$  being important,  $H^1(Q)$  will be increasing in  $Q$  for  $Q = Q_0^*$ . Furthermore, for small values of  $Q$ ,  $B_2^1(Q)$  type cost

<sup>4</sup> Cf. App 7, Part 1, Chapter 5

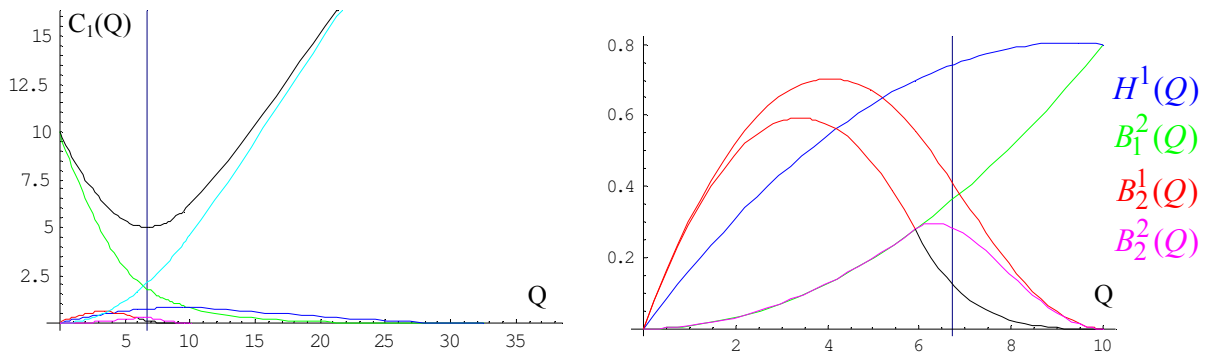
is also increasing in  $Q$ . Therefore, as  $\sigma_e$  increases, one decreases  $Q_1^*$  to reduce  $H^1(Q), H^2(Q), B_1^1(Q)$  and  $B_2^2(Q)$  type costs.

- If  $k$  takes **higher values** ( $1 \leq k \leq 10$ ), for  $Q = Q_0^*$ , both  $H^1(Q)$  and  $B_2(Q)$  are decreasing in  $Q$ . Furthermore,  $B_1(Q)$  type cost is relatively more important (than the previous case where  $k$  was smaller). If  $\sigma_e$  increases,  $H^1(Q), B_1(Q)$  and  $B_2(Q)$  increase. To reduce the overall cost incurred, one increases  $Q_1^*$ .

For higher values of  $\sigma_e$ , the following observations should be made: **a)**  $B_2(Q)$  is decreasing in  $Q$  for  $Q > Q_0^*$ , **b)**  $H^1(Q)$  is increasing in  $Q$  for values of  $Q$  close to  $Q_0^*$ .  $H^1(Q)$  is relatively more important than  $B_2(Q)$  since; for  $Q > Q_0^*$ , both the probability and the average quantity generating  $H^1(Q)$  type cost are higher. **c)** the cost pertaining to  $B_1^2(Q)$  (which is also increasing in  $Q$ ) is important; increasing  $Q$  in order to reduce the total  $B_1(Q)$  type cost has less impact.

As a result,  $Q_1^*$  decreases as  $\sigma_e$  increases.

$$k = 2; m = 1; \sigma_e = 0.4$$



**Figure 16. Decomposed cost function**

- If  $k$  is **very high** (i.e.  $k > 29/3$ ),  $Q_1^*$  may be in the interval  $U_x \leq Q_1^* \leq U_x/L_p$ . For  $\sigma_e = 0$ ,  $Q_1^* = Q_0^*$  and is close to  $U_x$  in order to reduce the shortage type 1 cost. For higher values of  $\sigma_e$ ,  $B_2(Q)$  has a weak impact on the optimization of the system which results from the trade off between  $B_1(Q)$  and  $H(Q)$  type costs.

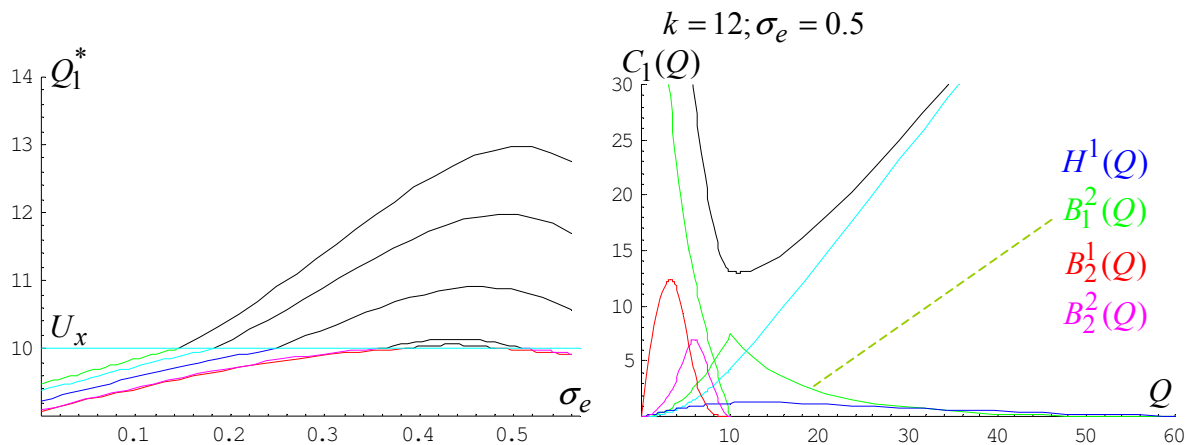
**Impact of  $\sigma_e$  on  $B_1(Q)$ :** For values of  $Q$  close to  $U_x$ ,  $B_1^2(Q)$  is the dominant component of  $B_1(Q)$ . For small values of  $\sigma_e$ , the marginal value earned from increasing  $Q$  (in order to reduce this component) is important since the interval of values that  $Q_{IS}$  can take is narrow and increasing  $Q$  has a direct impact on reducing this

cost. For higher values of  $\sigma_e$ , as the interval of values of  $Q_{IS}$  s.t.  $Q_{IS} < U_x$  is wider, the marginal effect of increasing  $Q$  is smaller. In other words, when  $\sigma_e$  increases, increasing  $Q$  has a less important impact on reducing  $B_1(Q)$  type cost (cf. App. 6.3 of Part 1).

**Impact of  $\sigma_e$  on  $H^1(Q)$ :** For small values of  $\sigma_e$ ,  $H^1(Q)$  is decreasing in  $Q$  for  $Q = Q_0^*$ , whereas for higher values of  $\sigma_e$ , it is increasing in  $Q$  for  $Q = Q_0^*$  (cf. App 7.2.). As a result, for small values of  $\sigma_e$ , in order to reduce  $B_1(Q)$  and  $H^1(Q)$ , one increases  $Q_1^*$  as  $\sigma_e$  increases, while for higher values of  $\sigma_e$ , in order to reduce the relatively important  $H^1(Q)$ , one decreases  $Q_1^*$ .

$k = 9.8; k = 10; k = 12; k = 15; k = 18$

zoomed view of cost components



**Figure 17.  $Q_1^*$  with respect to  $\sigma_e$  for uniformly distributed demand and errors (higher values of  $k$ )**

As observed in the figure above, for  $U_x \leq Q_1^* \leq U_x/L_p$  **a)** the higher is  $k$ , the smaller is the value of  $\sigma_e$  above which  $Q_1^* \geq U_x$  **b)** for very high values of  $k$ ,  $Q_1^*$  does not decrease even for high values of  $\sigma_e$ .

### Remark

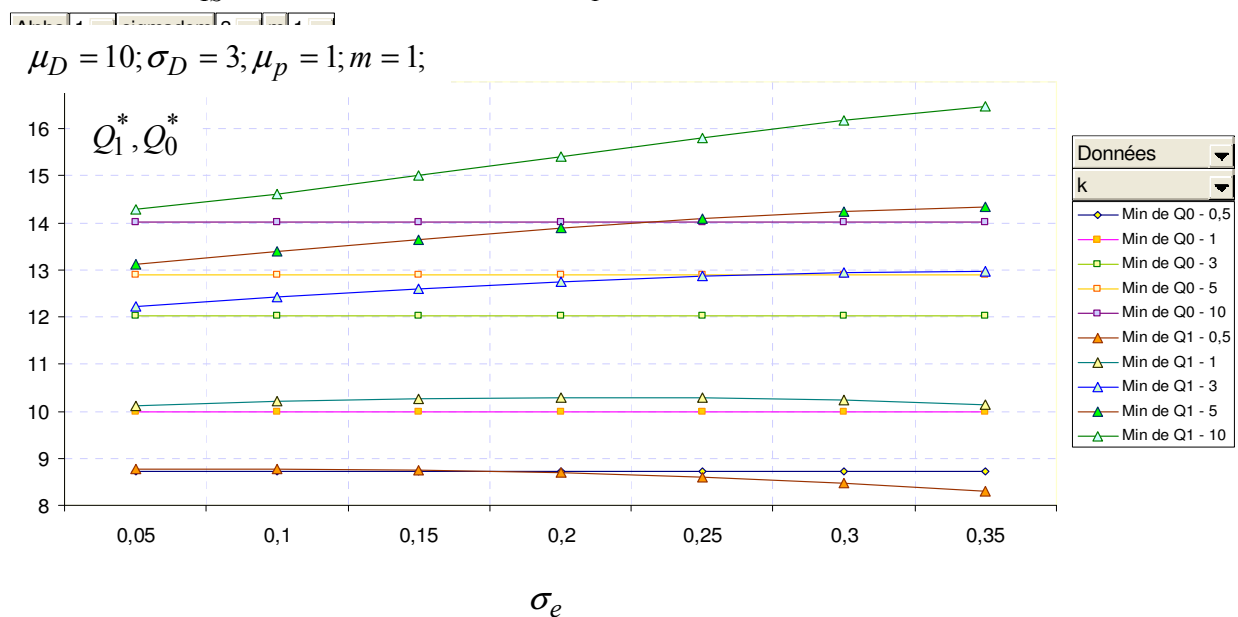
While in the deterministic demand case, we always have  $Q_1^* \geq Q_0^* = D$ , if demand is stochastic,  $Q_1^*$  may be smaller than  $Q_0^*$ . In the deterministic case, for  $\sigma_e = 0$ , we have  $Q_1^* = Q_0^* = D$ ; as  $\sigma_e$  increases, reducing  $Q$  would generate an additional  $B_2(Q)$  type cost (which is defined for  $0 < Q < D$ ). In the stochastic case, as  $\sigma_e$  increases, one has the opportunity to reduce  $B_2(Q)$  type cost by ordering less than  $Q_0^*$ .

If demand and errors are normally distributed<sup>5</sup>, results analogue to the case of uniform distributions are obtained, namely:

- In situations where the unit overage penalty is relatively more important than the unit shortage type 1 cost (i.e.  $k < 1$ ), for a given error rate  $\sigma_e$ ,  $Q_1^*$  may be smaller than  $Q_0^*$ . Furthermore,  $Q_1^*$  decreases as  $\sigma_e$  increases.
- In situations where the unit shortage type 1 cost is relatively more important than the unit overage cost,  $Q_1^*$  is higher than  $Q_0^*$  for almost all values of  $\sigma_e$ .

As the error rate grows, the gap between the two quantities widens; to cover against potential shortage type 1 situations that stem from observing low values of inventory in IS, one increases  $Q_1^*$ .

As a consequence, the length of the interval of potential values that  $Q_{IS}$  can take, which is proportional to the quantity ordered, increases. As  $\sigma_e$  takes large values, ordering more would increase even more this interval and the associated risk to observe very small values of  $Q_{IS}$ . Therefore, one decreases  $Q_1^*$ .



**Figure 18. Evolutions of  $Q_1^*$  and  $Q_0^*$  the optimal quantity with respect to  $\sigma_e$  for varying values of  $k$**

### Impact of higher values of $m$

If  $m$  increases,

<sup>5</sup> In this case, note that the value of  $\sigma_e$  should not exceed  $\approx 0.35$  in order to avoid assigning negative values to  $Q_{IS}$  (cf. section 2.5 of Chapter 4).

- values that  $Q_1^*$  takes are higher (than the case  $m=1$ ) to cover against a potential costly shortage type 2 cost
- for small values of  $k$ , the interval of values of  $\sigma_e$  s.t.  $Q_1^*$  is decreasing becomes smaller. Furthermore, the magnitude of the diminution of  $Q_1^*$  is less important due to the impact of  $B_2(Q)$  type cost which represents a counteracting force against  $H^1(Q)$ .

**Complementary information on the behavior of  $B_2(Q)$  type cost:**  $B_2(Q)$  is first increasing in  $Q$  (due to the augmentation of the average quantity in shortage which is the dominant factor) and then decreases as  $Q$  increases (due to the reduction of the probability to observe these cases which becomes the dominant factor) (cf. section 1.4.3 of Part 1). If  $\sigma_e$  increases, the value of  $Q$  at which  $B_2(Q)$  achieves its peak decreases since the second effect becomes dominant for smaller values of  $Q$ .

The higher is  $m$ , the higher will be the relative importance of  $B_2(Q)$ .

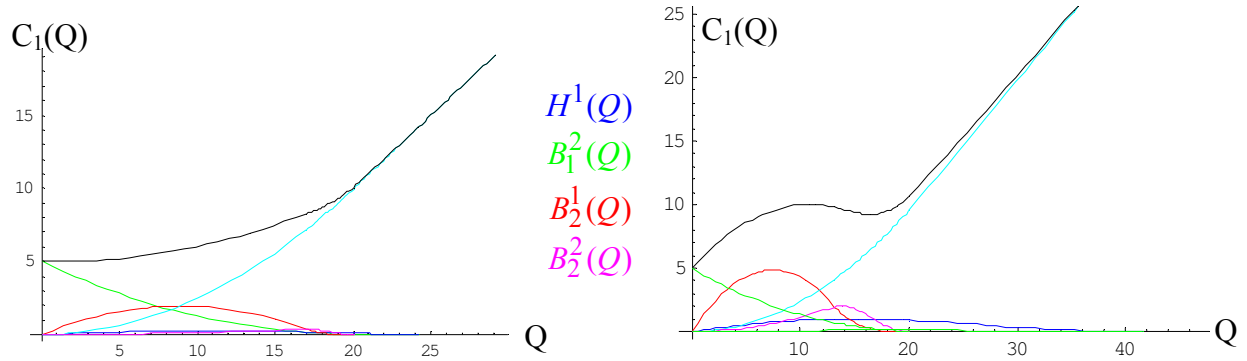
- for higher values of  $k$ ,  $m$  has almost no impact on the optimal policy; the probability  $P(Q_{PH} \leq D)$  is small, reducing the likelihood to observe a shortage type 2 cost.

**Observation:** In certain cases, optimizing the system in presence of inventory record inaccuracies consists in not ordering to avoid a costly shortage type 2 penalty.

Indeed, if  $k$  is **small** and  $m$  takes **very high values**, the shortage type 2 penalty will be relatively important. To reduce it, one should order either  $Q_1^* \approx U_x$  or  $Q_1^* = 0$ . The first strategy minimizes the total cost for small values of  $\sigma_e$ . But, for values of  $\sigma_e$  higher than a critical values, on the one hand, in order to reduce  $H^1(Q)$  and  $H^2(Q)$ , one should order less. On the other hand, decreasing  $Q_1^*$  augments the shortage type 2 cost, the optimal policy is therefore  $Q_1^* = 0$ .

$\mu_D = 10; \sigma_D = 3; \sigma_e = 0.1; k = 0.5; m = 20$

$\mu_D = 10; \sigma_D = 3; \sigma_e = 0.3; k = 0.5; m = 20$



**Figure 19. Decomposed cost function**

Note that this feature is observed for small values of  $k$ , otherwise ordering nothing would be too costly. For a given (small) value of  $k$ , the critical value of  $\sigma_e$  decreases as  $m$  increases.

### b) Analysis of the optimal cost

If  $\sigma_e = 0$ ,  $C_1(Q_1^*) = C_0(Q_0^*)$ . When distributions are uniform, if values of system parameters are s.t.  $Q_1^* \in C_1^{config1}(Q)^6$ ,  $C_1(Q_1^*)$  will be given by:

$$C_1(Q_1^*) = \frac{\sqrt{3}.h.U_x.(-16.k + (3 + k.(-4 + 3.m).(2 + k.(4 + m))).\sigma_e^2)}{16.(-2\sqrt{3}.(1 + k) + 3.(1 + k.m).\sigma_e + \sqrt{3}.(-1 + k.(-2 + m)).\sigma_e^2)}$$

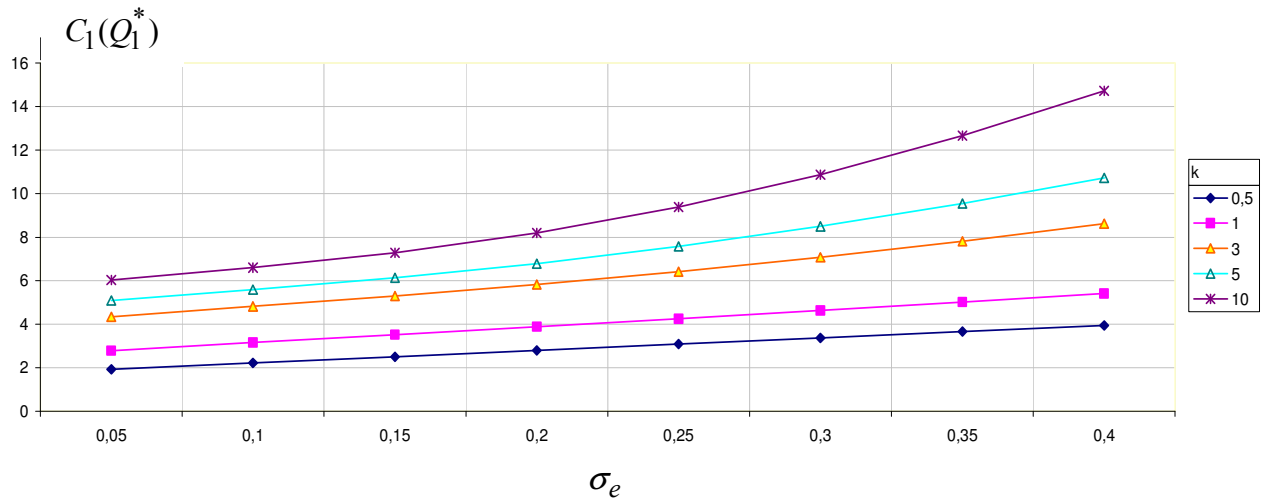
As the error rate increases, the cost of having inaccuracies increases. Figures below consider examples pertaining to normal distributions. For instance, if  $k=5$ , one would order  $Q_0^* = 12.9$  and incur  $C_0(Q_0^*) = 4.5$  in Model 0. If an error rate of  $\sigma_e = 0.15$  is considered, by optimizing the system in presence of errors, one orders  $Q_1^* = 13.65$  and incurs  $C_1(Q_1^*) = 5.74$ ; which means that, in comparison with  $C_0(Q_0^*)$ , a relative additional cost of 28% is incurred due to inaccuracies.

Such type of analysis would serve as a decision support basis for practitioners searching levers that best cope with the inventory inaccuracy issue.

<sup>6</sup> cf. App 1, Part 1, Chapter 5

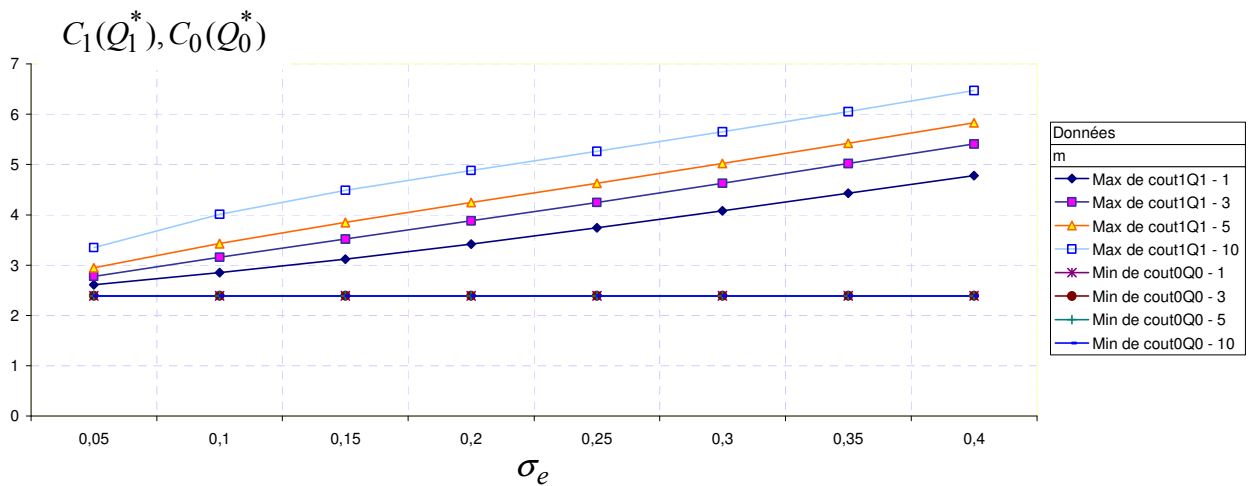


$$\mu_D = 10; \sigma_D = 3; m = 3; \mu_p = 1$$



**Figure 20. The optimal cost with respect to  $\sigma_e$  for varying values of  $k$**

$$\mu_D = 10; \sigma_D = 3; k = 1; \mu_p = 1$$



**Figure 21. Evolution of  $C_0(Q_0^*)$  and  $C_1(Q_1^*)$  with respect to  $\sigma_e$  for varying values of  $m$**

### 2.2.2. Extension of results

This section investigates the evolution of the optimal policy for  $\mu_p \neq 1$  and normally distributed demand and errors.

#### a) Evolution of the optimal policy for varying values of $\sigma_e$

##### The optimal quantity to order

We consider the case of  $m=1$  on the first base:

For small values of  $k$  ( $k < 1$ ),

- If  $\sigma_e = 0$ , for  $\mu_p < 1$ , by ordering less than  $Q_0^*/\mu_p$ , one would reduce  $H^1(Q)$  and  $H^2(Q)$  while increasing  $B_1(Q)$ .  $k$  being small, the augmentation of  $B_1(Q)$  is relatively less important, therefore,  $Q_0^* < Q_1^* < Q_0^*/\mu_p$ .

In an extreme case where  $\mu_p$  and  $k$  take very small values, two cases are observed: in order to reduce (or avoid) to support the costly overage cost, the decision will be either to order  $Q_1^* = 0$  (e.g.  $\mu_D = 10; \sigma_D = 3; k = 0.5$  and  $\mu_p = 0.65$ ) or  $Q_1^* < Q_0^*$  ( $\mu_p = 0.7$ ).

The higher is  $\mu_p$ , the lower is the relative importance of the overage cost; the lower will be the difference  $Q_1^* - Q_0^*$  for  $\sigma_e = 0$ .

For  $\mu_p > 1$ , one would order  $Q_1^* = Q_0^*$ .

- For higher values of  $\sigma_e$ , the evolution of  $Q_1^*$  depends on the ratio  $\frac{\sigma_e}{\mu_p}$  and the value of  $k$ .

The impact of  $\mu_p$  is to push  $Q_1^*$  to take lower values to reduce the overage cost  $H^2(Q)$  associated with cases  $D \leq Q_{IS} \leq Q_{PH}$  and  $D \leq Q_{PH} \leq Q_{IS}$ , whereas  $\sigma_e$  counteracts by pushing  $Q_1^*$  to take higher values to reduce potential shortage situations stemming from observing values of  $Q_{IS}$  smaller than  $Q_0^*$ .

**a.** If  $\mu_p$  takes **small values**, i.e. if  $\frac{\sigma_e}{\mu_p}$  is relatively high; **i)** since most of values of  $Q_{IS}$

will be smaller than  $Q_0^*$ , the dominant costs are  $B_1(Q)$  and  $H^1(Q)$  associated with cases  $Q_{IS} \leq D \leq Q_{PH}$  and  $Q_{IS} \leq Q_{PH} \leq D$ , **ii)**  $Q_0^*$  being small,  $P(Q_{IS} \leq D)$  is important and therefore,  $H^1(Q)$  and  $B_1^2(Q)$  are increasing in  $Q$  for  $Q = Q_0^*$ . If  $\sigma_e$  increases, they will increase even more **iii)** furthermore,  $k$  being small,  $H^1(Q)$  is relatively important.

Therefore, as  $\sigma_e$  increases, to reduce the expected total cost, one decreases  $Q_1^*$ .

### Observations

1. The smaller is  $\mu_p$ , the higher will be the relative effect of the overage cost, the higher will be the decrease of  $Q_1^*$  enabling to reduce the interval of potential values that  $Q_{IS}$  can take.

2. For a given value of  $\mu_p$ , we limit the maximum value that  $\sigma_e$  can take to satisfy  $\sigma_e < \mu_p/3 = (\sigma_e)_{\max}$ . If  $\mu_p$  takes a very small value (e.g. 0.7 in the example below), for  $\sigma_e = (\sigma_e)_{\max}$ ,  $Q_1^*$  may be inferior to  $Q_0^*$  since, by ordering less than  $Q_0^*$ , one has the

opportunity to reduce the relatively important  $H^1(Q)$  and  $B_1(Q)$  type costs stemming from cases  $Q_{IS} \leq Q_{PH} \leq D$  and  $Q_{IS} \leq D \leq Q_{PH}$ .

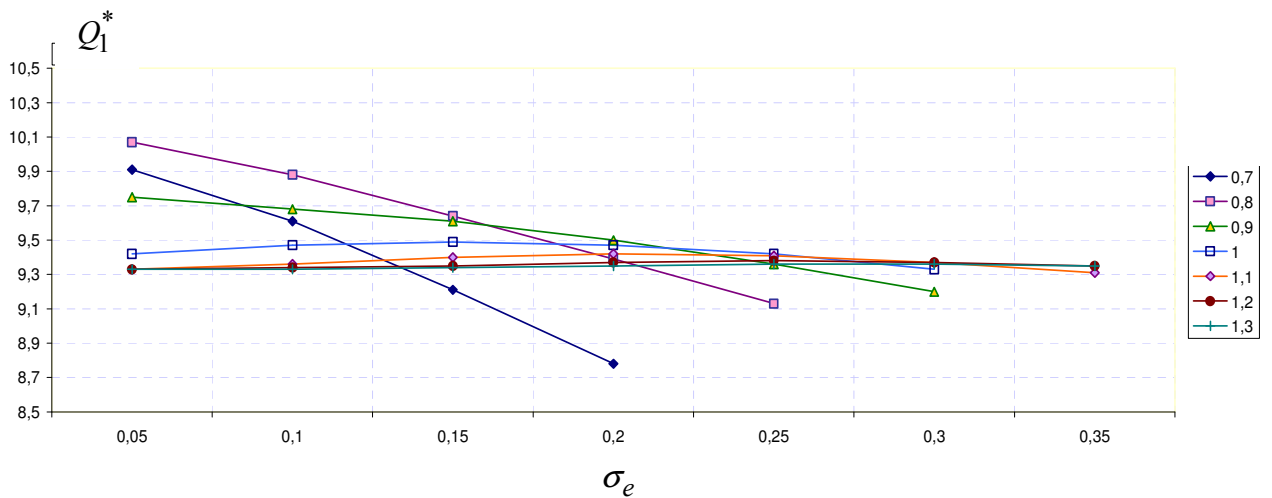
Note that, this is not true for a higher value of  $\mu_p$  for which **i)** the overage cost is relatively less important **ii)** there is a higher probability to observe a shortage type 2 cost for  $Q=Q_0^*$ .

**b.** If values of  $\mu_p$  and  $\sigma_e$  are such that  $\sigma_e$  is relatively more important than  $\mu_p$ , i.e. if

$\frac{\sigma_e}{\mu_p}$  is higher than in section **a.**, the evolution of  $Q_1^*$  is as follows:

- For small values of  $\sigma_e$ ,  $Q_1^*$  is increasing in  $\sigma_e$  to reduce the interval of values of  $Q_{IS}$  such that  $Q_{IS} < Q_0^*$  in order to lower the potential risk to incur shortage type 1 situations.
- For higher values of  $\sigma_e$ , the relative importance of costs pertaining to  $H^1(Q)$  and  $H^2(Q)$  increases. As a result, one decreases  $Q_1^*$  to reduce the expected total cost.

$\mu_D = 10; \sigma_D = 3; k = 0.7; m = 1;$



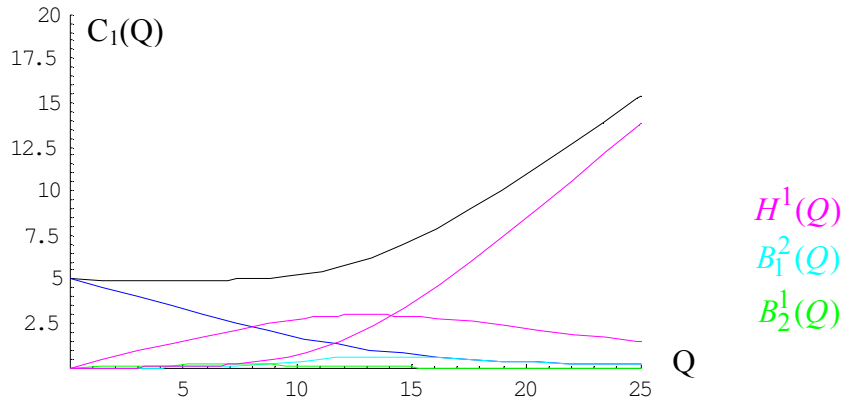
**Figure 22. The optimal quantity with respect to  $\sigma_e$  for varying values of  $\mu_p$  ( $k < 1$ )**

For **higher values of  $k$** , since the effect of  $H^1(Q)$  is even less important and the impact of  $B_1(Q)$  and  $B_2(Q)$  are dominant,  $Q_1^*$  is increasing in  $\sigma_e$  for almost all values of  $\mu_p$ .

### Impact of higher values of m

For small values of  $\mu_p$ , if k takes very small values, since  $P(Q_{PH} \leq D)$  is high (thus not critical),  $B_2(Q)$  will be increasing in Q for  $Q=Q_0^*$ . Due to the combined effect of  $B_2(Q)$  and  $H^1(Q)$  (cf. figure below),  $Q_1^*$  decreases as m increases.

$$\mu_D = 10; \sigma_D = 3; k = 0.5; m = 10; \mu_p = 0.7; \sigma_e = 0.2$$



**Figure 23. Decomposed cost function**

For higher values of  $\mu_p$ , as the relative importance of  $H^1(Q)$  decreases, even for  $m=1$ , quantities ordered are higher. Therefore, the likelihood of  $B_2(Q)$  to be decreasing in Q for these values is high. Thus, for a given value of  $\sigma_e$ , if m increases, one increases  $Q_1^*$ .

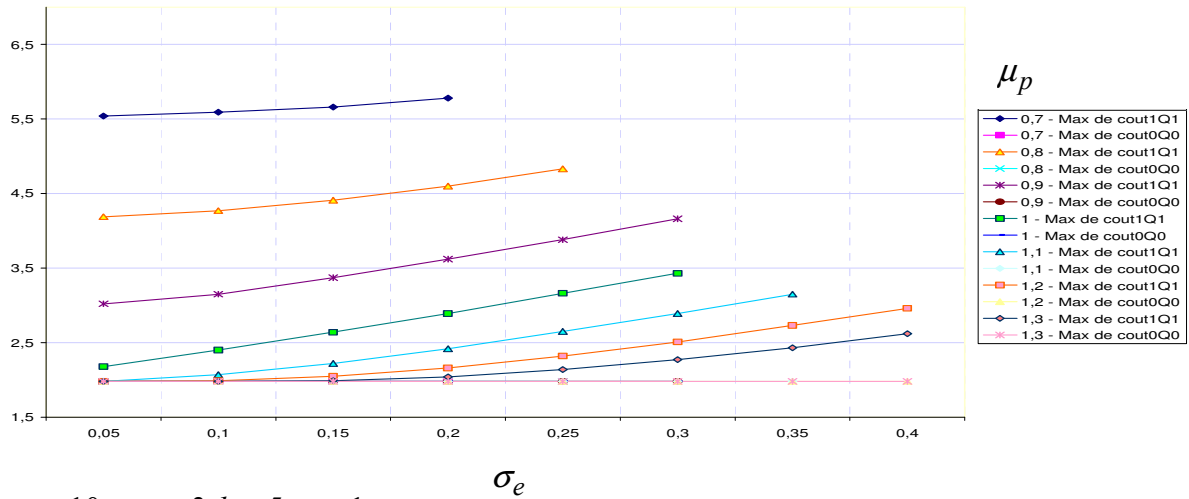
Furthermore, in order to reduce the risk of a shortage type 2 penalty,  $Q_1^*$  becomes increasing in  $\sigma_e$  for almost all values of  $\mu_p$  (except for very small values).

### The optimal cost

Figures below represent  $C_1(Q_1^*)$  and  $C_0(Q_0^*)$  versus  $\sigma_e$  for varying values of  $\mu_p$ , with  $m=1$ . The first figure is for a product for which  $k=0.7$  while in the second, k equals 5. For both products, the cost incurred augments as  $\sigma_e$  grows.

$$\mu_D = 10; \sigma_D = 3; k = 0.7; m = 1;$$

$$C_1(Q_1^*), C_0(Q_0^*)$$



$$\mu_D = 10; \sigma_D = 3; k = 5; m = 1;$$

$$C_1(Q_1^*), C_0(Q_0^*)$$

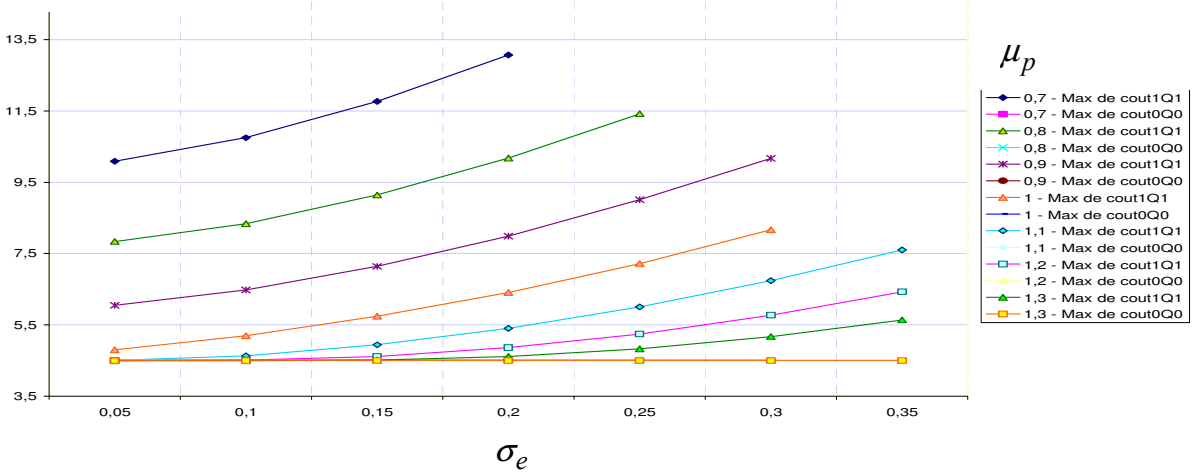


Figure 24.  $C_0(Q_0^*)$  and  $C_1(Q_1^*)$  with respect to  $\sigma_e$  for varying values of  $\mu_p$

For higher values of  $m$ , if  $\mu_p > 1$ ,  $C_1(Q_1^*)$  decreases as  $\sigma_e$  increases for small values of  $\sigma_e$  whereas, for higher values of  $\sigma_e$ ,  $C_1(Q_1^*)$  increases as  $\sigma_e$  increases. (cf. figure below for  $k=5$  and  $\mu_p = 1.1$ )

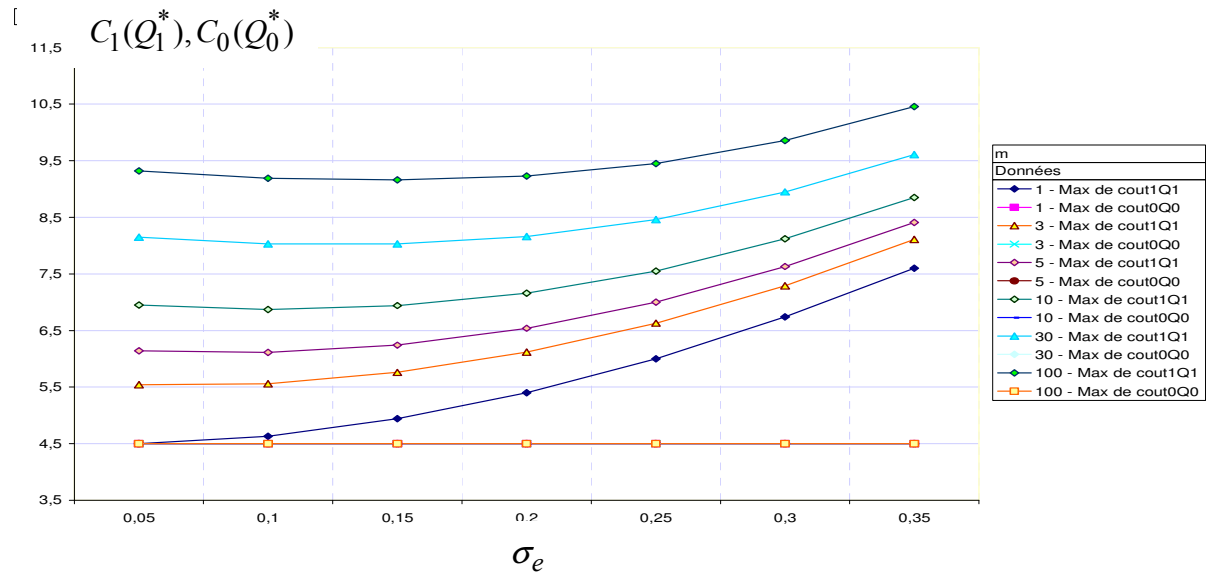


Figure 25.  $C_0(Q_0^*)$  and  $C_1(Q_1^*)$  with respect to  $\sigma_e$  for varying values of  $m$

### b) Evolution of the optimal policy for varying values of $\mu_p$

#### The optimal quantity to order

In order to evaluate how  $Q_1^*$  and  $C_1(Q_1^*)$  are impacted by inventory inaccuracies as  $\mu_p$  is varied, we first consider the case  $m=1$ .

- For values of  $\mu_p \leq 1$ ,

For  $\sigma_e=0$ , if  $k$  is small,  $Q_0^* < Q_1^* < Q_0^*/\mu_p$ . For higher values of  $k$  (i.e.  $k>1$ ), ordering more than  $Q_0^*/\mu_p$ , on the one hand, reduces  $B_1(Q)$  type cost (which is the dominant cost) and, on the other hand, increases the overage cost incurred. This solution is observed when the variability of demand is small (since  $B_1(Q)$  would be relatively more important in this case).

If  $k$  takes small values (i.e.  $k \leq 1$ ),

We first consider situations where  $\sigma_e$  is small in order to isolate and better understand the effect of  $\mu_p$ . This gives the following results:

**Observation 1:** For very small values of  $k$  and  $\mu_p$ ,  $H^1(Q)$  and  $H^2(Q)$  type costs are dominant. To reduce them, one orders a quantity which is even smaller than  $Q_0^*$ .

**Observation 2:** If  $\mu_p$  increases, the relative importance of the overage costs decreases while the shortage type 1 cost becomes relatively more important since almost all values of  $Q_{IS}$  are smaller than  $Q_0^*$  (even if  $\mu_p$  increases, this does not enable to get values of  $Q_{IS}$  close enough

to  $Q_0^*$ ). In order to reduce  $B_1(Q)$  type cost, one increases  $Q_1^*$  as  $\mu_p$  increases. Note that  $Q_1^*$  is higher than  $Q_0^*$  to reduce the length of the interval of  $Q_{IS}$  values that are smaller than  $Q_0^*$ .

**Observation 3:** For higher values of  $\mu_p$ , since values that  $Q_{IS}$  may take are closer to  $Q_0^*$ , the relative importance of the shortage type 1 cost decreases while  $H^2(Q)$  type cost becomes dominant. To reduce it,  $Q_1^*$  decreases (until it achieves  $Q_0^*$ ) as  $\mu_p$  increases.

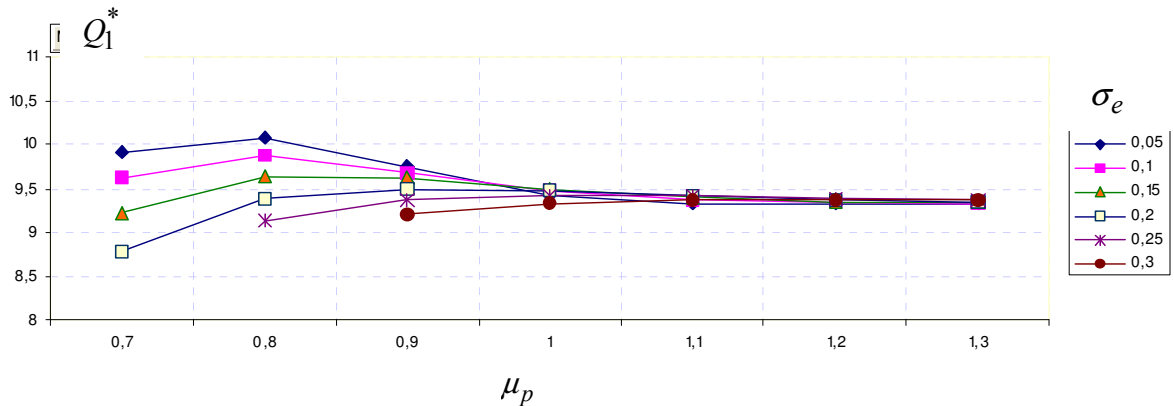
For the same values of  $k$ , **higher values of  $\sigma_e$**  have the following effect on the observations made above:

**Effect of  $\sigma_e$  on observation 1:** For a given small value of  $\mu_p$ , if  $\sigma_e$  increases, the interval of potential  $Q_{IS}$  values becomes wider, thus, the cost associated with overage situations increases. To reduce it, one decreases  $Q_1^*$  as  $\sigma_e$  increases.

**Effect of  $\sigma_e$  on observations 2 and 3:** As  $\mu_p$  increases, for reasons outlined in obs. 2 and 3,  $Q_1^*$  is first increasing in  $\mu_p$  (for small values of  $\mu_p$ ) and then decreases as  $\mu_p$  increases.

When  $\sigma_e$  increases, the interval of potential values for  $Q_{IS}$  becomes larger. That is why, if  $\sigma_e$  is very high, for increasing values of  $\mu_p$ ,  $Q_1^*$  increases but remains smaller than  $Q_0^*$ .

$$\mu_D = 10; \sigma_D = 3; k = 0.7; m = 1;$$



**Figure 26. The optimal quantity with respect to  $\mu_p$  for varying values of  $\sigma_e$  (for  $k < 1$ )**

If  $k$  takes **higher values** (i.e.  $k > 1$ ),

- Quantities ordered are higher
- For small values of  $\sigma_e$ , the evolution of  $Q_1^*$  is as presented in observations 1, 2 and 3, except that the likelihood to observe the increasing part in  $Q_1^*$  decreases as  $k$  increases.

- For higher values of  $\sigma_e$ ,  $Q_1^* > Q_0^*$  to lower the shortage type 1 penalty. As  $k$  takes higher values, since the relative importance of the overage cost decreases,  $Q_1^*$  becomes totally decreasing in  $\mu_p$ .

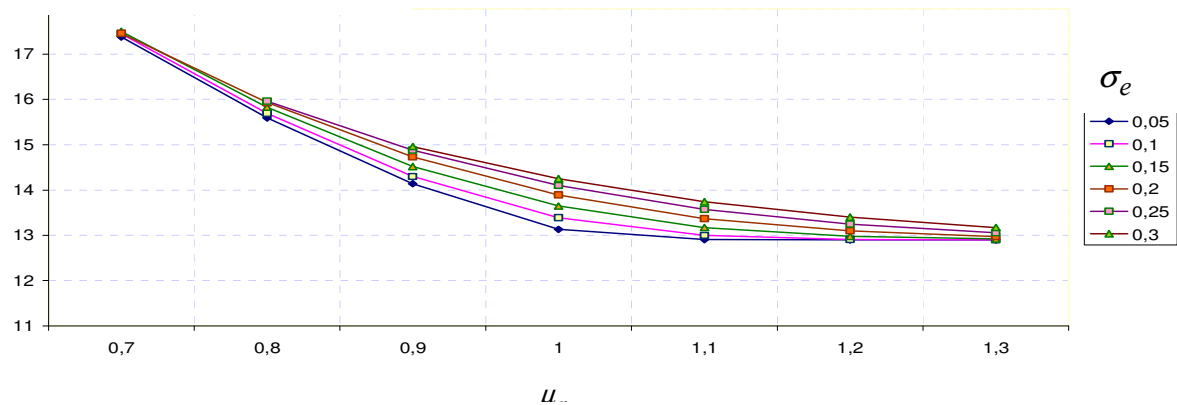
For each value that  $k$  takes, there is a critical point  $\mu_p$  such that for values of  $\mu_p$  smaller than this point,  $Q_1^*$  decreases as  $\sigma_e$  increases, whereas if  $\mu_p$  is higher than this point, one increases  $Q_1^*$  as  $\sigma_e$  increases.

**Observation 4:** The value of this point increases as  $k$  increases. Therefore, for a given value of  $\mu_p$ ,

- If  $k$  is small (i.e.  $k < 1$ ), the effect of  $\sigma_e$  on  $Q_1^*$  is as described above.
- If  $k$  takes a higher value (i.e.  $k > 1$ ), for a given value of  $\mu_p (< 1)$ ,  $Q_1^*$  increases as  $\sigma_e$  increases: to reduce potential shortage type 1 situations, one orders a quantity  $Q_1^*$  that ensures  $\mu_p \cdot Q_1^* > Q_0^*$ . (cf. figure below)

sinmademl3k15m11

$$\mu_D = 10; \sigma_D = 3; k = 5; m = 1;$$



**Figure 27. The optimal quantity with respect to  $\mu_p$  for varying values of  $\sigma_e$  (for  $k > 1$ )**

- For values of  $\mu_p > 1$ ,
  - If  $\sigma_e = 0$ ,  $Q_1^* = Q_0^*$  and thus  $\mu_p \cdot Q_1^* > Q_0^*$ . By ordering  $Q_0^*$  and observing a higher inventory level in IS, one takes the same risk as the system without errors. In other words,  $C_1(Q_1^*)$  equals  $C_0(Q_0^*)$  for  $\mu_p > 1$ .
  - For a positive value of  $\sigma_e$ ,  $C_1(Q_1^*) = C_0(Q_0^*)$  for values of  $\mu_p$  that are higher than a critical value (which is  $> 1$ ). The higher is  $\sigma_e$  (or  $k$ ), the higher would be this critical value.



### Impact of higher values of m

For all values of k,

- If  $\sigma_e = 0$ , for  $\mu_p < 1$ , almost all values of  $Q_{IS}$  being lower than  $Q_{PH}$ , m has no effect on  $Q_1^*$ .  
For  $\mu_p > 1$ ,  $Q_1^*$  is higher than  $Q_0^*$  and it increases as  $\mu_p$  increases to cover against a potential shortage type 2 penalty that is costly.
- For small values of  $\sigma_e$ , if the values that  $\mu_p$  takes are small,  $Q_1^*$  does not vary with m whereas for higher values of  $\mu_p$ ,  $Q_1^*$  increases as m increases. Furthermore, for values of  $\mu_p$  higher than a critical value,  $Q_1^*$  is increasing in  $\mu_p$  since:  
If  $\sigma_e$  is small, costs pertaining to the cases  $D \leq Q_{PH} \leq Q_{IS}$  and  $D \leq Q_{IS} \leq Q_{PH}$  are relatively important. If  $\mu_p$  increases, the cost associated with the interval of  $Q_{IS}$  values s.t.  $Q_{IS} < Q_{PH}$  decreases, whereas the risk to observe the case  $Q_{PH} \leq D \leq Q_{IS}$  grows. Furthermore, since  $m > 1$ , the shortage type 2 cost becomes dominant. To reduce it, one increases  $Q_1^*$ .
- If  $\sigma_e$  increases, for increasing values of m, the cost stemming from observing an information system inventory level that is higher than the physical inventory available is important even for small values of  $\mu_p$ . As a result,  $Q_1^*$  is totally increasing in  $\mu_p$ .

### Remark

If k is small and m is very high, one would order  $Q_1^* = 0$  and incur  $C_1(Q_1^*) = u_1 \cdot \mu_D$ . This is due to the effect of  $H^1(Q)$  type cost (cf. first scheme in the figure below) or the shortage type 2 penalty (cf. second scheme in the figure below) or their combined impact.

$$\mu_D = 10; \sigma_D = 3; \mu_p = 0.7; \sigma_e = 0.2; k = 0.5; m = 30$$

$$\mu_p = 1; \sigma_e = 0.2$$

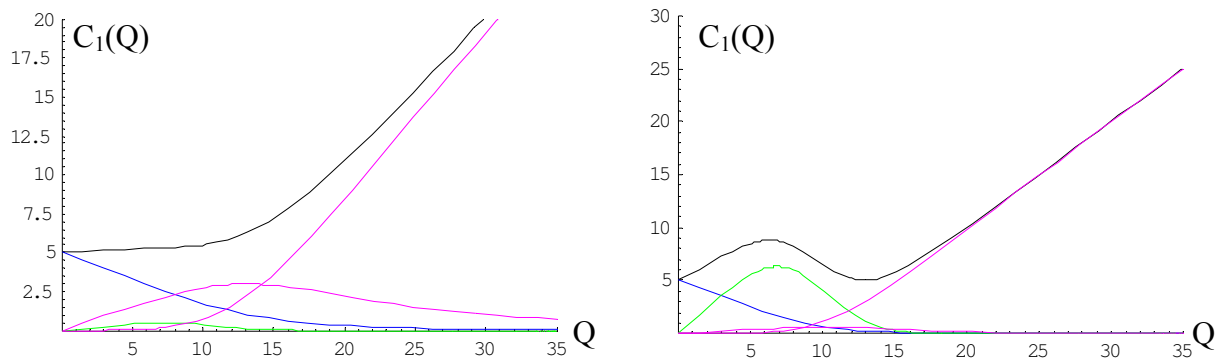


Figure 28. Decomposed cost function

## The optimal cost

The evolution of  $C_1(Q_1^*)$  with respect to  $\mu_p$  confirms the earlier finding that, when parameters pertaining to errors can be estimated, the performance can be improved by adjusting the IS inventory record to compensate for errors.

- For instance, in the example below, for  $m=1$ , since observing a shortage type 2 situation is as costly as a shortage type 1 situation, the expected total cost can be reduced by adjusting the value of  $Q_{IS}$  so that the on hand quantity that appears in the information system is higher than  $Q_{PH}$ . This enables to reduce the shortage type 1 cost without generating excessive penalties when earlier made commitments are not satisfied.

As observed in the graph below,  $C_1(Q_1^*)$  decreases as  $\mu_p$  increases (for  $\mu_p < 1$ ). This is due to the fact that: **i)** one decreases  $Q_1^*$  and therefore,  $H^1(Q)$  type cost is reduced **ii)** the average value observed in IS, i.e.  $\mu_p \cdot Q_1^*$ , increases and therefore  $B_1(Q)$  type cost decreases.

- If  $m$  is higher, one can reduce the expected total cost incurred by decrementing the value of IS inventory. Setting  $Q_{IS} = \mu_p^* \cdot Q$  where  $\mu_p^* < 1$  will reduce the cost since the costly shortage type 2 will be avoided.

As observed in the graph below,  $C_1(Q_1^*)$  is first decreasing in  $\mu_p$  and then increases as  $\mu_p$  increases. The augmentation in the optimal cost stems from the fact that: **i)**  $m$  is higher, therefore, the shortage type 2 penalty incurred is higher, especially for high values of  $\mu_p$  **ii)** as  $m$  takes higher values,  $Q_1^*$  is increasing in  $\mu_p$  for values of  $\mu_p$  that are higher than a critical value. As a result, the average cost incurred increases.

$$\mu_D = 10; \sigma_D = 3; k = 0.7; \sigma_e = 0.1;$$

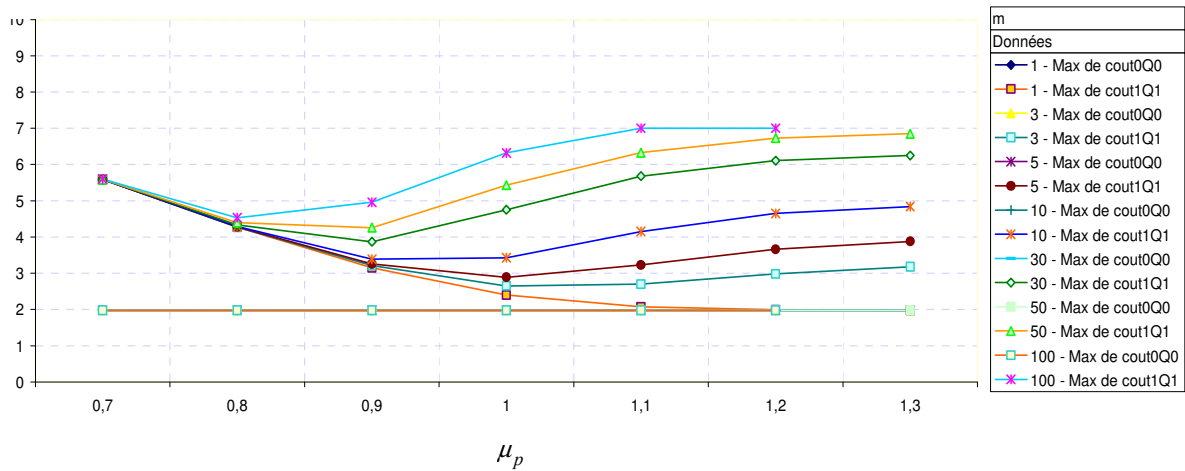


Figure 29.  $C_1(Q_1^*)$  and  $C_0(Q_0^*)$  with respect to  $\mu_p$  for varying values of  $m$

### 3. Mixte errors

This section considers the case of normally distributed random variables and mixte errors. Errors impacting the value of the on hand quantity that appears in the information system have two components: the first component is proportional to  $Q$  while the second is an additive type error. Therefore, there is a strong relationship between the earlier made observations and the results pertaining to the analysis of mixte errors.

#### 3.1. Optimal policy for varying values of $\sigma_e$

Again, if we first assume that  $m=1$ , the characteristics of the evolution of  $Q_1^*$  are as follows:

For  $\sigma_e = 0$ , the evolution of  $Q_1^*$  is similar to the multiplicative errors model (cf. section 2).

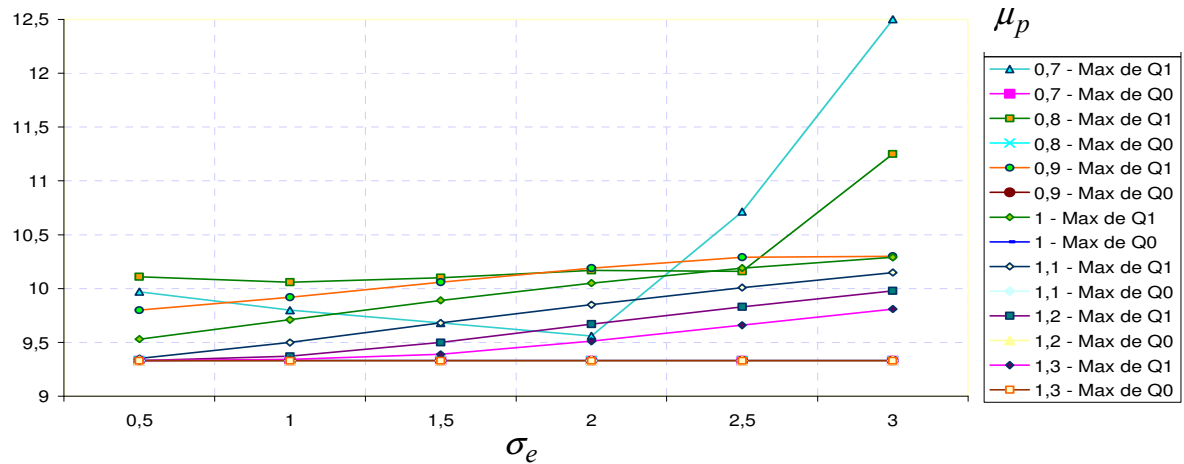
For higher values of  $\sigma_e$ ,

- If  $\mu_p = 1$ , the model is equivalent to the additive errors model with  $\mu_e = 0$ : for all values of  $k$ ,  $Q_1^*$  increases as  $\sigma_e$  increases (cf. section 1).
- For other values of  $\mu_p$ , the behavior of the optimal policy for varying values of  $\sigma_e$  is similar to the additive errors case. Indeed,  $\mu_p$  and  $\mu_e$  play an analogue role in the optimization.

A difference between the additive and mixte errors case is observed when  $k$  takes very small values and if almost all values of  $Q_{IS}$  are smaller than  $Q_{PH}$  (i.e.  $\mu_p$  and  $\sigma_e$  are small): to reduce the overage cost, which is proportional to  $Q$  in the mixte model, one

orders less than the additive model. For instance, for  $\mu_p = 0.7$ , if  $k=0.7$ , the difference  $Q_1^* - Q_0^*$  is quite small (cf. figure below) or in an extreme case where  $k=0.5$ ,  $Q_1^*$  is smaller than  $Q_0^*$ .

$\mu_D = 10; \sigma_D = 3; k = 0.7; m = 1;$



**Figure 30.** The optimal quantity with respect to  $\sigma_e$  for varying values of  $\mu_p$

As observed in the figure, for small values of  $k$  and high values of  $\sigma_e$  (cf.  $\mu_p = 0.7; \sigma_e = 2.5$ ), the optimal quantity consists in ordering  $Q_1^* = (3 \cdot \sigma_e) / \mu_p$  since, the truncated cost function is convex increasing in  $Q$ .

The **impact of higher values of  $m$**  on the optimal policy is similar to the additive errors model: depending on the typology of errors, i.e. whether on average, the quantity observed in the information system is more ( $\mu_p > 1$ ) or less ( $\mu_p < 1$ ) than the physical quantity available,  $C_1(Q_1^*)$  may increase or decrease as  $\sigma_e$  increases.

### 3.2. Optimal policy for varying values of $\mu_p$

Assuming  $m=1$  leads to the following results:

- For values of  $\mu_p < 1$ ,

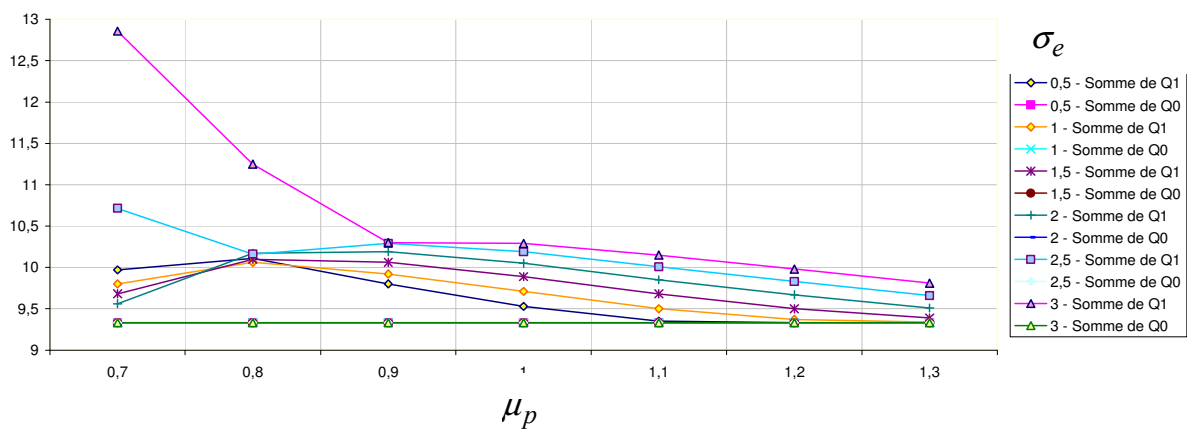
If  $k$  takes **small values** (i.e.  $k < 1$ ),

- If  $\sigma_e$  is small, the evolution of  $Q_1^*$  for varying values of  $\mu_p$  is as characterized in observations 1, 2 and 3 made in section 2.
- For a given value of  $\mu_p$  (except very small values),  $Q_1^*$  increases as  $\sigma_e$  increases (cf. section 3.1)

For a given very small value of  $\mu_p$ , if  $k$  is also small,  $Q_1^*$  would decrease as  $\sigma_e$  increases: since the overage cost is dominant ( $\mu_p$  and  $k$  are small), one decreases  $Q_1^*$  to reduce this cost component.

Furthermore, if  $\sigma_e$  takes very high values, one orders  $Q_1^* = 3 \cdot \sigma_e / \mu_p$  since the truncated cost function becomes totally increasing in  $Q$ . ( $\sigma_e = 2.5$  or  $3$  in the example below) Note that due to this effect, for  $\sigma_e = 3$ ,  $Q_1^*$  is totally decreasing in  $\mu_p$ .

$$\mu_D = 10; \sigma_D = 3; k = 0.7; m = 1;$$



**Figure 31.** The optimal quantity with respect to  $\mu_p$  for varying values of  $\sigma_e$

For **higher values** of  $k$ , the increasing part in  $Q_1^*$  is not observed.

- For values  $\mu_p \geq 1$ ,

$Q_1^*$  is decreasing in  $\mu_p$  and is equal to  $Q_0^*$  for values of  $\mu_p$  higher than a certain critical value.

For a given value of  $\mu_p$ , if  $\sigma_e$  increases, to reduce the risk to have a shortage type 1 cost (stemming from values of  $Q_{IS}$  smaller than  $Q_0^*$ ), one increases  $Q_1^*$ . That is why, the critical value of  $\mu_p$  above which  $Q_1^*$  is equal to  $Q_0^*$  increases as  $\sigma_e$  increases.

This same critical value decreases as  $k$  increases.

The **impact of higher values of  $m$**  is similar to the multiplicative errors model.

$$\mu_D = 10; \sigma_D = 3; k = 0.7; \sigma_e = 1;$$

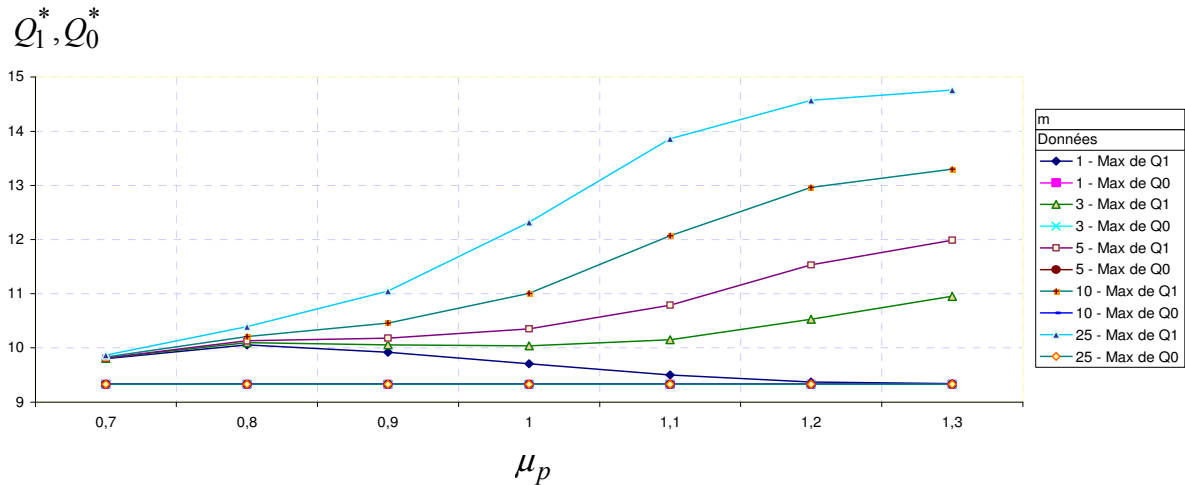


Figure 32.  $Q_1^*$  and  $Q_0^*$  with respect to  $\mu_p$  for varying values of  $m$

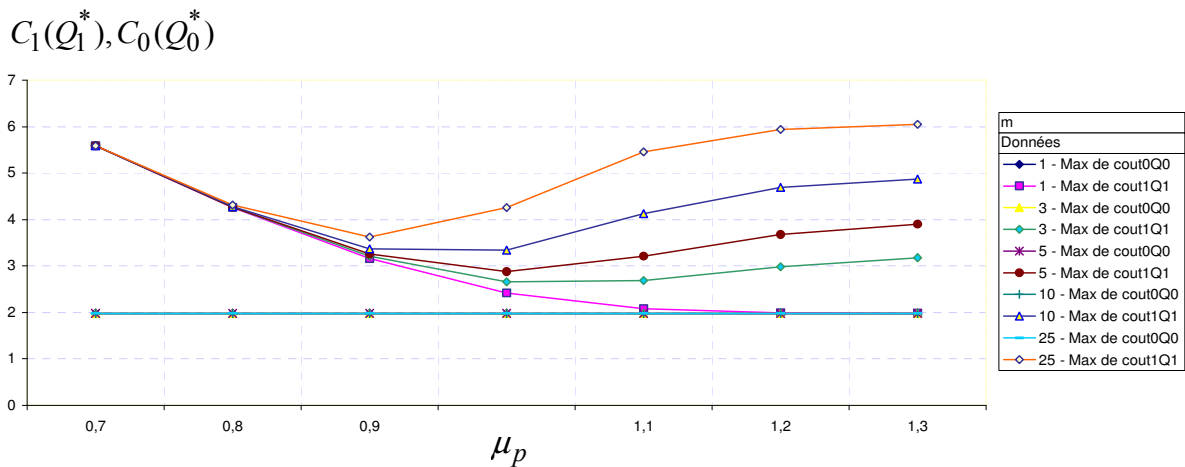


Figure 33.  $C_1(Q_1^*)$  and  $C_0(Q_0^*)$  with respect to  $\mu_p$  for varying values of  $m$

#### 4. Summary of research insights

- If the stochastic behavior of inventory record errors are known, this information can be used to optimize the system in presence of errors.
  - The optimal cost in presence of errors is always higher than the optimal cost of the system without errors.
  - The optimal quantity to order in presence of errors may be more or less than the quantity ordered in the system without errors, depending on values of model parameters.
- The typology of potential errors occurring in the data capture process will have an important impact on the design of the optimal policy
  - An optimal policy can be defined for different nature of errors (whether errors are additive, multiplicative or mixte)

- For a given nature of errors, observing a quantity in IS that is, on average, higher or lower than the physical quantity does not have the same impact, in terms of additional cost incurred.
- A general rule such as “the optimal cost incurred in an inventory system subject to inventory inaccuracies decreases as the error rate grows” cannot be established since in certain situations, for a given mean rate of errors, if the variability of errors is varied, the expected cost may decrease.
- The economical impact of inaccuracies is especially high for product categories for which the consequence of not satisfying an earlier commitment is important.
- Knowing parameters pertaining to errors enables managers to further optimize the performance of their inventory systems. Indeed, setting the value of the on hand quantity that appears in the information system equal to the quantity ordered adjusted by a factor that integrates the likelihood for errors occurring in the data capture process can even further improve performance in presence of errors.

## **Part 3: Benefits stemming from improving the performance of an inventory system**

To examine the relationship between inventory inaccuracies and supply chain performance, the previous part determined the optimal policy in presence of inventory inaccuracies. In this part, we conduct several analyses complementary to Part 2 to provide a better understanding of the impact of Auto ID on the performance of an inventory system. Hence, the first section of Part 3 provides a description of the different types of analyses realised while in the second and third section, we present results and insights obtained when considering the case of additive and multiplicative errors, respectively.

### **1. Evaluating the cost of inventory inaccuracies**

#### **1.1 Analysis of the cost of inventory inaccuracies if no action is taken**

As described in section 4 of chapter 4, there are two ways to manage an inventory system where there is a mismatch between the inventory record and the physical quantity available:

a) If managers are not aware of errors or simply ignore them, they would act as if there were no errors and the mismatches will remain uncorrected. As a result, the quantity ordered from the supplier will be  $Q_0^*$  and the cost incurred  $C_1(Q_0^*)$ .

b) Managers may have knowledge of errors. If, based on this information, they optimize the inventory system, i.e. order  $Q_1^*$  instead of  $Q_0^*$ , a cost of  $C_1(Q_1^*)$  will be incurred.

In this first analysis, we examine how much performance is degraded as a result of uncorrected inventory record errors. We evaluate the ratio  $R_3 = \frac{C_1(Q_0^*) - C_0(Q_0^*)}{C_1(Q_0^*)}$  for varying

error rates in order to get insights about conditions under which potential gains are the most important.

#### **1.2 Analysis on the split of the total savings**

As explained earlier, one part of the total savings, namely  $C_1(Q_0^*) - C_1(Q_1^*)$ , is achieved by optimizing the system with errors. Estimating this cost reduction enables to answer the question: “By how much the cost of inventory inaccuracies can be reduced due to a better replenishment policy that takes into account the probability for errors?” If parameters of errors are known and characterized, integrating this information into the ordering decision will enable to reduce cost.



The second part, namely  $C_1(Q_1^*) - C_0(Q_0^*)$ , is due to the elimination of inaccuracies. Since we are interested in getting insights on the implementation of Auto ID, we will suppose that actions enabling to eliminate errors mainly consist in deploying this technology to improve the reliability of the data capture process. Model 0 allows us to get a benchmark result for the maximum potential benefits of Auto ID.

In this second analysis, we use the ratios  $R_1 = \frac{C_1(Q_0^*) - C_1(Q_1^*)}{C_1(Q_0^*) - C_0(Q_0^*)}$  and  $R_2 = \frac{C_1(Q_1^*) - C_0(Q_0^*)}{C_1(Q_0^*) - C_0(Q_0^*)}$

to evaluate how the total savings is split.

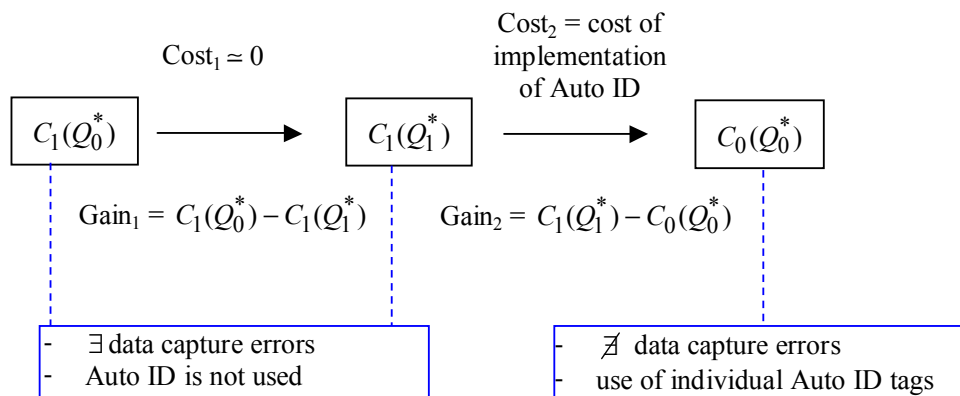
### 1.3 Taking into consideration the cost associated with the Auto ID technology

Since now, although we assume that, in model 0, no errors are done in the data capture process, we did not consider explicitly the cost of the Auto ID technology enabling an error free data update.

This analysis considers the cost associated with the implementation of Auto ID by seeking an answer to the question: “Is the Auto ID technology economically feasible?”

Taking into account the probability for errors when placing an order to the supplier can lead to important savings and does not necessitate the deployment of any particular system; enterprises can benefit from this improvement by simply adjusting their ordering quantity. That is why,  $Gain_1$  represented in the figure below is achieved at almost 0 cost.

The improvement from  $C_1(Q_1^*)$  to  $C_0(Q_0^*)$ , i.e.  $Gain_2$ , is possible if Auto ID is implemented at  $Cost_2$  within the wholesaler’s warehouse. Comparing  $Gain_2$  to  $Cost_2$  will enable to determine the break even point, i.e. the minimum value of the error rate such that the implementation of Auto ID is economically feasible for the wholesaler.



**Figure 1. Gains and costs associated with the improvement of an inventory system**

**The cost associated with Auto ID:** In this analysis, we will assume that the cost associated with the implementation of Auto ID mainly consists in the cost of Auto ID tags embedded to each unit of product purchased by the wholesaler, at a certain price per tag. The fixed costs of investments necessary for the technology (such as the system of readers, the infrastructure, the integration of basic applications, maintenance and support) are deliberately not included in our model. Estimates pertaining to these costs can be found in various studies (an example of cost estimates for Auto-ID tags and readers is outlined in App 1) and can be assumed not to vary with the model. The final net benefit stemming from the deployment of Auto ID can be obtained by considering the difference between the expected fixed cost calculated by a net present value type analysis and the benefit found in our model.

Therefore, when the Auto ID technology is implemented, if  $t$  represents the unit tag price, the product unit purchasing price will be  $P_A + t$ . Note that although we adopted this fairly simple hypothesis to model the unit tag price, in practice, the cost of Auto ID tags would depend on a number of factors such as industry adoption rates, whether tags will be used more than once, tag production volumes and the manner in which costs are applied among supply chain actors.

There are basically two ways to introduce the cost of the technology in our model:

### 1. By taking into account the cost of tags in the optimization

- Step 1: Determination of *modified* unit shortage and overage costs

The unit overage cost of this system is given by  $\bar{h} = h + t$

The unit shortage cost of this system is given by  $\bar{u}_1 = u_1 - t$

- Step 2: Determination of the *modified* optimal policy

#### If demand is normally distributed

If  $Q$  denotes the stock level after ordering, the total cost to minimize is given by:

$$C(Q) = (P_A + t - P_S) \cdot \int_{x=0}^Q (Q - x) f(x) dx + (P_V - P_A - t) \cdot \int_{x=Q}^{\infty} (x - Q) f(x) dx$$

where  $f(x)$  denotes the probability distribution of the normally distributed demand with parameters  $(\mu_D, \sigma_D)$

$$C(Q) = (P_A + t - P_S) \cdot (Q - \mu_D) + (P_V - P_S) \cdot \int_{x=Q}^{\infty} (x - Q) f(x) dx$$

which is convex and is minimized when  $Q = Q^*$  where  $Q^*$  is defined through

$$F(Q^*) = \frac{P_V - P_A - t}{P_V - P_S} = \frac{\bar{u}_1}{\bar{u}_1 + \bar{h}}$$

where  $F(x)$  denotes the cumulative density function of the normally distributed demand

That is 
$$Q^* = F^{-1}\left(\frac{\bar{u}_1}{\bar{u}_1 + \bar{h}}\right)$$

$$Q^* = \mu_D + z^* \cdot \sigma_D$$

where  $z^*$  satisfies  $P_N(z^*) = \frac{\bar{u}_1}{\bar{u}_1 + \bar{h}}$  ( $P_N$  denotes the unit normal distribution function)

The induced optimal objective function value can be written as:

$$C^*(Q^*) = \left[ (P_A + t - P_S) \cdot z^* + (P_V - P_S) \cdot I_N(z^*) \right] \cdot \sigma_D$$

where  $I_N$  is the unit normal loss function  $I_N(z) = \int_{x=z}^{\infty} (x-z) \cdot P_N(x) dx$

### If demand is uniformly distributed

The optimal quantity minimizing the total cost will be given by :

$$Q^* = \mu_D + \frac{\sqrt{3} \cdot (-h - 2 \cdot t + u_1) \cdot \sigma_D}{h + u_1}$$

The associated optimal cost would be  $C^*(Q^*) = \frac{\sqrt{3} \cdot (h + t) \cdot (u_1 - t) \cdot \sigma_D}{h + u_1}$

Hence, the benefit associated with the implementation of Auto ID can be evaluated by considering either the difference  $C_1(Q_0^*) - C^*(Q^*)$  or  $C_1(Q_1^*) - C^*(Q^*)$  if the wholesaler takes into account the probability for errors while ordering.

### **2. By taking into account the cost of tags *a posteriori***

This approach consists in integrating the cost of the technology in the final step of the trade off analysis; i.e. we first evaluate the savings achieved thanks to Auto ID as if tags were free by comparing  $C_1(Q_1^*)$  to  $C_0(Q_0^*)$ . Then, the cost of the technology given by  $Cost_{tag} = Q_0^* \cdot t$ , is integrated to the analysis. The net benefit resulting from the implementation of Auto ID will thus be given by:  $(C_1(Q_1^*) - C_0(Q_0^*)) - Cost_{tag}$

The second approach provides a good approximation of the exact calculation and is more simple to study. That is why, we adopted the second approach in our analyses in which we considered 3 scenarios where tag prices (provided by the Auto ID Center) vary between 5 cents and 20 cents in order to evaluate the tag price that yields positive benefits for given system parameters.

## 2. Additive errors

This section develops the analyses described above by assuming that errors perturbing inventory data records are additive.

### Result 1 - Effect of varying error rate on $R_3$

Being unaware of inventory data inaccuracies generates additional costs within a facility. When demand and errors are uniformly distributed (with  $\mu_e = 0$ ), the expression of  $R_3$  is as in the table below. Note that the expressions are simpler if  $m=1$ <sup>1</sup>.

k<1	$0 < \sigma_e < \frac{2k\sigma_D}{1+k}$
	$\frac{\sigma_e (-6(1+km)\sigma_D + (1+k)(-1+k(-2+m))\sigma_e)}{-24k\sigma_D^2 - 6(1+km)\sigma_D\sigma_e + (1+k)(-1+k(-2+m))\sigma_e^2}$
	$\frac{2k\sigma_D}{1+k} < \sigma_e < \frac{\mu_D}{\sqrt{3}} + \frac{k-1}{k+1}\sigma_D$
	$\frac{8k^3\sigma_D^3 - 12k^2(1+k)\sigma_D^2\sigma_e + 6(1+k)(1+k(1+k+m))\sigma_D\sigma_e^2 - k(1+k)^2(-1+m)\sigma_e^3}{8k^3\sigma_D^3 - 12(-2+k)k(1+k)\sigma_D^2\sigma_e + 6(1+k)(1+k(1+k+m))\sigma_D\sigma_e^2 - k(1+k)^2(-1+m)\sigma_e^3}$
k>1	$\frac{2\sigma_D}{1+k} < \sigma_e < \sigma_D$
	$\frac{-8k(-1+m)\sigma_D^3 + 12k(1+k)(-1+m)\sigma_D^2\sigma_e + 6(1+k)^3\sigma_D\sigma_e^2 + (1+k)^4\sigma_e^3}{-8k(-1+m)\sigma_D^3 + 12k(1+k)(1+2k+m)\sigma_D^2\sigma_e + 6(1+k)^3\sigma_D\sigma_e^2 + (1+k)^4\sigma_e^3}$
	$0 < \sigma_e < \frac{2\sigma_D}{1+k}$
	$\frac{\sigma_e (-6(1+km)\sigma_D + (1+k)(-1+k(-2+m))\sigma_e)}{-24k\sigma_D^2 - 6(1+km)\sigma_D\sigma_e + (1+k)(-1+k(-2+m))\sigma_e^2}$

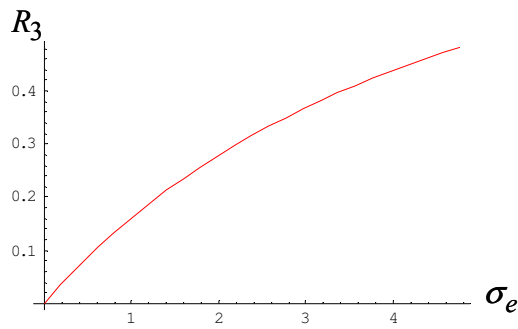
**Table 1. Expressions of  $R_3$  for additive errors**

For instance, if system parameters are as in the example below, i.e. if  $k = 5$ , by ignoring errors, one would order  $Q_0^* \approx 16$ . If we assume that due to errors, the value of the IS inventory record has a dispersion of  $\pm 2$  units in comparison with the physical quantity available, i.e.  $Q_{IS} = Q_{PH} \pm 2$ , (which is equivalent to set  $\sigma_e = 1.154^2$ ), demand will be satisfied based on a value of  $Q_{IS} \in [14, 18]$ . Eliminating inventory mismatches would yield a relative 13% savings in this case.

<sup>1</sup> cf. App 2, Part 3, Chapter 5

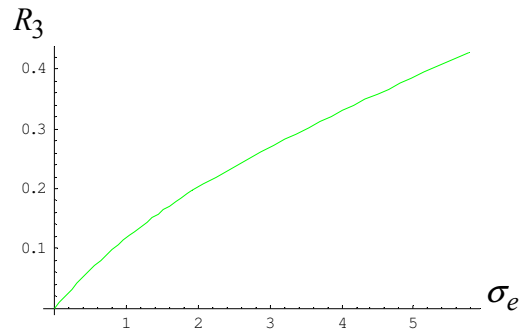
<sup>2</sup> Note that values of  $\sigma_e$  displayed in tables above correspond to reciprocally potential dispersions of  $\pm 0.5, \pm 1, \pm 2, \pm 3$  units.

$$\mu_D = 10; \sigma_D = 5.77; h = 1; k = 0.7; m = 3$$



standard dev.	0.288	0.577	1.154	1.732
R <sub>3</sub> (%)	5.24	9.99	18.21	25.09

$$\mu_D = 10; \sigma_D = 5.77; h = 1; k = 5; m = 3$$

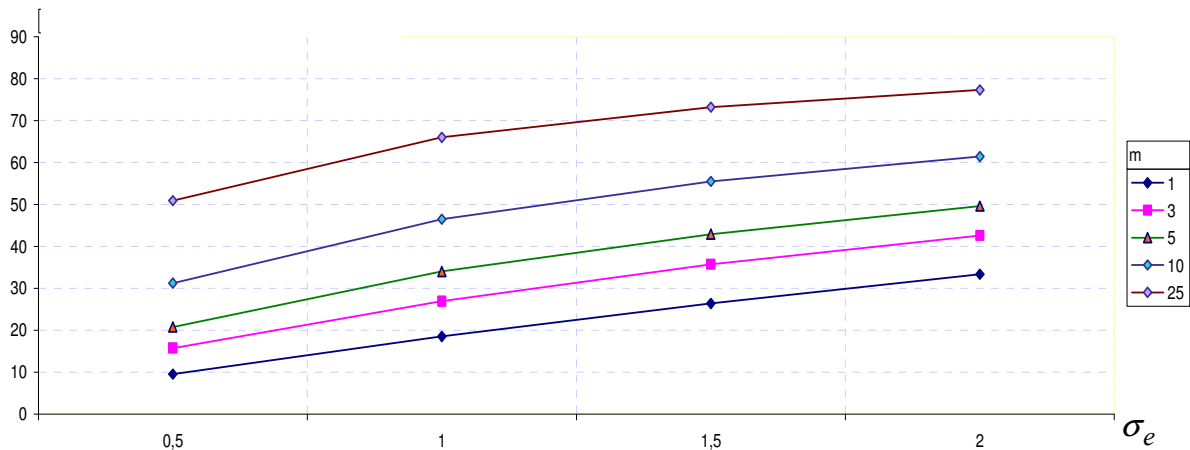


standard dev.	0.288	0.577	1.154	1.732
R <sub>3</sub> (%)	3.79	7.23	13.19	18.17

**Figure 2. Evolution of R<sub>3</sub> for uniform distributions and additive errors**

When nothing is done to correct errors, even for small error rates, the penalty of having mismatches between the physical and IS inventory levels can be considerable. For given values of  $k$  and  $m$ , as  $\sigma_e$  is varied, the penalty of ordering  $Q_0^*$  instead of  $Q_1^*$  increases: the less effective the current data capture process is, the more important the impact of Auto ID would be. Supply chains that are performing poorly because inventory data is erroneous will benefit the most from Auto ID.

If demand and errors follow normal distributions, e.g. if the distribution of demand is  $N(10,3)$ , we obtain the following figure for the different values of  $\sigma_e$  and  $m$  ( $k=0.7$ ):

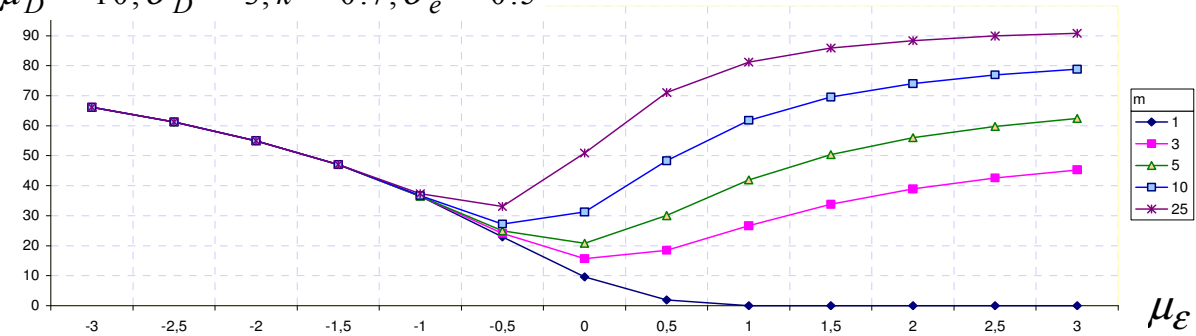


**Figure 3. Evolution of R<sub>3</sub> with respect to  $\sigma_e$  for varying values of  $m$**

Even for  $\sigma_e = 0.5$  error rate and a small shortage type 2 penalty ( $m=1$ ), one can achieve a 10% gain by improving the system. What is also of interest is, as in the case of uniform distributions, how fast  $R_3$  rises with  $\sigma_e$ . For higher error rates, the gain achieved can be up to 30%.

The evolution of  $R_3$  with respect to values that  $\mu_{\mathcal{E}}$  can take is as follows:

$$\mu_D = 10; \sigma_D = 3; k = 0.7; \sigma_e = 0.5$$



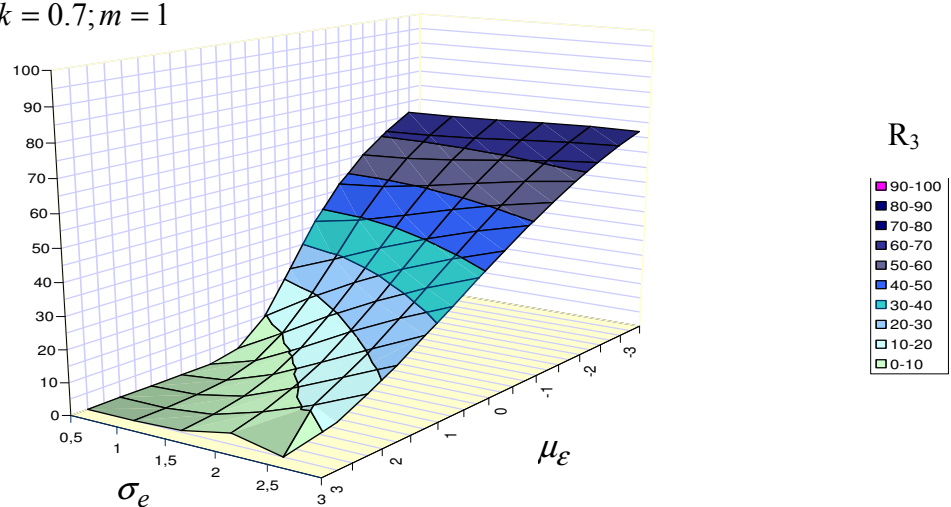
**Figure 4. Evolution of  $R_3$  with respect to  $\mu_{\mathcal{E}}$  for varying values of  $m$**

For  $m=1$  and a given value of  $k$ , as  $\mu_{\mathcal{E}} (< 0)$  is varied, the penalty of ordering  $Q_0^*$  instead of  $Q_1^*$  decreases: the more reliable the current data capture process is, the lower will be the effect of ordering  $Q_0^*$ . For high values of  $\mu_{\mathcal{E}}$ , observing a value of  $Q_{IS}$  higher than  $Q_{PH}$  does not generate an additional cost, i.e.  $C_1(Q_0^*) = C_0(Q_0^*)$ .

For  $m > 1$ , as observed for  $C_1(Q_1^*)$ ,  $C_1(Q_0^*)$  is first decreasing in  $\mu_{\mathcal{E}}$  and then increases as  $\mu_{\mathcal{E}}$  increases. The value of  $\mu_{\mathcal{E}}$  where the switch occurs depends on the values of  $\sigma_e, \sigma_D, k$  and  $m$ . That is why, one may incur a higher penalty for a smaller rate of  $\mu_{\mathcal{E}}$ . Furthermore, in situations where the quantity showed by IS is higher than the physically available quantity, depending on the value of  $m$ , the cost of having errors may be up to 80% (e.g.  $m=10$ ).

Finally, for managers who want to evaluate the combined effect of  $\mu_{\mathcal{E}}$  and  $\sigma_e$ , the following type of graph will be of interest:

$$\mu_D = 10; \sigma_D = 3; k = 0.7; m = 1$$



**Figure 5. Evolution of  $R_3$  for varying error rates for normal distributions**

### Result 2 - Effect of varying unit shortage type 2 cost on $R_3$

Our model explicitly captures the cost of not satisfying an earlier commitment: the wholesaler incurs a shortage type 2 penalty for each unit initially promised to but not delivered to stores. For the same error rate, the magnitude of Auto ID benefits would be different, depending on the product category.

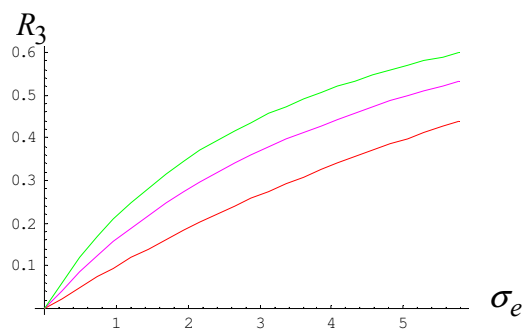
Results below would help managers interested in identifying which products are the most affected by inventory inaccuracies while planning the roll out of Auto ID technology.

$$\mu_D = 10; \sigma_D = 5.77; h = 1; k = 0.7;$$

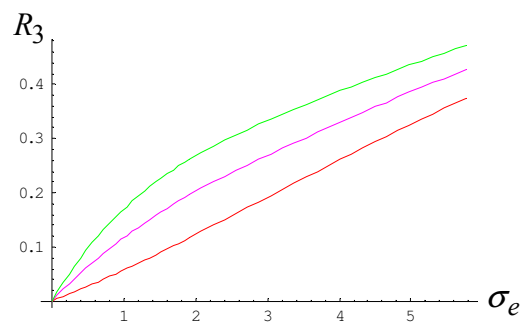
$$m = 1; m = 3; m = 5$$

$$\mu_D = 10; \sigma_D = 5.77; h = 1; k = 5;$$

$$m = 1; m = 3; m = 5$$



standard dev.	0,288	0,577	1,154	1,732
m=1	2,98	5,87	11,37	16,51
m=3	5,24	9,99	18,21	25,09
m=5	7,4	13,76	24,06	32,08



standard dev.	0,288	0,577	1,154	1,732
m=1	1,54	3,19	6,71	10,48
m=3	3,79	7,23	13,19	18,17
m=5	5,93	10,95	18,83	24,65

**Figure 6. Evolution of  $R_3$  with respect to  $\sigma_e$  for varying values of  $m$**

Results pertaining to normal distributions are as represented in Figure 3. If we consider two product categories  $P_1$  and  $P_2$  having the same (unit shortage type 1 penalty/unit overage penalty) ratio, i.e.  $k_1=k_2$ , and a different (unit shortage type 2 penalty/unit shortage type 1 penalty) ratio, i.e.  $m_1 < m_2$ , the penalty stemming from errors would be higher for  $P_2$ .

### Result 3 – Effect of varying unit shortage type 1 cost on $R_3$

For a given error rate characterized by  $\mu_e$  and  $\sigma_e$ , the penalty stemming from errors is less important for products having high values of  $k$ . Hence, as shown below, for normally distributed demand and errors (e.g. if demand follows a  $N(10,3)$ ),  $R_3$  decreases as  $k$  increases.

$$\mu_D = 10; \sigma_D = 3; \sigma_e = 1; m = 3$$

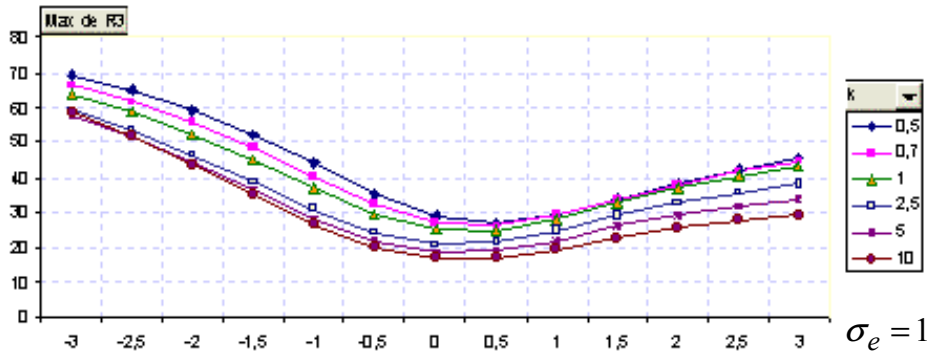


Figure 7. Evolution of  $R_3$  with respect to  $\mu_e$  for varying values of  $k$

#### Result 4 – Split of the total savings

By considering the ratio  $R_1$ , we evaluate the relative importance of the savings stemming from ordering the right quantity in presence of errors. For instance, as represented below, in a system where one orders  $Q_0^*$  although errors are made, the reduction stemming from ordering the appropriate quantity can be up to 30% of the total savings. The higher is  $\sigma_e$ , the higher would  $R_1$  be since  $Q_0^* < Q_1^*$  and the penalty of having errors is higher for small values of  $Q$ .

$$\mu_D = 10; \sigma_D = 5.77; k = 0.7; m = 1; m = 3; m = 5$$

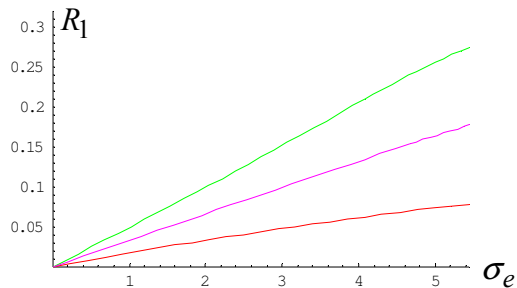
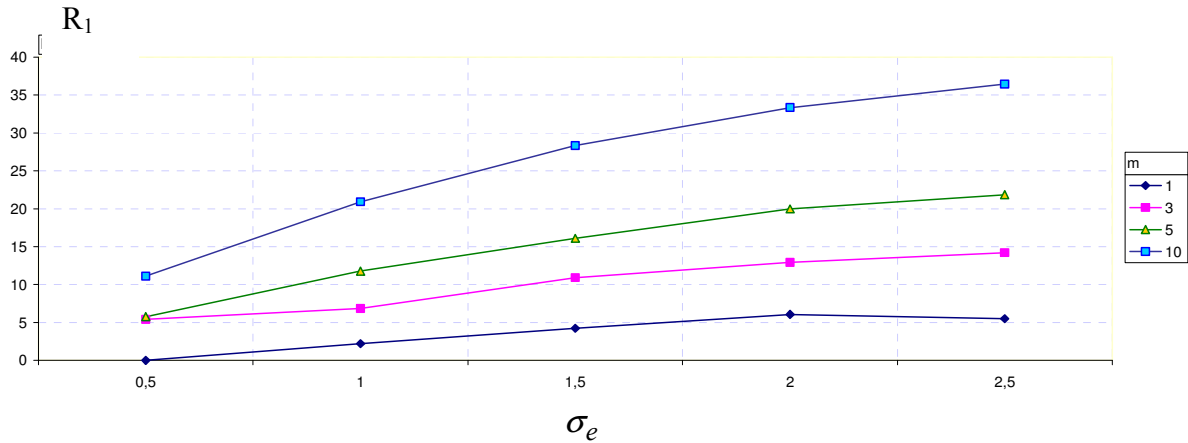


Figure 8. Evolution of  $R_1$  with respect to  $\sigma_e$  for varying values of  $m$

The result above is also valid when distributions are normal. For instance, the split of the total cost pertaining to the example in the section associated with Result 1 would be as follows:



$$\mu_D = 10; \sigma_D = 3; \mu_\varepsilon = 0; k = 0.7$$

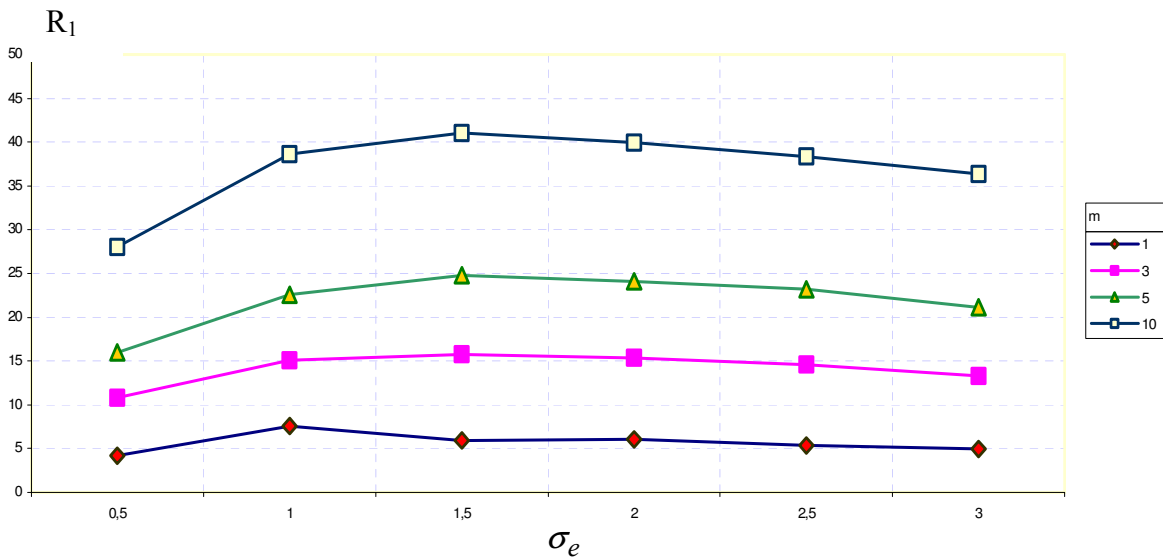


**Figure 9. Evolution of  $R_1$  with respect to  $\sigma_e$  for varying values of  $m$**

### Observation

When demand variability is high,  $R_1$  is increasing in  $\sigma_e$  for almost all values of  $\sigma_e$  whereas for smaller values of  $\sigma_D$ ,  $R_1$  may be decreasing in  $\sigma_e$  (cf. figure below) since when  $\sigma_D$  is small,  $Q_1^*$  is closer to  $Q_0^*$  and the interval of values of  $Q$  in which  $H^1(Q)$  and  $B_2(Q)$  are constant in  $Q$  is larger. Thus, errors have a similar impact for  $Q=Q_0^*$  and for  $Q=Q_1^*$ .

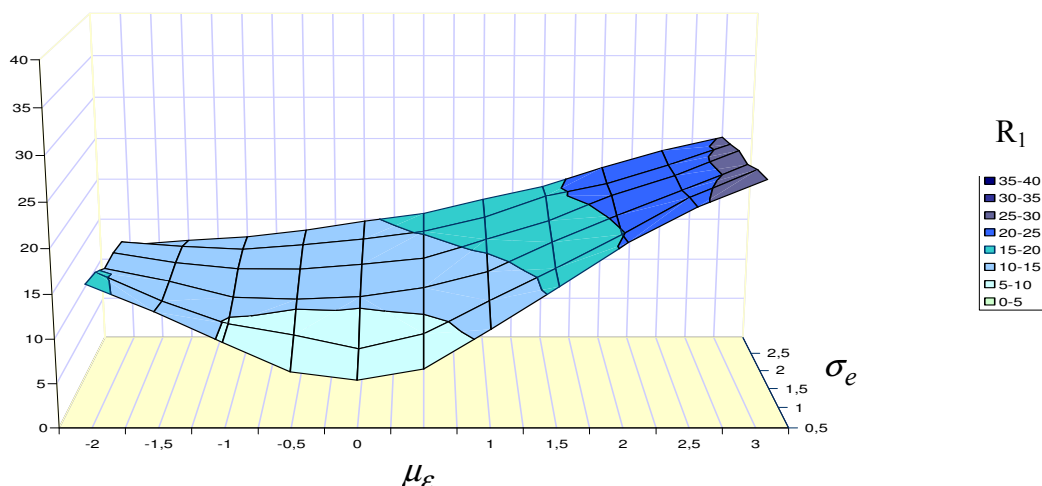
$$\mu_D = 10; \sigma_D = 1; k = 0.7$$



**Figure 10. Evolution of  $R_1$  with respect to  $\sigma_e$  for varying values of  $m$**

The figure below displays the combined effect of  $\mu_\varepsilon$  and  $\sigma_e$  on  $R_1$ :

$$\mu_D = 10; \sigma_D = 3; k = 0.7; m = 3$$

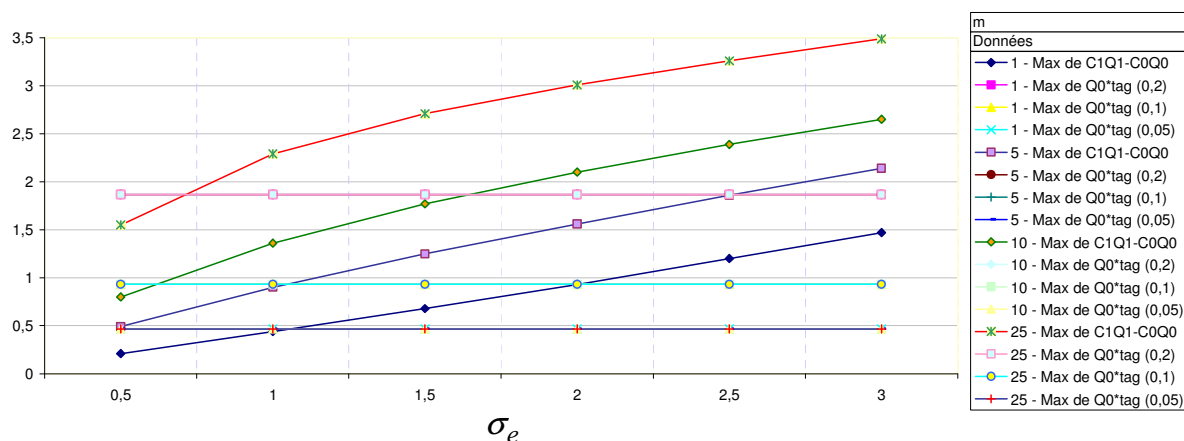


**Figure 11. Evolution of  $R_1$  for varying error rates for normal distributions**

### Result 5 – Taking into account the cost of the Auto ID technology

The less effective the current inventory management process (i.e. without Auto ID) is, the less important the tag price will be while deciding whether to implement Auto ID or not. The tag price for which the Auto ID implementation yields a positive benefit depends on values of model parameters. For instance, for two product categories  $P_1$  and  $P_2$  for which  $k_1=k_2$  and  $m_1 < m_2$ , the absolute penalty stemming from errors ( $C_1(Q_1^*) - C_0(Q_0^*)$ ) will be higher for  $P_2$ . As expected intuitively, for a given tag price, the break even point is reached at a smaller value of  $\sigma_e$  for  $P_2$ , thus, there is an interval of values of  $\sigma_e$  for which the decision to implement Auto ID for  $P_1$  type products is not justified while this action yields a positive return for  $P_2$  type products.

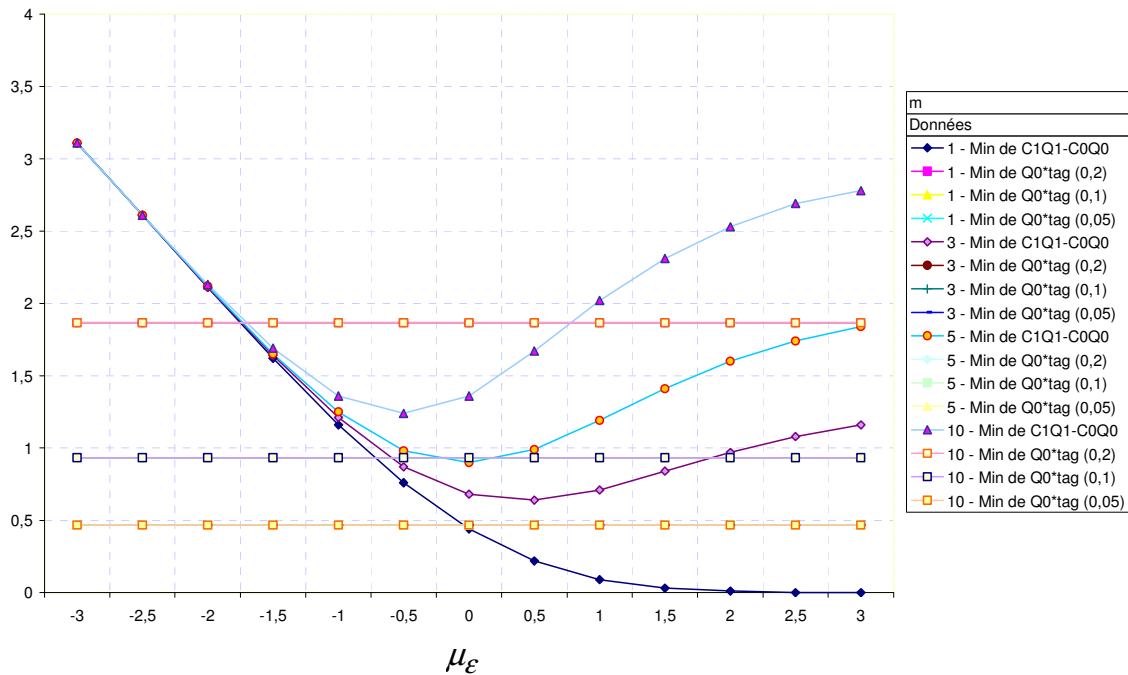
$$\mu_D = 10; \sigma_D = 3; \mu_e = 0; k = 0.7$$



**Figure 12.  $C_1(Q_1^*) - C_0(Q_0^*)$  with respect to  $\sigma_e$  for varying values of  $m$**

The cost benefit trade off curve with respect to  $\mu_{\mathcal{E}}$  is of special interest. The sign of errors ( $\mu_{\mathcal{E}} < 0$  or  $\mu_{\mathcal{E}} > 0$ ) has a strong impact on whether Auto ID yields a positive return or not. For instance, if  $m=1$ , for a given tag price, observing a higher value in IS (than the real quantity available) does not necessitate the deployment of a specific technology. This is not true for higher values of  $m$ : for a given tag price, if  $\mu_{\mathcal{E}} < 0$ , the break even point is less sensitive to  $m$ , whereas for  $\mu_{\mathcal{E}} > 0$ , the higher is  $m$ , the more likely the implementation of Auto ID would yield positive benefits.

$$\mu_D = 10; \sigma_D = 3; \sigma_{\mathcal{E}} = 1; k = 0.7$$



**Figure 13.**  $C_1(Q_1^*) - C_0(Q_0^*)$  with respect to  $\mu_{\mathcal{E}}$  and varying values of  $m$

Managers may also want to evaluate simultaneously the combined effect of  $\mu_{\mathcal{E}}$  and  $\sigma_{\mathcal{E}}$  on the potential savings that would result from the elimination of errors. The following type of graph provides them this information:

$$\mu_D = 10; \sigma_D = 3; m = 3; k = 0.7$$

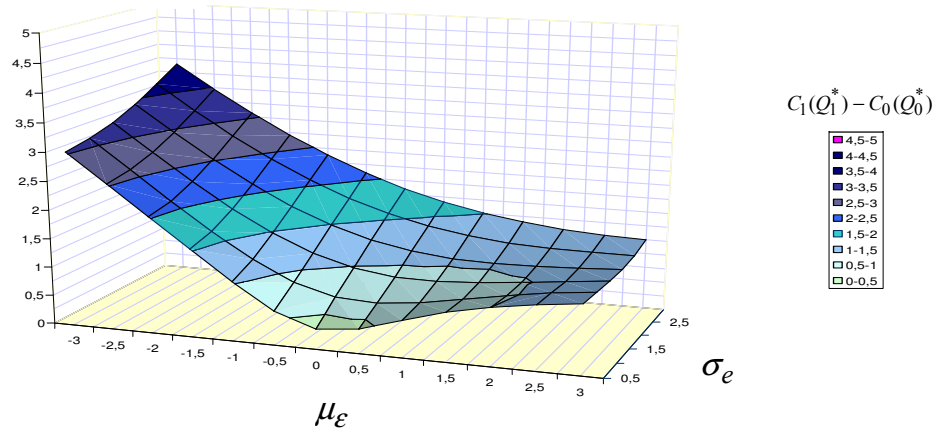


Figure 14.  $C_1(Q_1^*) - C_0(Q_0^*)$  for varying error rates ( $k=0.7$ )

$$\mu_D = 10; \sigma_D = 3; m = 3; k = 5$$

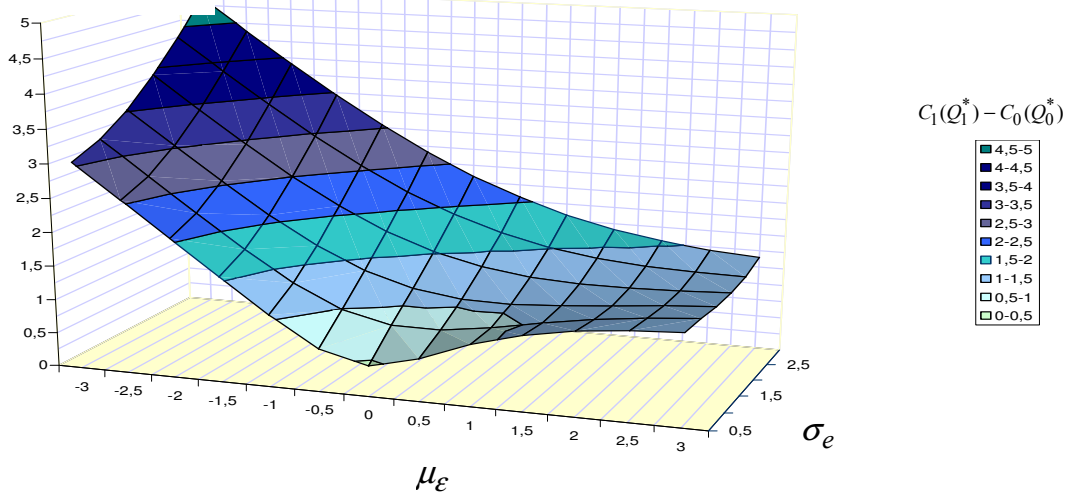


Figure 15.  $C_1(Q_1^*) - C_0(Q_0^*)$  for varying error rates ( $k=5$ )

### 3. Multiplicative errors

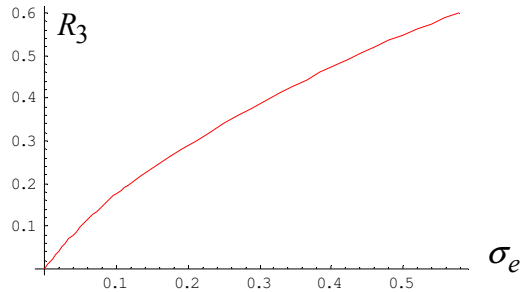
This section extends the analysis on potential savings to the case where errors perturbing inventory records are multiplicative.

#### Result 1 - Effect of varying error rate on $R_3$

Expressions pertaining to  $R_3$  for uniformly distributed demand and multiplicative errors can be found in App 3. To get further insights, we conducted numerical analyses. The first example is for a product category for which  $k = 5, m = 3$ : without taking into account the probability for errors, one would order  $Q_0^* \approx 16$ . If we assume that due to errors, the value of the IS inventory record has a dispersion of  $\pm 25\%$  in comparison with the physical quantity available, i.e.  $Q_{IS} = Q_{PH} \cdot (1 \pm 0.25)$ , (which is equivalent to set  $\sigma_e = 0.144$ ), demand will be

satisfied based on a value of  $Q_{IS} \in [12, 20]$ . The consequence of having this error is a relative 23% increase in the expected cost.

*Example* :  $h = 1; k = 5; m = 3; \mu_D = 10; \sigma_D = 5.77$



**Figure 16. Evolution of  $R_3$  with respect to  $\sigma_e$  for uniform distributions**

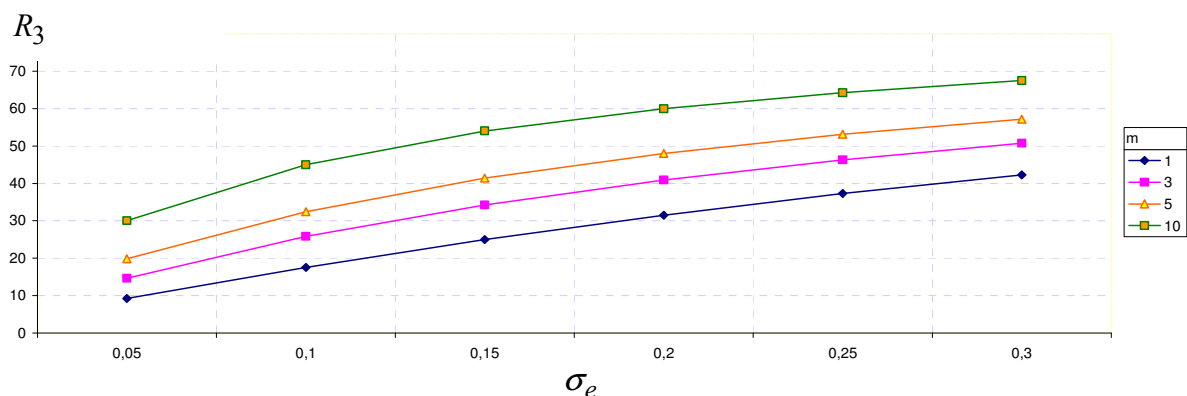
Similarly, savings corresponding to the situation where  $k=0.7$  can be found in the table below. Note that an error variance of 0.003 is equivalent to an average  $\pm 0.5\%$  dispersion of  $Q_{IS}$  values around  $Q_{PH}$ . Similarly,  $\sigma_e=0.006, 0.029, 0.058, 0.144$  correspond reciprocally to  $\pm 1\%, \pm 5\%, \pm 10\%$  and  $\pm 25\%$  of dispersion.

*Example* :  $h = 1; k = 0.7; m = 3; \mu_D = 10; \sigma_D = 5.77$

standard dev	0.003	0.006	0.029	0.058	0.144
$R_3$	0,44%	0,89%	4,23%	8,27%	18.61%

If demand follows a  $N(10,3)$  and if  $\mu_p = 1$ , we obtain the following figure for varying values of  $\sigma_e$  and different values of  $m$ :

$k = 0.7; \mu_p = 1$



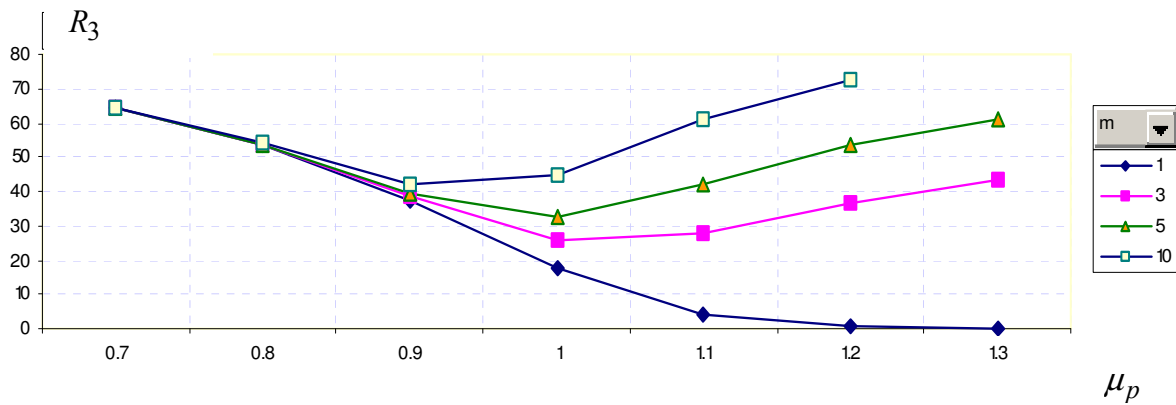
**Figure 17. Evolution of  $R_3$  with respect to  $\sigma_e$  for varying values of  $m$**

As previously,  $R_3$  increases as  $\sigma_e$  increases. Even for very small rates (e.g.  $\sigma_e=0.03$  or  $\sigma_e=0.05$ ) and intermediate values of  $m$  ( $m=3$ ) one would achieve reciprocally a relative 9%

and 15% cost reduction if there were no mismatches between the physical and information flow.

The evolution of  $R_3$  with respect to varying values of  $\mu_p$  is as follows:

$$\mu_D = 10; \sigma_D = 3; \sigma_e = 0.1; k = 0.7$$

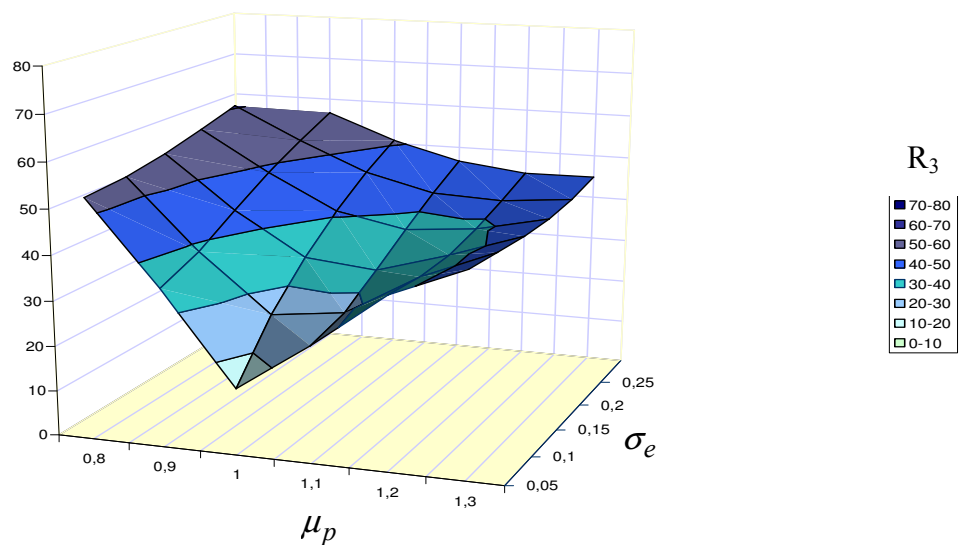


**Figure 18. Evolution of  $R_3$  with respect to  $\mu_p$  for varying values of  $m$**

For a given value of  $\sigma_e$ , there is a value of  $\mu_p$  such that the impact of errors is minimized. This represents a reference point to evaluate the net profit associated with the implementation of Auto ID: in situations where parameters pertaining to errors are not known exactly, comparing the potential savings achieved at this point to the cost of Auto ID will enable to have a first insight on whether implementing Auto ID yields a positive benefit or not.

The simultaneous consideration of  $\sigma_e$  and  $\mu_p$  would give further information on this value:

$$\mu_D = 10; \sigma_D = 3; m = 3; k = 0.7$$



**Figure 19. Evolution of  $R_3$  for different error rates for normal distributions**

## Result 2 - Effect of varying unit shortage type 2 cost on $R_3$

The variation of the penalty of having errors for different values of  $m$  is as illustrated in tables below for two sets of products: the first example is for  $k = 5$  while in the second example  $k = 0.7$  :

standard dev	0.003	0.006	0.029	0.058	0.144
m=1	0,24%	0,50%	2,56%	5,43%	15,00%
m=3	0,64%	1,29%	5,95%	11,20%	22,95%
m=5	1,03%	2,07%	9,13%	16,31%	29,54%

standard dev	0.003	0.006	0.029	0.058	0.144
m=1	0,24%	0,49%	2,39%	4,80%	11,65%
m=3	0,44%	0,89%	4,23%	8,27%	18,61%
m=5	0,63%	1,28%	6,01%	11,49%	24,55%

As the penalty associated with failures to satisfy an earlier commitment increases, ordering  $Q_0^*$  becomes more and more costly.

Analyses similar to those conducted for additive errors concerning the effect of varying values of  $k$  on  $R_3$  or the split of the total savings can also be developed for multiplicative errors. The following paragraph discusses the evaluation of the economical feasibility of Auto ID.

## Result 3 – Optimizing the system or deploying Auto ID technology?

Comparing the relative importance of  $C_1(Q_0^*) - C_1(Q_1^*)$  to  $C_1(Q_1^*) - C_0(Q_0^*)$  for varying system parameters would provide managers further insights when defining an appropriate Auto ID deployment strategy. Indeed, in warehouses where thousands of products that come in all different categories, shapes, sizes, unit cost parameters are handled, there are some cases in which the Auto ID implementation project yields positive benefits while in others, even optimizing the system without investing in a particular technology may generate considerable savings. Having a knowledge of these situations would permit managers to identify the product categories for which Auto ID is the most useful.

For instance, for products having the same value of  $m$ , the following results are observed:

- For very small values of  $\mu_p (<1)$ , for a given tag price, implementing Auto ID yields a positive benefit for almost all values of  $\sigma_e$ . In other words, the use of the Auto ID in warehouses where the overage cost incurred is high due to for instance, an important rate non identified phantom products will be cost justified (cf. figure 20).
- For higher values of  $\mu_p (<1)$ ,
  - if  $\sigma_e$  is smaller than a critical value, implementing Auto ID is not economically feasible. In this case, the cost reduction stemming from the optimization of the system with errors can be relatively important. For instance, if system parameters are such

that  $\mu_D = 10; \sigma_D = 3; k = 3; m = 1; t = 0.2$ , for  $\sigma_e \in [0, 0.15]$ ,  $R_1$  can be up to 15 % (cf. figure 21).

- if  $\sigma_e$  is higher than the critical value, since the relative importance of  $C_1(Q_1^*) - C_0(Q_0^*)$  in comparison with  $C_1(Q_0^*) - C_1(Q_1^*)$  increases, the likelihood for Auto ID to yield a positive benefit increases.

The value of this critical point decreases as  $k$  increases or as  $\mu_p$  decreases.

- For a given tag price, the higher is  $\mu_p$  (including values  $>1$ ), the more likely that the implementation of Auto ID to yield a positive benefit will be compromised. (except situations in which  $k$  and  $m$  are very high)

□  $\mu_D = 10; \sigma_D = 3; m = 1; k = 3$

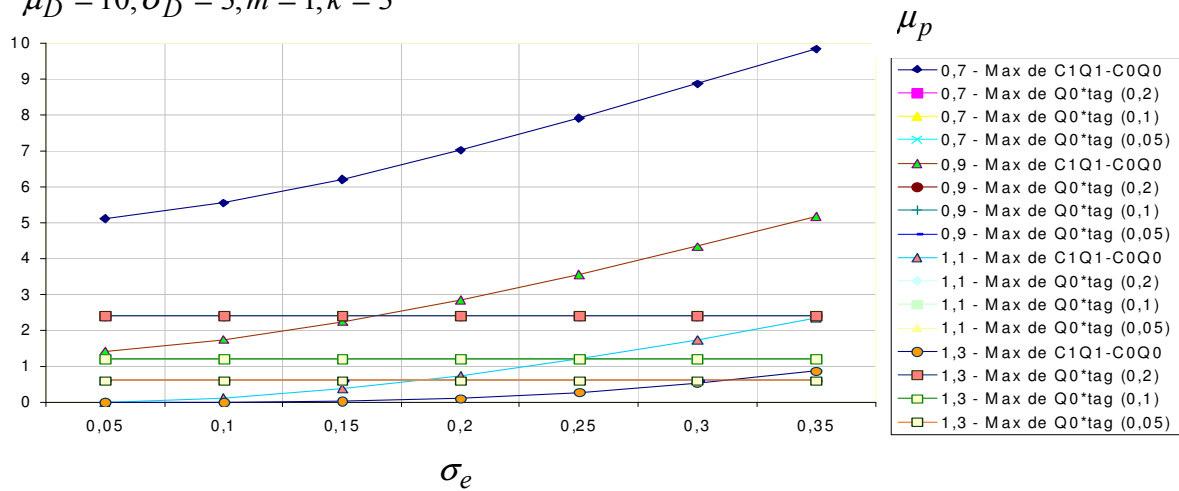


Figure 20.  $C_1(Q_1^*) - C_0(Q_0^*)$  with respect to  $\sigma_e$  for varying values of  $m$

$\mu_D = 10; \sigma_D = 3; m = 1; k = 3$

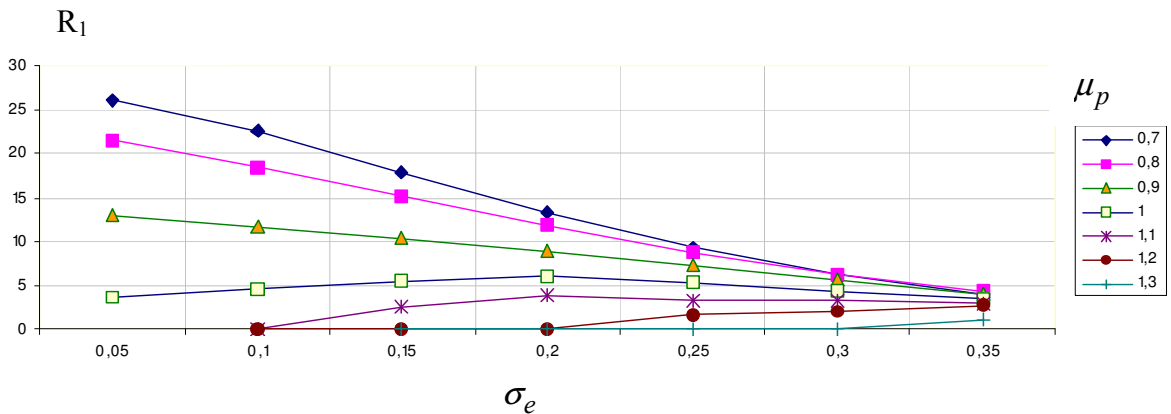


Figure 21.  $R_1$  with respect to  $\sigma_e$  for varying values of  $\mu_p$

For very high values of  $m$ , whatever the error rate (characterized by  $\mu_p$  and  $\sigma_e$ ), the Auto ID implementation is economically feasible. If  $m$  takes intermediate values, this observation is still valid for small values of  $\mu_p$  whereas for a given higher value of  $\mu_p$ , the deployment



of Auto ID yields a positive return only in situations where  $\sigma_e$  is great. Otherwise, it is not economically feasible to implement it.

The figures below represent, for a given value of  $k$  ( $k=0.7$  or  $5$ ), the evolution of the savings  $C_1(Q_1^*) - C_0(Q_0^*)$  for varying values of  $\sigma_e$ . The blue curves are for  $\mu_p=0.7$ , red ones for  $\mu_p=1$  and green curves correspond to  $\mu_p=1.2$ . For each value of  $\mu_p$ , two values of  $m$ , namely  $m=3$  and  $m=10$ , are represented. In the same figure, curves pertaining to the cost of the technology ( $t=0.10$  and  $t=0.20$ ) are also represented.

$$\mu_D = 10; \sigma_D = 3; k = 0.7$$

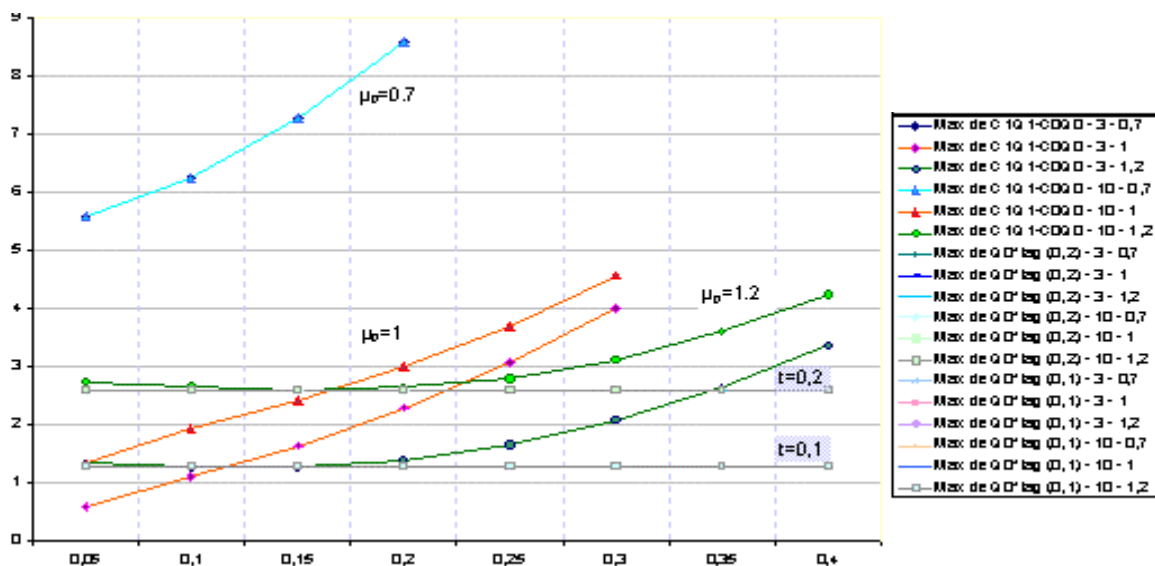
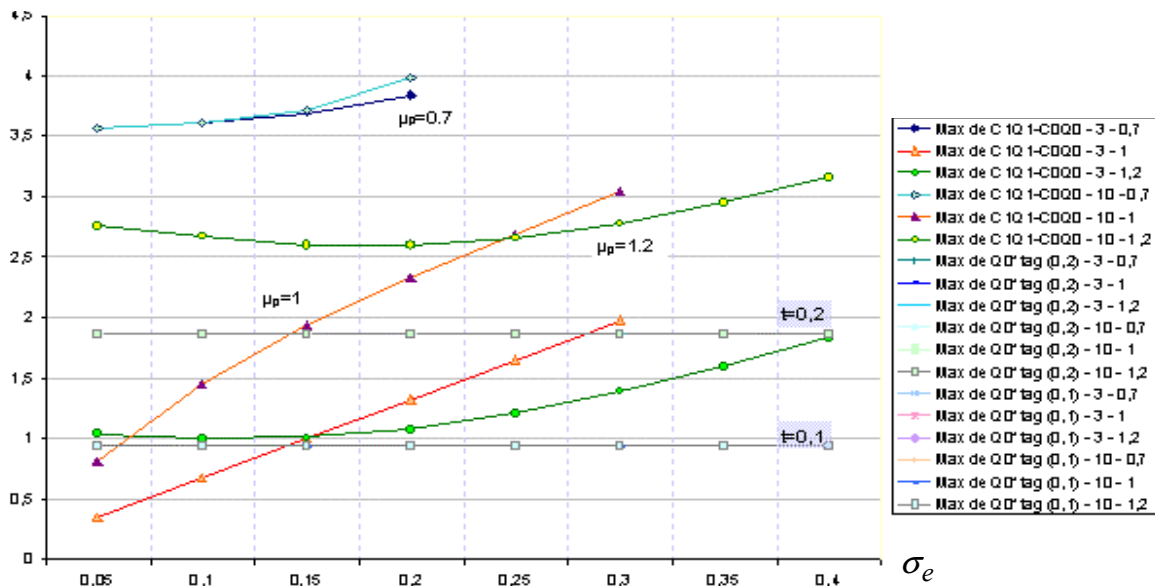


Figure 22. Cost benefit trade off analysis with respect to  $\sigma_e$  for varying values of  $\mu_p$  and  $m$

## CONCLUSION AND PERSPECTIVES

For many companies, inventory record inaccuracy is a major obstacle to achieving operational excellence. The most common approach in maintaining inventory record accuracy is the use of the bar code system and the realisation of periodic inventory audits. Our research is motivated by the potential ability of the new product identification and data capture technology developed by the Auto ID Center, namely the Auto ID technology, to address some of the issues supply chains are facing today. Our aim was to identify and characterize the main benefits of using this technology in supply chains and to quantify one of the improvements stemming from its implementation, namely the benefit of having more accurate inventory data records.

Our starting point was a real world issue: more and more companies are considering the use of Auto ID technology in their supply chains and are interested in evaluating the benefits and new functionalities associated with this system in order to compare it with the performance of the current industry wide used bar code system. Our objective was to provide practitioners with a clear and exhaustive description of the potentials of Auto ID, thereby offer insights into where to look for benefits and propose an approach to quantify one of the benefits. In order to do that, we organised our dissertation in two parts:

### **Part A**

The first part identifies the limitations of the bar code system and compares it with the new opportunities of using Auto ID on pallet, case or item level.

In this analysis, we are fully aware that every supply chain is unique; processes, products, supply chain configurations as well as current practices differ and therefore, whether certain types of benefits are realisable or not will also differ. However, we believe that the qualitative analysis presented in this part provides a significant value and guidance to companies thinking about implementing Auto ID. The use of Auto ID technology in supply chains and the way in which it affects the current supply chain processes has also been investigated by other researchers. Our analysis differs from the previous work by identifying and characterising the expected gains in a more structured way. The main idea of our analysis is that, the use of Auto ID, besides reducing the direct operating costs which result from automating processes that are currently conducted manually (e.g. the labour cost associated with manual confirmations and inspection procedures, the cost of the inventory counting activities, etc.), also contributes to the elimination or the reduction of potential uncertainties encountered within a supply chain (e.g. increased information on products, processes, demand, etc...). Therefore, in order to analyze how the use of Auto ID technology may improve supply chain processes, we followed a three-step-approach:

- We first identified two criteria, i.e. the degree of automation of the data capture process and the level at which data is monitored and managed by the system, as being the main factors enabling to compare the performance of different AIDC systems. Using this framework, we compared two sets of AIDC technologies: (the bar code system and UPC) versus (the RFID system and EPC).
- We then characterized the main sources of uncertainties in decision-making processes that hinder optimal supply chain performance. We distinguished four major sources of uncertainty where each type of uncertainty should be interpreted as a factor that generates variability in the quantity and/or the quality of products, delays or physical locations.
- The last step consisted in delineating how properties of the Auto ID technology can reduce or eliminate the sources of supply chain uncertainties to improve operations. This gives a clue to the question of how companies may benefit from using the Auto ID technology. For instance, the automatic identification property of this technology eliminates the uncertainty pertaining to the identity and location of products creating an opportunity to increase sales for both the manufacturer and the retailer by improving product availability at the store level. Furthermore, the item level identification property of the Auto ID technology enables to better monitor supply chain entities by distinguishing the individual characteristics of products. This functionality would be important in cases where a finer level of product information is necessary. For instance, due to this property, the uncertainty on the precise identity of products (including lot numbers and physical characteristics of products, the timing of operations performed, etc...) is eliminated, enabling supply chain actors to issue more targeted product recalls.

As stated in earlier chapters, besides the automatic and item level properties, the Auto ID technology enables also to share information across the supply chain. In cases where several actors need to exchange information on products to trace products or in situations where products have to be recalled, the Auto ID infrastructure enables to communicate item level information.

## **Part B**

In our qualitative analysis, we identified the Auto ID technology as a potential lever to know the exact identity, location and quantity of their inventory without conducting time consuming counts at several points along the chain and decided to build our quantitative study on the impact of this technology on reducing inventory inaccuracies. The literature review we conducted in the field of inventory management shows that almost all of the research conducted on this area assumes that a perfect knowledge of the inventory level is available. Furthermore, in practice, many enterprises are still unaware of how errors occurring in their data capture process can affect their performance. There is thus a scarcity of works that address the inventory record inaccuracy problem.

Our quantitative analysis starts by characterising an inventory system subject to perturbations that affect both the physical flow of materials and the information flow representing it. We then propose a general framework to represent this system and several models depending on the type of errors considered and the strategy of the IS data update procedure being used by the inventory system.

Our models use the Newsboy framework; a single replenishment of inventory is made long before the beginning of the selling period based on an estimation of demand that will be observed during the season. We consider a single-stage inventory system with inventory record inaccuracy. This demand is addressed in two steps: 1) An initial commitment is made to customers based on the inventory level recorded in IS 2) Some time after, products are shipped to customers. However, it may happen that it is not possible to fulfill the whole commitment because there are not enough physical products available in inventory. If the physical inventory exceeds the shipped quantity, there would be some leftover inventory at the end of the selling period.

Each of the models we developed corresponds to a special case of the general model described above, i.e.:

- in *Model 0* (the perfect system), no errors occur neither on the physical flow nor the information flow
- in *Model 3*, errors occur both in the physical flow and while updating the IS inventory data by measuring the physical flow
- in *Model 4*, errors occur in the physical flow but they are not detected by the IS since the update of inventory data is based on order information

Model 3 takes into account two types of errors simultaneously: errors on the physical flow and errors on the information flow. From this general model, we derive two different variants, each one corresponding to a special case of errors: Model 1 and Model 2.

- *Model 1* assumes that there are no errors on the physical flow but the information flow is prone to errors due to defects arising in the data capture process.
- *Model 2* assumes that the physical flow involves errors but that the data capture process is perfectly reliable.

Our analysis focuses then on the analysis of Model 1 which investigates the consequences of inaccurate inventory records on the performance of an inventory system and provides a quantification basis for the justification of the new Auto ID technology implementation. The justification is made on the basis of its impact on reducing the inventory holding cost and the cost associated with shortage situations stemming from errors on the information flow. We conduct several analyses such as: What is the optimal policy in presence of inventory

inaccuracies? What is the sensitivity of the optimal solution to the parameters of errors (mean and variance) and cost parameters? How much the system performance is degraded as a result of inaccuracies? Is the implementation of Auto ID technology justified, if yes, under what conditions?

Our work clearly demonstrates that maintaining accurate inventory records, records that reflect physical reality, is clearly crucial to the performance of enterprises, especially in cases where the penalty associated with the non satisfaction of an earlier commitment is high. In summary, among results we obtained in our study are the following (1) inventory record inaccuracy can lead to significant losses for companies, (2) implementing an effective inventory policy reduces the cost incurred but the major part of the gain stems from the elimination of record errors (3) corrective strategies such as a solution that consists in adjusting the value of the inventory recorded in the information system can recover a portion of the losses caused by inaccuracies, even if companies are not able (or choose not) to invest in an advanced technology such as the Auto ID system.

Our models and results show also that the gap encountered in the literature on the inventory inaccuracy issue can be filled by combining qualitative and quantitative type analyses on this topic.

## **Perspectives**

Results obtained in our research provide some interesting managerial insights and stimulate the development of further work. We will continue to investigate the use of Auto-ID technology and analyse the costs and benefits of applications that are expected to drive Auto-ID adoption in industry. Among research perspectives and specific areas for further study that are identified in our work, the following ones are of special interest:

- Consideration of other Newsboy type models (e.g. models with initial inventory at the beginning of the season) enabling to generalize our approach and complete the set of models considered in our work.
- Combination of the analysis of different models in terms of insights. We particularly refer here to a study which will consider the impact of Auto ID on reducing errors occurring in the physical flow of products as well as its impact on improving the reliability of the data capture process. As presented in our thesis, the first improvement can be quantified by comparing the cost of Model 2 vs. Model 0 while the second improvement will be evaluated by comparing the cost of Model 1 vs. Model 0. Summing up these two gains will aid to quantify the combined impact of the Auto ID technology for an inventory system which uses initially the Bar Code system.
- Extension of the inventory inaccuracy issue to a multi period inventory model setting. Although the multi period modelling version is much more complex, it is more realistic

and is expected to provide further insights to managers facing inaccuracies in inventory data, within a warehouse or a store. In this setting, an important question that concerns the way in which the information system inventory is reset should be answered. Several modelling approaches can be adopted for this purpose, i.e. 1) update  $Q_{IS}$  each time an operator finds an item out-of-stock while the inventory record shows in-stock during warehouse processes such as picking or replenishment, 2) update  $Q_{IS}$  by regularly counting inventory at a predetermined frequency, 3) set  $Q_{IS} = 0$  if the evolution of  $Q_{IS}$  is constant during a delay longer than a predetermined timeframe, 4) set  $Q_{IS} = 0$  when there is a claim from a customer not finding a product while the information system shows that there is enough inventory on store shelf. An assumption should be made on whether the model developed assumes that such information is used to update the inventory records.

- Evaluation of other levers enabling to reduce errors and comparison of their performance with the Auto ID technology. Examples of such methods enabling to control errors include: manually counting items stored within a facility, monitoring the data available to detect whether there are anomalies or not, etc... Concerning the first lever, an additional assumption on the presence of residual errors remaining after a physical count is performed can also be made. The cost associated with a counting activity will then depend on the characteristics of the residual errors (mean, variance, etc...). In a second step, it would be interesting to compare results stemming from the cost benefit trade-off analysis associated with these different levers of performance improvement.
- Consideration of other types of benefits enabled by Auto ID such as its effect on supporting reverse logistics or on planning supply chain activities. While the need for further investigation concerning the first point is accelerated by the recent governmental regulations that imply the recycling of most of consumer goods such as electronics or pharmaceuticals, the second point refers to the ability of Auto ID to support the implementation of a decentralised approach while planning supply chain activities.

# References

1. Christopher, M.; *Logistics and Supply Chain Management*; Ed. P. Publishing; 1992; London.
2. Edward, M.A., Cornelia, L.M., Vickery, S.K.; *Strategic supply chain capabilities for competitive advantage and firm success*; Journal of Business Logistics; 1996; Vol. 17.
3. Quinn, F.; *The payoff potential in supply chain management*; in Achieving Supply Chain Excellence Through Technology; I. Montgomery Research; Editor; 1999: San Francisco, California.
4. Mentzer, J.T.; *Supply Chain Management*; Thousands Oak; Ed. Sage; 2001; California.
5. Hendricks, K.B. and Singhal, V.R.; *The effect of supply chain glitches on shareholder wealth*; Journal of Operations Management; 2003; Vol. 21, p. 501-522.
6. Rickhardson, H.L.; *Packaging for today's demanding fulfilment*; Transportation & Distribution; 2000; Vol. 41(7), p. 72-75.
7. Hewitt, F.; *Demand satisfaction communities: New operational relationships in the information age*; International Journal of Logistics Management; 2000; Vol. 11(2).
8. Andel, T.; *The consumer electronics challenge*; Material Handling Management; 2001; Vol. 56(3): p. 48-49.
9. Karkkainen, M., Ala-Risku, T., and Framling, K.; *Integrating material and information flows using a distributed peer-to-peer information system*; in International Conference of Advanced Production Management Systems; 2002; Eindhoven, The Netherlands.
10. Hamilton, J.; *The European Union's consumer guarantees directive*; Journal of Public Policy & Marketing; 2001; Vol. 20(2): p. 289-96.
11. Wilder, C.; *Purchasing Analyzer*; InformationWeek; 17 May 1999; p. 79.
12. Delfmann, W. and Albers, S.; *Supply Chain Management in the global context*; Université de Koln; 2000.
13. Ireland, R. and Bruce, R.; *CPFR: only the beginning of collaboration*; Supply Chain Management Review; 2000: p. 80-8.
14. Bowersox, D. and Closs D.; *Logistical Management-The Integrated Supply Chain Process*; Mc Graw-Hill; 1996.
15. Tayur, S., Ganeshan, R., and Magazine, M.; *Quantitative Models for Supply Chain Management*; Kluwer's International Series; 1999.
16. Kambil, A. and Brooks, J.D.; *Auto-ID Across the Value Chain : From Dramatic Potential to Greater Efficiency & Profit*; Auto ID center; 2002 Sept.
17. Forger, G.; *ADC takes control*; Modern Materials Handling; 2000; Vol. 55(10).
18. Kärkkäinen, M., Ala-Risku, T., and Kiianlinna, P.; *Item identification Applications and Technologies*; TAI Research Center, Helsinki University of Technology; 2001.
19. Adams, R.; *Sourcebook of Automatic Identification and Data Collection*; Ed. V.N. Reinhold; 1990; New York, NY.
20. *Automatic Identification Manufacturers technology presentations*; AIM; 2000.
21. Karkkainen, M., Ala-Risku T., and Framling K.; *The product centric approach: a solution to supply network information management problems?*; 2003.
22. Agarwal, V.; *Assessing the benefits of Auto-ID Technology in the Consumer Goods Industry*; Auto ID Center; 2001 Dec.

23. Jones, L.; *Working without wires*; Industrial Distribution; 1999; Vol. 88(8).
24. *RFID: Just The Facts*; Red Prairie; 2003 Dec.
25. Retail Solutions Division; *50 ideas to revolutionizing the store through RFID*; NCR Corporation; 2003.
26. *RFID in the Consumer Industries*; Aberdeen Group; 2004 Mar.
27. Maddocks, R.; *RFID: Receiving You Loud And Clear*; 2003 Aug; [www.quebecoislibre.org](http://www.quebecoislibre.org).
28. Niemeyer, A., Pak, M.H., and Ramaswamy, S.; *Smart tags for your supply chain*; The McKinsey Quarterly; 2003(4).
29. Burnell, J.; *Standard Behavior: RFID Maturation is following well-worn technology development path*; Realtime; 2003 Sep.
30. Brock, D.L.; *The Compact Electronic Product Code*; Auto-ID Center; 2000.
31. Sarma, S., Brock, D.L., and Ashton, K.; *The Networked Physical World*; Auto-ID Center; 2000.
32. Lau, W. and Lee, B.; *On a responsive supply chain information system*; International Journal of Physical Distribution & Logistics Management; 2000; Vol. 30(7/8).
33. Kolluru, R. and Meredith, P.H.; *Security and trust management in supply chains*; Information Management & Computer Security; 2001; Vol. 9/5.
34. Lee, H.L. and Whang, S.; *Information Sharing in a supply chain*; International Journal of Manufacturing Technology and Management; 2000; Vol. 1(1).
35. Chappell, G., et al.; *Auto-ID on Demand: The Value of Auto-ID Technology in Consumer Packaged Goods Demand Planning*; Auto ID Center; 2003.
36. Fudenberg, D. and Tirole, J.; *Game Theory*; 1993; Cambridge, MA; MIT Press.
37. Dierkx, K.; *Taking supply chain visibility to the next level: powering the smart supply chain*; in Council of Logistics Management Annual Conference; 2000; Council of Logistics Management, New Orleans.
38. *Counting Down to RFID*; Insight Research; 2003 Sep.
39. Forrester, J.W.; *Industrial Dynamics*; Ed. M. Press; 1961; Cambridge, MA.
40. Murmann, P.A.; *Expected development time reductions in the German mechanical engineering industry*; Journal of Product Innovation Management; 1994; Vol. 11.
41. Hagel, J.; *Managing complexity*; McKinsey Quarterly; 1988; Vol. Spring: p. 2-23.
42. Feigin, G.E.; *Inventory Planning in large assembly supply chains*; in Quantitative Models For Supply Chain Management; KAP; Editor; 1999; Kluwer Academic Publishers: Boston/Dordrecht/London.
43. Strassner, M. and Fleisch, E.; *The Promise of Auto-ID in the Automotive Industry*; Auto ID Center; 2003 May.
44. Baglin, G., Bruel, O., Garreau, A., Grief, M., and Van Delft, C.; *Management Industriel et Logistique*; Série: Production et Techniques quantitatives appliqués à la gestion; Ed. Gestion; 2001.
45. Garg, A. and Lee, H.L.; *Managing Product variety: an operations perspective*; in Quantitative Models for Supply Chain Management; KAP; Editor; 1999; Kluwer Academic Publishers: Boston/Dordrecht/London.
46. Product diversity survey; Marketing Intelligence Service, Ltd.; 1997.
47. *Safeway Annual Report*; Safeway; 1997.



48. Machel, P.G.; *Supply chain strategy in a multinational environment*; in Improving Supply Chain Effectiveness in the Grocery Trade; 1993; London.
49. Pellew, M.; *Pan-European logistics: strategies for success in supply chain management*; Finance Times Business Limited; 1998.
50. Frazier, G.; *Organizing and managing channels of distribution*; Journal of Academic Marketing Science; 1999; Vol. 27(2): p. 226- 40.
51. Webb, K.L.; *Managing channels of distribution in the age of electronic commerce*; Industrial Marketing Management; 2002; Vol. 31: p. 95- 102.
52. Klassen, R.D. and Whybark, D.C.; *Barriers to the management of international operations*; Journal of Operations Management; 1994; Vol. 11: p. 385-96.
53. Daft, R.L.; *Organization Theory and Design*; 5th Ed; 1995; St Paul, MN; West Publishing Company.
54. Fisher, M.L. and Ittner, C.D.; *The impact of product variety on the automobile assembly: empirical evidence and simulation analysis*; Management Science; 1999; Vol. 45(6): p. 771-86.
55. Kotteaku, A.G., Laios, L.G., and Moschuris, S.J.; *The influence of product complexity on the purchasing structure*; Omega; 1995; Vol. 23(1): p. 27-39.
56. Van Donk, D.P. and Van Dam, P.; *Structuring complexity in scheduling: a study in a food processing industry*; International Journal of Operations and Production Management; 1996; Vol. 16(5): p. 54-63.
57. Adani, M., et al.; *The integrated management of logistic chains in the white goods industry: A field research in Italy*; International Journal of Production Economics; 2002; Vol. 69: p. 227-238.
58. Suzue, T. and Kohdate, A.; *Variety Reduction Program: A Production Strategy for Product Diversification*; Ed. P. Press; 1990; Cambridge, MA.
59. Peronaa, M. and Miragliotta, G.; *Complexity management and supply chain performance assessment. A field study and a conceptual framework*; International Journal of Production Economics; 2002.
60. Van der Vorst, J. and Beulens, A.; *Identifying sources of uncertainty to generate supply chain redesign strategies*; International Journal of Physical Distribution & Logistics Management; 2002; Vol. 32(6).
61. Van der Vorst, J., et al.; *Supply Chain Management in Food Chains: Improving Performance by Reducing Uncertainty*; International Transactions in Operational Research; 1998; Vol. 5(6).
62. Wilding, R.; *The supply chain complexity triangle: uncertainty generation in the supply chain*; International Journal of Physical Distribution & Logistics Management; 1998; Vol. 28(8): p. 599-616.
63. Davis, T.; *Effective supply chain management*; Sloan Management Review; 1993; Vol. Summer: p. 35-46.
64. Persson, G.; *Logistics process redesign: some useful insights*; International Journal of Logistics Management; 1995; Vol. 6(1): p. 13-25.
65. Mason-Jones, R. and Towill, D.R.; *Shrinking the supply chain uncertainty circle*; Control; 1998(September): p. 17-22.
66. Bel, G., et al.; *Strategic decision making in production planning with genetic algorithms*; in Computer Integrated Manufacturing and Automation Technology; 1996; INPG, France.

67. Applequist, G.E., Pekny, J.F., and Reklaitis, G.V.; *Risk and uncertainty in managing chemical manufacturing supply chains*; Computers and Chemical Engineering; 2000; Vol. 24: p. 2211-2222.
68. Sharma, K.; *Managing on the edge of instability*; in Logistic Information Management; G. Brace; Editor; 1997; Sterling Publishing; London.
69. Landeghem, G. and Vanmaele, H.; *Robust planning: a new paradigm for demand chain planning*; Journal of Operations Management; 2002; Vol. 319.
70. Brock, D.L.; *The Virtual Electronic Product Code*; Auto ID Center; 2002 May.
71. Brock, D.L.; *The Electronic Product Code - A Naming Scheme for Physical Objects*; Auto ID Center; 2001 Jan.
72. DeJong, C.A.; *Material handling tunes in*; Automotive Manufacturing & Production; 1998; Vol. 110(7): p. 66-9.
73. Moore, B.; *Bar code or RFID: Which will win the high speed sortation race?*; Automatic ID News; 1999; Vol. 15(7): p. 29-30, 34 and 36.
74. Ollivier, M.; *RFID enhances materials handling*; Sensor Review; 1995; Vol. 15(1): p. 36-9.
75. HiPoint Technology; 2002 Nov; [www.hi-point.com/resources.html](http://www.hi-point.com/resources.html).
76. Alexander, K., et al.; *Focus on the Supply Chain: Applying Auto-ID within the Distribution Center*; Auto ID Center.
77. Kärkkäinen, M. and Holmström, J.; *Wireless product identification: enabler for handling efficiency, customisation and information sharing*; Supply Chain Management: An International Journal; 2002; Vol. 7(4).
78. Bylinsky, G.; *Hot new technologies for American factories*; in Business2; 2002 Jun.
79. Caballero, M.J., et al.; *Waiting in line: a primary investigation*; in Marketing: The Next Decade; 1985; Klein, D.M. and Smith, A.E. (Eds).
80. Alcott, M.J.; *Grocers move to ease life in not-so-fast lane*; Sacramento Bee; 1991.
81. *Identifying the Market for RFID Transponders*; Gartner; 2000.
82. Johnson, J.R.; *RFID gets the green light*; Warehousing Management; 2000; Vol. 7(4): p. 28-29.
83. Brown, A.; *Appraising intangible benefits from information technology investment*; in 1st European Conference on IT Investment Evaluation; 1994 Sep; Henley UK.
84. Giaglis, M., Mylonopoulos, N., and Doukidis, I.; *The ISSUE methodology for quantifying benefits from information systems*; Logistics Information Management; 1999; Vol. 12(1/2).
85. Jayaram, J., Vickery, K., and Droge, C.; *The effects of information system infrastructure and process improvements on supply-chain time performance*; International Journal of Physical Distribution & Logistics Management; 2000; Vol. 30(3/4).
86. Chappell, G., et al.; *Auto-ID on the Line: The Value of Auto-ID Technology in Manufacturing*; Accenture; 2003.
87. Alexander, K., et al.; *Applying Auto-ID to Reduce Losses Associated with Product Obsolescence*; Auto ID Center.
88. *Where to Look for Incremental Sales Gains: The Retail Problem of Out-of-Stock Merchandise- A Study conducted by Andersen Consulting for the Coca-Cola Retailing Research Council*; Accenture; 1996 January.
89. Shulman, R.; *Perishable systems take center stage*; Supermarket Business; 2001; Vol. 56(4): p. 47-8.

90. Kärkkäinen, M.; *Increasing efficiency in the supply chain for short shelf life goods using RFID tagging*; International Journal of Retail & Distribution Management; 2003; Vol. 31(10).
91. Mitchell, S.H.; *Managing fraud trends*; Secured Lender; 1997: p. 104-8.
92. Roberti, M.; *RFID Can Benefit Manufacturers*; 2004; [www.rfidjournal.com](http://www.rfidjournal.com).
93. Hook, C.; *RFID Can Provide A Defense Against Counterfeiting*; TIRIS News; 1997.
94. DeJong, C.A.; *Material handling tunes in*; Automotive Manufacturing & Production; 1998; Vol. 110(7): p. 66-69.
95. Fildes, N.; *RFID could make toothpaste the next big thing*; Wall Street Journal; 2003.
96. Byrnes, J., Sheffi, Y., and Wass, J.; *Auto-ID: Selective or Comprehensive System?*; 2002.
97. Gragg, J.; *The Emergence of RFID Technology in modern Society*; Oregon State University; 2003 Nov.
98. *The cost of Wal-Mart's RFID edict*; RFID Journal; 2003 Sep.
99. *The best thing since the bar-code*; in *The Economist*; 2003 Feb.
100. TI Corp; *TI's RFID Smart Labels track leading brand sportswear through Production, Shipping, and Distribution - and reduce Shrinkage and 'Grey' Importing*; 2001; [www.ti.com](http://www.ti.com).
101. *Oil refinery checks valves safely and accurately with RFID tags*; in *Frontline Solutions*; 2000 Feb.
102. McGinity, M.; *RFID: Not Your Father's Bar Code*; IEEE distributed systems online; <http://dsonline.computer.org/0308/f/newsp.htm>.
103. d'Hont, S.; *The Cutting Edge of RFID Technology and Applications for Manufacturing and Distribution*; Texas Instrument TIRIS; 2000.
104. Feare, T.; *Pump up the volume*; *Modern Materials Handling*; 2000; Vol. 55(3): p. 55-59.
105. Thomas, D.; *Tesco To Extend Trial Of RFID Tags To DVDs*; in *Computerweekly*; 2003 May.
106. Mital, T.; *The Emergence of RFID Technology, ISRC Future Technology Topic Brief: Radiofrequency Identification*; Bauer College of Business administration - University of Houston; 2003 Sep.
107. Burnell, J.; *Pallet-tracking pilot will put RFID to the test*; in *Frontline Solutions*; 2002; p. 58-9.
108. Robson, A.; *Smart new technologies for managing the real-time supply chain*; in *Council of Logistics Management (CLM)*; 2002; San Francisco - CA.
109. Rizzotto, P. and Wolfram, G.; *Intelligent tagging-getting supply chain smart!*; in *Official ECR Europe Conference*; 2002; Barcelona - SP.
110. Pietrucha, B.; *USPS Tests Mail Tracking, Electronic Courier Service*; in *Newsbytes*; 1998.
111. O'Conner, M.C.; *Airline Interest in RFID on the Rise*; in *RFID Journal*; 2003; <http://www.rfidjournal.com>.
112. Group, T.R.; *Collecting Tolls On The Move At The Tyne Tunnel, UK*; in *RFID News*; 2000; p. 5.
113. Brock, D.L.; *Smart Medicine The Application of Auto-ID Technology to Healthcare*; Auto ID Center; 2002 Feb; <http://www.autoidlabs.com/whitepapers>.
114. Chiesa, M., et al.; *RFID a week long survey on the technology and its potential*; *Harnessing Technology Project - Interaction Design Institute Ivrea*; 2002.
115. Vollmann, T.E., Berry, W.L., and Whybark, D.C.; *Manufacturing Planning and Control Systems*; Hardcover (2nd) Ed; Dow Jones-Irwin; 1988; Homewood, IL,.

116. Yao, A.C. and Carlson, J.G.; *The impact of real-time data communication on inventory management*; International Journal of Production Economics; 1999; Vol. 59(1-3).
117. Armistead, C.G. and Mapes, J.; *The impact of supply chain integration on operating performance*; Logistics Information Management; 1993; Vol. 6.
118. Tallon, P.P., Kraemer, K.L., and Gurbaxani, V.; *Executives' perceptions of the business value of information technology: a process oriented approach*; Journal of Management Information Systems; 2000; Vol. 16.
119. Strassmann, P.A.; *The Business Value of Computers*; Information Economics Press; 1990; New Canaan, CT.
120. Brandyberry, A., Rai, A., and White, G.P.; *Intermediate performance impacts of advanced manufacturing systems: an empirical investigation*; Decisions Sciences; 1999; Vol. 30.
121. Shin, N.; *Does information technology improve coordination? An empirical analysis*; Logistics Information Management; 1999; Vol. 12(1/2).
122. Dawson, A.; *Supply chain Technology*; Work Study; 2002; Vol. 51(4).
123. Willcocks, L.; *Evaluating information technology investments, research findings, and reappraisal*; Journal of Information Systems; 1992; Vol. 2: p. 243-68.
124. Alexander, K., et al.; *Focus on Retail: Applying Auto-ID to Improve Product Availability at the Retail Shelf*; Auto ID Center.
125. Rogers, D.S., Daugherty, P.J., and Stank, T.P.; *Enhancing service responsiveness: the strategic potential of EDI*; International Journal of Physical Distribution & Logistics Management; 1992; Vol. 22(8): p. 15-20.
126. Walton, L.W. and Miller, L.G.; *Moving toward LIS theory development: a framework of technology adoption within channels*; Journal of Business Logistics; 1995; Vol. 16(2): p. 117-35.
127. Talluri, S.; *An IT/IS acquisition and justification model for supply-chain management*; International Journal of Physical Distribution & Logistics Management; 2000; Vol. 30(3/4).
128. Croom, S.; *The implication of electronic procurement for major account management*; Journal of Selling and Major Account Management; 1999; Vol. 1(4): p. 47-63.
129. Ranchhod, A. and Hackney, R.; *Internet transactions and physical logistics: conflict or complementarity?*; Logistics Information Management; 2001; Vol. 14(1/2).
130. Roach, S.; *Services under siege- the restructuring imperative*; Harvard Business Review; 1991; Vol. 69.
131. Loveman, G.; *An assessment of the productivity impact of information technologies*; in Information Technology and the Corporation of the 1990s: Research Studies; T.J.a.M. Allen, M.S.; Editor; 1994; MIT Press: Cambridge, MA.
132. Hitt, L. and Brynjolfsson, E.; *Productivity, business profitability, and consumer surplus: three different measures of information technology value*; MIS Quarterly; 1996; Vol. 20(2): p. 121-37.
133. Barua, A., Kriebel, C., and Mukhopadhyay, T.; *Information technologies and business value: an analytic and empirical investigation*; Information Systems Research; 1995; Vol. 6(1).
134. Barua, A. and Lee, B.; *The IT productivity paradox revisited: a theoretical and empirical investigation in the manufacturing sector*; The International Journal of Flexible Manufacturing Systems; 1997; Vol. 9(2): p. 145-66.
135. Ross, A.; *A multi-dimensional empirical exploration of technology investment, coordination and firm performance*; International Journal of Physical Distribution & Logistics Management; 2002; Vol. 32(7): p. 591-609.

136. Byrd, T.A. and Davidson, N.W.; *Examining possible antecedents of IT impact on the supply chain and its effect on firm performance*; Information and Management; 2003; Vol. 41.
137. Brynjolfsson, E. and Hitt, L.; *Paradox lost? Firm level evidence on the returns to information systems spending*; Management Science; 1996 April: p. 541-58.
138. Loveman, G.W.; *Assessing the productivity impact of information technologies*; in Information Technology and the Corporation of the 1990s; T.J.a.S.-M. Allen, M.; Editor; 1994; Oxford University Press: New York, NY.
139. Kekre, S., Mukhopadhyay, T., and Srinivasan, K.; *Modeling Impacts of Electronic Data Interchange Technology*.
140. Turner, J.; *Organizational performance, size and the use of data processing resources*; Center for Research in Information Systems, New York University; 1985.
141. Weil, P.; *The relationship between investment in information technology and firm performance: a study of the valve manufacturing sector*; Information Systems Research; 1992; Vol. 3.
142. Cardinali, R.; *Assessing technological productivity gains: Benson and Parker Revisited*; Logistics Information Management; 1998; Vol. 11(2).
143. Shao, B.M. and Lin, W.; *Technical efficiency analysis of information technology investments: a two-stage empirical investigation*; Information & Management; 2002; Vol. 39: p. 391-401.
144. Rouwenhorst, B., et al.; *Warehouse design and control: Framework and literature review*; European Journal of Operational Research; 2000; Vol. 122: p. 515-533.
145. Ballantine, J.A., Galliers, R.D., and Stray, S.J.; *Information system/technology investment decisions - the use of capital investment appraisal techniques in organisations*; in Proceedings of the 1st European Conference on IT Investment Evaluation; 1994; Henley.
146. MacArthur, P.J., Crosslin, R.L., and Warren, J.R.; *A strategy for evaluating alternative information system designs for business process reengineering*; International Journal of Information Management; 1994; Vol. 14: p. 237-51.
147. Giaglis, G.M. and Paul, R.J.; *It's time to engineer re-engineering: investigating the potential of simulation modelling in business process redesign*; in Business Process Modelling; B. Scholz-Reiter and E. Stickel; Editors; 1996; Springer-Verlag: Berlin. p. 313-32.
148. Nissen, M.E.; *Valuing IT through virtual process measurement*; in 15th International Conference on Information Systems; 1994; Vancouver.
149. Keller, G. and Hamid, N.; *Justifying New Technology Acquisition Through its Impact on the Cost of Running an Inventory Policy*; IIE Transactions; 1998; Vol. 20(3).
150. Wolstenholme, E., Henderson, S., and Gavine, A.; *The Evaluation of Management Information Systems: A Dynamic and Holistic Approach*; 1993; Wiley.
151. Sharif, A.M. and Irani, Z.; *Research note: theoretical optimization of IT/IS investments*; Logistics Information Management; 1999; Vol. 12(1/2): p. 189-96.
152. Walsham, G.; *Interpreting Information Systems in Organizations*; 1993; Chichester; John Wiley & Sons.
153. Haberman, A.; *Twenty-Five Years Behind Bars*; Alan L. Ed; 2001; Cambridge, MA; Harvard University Press.
154. Trunk, C.; *Using bar codes for warehouse control*; Material Handling Engineering; 1994; Vol. 49(10): p. 48-52.
155. Bushnell, R.; *Test your bar code competency*; Modern Materials Handling; 1995; Vol. 50(7).

156. Knill, B.; *The bar code route through manufacturing and distribution*; Material Handling Engineering; 1994; Vol. 49(5).
157. Hill, J. and Cameron, B.; *Automatic Identification and Data Collection: Scanning Into the Future*; Ascet; 2000; Vol. 2.
158. Brown, S.A.; *Revolution at the checkout counter: the explosion of bar code*; 1997; Cambridge, MA; Harvard University.
159. Lindau, R. and Lumsden, K.; *The use of automatic data capture systems in inventory management*; International Journal of Production Economics; 1999; Vol. 59.
160. Manthou, V. and Vlachopoulou, M.; *Bar-code technology for inventory and marketing management systems: A model for its development and implementation*; International Journal of Production Economics; 2001; Vol. 71.
161. White, E.; *The root cause of the problem*; Apics the performance advantage; 2002 Feb.
162. McFarlane, D.; *Auto-ID Based Control : An Overview*; Auto ID Center; 2002 May.
163. García, A., et al.; *Auto-ID in Materials Handling*; Auto ID Center; 2003 May.
164. Chappell, G., et al.; *Auto-ID on Delivery: The Value of Auto-ID Technology in the Retail Supply Chain*; 2003.
165. Chappell, G., et al.; *Auto-ID in the Box: The Value of Auto-ID Technology in Retail Stores*; Auto ID Center; 2003.
166. Alexander, K., et al.; *Applying Auto-ID to Reduce Losses Associated with Shrink*; Auto ID Center.
167. *Meeting the retail RFID Mandate*; AT Kearney; 2003 Nov.
168. Violino, B.; *Manufacturing Gains in Efficiency*; 2004; [www.rfidjournal.com](http://www.rfidjournal.com).
169. Wheeler, F.P.; *Executive support: current benefits and future opportunities*; in 1st European Conference on IT Investment Evaluation; 1994; Henley.
170. Kelley, M.R.; *Productivity and information technology: the elusive connection*; Management Science; 1994; Vol. 40(11): p. 1406-25.
171. *Databases are Plagued by Reign of Error*; in *The Wall Street Journal*; 1992.
172. Laudon, K.C.; *Data Quality and Due Process in Large Interorganizational Record Systems*; in ACM; 1986.
173. Strong, M.D., Wang, L., and Wang, R.Y.; *Data quality in context*; in ACM; 1997.
174. Redman, T.; *Improve data quality for competitive advantage*; Sloan Management Review; 1995; Vol. 36(2).
175. Hurwitz, D.; *Data capture for MRP-II systems*; Society of Manufacturing Engineers; 1985.
176. Wang, Storey, and Firth; *A Framework for Analysis of Data Quality Research*; IEEE Transactions on Knowledge and Data Engineering; 1995; Vol. 7(4): p. 623-640.
177. Wang and Strong; *Beyond Accuracy: What Data Quality Means to Data Consumers*; Journal of Management Information Systems; 1996; Vol. 12(4): p. 5-34.
178. Morey, R.C.; *Estimating and Improving the Quality of Information in the MIS*; in ACM; 1982.
179. Srivastava, J. and Rotem, D.; *Dynamic Maintenance of Approximate aggregate views*; in 7th Symposium of Principals of database systems; 1988; Austin.
180. Kwan, S. and Rotem, D.; *Analysis of trade off between data accuracy and performance of databases*; Information Systems; 1986; Vol. 21(8).



181. Ghosh, S.P.; *Statistical databases: Normal Forms*; IEEE Transactions on Knowledge and Data Engineering; 1991.
182. Tuttle, A.; *Who do you trust*; Industrial Distribution; 2002; Vol. 91(3).
183. UCCnet; *The Value of Clean Data*; 2003; <http://knowledgebase.uccnet.org/press-Room/publications>.
184. Vermeer, B.H.P.J.; *Data Quality and Data Alignment in EBusiness*; 2001; Eindhoven; Eindhoven University Press Facilities.
185. Mullaney, T.J. and Coy, P.; *This Gift Just Keeps On Giving*; in BusinessWeek; 2003.
186. Singh, J.; *The importance of information flow within the supply chain*; Logistics Information Management; 1996; Vol. 9(4).
187. Chopra, S. and Meindl, P.; *Supply chain management Strategy, Planning and Operation*; Ed. P. Hall; 2001; New Jersey.
188. Bergman, R.; *A B count frequency selection for cycle counting supporting MRP 2*; Production and Inventory Management Review; 1998 May.
189. Neeley and Parley; *A framework for cycle counting*; Production and Inventory Management; 1983; Vol. 24(4).
190. Bernard, P.A.; *Cycle counting: the missing link*; Production and Inventory Management; 1985; Vol. 25(4): p. 27-40.
191. Graff, R.T.; *The limitations of cycle counting*; Production and Inventory Management Journal; 1987; Vol. Fourth Quarter: p. 39-43.
192. Buck, J.R. and Sadowski, R.P.; *Optimum stratified sampling*; IIE Transactions; 1983; Vol. 15: p. 119-126.
193. Martin, W. and Goodrich, S.; *Minimising sample size for given accuracy in cycle counting*; Production and Inventory management; 1987; Vol. 28(4).
194. Covin, S.; *Inventory accuracy: one of your first hurdles*; Production and Inventory Management; 1984; Vol. 21(2).
195. French, R.L.; *Accurate WIP Inventory- a critical MRP System Requirement*; Production and Inventory Management; 1980; Vol. First Quarter.
196. Millet, I.; *A Novena to Saint Anthony, or How to Find Inventory by Not Looking*; Interfaces; 1994; Vol. 24(2).
197. De Horatius, N.; *Critical Determinants of Retail Execution*; 2002; Harvard Business School.
198. Morey, R.C.; *Estimating Service Level Impacts from changes in cycle count, buffer stock or corrective action*; Journal of Operations Management; 1985; Vol. 5(4).
199. Raman, A., DeHoratius, N., and Ton, Z.; *Execution: the missing link in retail operations*; California Management Review; 2001; Vol. 43.
200. Sheppard, G. and Brown, K.; *Predicting Inventory Record Keeping Errors with Discriminant Analysis: A field experiment*; International Journal of Production Economics; 1993; Vol. 32(1).
201. Chopra, V.; *How to set up an effective inventory accuracy program*; in 29th Annual APICS International Conference Proceedings; 1986.
202. Young, J.B.; *The limits of cycle counting*; in 29th Annual APICS International Conference Proceedings.
203. *Cost Justifying Automatic data collection projects*; Bar Code and Data Collection Systems; 2004.

204. Bernard, A.; *Cycle counting: the missing link*"; Production and Inventory Management; 1985; Vol. 25(4).
205. Meyer, H.; *Inventory accuracy-is it worth it?*; Production and Inventory Management; 1990; Vol. 25(4).
206. Ernst, R., Guerrero, J.L., and Roshwalb, A.; *A quality control approach for monitoring inventory stock levels*; Journal of Operational Research Society; 1993; Vol. 44(11).
207. Brown, K.L., Inman, R.A., and Calloway, J.A.; *Measuring the impacts of inventory inaccuracy in MRP inventory and delivery performance*; Production Planning and Control; 2001; Vol. 12.
208. Krajewski, L.J., Ritzmann, B.E., and Wong, D.S.; *Kanban, MRP and shaping the manufacturing environment*; Management Science; 1987; Vol. 33.
209. Kumar, S. and Arora, S.; *Effects of Inventory Miscount and non inclusion of the lead time variability on inventory system performance*; IIE Transactions; 1992.
210. Fleisch, E. and Tellkamp, C.; *Inventory inaccuracy and supply chain performance: a simulation study of a retail supply chain*; International Journal of Production Economics; 2004 Feb.
211. Sandoh, H. and Shimamoto, H.; *A theoretical study on optimal inventory taking frequency for retailing*; Journal of Retailing and Consumer Services; 2001; Vol. 8.
212. Iglehart, D. and Morey, R.C.; *Inventory systems with imperfect asset information*; Management Science; 1972; Vol. 18(8).
213. Kang, Y.; *Information inaccuracy in information systems*; 2003; MIT.
214. Gaukler, G., Seifert, R.W., and Hausman, W.H.; *Item level RFID in the retail supply chain*; Stanford University; 2003.
215. Axsater, S.; *Inventory Control*; International Series in Operations; 2000; Kluwer Academic Publishers.
216. Piasecki, D.; *Inventory Accuracy: people, processes and Technology*.
217. Giard, V.; *Gestion de la production et des flux*; Production et techniques quantitatives appliquées à la gestion; Ed. Economica; 2003.
218. Silver, E.A., Pyke, D.F., and Peterson, R.; *Inventory Management and Production Planning and Scheduling*; Wiley; 1998.
219. Beck, A.; *How can RFID help to reduce shrinkage?*; Scarman C., University of Leicester; 2003.
220. Van den Berg, J.P. and Zijm, W.H.M.; *Models for warehouse management: Classification and examples*; International Journal of Production Economics; 1999; Vol. 59: p. 519-528.
221. Johnson P.M.; *Inventory Shrinkage: Where Do the Missing Profits Go?*; Outcalt & Johnson: Retail Strategists, LLC.
222. Hollinger R.C. and Davis J .L.; *National Retail Security Survey Report*; Department of Sociology and the Centre for Studies in Criminology and Law, University of Florida; 2001.
223. *Supermarket Shrink Survey*; National Supermarket Research group; 2001; [www. Trax-usa.com/research/home2.html](http://www.Trax-usa.com/research/home2.html).
224. Lightburn A.; *2002 Unsealables benchmark report*; Joint Industry Insealables Committee, Foods Marketing Institute of Grocery Manufacturers of America.
225. Maiden, N., et al.; *A cooperative scenario based approach to acquisition and validation of system requirements: How exceptions can help!*; Interacting with Computers; 1999; Vol. 11: p. 645–664.



226. Marcel B.; *Verify at source and train staff*; Logistics Information Management; 1995; Vol. 8(3).
227. Manthou, V., Notopoulos, P., and Vlachopoulou, M.; *Information systems design requirements for inventory management : A conceptual approach*; International Journal of Production Economics; 2002.
228. Nahmias, S.; *Production and Operations Analysis, Fourth Edition*; Mc Graw-Hill Irwin; 2001.
229. Khouja, M.; *The Single Period (Newsvendor) Problem: Literature Review and Suggestions for Future Research*; Omega; 1999; Vol. 27: p. 537-553.
230. Rekik, Y., Sahin, E., and Dallery, Y.; *A comprehensive analysis of the Newsboy Model with unreliable supply*; Ecole Centrale Paris; 2004.
231. Noori, A.H. and Keller, G.; *One period order quantity strategy with uncertain match between the amount received and the quantity requisitioned*; Infor; 1986; Vol. 24(1): p. 1-11.