THE IMPLICATIONS OF JUDGEMENTAL INTERVENTIONS INTO AN INVENTORY SYSTEM

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Abstract

Physical inventories constitute a considerable proportion of companies' investments in today's competitive environment. The trade-off between customer service levels and inventory investments is addressed in practice by formal quantitative inventory management (stock control) solutions. Given the tremendous number of Stock Keeping Units (SKUs) that contemporary organisations deal with, such solutions need to be fully automated. However, managers very often judgementally adjust the output of statistical software (such as the demand forecasts and/or the replenishment decisions) to reflect qualitative information that they possess. In this research we are concerned with the value being added (or not) when statistical/quantitative output is judgementally adjusted by managers. Our work aims to investigate the effects of incorporating human judgement into such inventory related decisions and it is the first study to do so empirically. First, a set of relevant research questions is developed based on a critical review of the literature. Then, an extended database of approximately 1,800 SKUs from an electronics company is analysed for the purpose of addressing the research questions. In addition to empirical exploratory analysis, a simulation experiment is performed in order to evaluate in a dynamic fashion what are the effects of adjustments on the performance of a stock control system.

The results on the simulation experiment reveal that judgementally adjusted replenishment orders may improve inventory performance in terms of reduced inventory investments (costs). However, adjustments do not seem to contribute towards the increase of the cycle service level (CSL) and fill rate. Since there have been no studies addressing similar issues to date, this research should be of considerable value in advancing the current state of knowledge in the area of inventory management. From a practitioner's perspective, the findings of this research may guide managers in adjusting order-up-to levels for the purpose of achieving better inventory performance. Further, the results may also contribute towards the development of better functionality of inventory support systems (ISS).

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Love to my lovely children Afif and Hanhan for bringing so much happiness and strength to my life. Finally, I would like to thank, with much respect, my amazing husband Taufika Ophiyandri for his continuing support, patience, encouragement for all my work and for his loving care, sacrificing of his valuable time and his commitment to my achievements.

Dedication

I dedicate this piece of work to my dearest husband Bang Phy
& my lovely children Afif and Hanhan

Declaration

This thesis is submitted under the University of Salford requirements for the award of a PhD degree by research. Some research findings were published in refereed conference proceedings prior to the submission of the thesis during the period of PhD studies.

The researcher declares that no portion of the work referred to in the thesis has been submitted in support of an application for another degree or qualification to the University of Salford or any other institution.

Inna Kholidasari

Chapter 1. INTRODUCTION

1.1. Outline

This research is concerned with the effects of incorporating human judgement into inventory-related decisions. In particular, we[1] focus on the case of service/spare parts inventories. This introductory chapter describes the motivation behind this research by placing the study in a business context. Section 1.2 discusses the research background, followed by the need for the research in Section 1.3. The aim and objectives of the research are given in Section 1.4. Finally, Section 1.5 focuses on the structure of this thesis.

1.2. Research background

Physical inventories constitute a considerable proportion of companies' investments in today's competitive environment. According to the 22nd Annual State of Logistics Report, the world is currently sitting on approximately $8 trillion worth of goods held for sale (Wilson, 2011). About 10% of that value relates to spare parts; according to US Bancorp, spare parts relate to a $700 billion annual expenditure, constituting about 8% of the US gross domestic product (Jasper, 2006). Mobley (2002) argues that maintenance costs typically account for 15-60% of the total value of an end product, validating the figures presented above with regards to spare parts expenditure. The following statistics are also relevant: two relatively recent reports by the Aberdeen Group (2005) and Deloitte (2006)

[1]The use of the word "we" throughout the thesis is purely conventional. The work presented in this PhD thesis is the result of research conducted by the author alone, albeit with support from an academic institution.

identify the increasing importance of the spare parts business. As stated in the latter report, the combined revenues of many of the world's largest manufacturing companies are more than US$1.5 trillion. Furthermore, on average, service revenues account for more than 25% of the total business. To the best of our knowledge, such figures have not been published for the United Kingdom alone, but based on the above it is clear that small improvements regarding the management of maintenance and of spare parts may be translated into substantial cost savings, with a considerable contribution to the country's economy.

Moreover, inventories play an important role in improving the service level and reducing the operation cost of logistic systems. Companies strive to ensure high customer satisfaction, and off-the-shelf availability is almost a necessity under current supply chain arrangements. The trade-off between customer service levels and inventory investment is addressed in practice by formal quantitative inventory management (stock control) solutions. Commonly, an inventory system consists of a three-stage process. Firstly, stock-keeping units (SKUs) are classified into various categories based on some common characteristics (such as underlying demand patterns, volume of sales, price, importance, etc.). Next, specific methods are used for each category in order to extrapolate requirements into the future. Finally, various stock control formulations are employed in order to convert the forecasts into inventory decisions (when and how much to order). Given the tremendous number of SKUs that contemporary organisations deal with, the solutions need to be fully automated. However, although such systems are indeed in principle fully automated, what most often happens in practice is this: managers intervene in the system and use their judgement to adjust or decide on various quantitative elements. For example, they may impose fully subjective (experience-driven) criteria for the purpose of classifying an SKU, based on demand frequency, demand value, or the criticality of the items being classified (Silver et al., 1998; Naylor, 1996). Also, managers often set the boundaries of SKU classification in an arbitrary way (e.g. William, 1984; Eaves, 2002), despite the existence of more logically coherent approaches such as those proposed by Johnston and Boylan (1996) and Syntetos and Boylan (2005). Even more frequently, they judgementally adjust a statistical forecast or a replenishment decision. If, for example, the forecast produced by the system for a particular SKU is 10 units, then a manager may introduce some qualitative information and amend the forecast to, say, 15 units, thus overriding the system. Similarly, a replenishment decision of 15 units may be reduced to reflect additional information available to the manager, about, for example, some increased competition (due to a competitor reducing their prices) likely to occur in the near future. The process discussed above is depicted in the following figure (Figure 1.1).

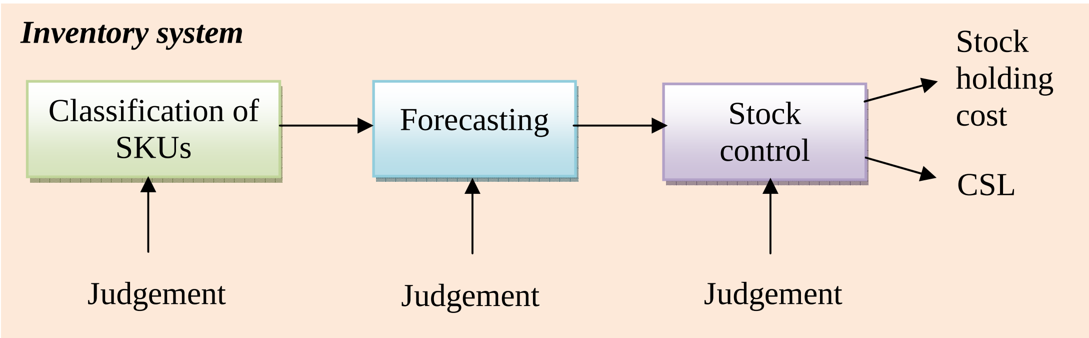

Figure 1.1 The incorporation of human judgement into an inventory system

Although there is a growing body of empirical knowledge in the area of judgementally adjusting statistical forecasts, there has been little discussion about judgemental adjustments neither to SKU classification; nor at the moment there a single empirical study that explores the effects of such judgemental adjustments into replenishment decisions. This is most important in terms of developing our understanding of the process of training provision and design of decision support systems. All these issues are discussed later on in this thesis in more detail.

1.3. Need for the research

Because of the tremendous number of SKUs that both manufacturing and service organisations deal with, it is clear that the inventory task needs to be automated. Automation here implies fully quantitative models that can run on their own without human intervention, thus relying upon statistical, generalisable principles. Such models rely upon past information that is available to the system and thus may not of course capture contextual knowledge that managers may possess. For example, experts/managers may know that institutions are in the process of change, or that a product promotion is about to take place, that certain actions are being undertaken by competitors that will affect demand for the product, or that a manufacturing problem exists. The impact of these events is specific, and cannot be included in the model being used. Similarly, a variable that is difficult to measure may be missing from the model. Judgement may be used when insufficient data is available to support statistical methods, or situations arise where exceptional events are known to be occurring in the future. In practice, managers adjust the output of automated systems by altering some quantities, and this is not necessarily a bad thing. As Soergel (1983) and Jenks (1983) pointed out, it is judgement alone that can anticipate one-time events which, if not accounted for, could have severe negative consequences for the organisation.

Many studies have discussed the effect of human intervention on statistical forecasting models. For example, Cerullo and Avila (1975) surveyed 110 large companies and found that 89% used judgemental forecasting alone or a combination of judgement and a formal model. Klein and Linneman (1984) surveyed 500 of the world's largest corporations and found that the overwhelming majority of corporate planners identified severe limitations in using purely statistical techniques. A survey of corporations in the United States (Sanders and Manrodt, 1994) found that 57% of respondents always used judgemental methods, and

21% did so frequently. Furthermore, 45% of the respondents said that they always adjusted their statistical forecasts and 37% did so sometimes. In a study of Canadian firms, Klassen and Flores (2001) reported that 80% of the respondents that used computer-based forecasts used judgement to adjust them.

A plethora of studies look at this phenomenon in regards to forecasting. However, in terms of inventory systems, practitioners often adjust the stock replenishment order, not the forecast. Kolassa et al. (2008) report that judgemental adjustments of stock control quantities occurs more often than forecast-related adjustments.

A distinction needs to be made at this point between: i) solely employing judgement as a means of predicting the future, and ii) the use of quantitative methodologies adjusted by managers in order to reflect qualitative information. In this research we refer to the latter, and although there are numerous studies that look at this phenomenon when it comes to forecasting, there are no studies at all that examine: i) the effects of judgementally adjusting classification rules, ii) the effects of judgementally adjusting replenishment decisions, and iii) the cumulative effect of adjusting more than one aspect of the system under concern. In this research we are concerned with the effects of judgement on replenishment decisions.

This constitutes precisely the purpose of this PhD research, which aims at analysing the effects of judgemental adjustments into inventory control. Since this research includes elements of Operations Management (OM)/Operational Research (OR) and behavioral aspects of decision-making, it should contribute and advance knowledge in the field of behavioural operations. Croson et al. (2013) argued that research in behavioural operations analyses decisions and the behaviour of individuals/small groups of individuals to gain a deeper understanding of operations processes, and make better recommendations on how to design and improve the operations processes. Furthermore, Bendoly et al. (2006)

reported that this field of study should be very much associated with inventory management and production management; however, this is the first study that attempts to do so and currently (and as discussed above), to the best of our knowledge, there is not a single paper in the academic literature that addresses this issue.

We do so by means of analysing an extended empirical database coming from the electronics industry. Managers in the company under consideration adjust inventory quantities, often providing a qualitative justification for their action. Linking the effects of adjustments to the justification provided for such adjustments has never been discussed in the academic literature before; this linkage (on its own) is perceived as a major contribution of the thesis.

The fact that this work is based on a single case can be justified partly by the lack of any previous research in this area, but mostly on the sensitivity of the information required to perform such a study. Adjustments reflect a manager's personal opinion and such data cannot be easily retrieved. In addition, and as will be explained later in this report, the very construction of the database was a very difficult exercise since the company provided only fragmented information which needed to be constructively put together.

The company under discussion represents the European logistics operations of a major international electronics manufacturer. The entire database relates to service parts used for supporting the final pieces of equipment (such as printers) sold in Europe. This category of items is very difficult to control as the majority of these items are in very low (intermittent) demand and tend to be expensive due to high stock investments (Martin et al., 2010). The researchers under concern reported that the quantitative models and forecasting techniques described in the literature are not sufficient to control spare/service parts inventories and new avenues for contribution in this area should emphasise the qualitative aspects of the problem as well. The same of course is true for all intermittent demand items; although the database available for the purposes of this research relates to service parts, there is a safe extension of our discussion and findings to all intermittent demand products.

1.4. Aim and objectives

This study aims to explore the effects of incorporating human judgement into inventory decision-making. From a theoretical perspective there is tremendous scope for contributing and further advancing the current state of knowledge, since there have been no studies addressing this issue to date. From a practitioner's perspective, the findings of this research result into tangible suggestions and recommendations to inventory managers of service parts and beyond, in addition to the obvious implications for decision support systems design and improvement.

The aim of the research is reflected in the following objectives:

1. To critically review the literature on how judgement relates to the main functions of an inventory system.
2. To assess the implications of judgemental adjustments on real data, focusing on replenishment orders.
3. To link the performance of adjustments with the managers' justification for introducing such adjustments in the first place.
4. To understand for the first time how managers adjust inventory-related decisions.
5. To evaluate the circumstances under which human judgement leads to performance improvement.
6. To derive a number of insights with regard to practical applications and a number of suggestions for improving the functionality of software packages.

1.5. The structure of the thesis

The remainder of this thesis is organised as follow:

Chapter 2 provides a literature review of issues related to demand categorisation, forecasting and stock control. Each element of the inventory management system is presented under a separate section of the chapter. The literature review focuses on the intermittent demand context since the empirical data used in this research relates to service/spare parts. Such SKUs are known to be almost invariably characterized by intermittent demand structures.

In *Chapter 3* the issue of judgemental adjustments into an inventory system is discussed. The relevant part of the forecasting literature is widely reviewed along with the very few contributions that have emphasized demand categorisation as well as stock control. This chapter also discusses learning and forgetting effects in the manufacturing domain (because of its relevance to the focus of this research), and presents a state of the art into the new paradigm of inventory management. Information about enterprise resource planning (ERP) systems is also provided as this links to the case organisation. The company under concern perform inventory management under an ERP solution and in that respect a clear understanding of how such solutions operate (in particular with regards to inventory management) is viewed as imperative to provide. Finally, a theoretical framework for this research is also presented.

Chapter 4 outlines the case organisation, the construction of the empirical database used for experimentation purposes and the research questions developed to guide the experimental part of the empirical investigation. The research methodology is also discussed in detail in this chapter.

In *Chapter 5*, the empirical data analysis (based on the theory of inventory systems presented in Chapters 2 and 3, and the research questions generated in Chapter 4) is discussed. A simulation experiment is developed for the purpose of addressing the research questions.

Finally, *Chapter 6* focuses on the conclusions of this research, implications of our work for real world practices, the limitations associated with our research and important avenues for further work in this area.

The organisation of this thesis is pictorially represented in Figure 1.2.

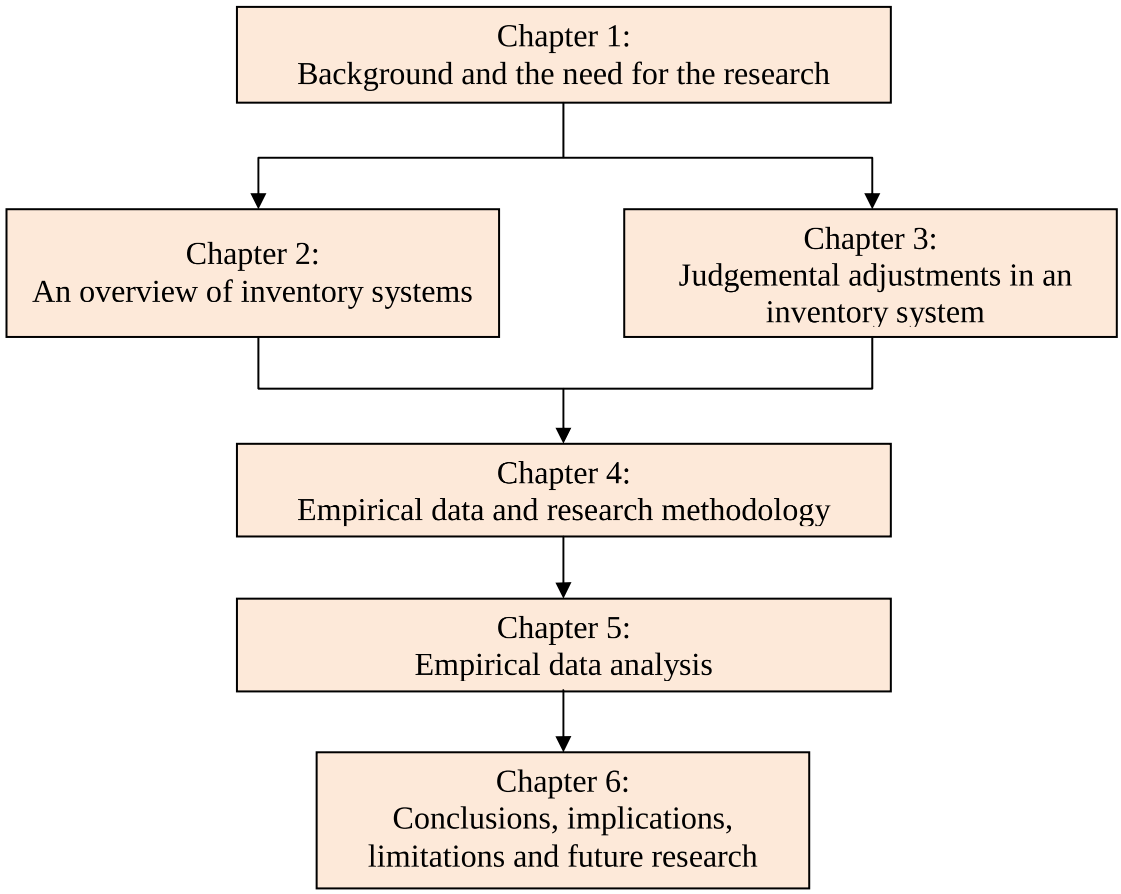

Figure 1.2 The organisation of the thesis

Chapter 2. AN OVERVIEW OF INVENTORY SYSTEMS

2.1. Introduction

This chapter sets the context of our investigation by presenting an overview of the typical operation of an inventory system. Issues related to judgemental adjustments in such a system are discussed in detail in Chapter 3.

As discussed in the previous chapter, SKU classification, forecasting and inventory control are important elements of an inventory system. Each element relies upon a set of appropriate methods in order to produce the final decision. For example, with regards to forecasting, many quantitative and qualitative models may be used. Managers/practitioners need to decide on the most appropriate ones by considering the characteristics of demand patterns. Alternatively, the software package may automatically select such a model.

The overview of inventory systems is depicted in Figure 2.1, followed by explanatory discussion.

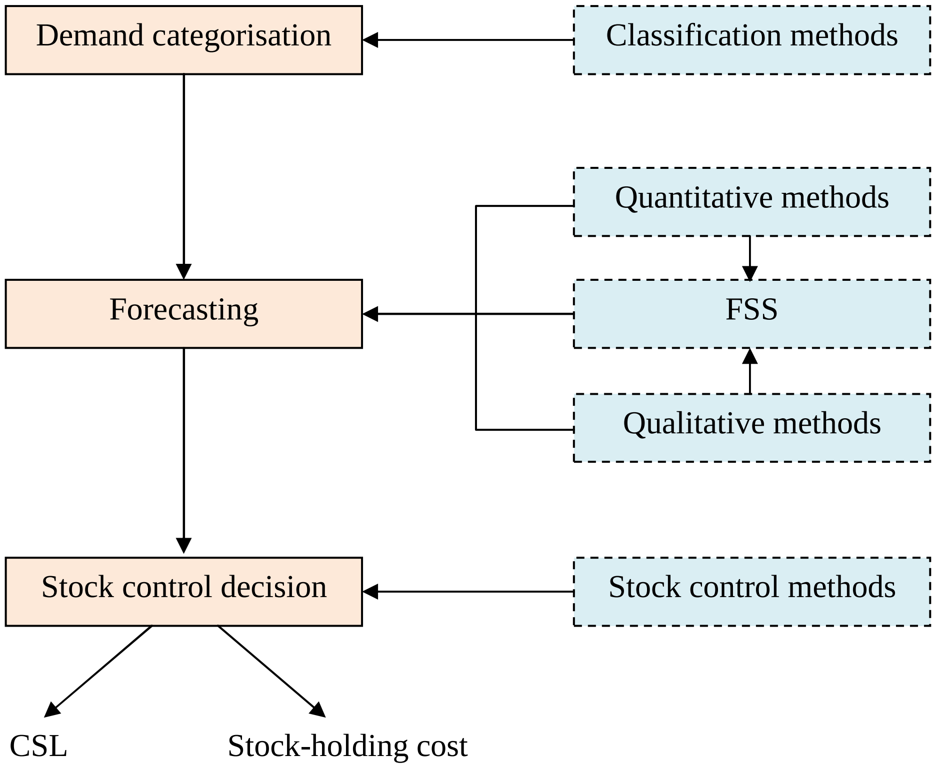

Figure 2.1 An overview of a typical inventory system

Demand classification methods have been extensively discussed over the years (by, for example, Johnston and Boylan, 1996; Eaves, 2002; Syntetos and Boylan, 2005 and Teunter et al. 2010; we return to this issue in sub-sections 2.2.1 and 2.2.2 to discuss in detail methods of demand classification). The purpose of demand categorisation[2] is to decide on the appropriate forecasting and inventory control methods to be used for each selected category to extrapolate requirements into the future and decide on replenishments actions respectively. With regards to the forecasting task in particular, systems to support or facilitate such a task (forecasting support systems, or FSS) have also been developed to improve the performance of forecasting (selection of quantitative methods or indication of the need for qualitative input). The output of the forecasting process constitutes the input into stock control systems. For the performance of the entire system is then typically reflected into two main things: inventory costs and service levels achieved.

[2]The words ‘categorisation’ and ‘classification’ are used interchangeably in this thesis.

In an inventory system, every stage (demand classification, forecasting, and stock control decision-making) maybe completely automated, or parts of the process may be decided or adjusted by managers. For example, a manager may impose particular categorisation criteria and cut-off values, while the forecasting and stock control tasks are fully optimised by the software in use. Alternatively, the software may be used to determine demand categorisation and stock control decisions while forecasting operates in a semi-automated fashion with judgemental adjustments; and all the combinations thereof. Furthermore, both the tasks of forecasting and inventory control introduce various possibilities for human intervention. Managers may intervene in the process of selecting the methods, or the parameters of the methods to be used or both, in addition of course to directly adjusting directly the forecasts or replenishment decisions themselves. In this research we are concerned with the intervention in the final output of the system.

2.2. Demand categorisation

A demand classification scheme constitutes an essential element of an inventory system since it benefits the decision-maker in terms of deciding the appropriate forecasting and stock control methods to be used on the right products (Boylan et al., 2008; Syntetos et al., 2009a). Since the organisation deals with a large number of SKUs, with a variety of characteristics, it is not effective to evaluate them on an individual basis. SKUs with relatively similar characteristics need to be grouped into categories in order to facilitate decision making and allow managers to focus their attention on the most important ones. The following sub-sections discuss issues related to demand categorisation and how demand categorisation procedures develop, based on demand characteristics.

2.2.1. ABC classification scheme

Demand can be classified according to a number of factors, such as the underlying demand characteristics, criticality, and cost. One common type is the ABC (Pareto) classification scheme. Silver et al. (1998) explained that a Pareto report lists the SKUs in descending or ascending order based on demand frequency, demand volumes or demand profit, and then divides the ranked SKUs into relevant categories. Category A is assumed to consist of the most important SKUs and therefore requires the highest service level, category B contains SKUs of moderate importance, and relatively unimportant SKUs are placed in category C (Lengu, 2012). However, in the spare/service parts context, the C items may become an important or critical category if managers consider the carrying cost of such items within the inventory. As the majority of spare/service parts are demanded in relatively low quantities in every period (less than once per month: Teunter et al., 2010) and because obsolescence is highly likely, such items may indeed end up being more important than A items.

ABC classifications based on demand frequency/volume are often used in conjunction with other criteria; the value (SKU cost × quantity required) criterion is the most commonly applied one. Originally, the ABC classification was designed for three classes; the method can, however, be extended to include more. For example, Syntetos et al. (2009a) addressed the issue of demand classification for the purpose of suggesting forecasting and stock control policies for increasing service levels and reducing stock-holding costs in an after-sales business context. This study investigated data from a manufacturing company which initially classified its products into six categories, based on demand frequency.

ABC classifications typically rely upon a single criterion. However, multi-criteria classifications have been developed to account for the certainty of supply, the rate of obsolescence, lead time, cost of review and replenishment, design and manufacturing process technology, and substitutability (see e.g. Flores and Whybark, 1987; Partovi and Burton, 1993; Buzacott, 1999; Ramanathan, 2006; Ng, 2007; Zhou and Fan, 2007; Chen et al., 2008). Moreover, various multi-criteria methodologies have been considered, including weighted linear programming, the analytic hierarchy process (AHP), and operation-related groups (ORG). An alternative to multi-criteria methodologies is to use multiple way classification, e.g. a two-way classification by purchase cost and demand value (Teunter et al., 2010).

2.2.2. Demand characteristics

SKUs can be classified into relevant groups based on the characteristics of demand (for example, number of orders for a particular period, demand size, and lead time between demands). We now examine a number of studies which discuss various categorisation procedures based on demand characteristics.

Williams (1984) proposed classification methods (for constant and variable lead time) based on the variance of demand during lead time (DDLT). The variance of DDLT is composed from three factors: the number of orders, the demand size of these orders and the length of the lead times. By considering the mean lead time $\bar{L}$, the mean demand arrival rate (Poisson) λ, and the squared coefficient of variation of demand sizes $\frac{C_x^2}{\lambda \bar{L}}$, the demand for constant lead time (variance (L)=0) is categorised as shown in Figure 2.2 (the cutoff values constitute a managerial input).

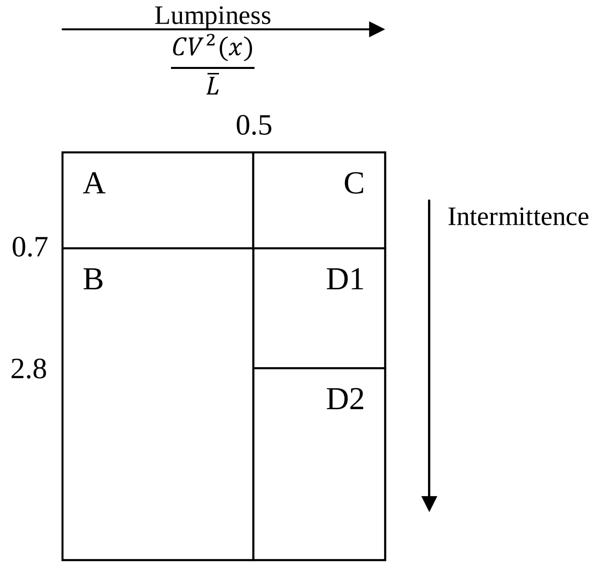

Figure 2.2 Williams' categorisation scheme
(source: Williams, 1984, pp. 942)

The intermittence of demand is indicated by $\frac{1}{\lambda \bar{L}}$. The higher the ratio, the more intermittent demand is. $\frac{C_x^2}{\lambda \bar{L}}$ indicates the lumpiness of demand. The higher the ratio, the lumpier demand is. Lumpiness depends on the intermittence and variability of the demand sizes. The classified into three categories using the parameters $\frac{1}{\lambda \bar{L}}$ and $\frac{C_x^2}{\lambda \bar{L}}$: category A, and C - smooth; category B - slow moving; category D1- sporadic; category D2- highly sporadic.

Two demand categorisation methods for non-constant lead times were developed from this study. The first is constructed based on the size of the three summand factors discussed above, and classifies demand into smooth, slow-moving, sporadic, and sporadic with highly variable lead time. The second method assumes that in any lead time, demand has a probability of being zero (*p*) and if it is non-zero, it equals a random variable (*y*). The product is classified using p and c_y^2 (squared coefficient of variation of non-zero demand) as slow-moving demand if $p>0.25$ and $c_y^2 \leq 0.4$ and sporadic demand if $p>0.7$ and $c_y^2>0.4$.

This study did not intend to develop a generalised solution as the break-point values used for the categorisation parameters were decided based on the characteristics of the particular sample used in the study. It is therefore questionable whether this classification would be effective when used to classify SKUs in other datasets. In addition, these break-points are defined without considering the relative performance of different forecasting methods and inventory policies.

Eaves (2002) developed a demand pattern classification scheme based on three lead time demand components discussed above: i) transaction variability, ii) demand size variability, and iii) lead-time variability. This study used demand data from the Royal Air Force (RAF) and found that it was not sufficient to distinguish a smooth demand pattern simply on the basis of transaction variability. Figure 2.3 shows the Eaves categorisation scheme (that evolved from that developed by Williams, 1984) which divides demand patterns into smooth (category A), slow-moving (category B), irregular (category C), erratic (category D1), and highly erratic (category D2). The cutoff values were decided based on the characteristics of the particular demand dataset and sufficient sub-sample size considerations. The cut-off points were as follows: transaction variability: 0.74; demand size variability: 0.10; lead time variability: 0.5.

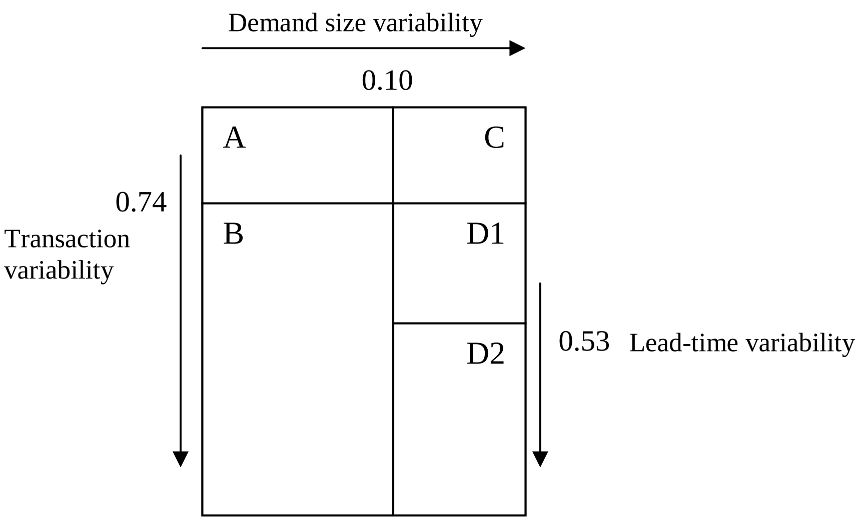

Figure 2.3 Eaves' categorisation scheme
(source : Eaves, pp. 127)

The objective of the demand categorisation methods of the above two studies was to define the appropriate forecasting and inventory control methods for the resulting categories. The boundaries of the demand categories were determined arbitrarily by the managers at which point estimation procedures and stock control methods were selected in order to forecast future requirements and manage stock efficiently.

Syntetos and Boylan (2005) established a more logical approach than that presented above, based on the work conducted by Johnston and Boylan (1996). The demand categorisation procedures suggested rely on the premise that is preferable to first compare alternative forecasting (and stock control) methods for the purpose of establishing regions of superior performance and then classify the SKUs based on the results. That is, if the purpose of demand classification is indeed to select the most appropriate forecasting and stock control methods, then we should start from these methods and by means of comparing them identify regions of superior performance. Classification then naturally follows in a meaningful manner. The work of Johnston and Boylan (1996) considered simulated Mean Squared Errors for the purpose of comparing alternative forecasting methods (Croston's method (Croston, 1972) and Single Exponential Smoothing, SES) resulting in the identification of the average inter-demand interval as an important classification parameter (to distinguish between intermittent and non-intermittent demand). Syntetos and Boylan (2005) took this work further by means of analysing theoretical MSE expressions and identifying an additional classification parameter that relates to the variability of the demand sizes, when demand occurs. The rule proposed was empirically validated on 3,000 intermittent demand series from the automotive industry.

The theoretical rule is expressed in terms of the squared coefficient of variation of the demand sizes (CV^2) and the average inter-demand interval (p). The methods compared were: Croston, SES and the Syntetos-Boylan Approximation (Syntetos and Boylan, 2005). The rule results in a four-quadrant solution presented in Figure 2.4.

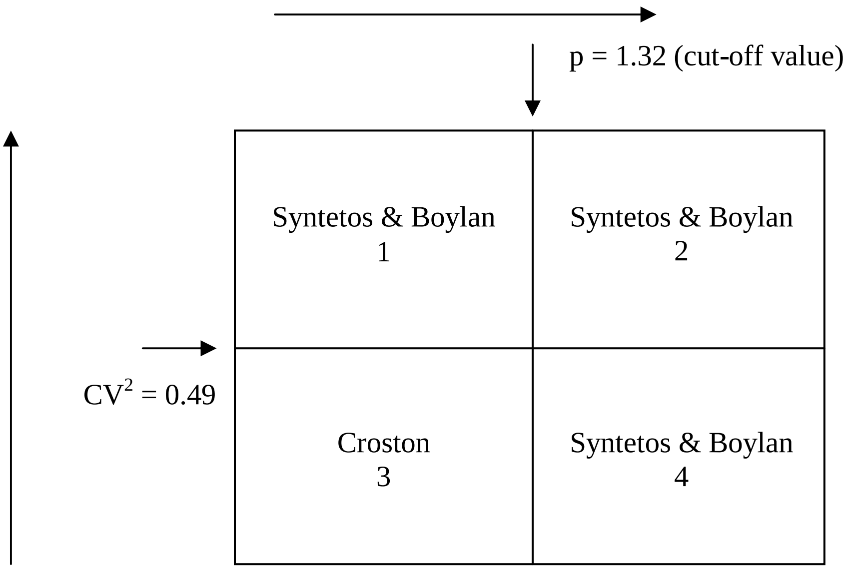

Figure 2.4 Syntetos and Boylan categorisation scheme
(source: Syntetos et al., 2005, pp. 500)

There is a direct suggestion now of the forecasting method to be used in each category. In addition, the cut-off points are the outcome of a generalised analytical comparison (albeit under specific modeling assumptions).

Kostenko and Hyndman (2006) revisited the categorisation procedure proposed by Syntetos and Boylan (2005) in terms of some approximate simplifying assumptions that permitted the easy four-quadrant approach presented above, and suggested a linear function for separating between Croston and the Syntetos-Boylan Approximation (which is discussed in detail sub-section 2.3). Heinecke et al. (2013) conducted a simulation experiment to empirically investigate the performance of the above discussed procedures using more than 10,000 SKUs from three different industries (electronics, military, and automotive). The results indicated that the categorisation scheme proposed by Kostenko and Hyndman (2006) performed well but it is questionable whether the small gains in accuracy improvement worth the additional complexity of the scheme.

Syntetos et al. (2009a) conducted a study on demand categorisation for a European spare parts logistics network, in order to facilitate decision making with respect to forecasting and stock control, and to enable managers to focus their attention on the most important SKUs. This research considered the cumulative demand frequency versus cumulative demand value (demand value = SKU cost × quantity required) as a demand classification parameter. This scheme resulted in six categories of items with each category being associated with a specific treatment in terms of forecasting and stock control.

Syntetos et al. (2010a) suggested that it is important for organisations to classify their SKUs in order to assign higher service-level targets to some critical-item categories and identify obsolete SKUs that are very slow moving. In that study, the researchers conducted a demand categorisation of 2,156 SKUs using the ABC (Pareto) classification based on their contribution to profit (sales volumes × net profit). The results revealed the scope for improving the system through increased managerial attention to the best selling items and also to obsolete SKUs.

2.3. Forecasting

Forecasting is the process of making predictions about events that will happen in the future. In business, demand forecasting is the basis for all planning and control activities. In an inventory context, based on the underlying demand patterns of products, forecasting procedures are generally divided into fast-moving and slow-moving demand methods. Fast-moving demand is associated with a regular demand for an item (in other words, demand occurs in almost every period (e.g. production days, weeks, or months)), whereas slow-moving demand is associated with sporadicity, when some (many) time periods show no demand at all. The latter is also known as an intermittent demand pattern (Silver et al., 1998; Syntetos and Boylan 2001; 2005; 2006; Willemain et al., 2004).

Many forecasting procedures for fast-moving items have developed and are regarded as well established methodologies. These are commonly based on the assumption that demand follows the normal distribution. However, this assumption is inadequate when the forecasting method is applied to an intermittent demand pattern, since such demand occurs sporadically, sometimes with a high variability of demand size (i.e. a lumpy demand pattern). Numerous studies have considered the statistical distribution of intermittent demand items. Syntetos et al. (2012) conducted goodness-of-fit tests of various statistical distributions (Poisson, Negative Binomial Distribution [NBD], Stuttering Poisson, Normal, and Gamma) by employing the Kolmogorov-Smirnov test, and investigated the implications of particular distributions on the stock control performance. Three empirical spare parts datasets were used for the empirical analysis and it was found that the Negative Binomial Distribution (NBD) performs best in an inventory context.

The aim of the forecasting task is to provide the parameters (mean and variance) of a demand distribution over lead-time (the interval between a replenishment order and its arrival in the inventory) for facilitating the stock-control decisions. Thus, it is important to decide on an appropriate forecasting procedure based on the characteristics of the demand. The empirical dataset used in this research relates to service parts data provided by the European logistics head office of an electronics manufacturer. Since demand for service parts arises whenever a component fails or requires replacement, such items are typically slow-movers or intermittent in nature (Martin et al. 2010; Syntetos et al., 2012). When a demand occurs, the demand size may be constant or variable, perhaps highly so (Nikolopoulos et al., 2011; Syntetos et al., 2009b, 2010a, 2010b; Teunter et al., 2011). In addition, the items in this demand category are often at greatest risk of obsolescence

(Porras and Dekker, 2008; Nikolopoulos et al., 2011). In the following section, we will discuss intermittent demand procedures as these methods are relevant to the empirical data used in this research, whereas a discussion of forecasting methods for fast-moving demand can be found in *Appendix A*.

2.3.1. Quantitative methods

Quantitative methods are based on algorithms of varying complexity to analyse historical data typically available in a time series format for the specific variable (s) of interest. Most commonly, this means that a time series of demand information is available and analysed for the purpose of extrapolating requirements into the future. Quantitative forecasting methods are used when sufficient information is available and when it may be reasonably assumed that whatever happened in the past will also persist into the future. The word 'sufficient' needs of course to be qualified. This depends on which method is to be employed. For example, if we are to consider a seasonal forecasting method then a few years of complete histories of demand need to be available in order to estimate the annual seasonal pattern.

The estimation procedures typically used in the area of intermittent demand can be divided into two categories (Lengu, 2012): i) the methods that estimate the mean demand level directly (e.g. single exponential smoothing (SES) and simple moving average, or SMA), and ii) those that build demand-level estimates from constituent elements (e.g. Croston's method, Syntetos and Boylan Approximation or SBA).

2.3.1.1. Simple Moving Average (SMA)

One of the averaging methods commonly used for intermittent demand is the simple moving average (SMA) method. According to this method, the forecast for the next time period (or for any period for that matter, due to the underlying stationarity assumption) is the average of the *n* most recent observations. In every time period then, the oldest observation is dropped and the most recent one is included (Makridakis et al., 1998). Sani and Kingsman (1997) conducted a simulation study that compared various forecasting methods (including Croston method and SMA). Their analysis used multiple criteria (cost and service level), and found that SMA provided the best overall performance.

2.3.1.2. Exponentially Weighted Moving Average (EWMA)

Exponentially Weighted Moving Average (EWMA) or Single Exponential Smoothing (SES) is perhaps the most commonly used method in an intermittent demand context due to a combination of its simplicity and robustness (Willemain et al., 2004). This method implies the assignment of exponentially decreasing weights as the observations get older, and updates estimates in every inventory review period whether or not demand occurs during this period (Makridakis et al., 1998). (Other forms of exponential smoothing have been developed for demand patterns that may contain trend and/or seasonal components. Intermittent demand may indeed be associated with such components which are impossible though to identify due to the presence of zeroes. As such we rely upon level type methods.) If y_t is the demand during period *t*, then the SES estimate of demand during period *t* + 1 (product at the end of period *t*) is given by

$$y'_t = y'_{t-1} + \alpha e_t = \alpha y_t + (1 - \alpha) y'_{t-1}$$

where α is the smoothing constant value used ($0<\alpha<1$) and e_t the forecast error in period *t*.

2.3.1.3. Croston's method

Croston (1972) identified the inadequacy of exponential smoothing in dealing with intermittent demands; this relates to an upward bias of the method resulting from placing most weight on the most recent observation. Following a demand occurrence then, the forecast is unnecessarily high leading to potentially very high replenishments and extra stock. Croston's method builds demand estimates from constituent elements, namely the demand sizes and the intervals between demand occurrences. Exponential smoothing is applied to each of the constituent series by updating only at the end of demand occurring periods. The following notation is used to define Croston's method mathematically:

$y_t = x_t z_t$ =demand for an item at time t

z_t = size of demand

x_t = binary indicator of demand at time t

z''_t = Croston's estimate of mean demand size

p''_t = Croston's estimate of mean interval between demands

q = time interval since last demand

α = smoothing parameter

If

$$y_t = 0$$

$$z''_t = z''_{t-1}$$

$$p''_t = p''_{t-1}$$

$$q = q + 1$$

else

$$z''_t = z''_{t-1} + \alpha\left(y_t - z''_{t-1}\right)$$

$$p''_t = p''_{t-1} + \alpha\left(q - p''_{t-1}\right)$$

$$q = 1$$

Combining the estimates of size and interval provides the estimate of mean demand per period:

$$y''_t = \frac{z''_t}{p''_t}$$

The method updates the estimates after demands occur; if a review period *t* has no demand, the method just increments the count of time periods since the last demand with no updating.

Croston assumed demand to occur as a Bernoulli process, rendering the intervals between demands independent and identically distributed, with the demand sizes also being assumed to be independent and distributed based on the normal distribution.

Croston's concept has been claimed to be great value for manufacturer that deal with intermittent demand and available in ERP type solution (Syntetos and Boylan, 2001; Teunter et al., 2011). However, this method has disadvantages as it is positively biased since the demand size and the inter-demand interval ratio fail to produce accurate estimates of demand per time period (Syntetos and Boylan, 2001). The biased is true for all point in time and issue points only. Moreover, Croston procedure is not updating after periods with zero demand renders the method unsuitable for dealing with obsolescence issue (Teunter et al., 2011).

Leven and Segerstedt (2004) presented a modification of the Croston method which can be applied to both fast-moving and slow-moving items and, according to them, can be useful as a practical forecasting method. The modified Croston (MC) for mean demand is as follows:

$$\hat{d}_n = \hat{d}_{n-1} + \alpha \left(\frac{X_n}{T_n - T_{n-1}} - \hat{d}_{n-1} \right)$$

where *n* = is an index counting the periods in which demand occurs; X_n, the measured demand quantity during the *n*th period in which demand occurs; T_n, the time period in which the quantity X_n is demanded, $\hat{d}_n$, the forecasted (mean) demand rateclaculated at the end of period T_n; α, a smoothing constant.

The MC method was reviewed by Boylan and Syntetos (2007) who found that there is an invalid measurement when calculating forecast accuracy. This study also found that MC method has a higher mean square forecast error than Croston's method. Furthermore, through a simulation experiment, the authors identified a biased forecast in the MC method, especially for highly intermittent series, which found that the bias of the modified Croston estimator is greater than the original Croston method and also the bias of SES.

2.3.1.4. Syntetos-Boylan approximation (SBA)

Syntetos and Boylan (2001) showed that Croston's estimator is biased, and developed a modification to his method. The authors found that a mistake was made in Croston's mathematical derivation of the expected demand estimate (Syntetos and Boylan, 2001). Croston's expected estimate of demand per period would be:

$$E\left(y_t''\right) = E\left(\frac{z_t''}{p_t''}\right) = \frac{E(z_t'')}{E(p_t'')}$$

The bias arises because, if it is assumed that estimators of demand size and demand interval are independent, then

$$E\left(\frac{z_t''}{p_t''}\right) = E\left(z_t''\right) E\left(\frac{1}{p_t''}\right)$$

but

$$E\left(\frac{1}{p_t''}\right) \neq \frac{1}{E(p_t'')}$$

thus indicating that Croston's method is indeed biased (Syntetos and Boylan, 2005). The SBA was then developed to outperform Croston's method. The new estimator of mean demand is as follows:

$$y_t'' = \left(1 - \frac{\alpha}{2}\right)\frac{z_t''}{p_t''}$$

where α is the smoothing constant value used for updating the inter-demand intervals.

A number of studies assessed SBA as superior to Croston and a very robust forecasting method (see, e.g., Eaves and Kingsman, 2004; Syntetos and Boylan, 2006; and Gutierrez et al.,2008).

2.3.1.5. Teunter-Syntetos-Babai (TSB) method

Teunter et al. (2011) developed a new forecasting method for intermittent demand that incorporated inventory obsolescence in its model. This model is a modification of Croston method. The difference between these methods is, when Croston method updates demand interval, the TSB method updates the demand probability (inverse of demand interval). In other words, TSB model is using separate simple exponentially smoothed estimates of the demand probability and the demand size. Since demand probability can be updated in every period, this method is unbiased and can be used to estimate the risk of obsolescence (although in fact it cannot prevent obsolescence completely) as well as relate forecasting to other inventory decisions. This method achieves a high flexibility by using different smoothing constant for demand size and demand probability. The new estimator of mean demand and the probability of demand occurrence is as follows:

If$p_t = 0 :\ p'_t = p'_{t-1} + \beta(0 - p'_{t-1}),\ \ z'_t = z'_{t-1},\ \ Y'_t = p'_t z'_t$

If $p_t = 1 :\ p'_t = p'_{t-1} + \beta(1 - p'_{t-1}),\ \ z'_t = z'_{t-1} + \alpha(z_t - z'_{t-1}),\ \ Y'_t = p'_t z'_t$

where

y_t :Demand for an item in period *t*.

y'_t :Estimate of mean demand per period at the end of period t for period *t* + 1.

z_t :Actual demand size in period *t*.

z'_t :Estimate of mean demand size at the end of period *t*.

p_t :Demand occurrence indicator for period *t*, so that

$$p_t = \begin{cases} 1\ if\ demand\ occurs\ at\ time\ t \\ 0\ otherwise \end{cases}$$

p_t' : Estimate of the probability of a demand occurrence at the end of period *t*.

α, β : Smoothing constant ($0 \leq \alpha, \beta \leq 1$).

A special case of the TSB model is when both smoothing constants are set to one ($\alpha = \beta = 1$); then TBS gives $y_t' = 0$ if $p_t = 0$ and $y_t' = y_t$if $p_t = 1$. Thus, the TSB method is identical to the naïve method, a forecasting method that uses the last observed demand as the forecast for future periods.

2.3.1.6. Bootstrapping method

Bootstrapping, introduced by Efron (1979), is a resampling method that exploits the similarities of the population sample for statistical inference (estimating the mean, variance, confidence intervals, and other statistics). Basic bootstrapping is also commonly referred to in statistical literature as 'case resampling'. Basically, the procedure constructs an approximate population by replicating the sample. Equivalently, the original sample is viewed as the population and a sampling process with replacement is introduced (Syntetos, 2001).

In more detail, the procedure may be explained as follows: suppose we have a sample $x = (x_1, x_2, \dots, x_n)$ which has been drawn randomly from an unknown distribution *F* (*x* is an independent and identically distributed variable). The problem is to estimate the unknown population parameter y_F. A bootstrapped sample is drawn with replacement from the original observations and the parameter of interest is estimated, $\hat{y}_{F,1}$. This procedure is repeated *k* times and finally we approximate the distribution of the estimates of y_F, $\hat{y}_F$, by the bootstrap distribution$\left(\hat{y}_{F,1}, \hat{y}_{F,2}, \dots \dots ., \hat{y}_{F,k}\right)$. The bootstrap point estimate for the mean and standard error (*s.e.*) of the parameter of interest to us can then be calculated as follows:

$$\bar{y}_F = \frac{\sum_{j=1}^{k} \hat{y}_{F,j}}{k}$$

$$s.e.(\hat{y}_F) = \left[\frac{\sum_{j=1}^{k}\left(\hat{y}_{F,j} - \bar{y}_F\right)^2}{k-1}\right]^{1/2}$$

A few parametric bootstrapping approaches have been described in the academic literature to deal with intermittent demand (e.g. Snyder (1999), using the parametric bootstrap method to approximate the lead time demand distribution). Moreover, in the area of inventory management, Wang and Subba Rao (1992) used basic bootstrapping for the purpose of deriving reorder points, and found that the procedure performed well in comparison with normal distribution and other methods, regardless of whether the demand was independent or auto-correlated. Bookbinder and Lordahl (1989) also suggested that it is preferable to use the basic bootstrap procedure in those situations where a 'non-standard' (e.g. a bimodal) demand distribution is suspected.

Willemain et al. (2004) developed a modified bootstrap method for forecasting the distribution of the sum of intermittent demand over a fixed lead time. A two-state Markov process was used to estimate transition probabilities and to generate a sequence of zero/non-zero values over a forecast horizon. The jittering process is designed on a non-zero demand value to allow greater variation (than that observed) around larger demand. The distribution of intermittent demands over a fixed lead time is obtained by repeating the steps of the bootstrap approach. A comparison between the bootstrapping approach and other intermittent forecasting methods (exponential smoothing and Croston method) in conjunction with the normality assumption was conducted using datasets from nine industrial companies. The analysis found that the bootstrapping method produces more accurate forecasts of the distribution of demand over a fixed lead time than exponential smoothing or Croston's method.

As previously discussed, this thesis uses service parts data from a European logistics company. This case organisation implements an ERP package, SAP R/3 (this issue is discussed in sub-section 4.5) the material management (MM) module of which is used to control their inventory system. Many intermittent demand forecasting methods have been developed over the years, and the SAP/ R/3 software has contained time-series forecasting methods (such as SMA and exponential smoothing techniques), whilst the Croston method is included in an upgraded version of the software (SAP APO).

2.3.2. Qualitative methods

When quantitative information is not available or significant changes in environmental conditions affect the relevant time series, qualitative methods constitute an alternative for predicting the future. Qualitative or judgemental forecasting techniques generally rely upon the judgement of experts to generate forecasts. The advantage of such methods is that they can identify systematic change more quickly and interpret better the effect of such change on the future. There are many methods that may be classified as qualitative, including historical analogies (this method attempts to find analogies between the thing to be forecast and some historical event or process and is applied to forecast the sales of new product or new service), the Delphi method (this method seeks to rectify the problems of face-to-face in the group of experts, and grass-root analysis (this method is projection of estimates by grass-root level people like sales force who are close to consumer (Makridakis et al., 1998; Hanke and Wichern, 2009).

A pure judgemental technique is a forecasting method which involves no overt manipulation of data; only the judgement of the forecaster is used. One of the commonest methods is the ‘jury of execution opinion’. Under this method, a company brings together executives from sales, production, finance, purchasing and administration so as to achieve a broad coverage in experience and opinion. The advantages of this approach are that it provides forecasts quickly and easily, it does not require the preparation of elaborate statistics, and it brings together a variety of specialised viewpoints. In some circumstances, this is the only feasible means of forecasting, especially in the absence of adequate data, or when substantial changes are taking place in the environment. It is also possible to make the forecasts become a reality. One of the main drawbacks of this approach is that it puts the estimators in personal contact with one another. The weight assigned to each executive’s assessment will depend in large part on the role and personality of that executive in the organisation. Thus the greatest weight will not necessarily be given to the assessment made by the executive with the best information or the best ability to forecast the future.

Although qualitative methods are commonly applied in Industry, there has not been (to the best of our knowledge) not even one study that discusses such applications in the context of intermittent demand.

2.4. Forecasting support systems (FSS)

Company managers often use computerised support systems to produce forecasts of demand for their products (Goodwin et al., 2011). A software package which is developed to support the forecasting function is called a forecasting support system (FSS). These computerised support systems have been developed rapidly for fast-moving demand items. However, recently, the results of intermittent demand research have been implemented in software products (Fildes et al., 2008). Similarly, an intermittent demand forecasting system (IDFS) was designed by Petropoulos et al. (2013). The actions of individual users of an experimental demand forecasting support system were analysed by Goodwin et al. (2006). This study found that those who devoted a large proportion of their time familiarising themselves with the FSS before applying it to a trial set of data tended to achieve more accurate forecasts. This study shows that there can be considerable variation in approach among those using FSS, with choice tending to be dependent on the level of familiarity.

In the context of judgementally adjusted forecasts, Nikolopoulos and Assimakopoulos (2003) and Fildes et al. (2008) stated that FSS is needed to enhance the adjustment process and to combine the statistical forecasts and the judgemental adjustments more effectively. These systems should be designed to take into account the possible integration of judgemental and statistical forecasts, to enable the users to intervene efficiently in the system (Fildes et al., 2006; Lawrence and O'Connor, 2005). Moreover, Goodwin et al. (2011) argued that support systems are intended to combine the strengths of human judgement with those of machines; hence a system can provide guidance as to when judgemental inputs are most appropriate.

McCarthy et al. (2006) also suggested that one important area of future research is the design of forecasting support systems that combine statistical forecasts and the judgement of experts. Such combinations have proved to be most successful in providing high forecasting accuracy. However, how these systems and related organisational processes should be designed is not well understood. Decision support generally suggests two basic approaches: (1) restriction of the forecasters' options, and guidance through the forecasting process (for example, the system prevents users from adjusting an automatically produced forecast), and (2) guidance through the forecasting process (the selection of the forecasting methods, outcome feedback, or forecasting accuracy being explicitly explained, especially to the untrained user).

Recently, the impact of special events and integration of judgemental intervention on forecasting has been considered in the development of a modern FSS (Petropoulos et al., 2013). Nevertheless, there is no single academic publication which discusses computerised support systems for judgemental adjustments of stock control decision making.

2.5. Stock control system

Inventory control is an essential function in the supply chain because of the mismatch between supply and demand. It determines the safety stock that needs to be kept (and the resulting replenishment quantities both in terms of their size and timing) in order to ensure that products are readily available (with a specified probability to meet the service-level targets) when the customers require them. There are many types of inventory, such as those pertaining to raw materials, work-in-progress products, and finished goods held by suppliers, manufacturers, distributors and retailers. In this research, we are interested only in methods that deal with finished goods inventories; although service parts are not finished products, they are indeed treated as such. Furthermore, the inventory plays a significant role in the supply chain's ability to support a company's competitive strategy; if this strategy requires a very high level of responsiveness (high customer service level) the inventory can be used to achieve this by locating large amounts of stock close to the customer. Below we define various terms in order to be able to explain the inventory system process:

1. On-hand stock

This is stock physically available in a company to satisfied demand. The amount can never be negative. If a company stocks a large number of products, the probability that demand will be satisfied is high. However, increasing the amount of on-hand stock will also increase the carrying costs. To trade-off these situations and achieve the required customer service level (CSL), each company needs to apply an appropriate stock control policy.

2. Net Stock

Net stock is equal to the difference between on-hand stock and backorders. Under complete backordering, if demand occurs during the stock-out, the net stock will be negative just before the next replenishment arrives. At the same time, if all demands that are made during the stock-out are lost, then the net stock will remain at zero level throughout the stock-out period.

3. Inventory position

The inventory position is defined as:

Inventory position = (on hand) + (on order)
- (backorders) – (committed)

Stock on hand is the amount of stock physically on the self; a stock-out happens if the stock on hand drops to or below zero. The on-order stock is inventory that has been requisitioned but not yet received by the stocking point under consideration. Backorders are units that have been ordered by customers but have not yet been delivered. The 'committed' quantity is required if stock cannot be used for other purposes in the short run.

The inventory position may be reviewed based on either continuous or periodic review models, based on a number of control parameters and a decision is being made as to whether an order is to be placed and how large the orders need to be; this decision is determined by the inventory policy. Inventory policies are decision rules that address the questions of when and how much to order for each SKU by considering the trade-offs between the costs and benefits of alternative solutions. They take into account a number of factors, including the inventory position, the anticipated demand, and different cost and customer service level factors. As briefly mentioned above, inventory policies can be classified as continuous review or periodic review systems/policies (Silver et. al., 1998):

a. Continuous review

In a continuous review system, the inventory position is reviewed continuously and a replenishment order is triggered as soon as the inventory position reaches the reorder point.

There are several continuous review inventory policies:

i) Order point, order quantity (s, Q) system

In this continuous system, a fixed quantity Q is ordered whenever the inventory position drops to the reorder point (s) or lower. The inventory position (not the net stock) is used to trigger an order, and because it includes the on-order stock, takes proper account of the material requested but not yet received from the supplier. In contrast, if net stock was used for ordering purposes, an order might be unnecessarily placed today despite a shipment being due in tomorrow.

The (s, Q) system is often called a 'two-bin' system, as one physical form of implementation is to have two bins for storage of an item. As long as units remain in the first bin, demand is satisfied from it. The amount in the second bin corresponds to the order point. Hence, when this second bin is open, replenishment is triggered. When the replenishment arrives, the second bin is refilled and the remainder is put into the first bin. The physical two-bin system operates properly only when no more than one replenishment order is outstanding at any point in time. To use the system, it may be necessary to adjust Q upwards so that it is appreciably larger than average demand during lead time.

The advantages of this type of inventory policy are its simplicity that errors are unlikely to occur, and that the production requirements for the supplier are predictable. The disadvantage is that the system may be not be able to cope effectively with a situation where individual transactions are large, or if the transaction that triggers the replenishment in a (s, Q)system is sufficiently large that a replenishment of size Q does not even raise the inventory position above reorder point.

ii) Order point, order-up-to level (s,S) system

In this type of continuous inventory control, replenishment is being made whenever the inventory position drops to order point s or lower. However, a variable replenishment quantity is used, ordering enough to raise the inventory position to the order-up-to level S. If all demand transactions are unit-sized, the two systems ((s,Q) and (s,S)) are identical, as the replenishment requisition will always be made when the inventory position is exactly at s, that is $S = s + Q$. If the transaction can be larger than the unit size, the replenishment quantity in the (s, S) system becomes variable.

The advantages of this policy are:

- The best (s, S) system can be shown to have total costs of replenishment, carrying inventory, and shortage no larger than those of the optimum (s, Q) system. However, the computational effort to find the best (s, S) pair is substantially higher.
- (s, S) is frequently encountered in practice. However, the values of the control parameters are usually set in a rather arbitrary fashion.

One disadvantage of the (s,S) system is the variable order quantity, meaning that suppliers can make errors more frequently (and they certainly prefer the predictability of a fixed order quantity).

b. Periodic review

In a periodic review system (in practice all policies are really of periodic form), the inventory position is only reviewed at discrete points in time, and an appropriate order made if the inventory position at that point is at or below a reorder point. There are several continuous review inventory policies such as:

i) Periodic-review, order-up-to level (R,S) system

The control procedure is that every R units of time, enough is ordered to raise the inventory position to the level s. Because of the periodic review property, this system is much preferred to order point systems in terms of coordinating the replenishment of related items. The coordination afforded by a periodic review system can provide significant savings.

The (R, S) system offers a regular opportunity (every R units of time) to adjust the order-up-to levels, a desirable property if the demand pattern is changing over time. The disadvantage of this system is that the carrying costs are higher than in continuous review systems.

iii) (R,s,S) System

This is a combination of the (s, S) and (R, S) systems. Every R units of time, the inventory position is checked. If it is at or below the reorder point s, the order placed is sufficient to raise it to S. If the position is above s, nothing is done until at least the next review.

The (s, S) system is the special case where $R = 0$, and the (R, S) system is the special case where $s = S - 1$. Alternatively, one can think of the (R, s, S) system as a periodic version of the (s, S) system. As just mentioned, the (R, S) situation can also be viewed as a periodic implementation of (s, S), with $s = S - 1$.

The advantage of this system is that it produces a lower total of replenishment, carrying, and shortage costs than does any other system. However, the disadvantages are:

- the computational effort needed to obtain the best values of three control parameters is more intense than that for other systems;
- it is more difficult to understand and to communicate to others than some systems.

The distinction between fixed order sizes and variable order sizes is, in a fixed order size system, the replenishment order is always of a fixed size. In contrast, in a variable size system, order is replenished to raise the inventory position up to the order-up-to level. The variable order system is also known as the reorder point, order-up-to (OUT) level system.

The reorder point and the order quantity (or the order-up-to level) is set at a level so as to meet a pre-specified target customer service level. In practice, three definitions for customer service level are commonly used:

(a) cycle service level (P_1) is the probability of no stock-out in a replenishment cycle;

(b) fill rate (P_2) is the fraction of demand that can be satisfied immediately from stock on hand.

(c) ready rate (P_3) is the fraction of time during which stock on hand is positive.

4. Safety stock

Safety stock is held to counter uncertainty. Demand is uncertain and may exceed expectations, and thus companies hold a safety inventory to satisfy any expectedly high demand. The average stock in the system depends on the safety stock, which is the expected stock just before a new replenishment arrives. The safety stock in turn depends on how unfilled demand is treated. Obviously, if backorders are allowed, the net stock (=stock on hand – backorders) can take positive as well as negative values.

The forecast results become the input for the inventory system. Forecasting provides the mean and variance of a hypothesised demand distribution as the basis from which to derive the inventory parameters. A number of authors have proposed algorithms for calculating the parameters of inventory policies (for example, Matheus and Gelders, 2000; Teunter et al.,2010; Syntetos et al., 2012).

Minimising forecast error is needed to improve forecast and inventory control performance:

$$e = min\{e = y_{t+1} - f_{t+1}\}$$

The implications of forecast error for inventory control are:

1) A large positive error (if e>0) means that backlog or penalty cash will be paid and the company cannot achieve CSL.
2) A large negative error (if e<0) means that holding costs will increase.

In order to reduce costs, therefore, managers need to determine an appropriate inventory policy.

For slow-moving demand, most of the academic literature makes the practical assumption that demand occurs following a compound Poisson process (e.g. Archibald and Silver, 1978; Babai et al., 2011) which is associated with the memoryless property of the exponential distribution of the demand intervals. However, this assumption is not always true when considering one single part, since it implies that once replaced, the part will likely fail shortly again. Subsequently, the Poisson demand process assumption advises excess stock (Smith and Dekker, 1997).

Based on a queuing theory approach, Babai et al. (2011) established a method for determining the optimal order-up-to level in a single echelon inventory system under a compound Poisson process demand and stochastic lead time. This study also developed an algorithm used to compute the optimal solution. By means of a numerical investigation, it was shown that the method is very efficient in calculating the optimal order-up-to level and has relatively quick convergence especially for slow moving items.

Another study, by Teunter et al. (2010), assumed that the lead time demand follows a compound binomial distribution to construct a method for determining order-up-to level for intermittent demand items in a periodic review system. A numerical study using 5,000 SKUs was conducted to test the new approach against the classical OUT policy. The results showed that the new method performs well in reducing the average inventory level needed to achieve a certain service level.

Saidane et al. (2013) developed an inventory model where the stock is controlled according to a base-stock policy; this is often used in spare parts inventory control. Base-stock refers to the minimum inventory to maintain operations effectively. The model assumed that demand intervals follow an Erlang distribution, and the demand sizes follow a Gamma distribution. By conducting a numerical investigation using this model, it was found that the optimal base-stock level decreases as expected, and it keeps decreasing in the average demand inter-arrivals (when the number of Erlang phase k is increased and the variability of the demand sizes is decreased).

2.6. Conclusions

Inventory systems commonly comprise three stages: SKU classification (which assigns SKUs into appropriate categories based on a number of criteria); demand forecasting (which extrapolates requirements into the future); and stock control modelling (that converts forecasts into inventory decisions). Many quantitative and qualitative methods have been developed, and specific software packages have been established to assist managers/practitioners in making inventory decisions. In deciding which method is the most appropriate, demand characteristics are the most important aspects to consider. Moreover, employing the appropriate model at every stage of the inventory system will positively affect performance (achieving customer service level and reducing stock-holding costs) of the system.

Chapter 3. JUDGEMENTAL ADJUSTMENTS IN AN INVENTORY SYSTEM

3.1. Introduction

In this chapter, the process of incorporating judgemental adjustments in an inventory context is reviewed. Plenty of research discusses the issue of judgemental adjustments of statistical forecasts; however, there have been no attempts to investigate human intervention into the task of replenishing stock. The academic literature on the former issue collectively reports varying results. Some researchers have argued that adjustments may provide a benefit in terms of the performance of the system, while others have come to a rather negative conclusion. This chapter critically reviews previous work in this area. The role of the Moving Average method is also explicitly considered since this method is used by the case organisation. We also discusses learning effects in a manufacturing system context (because of the direct relevance to this study) as well as a new emerging paradigm of inventory management studies that focuses very much on the human factor and qualitative considerations. Enterprise resource planning (ERP) systems are also reviewed to enable a linkage with the practices employed by the case organisation. Finally, a theoretical framework is presented as an outcome of the synthesis of the literature to guide the experimental part of the thesis.

3.2. Judgemental adjustments in SKU classification

Human intervention may occur at every stage of an inventory system (categorisation of SKUs, forecasting, stock control decisions). Much academic literature discusses the aims, criteria and procedures of categorisation of SKUs (Johnston and Boylan, 1996; Silver et al., 1998; Eaves, 2002; Syntetos et al., 2005). However, no specific academic literature investigates the issue of judgemental intervention in the process of categorisation. This is partly due to the fact that categorisation is a judgmentally driven process anyway. In most of the applications, both the establishment of the classification criteria and the specification of their cut-off values are the outcome of judgement rather than sound statistically based generalisable procedures. We may think of the most widely applied procedures, for example, of ABC based classifications. These rely upon criteria that despite their intuitive appeal have not been generated from an inventory control theory perspective (Teunter et al. 2011). This is true not only for single criteria ABC analyses but also for multi-criteria or multiple-way ABC classification schemes. Similarly, demand characteristics based schemes also lack connection to statistical analysis. So the argument being made here is that actually demand categorisation is predominantly judgemental anyway in nature and what is missing is further work (along the lines suggested by Johnston and Boylan, 1996; Syntetos et al., 2005; Teunter et al., 2011) to establish sound generalisable solutions. Currently, managers do intervene in hard coded classification solutions available in software packages. But the very software solutions have been created in a judgementally driven way rather than being suggested on the basis of their statistical rigour, as it happens in the case of forecasting and stock control.

3.3. Judgemental adjustments in forecasting

A comprehensive body of knowledge with regard to judgemental forecasting has been developed over the years, e.g. Fildes et al. (2009); Syntetos et al. (2009b, 2010b). Over the last two decades there has been a considerable increase in specialisation with respect to forecasting research, as reflected in the design and development of software solutions. So it is indeed surprising that the dominance of judgemental procedures has not decreased over the years given the increased availability of many statistical procedures, easier access to computers and recent improvements in decision software (McCarthy et al., 2006). In forecasting research, the explanation and the improvement of human forecasting behaviour constitute interdisciplinary issues and have been subject to extensive empirical field and laboratory research (Leitner and Leopold-Wildburger, 2011).

3.3.1. Laboratory studies

Laboratory studies rely upon the use of participants in a laboratory (i.e. controlled) environment, where largely abstract forecasting tasks are performed. Such studies have been criticised for not being representative of real-world settings (Bunn and Wright, 1991). This kind of research gives rise to some insights and it may render experiments reliable in a statistical sense; however, the behaviour of the participants may be different from that which occurs in a natural setting.

Much laboratory research has been conducted on judgemental forecasting. Lim and O’Connor (1996) designed a laboratory study by grouping people on the basis of those presented only with the time series of interest, people presented with both the time series and the statistical forecasts, people presented with a single piece of information that was causally related to the time series, and people presented with the time series, the statistical forecast and the causal cue. Remus et al. (1996) conducted an experiment using 54 undergraduate students to investigate the effect of different types of feedback on judgemental forecasting. Subjects were asked to make repetitive judgemental forecasts while they received different types of feedback (such as *task information feedback*, *outcome feedback*, and *cognitive information feedback*)[3]. The results of this experiment showed task information feedback to be the most effective type for improving the accuracy of judgemental forecasts, and that combining task feedback with cognitive information feedback did not significantly improve performance. Another laboratory research was conducted by Goodwin (2000) to compare the methods of mechanical integration of judgemental forecasts with statistical forecast method. This study introduced the terms of *combining* and *correction* the forecasts. *Combining* the forecast is obtained by calculating a simple or weighted average of independent judgemental and statistical forecasts (Clement, 1989). Correction methods is using the regression to forecasts errors in judgemental forecast and then removing this expected error. This mechanical integration is conducted by using sixteen subjects, *Forecast Pro* software package, eight data series, and introduce the non-series information such as promotion events. The experiment results found that, although it has received less attention in the literature than *combination*, *correction* is recommended technique for harnessing the complementary strength of judgement and statistical method.

Certain procedures are followed to design an experiment to be conducted in a laboratory study addressing judgemental forecasting. To achieve the research objectives, experiments are designed based on interest, understanding, simplicity and resource availability, making a full representation of the realworld hard to achieve. Eroglu (2006) stated that behaviour in a laboratory study differs from a natural setting, making the results unrealistic. Despite

[3] Remus et al. (1996) explained that task information feedback is the information which is prompting on the underlying structure of the time series, outcome feedback is the information that available as graphical indicators of forecasting accuracy, and cognitive information feedback is the information that prompting on desirable forecasting behaviors.

being more reliable than a field study because the researchers can control the variables, a laboratory study is thus not without weakness.

3.3.2. Empirical studies

Empirical studies of judgemental forecasting using experts/managers in a real-world setting provide the greatest potential for the demonstration of the validity of human judgement. Since no artificial ceiling is put on human performance, this provides good descriptive research. However, as the researcher has no control, cause and effect is difficult to determine (Bunn and Wright, 1991). Empirical study of judgemental forecasting is conducted to profile differences between users of quantitative methods and users of judgemental methods; it also profiles differences between different judgemental forecasting processes in order to assess the effect of task properties' feedback on the accuracy of time series forecasts (Sanders and Manrodt, 2003; Sanders, 1997).

Collopy and Armstrong (1992) suggested that one way to determine the most appropriate procedures for extrapolation is to ask forecasting experts. This study reported the opinions of 49 forecasting experts on guidelines for extrapolation methods. By using a questionnaire that asked experts about their role, experience and what criteria they would select, the research concluded that the experts agreed that seasonality, trend, aggregation and discontinuities were key features to use for selecting extrapolation methods. This study also found that 73% of the experts believe that improved accuracy can be gained by combining judgement with extrapolation method.

Empirical study of judgemental forecasting does have some drawbacks. These include differences in the viewpoints of modeler and experts, an uncontrolled experiment setting that can cause results to be unreliable, and difficulties in establishing the general model (Bunn and Wright, 1991). Several reasons may cause the accuracy of field study results to suffer: uncontrollable or external variables may distort forecast data, forecasters can have undisclosed motives that drive their behaviour and performance, and a company may operate under unique circumstances. Besides these, a product's short life-cycle may make it more difficult to study patterns. In contrast, there are some benefits of empirically studying judgemental forecasting, in particular that it is more realistic than laboratory studies (Bunn and Wright, 1991).

Goodwin and Wright (1993) argued that most of the following characteristics can be found in real-life forecasting settings but have been absent in many laboratory studies: both time series and contextual information may be available, there may be no basis for assuming constancy in the time series pattern, and organisational and political influences may impact on the forecast. The forecaster may have some control over the variable to be forecast and may have expertise in relation to it, and a direct interest in the outcome, hence preferring some outcomes to others. There may also be incentives for accurate setting. The forecasting task itself may be familiar to the judgemental forecaster. Finally, the forecast made may affect the behaviour of the environment, and regular feedback on past performance may not be available.

Empirical studies also found that positive adjustments on forecasting were much less likely to improve accuracy than negative adjustments, (Fildes et al., 2009). Further, small adjustments have been found not to be very effective in the analysis of fast-moving demand data (Fildes et al., 2009) and also for intermittent demand (Syntetos et al., 2009b). These results may be useful towards developing our understanding of the implications of judgemental adjustments in the whole inventory system, and may be most useful in terms of introducing potential amendments to Forecast Support Systems.

3.4. The relevance of human intervention in forecasting

Studies comparing judgemental forecasts to statistical forecasts have led to mixed results (Sanders and Ritzman, 1995). Previously, judgement was thought to be the enemy of accuracy as there is some evidence that relevant adjustments may decrease accuracy. Carbone et al. (1983), for example, found that judgemental adjustment to forecasting by novices (such as students) did not improve accuracy since the subjects may not have had either expertise in the industries from which the data came or practical experience of forecasting. This finding is supported by Carbone and Gorr (1985), whose paper reports the results of experiments conducted among students in order to examine the relative accuracy of judgemental forecasts compared to quantitative forecasts. The study concluded that quantitative forecasts were associated with the highest accuracy. In another study, Nikolopoulos (2010) argued that, for forthcoming special events, forecasters prefer to use their own judgement, but human interventions in such forecasting tasks found to be deficient.

Sanders (1992) compared judgemental and statistical forecasting using artificially created time series. The statistically based forecasts were generated using two different smoothing models (simple smoothing and Winters' model) depending on time series characteristics. The judgemental forecasts were generated by 38 subjects and each subject was randomly assigned two time series and provided with historical demand. For the purpose of evaluating forecast performance, the mean absolute percentage error (MAPE) was used, whereas the mean percentage error (MPE) was used to measure level of forecast bias. This study found that the judgemental forecasting to be biased and less accurate than the statistical forecasting. The same results were indicated by O'Connor et al. (1993), who examined the performance of judgemental and statistical forecasting and found judgemental forecasts to be significantly worse than the statistical ones, both when discontinuity were present in the series and when the series was stable. The researchers stated that the main problem with judgemental adjustments was that forecasters overreacted in response to random fluctuations in the time series, thus adjusting statistical forecasts in response to a signal which did not exist. In terms of selecting a statistical confidence interval in time series forecasting, O'Connor and Lawrence (1989) evaluated 33 real-life time series and concluded that judgemental confidence intervals were initially excessively over-confident.

Moreover, judgement may simply be explained in terms of a desire on the part of the manager for a sense of ownership of the process (Goodwin, 2002) and forecasters tend to underweight statistical forecasts in favour of their own judgements (Lim and O'Connor, 1995). Yaniv (2004) suggested that managers tend to attach less weight to the advised forecast than to their own prior estimate, since they have greater access to and belief in the rationale underlying their own view than the reasons underpinning advice. Furthermore, when advice is available from multiple sources, managers seem to give more weight to advice from those they consider more experienced (Harvey and Fischer, 1997). However, possession of technical knowledge (that is, knowledge of statistical forecasting methods, and knowledge of the biases inherent in human judgement) did not improve the accuracy of judgemental forecasting (Sanders and Ritzman, 1992; Edmundson, 1990). Nor does judgemental forecast accuracy improve if adjustment is not made based on independent sources or where multiple sources are themselves correlated (Yaniv and Kleinberger, 2000). Goodwin and Fildes (1999) stated that forecasters make adjustments to statistical forecasts when they are reliable and ignore them when adjustments are needed.

At the same time, much current research has found an improvement in accuracy resulting from judgemental adjustment. Judgemental adjustment is recognised as an indispensable component of forecasting (Lawrence et al., 2006). Goodwin and Wright (1993) suggested several reasons as to why businesses and organisations use judgemental forecasting methods: lack of staff with skills in the application of statistical methods, insufficient data to develop reliable statistical measures, statistical models based on certain assumptions may be slow to react to change, and complex statistical forecasting may lack transparency for users of forecasts.

Lawrence et al. (2006) concluded that adjustments can improve the accuracy of statistical forecasts under the right conditions, namely, when the statistical forecasting is insufficient in its estimation of the underlying time series pattern. Willemain (1989) conducted a laboratory experiment using artificial data to evaluate the effects of graphical adjustment on forecast accuracy. The study concluded that judgemental adjustments had little effect if the statistical forecasts were nearly optimal, but where they were poor, then the judgemental adjustments increased accuracy. The same finding was obtained when the experiment was conducted using real-life data (Willemain, 1991). Others studies, for example, Mathews and Diamantopoulos (1986, 1989, 1992), examined the effectiveness and benefits of subjective revision on the accuracy of forecasts. The authors concluded that the value of the revision depends on how managers select forecasts for revision (in terms of forecasting error values). If the manager fails to identify poor forecasts then subjective revision seems ineffective. The results of these studies give general support to the practice of human intervention in forecasting as a means of improving forecasting accuracy.

A further condition occurs when the forecaster has salient information that is not available in the statistical method, such as knowledge of a forthcoming sales promotion. Goodwin and Fildes (1999) concluded that combining human judgement with statistical forecasting is efficient when time series are not disturbed by sporadic events. Lawrence et al. (1986)

suggested that combined forecasts may improve forecast accuracy when time series have a short time horizon.

From the literature reviewed above, it can be seen that the effects of judgemental adjustments on forecast accuracy are mixed. The differences are caused by many factors:

1. Subject performing the adjustments

Subjects associated with different backgrounds, such as managing the functions of a company, being analysts or students, have varying levels of knowledge, skills and motivation. Moreover, there were variations in the number of subjects used in the various studies.

2. Data

Data used in the forecasting research associated with human judgement came from different sources, such as real data from one or many companies, data generated artificially using forecasting software, or data sourced from M-competition (a forecasting competition organised by Prof. Makridakis: see Makridakis et al., 1982). The different attributes of sources of data may obviously affect the results of the study.

3. Methodology

The methodology used in various studies was different. Judgement may be applied early in the forecasting process, such as when deciding on the forecasting model. Different forecasting results may be produced by deploying different forecasting models (e.g. Carbone et al., 1983). Human judgement may occur in the middle of the forecasting process, for example when the decision maker chooses the parameters (for example, when the alpha value is selected for an exponential smoothing model). Alternatively, human intervention may come at the end of the forecasting process, such as when results are adjusted in order to get the final forecast. This research is interested in this last step, i.e. we are concerned with the process of adjusting forecasts as final decisions.

4. Performance metrics

Studies can use different measurement in analysing system performance. Much research has based its investigation of the performance of judgemental forecasting on forecast accuracy (e.g. Carbone and Gorr, 1985; Wolfe and Flores, 1990; Goodwin, 2002). Recent studies have also discussed the implications of judgemental forecasting on stock-control performance (see Syntetos et al., 2009b and Syntetos et al., 2010b). Obviously, many of the findings from these studies cannot be generalised. Eroglu (2006) indicates that the focus of most studies of judgemental adjustment has been on accuracy. Only a few studies have addressed the effects of feedback on judgemental adjustment and have largely neglected the learning that occurs when forecasters make repeated judgemental adjustments.

Some questions arise from this contradictory evidence of judgmental forecasting research, such as how and when judgement can be improved by model-based forecasts (Fildes et al., 2008). Bunn and Wright (1991) made three points in a review that compares mixed results on the relative efficacy of judgemental versus statistical forecasts. Firstly, they maintained that the studies that emphasise the fallacies of human judgement and favour statistical forecasts underestimate the effectiveness of human judgement in real life, since these studies have serious methodological limitations. Secondly, studies of human judgement mainly focus on past events; however, judgemental forecasting involves future events which may imply different underlying cognitive processes. In general, people tend to be more confident about their judgement when they relate it to past or present information. Human judgement related to future events (such as judgemental forecasting and judgemental adjustments) should thus be studied in its own right. Finally, they recognised the comparative advantages and disadvantages of judgemental and statistical forecasting, and recommended that both be combined to improve the accuracy of the final forecast.

3.5. Combining forecast procedures

The studies of combining forecasts have been reviewed extensively; they mostly come to the conclusion that combining forecasts may improve the accuracy of forecasting. It was also found that simple combination methods often work relatively better than more complex combinations (Makridakis et al, 1979).

The study by Clement (1989) concluded that combining forecasts improves accuracy and decreases the variance of forecasting errors with little or no increase in cost. Moreover, this study argued that simpler approaches to combining forecasts provide adequate improvements in accuracy so that managers with relatively little experience can use these approaches.

Makridakis (1989) suggested that combining forecasts may produce better forecast accuracy than individual forecasting methods, since it averages the forecasting errors. This study identified several factors that decrease the accuracy of individual forecasting methods and increase the size of errors. These factors are: i) measuring the wrong thing, for example to estimate demand we measure such things as order, production, shipments, etc. ii) the changes in measurement errors, iii) the assumption that patterns and relationships of the data are constant, and iv) using models that minimise past errors. Makridakis (op.cit.) also suggested using sensible and/or complementary methods to improve the accuracy of combining forecasts, while maintaining the idea of using simple combination procedures. Moreover, this study argued that by the appropriate choosing the models to include in the combining and by defining the correct weight of each method, combining forecasting methods may elicit the judgement and knowledge of decision makers while still limiting the advantage of using an objective and consistent approach.

The combination of statistical and judgemental forecasting methods has been investigated widely. These forecasting methods make valuable and complementary contributions to improving performance. While a statistical method may be able to filter time series patterns from noisy data (when judgemental forecasters tend to see false patterns in noise and to overreact to random movements in series), judgement can be used to anticipate the effects of special events that occur in the future (Goodwin, 2000a). This study investigated the process of integrating judgemental forecasts with statistical methods. The forecast accuracy between judgemental and statistical forecasting when using three strategies (correcting the judgemental forecasting using Theil's optimal linear correction, combining the simple average of judgemental and statistical time series forecasts, and using both the above approaches) was compared. Analysis of laboratory studies and the use of empirical data provided by companies were considered. The results showed that the most appropriate role of statistical methods is to correct judgemental forecasts. Another laboratory study to test the performance of the combination of judgemental and statistical forecasting was done by Goodwin (2000b). Using a voluntary integration approach, that is when the judge is able to use the statistical forecast during the process of forming the judgemental forecast, the experiment's results showed that overreaction to noise in judgemental forecasting might be mitigated by providing a statistical forecast; the forecaster then indicates explicitly the changes (and also the reason for making these changes) to the statistical forecast.

Fang (2003) argued that forecasts encompassing tests[4] are a valuable tool in getting an insight into why competing forecasts may be combined to produce a composite forecast which is superior to the individual forecasts. Encompassing tests for forecast combination were earlier developed by Harvey et al. (1998). Forecast encompassing tests can be implemented using regression analysis. An encompassing test was also considered by

[4] The concept of forecast encompassing relates to whether or not one forecast encapsulates all the use predictive information contained in second forecast (Clements and Harvey, 2007)

Costantini and Pappalardo (2010) in order to develop a hierarchical procedure to increase the efficiency of forecast combination.

Zou and Yang (2004) developed an algorithm to convexly combine the models used real data for conducting a simulation experiment in order to compare the performance of this new approach and the model selection approach. The results of the simulation showed that the new approach performs better in forecasting than other model selection approaches. A simple model-selection criterion to select among forecasts was used in a simulation experiment conducting by Hibon and Evgeniou (2005). The results showed that combination forecasts were superior, but that the best individual method performed similarly if the forecasters always used the same method. The same result was found when the experiment was run with a forecaster who used different methods or combinations for each time series. Thus, there is no inherent advantage in combining the forecasts. This finding challenged the belief that came from most of the forecast combination studies (which stated that combining forecasts is better than using individual forecasting methods). In addition, this study found that choosing an individual method (chosen by the selection method used in this study) is more risky than choosing the combination methods.

Boylan and Johnston (2003) developed theoretical rules to specify the parameters in the combination of moving averages forecasting models in a steady-state condition. Three parameters of moving average method were considered for the combination: length of greater moving average, length of shorter moving average, and the weighting to be given to the former. The robustness of combinations of moving averages and exponentially weighted moving averages (EWMA) was compared, and it was found that the combination approaches (especially for equal weight combinations) were more robust than EWMA

3.6. The robustness of Simple Moving Average (SMA) method

In this section, we discuss some issue related to the Simple Moving Average (SMA) method due to the fact that this approach is used for extrapolation purposes by the case organisation.

Commonly, a moving average forecasting model is used when substantial randomness is contained in a series, since the randomness can be eliminated by using the average of a fixed subset size of the series as a forecast for the coming period (Makridakis and Wheelwright, 1989). The average values of the subset series are moved forward since the oldest member of the series is excluded when a new observation becomes available. Moving average models have many different variations, such as simple moving average, multiple moving average and exponential moving average. This method requires only one parameter to be selected, namely the number of data points to include in the average (or correspondingly, when referring to EWMA, the alpha value).

These procedures have a successful history of capturing data trends in many organizations and most big institutions use the simple moving average method in their activities. Sanders and Manrodt (1994) found moving average procedures to be the most familiar and most used quantitative technique in US corporations. Furthermore, moving averages are used in order to deal with intermittence (Sani, 1995).

In inventory systems, simple average (weights all the data the same) and exponential smoothing (places more emphasis on the most recent data rather than the older data) is often used (Boylan and Johnston, 2003), since these forecasting methods are relatively easy to implement and also understandable by managers. Moreover, the SMA method is also used in the context of intermittent demand in many real-world cases and reflects a popular industry approach to forecasting such items (Syntetos, 2001; Syntetos and Boylan, 2005). Besides its simplicity, the robustness of the SMA method might be another reason why most organisations apply this procedure.

The robustness of moving average forecasting methods has been investigated in many studies. Johnston et al. (1999) compared the sampling error of the variance of SMAs to EWMA. The authors argued that EWMA is optimal for a steady-state model when the optimal smoothing constant is used. However, if the smoothing constant is mis-specified, then the method is no longer optimal. In the inventory control area, the SMA method may produce lower inventory costs than EWMA (Sani and Kingsman, 1997). Syntetos and Boylan (2005) conducted a simulation experiment to compare four forecasting methods (SMA, Single Exponential Smoothing, Croston's method, and Syntetos-Boylan Approximation) using 3,000 real intermittent demand data series from the automotive industry. The mean signed and relative geometric root-mean-square errors were measured and it was found that the out-of-sample comparison results indicated superior performance of the Syntetos-Boylan Approximation. However, the experimental results showed that SMA performs also very well and is robust to the presence of outliers.

In this research, the case organisation calculates the demand forecast using the SMA method for twenty-four weeks. The results were used to calculate the order up to (OUT) level. This OUT level is used as a benchmark to define the final OUT level. There may indeed be a relationship between these two levels. As a result, we will attempt in Chapter 5 to investigate the explanatory power of *SMA-based OUT replenishment* level by carrying out regression analysis. So far, no study has discussed this issue in the inventory control area.

3.7. Judgemental adjustments of inventory parameters

Demand parameters used in inventory models are identified from forecasting results (the mean and variance of a hypothesised demand distribution). It is essential to understand that the performance of any inventory system depends on the performance of demand forecasting. Nevertheless, demand forecasting and stock control have been evaluated independently of each other, and little empirical work has been conducted on forecasting adjustments which address the interaction between forecasting and stock control (Syntetos et al., 2009b; Syntetos and Boylan, 2008). In this section we first review the evidence on the issue of judgementally adjusting inventory parameters through laboratory studies, followed by the review of work that emphasises empirical aspects.

3.7.1. Laboratory inventory studies

Laboratory inventory studies involve experiments or simulations to represent and analyse a real system, and much research has been conducted in this way. Commonly, laboratory inventory studies discuss inventory problems in the supply chain domain. Supply Net Game and Beer Game are the common simulation games utilized in the supply chain and inventory studies (Delhoum, 2008). The author explained that the Supply Net Game represents a pull logistic and production network and proceed with the "anchoring and adjustment heuristic"[5] for the replenishment of inventories. System dynamics is adopted for simulation tool and is designed to minimize the inventory cost and optimize the reduction of the bullwhip effect. Moreover, the relationship between cost and behavior, and the correlation between performance and understanding feedback is also identified in this simulation game since a system thinking intervention under a controlled experiment with learning evaluation is includes in this simulation game. Where the Supply net game

[5]Anchoring and adjustment heuristic is a mental procedure utilised by most people in oder to make inferences about uncertain events in everyday life (Tversky and Kahneman, 1974)

only incorporates four participants/organisations, the Beer Game is designed for all sectors in supply chain, including factory, distributor, wholesaler, retailer, and customer. In the Beer Game, players receive order from downstream sectors which they fill as long as their inventories allow it. Afterwards, they place orders with the upstream position to replenish their stocks (Sterman, 2000). Judgemental adjustment from decision maker is incorporated in this game.

Many studies in supply chain management use the framework of Beer Game for their experiments. For example, Ancarani et al. (2013) used Beer Game in their human experiments to investigate the impact of stochastic lead-times on inventory holdings and the extent of the bullwhip effect. The participants of this experiment were graduate students with background in Operations Management. This study found that, in terms of stochastic lead-times, a higher variance of orders at every echelon of the supply chain. Furthermore, the experiment result indicates that subjects tend to hold fewer inventories when supply chain is characterised by both demand uncertainty and stochastic lead-times. The Beer Game also used to analysed the influence of with regard to the bullwhip effect in environments of reverse logistic (Adenso-Diaz, et al., 2012). The experiments results confirmed that the stock and work in progress adjustments controllers are the factors that increase bullwhip more significantly, followed by forecasting technique used, the sharing information among the links, and the final customer demand variability.

Mileff and Nehez (2006) established a model to investigate inventory holding under a classical single-customer and single-supplier problem with the game theory method. Moreover, Croson and Donohue (2006) studied the phenomenon of bullwhip effect (the tendency of orders to increase in variability as one moves up a supply chain) from a behavioural perspective in the context of a simple supply chain subject to information lags and stochastic demand. This study conducted two experiments and found that the bullwhip effect still exists when normal operational causes (e.g. batching, price fluctuations, demand estimation, etc.) are removed, and also remains when information on inventory levels is shared. Other research by Anderson and Morrice (2000) developed a simulation game designed to teach service-oriented supply chain management principles and to test whether managers use them effectively. They found that simulation design is useful in investigating the impacts of information sharing between managers in service capacity decision making.

3.7.2. Empirical inventory studies

Scudder and Hill (1998) asserted that there is a gap between industry needs and academic research that can be largely explained by the methods used to perform research in operation management. This study suggested that academics in the operations management field need to develop more empirical research. Moreover, Gattiker and Parente (2007) concluded that many techniques and theories ignore the important characteristics of real systems and are therefore perceived to be difficult to put into practice. Even when methods are known and do apply, they may be difficult to implement due to lack of information. These are the reasons why most companies cannot afford the facility of sophisticated inventory control systems and why a lean inventory approach alone cannot reduce the inventories.

Many studies of demand/sales forecasting focus on improving forecast performance and integrating judgement with statistical methods, rather than on their implications for stock control. Kolassa et al. (2008) reported in a conference presentation in the International Symposium of Forecasting that judgemental adjustments to stock control quantities occur more often than forecasting-related adjustments. Syntetos et al. (2011) explored the effects of adjusting forecasts and/or replenishment orders by deploying a system dynamics (SD) methodology in a simulated three-stage supply chain. Nevertheless, this research was based on very realistic assumptions. A deterministic demand pattern was assumed for the purposes of experimentation. Three stock control policies (the linear Anchor and Adjust; the re-order point *s*, order-up-to-level *S*; and the order-up-to-level *S*) were applied at every stage of the system, whereas the single exponential smoothing forecasting model ($\alpha = 0.2$, lead time = 3 weeks) was chosen to investigate the performance of the system. The nature of adjustments (persistent pessimistic and optimistic) and point of intervention (stage at which the managers intervene to make the adjustments) were considered in performance evaluation. Performance was captured through the factory stock amplification ratio (the maximum change in stock at the factory level to the maximum change in forecast or orders as a consequence of judgemental adjustments, Sterman, 2000). This research found that human intervention in forecasting seems to have more significant effects than judgemental order adjustments. In particular, it was found that the impact of the forecast and order adjustments is less prominent as the intervention point moves upstream in the supply chain; and also, the re-order point *s*, order-up-to-level *S* inventory control policy appears to be less sensitive to judgemental adjustments. In addition, some applicable suggestions for managers may be developed from the results of the experiment. Other than the previous two studies there is no other academic discussion on the effects of judgemental adjustments on replenishment orders and their implications for the performance of inventory systems.

3.8. Learning and forgetting effects in manufacturing systems

Since the very issue of judgemental adjustments in an inventory context has not been discussed before, the learning aspects of this issue are also not present in the literature. Since this is an important aspect that we would like to investigate in this research, we approach this area (of the purpose of developing our understanding on pertinent details) mostly from a manufacturing systems perspective, where the literature is rich.

The performance of manufacturing systems improves with practice (repetitive operations) as demonstrated through decreasing the cost and/or the time required in producing each successive unit after repetitive manufacturing operations (Towill, 1990; Alamri and Balkhi, 2007). The phenomenon is reflected by the learning curve theory introduced by Wright in 1936. This theory shows an exponential relationship between direct man-hour input and cumulative production (Jaber and Boney, 1996a). It means that as production accumulates, the unit time decreases by a constant percentage (e.g. 90%, 80%, etc.) each time the quantity doubles.

Wright's learning model implies that production time can be neglected as the total production takes on relatively larger values. This is an unreasonable conclusion since, as with real-world problems, after a certain time a production system reaches a steady-state situation. A theoretical drawback of Wright's model was corrected by the De Jong bounded learning curve function (Jaber and Boney, 1996b). De Jong's model includes both a fixed and a variable component. The fixed component represents the minimum task time per unit produced, whereas the variable time is subject to learning (Jaber and Boney, 1996b). Another study which discusses the manufacturing lot-size problem under both the bounded and unbounded learning situation is that by Fisk and Ballou (1982). Jaber and Boney (1996b) simplify the solution presented by Fisk and Ballou and consider the assumption in the De Jong learning curve.

The forgetting curve is developed to account for the effects of the time required for producing the units after a break in production process. Several learn-forget curve models have been developed. Jaber and Boney (1996a) constructed the learn-forget curve model (LFCM) by assuming that the forgetting slope is mathematically dependent on the learning slope, the quantity of items to produce, and the minimum break at which total forgetting occurs. It implies that when there is no learning involved, there is nothing to forget, and when a subject improves rapidly, the forgetting slope is unimportant. By using the LFCM, Jaber and Boney (2003) identified the characteristics of the learning and forgetting model: (1) the amount of experience gained before interruption occurs in the learning process influences the level of forgetting, (2) the length of the interruption interval influences the level of forgetting, (3) the relearning rate is the same as the original learning rate, (4) the power function is appropriate for capturing forgetting, (5) learning and forgetting are mirror images of each other, (6) the level of forgetting depends upon the rate at which a worker learns, and (7) the nature of the task being performed influences the amount of forgetting. Other models are the variable regression to variant forgetting model (VRIF) (Elmaghraby, 1990), the variable regression to variable forgetting model (VRVF) (Carlson and Rowe, 1976), the recency model (RC) (Nembhard and Uzumeri, 2000), and the power integration diffusion model (PID) (Sikstrom and Jaber, 2002).

Jaber and Boney (1997) reviewed the VRIF, VRVF and LFCM models. Two hypotheses were constructed: (1) when total forgetting occurs, the performance time on the forgetting curve reverts to a unique value equivalent to the time required to produce the first unit with no prior experience, and (2) the performance time on the learning curve equals the forgetting curve at the point of interruption. The VRIF model was consistent with only the first hypothesis, whereas the VRVF model was consistent with the second one. The LFCM model was consistent with both hypotheses.

Alamri and Balkhi (2007) developed learning and forgetting model for an infinite production planning horizon and took into consideration the fact that items deteriorate while they are in storage. The demand and product deterioration rates in this model are defined as an arbitrary function, thus this model is appropriate to compute the production rate at any given time. The steady-state characteristics of batch production time for a constant demand under learning and forgetting were studied by Teyarachakul et al. (2008).

Regarding the linkage between quality and learning, Jaber and Guiffrida (2004) developed the quality learning curve (QLC). This model is a combination of two learning curves. The first describes the reduction in time for each additional defective unit produced and the second describes the reduction in time for each additional defective unit reworked. This research suggested a caution to managers not to speed up the production process as the pattern of the curve shows a convex behaviour. Moreover, Jaber and Guiffrida (2008) developed a new learning curve by considering the interruption of the production process to bring the process under control again. This model demonstrated the same behavioural patterns as that of Jaber and Guiffrida (2008). Another result indicates that the performance of the production process may improve when the percentage of production time that represents process restoration time is smaller than the production learning rate. Jaber et al. (2008) extended the economic order quantity (EOQ) model by assuming that the percentage defective per lot decreases according to a learning curve. Two models were developed; the first assumes an infinite planning horizon and the second a finite planning horizon. The studies above corrected Wright's learning curve limitation which assumes that all units produced are of acceptable quality.

A forecasting support system (FSS) with an adaptive learning mechanism was developed by Petrovic and Burnham (2006) for demand forecasting (DSS-DF). DSS-DF was constructed by combining four forecast values (two of them represent subjective judgements on future demand, and two additional forecasts are obtained using time series analysis based on decomposition and a autoregressive integrated moving average model) and applying fuzzy IF-THEN rules. Next, a new learning mechanism was developed and incorporated into the DSS-DF to adapt the rule bases that combine the individual forecast values. This forecasting support system was shown to offer some advantages over traditional forecasting methods.

In regard to a supply chain system, another learning model, known as the reinforcement learning (RL) model was used by Chaharsooghi et al. (2008). Basic idea of this learning technique is based on constant interaction between the learning agent and environment. The agent select an action and the environment respond to it and present a new situation to agent. The learner is not told which actions to perform in each situation but instead must find actions that will give the most reward. In this paper, the supply chain is considered as a combination of various multi-agent systems collaborating with each other and aims to make a proper learning mechanism for these agents. Under the learning mechanism, agents learn how to react to the changing environment. The results showed that RL is a powerful method to solve the supply chain ordering problem.

The effect of learning and communication on the bullwhip effect in the supply chain was investigated by Wu and Katok (2006). By using the beer distribution game in a controlled laboratory setting, the study tests four behavioural hypotheses (bounded rationality, experiential learning, systems learning and organisational learning). These results indicate that while training may improve individuals' knowledge and understanding of the system, it does not improve supply chain performance unless supply chain partners are allowed to communicate and share this knowledge. The results indicate that the bullwhip effect is caused by insufficient coordination between supply chain partners.

The effectiveness and efficiency of the learning-forgetting-relearning process in a dynamic environment are reported by Davidovitch et al. (2008). The simulation used is the project management trainer (PMT) teaching tool and focuses on the effect of a history recording mechanism on the learning-forgetting process. This paper introduces two types of history mechanism: (1) the automatic history mechanism, in which the scenario's states are always saved, and (2) the manual history mechanism, in which the trainee has to show an active involvement and save the selected states manually. The findings indicate that for the initial learning phase, the manual mechanism is better than the automatic mechanism.

From the literature discussed above, it is obvious that learning and forgetting occurs in most inventory systems as they inevitably contain repetitive processes and incorporate the intervention of managers in making stock control decisions. The pattern of learning and forgetting in an inventory process depends on the circumstances and environment of the system. Furthermore, the performance of the inventory system can be improved by recognising and analysing the effects of the learning and forgetting of judgemental adjustments made by managers.

This study adopted the learning and forgetting effect theory as an approach for the analysis of the learning and forgetting effect on making adjustments to replenishment orders. As a conclusion, and having discussed the learning and forgetting effect in the manufacturing system, it may be acknowledged that this phenomenon also occurs in judgemental replenishment ordering. As a result, we reflect this issue into a research question of the study which will be explained in section 4.7; its analysis is presented in section 5.10.

3.9. The need for a new paradigm of inventory management

A new paradigm means a fundamentally new way of thinking in a given field, which includes different actual principles and practices (Chikan, 2009). Although the traditional inventory paradigm provides the basis for inventory management studies, it lacks historical background for conducting organisational studies. As a result, the relationship between business practice and research is not common. A company introduces a new approach, some innovation that corresponds to the requirements of the changing environment. Since practitioners are faster in seeking and introducing new ways of doing things (note the impact on the characteristics of today’s economy, such as service economy, e-economy, network economy, knowledge-based economy, responsible economy and global economy), innovative business practice does not follow research results.

Compared to other components of business activity, the management and economics literature includes a relatively small number of papers about inventories. It seems that inventory research finds it either hard or uninteresting to follow those changes which happen to influence practical inventory management (Chikan, 2007). Moreover, Chikan (2001) stated that development through the practice of business has been transformed, but this development has attracted less than appropriate interest of academics. This results in theories of business coming late; some parts of business activity have been successfully modelled, but the theory cannot give an answer to most questions about the present nature of business or cannot predict its development.

The new role of inventory means a new inventory paradigm**,** based on the recognition of a gap between the interests of higher- and lower-level managers when handling inventories. The former are interested in the contribution of inventories to the fulfillment of the aims of the company: meeting customers' needs at a profit. For the latter, inventories are required for smooth operation and avoiding disturbances.

According to above circumstances, a new inventory paradigm has strategic importance for companies in three interconnected dimensions: (1) inventory as contributing to value creation, (2) inventory as a means of flexibility, and (3) inventory as a means of control.

As a part of this development, a new branch of company operation has emerged, reverse logistics, which typically includes keeping inventories of items waiting for re-manufacturing, repair or recycling. A comparison of the traditional and the new paradigm can be seen in Table 3.1.

Table 3.1 Comparison of the Traditional and the New Paradigm

Traditional	New
• Inventories can be managed independently of other company functions. • Inventories serve as buffer between functions and processes. • Cost is the performance measure	• Inventories are an integrated part of the value chain in close relationship with other company functions • Inventories serve as strategic tools in achieving customer satisfaction and profit simultaneously. • Performance measures are based on the contribution of inventories to finding better solutions to customer needs than competitors are able to.

(source:Chikan, 2007, pp. 60)

Inventory management is a part of operation management. Schmenner and Swink (1998) suggested that the field of operations management has been criticised for the inadequacy of its theory. The academic field of operations management (like many disciplines) currently struggles with applicability to practice (Gattiker and Parente, 2007). Wacker (1998) concluded that this situation is the impact of imbalances of theory-building in operation management. This study classified the methodology of operation management research as shown in Figure 3.1:

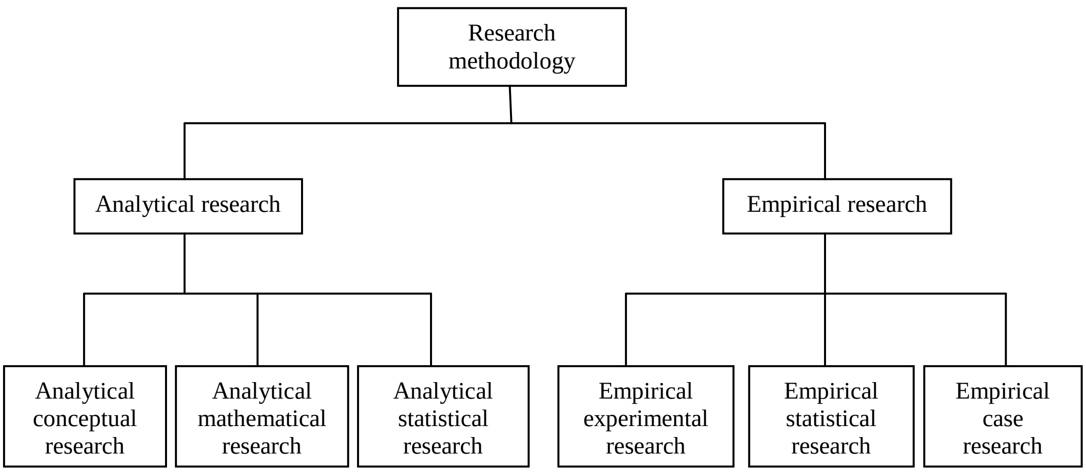

Figure 3.1 Classification of methodology in operation management research.
(source: Wacker, 1998, pp. 376)

Moreover, Wacker (1998) showed that, over the five-year period (1991-95), the most popular methodology was analytical mathematical methodology. The next most popular methodology was analytical conceptual, followed by empirical statistical, and empirical case studies. Although empirical research is a critical component of the theory-building process in operation management, both empirical experimental and analytical statistical are not popular methodologies in the operation management research. The empirical research methodology is the most difficult to implement in inventory management study, since the environment must be closed to 'contamination' effects. However, operation management systems, particularly inventory systems, are frequently open systems and therefore subject to the contamination effect.

Another study, by Bendoly et al. (2006), reviewed the rate of publication of operation management research over the past 20 years and found that it has been relatively stable regardless of recent acknowledgements concerning the importance of incorporating behavioural issues into operation management work. Behavioural experiments are a well-established research methodology for studying human factor issues in many disciplines, providing a way to create conditions where natural behaviour can be observed without a loss of generalisation. Regarding this issue, a new paradigm assumption of experimental work is needed. This study proposed a classification of the assumptions in operation management models:

1. Intentions which are referred to the accuracy of the model in reflecting the actual goals of the decision makers.
2. Actions which are referred under the rules or implied behaviour of human players in the model.
3. Reactions which are referred to the human players' response to model parameter changes (e.g. situational changes driven by management rules and decisions).

It is evident that behavioural gaps in intention, action, and reaction assumptions naturally arise in many operational contexts. Table 3.2 shows the model assumptions and possible behavioural gaps in inventory system and supply-chain management.

Table 3.2 Model assumptions and possible behavioural gaps in inventory and supply chain management.

OM context (task examples)		Assumption categories		
		Intentions	Actions	Reactions
Inventory management (inventory quality and location; timing of replenishment)	Common modelling assumptions:	Minimise the sum of holding and stock-out costs	Assume optimal order rules are followed	Unmet demand is backlogged
	Possible behavioural gaps or implications:	May not weight these two costs equally	Not followed due to bounded rationality	Backordering may be independent of length of wait
Supply chain management (collaborative forecasting and planning, multi-party coordination)	Common modelling assumptions:	Reduce supply chain average costs	Savings splits will not impact actions if everyone “gains”	Locus of control is immaterial
	Possible behavioural gaps or implications:	May underweight downside risk aversion	Ignore impact of perceived fairness on behaviour	Adversity to loss of control

(source: Bendoly et al., 2006, pp.743)

The model assumption developed by Bendoly et al. (2006) is also discussed in Tokar (2010) as the framework for behavioural research in supply-chain management and logistics.

Beach et al. (2001) discussed qualitative research methodology related issues, suggesting that qualitative research is concerned with building rather than testing the theory. Although qualitative research methods are unlikely to produce a model that could purport to be a definitive representation, they can help explain the observed phenomenon in terms of the interactions between system variables. Moreover, quantitative methods are not usually appropriate when the phenomenon is complex in structure, and parameters are unknown.

Boney and Jaber (2011) discussed the issue of an environmentally responsible inventory model, intended to reduce environmental problems by improving design, production and other activities in manufacturing and inventory systems. Non-cost metrics related to the environmental consequences of inventory activities are proposed such as: (i) reducing the complexity of the products, (ii) reducing the lead time of products, (iii) changing the location of production, stores and even customers so as to reduce the likelihood of demand changes and potential waste, (iv) the time response, system stability and the levels of shortages and surpluses, (v) running the stores, e.g. energy use, material use, emissions, and the efficiency of the technology used. This model needs support from all of the inventory players (international organisations, nation states, local government, companies and other organisations, and individuals) in implementation.

Chikan (2011) discussed the managers' view of a new inventory paradigm, stating that the new paradigm did not conflict with the old one. The new inventory paradigm keeps the core of the inventory problem but handles it in a manner more integrative with changes of general mission of the company and the development of other company functions. The analysis of surveys in that research suggested that the average company manager basically agreed with the approach to the influencing factors of inventory management (a focus on competitiveness, functional integration, process orientation and network chain between the actors within the economy). Furthermore, managers emphasised the importance of the supply-chain approach, and they liked to put inventories into this framework.

In this research, we attempt to examine the implications of human intervention on inventory control systems. The data we used for the analysis is the empirical dataset provided by the logistics head office of a manufacturing company. By deploying an empirical experiment, this research is intended to fill the gap between academic studies on inventory research and real-life systems which are needed by organisations. Furthermore, this research attempts to follow the new paradigm of inventory research approach, by introducing human factors (managers/decision makers), particularly the behaviour of managers when making adjustments to replenishment order decisions.

3.10. Enterprise Resource Planning

This section discusses issues related to enterprise resource planning (ERP) systems. It is viewed as imperative that the relevant aspects are considered since the case organisation operates under an ERP package (SAP R/3). ERP is ‘a business management system that comprises integrated sets of comprehensive software, which can be used, when successfully implemented, to manage and integrate all the business functions within an organisation’ (Shehab et al., 2004). This software system includes order management, manufacturing, human resources, financial systems, and distribution, with external suppliers and customers with shared data and visibility (Chen, 2001). As a result, companies will have more real-time visibility and control over their operations (Gargeya and Brady, 2005).

The ERP terminology was first proposed by the Gartner Group in the early 1990s (Mabert et al., 2003) although according to Jacobs and Weston (2007) and Leon (2008), the evolution of ERP dates from the 1960s. It began with inventory management and control in the 1960s, progressing to material requirement planning (MRP) in the 1970s, manufacturing resource planning (MRP II) in the 1980s, and finally to ERP in the 1990s. Details of ERP evolution are described in *Appendix B*.

The ERP system consists of several modules, the names and numbers of which differ from one vendor to another. There are generally six modules, namely: Material Management, Quality Management, Human Resources, Project Management, Financial and Accounting, and Sales and Distribution (Shehab et al., 2004). Themodule most closely related to this study is the Material Management (MM) module because it covers all activities related to material acquisitions (purchasing) and control (inventory and warehouse).

3.10.1. Material Management module

Mendelson (2000) states that the MM module is designed to support the procurement process and optimise the logistics pipeline within the enterprise. It enables automated supplier evaluation and can lower procurement and warehousing costs with accurate inventory and warehouse management. It also integrates invoice verification. The module is additionally designed to support foreign trade processing, such as customs declarations.

The MM module consists of several sub-menus, such as inventory management, purchasing, warehouse management, and materials planning. The capabilities of such sub-modules are described in Table 3.3.

Table 3.3. Function of MM sub-menus.

Sub-menu	Function/capability
Inventory management	Processing incoming goods receipts, reviewing material stock balances and locations, transferring material quantities for use in other areas of factory, and reviewing and changing material receipt records
Purchasing	Creation of purchase orders for raw materials and services, creation of vendor master records, creation and maintenance of procurement contracts and negotiated quota arrangements, and Request for Quotes (RFQ) for identifying new vendors who might qualify as potential future suppliers
Warehouse management	Materials storage management: creating specific storage bins, storage requirements, hazardous material specifications, material counting strategies, and material location transfers
Materials planning	Developing forecasts to create working scenarios of materials demand and to establish how the procurement team might respond to demand, MRP (what is needed, when and how materials will be purchased)

One of the key criteria for good inventory control is materials planning as it monitors stocks to ensure material availability. Rizki (2008) states that SAP R/3 has a special materials planning function that can determine automatically what material is required, its quantity, and when it is required. Moreover he states that there are two types of standard materials planning procedures in SAP/R3: Traditional Material Requirements Planning (MRP) and Consumption Based Planning (CBP). There are three procedures in material planning in CBP (SAP Library, 2001):

In *reorder point planning*, SAP checks whether the stocks are below the reorder point. Should this happen, SAP will create a procurement proposal. The reorder point can be set manually or automatically. The reorder and safety stock levels are determined manually in the appropriate material master, while in the automatic function, the reorder and stock levels are defined by an integrated forecasting program which considers historical consumption data.

Forecast-based planning also uses historical data and forecast values to estimate future requirement. It is carried out at regular intervals (daily, weekly or monthly) and can be specified for each material.

In *time-phased planning*, materials are provided with an MRP date in the planning file which is set when creating a material master and is re-set after each planning run. It represents the date on which the material is to be planned again and is calculated on the basis of the planning cycle entered in the material master.

3.11. Theoretical framework

According to Miles and Huberman (1994) a theoretical framework aims to explain the main concepts of the research, its key factors, its variables and its relationships, either graphically or in narrative form. The theoretical framework of this research is presented in Figure 3.2.

This research evaluates the effects of human intervention on a statistical inventory system. Human judgement may occur at every stage of an inventory system (SKU classification, forecasting and stock control). Nevertheless, this study is only concerned with the effects of human intervention on stock control decision making. Since there is no single academic publication which discusses the empirical effects of judgemental adjustments in inventory control, we refer to such adjustments in a forecasting context to motivate the development of various research questions (to be discussed in the next chapter).

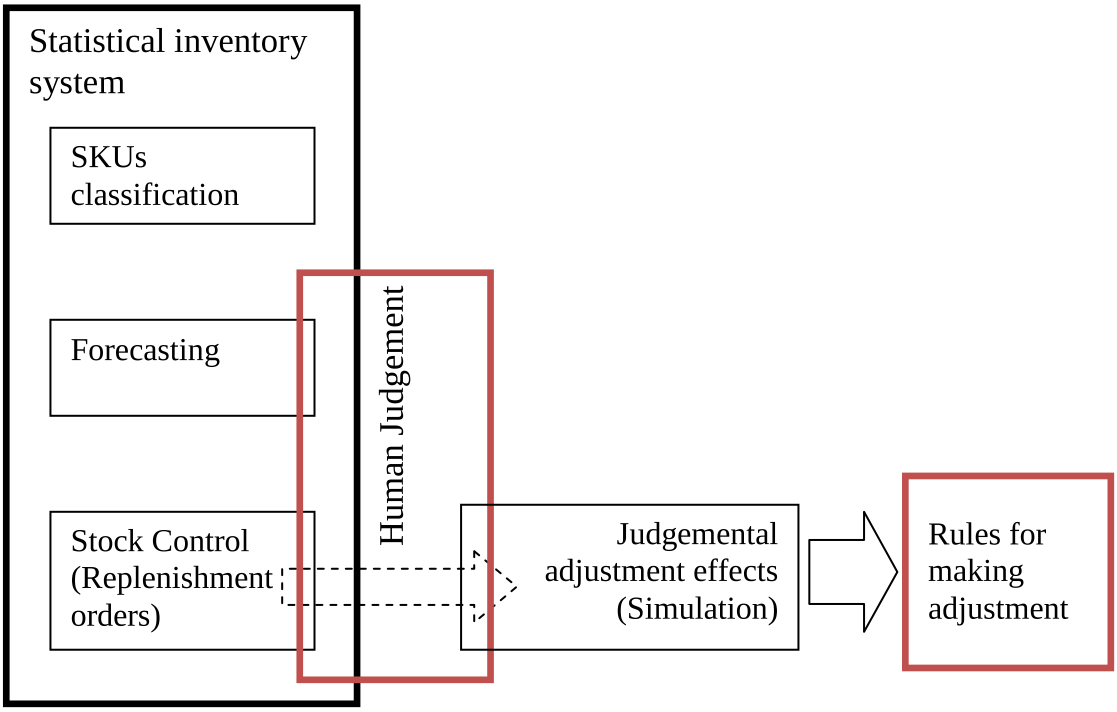

Figure 3.2 Theoretical framework of the research

In the case organisation, managers often change the replenishment order generated by statistical software (we return to this issue in section 4.2 of the next chapter where the case organisation is discussed in detail). The judgemental adjustments from the manager can affect the performance of the stock control system. The effect of the adjustments on the replenishment order decisions are evaluated through simulation. The expected output of this study is a set of practical suggestions for making adjustments to statistical replenishment orders.

3.12. Conclusions

The purpose of this chapter was to provide a review of the literature on human intervention in inventory management systems. From all the literature examined, it can be concluded that the performance of an inventory system is dependent on the performance of its most salient functions (SKU categorisation, forecasting and stock-control). Organisations can measure the performance of their inventory system by analysing stock-holding costs, and the extent to which they achieve their service-level goals. Statistical models are commonly used in determining the type of product, the forecasting method and the policy of the stock-control system. Most organisations use a software package to facilitate the process of decision-making. Furthermore, there is much evidence that shows that managers/decision-makers regularly use their judgement in the process of decision-making, and the resulting changes they make affect inventory system performance. However, so far there are no publications that discuss the implications of human intervention in an inventory system. A study which examines this issue is needed, along with the development of suggestions for improving the functionality of software packages. The literature of learning effects in manufacturing systems and the need for a new paradigm for inventory study (that is emphasizing the importance of empirical aspects and the human factor) were also discussed in this chapter to motivate the development of our experimental approach to research (to be discussed in the next chapter). Issue related to the Moving Average forecasting method and as approaches applied to conduct the empirical analysis in Chapter 5. The ERP systems were also considered as they reflect key important aspects of the case organisation. Finally, a theoretical framework of this research has been developed based on the literature reviewed.

Chapter 4. RESEARCH METHODOLOGY

4.1. Introduction

In this chapter, details related to the case organisation and to the empirical data used in this research are reported. A set of research questions are established following the review of literature in previous chapters; these questions will be explored empirically in the next chapter. The research classification and the methodology adopted for the purposes of this work are presented. Finally, explanations for the research philosophy, approach, strategy and techniques selected to meet the research objectives are given.

4.2. Case organisation

The organisation represents the European Logistics head office of a Japanese electronics manufacturer. The company was established in the 1950s as an exporting company delivering goods and services such as industrial products, home appliances and business supplies to customers through their global network. The case organisation has 16 production sites and 52 sales sites in 44 countries and regions of the world, with approximately 30,000 employees.

The European Parts Distribution Centre (EPDC), located in Germany, is the control tower of the central stock holding of service parts for Europe. Whereas physical flows initiate in Germany, information is controlled from Manchester, UK. Most of the spare parts are produced in the Far East, with China being the primary source of supply. The organisation also has manufacturing plants in Japan, Taiwan, Malaysia, and one small manufacturing facility in the UK, based in north Wales. Due to the geographical location of the suppliers, the average lead-time for ordering is about 60 days (including a 30-day average transit time for sea freight).

The organisation has implemented an ERP package, SAP R/3 (SAP-AG, Germany), discussed in more detail later in this section. The case organisation applies an environmental programme known as the 5R Concept: *Refusal* to purchase environmentally burdensome material; *Reduction* of waste material; *Reuse* of waste material without processing; *Reform* (reuse of materials in a different form), and *Recycle* (reuse of materials as a resource) (Syntetos, 2013[6]). The programme was established to deal with regulation concerns about waste electrical and electronic equipment (WEEE) and restrictions on certain hazardous substances (RoHS). Further explanation regarding these issues can be found in *Appendix C* and *Appendix D* respectively. The directives were proposed by the European Commission in 2001 turning into European Law in February 2003. The WEEE directive holds producers responsible for the new standard of taking back the products and ensuring they pay for their re-use and recycling (Environment Agency, 2012). RoHS regulations restrict the marketing of electrical and electronic equipment containing more than the permitted levels of certain hazardous substances (Environment Agency, 2012).

Many changes have to be made at all levels of an organisation in order to balance environmental concerns with day-to-day business. For example, obsolete items should receive considerable attention from inventory managers, and spare parts managers are obliged to scrap parts being used in new machines if they contain hazardous substances. On the other hand, the environmental policy adopted by the case organisation holds benefits for marketing/promotion-related activities, for example, the standardisation of a

[6] Private communication by the Company to Professor Aris A. Syntetos.

‘green’ policy for the packaging process which had previously been diverse (Syntetos et al., 2009a).

4.2.1. ERP system in case organisation

The case organisation adopted SAP R/3 as their ERP system software in 2001. SAP-AG is a leading ERP vendor (Ibrahim, 2007; Shehab et al., 2004). In this software, the materials management (MM) module is essentially used to control spare parts (service parts). The MM module functions are based on the way that materials are managed in the ERP production planning philosophy. Demand that triggers the orders can be expressed as actual orders or demand forecasts. Users are required to specify demand categories and stock is controlled periodically with the review period being set at a week or month, etc. Decisions on replenishment are made in terms of a min-max system (equivalent to the (s, S) policy) or versions of it (for example in the case organisation the S only is required and this can be calculated through the system). (Other stock control procedures may obviously be implemented as well, albeit with manual specifications and inputs.) The safety stock determination in SAP is also limited, since for example ‘no fill rate’ objectives can be defined. The software also contains forecasting functionality. Although many time-series forecasting methods are incorporated, such as moving averages as well as simple or more elaborate exponential smoothing techniques, many problems arise when dealing with spare parts since, as discussed in the previous chapters, demand for such items is usually intermittent in nature, requiring different forecasting methods (such as Croston’s estimator) specifically developed for such patterns (Syntetos et al., 2009a).

4.2.2. Empirical data

The database available for the purposes of this research consists of the individual demand histories of various stock keeping units (SKUs). The demand histories have been made available to us in a time-series format covering weekly information from April 2009 to

August 2011. Demand is intermittent in nature, meaning that it occurs at random with some time periods showing no demand at all. The actual database was provided in a fragmented way; that is, a considerable amount of time and effort was put into organizing the data in a usable way and validating the accuracy of the relevant information. We discuss in this chapter the work behind constructing the final database. Descriptive statistics with regards to the empirical time series follow in the next chapter.

4.2.2.1. SKUs classification

The case organisation previously categorised the SKUs based on the demand frequency. Since the demand frequency of C items is very low, only A and B items are planned manually outside SAP. Moreover, the categorization system is not linked to SKU characteristics and stock value. Consequently, low demand value parts are planned in the same way as high demand value parts. Moreover, the opportunity to reduce stock order frequency for low value parts is not utilized. The review of the situation revealed the need to amend the classification scheme and it exposed the opportunity to handle more efficiently the high value parts that were critical to the control of stock value.

Such condition motivated the organisation to revise the SKU categorisation scheme by considering the cumulative demand value based Pareto classification (category A: 80 per cent; category B: 95 per cent and category C: 100 per cent)[7]. A demand value (DV) can be defined as:

$$DV = \text{SKU cost} \times \text{quantity required}$$

This new categorization scheme was implemented in 2006. This scheme had produced typical Pareto outcomes where the number of SKUs of A items category has significantly lower than that of the number of SKUs of A items category resulted from old categorisation scheme. The new category A that has low number of SKUs allow the

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[7] The new SKUs categorisation scheme is a part of project facilitated by the Engineering and Physical Sciences Research Council (EPSRC, UK) Grant No. EP/D06942/1.

managers to give extra attention to this high value category. Where A items make up for 80 per cent, B items category makes it up until 95 per cent of total DV (80 + 15 per cent). Furthermore, C items category consists the parts related to new models introduced in the market, the discontinued parts and also the SKUs that have a problem in the supply chain such as manufacturing capacity related constraints on the supplier's side and endemic design faults causing failures in the field. In this research we used only A and B items category as C parts are manage outside the system through a manual process.

4.2.2.2. Forecasting and stock control

The original data provided by the company was contained in two folders (Folder A and Folder B) representing items from classes A and B respectively. No information was made available with regards to the C items. Each folder consists of 28 Microsoft Office (MS) Excel files each containing data per calendar month and consisting in turns of three sheets, namely RAW, DATA CALCS, and NEW ROP. Figure 4.1 below shows an example of a RAW sheet for A items.

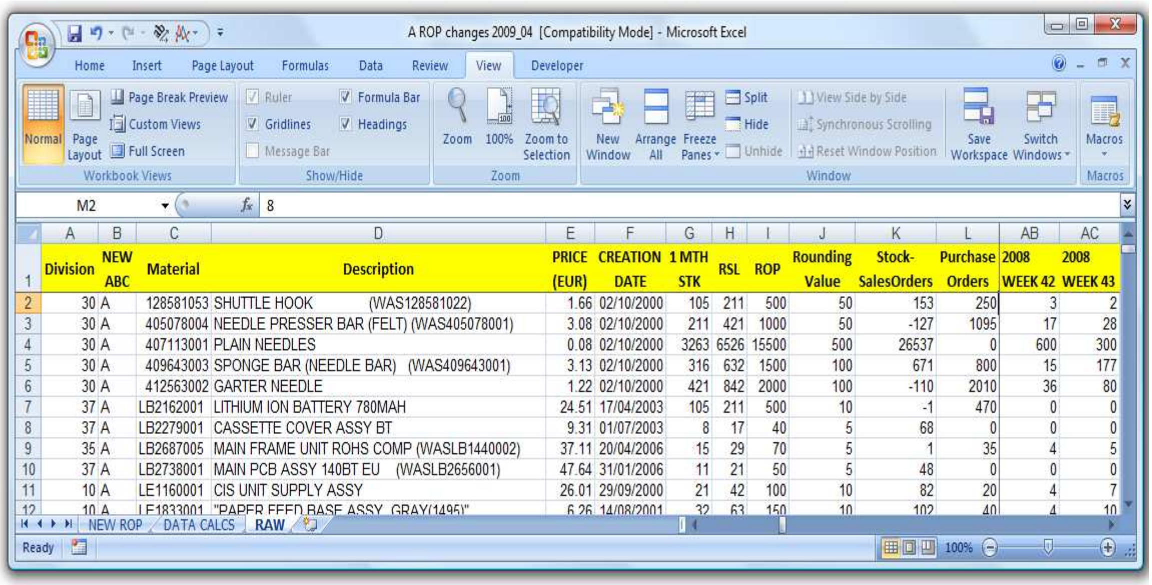


Figure 4.1 RAW sheet of original data

The RAW sheet provides information related to the division under which the spare parts are managed (column A). This piece of information is of no relevance to our research, and further clarifications with regard to the divisions were not thought to be needed. Column B presents the inventory class of the item concerned. In total, there are 4,661 A-class SKUs and 15,365 B-class SKUs. The code of each SKU and its description are available in columns C and D respectively. Column E presents the price of the spare parts (in Euros (€)). The prices of spare parts are between €0.02 and €254.85 for A items and €0.02 and €425.44 for B items. Column F shows the date when the SKU was introduced in the company's system.

With regards to forecasting, at the end of every month, a six-month (24 weeks) Simple Moving Average (SMA(24)) forecast is produced. (This is indicated in the DATA.CALS sheet; the information included in those sheets is presented in Figure 4.2. Column AA indicates the forecasts discussed above (we return to the discussion of the rest of the information presented in those sheets later in this section.) The case organisation has informed us that managers incorporate judgement into the forecasting of A items, whereas for B items the totally automatic control processing system is applied. The SMA method is simple and performs very well; it also proves to be a very robust forecasting method. However, some forecasting methods are more appropriate for intermittent demand, such as the Croston method, SBA and the more recently developed TSB method (Teunter et al., 2011); see sub-section 2.3.1. Such forecasting methods are not available within SAP R/3 although Croston's method itself is included in an upgraded version of the software, SAP APO (Advanced Planning and Optimisation). There is an opportunity for better forecasting if the organisation decides to upgrade to the SAP APO although the considerable monetary investment has obviously been an important concern.

Column G indicates what is termed as 'one month's stock'. This is calculated by multiplying the 24 weeks SMA (SMA(24)), which is the expected value of demand over a week, by 4 (weeks) to calculate the relevant amount over a month. Although this value is not used directly for any calculations it does convey some information as to the anticipated demand over a month rather than a week. This SMA(24) is also used to compute the safety stock for every SKU by multiplying it by a safety target (expressed in terms of time requirements). This safety target equates to eight weeks availability for A items and 12 weeks for B items. The safety stock for each material is presented in column H (and is termed RSL, required service level, in the company). Following this, the order frequency and the lead times are also taken into account in order to calculate the order-up-to (OUT) level for every SKU.

Inventory control takes place through a periodic Order-Up-To (OUT) level system; which in the company is, erroneously, referred to as a re-order point (ROP) system. The OUT replenishment level is calculated at the end of every month by multiplying the SMA(24) forecast by 19 (8 weeks RSL, i.e. safety stock + 9 weeks lead time + 2 weeks order frequency adjustment) in the case of A items, and 23 (12 weeks target safety stock + 9 weeks lead time + 2 weeks order frequency adjustment) in the case of B items.

Lead times are assumed to be fixed and equal to nine weeks (average lead times are 60 days). The periodic nature of the system is reflected in the order frequency adjustments of two weeks. The target safety stock and order frequency for both the A and B items was decided in an arbitrary way, and there is no explanation as to why the managers decided on a two-week order frequency. The weighted average (column AB) is defined by grouping the last 24-week period into six groups, then calculated using the equation below:

$$Weighted\ average = \frac{\left((\sum_{i=1}^{4} x_i) + (\sum_{i=5}^{8} x_i) + (\sum_{i=9}^{12} x_i) + (\sum_{i=13}^{16} x_i) + (\sum_{i=17}^{20} x_i) + (\sum_{i=21}^{24} x_i)\right)/31}{4}$$

where: x_i = demand in week i

Further, SD (column AC) is the standard deviation of the last 24 weeks' data, calculated using the equation below:

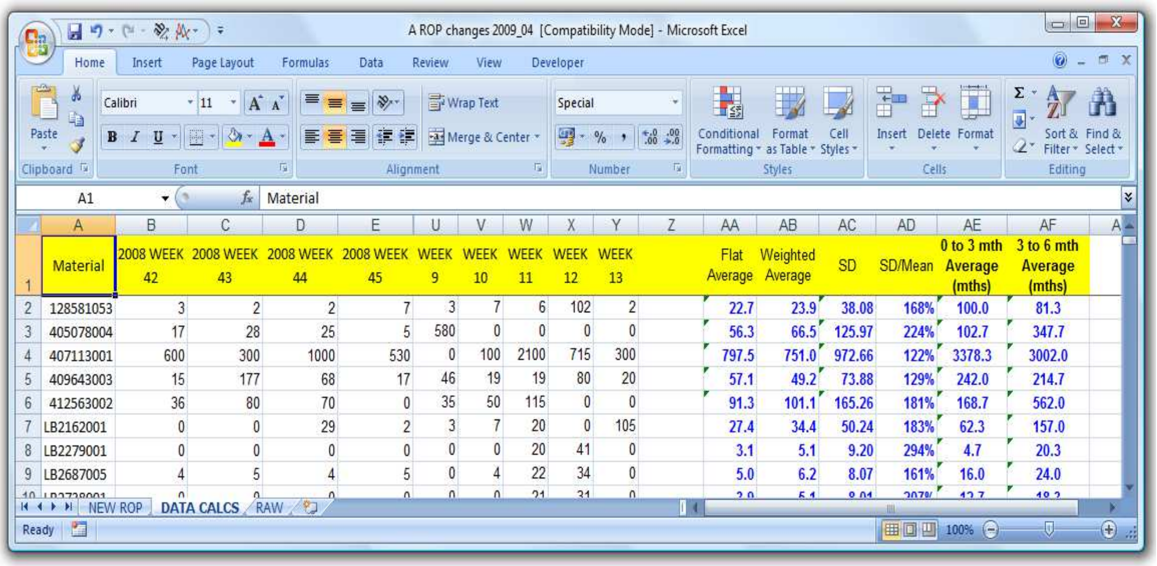
$$SD = \sqrt{\frac{1}{n-1}\sum_{i=1}^{24}(x_i - \bar{x})^2}$$

'0 to 3 months average' (column AE) is the average of demand for the first three-month period (week 1 to week 12) and the equation is:

$$0\ to\ 3\ months\ average = \bar{x} = \frac{\sum_{i=1}^{12} x_i}{12}$$

'3 to 6 months average' (column AF) is the average of demand for the last three-month period (week 13 to week 24) and the equation is:

$$0\ to\ 3\ months\ average = \bar{x} = \frac{\sum_{i=1}^{12} x_i}{12}$$



Material	2008 WEEK 42	2008 WEEK 43	2008 WEEK 44	2008 WEEK 45	WEEK 9	WEEK 10	WEEK 11	WEEK 12	WEEK 13		Flat Average	Weighted Average	SD	SD/Mean	0 to 3 mth Average (mths)	3 to 6 mth Average (mths)
128581053	3	2	2	7	3	7	6	102	2		22.7	23.9	38.08	168%	100.0	81.3
405078004	17	28	25	5	580	0	0	0	0		56.3	66.5	125.97	224%	102.7	347.7
407113001	600	300	1000	530	0	100	2100	715	300		797.5	751.0	972.66	122%	3378.3	3002.0
409643003	15	177	68	17	46	19	19	80	20		57.1	49.2	73.88	129%	242.0	214.7
412563002	36	80	70	0	35	50	115	0	0		91.3	101.1	165.26	181%	168.7	562.0
LB2162001	0	0	29	2	3	7	20	0	105		27.4	34.4	50.24	183%	62.3	157.0
LB2279001	0	0	0	0	0	0	20	41	0		3.1	5.1	9.20	294%	4.7	20.3
LB2687005	4	5	4	5	0	4	22	34	0		5.0	6.2	8.07	161%	16.0	24.0

Figure 4.2 Data calculation sheet for original data

Figure 4.3 and Figure 4.4 show the stock control system for the A and B items respectively.

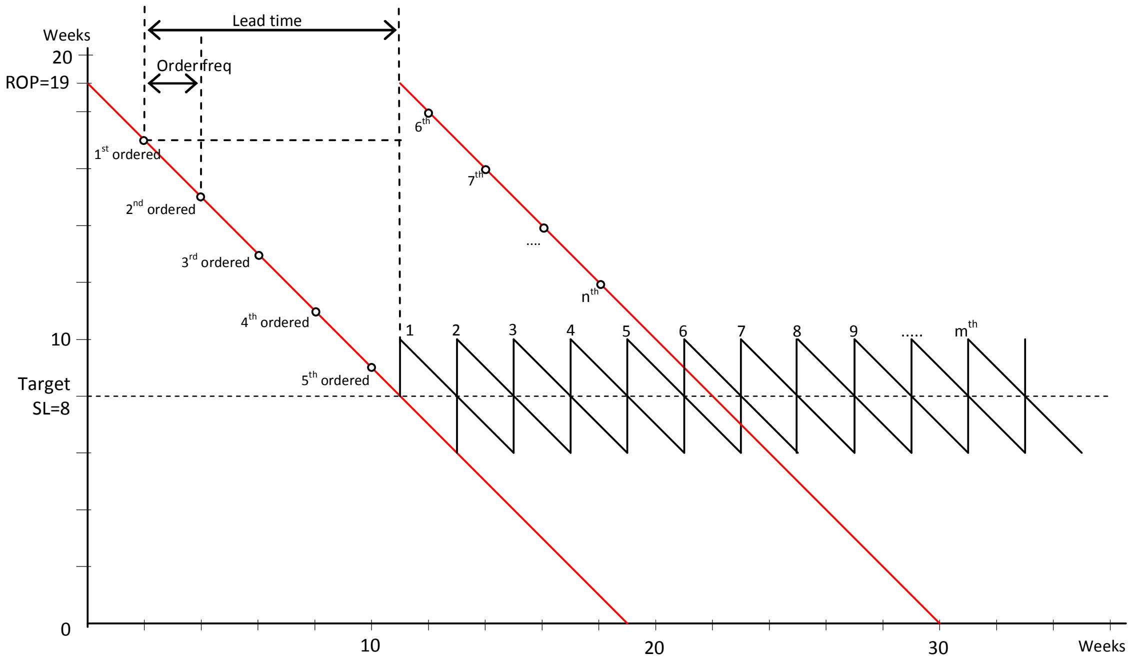


Figure 4.3 Stock control system for A items

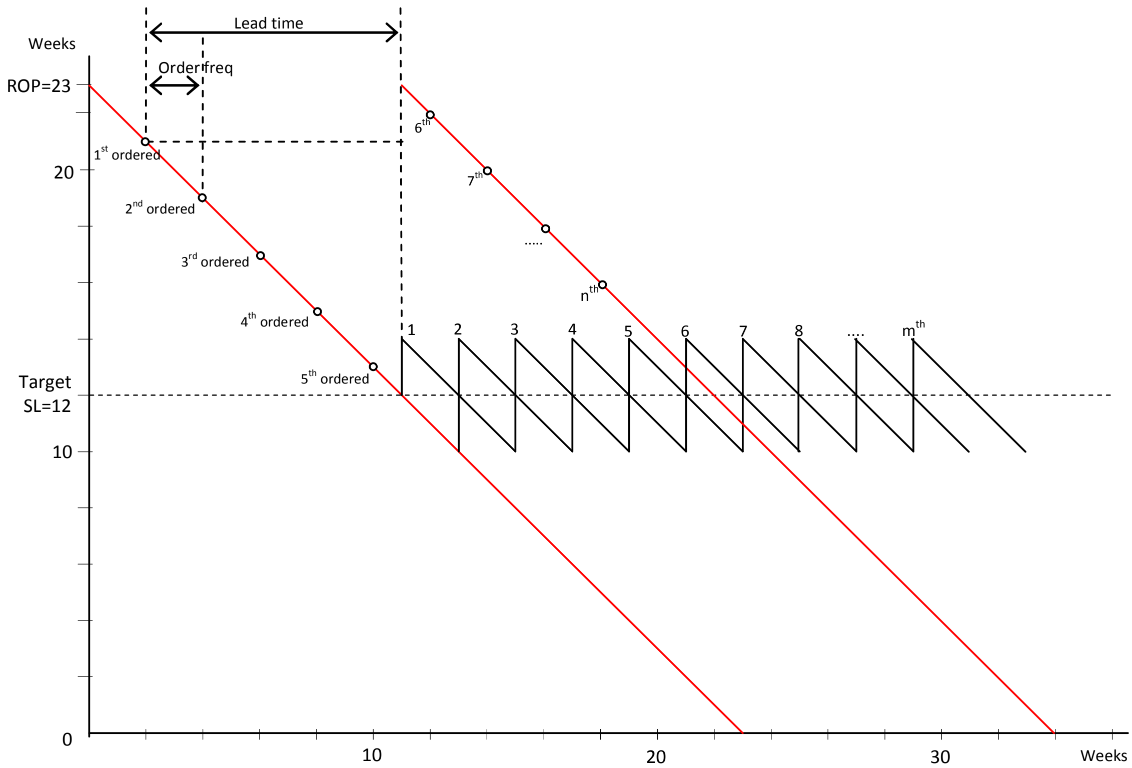


Figure 4.4 Stock control system for B items

As the order review frequency is two weeks and the average lead time is 9 weeks (fixed), the arrival of the first order, the second order, and so on, will be at weeks 11, 13, etc., respectively. This system is known as the periodic-review order-up-to level (*R*, *S*) system where *R* is the review period and *S* the OUT level. Stock control is governed by the following procedure: every *R* unit of time, the inventory position (which is the actual number of units in stock + the quantity expected to be received) is checked against an optimised OUT level (*S*) and an order is placed to raise the inventory position to the level of *S* (see section 2.5. for more explanation of this stock control policy).

Column J presents a rounding (which is a manual decision made by a manager) to the nearest integer that needs to be used for placing an order; for example if the rounding value is 10, then an order initially calculated as 7 would be raised to 10. The 'stock-sales' value (column K) is the actual stock on hand (actual stock minus all sales orders). These values are calculated by subtracting all the outstanding sales orders from the actual stock. Finally, the purchase orders (column L) are previously-placed orders that are outstanding at the moment.

The next sub-section will present the NEW ROP sheet (the last piece of important information) and will discuss replenishment related details..

4.2.3. Judgemental adjustment process

Initially, the OUT level is produced by the SAP system (hereafter termed as the *System OUT replenishment level*) and when managers feel is necessary they may alter it by integrating their own judgement. This should ideally reflect information that is not captured in the quantitative data – this is at least the rationale behind such interventions as far as the top management is concerned. When making the adjustments, another OUT level (called NEW ROP in the company database and in this research this will be referred to as the *SMA-Based OUT replenishment level*) is taken into account which is the one calculated based on the descriptions provided in the previous sub-section. So essentially managers make adjustments to the *System OUT replenishment level* by considering the OUT level calculated using the company's formula. The adjusted OUT level is the manager's final decision for theend of the current month and will be used to drive replenishment decisions in the following month. This will be referred to as the *Final OUT replenishment level*. On the other hand, if managers do not make any changes to the order replenishment level, the *System OUT replenishment level* is recorded as the final decision for the current month and it constitutes the initial OUT level for the next period.

For example, in Figure 4.5 it can be seen that the *System OUT replenishment level* in September 2009 is 1,000 units (in column M). The *SMA-Based OUT replenishment level* is shown in column N (347 units) using their own formula. By considering the OUT level in column N and any potential contextual information which (for example) may be that demand is perceived to be decreasing (justification provided in column P), the manager adjusts the initial OUT level to 500 units (column O). This OUT level is the final decision and will be the OUT level for October 2009 (column Q).

From a theoretical perspective, justification of adjustments such as that related to 'decreasing demand' (provided in column P) should be related to forecasting. This is because the underlying structure of the series (such as that related to a trend) should be important for extrapolation purposes only. However, in the case of the company considered in our research such a justification is offered in the context of inventory rather than forecasting. Clearly this stems from the lack of judgemental adjustments in the preceding stage of forecasting – should that be the case most probably the perceived 'decreasing demand' would be taken into account when adjusting forecasts – and it generates a number of interesting questions on the interface between adjusting at the forecasting and or at the inventory stage. This issue is further discussed in the last chapter of the thesis.

Figure 4.6 shows the process of adjustments to the OUT level.

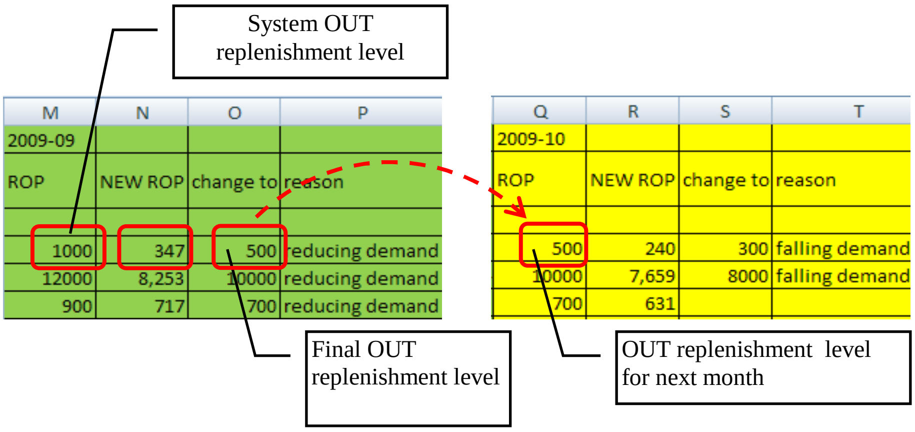


Figure 4.5 An example of the adjustment process

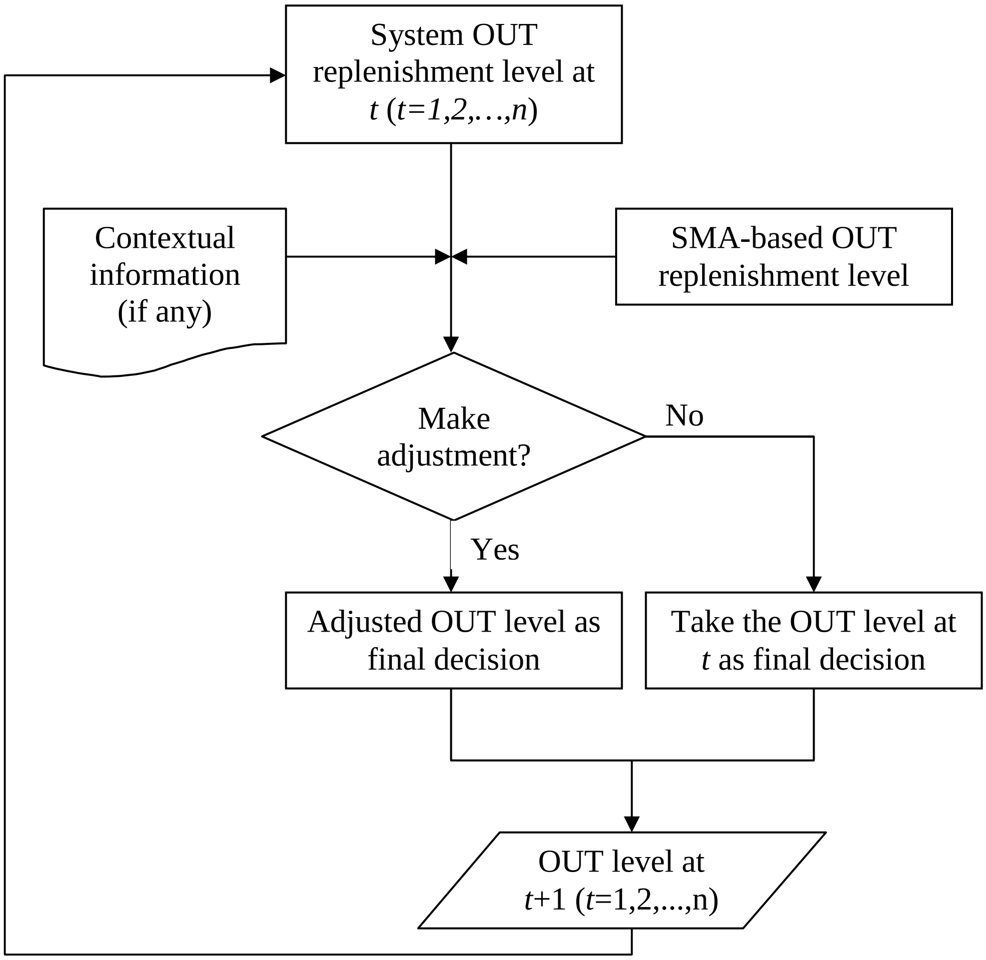
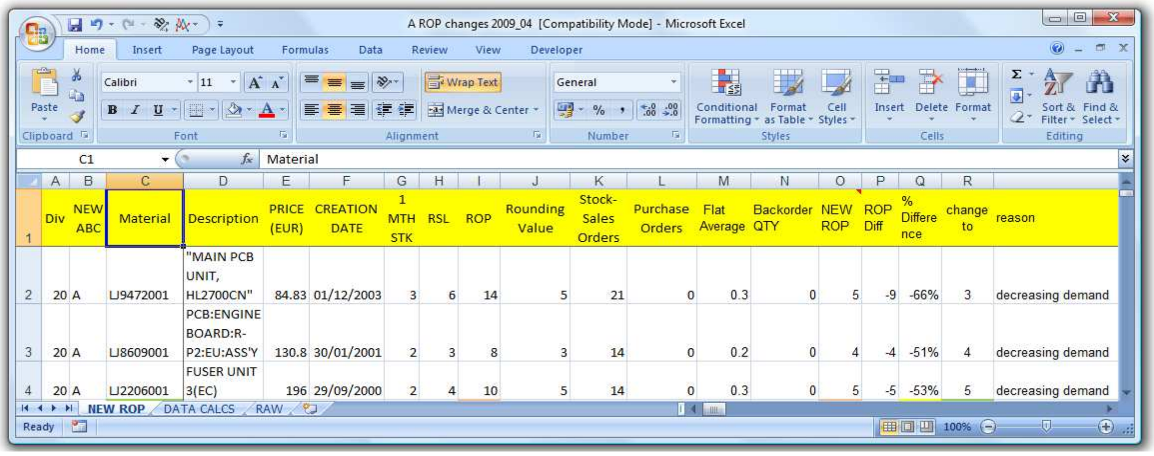


Figure 4.6 The process of adjustments to the OUT level.

A justification has been recorded for the majority of the adjustments performed by the managers. Data pertaining to the *System OUT replenishment level*, the *SMA-Based OUT replenishment level*, the difference between these two replenishment order methods the *Final OUT replenishment level* and the reason/justification behind such changes (judgemental adjustments) are presented in the NEW ROP worksheet (Figure 4.7).



Div	NEW ABC	Material	Description	PRICE (EUR)	CREATION DATE	1 MTH STK	RSL	ROP	Rounding Value	Stock-Sales Orders	Purchase Orders	Flat Average	Backorder QTY	NEW ROP	ROP Diff	% Difference	change to	reason
20	A	LJ9472001	"MAIN PCB UNIT, HL2700CN"	84.83	01/12/2003	3	6	14	5	21	0	0.3	0	5	-9	-66%	3	decreasing demand
20	A	LJ8609001	PCB:ENGINE BOARD:R-P2:EU:ASS'Y	130.8	30/01/2001	2	3	8	3	14	0	0.2	0	4	-4	-51%	4	decreasing demand
20	A	LJ2206001	FUSER UNIT 3(EC)	196	29/09/2000	2	4	10	5	14	0	0.3	0	5	-5	-53%	5	decreasing demand

Figure 4.7 NEW ROP sheet of original data

4.3. Construction of the database

A comprehensive database needs to be constructed for further experimentation with the empirical information discussed in the previous sub-sections. Addressing the research questions of this work (the development of which is discussed in detail later in this chapter) necessitates the presentation of information in a time-series format to enable not only descriptive analysis to be performed but also simulation of various scenarios over time to be conducted. Since empirical data was provided in files that correspond to months, the first task was to compile this information into a single file. The working principle in this stage was to have one SKU per row. The process of data compiling is described below. For example, Figure 4.8a and Figure 4.8b show data from March and April 2009 respectively. SKU codes (what is termed as Material codes) from these months (column A) are copied to one new file. Because the SKUs sequence in March 2009 is different from that in April 2009, we have to make adjustments resulting eventually in one row consisting of solely one SKU.

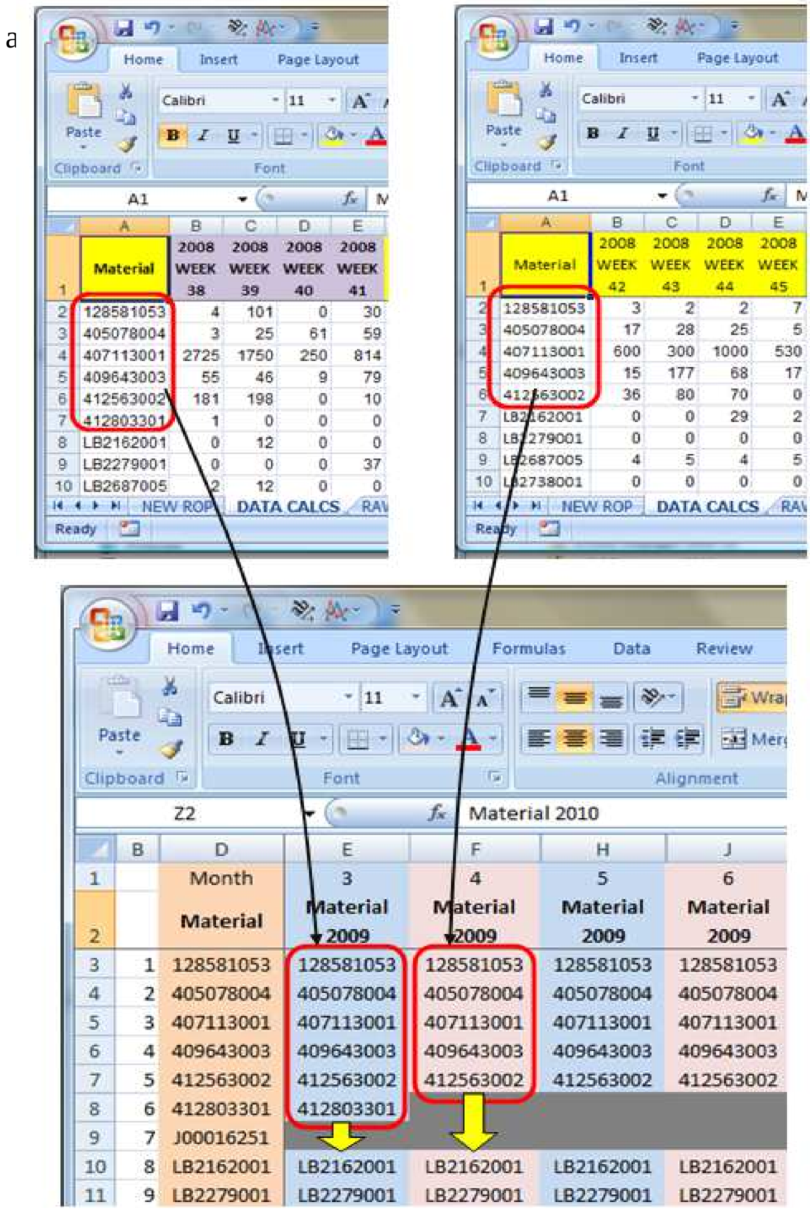
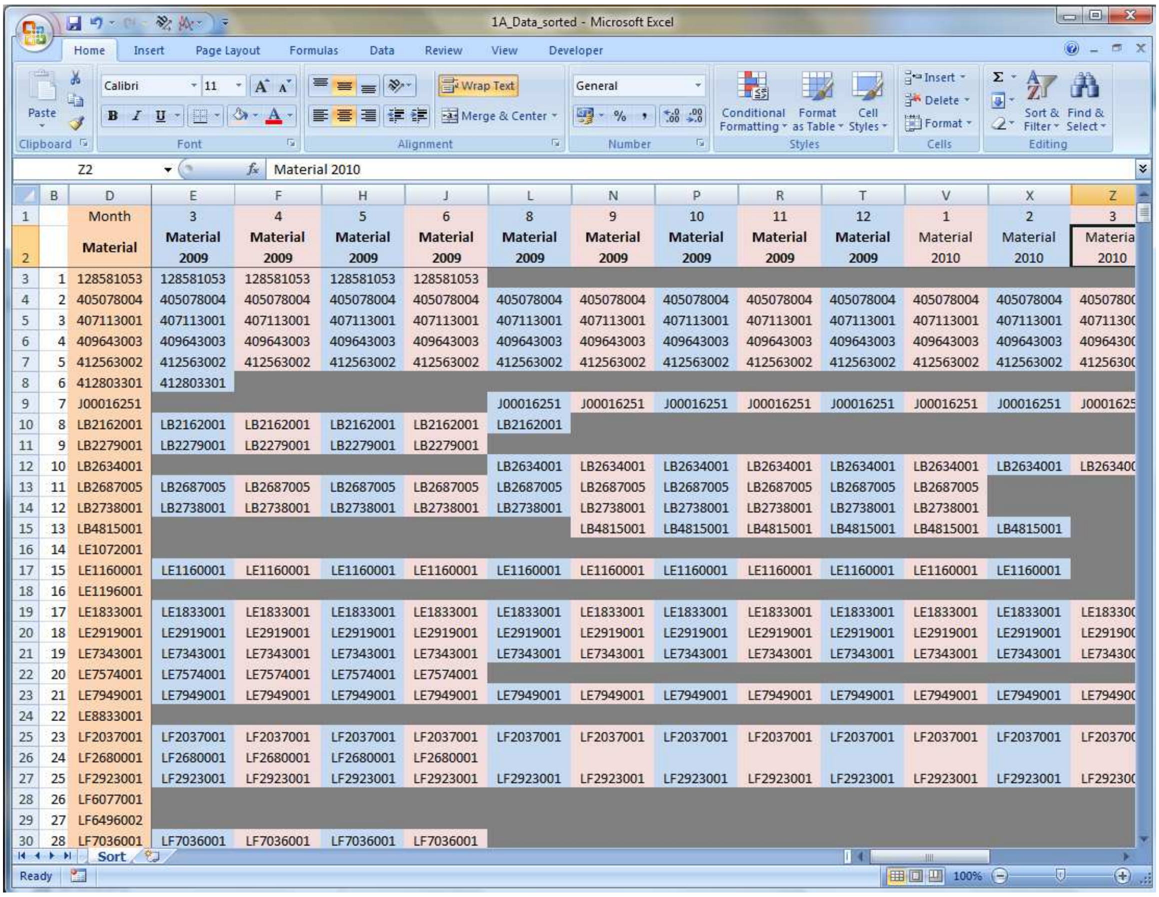


Figure 4.8 Compiling information into a time-series format

This process was repeated for all SKUs (materials) and all months and the result can be seen in Figure 4.9. Column D contains all SKU codes for entire time horizons.



	B	D	E	F	H	J	L	N	P	R	T	V	X	Z
1		Month	3	4	5	6	8	9	10	11	12	1	2	3
2		Material	Material 2009	Material 2009	Material 2009	Material 2009	Material 2009	Material 2009	Material 2009	Material 2009	Material 2009	Material 2010	Material 2010	Materia 2010
3	1	128581053	128581053	128581053	128581053	128581053								
4	2	405078004	405078004	405078004	405078004	405078004	405078004	405078004	405078004	405078004	405078004	405078004	405078004	40507800
5	3	407113001	407113001	407113001	407113001	407113001	407113001	407113001	407113001	407113001	407113001	407113001	407113001	4071130
6	4	409643003	409643003	409643003	409643003	409643003	409643003	409643003	409643003	409643003	409643003	409643003	409643003	4096430
7	5	412563002	412563002	412563002	412563002	412563002	412563002	412563002	412563002	412563002	412563002	412563002	412563002	4125630
8	6	412803301	412803301											
9	7	J00016251					J00016251	J00016251	J00016251	J00016251	J00016251	J00016251	J00016251	J0001625
10	8	LB2162001	LB2162001	LB2162001	LB2162001	LB2162001	LB2162001							
11	9	LB2279001	LB2279001	LB2279001	LB2279001	LB2279001								
12	10	LB2634001					LB2634001	LB2634001	LB2634001	LB2634001	LB2634001	LB2634001	LB2634001	LB263400
13	11	LB2687005	LB2687005	LB2687005	LB2687005	LB2687005	LB2687005	LB2687005	LB2687005	LB2687005	LB2687005	LB2687005		
14	12	LB2738001	LB2738001	LB2738001	LB2738001	LB2738001	LB2738001	LB2738001	LB2738001	LB2738001	LB2738001	LB2738001		
15	13	LB4815001						LB4815001	LB4815001	LB4815001	LB4815001	LB4815001	LB4815001	
16	14	LE1072001												
17	15	LE1160001	LE1160001	LE1160001	LE1160001	LE1160001	LE1160001	LE1160001	LE1160001	LE1160001	LE1160001	LE1160001	LE1160001	
18	16	LE1196001												
19	17	LE1833001	LE1833001	LE1833001	LE1833001	LE1833001	LE1833001	LE1833001	LE1833001	LE1833001	LE1833001	LE1833001	LE1833001	LE18330
20	18	LE2919001	LE2919001	LE2919001	LE2919001	LE2919001	LE2919001	LE2919001	LE2919001	LE2919001	LE2919001	LE2919001	LE2919001	LE29190
21	19	LE7343001	LE7343001	LE7343001	LE7343001	LE7343001	LE7343001	LE7343001	LE7343001	LE7343001	LE7343001	LE7343001	LE7343001	LE73430
22	20	LE7574001	LE7574001	LE7574001	LE7574001	LE7574001								
23	21	LE7949001	LE7949001	LE7949001	LE7949001	LE7949001	LE7949001	LE7949001	LE7949001	LE7949001	LE7949001	LE7949001	LE7949001	LE79490
24	22	LE8833001												
25	23	LF2037001	LF2037001	LF2037001	LF2037001	LF2037001	LF2037001	LF2037001	LF2037001	LF2037001	LF2037001	LF2037001	LF2037001	LF20370
26	24	LF2680001	LF2680001	LF2680001	LF2680001	LF2680001								
27	25	LF2923001	LF2923001	LF2923001	LF2923001	LF2923001	LF2923001	LF2923001	LF2923001	LF2923001	LF2923001	LF2923001	LF2923001	LF29230
28	26	LF6077001												
29	27	LF6496002												
30	28	LF7036001	LF7036001	LF7036001	LF7036001	LF7036001								

Figure 4.9 Complete database over time

From Figure 4.9, it can be seen that not all SKUs are associated with every time period. This indicates that managers decide not to replenish stock for these particular SKUs during specific months. It might be due to that the particular SKU is discontinued.

Adjustments of row in weekly demand data in each file (monthly) are also required. The purpose is to obtain SKU's weekly demand data to have the same row number with SKUs database shown in Figure 4.9. After all weekly-demand data had been adjusted, it was copied into one new sheet to have a complete database. Figure 4.10a, Figure 4.10b and Figure 4.10c show how this process is carried out.

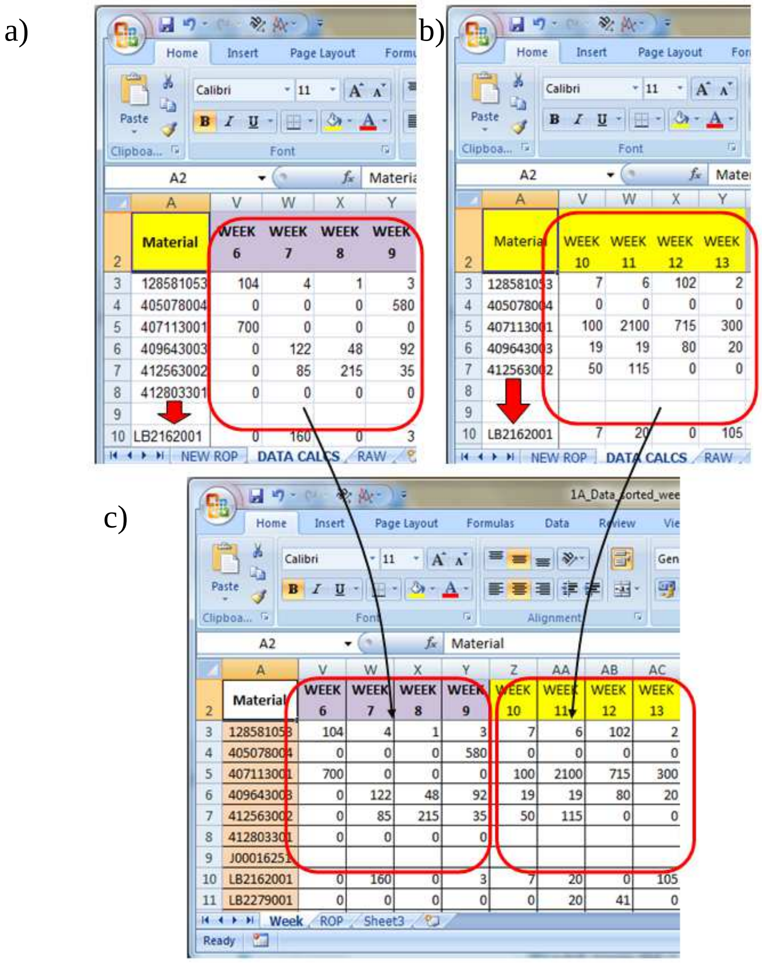
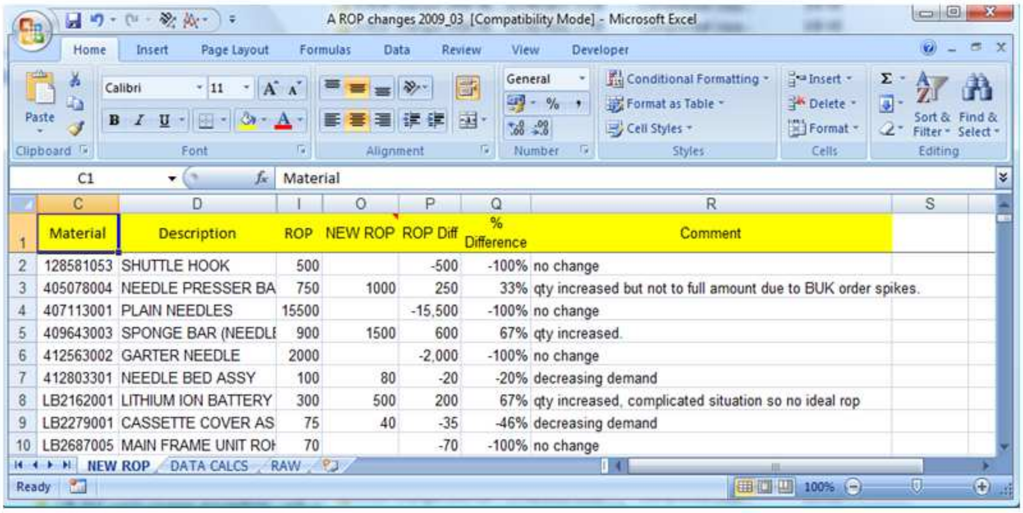


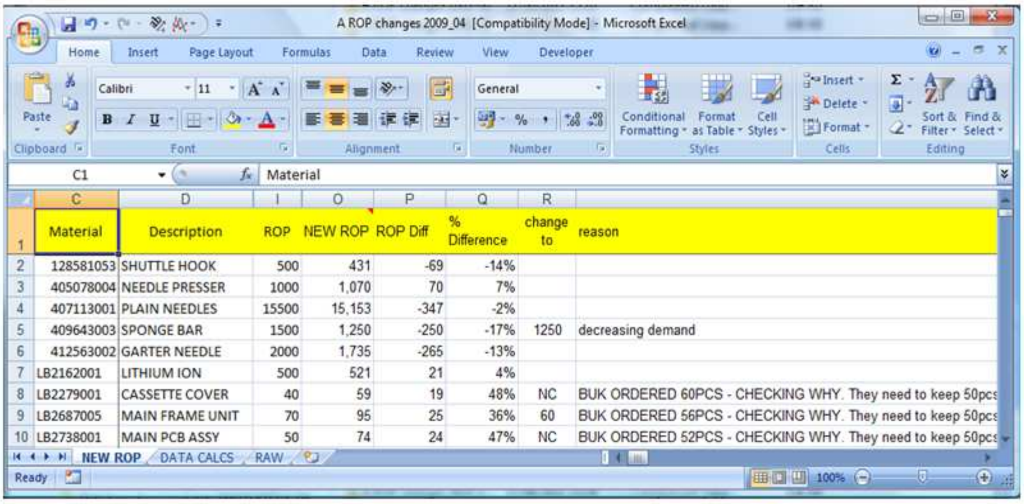
Figure 4.10 Weekly demand data for whole time horizons

The next step in terms of database processing was to establish the detailed OUT-level data (such as the OUT level resulting from the system, the OUT level calculated by the company's formula, the changes to the OUT level made by the manager, and the reasons for the adjustments). The original data can be seen in Figure 4.11 (an example of data from March 2009 and April 2009).



A ROP changes 2009_03 [Compatibility Mode] - Microsoft Excel

	Material	Description	ROP	NEW ROP	ROP Diff	% Difference	Comment
2	128581053	SHUTTLE HOOK	500		-500	-100%	no change
3	405078004	NEEDLE PRESSER BA	750	1000	250	33%	qty increased but not to full amount due to BUK order spikes.
4	407113001	PLAIN NEEDLES	15500		-15,500	-100%	no change
5	409643003	SPONGE BAR (NEEDLI	900	1500	600	67%	qty increased.
6	412563002	GARTER NEEDLE	2000		-2,000	-100%	no change
7	412803301	NEEDLE BED ASSY	100	80	-20	-20%	decreasing demand
8	LB2162001	LITHIUM ION BATTERY	300	500	200	67%	qty increased, complicated situation so no ideal rop
9	LB2279001	CASSETTE COVER AS	75	40	-35	-46%	decreasing demand
10	LB2687005	MAIN FRAME UNIT ROI	70		-70	-100%	no change



A ROP changes 2009_04 [Compatibility Mode] - Microsoft Excel

	Material	Description	ROP	NEW ROP	ROP Diff	% Difference	change to	reason
2	128581053	SHUTTLE HOOK	500	431	-69	-14%		
3	405078004	NEEDLE PRESSER	1000	1,070	70	7%		
4	407113001	PLAIN NEEDLES	15500	15,153	-347	-2%		
5	409643003	SPONGE BAR	1500	1,250	-250	-17%	1250	decreasing demand
6	412563002	GARTER NEEDLE	2000	1,735	-265	-13%		
7	LB2162001	LITHIUM ION	500	521	21	4%		
8	LB2279001	CASSETTE COVER	40	59	19	48%	NC	BUK ORDERED 60PCS - CHECKING WHY. They need to keep 50pcs
9	LB2687005	MAIN FRAME UNIT	70	95	25	36%	60	BUK ORDERED 56PCS - CHECKING WHY. They need to keep 50pcs
10	LB2738001	MAIN PCB ASSY	50	74	24	47%	NC	BUK ORDERED 52PCS - CHECKING WHY. They need to keep 50pcs

Figure 4.11 Original data of detailed OUT level

The manipulation process is described in the following figure. First is by adjusting the row of material in each monthly data, so each material has the same row position with material data base shown in Figure 4.9. After completion, all monthly data is combined into a single file (Figure 4.12c).

a)

b)

c)

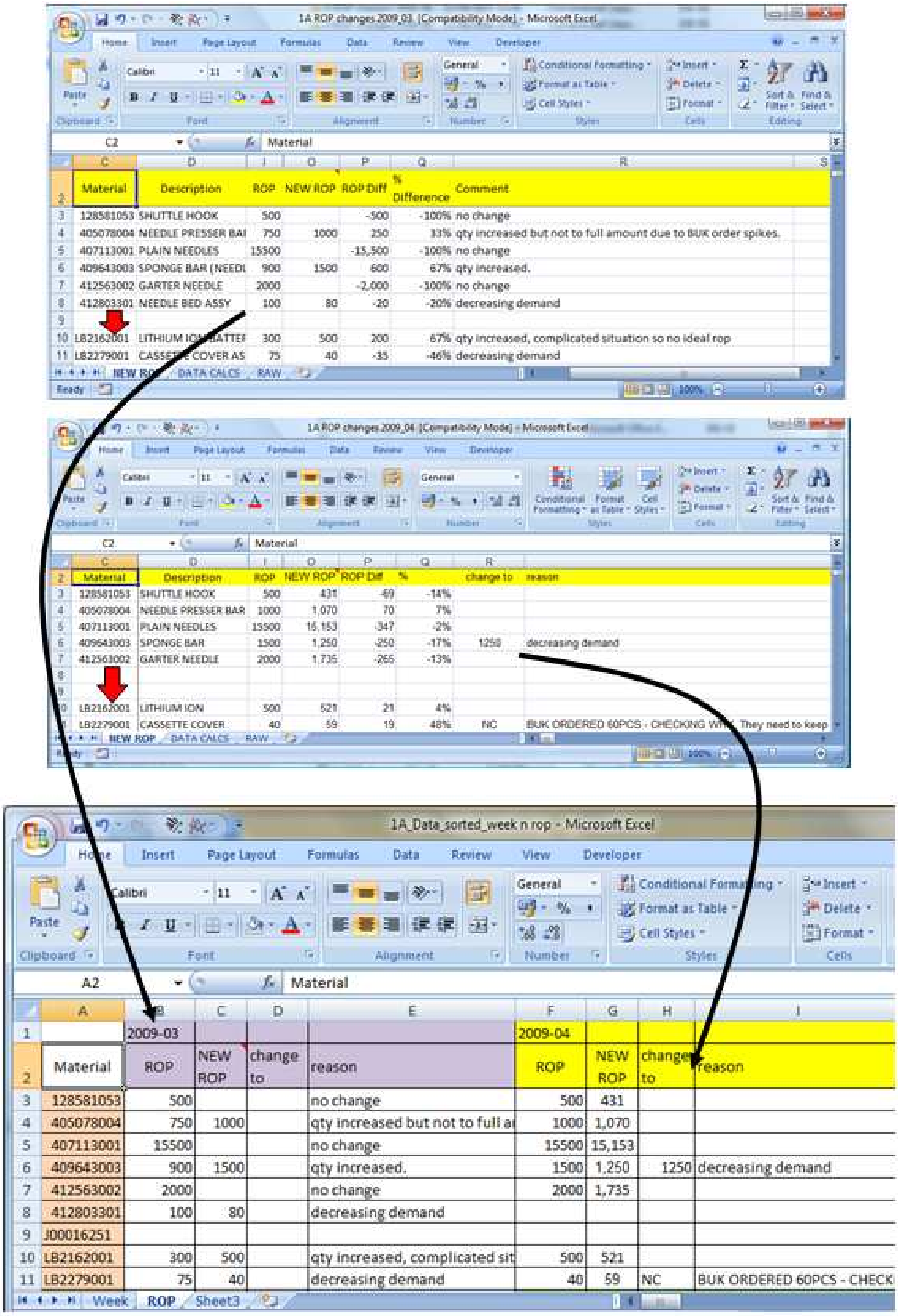
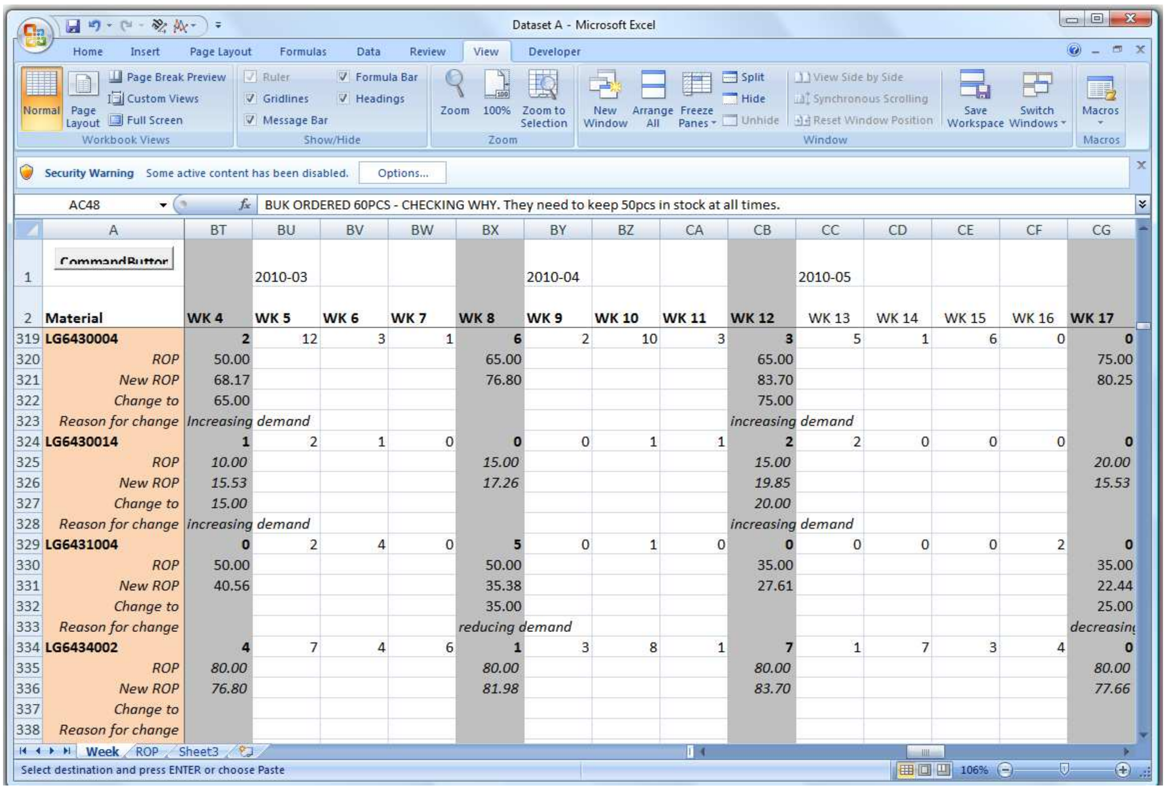


Figure 4.12 Detailed ROP for whole time horizons

The final step of data handling is to build the complete database, a task that has been accomplished by deploying Excel Visual Basic for Applications (VBA). The result can be seen in Figure 4.13.

Syntetos et al. (2009b) identified the process of constructing the database needed for experimentation purposes as a very important one in empirical research. This aspect of empirical research is generally under-estimated in importance although it arguably constitutes one of the most important factors towards conducting a comprehensive experiment. The process of constructing and validating the database used for the purposes of this research was a very challenging one and particularly demanding in terms of time investment. Thus it was viewed as necessary to include details here and devote an entire section to this issue.



	A	BT	BU	BV	BW	BX	BY	BZ	CA	CB	CC	CD	CE	CF	CG
1	CommandButton		2010-03				2010-04				2010-05				
2	Material	WK 4	WK 5	WK 6	WK 7	WK 8	WK 9	WK 10	WK 11	WK 12	WK 13	WK 14	WK 15	WK 16	WK 17
319	LG6430004	2	12	3	1	6	2	10	3	3	5	1	6	0	0
320	ROP	50.00				65.00				65.00					75.00
321	New ROP	68.17				76.80				83.70					80.25
322	Change to	65.00								75.00					
323	Reason for change	Increasing demand								increasing demand					
324	LG6430014	1	2	1	0	0	0	1	1	2	2	0	0	0	0
325	ROP	10.00				15.00				15.00					20.00
326	New ROP	15.53				17.26				19.85					15.53
327	Change to	15.00								20.00					
328	Reason for change	increasing demand								increasing demand					
329	LG6431004	0	2	4	0	5	0	1	0	0	0	0	0	2	0
330	ROP	50.00				50.00				35.00					35.00
331	New ROP	40.56				35.38				27.61					22.44
332	Change to					35.00									25.00
333	Reason for change					reducing demand									decreasin
334	LG6434002	4	7	4	6	1	3	8	1	7	1	7	3	4	0
335	ROP	80.00				80.00				80.00					80.00
336	New ROP	76.80				81.98				83.70					77.66
337	Change to														
338	Reason for change														

Figure 4.13 Complete database for A items

4.4. Detailed research questions

This section develops the main research questions that we attempt to answer through our empirical investigation. We develop exploratory research questions rather than formal hypotheses for the following reasons. According to Armstrong (1988), hypothesis testing should be avoided in the scientific research such as the studies in the field of forecasting since it leads to a lack of an understanding of the final outcomes. Hypothesis testing forces the researcher to investigate only if something is statistically significant or not rather than understanding the outcome of the research. In addition, this research follows the methodological structure of previous research in this field (study conducted by Syntetos et al., 2009b) where a case is being made for the use of research questions rather than hypotheses.

Many studies have concluded that managerial interventions in statistical forecasts improve forecast accuracy (Angus-Leppan and Fatseas, 1986; Lawrence et al., 1986; Mathew and Diamantopoulos, 1986, 1990, 1992; Diamantopoulos and Mathews, 1989; Wolfe and Flores, 1990, Syntetos et al., 2009b). Goodwin (2000a) suggested that the use of judgemental adjustments to statistical forecasts is justified when non-time series information has predictive power and this information is difficult to capture in a statistical model. This finding is supported by Goodwin (2005) and Sanders and Ritzman (2001) who argued that judgement can be valuable when the forecasters have important information about forthcoming events that is difficult to capture in a statistical model. One would expect that the benefits of judgemental adjustments that have been reported in the forecasting literature (the details of which are discussed in Chapter 3) should also apply in terms of replenishment orders. So it is natural that the first important question that this research will attempt to answer relates to any potential improvements resulting from judgementally adjusting stock control decisions. The first research question is the following:

Q1. Is there any improvement in judgementally adjusting stock control-related decisions and if so why?

Forecasting related research suggests that the size and sign of adjustments have some explanatory power in terms of performance. When judgemental adjustmentsare integrated with statistical forecasting, the decision regarding whether a statistical forecast needs adjusting and the estimate of the size of the adjustment are requirements of the adjustment process (Lawrence et al., 2006). Some studies (e.g. Fildes et al., 2009) conducted to investigate the effects of incorporating judgement into statistical forecasts found large adjustments to be more effective in improving forecast accuracy than small adjustments. Syntetos et al. (2009b) found that large negative adjustments perform well in improving forecast accuracy. This knowledge is most useful in terms of potential amendments to FSS. In order to improve the effectiveness of FSS functions, Lee et al. (2007) reported an experiment that investigated the effectiveness of providing support for the use of analogies in sales forecasting. (By analogies we mean the similarity of conditions between past and forthcoming events; thus the environment of these conditions is relatively predictable, for example the environment of similar promotion campaigns.) This study argued that by providing contextual information of similar events, forecasters are supported in their efforts to determine how much they should adjust statistical sales forecasts. These studies indicate that the performance of judgemental forecasting may be increased by knowing the implications of the sign and size of adjustments. This benefit may also be found in an inventory context. We may expect that the performance of a stock control system can be improved by analysing the behaviour of human intervention in inventory decisions in terms of the sign and size of adjustments and their effect for improving the inventory performance. Accordingly, the second research question of this study is:

Q2. How the sign and size of the adjustments affects the performance of inventory system?

Documentation of reasons that a particular forecasting model is chosen and why adjustments of forecasts are made is important in reducing bias in relevant processes (Goodwin, 2000). Such documented reasons could be used in determining why a forecast is potentially erroneous since the rationale of decision making on the part of the forecaster is recorded and can be evaluated. In addition, models of the forecaster's behaviour should explain when and how individuals incorporate judgement into their predictions (Stekler, 2007). In the area of judgementally adjusted stock control decisions, it seems that providing justification for adjustments may be associated with an improved performance of the stock control system. This research uses data where the justification for adjustments is available in the majority of cases. An evaluation is conducted to assess whether offering a justification for the adjustments seems to improve the performance of the inventory system. This analysis constitutes a major contribution to the inventory literature since no research has covered similar aspects before. The third research question of this study is:

> **Q3. Is any improvement achieved by the adjustments for which justification is offered as compared to those without a justification and if so why?**

In statistics, bias is defined as the characteristic of an experimental or sampling design that systematically (non-randomly) affects the results of a study (Evans, 1992). In this research, we can say that bias is a systemic inaccuracy due to the characteristics of the process employed in making adjustments to replenishment orders. Tversky and Kahneman (1974) argued that by making judgemental adjustments, people assessing probabilities and predicting values are using heuristic principles. The researchers argued that, sometimes, heuristic principles have systemic errors; thus they concluded that biases are found in the intuitive judgement of probability. Moreover, Carter et al. (2007) argued that from a managerial standpoint, understanding the nature of decision biases is the first step in the process of deciding how to manage them. These authors also developed a taxonomy of judgement and decision-making biases which can impact supply management decision-making, such as availability cognition, base rate, presentation, and control illusion.

In the field of forecasting, many studies have investigated the issue of bias in judgementally adjusting forecasts (see, for example, Diamantopoulos and Mathews, 1989; Matthews and Diamantopoulos, 1990; Goodwin and Wright, 1994) as forecasters operate in an environment where there are either implicit or explicit biases (Lawrence and O'Connor, 2005). Forecasters may adjust forecast results for a particular reason, and there are clearly two directions in which bias may occur resulting in either under- and over-forecasting. For example, a manager may increase a statistical forecast to achieve a sales target or to get priority from a supplier or conversely may decrease a forecast if for example inventory cost reductions drive current operations. Biased/unbiased judgementally adjusted forecasting affects the accuracy of its results. The relationship between the forecaster's characteristics and forecasting performance is evaluated by Eroglu and Croxton (2010). This research considers a number of types of bias (optimism bias, anchoring bias, and over-reaction bias) to explore the effects of particular individual differences (personality, motivational orientation, and work locus of control) on forecasting performance. The researchers found that a forecaster's personality and motivational orientation have significant effects on forecasting bias, whereas work locus of control does not. As judgemental forecasting introduces bias and the effects of bias impact on the performance of forecasting, it seems possible that bias can also be found in the process of inventory decision making. By analysing whether a judgmentally adjusted stock control decision is biased or not, further analysis may be conducted in order to investigate how and why managers made adjustments. Therefore, this research investigates the biases in inventory decision making and this aspect forms the fourth of the research questions:

Q4. Are judgementally adjusted stock control decisions biased?

Although the phenomena of learning and forgetting occurs in manufacturing systems (Towill, 1990; Alamri and Balkhi, 2007) and many learning models have already been developed (see section 3.9) there is some evidence that there is no learning effect in the forecasting function (Syntetos et al., 2009b). Klassen and Flores (2001) showed that there is no learning perspective from the organisation or from individual forecasters over time. Moreover, when examined the way of people to utilize contextual information in conjuction with time series to produce a forecast, Lim and O'Connor (1996) found that people did not seem to learn over time to modify their behavior when adjusting statistical forecasts. The findings above is supported by Nikolopoulos et al. (2006) when isvestigated an organisational and individual learning perspective within the organisation. This study reported the gaps in the learning loop within the company as there is no performance improvement over time of forecasting resulted by software system as well as the judgementally adjusted forecasts. On the other hand, Lee et al. (2007) suggested that forecasters often use information from analogous events from the past to help to estimate the effect of an anticipated special event. In terms of improving the performance of judgemental adjustments, Bolger and Wright (1994) interpreted the pattern of performance in terms of *ecological validity* and *learnability*. *Ecological validity* is the degree to which experts are required to make judgements inside or outside the domain of their professional experience. *Learnability* is the degree to which good judgement can be learned in a domain-related task. It is obvious that learning effects occurs in most inventory system since this system contain repetitive processes and incorporated human intervention in making stock control decision. Our study attempt to investigate this issue as the performance of inventory system may be improved by recognising the behaviour of manager in making adjustments on replenishment order decisions. Thus, the next research question is:

Q5. Is there any learning taking place in the process of adjusting stock control quantities and if so how?

In the forecasting area, it has been shown that combining the forecasts produced by different methods may lead to a performance that is better than that of the individual forecasts themselves (Makridakis and Hibon, 1979). The case study organisation implemented three replenishment order methods: *System OUT replenishment level*, the *SMA-Based OUT replenishment level*, and the *Final OUT replenishment level*. By combining these methods, it is reasonable to expect that the performance of the inventory system (service level, fill rate, and cost) may improve as compared to that resulting from the replenishment suggestions of a single method. Accordingly, our sixth research question is:

Q6. What is the effect of combining methods on the calculation of the OUT level?

Many organisations implement the SMA forecasting method because it is simple to use and is familiar to managers (Boylan and Johnston, 2003). The case study organisation employs SMA forecasting to calculate the SMA-based OUT replenishment level which in turns is taken into account (jointly with any external information) to adjust *System OUT replenishment level*. Hence, it will be interesting to discover the relationship between the SMA-based OUT replenishment level and the Final OUT replenishment level, and whether the influence of the former to the latter is statistically significant. Thus, the next research question is:

Q7. What is the explanatory power of the *SMA-Based OUT replenishment level* on the *Final OUT replenishment level*?

4.5. Research classification

According to Collis and Hussey (2009), research can be classified into four types, according to its purpose, its process, its logic and its outcome. The *purpose* of the research relates to the reason why it is conducted, while the *process* relates to the way in which the data were collected and analysed. The *logic* of the research involves the decision whether the research moves from the general to the specific or vice versa, and the *outcome* may be either the solution to a particular problem or a general contribution to knowledge. Table 4.1 presents the classification of research.

Table 4.1 Classification of main types of research

No	Basis of classification	Type of research
1	Purpose of the research	Exploratory, descriptive, analytical, or predictive research
2	Process of the research	Quantitative or qualitative research
3	Logic of the research	Deductive or inductive research
4	Outcome of the research	Applied or basic research

(source: Collis and Hussey, 2009, pp. 4)

Exploratory research is conducted when there are few or no earlier studies on the topic (Collis and Hussy, 2009). Cooper and Schindler (2002) add that exploratory study is useful when possible problems that might arise during the study are not clearly identified. Accordingly, the current study is exploratory in nature because the availability of literature on the phenomenon being investigated is very limited. Further, as far as we know, this study is the first to investigate the effects of human intervention on stock control decisions.

The process and logic of the research involve quantitative and semi-deductive research respectively. Details of the research process (or research choice) can be found in sub-section 4.6.4 and of the research logic (research approach) in sub-section 4.6.2.

By its outcome, this is applied research since the findings resulting from empirical data analysis are expected to solve a particular problem in inventory systems, and to improve management practice and policy in this area.

4.6. Research methodology

The description of the research methodology employed here follows the ‘Research Union’ conceptual framework proposed by Saunders et al. (2009). This approach enables a clear definition of any research process from the underlying philosophical considerations to the data collection and analysis methods. Before we introduce the various concepts underlying this research, an outline of the exact sequence of activities performed will better link the forthcoming discussion to the research itself.

Following a critical review of the literature, a number of research questions were developed to provide guidelines as to what sort of adjustments practitioners tend to perform. These might relate to their size, frequency, sign (positive or negative), and when the adjustments are performed. A link may be made to the underlying demand pattern and data characteristics; for example, people tend to adjust forecasts when demand is repeatedly high. An empirical database was then constructed to facilitate exploration of the extent to which the theoretical claims based on previous research might be sustained. This empirical database contained actual demand information, statistical forecasts, statistically-derived system replenishment decisions and judgementally adjusted replenishment decisions (and in many cases the adjustments were accompanied by a justification). As such, it enabled an exploratory analysis as well as simulating the effects of judgemental adjustments (using Visual Basic embedded in Excel).

After collection of all the information, the research questions are revisited and tangible suggestions made to practitioners. We will elaborate on the process discussed above later in this section, with a detailed diagram that presents the research.

4.6.1. Research philosophy

The research philosophy relates to the development of knowledge and the nature of that knowledge and contains important assumptions about the way we see the world (Saunders et. al., 2009). There are three major ways of thinking about research philosophy: epistemology, ontology and axiology (Saunders et al., 2009) and each philosophy can be seen as a continuum.

Epistemology is concerned with the study of knowledge and what we accept as being valid, in other words, examination of the relationship between the researcher and what is being researched (Collis and Hussey, 2009) or the relationship between the researcher and the participant (Teddlie and Tashakkori, 2009). Some scholars name the spectrum of epistemology differently, but the meanings are the same. Saunders et al. (2009) define the extremes of the spectrum of epistemology as positivism and interpretivism; Easterby-Smith et al. (2004) use the terms positivism and social constructivism, while Collis and Hussey (2009) refer to it as positivism and phenomenology.

Positivism is the epistemological position where the social world exists externally; it holds that its properties should be measured through objective methods (Easterby-Smith et al., 2004). Bryman and Bell (2011) and Denscombe (2010) relate positivism to the application of methods from natural science to the social sciences. On the other hand, interpretivism attempts to minimise the distance between the researcher and what is being researched (Collis and Hussey, 2009).

The current research aims to explore the effects of incorporating human judgement into inventory decision making. Data gathering involves the simulation results of the performance of judgemental adjustments in a real-world context. The focus is on the effect of those adjustments (analysis to be performed via simulation) which emphasises generalisation (although arguably such generalization may not be achievable). Hence, the epistemological assumptions of this research lie at the positivism pole.

Ontology relates to assumptions about the nature of reality (Collis and Hussey, 2009; Easterby-Smith et al., 2004 and Saunders et al., 2009). The ontology continuum spans objectivism to subjectivism. Objectivism assumes that social entities exist in reality externally to social actors, while subjectivism supports the notion that social phenomena stem from the perceptions and consequent actions of social actors (Saunders et al., 2009). Lincoln and Guba (1985) add that positivists believe that there is a single reality, while the constructivist or interpretivist defines reality as multiple. This research relies upon an objective (yet not necessarily generalisable) outcome of simulation analysis, so it is clear that on the ontological continuum objectivism is favoured.

Axiology is a branch of philosophy that studies the judgements being made about 'values' (Saunders et al., 2009). It is a continuum on which an assumption has to be made as to whether the research is 'value free' and unbiased or 'value laden' and biased (Collis and Hussey, 2009). As this research involves the quantitative output of well-structured simulation experiments (where the findings are, or the intention at least is to produce findings that are, unbiased), our axiological assumptions lie at the 'value free' pole.

Following this explanation of the differences between the three philosophies, Table 4.2 summarises the difference between positivist and interpretivist approaches in general (Lincoln and Guba, 1985), and Figure 4.14 depicts the philosophical positioning of this research.

Table 4.2 Contrasting positivist and interpretivist

Axioms about	Positivist paradigm	Naturalist (constructivist/ interpretivist) paradigm
Ontology: the nature of reality	Reality is single, tangible, and fragmentable	Realities are multiple, constructed, and holistic
Epistemology: the relationship of knower to the known	Knower and known are independent, a dualism	Knower and known are interactive, inseparable
Axiology: the role of values	Inquiry is value-free	Inquiry is value-bond

(source: Lincoln and Guba, 1985, pp. 8)

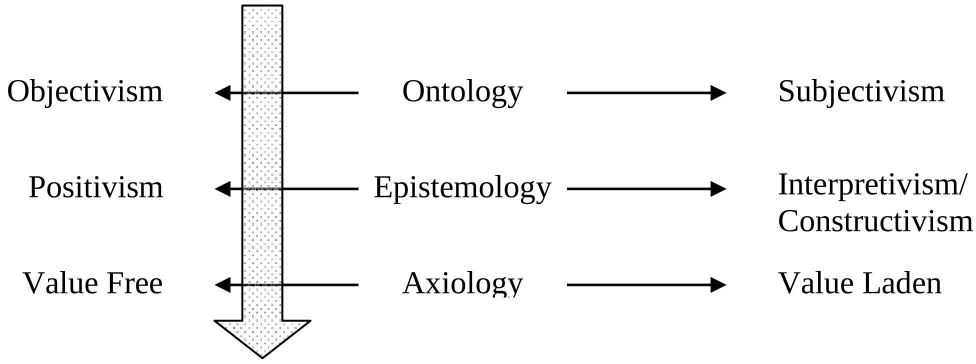


Figure 4.14 Philosophical positioning of the research

4.6.2. Research approach

Underneath the philosophical positioning of any piece of research lies the actual approach employed to address the research questions under examination. Such approaches may generally be classified as inductive or deductive (Saunders et al., 2009), a terminology which also comprises the logic of the research (Hussey and Hussey, 1997).

Bryman and Bell (2011) define the deductive approach as the relationship between theory and research in which the latter is conducted with reference to hypotheses and ideas inferred from the former. In the inductive approach, the former is generated out of the latter. In other words, induction refers to the process of starting with a particular case and potentially ending up with a claimed theory. The deductive approach, on the other hand, commences with a generalisable theory and attempts to assess the extent to which such a theory applies to a specific case. In more detail, deduction implies the development of a theory and hypothesis (or hypotheses) prior to the design of a research process to be employed for testing such hypotheses. According to the inductive approach, data is first collected and then a theory is developed as a result of data analysis. In business studies it is very rare that a research project is classified as either purely deductive or inductive. Usually, it falls somewhere between these two extremes. As stated by Cooper and Schindler (2002), deductive and inductive approaches are applied sequentially in a research project and can be combined. For example, the hypothesis is developed to explain the phenomenon in question, then a study is designed to test the hypothesis. In addition, Remenyi et al. (1998) argue that the relation between data and theory is complex and it is difficult to clearly justify which comes first. They explain that it is impossible to generate theory without data, but on the other hand data cannot be collected without a theoretical framework. In other words, we may say that both deductive and inductive approaches are commonly deployed together in management research to achieve the research objective.

Our approach may be characterised as semi-deductive; it is outlined in Figure 4.15 and then presented in more detail in Figure 4.16.

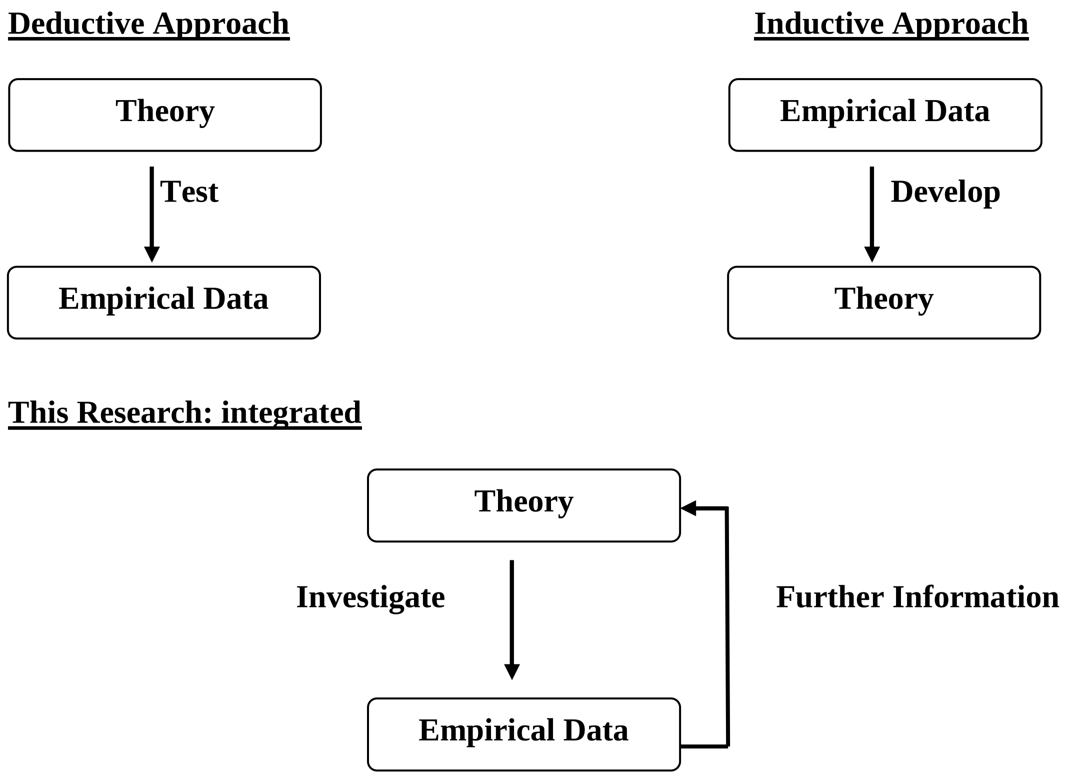


Figure 4.15An integrated (semi-deductive) research approach

First, we develop research questions based on the literature review. Since judgementally adjusted stock control decision theory is rare, we cite the underpinning theory of judgmental forecasting instead. This is valid because stock control and forecasting in inventory systems are closely related. Development of the research questions means that we are implementing the inductive approach.

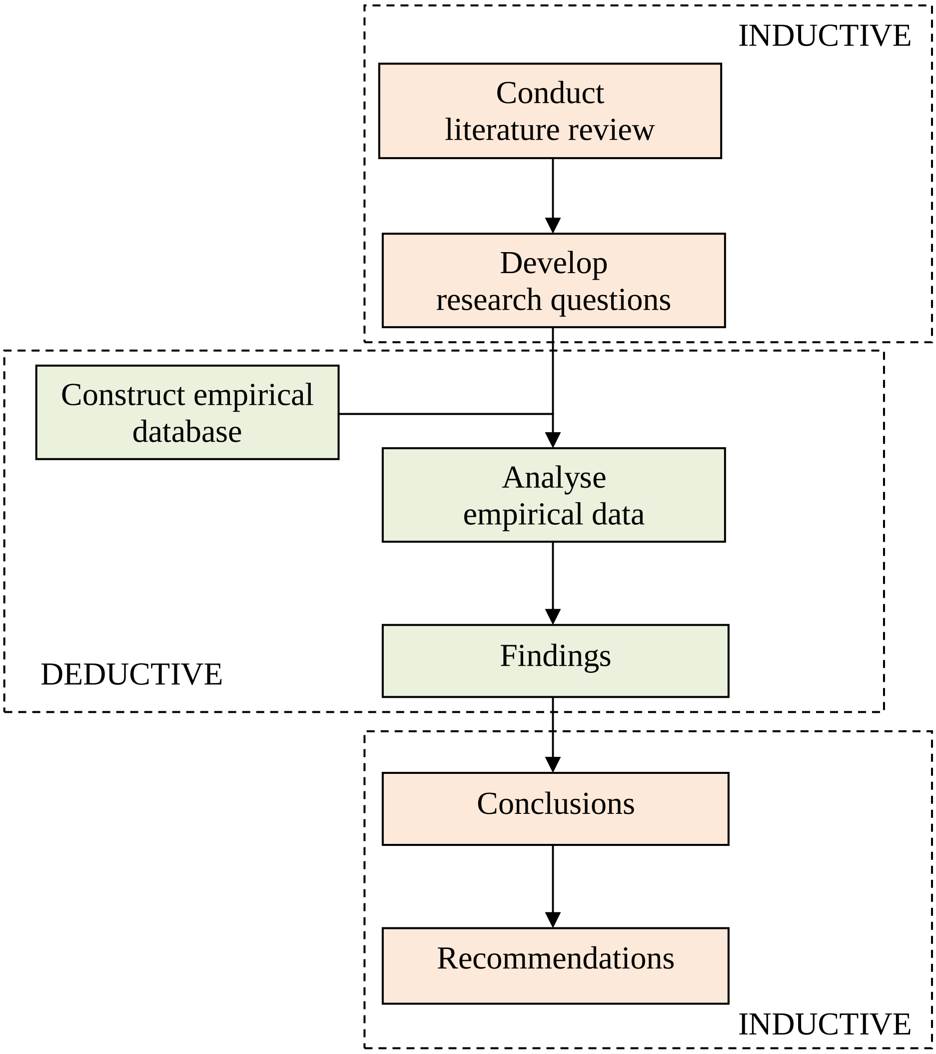


Figure 4.16 The research approach in detail

Furthermore, the exploratory analysis of the constructed empirical database addresses the research questions by conducting a simulation experiment. The simulation process, which will produce the findings of the research, is the deductive part. Finally, we use the findings to generate some conclusions; this means that we introduce knowledge to the theory from the data, a process which is clearly inductive.

4.6.3. Research strategy

A research strategy constitutes a general plan of how the researcher will go about answering the research questions (Saunders et al., 2009). There are many types of research strategies and various scholars classify them in different ways. For example, Saunders et al. (2009) refer to experiments, surveys, case studies, action research, grounded theory, ethnography and archival research. Bryman (2008) defines a research strategy as a research design which consists of five types: experimental design, cross-sectional or survey design, longitudinal design, case study design, and comparative design. Yin (2009) defines it as a method which can be placed into five categories: experiment, survey, archival analysis, history and case study. In addition, according to Yin (op.cit.), in choosing a research strategy there are three conditions to be considered: the type of research question, the extent of control an investigator has over actual behavioural events and the degree of focus on contemporary as opposed to historical events. Table 4.3 displays these conditions and their relation to research strategy.

Table 4.3 Relevant situations for different research methods

Method	Form of Research Question	Requires Control of Behavioural Events?	Focuses on Contemporary Events?
Experiment	How, Why?	Yes	Yes
Survey	Who, What, Where, How Many, How Much?	No	Yes
Archival Analysis	Who, What, Where, How Many, How Much?	No	Yes/No
History	How, Why?	No	No
Case Study	How, Why?	No	Yes

(source: Yin, 2009, pp. 8)

This research investigates contemporary events: the process of judgementally adjusting stock control decisions. The research involves a number of control parameters, upon which the performance of the inventory system is dependent and essentially sensitivity analysis is conducted to reach conclusions. As discussed by Cooper and Schindler (2002), if a researcher intends to investigate the effect of certain variables on other variables then the experimental method is appropriate. Further, this research involves the 'how' and 'why' questions as generated in section 4.4. These are answered by experiment and statistical analysis. Based on the above discussion, it is clear that the most suitable research strategy for this study is experiment.

4.6.4. Research choice

Saunders et al. (2009) use the term 'research choice' to distinguish the options available for data collection and data analysis. In general, the options are whether to use the qualitative method, quantitative method, or a combination of the two (Figure 4.17). Collis and Hussey (2009) refer to qualitative data as data in nominal form, and quantitative data as data in numerical form. The research that combines both the qualitative and quantitative methods is referred to as 'mixed method' (Teddlie and Tashakkori, 2009). Table 4.4 presents the differences in these three research choices.

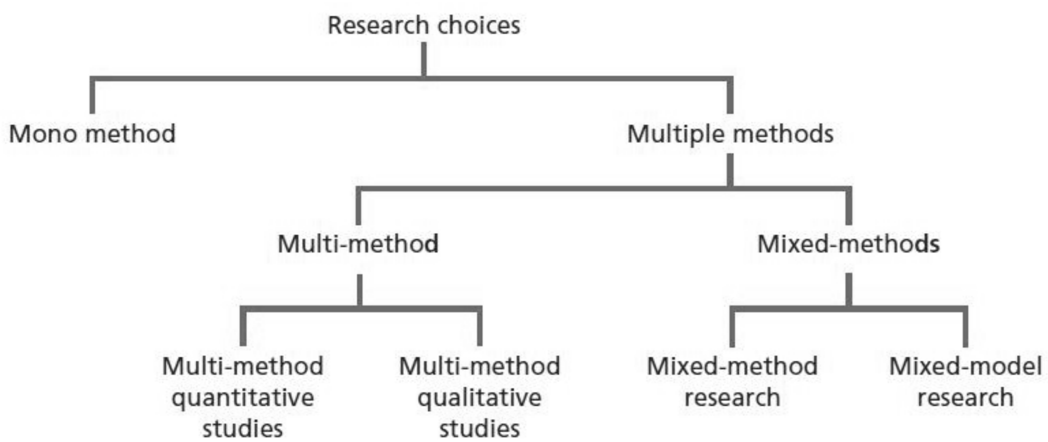


Figure 4.17 Research choices
(source: Saunders et al., 2009, pp. 152)

Table 4.4 Dimension of contrast among the three research choices

Dimension of contrast	Qualitative Position	Mixed Method Position	Quantitative Position
Methods	Qualitative methods	Mixed methods	Quantitative methods
Researchers	QUALs	Mixed methodologists	QUANs
Paradigms	Constructivism (and variants)	Pragmatism; transformative perspective	Postpositivism Positivism
Research questions	QUAL research questions	MM research questions (QUAN plus QUAL)	QUAN research questions; research hypothesis
Form of data	Typically narrative	Narrative plus numeric	Typically numeric
Purpose of research	(Often) explanatory plus confirmatory	Confirmatory plus exploratory	(Often) confirmatory plus exploratory
Role of theory; logic	Grounded theory; inductive logic	Both inductive and deductive logic; inductive-deductive research style	Rooted in conceptual framework or theory; hypothetico-deductive model
Typical studies or designs	Ethnographic research designs and others (case study)	MM designs, such as parallel and sequential	Correlational; survey; experimental; quasi-experimental
Sampling	Mostly purposive	Probability, purposive, and mixed	Mostly probability
Data analysis	Thematic strategies: categorical and contextualizing	Integration of thematic and statistical; data conversion	Statistical analyses; descriptive and inferential
Validity/trust worthiness issues	Trustworthiness; credibility; transferability	Inference quality; inference transferability	Internal validity; external validity

(source: Teddlie and Tashakkori, 2009, pp. 22)

Accordingly, in line with its research paradigm and in order to achieve the research objectives, this research adopts a single method approach, which is the quantitative approach. Data is in numerical form and is analysed using statistical methods.

4.6.5. Time horizons

The 'time horizon' is a term employed to analyse whether the research investigation focuses on one particular time or over a period of time. Saunders et al. (2009) describe the first as cross-sectional and the second as longitudinal study. In cross-sectional studies, the researcher examines one particular phenomenon at a particular time, whereas in longitudinal studies he/she examines changes in phenomena over a period of time.

This study does not intend to investigate changes in the phenomenon being analysed over time, or compare how the phenomenon changes from one particular time to another. Thus, the time horizon of the research is cross-sectional.

4.6.6. Research techniques

Research techniques refer to the method of collecting data and the procedures for analysis. In general, as the research strategy is experiment, data is gathered from one organisation that has relevant experience in judgemental adjustments, and more specifically from a company that can meet the aims and objectives of this research.

The quantitative information to be used for this study relates to an empirical database that contains, in a time-series fashion, historical demand information, statistical (system) forecasts, statistical (system) replenishment decisions and the judgemental adjustments superimposed on the system replenishments leading to the final replenishment decisions. Simulation may then be performed in order to evaluate in a dynamic fashion the added value (if any) of employing judgement. Details of the simulation process are presented in section 5.5. Using the database, we will be able to relate performance to the underlying demand characteristics, enabling us to provide an answer as to when adjustments are beneficial.

4.7. Conclusions

This research uses the data from an organisation representing the European Logistics head office of a Japanese electronics manufacturer. This organisation has implemented an ERP package, SAP R/3. This software is used to define the initial value of replenishment order decisions before it is adjusted by the managers based on external information. Empirical data from this case organisation and the process of adjustment of the order-up-to (OUT) levels was explained, followed by the construction of a database to facilitate empirical analysis through simulation. Finally, the research questions were formulated based on the literature review. These research questions will be addressed through the empirical data analysis presented in Chapter 5.

In this chapter we also discussed the research methodology followed in this work. The research paradigm of this study lies at the positivist end of the spectrum. It employs experiment as the research strategy and quantitative methods as the research choice.

Figure 4.18 summarises the methodological approach used in this study.

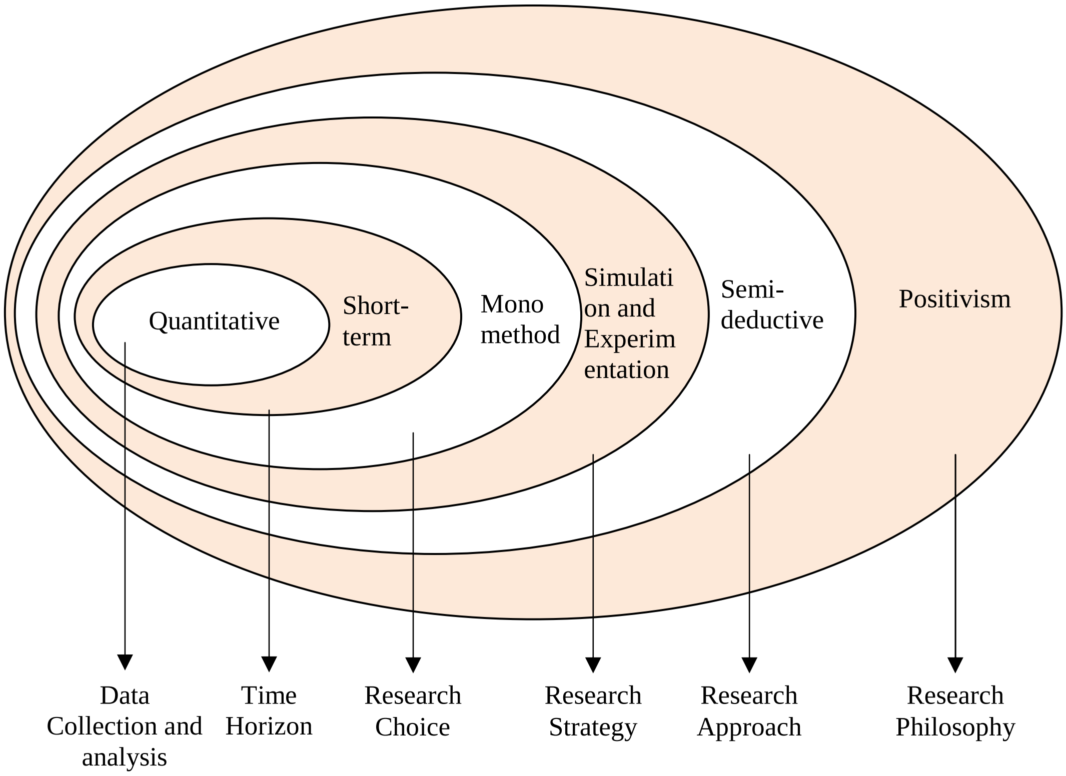


Figure 4.18 The research onion of this work

(source: Saunders et al., 2009, pp. 108)

Chapter 5. EMPIRICAL DATA ANALYSIS AND FINDINGS

This chapter describes the analysis of the Stock Keeping Units (SKUs) available for the purposes of this research (in terms of the demand data, prices etc), the judgemental adjustments performed to the Order-Up-To (OUT) levels and the justification provided by managers when performing adjustments. Analysis is also conducted, partly through simulation, to answer the research questions developed in the previous chapter.

The data was gathered from June 2009 to August 2011. In total, 359 A-class and 1,454 B-class SKUs are considered for the purposes of this research. The total number of SKUs appearance for the whole period was 4,661 times for A-class and 15,365 times for B-class. Since managers do not necessarily make adjustments (or provide justifications when they do so) for each and every period related OUT level, relevant data is extracted depending on the task (research questions addressed) out of the total database and analysed accordingly. Accordingly, adjustment of OUT level was made 1,461 and 2,958 times for A-class and B-class respectively.

5.1. Demand descriptive statistics

First, it is viewed as imperative to develop an understanding on the nature of the demand and its characteristics. Demand per period, demand sizes, and inter-demand intervals are considered for that purpose. The demand data characteristics are summarised in Table

5.1and Table 5.2 for the A and B items respectively. We present the key percentiles of the distribution of the mean, standard deviation (SD) and coefficient of variation (CV) for the three variable discussed above (demand, demand sizes and inter-demand intervals). The descriptive statistics are rounded to the 2nd decimal place.

Table 5.1 Demand data series characteristics for A items

1,461SKUs	Demand per period			Demand size			Demand Interval		
	Mean	SD	CV	Mean	SD	CV	Mean	SD	CV
Min	6.97	16.54	0.13	0.00	0.00	0.00	1.00[8]	0.00	0.53
25th percentile	24.79	77.26	0.26	1.58	1.79	0.59	1.00	0.00	1.57
Median	32.20	106.57	0.32	6.92	5.40	0.94	1.09	0.36	2.14
75th percentile	51.55	139.22	0.40	26.48	18.53	1.36	1.41	0.87	3.19
Max	104.53	470.24	0.70	1143.29	951.38	4.90	24.00	15.56	6.36

Table 5.2 Demand data series characteristics for B items

2,958 SKUs	Demand per period			Demand size			Demand Interval		
	Mean	SD	CV	Mean	SD	CV	Mean	SD	CV
Min	1.44	5.06	0.07	0.00	0.00	0.00	1.00	0.00	0.57
25th percentile	4.16	12.58	0.18	0.71	1.04	0.50	1.25	0.52	0.37
Median	5.21	21.52	0.24	2.04	2.62	0.69	1.77	1.07	0.57
75th percentile	6.65	34.25	0.34	5.54	7.06	0.95	3.00	2.06	0.75
Max	14.59	143.66	0.63	554.96	779.57	3.31	11.50	12.02	1.89

It can be seen from the tables that both the demand per period and demand size distributions are particularly skewed – please notice the considerable differences between the 75th percentile and the maximum. The same is true for the average inter-demand intervals the distribution of which for the A-items is graphically presented in Figure 5.1.

[8] The number of SKUs with demand interval value=1 is 38% for A-class

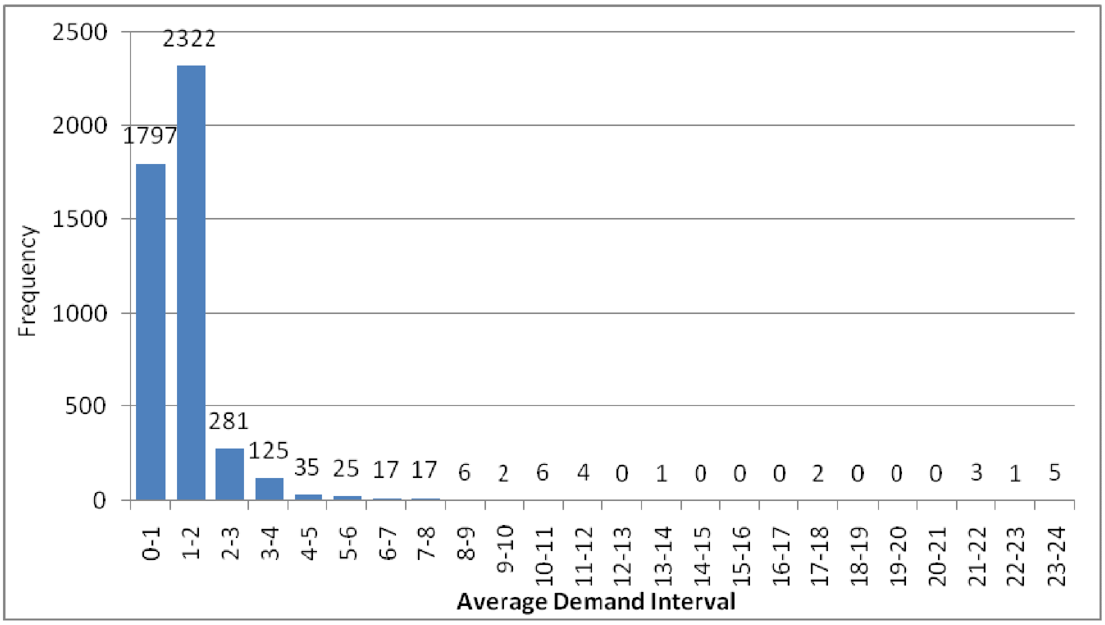


Figure 5.1 The distribution of average inter-demand interval for A items.

Intermittent demand (and demand size/inter-demand interval) distributions are indeed known to be very skewed and previous empirical studies have confirmed such a fact (Syntetos et al., 2009b, 2010a, 2010b; Teunter et al., 2010; Nikolopoulos et al., 2011). For a summary of arguments on this issue of statistical distributions in an intermittent demand context please refer to Syntetos et al. (2012). As expected the demand sizes for the A items appear to be (considerably) higher than those related to the B items whereas the inverse is true with regards to the inter-demand intervals.

5.2. Price of the SKUs

Information related to SKU prices[9] has been made available to us by the company. There are 359 and 1,454 SKUs for A and B items respectively. The price varies between €0.02

[9] Please note that those are final selling prices as opposed to cost information that is typically available in empirical studies. We argue that profit margins are relatively constant in a service parts context rendering prices differing from cost by a constant amount across all SKUs. This is important when we analyse inventory costs and implications since inventory theory has been built upon item costs, and inventory holding costs are calculated taking into account the cost of an items not its price.

and €254.85 for A items and €0.02 and €425.44 for B items. Table 5.3 shows the range of service[10] parts prices for the A and B items.

Table 5.3 Spare parts prices for A items and B items.

Description	A items (€)	B items (€)
Min	0.02	0.02
25th percentile	5.69	0.87
Median	19.09	4.09
75th percentile	35.67	18.12
Max	254.85	425.44

It can be seen from Table 5.3 that the range of prices for the B items is wider than that related to the A items with the maximum price being almost twice as big. The price of material is an important factor to be considered since the case organisation carried out the SKUs classification based on demand value (volume × price). In this classification method, SKUs are distinguised based on their value or benefit to the organisation, as a result the items that have more value get more attention from manager.

Regarding the judgemental adjustments performed by managers on the OUT levels it seems that they have not been taking into account the price of the relevant SKUs when coducting such adjustemnets. This can be seen from the justification asscociated with them. Most of the reasons provided for adjusting the OUT levels are merely related to the demand for spare parts (or in fact the perceived demand for spare parts), their inventory position, and/or replenishment orders related information, but not the SKU prices. We return to this issue in section 5.4, where the justifications of judgemental interventions are discussed.

There are a number of studies commenting on the importance of cost analysis in an inventory control context. Teunter et al. (2010) proposed a new cost criterion for ranking SKUs which takes criticality of SKUs into account through the shortage cost. In most practical situations, the measurement of criticality is based on the rate of demand value

[10] The words ‘service’ and ‘spare’ parts are used interchangeably in this research.

(price multiplied by demand volume) or the demand volume for an SKU or the functioning of a spare part of equipment in the service/maintenance industries. By conducting experiments using three real-life datasets, it was found that the cost criterion outperformed the traditional demand value and demand volume criteria and also a criterion proposed by Zhang et al. in 2001 for minimising the safety stock cost. The results indicate the inventory cost reductions resulting from employing the new approach with no penalty in the customer service level achieved. Syntetos et al. (2009a) proposed a modified periodic OUT-level policy that relies on inter-demand intervals and demand sizes, when demand occurred. This policy is employed in a simulation experiment using actual lead-times and unit cost information. The results indicate the inventory cost reduction resulting from the employment of the new approach. In another study, Syntetos et al. (2010b) explored forecasting- and stock control-related opportunities for increasing service levels and reducing costs in the wholesale context. There are still no studies that discuss the relation between cost and judgementally adjusted stock control decisions.

Figure 5.2 and Figure 5.3 present the distribution of the SKU prices for the A and B items respectively.

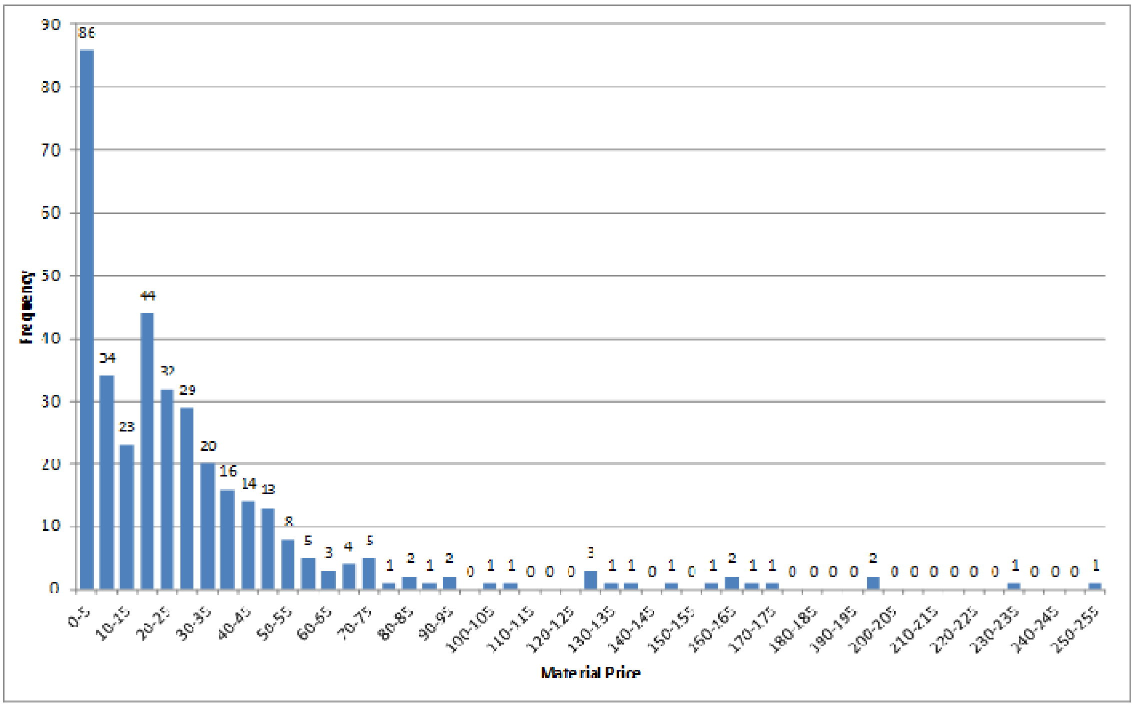


Figure 5.2 Distribution of material price for A items

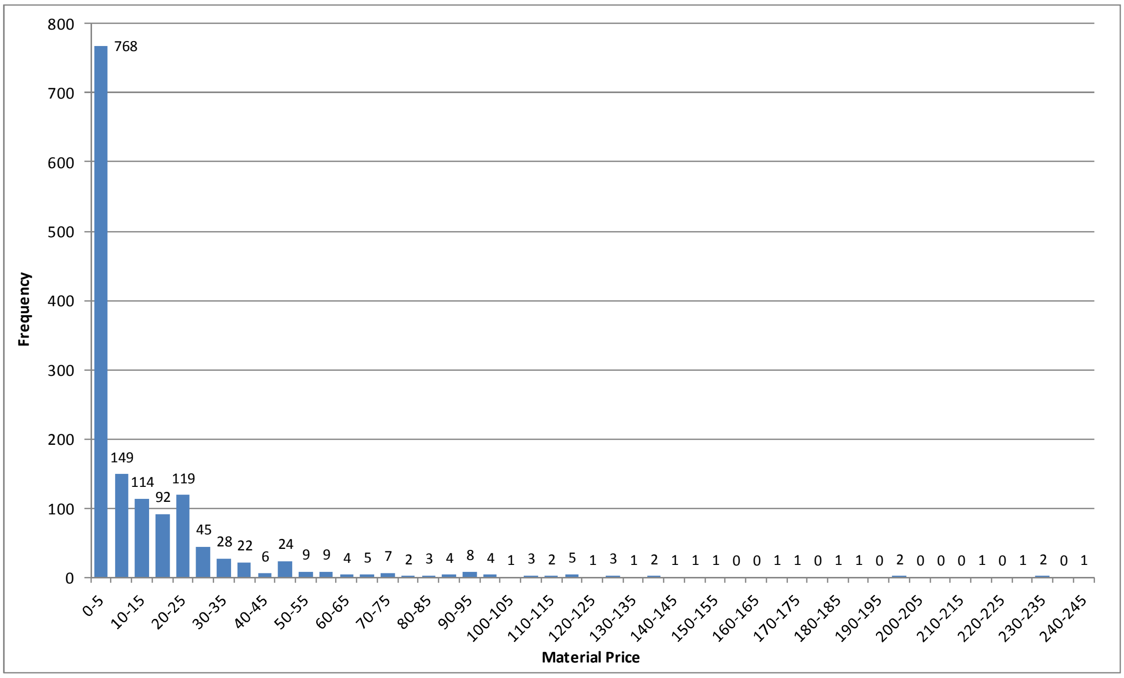


Figure 5.3 Distribution of material price for B items

It can be seen (as already discussed in Table 5.3) that B items are associated with a higher cost (price). However, B items have been also shown to be (by the very definition of the ABC classification performed by the company) more intermittent in nature, resulting presumably in higher obsolescence and having a much greater impact on stock stock-holding costs. Although A items are ‘officially’ defined as more important in terms of frequency of occurring, B items may in fact require more attention from managers with regards to stock control. These findings are in line with the theories reviewed in Chapter 2.

5.3. Analysis of judgemental adjustments

In this section we conduct an analysis of the adjustments performed on the initial-OUT level in every inventory period. Correspondingly, the magnitude of the adjustments (and their sign) may be calculated by observing the difference between two consecutive Final OUT replenishment levels. Please recall, that the initial OUT level in each period is judgementally adjusted (taking also into account the SMA-based OUT replenishment level) and that results into the Final OUT replenishment level (that is used for stock control purposes) that is used as the initial one in the next time period.

Adjustments are assessed and analysed in terms of the distribution of their signed size, absolute size, relative signed sizeand relative absolute size, to capture collectively the characteristics of both magnitute and direction (both in absolute and relative terms, the latter relating to the level of the demand). The relative signed size and absolute size are calculated by divided the difference between successor and predecessor Final OUT replenishment levels over the predecessor Final OUT replenishment level. The goodness-of-fit of various plausible theoretical statistical distributions is analysed using the Kolmogorov-Smirnov (K-S) test. The K-S test is chosen since there is no requirement for grouping the data into categories, which is limiting requirement associated for example with the Chi-Square test. When applying the Chi-Square test, the data needs to be grouped into categories to ensure that each is associated with an expected frequency of a minimum of a certain number of observations (Syntetos et al., 2012; Lengu, 2012). Since the demand nature of data used in this study is intermittent, consequently the adjustment data is also intermittent, it would be difficult to meet the minimum and average expected frequencies of the categories. Moreover, the critical values used in the K-S goodness-of-fit test are independent of the hypothesised distribution. This means that the test does not rely on assumptions that the data is drawn from a particular probability distribution. Thus, the computation required when using the K-S test is simple and less time-consuming.

However, the K-S test assumes continuous distributional functions, which is not in accordance with the random variables to be tested (adjustments). This is a major drawback although we would very much like anyway to consider continuous distributions due to the fact that they are generally more flexible than discrete distributions and they do provide good approximations. For a summary of arguments in favour of the K-S test the interested reader is referred to Lengu (2012).

We consider distributions with no more than 2 parameters. The number of parameters is limited to two to reflect a trade-off between goodness-of-fit and computational requirements. Single or two-parameter distributions are easier to handle and in an inventory control context they constitute the norm. The goodness-of-fit tests are conducted by deploying the *EasyFit* Software. There are nine theoretical distributions that have been considered, for both the absolute and signed cases analysed. In the former case, distributions defined only in the positive domain have been considered. These distributions are shown in Table 5.4. The critical values have been computed based on K-S statistical tables for 1% and 5% significant levels. We consider that: i) there is a 'strong fit' if the P-value is less than the critical value for 5%; ii) there is 'good fit' if the P-value is less than the critical value of 1% but larger than that for 5%; and iii) there is a 'no fit' if the P-value is larger than the critical value for 1%.

Table 5.4 Theoretical distributions being tested

No.	Absolute size and relative absolute size adjustments	Signed size and relative signed size adjustments
1	Cauchy	Cauchy
2	Exponential	Error function
3	Gamma	Gumbel max
4	Gumbel max	Gumbel min
5	Gumbel min	Logistic
6	Logistic	Normal
7	Normal	Uniform
8	Uniform	Hypersecant
9	Weibull	Laplace

5.3.1. Goodness-of-fit tests and distributional considerations

Considering that managers have not been performing adjustments in every period for each SKU, we end up with 1,461 (31.35%) and 2,958 (19.25%) adjustments for the A and B items respectively. The goodness of fit tests indicate that none of the distributions provide a strong fit when all the adjustments are considered collectively across the two classes of items. That is, we have first attempted to assess a potential goodness of fit on all the adjustments performed in the A and B items (separately for each category). This was partly expected since adjustments should relate closely to the characteristics of a particular SKU. However, we did wish to check for any 'universal' conclusions. The results indicate that adjustments have to be considered separately for each SKU and we return to this issue later in this sub-section. The detailed results of the goodness-of-fit testsdiscussed above are shown in *Appendix E*and the summary of the best fitting distributions can be seen in Table 5.5.

The distribution of the signed size of adjustments, absolute size of adjustments, relative signed size and relative absolute size and the fitted distributions for the A items are indicated in Figure 5.4, Figure 5.5, Figure 5.6, and Figure 5.7, respectively. For all distribution graphs, the horizontal axis (*x*) represents the interval of adjustment data and the vertical axis (*f*(*x*)) represents the probability density function (PDF) of the theoretical distribution (please see Table 5.5 for the best fitting distribution) and the number of adjustments in the corresponding interval.

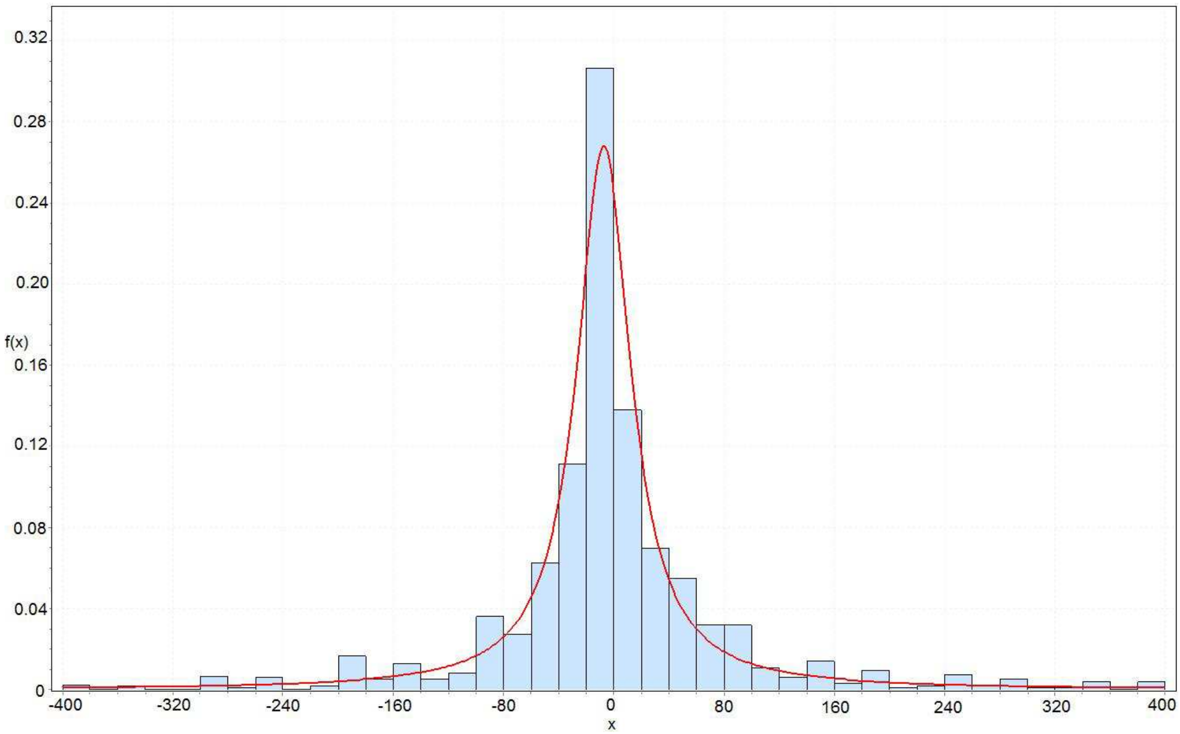


Figure 5.4 Distribution of the signed size of adjustments for A items

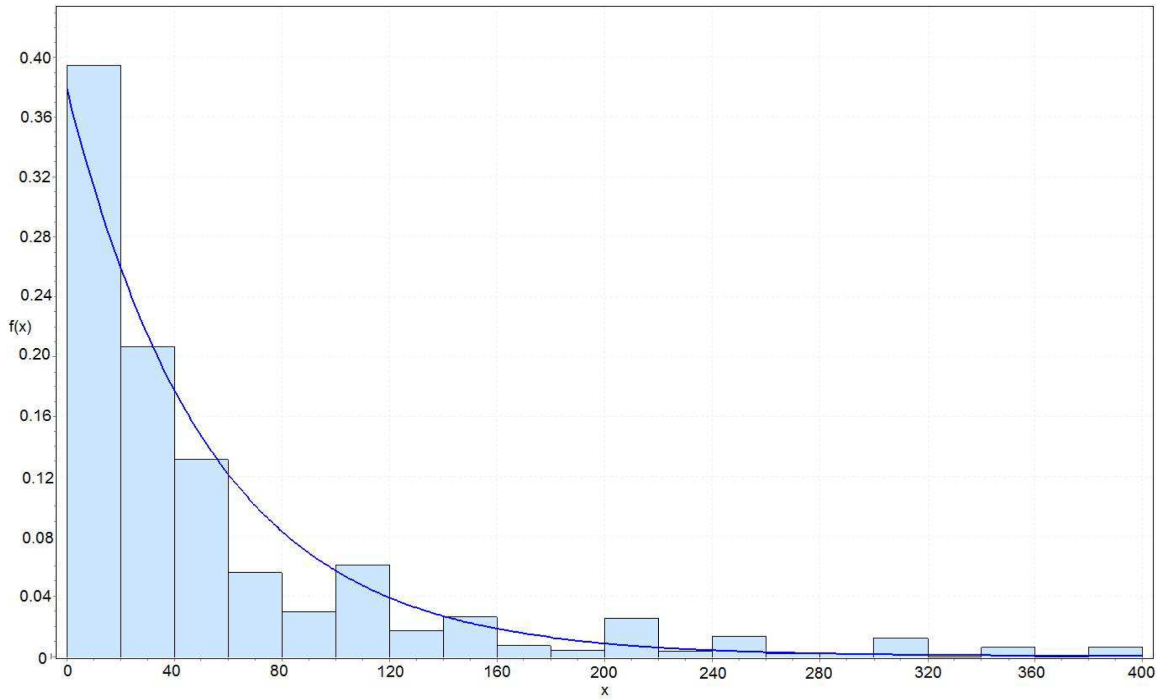


Figure 5.5 Distribution of the absolute size of adjustments for A items

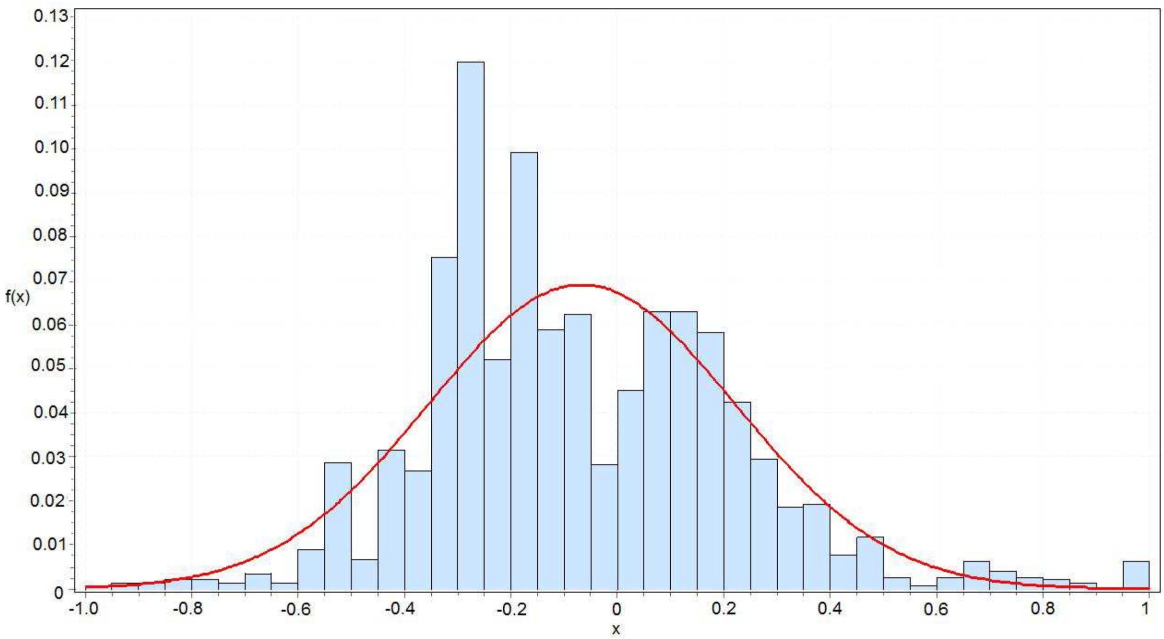


Figure 5.6 Distribution of the relative signed size of adjustments for A items

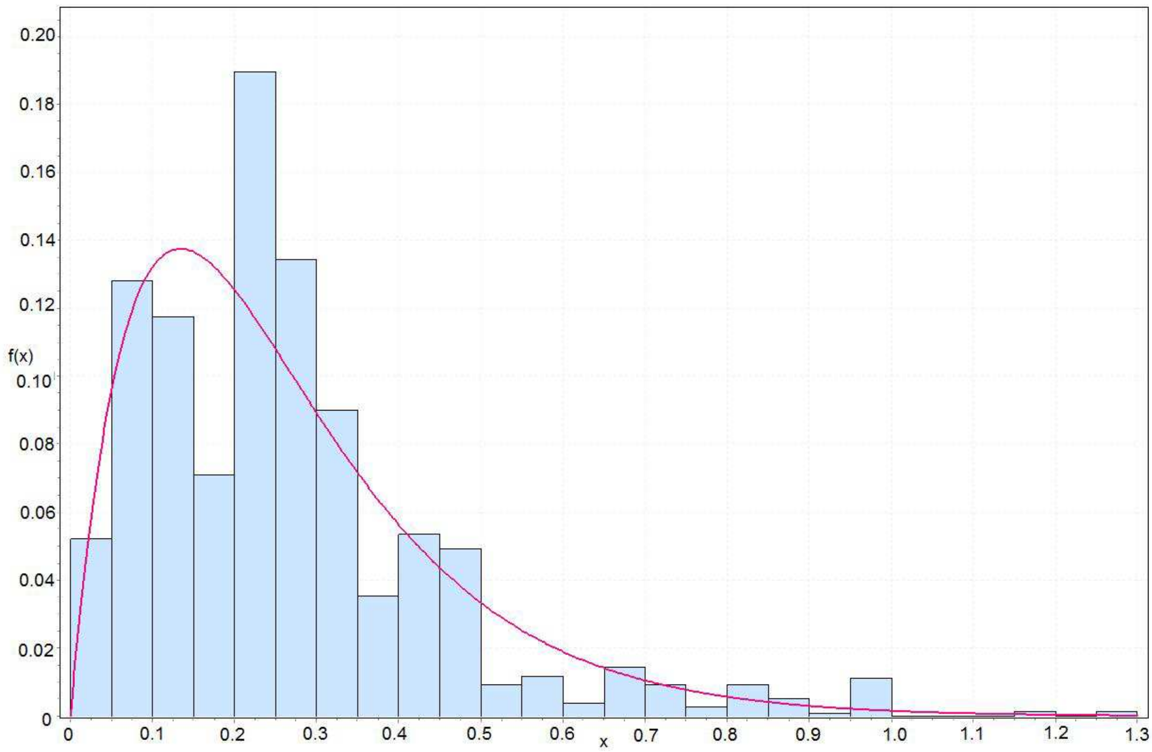


Figure 5.7 Distribution of the relative absolute size of adjustments for A items

Figure 5.4 indicates that most decisions made by the managers related to decreasing the OUT level up to 20 units (29.23% of total decisions). For the absolute size of adjustments, it was similarly found that those are associated with a mode interval of [0 – 20] units (Figure 5.5).Relatively small adjustments are known to be very popular in the forecasting domain representing mostly reaction to noise or a need on the part of the forecaster (stock controller in this case) for a sense of ownership of the process. However, a qualification of ‘small’ is required here that may not be perceivable unless a ‘relative’ analysis is performed.

Figure 5.6 and Figure 5.7 show the relative signed size and relative absolute size of adjustments. There are two considerable spikes in the former case, where the mass function though is indeed concentrated in the centre. On the other hand, the relative absolute size of adjustments seems to peak at [20% – 25%]. The above analysis, confirms previous results in the forecasting literature on the prevalence of relatively small adjustments.

The distribution of the signed size of adjustments, absolute size of adjustments, relative signed size and relative absolute size of B items is shown in Figure 5.8, Figure 5.9, Figure 5.10, and Figure 5.11 respectively.

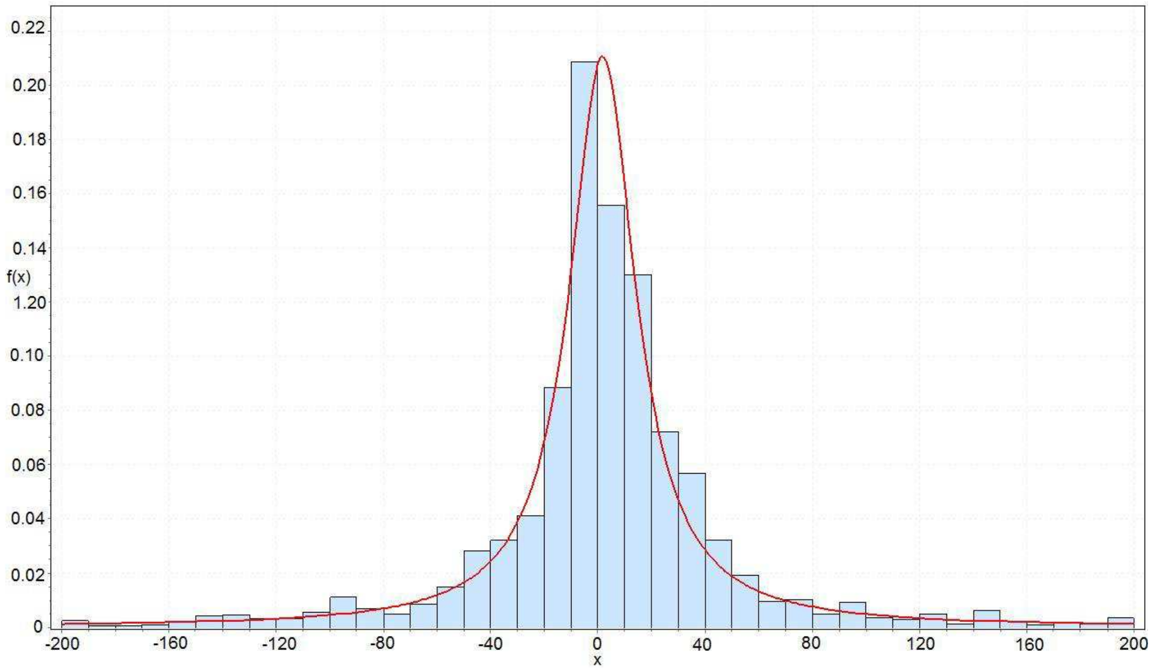


Figure 5.8 Distribution of the signed size of adjustments for B items

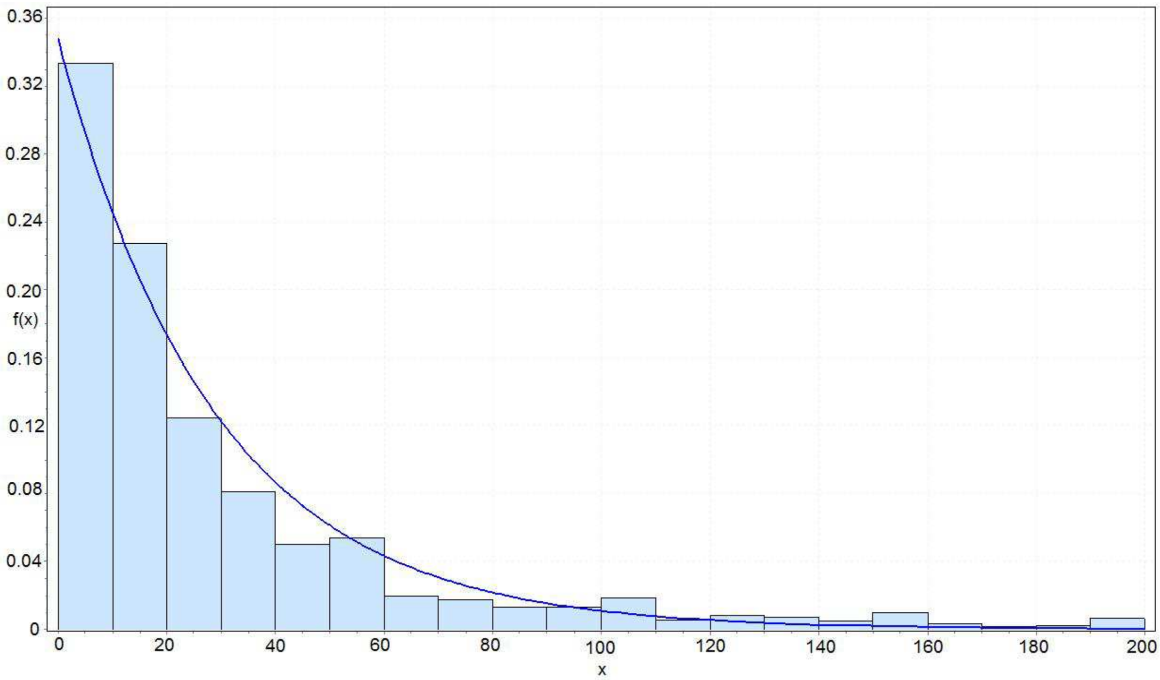


Figure 5.9 Distribution of the absolute size of adjustments for B items

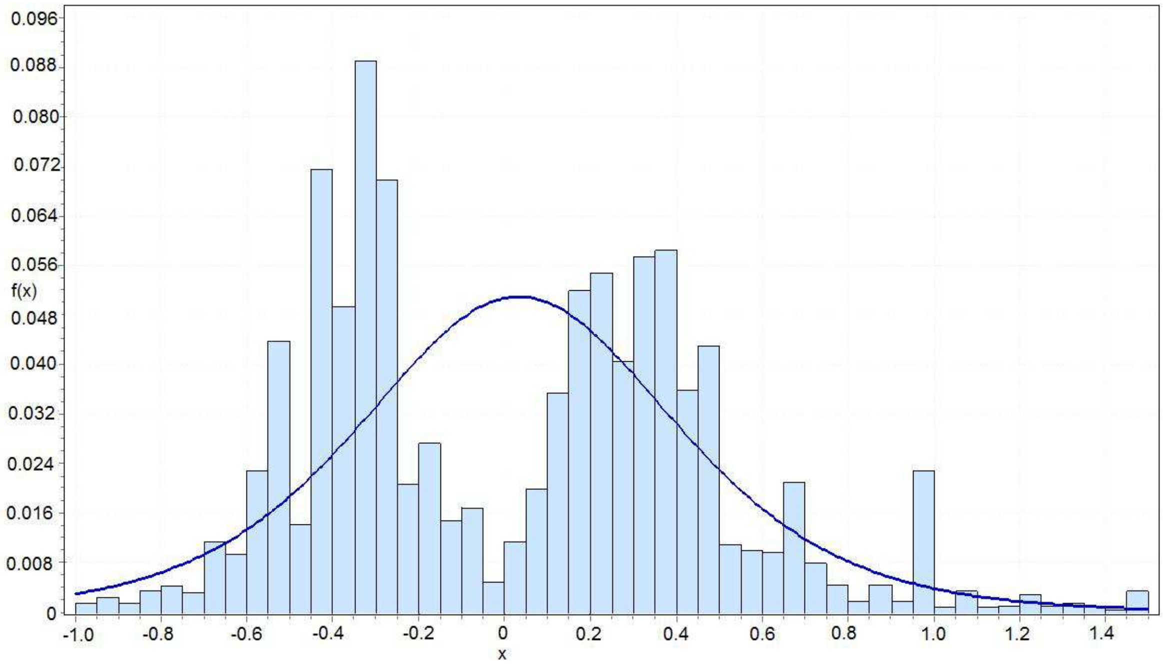


Figure 5.10 Distribution of the relative signed size of adjustments for B items

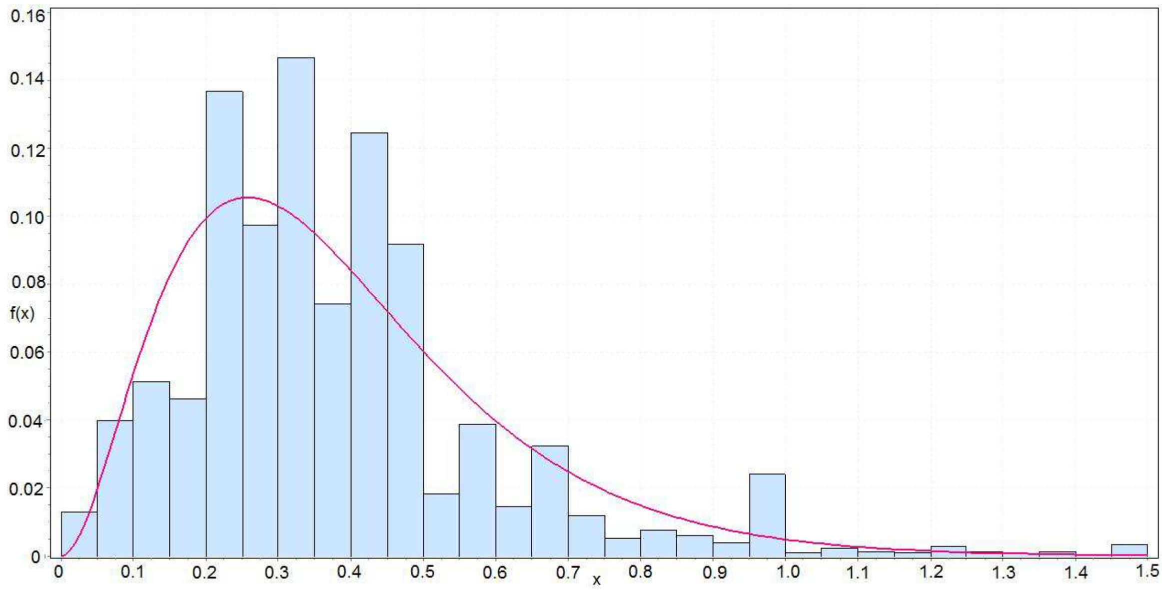


Figure 5.11 Distribution of the relative absolute size of adjustments for B items

Figure 5.8 shows that the most frequent decisions made by the manager are to increase the OUT level by 0 – 10 units; these constitute nearly 20% of all decisions. In line with this, the absolute size of adjustments also indicates that 1,175 (39.72%) of decisions are to increase/reduce the OUT level within the range of [0–10] units.

In relative terms, and similar to the patterns identified for the A items, the distribution of the relative signed adjustments in B items is associated with two spikes. The peak related to negative and positive adjustments occurs at the [-30% – -35%] (261 judgements) and [35% –40%] (189 judgements) interval respectively. The relative absolute size of the adjustments is [30% and 35%]. It seems that greater adjustments are performed for the B items rather than A and this may be related to the greater eventual importance of such items from a stock control perspective (both in terms of obsolescence and stock holding costs) discussed earlier in this chapter. The above analysis is summarised in Table 5.5 where the best fitting distributions for each case is also indicated.

Table 5.5 Adjustment distributions for A items and B items.

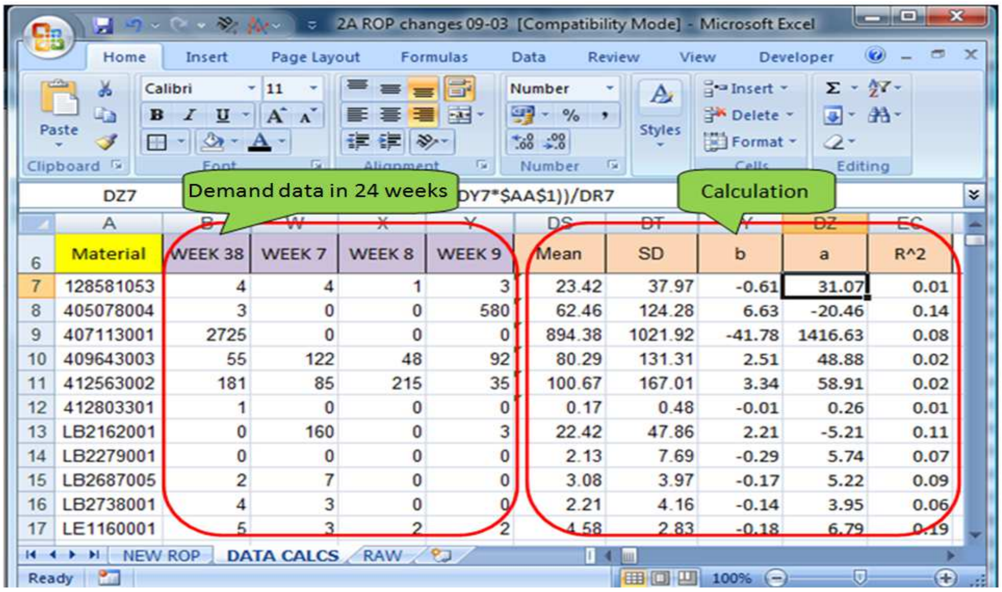
	A items	B items
Signed size of adjustment	• Most adjustments are between 0 – -20 units • Cauchy distribution	• Most adjustments are between 0 – 10 units • Weibull distribution
Absolute size of adjustment	• Most adjustments are between 0 – 20 units • Gamma distribution	• Most adjustments are between 0 – 10 units • Gamma distribution
Relative signed size of adjustment	• Most adjustments are between -25% – -30% (negative adjustments) and 5% – 15% (positive adjustments) • Cauchy distribution	• Most adjustments are between -30% – -35% (negative adjustments) and 35% –40% (positive adjustments) • Cauchy distribution
Relative absolute size of adjustment	• Most adjustments are between 20% – 25% • Gamma distribution	• Most adjustments are between 30% – 35% • Cauchy distribution

Returning to the issue of the goodness of fit, since there is no single theoretical distribution (from those assessed in this study at least) that fits (strongly) the adjustments when those are considered across SKUs, goodness-of-fit tests were conducted for each SKU (across time) separately. There are 138 SKUs considered for these purposes in the A category and 325 B-class items. The criterion for selection is based on SKUs that have at least five adjustments. For the A items it is found that the Cauchy distribution provides a strong fit for most series of signed sizes of adjustment (80.0 %) and relative signed sizes of adjustment (83.8%), whereas the Gamma distribution provides a strong fit for the absolute size of adjustments (76.3%) and the relative absolute size of adjustments (88.8%). Similar results are reported for the B items, where the Cauchy is associated with a strong fit for 95.0% of the relative signed size of adjustments and the relative absolute size of adjustment (95.0%). The Gamma distribution offers a strong fit for the absolute size of adjustments (97.5%), whereas the Weibull distribution performs very well on the signed size of adjustments (95.0% cases of strong fit). The detailed results are presented in Appendix F.

Knowledge of particular distributions that provide a good fit to the adjustments is extremely useful towards the design of relevant decision support systems (DSS). Since the parameters of the distributions can be calculated based on past data (past adjustments) percentiles may be specified that relate to, for example, authorization points. That is, adjustments greater than *x* amount (expressed either in signed/absolute or relative terms) need to be authorized whereas adjustments below the authorization point may be freely conducted. In forecasting area, Fildes et al. (2009) revealed that small adjustment (less than 10% relative to the baseline forecast) affected the forecast accuracy negatively because this group of adjustments only response to noise.

5.4. Analysis of the justification of adjustments

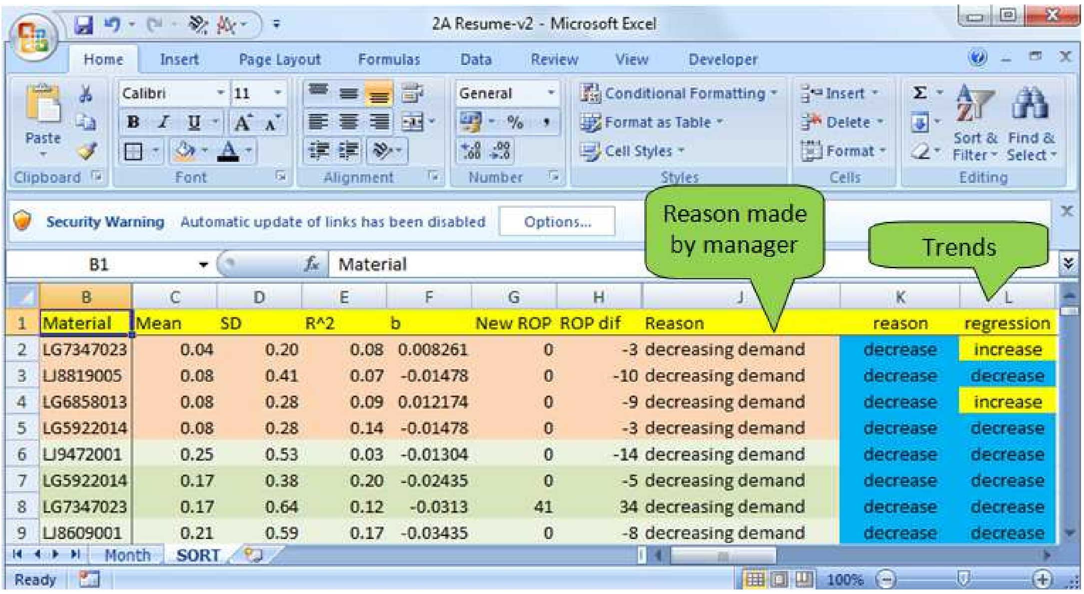
In this section we consider the justifications provided for performing adjustments and this is perceived as a contribution on its own since no similar analysis has been conducted in the past neither in the field of forecasting nor obviously in the field of inventory control. The majority of the justifications provided for adjusting the OUT levels relate to perceived changes in the underlying demand patterns; managers will indicate ‘increasing’ or ‘decreasing’ demand as the reason for altering the OUT levels. A linear regression analysis is considered using the past 24 weeks' demand data (for each point of intervention/ adjustment when such a justification has been provided) to assess whether or not a non stationary behaviour (positive or negative slope) is present on the data. An example of this analysis can be seen in Figure 5.12 where we indicate the Excel presentation of the results in terms of the calculation of the intercept (a) and slope (b). Due to the shortness of the demand data available, no attempts have been made to assess the statistical significance of the regression results.



	Material	WEEK 38	WEEK 7	WEEK 8	WEEK 9	Mean	SD	b	a	R^2
7	128581053	4	4	1	3	23.42	37.97	-0.61	31.07	0.01
8	405078004	3	0	0	580	62.46	124.28	6.63	-20.46	0.14
9	407113001	2725	0	0	0	894.38	1021.92	-41.78	1416.63	0.08
10	409643003	55	122	48	92	80.29	131.31	2.51	48.88	0.02
11	412563002	181	85	215	35	100.67	167.01	3.34	58.91	0.02
12	412803301	1	0	0	0	0.17	0.48	-0.01	0.26	0.01
13	LB2162001	0	160	0	3	22.42	47.86	2.21	-5.21	0.11
14	LB2279001	0	0	0	0	2.13	7.69	-0.29	5.74	0.07
15	LB2687005	2	7	0	0	3.08	3.97	-0.17	5.22	0.09
16	LB2738001	4	3	0	0	2.21	4.16	-0.14	3.95	0.06
17	LE1160001	5	3	2	2	4.58	2.83	-0.18	6.79	0.19

Figure 5.12 Slope of demand pattern

Once the behaviour of the data has been established, a comparison is conducted with the justification provided in order to assess their consistency; please see Figure 5.13.



	Material	Mean	SD	R^2	b	New ROP	ROP dif	Reason	reason	regression
2	LG7347023	0.04	0.20	0.08	0.008261	0	-3	decreasing demand	decrease	increase
3	LJ8819005	0.08	0.41	0.07	-0.01478	0	-10	decreasing demand	decrease	decrease
4	LG6858013	0.08	0.28	0.09	0.012174	0	-9	decreasing demand	decrease	increase
5	LG5922014	0.08	0.28	0.14	-0.01478	0	-3	decreasing demand	decrease	decrease
6	LJ9472001	0.25	0.53	0.03	-0.01304	0	-14	decreasing demand	decrease	decrease
7	LG5922014	0.17	0.38	0.20	-0.02435	0	-5	decreasing demand	decrease	decrease
8	LG7347023	0.17	0.64	0.12	-0.0313	41	34	decreasing demand	decrease	decrease
9	LJ8609001	0.21	0.59	0.17	-0.03435	0	-8	decreasing demand	decrease	decrease

Figure 5.13 Comparison between trends and reason for judgement made by manager

There are 1,461 A-class (31.35%) and 2,958 B-class SKUs (19.25%) associated with a justification (reason provided) for adjusting an OUT level. 1,160 (79.40% of those) A-class SKUs relate to a consistency between what was identified by the managers and what our analysis has shown. That is, there was for example an increasing demand when such an increase was perceived by the managers. However, there was a great proportion of SKUs (20.6%) associated with the managers seeing a direction in the evolution of the demand series opposite to what was actually happening (184 demand patterns perceived as increasing, when in fact demand was decreasing, and 117 demand patterns where the opposite was the case).

For B-class SKUs, there are 2,234 (75.52%) cases where the justification and actual behaviour of the series were in accordance and 724 (24.48%) cases where a wrong direction of the demand data was perceived (388 decreasing demand patterns were perceived as increasing, and 336 increasing demand patterns were perceived as decreasing).

Figure 5.15 show inconsistencies between the demand data pattern and the reason provided by the decision maker for justifying his/her adjustments.

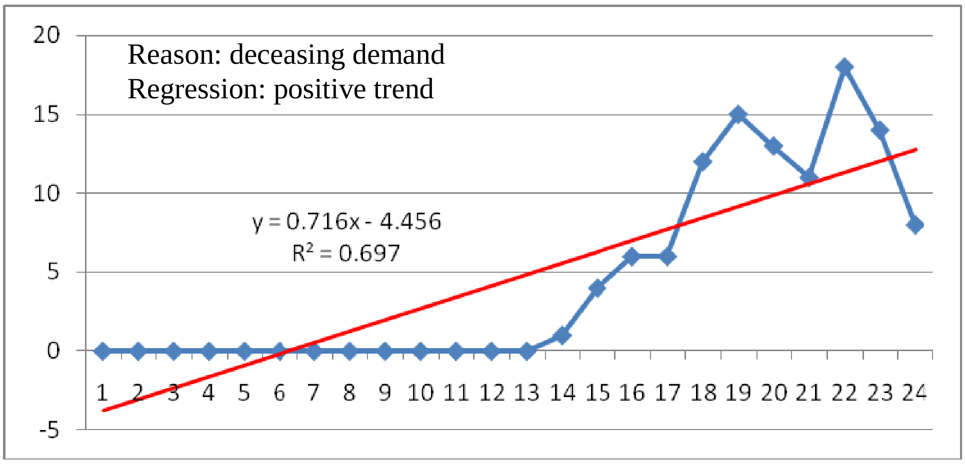


Figure 5.14 Example of inconsistency (the reason for making an adjustment is 'decreasing demand' while the demand is increasing over time)

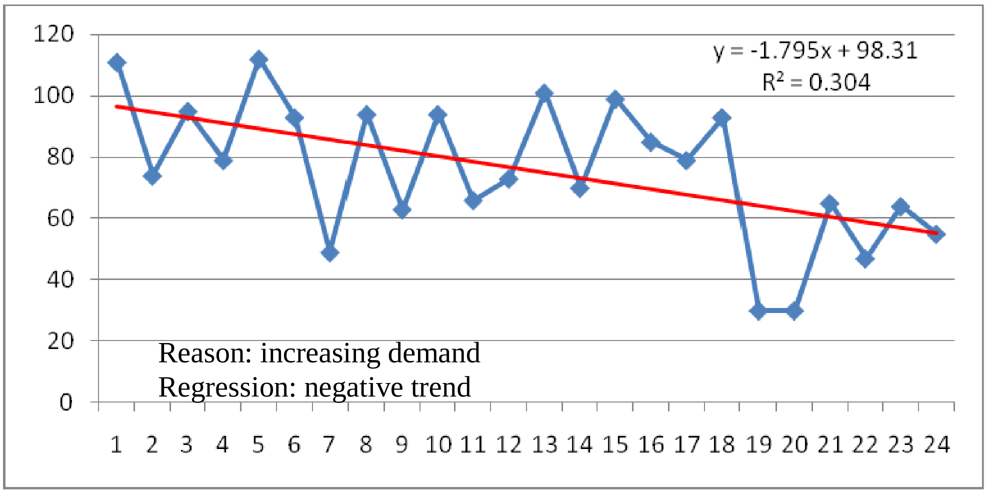


Figure 5.15 Example of inconsistency (the reason for making an adjustment is 'increasing demand' while the demand is decreasing over time)

Following from the analysis conducted above, we have attempted to cluster all the justifications into conceptually uniform categories, resulting in 24 such categories. These categories are presented in Table 5.6 and Table 5.7 for the A and B items respectively. Details related to the explanations provided by managers for each category can be found in *Appendix G*. Excluding the adjustments associated with no justification, the main reason behind performing adjustments is associated with a perceived decreasing (40.9%, 45.45%) or increasing (16.6%, 42.79%) demand items (for the A and B class items respectively). Figure 5.16 and Figure 5.17 present the distribution of the number of judgements for every category of justifications for the A and B items respectively.

Table 5.6 Number of adjustments per justification category(A items)

No.	Code	Reason	Number of adjustments	Percentage of adjustments
1	10	I-No reason	288	19.7%
2	11	I-Backorder	24	1.6%
3	12	I-Low stock	2	0.1%
4	13	I-Certain period	0	0%
5	14	I-Steady demand	0	0%
6	15	I-Increasing demand	242	16.6%
7	16	I-Order spike	8	0.5%
8	17	I-Min ROP	0	0%
9	18	I-Large demand	0	0%
10	19	I-ROP too low	0	0%
11	40	I-Flat demand	0	0%
12	41	I-Replacement part	2	0,1%
13	42	I-Not classified yet	1	0.1%
14	20	D-No reason	276	18.9%
15	21	D-Order spike	4	0.3%
16	22	D-Steady demand	0	0%
17	23	D-Decreasing demand	598	40.9%
18	24	D-Min ROP	0	0%
19	25	D-Running down stock	1	0.1%
20	26	D-Slow demand	0	0%
21	27	D-Hardly demand	1	0.1%
22	28	D-Replacement part	6	0.4%
23	29	D-Bulk order	4	0.3%
24	30	D-Not classified yet	4	0.3%

I=increase, D=decrease

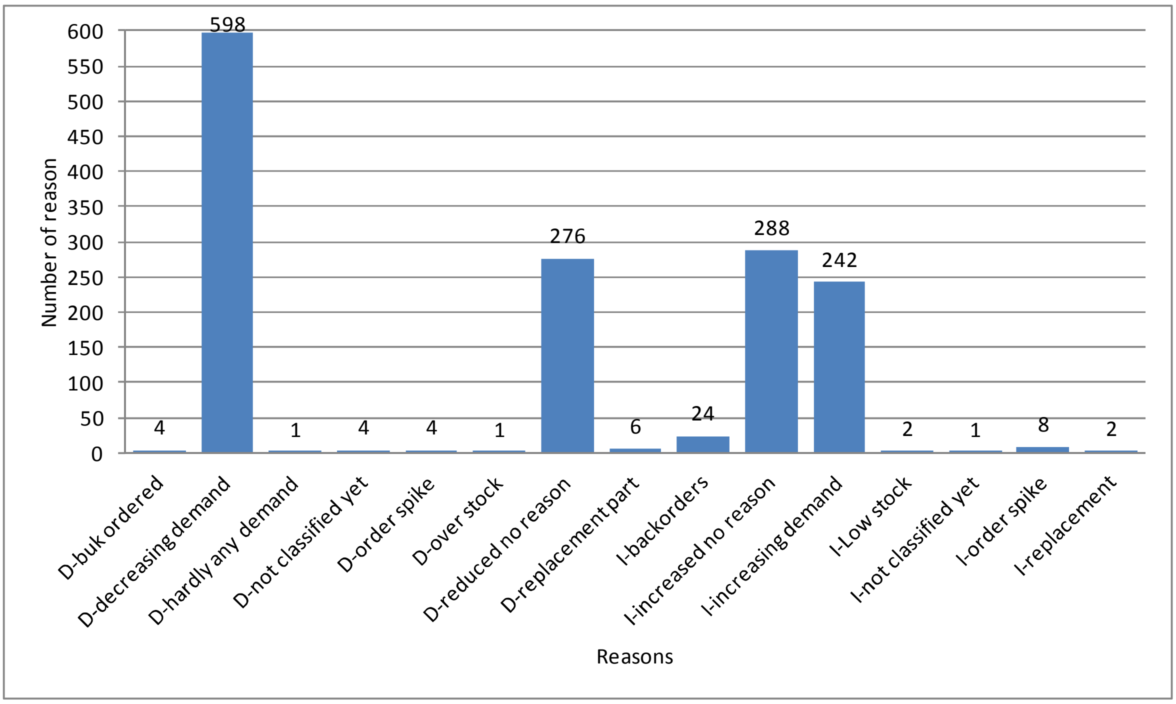


Figure 5.16 Distribution of adjustments per justification category (A items)

Table 5.7 Number of adjustments per justification category(B items)

No.	Code	Reason	Number of adjustments	Percentage of adjustments
1	10	I-No reason	605	38.76%
2	11	I-Backorder	162	10.38%
3	12	I-Low stock	3	0.19%
4	13	I-Certain period	13	0.83%
5	14	I-Steady demand	59	3.78%
6	15	I-Increasing demand	668	42.79%
7	16	I-Order spike	3	0.19%
8	17	I-Min ROP	1	0.06%
9	18	I-Large demand	12	0.77%
10	19	I-ROP too low	2	0.13%
11	40	I-Flat average	1	0.06%
12	41	I-Replacement part	0	0.00%
13	42	I-Not classified yet	32	2.05%
14	20	D-No reason	528	37.80%
15	21	D-Order spike	16	1.15%
16	22	D-Steady demand	93	6.66%
17	23	D-Decreasing demand	635	45.45%
18	24	D-Min ROP	30	2.15%
19	25	D-Over stock	1	0.07%
20	26	D-Slow demand	61	4.37%
21	27	D-Hardly demand	15	1.07%
22	28	D-Replacement part	6	0.43%
23	29	D-Bulk order	5	0.36%
24	30	D-Not classified yet	7	0.50%

I=increase, D=decrease

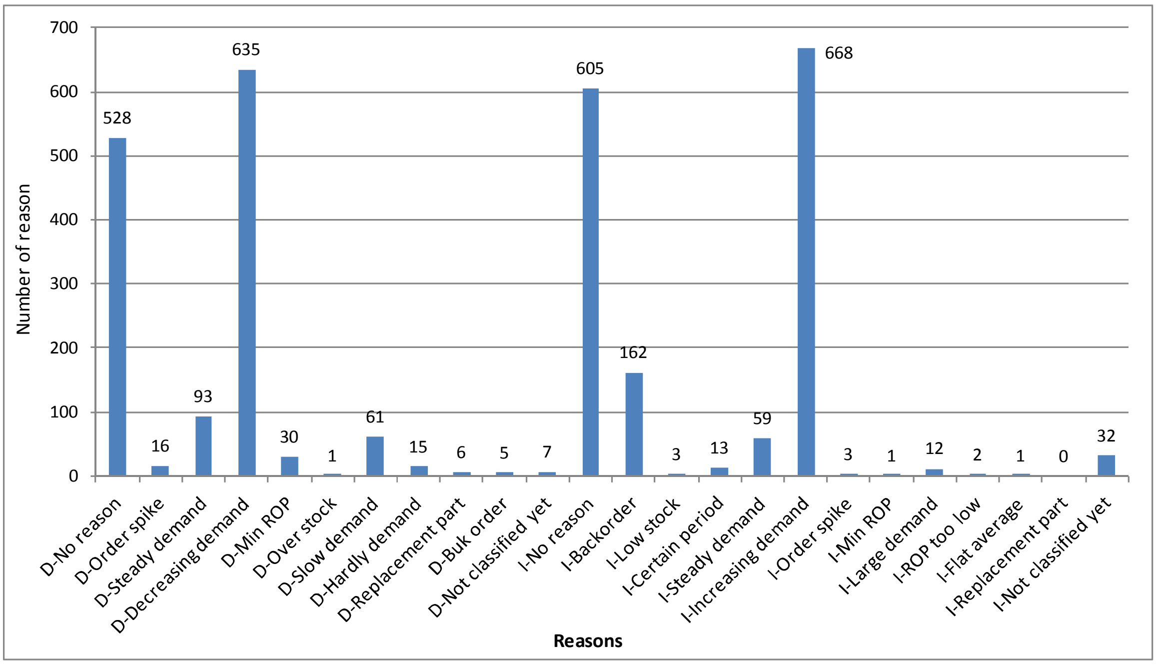


Figure 5.17 Distribution of adjustments per justification category (A items)

Above results indicate that, in adjusting the Order-Up-To level, managers may make significant errors. This is because they make it in arbitrary way. Other possibility is because adjustments often reflect a sense of ownership on the part of the managers. Up to now, there is still no method discussing about this. Furthermore, it may reflect that different important contextual information is already informed to managers, but for a report, managers always report the same justification for their convenience.

The linkage between the provision (and type) of justifications and inventory control performance is assessed later in this chapter.

5.5. Simulation experiment

Simulation is the process of designing a model of a real system for the purpose of evaluating the system's behaviour by conducting experiments with this model (Shannon, 1975; Pidd, 1998). As a decision-support tool, a simulation experiment attempts to recognise the system's behaviour by asking 'what-if' questions and using the model to predict the likely outcome (Robinson, 1994; Sargent, 2008). In this study, a computer simulation experiment has been designed to quantify the inventory performance and evaluate the implications of judgemental adjustments in an inventory system, focusing on replenishment orders. Computer simulation is one of the most widely used research methodologies employed in the field of OM (Amoako-Gympah and Meredith, 1989; Pannirselvam et al., 1999; Pidd, 1998); however, only a few published simulation studies actually refer to empirical situations. The majority of them are built upon theoretically generated data (Shafer and Smunt, 2004). The simulation model built for the purposes of this research is an empirically driven tool based on which we attempt to evaluate what would have happened in practice if specific scenarios were employed. It is constructed as closely as possible to the actual real world system and the analysis is based on empirical rather than artificial data. The database is arranged in Microsoft Excel software worksheets and then Visual Basic Application code is developed regarding the inventory performance evaluation (the code of the simulation can be found in *Appendix H*).

5.5.1. Conceptual model of simulation

Conceptual modelling, the process of abstracting a model from a proposed real system, is a very important aspect of simulation (Zeigler, 1976; Law, 1991; Pidd, 2003). Robinson (2008) argued that it contains objectives, inputs (experimental factors), output (responses), and model content (assumptions and simplifications of the model). The objective of our simulation experiment is to evaluate the inventory performance of unadjusted and adjusted replenishment order policies. The differences of simulation results between adjusted replenishment order and the benchmark method applied in the organisation are also analysed. Moreover, the empirical database is used as the experimental factors or inputs of the simulation. The empirical database available for this research consists of the individual data series of 359 and 1,454 SKUs for A and B-class items respectively. However, only

179 A-class and 228 B-class SKUs are being utilized for simulation purposes on the basis of having at least eight consecutive replenishment order observations. We appreciate that this may indeed look ad-hoc but a decision needed to be made with regards to the trade-off between sufficient data considerations and the meaningful output of the simulation experiment. Demand data series over 26 periods (monthly), the prices of SKUs and the replenishment order (unadjusted and adjusted) data is needed for this experiment. Lead time is equal to two months (average lead times are 60 days).

We consider three opportunities for replenishing stock: the System OUT replenishment level (unadjusted OUT level), the Final OUT replenishment level (adjusted OUT level), and the SMA-Based OUT replenishment level. As explained in previous chapter, the System OUT replenishment level is defined as the OUT level produced by the SAP system, the Final OUT replenishment level constitutes the judgementally adjusted order up to replenishment level, whereas SMA-Based OUT replenishment levels are calculated every month using the company's formula.

In terms of the output of the simulation experiment we record the inventory investment (inventory holding cost), cycle service level (CSL) and fill rate for each SKU. Inventory investment is the cost for carrying inventory volume in a given period (Silver et al., 1998). The inventory investment is obtained by multiplying the average of inventory volume (inventory position) of a particular SKU with its cost (approximated by its price), whereas the inventory position is calculated as below:

$$\text{Inventory position}_t = \text{Stock level}_t + \text{Receipt order}_{t-2} - \text{Demand}_t$$

where t is the current time period (monthly). Receipt order_{t-2} is the order placed 2 period ago and received in period t (due to lead time = 2 periods). On the other words, we may say that inventory position is the stock on hand at the end of the period.

The CSL is the probability that demand will be satisfied from stock on hand during lead time, whereas the fill rate is the rate (or percentage) of demand satisfied directly from stock (Syntetos and Boylan, 2008). The CSL is calculated as:

CSL = 1 – the percentage of stock-outs in the simulation length

The fill rate is obtained by the following formula:

$$Fill\ rate = \frac{\sum_{t=1}^{26} demand - \sum_{t=1}^{26} back\ orders}{\sum_{t=1}^{26} demand} x\ 100\%$$

Two scenarios are considered for simulation purposes. The difference between these scenarios is in terms of the calculation of the order to be placed for replenishment purposes. The first one is an intuitively appealing representation of the process, whereas the second is the standard one used in analytical evaluations of the OUT policy.

In the first scenario, the stock on hand and the orders are calculated as follows:

$\text{Stock}_t = \text{Stock}_{t-1} - \text{Demand}_t + \text{Order}_{t-2}$

$\text{Order}_t = \text{OUT Level}_t - \text{Stock}_t$

In the second scenario, the stock on hand is calculated as above but the order quantity is defined as

$\text{Order}_t = \text{OUT Level}_t - \text{OUT Level}_{t-1} + \text{Demand}_t$

5.5.2. Validation and verification of the simulation model

The correctness of a conceptual model is obtained through model verification and validation, which is carried out in parallel with each of the processes of conceptual modelling, model coding, experimentation and implementation (Robinson, 2008; Sargent, 2008). Robinson (1994) explained that the validation in simulation is to test the accuracy and the ability of the model to meet the objectives of the simulation. This test is conducted by checking that the overall behaviour of the model is representative of the real world. Only when these tests have been completed can examination be performed with confidence. Moreover, verification is a test to ensure that the logic of each element in the model is checked (analogous to program debugging); it is performed during the model coding. In our research, validation is carried out when defining the formulas needed for inventory performance measurement, such as the way we calculate the average inventory position, backordered demands and order quantity. These formulas are evaluated by checking the rationale of causal relationships between the input-output of the model's structure.

The verification process is performed during the development of the model coding to ensure that the model is properly realised in the computer program and its implementation is correct. Incorrectness in computer programs may be caused not only by the conceptual modeling, the computer program or the computer implementation but also by the data (Sargent, 2008). The simulation experiment in this research is verified by checking that all formulas and calculations for addressing the research questions are properly written in the code of computer program. The following figure (Figure 5.18) presents the simulation model adopted for the purposes of this research (adapted from Robinson, 2004).

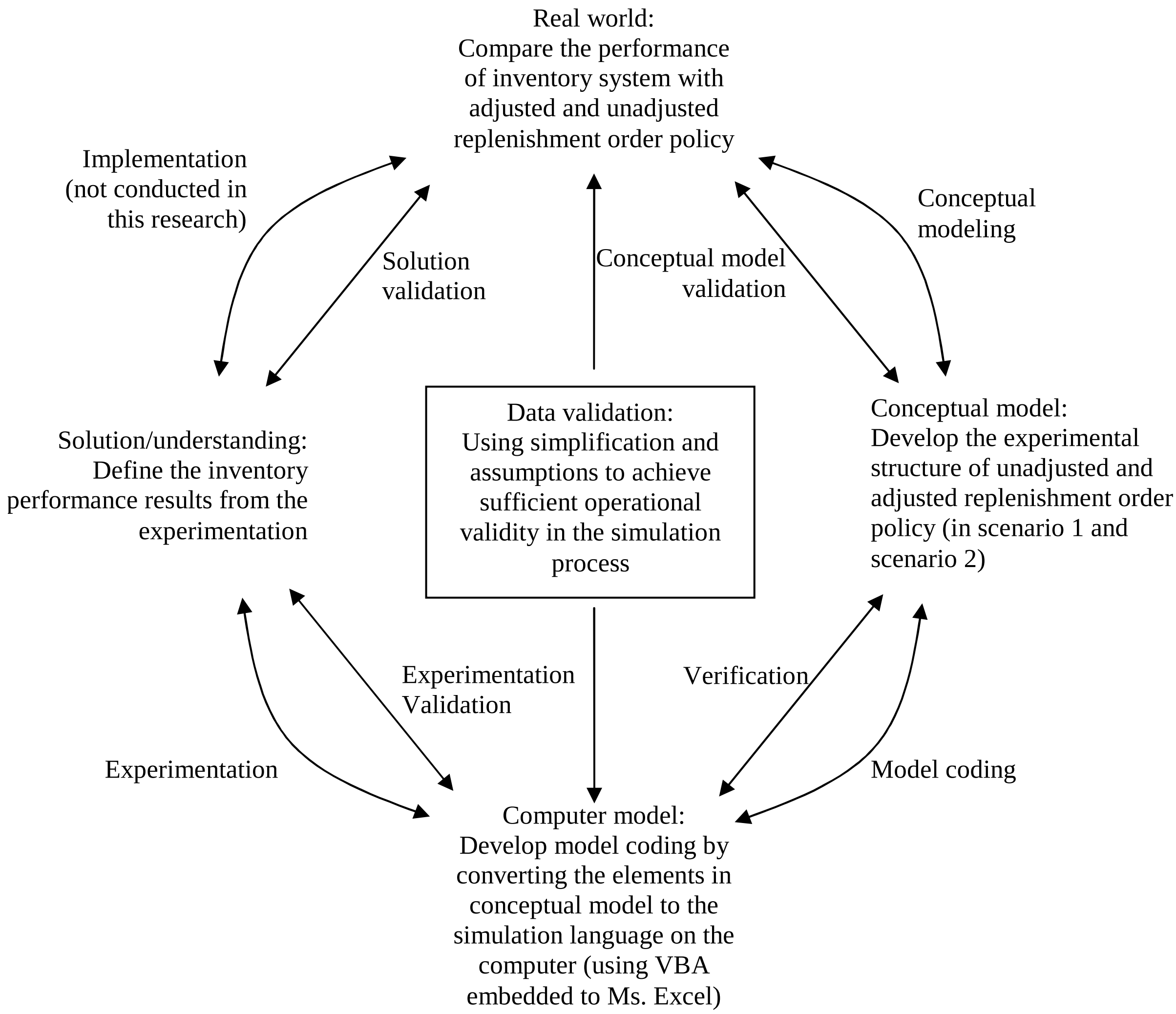


Figure 5.18 Verification and validation of the simulation model

5.5.3. Simulation results

Table 5.8 and Table 5.9 present the results obtained from the two simulation scenarios conducted on A and B items respectively. As can be seen from Table 5.8, the total inventory investment related to adjusted orders is slightly lower than the unadjusted ones for both scenarios. The decrease of inventory investment is about 0.61% and 3.16% for scenario 1 and 2 respectively resulting in an increase on the service level and fill rate for scenario 1, but not for scenario 2. The increase of CSL and fill rate in scenario 1 is not very significant, since it is of the order of 0.07% and 0.03% respectively. On the other hand, the CSL in scenario 2 is decreased from 0.9239 to 0.9048 (-2.07%), while the fill rate decreases from 0.9481 to 0.9299 (1.92%). Considering the trade-off between inventory cost and service, it seems that judgemental adjustments account for an improvement in terms of inventory investment at the expense though of an expected service reduction.

Considering the simulation results of the SMA-based OUT replenishment level as the benchmark, it can be seen that for both scenarios, the adjusted OUT level requires an increase of the total inventory investment. The increase on inventory investment is about 3% and 6% for scenario 1 and 2 respectively resulting, as expected, in an increase of the service provision.

Turning now to the results for B items, it can be seen from Table 5.9 that the Final OUT replenishment level is associated with a higher inventory investment as compared with the System OUT replenishment level for both scenarios. The increase is 0.95% and 0.10% for scenario 1 and 2 respectively. This increase also results to the increase of the service provision, though it is not particularly prevalent (less than 1%).

Table 5.8 The simulation results for A items

Scenario	System OUT replenishment level			Final OUT replenishment Level			SMA-based OUT replenishment Level		
	Total inventory investment (€)	Average CSL	Average fill rate	Total inventory investment (€)	Average CSL	Average fill rate	Total inventory investment (€)	Average CSL	Average fill rate
Scenario 1	1,075,021.16	0.991	0.993	1,068,503.32	0.991	0.993	1,036,225.99	0.991	0.993
Scenario 2	750,396.71	0.924	0.948	726,701.38	0.905	0.930	685,263.18	0.861	0.892

Table 5.9 The simulation results for B items

Scenario	System OUT replenishment level			Final OUT replenishment Level			SMA-based OUT replenishment Level		
	Total inventory investment (€)	Average CSL	Average fill rate	Total inventory investment (€)	Average CSL	Average fill rate	Total inventory investment (€)	Average CSL	Average fill rate
Scenario 1	131,876.06	0.986	0.962	133,133.96	0.987	0.965	135,393.53	0.988	0.968
Scenario 2	108,468.63	0.889	0.891	108,580.07	0.889	0.893	109,746.42	0.886	0.892

Comparing the inventory investment of SMA-based OUT replenishment level with the adjusted one, it can be seen that the latter produces lower cost, but the difference is indeed very small: 1.67% (€2,260) in scenario 1 and 1.06% (€1,166) in scenario 2. However, and although this naturally leads to a slight decrease in the service measures under scenario 1, in scenario 2 the opposite occurs. This, in theory, indicates that adjustments lead not only to less safety stocks (as expressed through the inventory investment) but also to better service provision. It is true that the differences observed are very small but nevertheless the results favour conclusively the judgementally adjusted OUT levels.

The above findings are consistent with the results presented in most relevant studies in the forecasting field where judgemental adjustments seems to account for (considerable) performance improvement (Diamantopoulos and Mathews, 1989; Mathews and Diamantopoulos, 1986, 1990, 1992; Lawrence et al., 1986; Angus-Leppan and Fatseas, 1986; Wolfe an Flores, 1990; Syntetos et al., 2009b). However, the results indicate that there may be less benefit resulting from judgementally adjusting stock control decisions than statistical demand forecasts. This finding is in agreement with the Syntetos et al. (2011) findings which showed that judgemental forecast adjustments have more prominent effects than judgemental order adjustments.

From the above discussion we may provide an answer to the first research question, about the potential performance improvement resulting from judgementally adjusting stock control-related decisions; we find that human intervention seems to offer a reasonable advantage in stock control decision making.

5.6. The effects of the sign of adjustments on inventory performance

The purpose of this analysis is to evaluate the effects of the sign of adjustments (positive/increasing adjustment and negative/decreasing adjustment) on inventory performance. To conduct such analysis, we consider the average adjustment per SKU across time as it would simply be impractical to analyse the effects of each adjustment separately. The average adjustment is used to classify SKU into two categories: positive and negative average adjustment. The next step is to analyse the inventory performance for each of these two groups in terms of inventory investment, cycle service level (CSL) and fill rate across all the SKUs in that group. The results are shown in Table 5.10 and Table 5.11 for the A and B items respectively.

The results of simulation for the A items indicate that the inventory investment related to the adjusted replenishment orders is lower than that corresponding to the System OUT replenishment orders with the exception of the positive adjustment category in scenario 1. Regarding the service measures, there is no significant difference between the two replenishment order methods for scenario 1. Whereas for scenario 2, the service level and fill rate of adjusted replenishment orders tends to be lower than the unadjusted ones, particularly for the positive adjustment category. Thus, we may say that the negative adjustments perform better than the positive ones in improving the performance of the inventory system. In addition, we may see that there is always a trade-off between cost and service level.

Table 5.10 The effect of sign adjustments on inventory performance for A items

Scenario	Classification	System OUT replenishment level			Final OUT replenishment Level			SMA-based OUT replenishment Level		
		Total inventory investment (€)	Average CSL	Average fill rate	Total inventory investment (€)	Average CSL	Average fill rate	Total inventory investment (€)	Average CSL	Average fill rate
Scenario 1	Negative	68,967.05	0.997	0.997	67,733.45	0.997	0.997	66,237.29	0.997	0.997
	Positive	7,774.83	0.977	0.983	7,932.64	0.979	0.984	7,996.25	0.978	0.984
Scenario 2	Negative	63,344.46	0.944	0.965	62,258.97	0.932	0.952	61,340.38	0.887	0.910
	Positive	4,687.58	0.877	0.908	4,493.26	0.842	0.878	4,476.91	0.800	0.851

Table 5.11 The results of sign adjustments on inventory performance for B items

Scenario	Classification	System OUT replenishment level			Final OUT replenishment Level			SMA-based OUT replenishment Level		
		Total inventory investment (€)	Average CSL	Averagef ill rate	Total inventory investment (€)	Average CSL	Averagef ill rate	Total inventory investment (€)	Average CSL	Averagef ill rate
Scenario 1	Negative	56,492.58	0.990	0.968	56,466.85	0.990	0.969	54,478.44	0.991	0.971
	Positive	10,308.45	0.975	0.947	10,551.40	0.978	0.956	10,644.65	0.979	0.958
Scenario 2	Negative	50,222.58	0.907	0.916	50,084.03	0.904	0.913	49,564.00	0.904	0.910
	Positive	8,159.44	0.835	0.818	8,322.16	0.843	0.833	8,426.52	0.832	0.840

For B items, the negative adjustment category for Final OUT replenishment level produced lower inventory investment compare to System OUT level. For scenario 1, this category is not associated with much difference of CSL and fill rate between the Final OUT replenishment level and System OUT replenishment level. Whereas in scenario 2, we find that the Final OUT replenishment level has lower values of CSL and fill rate. On the other hand, the inventory investment on the positive adjustment category of the adjusted replenishment orders is higher than the unadjusted ones. The increase on both scenarios is between €162.72 and €242.95. It raises the CSL by 0.31% to 0.95%, and fill rate by 0.94% and 1.80%. Thus, as the results are the same with the A-class items we may conclude that negative adjustments may deliver more benefit than the positive adjustments towards the improvement of inventory system.

The comparison between the SMA-based OUT replenishment level and the Final OUT replenishment level indicates that the negative adjustments seem to increase the inventory investment whereas the opposite is true for positive adjustments.

Regarding CSL and fill rate, the experiment results produce similar values, except for the value of scenario 2 of A items where the CSL and fill rate of SMA-based OUT replenishment level is significantly lower than the Final OUT replenishment level. Moreover, the Final OUT replenishment level seems to be associated with better CSL and fill rate than the SMA-based OUT replenishment level on both signs of adjustment, except from scenario 1. It can be seen that for A items in scenario 1, and for B items in both scenarios, the CSL and fill rate increases between 0.0 - 0.045, while the decrease is only between -0.001 to -0.002 for A items in scenario 2. This indicates that, even when SKUs are categorised by the sign of adjustments, the adjusted replenishment orders perform better than the SMA-based OUT replenishment level ones.

The results also show that the values of CSL and fill rate with negative adjustments seem higher than those with positive adjustments for each scenario for both categories of items. This result is in line with the findings of judgemental forecasting research which has found that large negative adjustments perform well in increasing forecast accuracy for products that are subject to intermittent demand (Syntetos et al., 2009b) and also for fast moving demand (Fildes et al., 2009). These forecasting studies argued that negative adjustments are more effective than positive adjustments since they reflect genuinely important pieces of information. Furthermore, the relatively poor performance of positive adjustments may be a result of an optimism bias on the part of the forecasters (the issue of bias in judgementally adjusted replenishment order decisions will be discussed in section 5.9). Forecasters tend to over-weight the statistical system's forecast when contextual information is available (but in the absence of reliable evidence). Alternatively, excessive upward adjustments may be motivated by political factors such as pressure from senior management. Insights from the judgemental forecasting research cited above may explain why negative adjustments on replenishment order decisions perform better than positive adjustments.

In the case of this company, managers tend to decrease the OUT level of A items mostly between [0- −20] units (see analysis in section 5.3 above). For B items, however, most adjustments made by the manager are between [0-10] units. This indicates that negative adjustments occur more on A items than B items. This result is consistent with the value of CSL and fill rate resulting from the Final OUT replenishment level for each category. If we compare the average CSL and fill rate of the Final OUT replenishment level between A items and B items, we find that A items have greater values than B items (CSL for A and B items is 0.938 and 0.929 respectively; fill rate for A and B items is 0.953 and 0.918 respectively).

5.7. The effects of the absolute size of adjustments on inventory performance

Two pieces of analysis are conducted to explore the effects of the size of adjustments. The first one is conducted using the average of the absolute size of the adjustments (the sign of adjustments is not considered in calculating the average). The second relates to the absolute average size of the adjustments (taking the average size of the adjustments, considering the positive/negative sign of adjustments, and then calculating the absolute value of that average). After calculating the average of absolute and average of absolute signed adjustments, the next step is to calculate the percentage adjustment from the average demand for every SKU for the purpose of classifying the SKUs into small, medium, and large adjustments categories. For this categorisation, we consider these to be:

i) small adjustments if: 0 < average adjustment/average demand ≤ 10%,

ii) medium adjustments if: 10% < average adjustment/average demand ≤ 20%,

iii) large adjustments if: average adjustment/average demand > 20%.

Then the inventory performance (inventory investment, CSL, and fill rate) is compared for each category in every scenario. This performance analysis is based on the average of the adjustment across time since the signs of adjustments for each SKU cannot be useful.

5.7.1. The average of the absolute size of the adjustments

After obtaining the results of average adjustment/average demand for each SKU, we find that the above grouping does not fit the range of average absolute adjustment of B items. The smallest value of average adjustment/average demand is 11.18%. As a result, for B items, we change the grouping into: less than or equal to 20% for small adjustments, between 20% and 40% for medium adjustments, and above 40% for large adjustments. Applying this new grouping to A items is not inappropriate because the highest adjustment/average demand value is 38.07%. Thus, the categorisation for A items stays as discussed above in 5.7.

Table 5.12 and Table 5.13 show the inventory performance analysis results for A and B items respectively.

The simulation results indicate that, for A-class items, the inventory investment of adjusted replenishment orders is lower than that associated with unadjusted replenishment orders. In term of CSL and fill rate, the Final OUT replenishment levels are associated with the same or higher values than the System OUT replenishment level related ones, for scenario 1. This indicates that the adjusted replenishment orders decrease the inventory cost whilst resulting in higher customer service level and fill rate. However, this is not the case for scenario 2. The decrease of inventory cost also results to the decrease of CSL and fill rate value.

Further analysis on the size of the adjustment for both scenarios reveals that 'large adjustment' category (higher than 20%) results to the best performance as the decrease of inventory cost is not accompanied by an expected decrease of service provision.

Table 5.12 The results of absolute of adjustment on the inventory performance analysis for A items

Scenario	Classification	System OUT replenishment level			Final OUT replenishment Level			SMA-based OUT replenishment Level		
		Total inventory investment (€)	Average CSL	Average fill rate	Total inventory investment (€)	Average CSL	Average fill rate	Total inventory investment (€)	Average CSL	Average fill rate
Scenario 1	< 10%	24,067.72	0.991	0.993	23,847.71	0.991	0.993	23,250.42	0.992	0.993
	10-20%	21,455.81	0.985	0.989	21,206.15	0.989	0.991	20,268.10	0.986	0.991
	>20%	32,000.71	1.000	1.000	31,304.22	1.000	1.000	31,300.42	1.000	1.000
Scenario 2	< 10%	17,691.09	0.921	0.950	17,087.29	0.898	0.928	16,053.79	0.862	0.893
	10-20%	18,962.38	0.910	0.922	18,420.20	0.903	0.916	18,455.09	0.810	0.853
	>20%	31,378.56	1.000	1.000	31,244.74	1.000	1.000	31,308.42	1.000	1.000

Table 5.13 The results of absolute of adjustment on the inventory performance analysis for B items

Scenario	Classification	System OUT replenishment level			Final OUT replenishment Level			SMA-based OUT replenishment Level		
		Total inventory investment (€)	Average CSL	Average fill rate	Total inventory investment (€)	Average CSL	Average fill rate	Total inventory investment (€)	Average CSL	Average fill rate
Scenario 1	< 20%	646.82	1.000	1.000	655.42	1.000	1.000	791.41	1.000	1.000
	20-40%	4,936.22	0.988	0.987	4,964.34	0.988	0.988	5,281.42	0.990	0.989
	>40%	61,276.45	0.985	0.949	61,456.04	0.986	0.953	59,107.47	0.987	0.956
Scenario 2	< 20%	557.58	0.983	0.997	560.30	0.988	0.998	664.07	0.983	0.995
	20-40%	4,215.67	0.897	0.915	4,221.67	0.897	0.919	4,314.99	0.906	0.927
	>40%	53,658.98	0.879	0.873	53,672.81	0.879	0.874	53,068.26	0.870	0.870

The opposite result was found for B-class items where adjusted replenishment orders seem to be associated with a higher inventory investment compared to the unadjusted ones although the differences are very small (mostly less than 0.5%). The slight increase in cost also results in a small improvement of the CSL and fill rate. From the results we may see that the best performance is resulting from the ‘large adjustment’ category; the smallest increase in inventory investment may result in the highest CSL and fill rate as compared to other categories.

From the comparative analysis of SMA-based OUT replenishment levels and Final OUT replenishment level, we found that for A items, the inventory investment of SMA-based OUT replenishment levels is lower than the Final OUT replenishment levels for all of the adjustments categories when considering scenario 1.In scenario 2, this is true only for the ‘small adjustment’ category. Different results were found for B items, where the inventory investment of SMA-based OUT replenishment level is usually higher than the Final OUT replenishment level related one in the small and medium adjustment categories.

In term of service level and fill rate of A items, the same values are found between the SMA-based OUT replenishment level and Final OUT replenishment level for scenario 1. However, most of CSL and fill rate associated with the Final OUT replenishment levels seem to be higher compare with the SMA-based ones in scenario 2. Moreover, the highest service level and fill rate is resulted from the ‘medium adjustment’ category. However, it is difficult to make a conclusion regarding the CSL and fill rate for B items since no pattern can be found in the simulation results.

5.7.2. The absolute average size of the adjustments

Table 5.14 shows the result of the analysis on the absolute average size of adjustments of A items. It can be seen that generally Final OUT replenishment levels result in lower inventory investment compared to System OUT replenishment levels. The decrease is between 0.23% and 6.88%. The decrease of inventory investment produces only a slight increase of CSL and fill rate for scenario 1. The lowest inventory investment is resulted from the large (>20%) adjustment category. However, in scenario 2 the decrease of inventory investment also produces lower CSL and fill rate.

In Table 5.15 we can see the simulation result for B items. Most of the inventory investments of Final OUT replenishment levels are higher than the System OUT replenishment level ones, which consequently increase the CSL and fill rate except for the large adjustment category in scenario 2.

Moreover, it can be seen that the inventory investment of SMA-based OUT replenishment levels is generally lower than that associated with the Final OUT replenishment levels in the medium and large adjustment categories. On the other hand, inventory investment of SMA-based OUT replenishment levels seems to have higher values than the Final OUT replenishment levels one for the SKU in the ‘small adjustments’ category. In addition, the highest service level and fill rate results from the ‘large adjustments’ category for A items and medium and large categories for B items.

Table 5.14 The results of absolute signed of adjustments on the inventory performance analysis for A items

Scenario	Classification	System OUT replenishment level			Final OUT replenishment Level			SMA-based OUT replenishment Level		
		Total inventory investment (€)	Average CSL	Average fill rate	Total inventory investment (€)	Average CSL	Average fill rate	Total inventory investment (€)	Average CSL	Average fill rate
Scenario 1	< 10%	7,404.17	0.991	0.992	7,387.28	0.991	0.992	7,436.89	0.991	0.992
	10-20%	6,281.54	0.985	0.990	6,333.51	0.986	0.993	6,213.64	0.986	0.992
	>20%	63,838.53	0.993	0.994	62,637.28	0.994	0.994	61,168.40	0.994	0.994
Scenario 2	< 10%	4,279.89	0.934	0.944	3,985.36	0.900	0.915	4,052.60	0.833	0.858
	10-20%	3,061.30	0.890	0.944	2,972.39	0.863	0.935	2,647.93	0.848	0.898
	>20%	58,982.36	0.932	0.953	58,093.04	0.928	0.946	57,430.49	0.888	0.915

Table 5.15 The effects of absolute signed of adjustments for B items

Scenario	Classification	System OUT replenishment level			Final OUT replenishment Level			SMA-based OUT replenishment Level		
		Total inventory investment (€)	Average CSL	Average fill rate	Total inventory investment (€)	Average CSL	Average fill rate	Total inventory investment (€)	Average CSL	Average fill rate
Scenario 1	< 10%	7,947.48	0.983	0.970	7,960.87	0.985	0.976	7,930.56	0.987	0.979
	10-20%	4,243.13	0.982	0.971	4,428.07	0.983	0.977	4,575.42	0.987	0.984
	>20%	54,610.42	0.990	0.955	54,629.30	0.990	0.955	52,617.11	0.989	0.955
Scenario 2	< 10%	5,933.73	0.877	0.876	5,995.12	0.880	0.883	6,181.46	0.875	0.874
	10-20%	3,716.33	0.916	0.915	3,795.88	0.921	0.924	3,774.87	0.914	0.930
	>20%	48,731.96	0.886	0.891	48,615.19	0.883	0.888	48,034.19	0.882	0.890

The results on inventory investment for A and B items suggest that the extent of the advantage associated with the size of adjustments is not yet clear, because the results of the analysis for both classes of items, both scenarios, and both types of descriptive summarization considered (absolute and absolute sign) are too varied. However, if we focus on the CSL and fill rate, we may say that for A items, the performance of the 'large adjustments' group is higher than that of other groups, whereas medium and large adjustment categories perform better on B items.

In the area of judgemental forecasting, Fildes et al. (2009) argued that large adjustments may improve forecast accuracy more effectively than small adjustments since the small adjustments are merely a response to non-existing patterns. The same results are also found by Diamantopoulos (1986, 1990, 1992), and Diamantopoulos and Mathews (1989). Moreover, O'Connor and Lawrence (1989) found that judgemental confidence intervals in time series forecasting were initially excessively over-confident. This situation may also exist in judgemental stock control decision making where the large adjustments might only represent overreaction by the decision maker in response to the available contextual information.

For B items, as we mentioned above, large and medium adjustments perform better for CSL and fill rate values but not for reducing inventory investment. If the organisation focuses on the achievement of service level target, thus the manager needs to be very careful with the small adjustments since the wrong decision made by the manager on B items will directly increase the holding cost (due to the analysis result of price of materials explained in section 5.2 that shows the most B items are more expensive than A items).

In the forecasting field, the decision maker needs to consider adjustments based on statistical forecasting and also estimates of the size of the adjustment (Lawrence et al., 2006).From these findings we may say that the benefits of making adjustments on stock control decisions not only depends on the size of adjustments made by the manager, but also on the demand characteristics of the item.

In addition, the procedure for calculating the absolute size of adjustments is also the factor that affects the results of this analysis. For example, the above analyses (absolute adjustments and absolute sign adjustments) offers significantly (not in a statistical sense) different experiment results of A and B items for both scenarios. These differences introduce complications towards the interpretation of the results and reaching specific conclusions. In the forecasting area, conflicting results due to different forecasting accuracy measurements (percentage errors, relative errors, and scaled errors) often occur since each measure is associated with specific limitations. The inconsistency of the results may also be due to the nature of the demand data. This issue is investigated by Davydenko and Fildes (2013) that suggest that the well-known forecast error measures seem not suitable for judgemental adjustment forecasting and then attempt to develop an appropriate procedure for measuring judgemental forecasting accuracy.

5.8. The effects of justification of adjustments on inventory performance

This part of the analysis examines the effects of the reasons for adjustments on inventory performance. It is achieved by calculating the number of justification adjustments for each SKU. Then, the adjustments are separated into four categories based on the number of justifications for the adjustments:

i) Justifications <25%;

ii) 25%<Justifications<50%;

iii) 50%<Justifications<75%;

iv) Justifications>75%.

Furthermore, the inventory performance (inventory investment, CSL and fill rate) is compared for each category in every scenario.

Table 5.16 and Table 5.17 show the results associated with the justification for the adjustments on the inventory performance for A and B-class items respectively.

By comparing the inventory investment associated with the System OUT replenishment levels and the Final OUT replenishment levels of A-class, we found that, in the majority of cases all justification categories result in lower inventory investments without that implying a decrease in the service provision. In fact the opposite is the case.

For B-class items, regarding the inventory investment, SKUs which are associated with justifications between 25% and 50% for scenario 1 and those between 25% and 75% for scenario 2 seems to be associated with the best comparative performance. The decrease in inventory investment in the particular categories resulted to a positive contribution to CSL and fill rate.

In terms of CSL and fill rate, it can be seen from scenario 1 in Table 5.16 that the same CSL and fill rate values are obtained for both replenishment order procedures. Moreover, in scenario 2, for A-class items, the CSL and fill rate associated with the Final OUT replenishment levels tend to be higher than that related to the SMA-based OUT replenishment levels. A considerable increase of the CSL and fill rate values from the SMA-based OUT replenishment levels to adjusted replenishment orders were found on the SKUs that have justification more than 75%. The increase of CSL and fill rate under this category is 16.7% and 18.9% respectively. For B items, the results are varied. However, we can see that the highest increase in CSL and fill rate when moving from the SMA-based OUT replenishment levels to Final OUT replenishment levels is given by SKUs that have justification more than 75%, which is the same as the result for A items.

Table 5.16 The results of justification of adjustments on the inventory performance analysis for A items

Scenario	Classification	System OUT replenishment level			Final OUT replenishment Level			SMA-based OUT replenishment Level		
		Total inventory investment (€)	Average CSL	Average fill rate	Total inventory investment (€)	Average CSL	Average fill rate	Total inventory investment (€)	Average CSL	Average fill rate
Scenario 1	Just <25%	1,455.67	1.000	1.000	1,437.63	1.000	1.000	1,448.40	1.000	1.000
	25%<Just<50%	45,301.16	0.992	0.994	44,227.83	0.992	0.994	42,661.12	0.992	0.994
	50%<Just<75%	30,439.24	0.979	0.980	30,374.31	0.980	0.981	30,348.16	0.980	0.981
	Just>75%	328.18	1.000	1.000	318.30	1.000	1.000	361.24	1.000	1.000
Scenario 2	Just <25%	2,302.08	0.991	0.997	6,645.19	0.943	0.938	6,536.40	0.944	0.943
	25%<Just<50%	51,912.72	0.921	0.947	52,030.02	0.900	0.925	49,443.21	0.850	0.881
	50%<Just<75%	18,831.17	0.883	0.914	13,913.56	0.891	0.939	13,054.94	0.841	0.899
	Just>75%	143.01	1.000	1.000	127.87	1.000	1.000	63.39	0.833	0.811

Table 5.17 The results of justification of adjustments on the inventory performance analysis for B items

Scenario	Classification	System OUT replenishment level			Final OUT replenishment Level			SMA-based OUT replenishment Level		
		Total inventory investment (€)	Average CSL	Average fill rate	Total inventory investment (€)	Average CSL	Average fill rate	Total inventory investment (€)	Average CSL	Average fill rate
Scenario 1	Just <25%	31,416.74	0.986	0.958	31,681.23	0.986	0.960	30,440.71	0.988	0.964
	25%<Just<50%	15,963.83	0.988	0.970	15,882.38	0.990	0.973	15,622.48	0.990	0.974
	50%<Just<75%	18,831.69	0.982	0.962	18,856.64	0.987	0.970	18,545.67	0.985	0.967
	Just>75%	588.76	0.992	1.000	598.00	0.992	1.000	514.23	0.992	1.000
Scenario 2	Just <25%	25,935.91	0.887	0.887	25,969.53	0.886	0.885	25,545.11	0.879	0.881
	25%<Just<50%	14,814.54	0.914	0.907	14,810.91	0.916	0.915	14,775.70	0.917	0.919
	50%<Just<75%	17,507.99	0.875	0.881	17,498.92	0.875	0.888	17,532.18	0.893	0.897
	Just>75%	123.58	0.650	0.827	126.83	0.667	0.850	137.52	0.642	0.847

The above findings show that the SKUs associated with more than 75% justifications produce the highest stock control performance. The reasons or justifications behind managers changing the OUT level produced by the software system in the past may be the factor that helps the decision maker to make adjustments. In their forecasting study, Onkal et al. (2008) reported that the explanation accompanying the adjusted forecasts helps the decision maker to define the appropriate size of adjustments and gives more benefits from further modifications. Moreover, this may be useful in the learning process for practitioners towards an understanding of why decisions may be erroneous (Stekler, 2007). Levitt and March (1996) argued that the procedure to store and access information, particularly when forecasters seek to make judgements, is the important consideration in the documentation of contextual information. The case organisation has documented some of the justifications for the adjustments made by managers; however, managers seem to change the OUT level frequently without giving any reason (see the justification of adjustment analysis in section 5.4). As we know that the case organisation does not document the reason for adjustment in detail, and is indeed unaware of the importance of contextual information (for convenience they always report the same justification), it is recommended that the company improves its documentation procedure in order improve their judgemental stock control performance. The justification for adjustments should be determined not only when the decision maker makes an adjustment, but also how, presenting the reason why judgement is incorporated into the decision. These factors are important to reduce bias in judgemental adjustment forecasting (Goodwin, 2000), and may also be important in judgemental stock control systems. The above discussion may answer our research question about improving stock control performance by the adjustments when justification is offered on adjusted replenishment order decisions, since we found that the SKUs associated with more justifications are also associated with better performance.

5.9. The effect of bias of adjustments on inventory performance

Many studies have investigated bias in judgementally adjusting forecasts (for example Diamantopoulos and Mathews, 1990; Mathews and Diamantopoulos, 1990; Goodwin and Wright, 1994) although based on our knowledge so far, there is no study about this issue in the stock control area. Thus, in making judgemental adjustments, managers tend to use heuristic principles while taking contextual information into consideration. Heuristic principles have systematic errors (Tversky and Kahneman, 1974).

For this analysis, identification of bias of adjustments on inventory performance is achieved by calculating the average adjustments per SKU (across time). Then the maximum and minimum values of adjustments are defined. The next step is to calculate the value of 10% of the maximum of negative adjustments and 10% of the minimum of positive adjustments, to classify the average of adjustment as positive biased, unbiased or negative biased. For this categorisation, we consider:

- Positive biased if the average adjustment per SKU > 10% max
- Unbiased if min 10% < the average adjustment per SKU < 10% max
- Negative biased if the average of adjustment per SKU < 10% min

Next, the average of inventory performance between groups is compared.

Table 5.18 and Table 5.19 show the results of bias on the inventory performance analysis for A and B-class items respectively.

For A items, it can be seen that inventory investments associated with the Final OUT replenishment level are generally lower than that the System OUT replenishment level ones for both scenarios. With regards to the CSL and fill rate, in scenario 1, we found that there are no differences between the Final OUT replenishment levels and the System OUT replenishment levels with the exception of the ‘positive biased adjustment’ category. Whereas for scenario 2 we found that the service level and fill rate of the Final OUT replenishment levels seems to have a lower value than that of the System OUT replenishment level for all adjustment categories. Moreover, we can conclude from this analysis that the 'negative biased adjustment' category perform well in improving the performance of the inventory system since this category resulted in the lowest inventory investment and does not imply (or it does only marginally) a reduction of the CSL and fill rate.

In the analysis of B items we found that the inventory investment of the Final OUT replenishment levels seems to be lower than that of the System OUT replenishment levels only in the 'negative biased adjustment' category for both scenarios. In this category, for scenario 1, the CSL and fill rate value is the same for both replenishment order methods. For scenario 2, the 'negative biased adjustment' category did not affect much the CSL and fill rate value. This indicates that negative bias results in better results than the other categories. It means that, if the managers make adjustments without any rationale or adjust the OUT level in arbitrary way, the negative adjustments seems perform better compare to the positive ones. This finding is in line with the sign of the adjustments analysis in section 5.6 where we found that the negative adjustments produce the best performance.

When comparing the SMA-based OUT replenishment levels and the Final OUT replenishment levels, we can see that the inventory investment of the former is lower than that of the latter for the negative biased and unbiased adjustments categories, whereas for the positive biased category, the opposite is the case Furthermore, in terms of the CSL and fill rate, it can be seen from Table 5.18 that the highest CSL and fill rate for A items resulted from the negative bias adjustments category for both scenarios. For B items, the highest CSL and fill rates were produced by the unbiased adjustments category. For all items, it also appears that the 'positive-biased adjustments' category produced the lowest CSL and fill rate. This finding seems to be consistent with research on judgemental forecasting by Syntetos et al. (2009b) who found that positive adjustments lead to unsatisfactory performance of the inventory system; they argued that optimistic bias would lead to positive adjustments being made in the absence of reliable evidence that the forecast does need an upward adjustment, or lead to over-enthusiastic upward adjustment when such evidence was available. Moreover, there is evidence in judgemental adjustment forecasting that the source of contextual information constitutes a major factor that influences the frequency and magnitude of adjustments (Onkal, et al., 2013). In that study, the source of information based on direct experience gives more effects on the level of adjustment compared with the information based on assumption. This phenomenon might also take place when judgementally adjusting stock replenishment decisions.

The above discussion implies that biases also exist in the area of judgementally adjusting replenishment decisions. This may answer our fourth research question, i.e. whether or not judgementally adjusted stock control decisions are associated with bias. In addition, in order to obtain the benefits of making adjustments in stock control decisions, it is important to understand the nature of decision biases in deciding how to manage those biases in the process (Carter et al., 2007).

Table 5.18 The results of the bias of adjustments on the inventory performance analysis for A items

Scenario	Classification	System OUT replenishment level			Final OUT replenishment Level			SMA-based OUT replenishment Level		
		Total inventory investment (€)	Average CSL	Average fill rate	Total inventory investment (€)	Average CSL	Average fill rate	Total inventory investment (€)	Average CSL	Average fill rate
Scenario 1	Negative biased	200.66	1.000	1.000	196.54	1.000	1.000	180.84	1.000	1.000
	Unbiased	76,697.36	0.992	0.993	75,559.27	0.992	0.993	74,080.02	0.992	0.993
	Positive biased	297.76	0.968	0.985	330.02	0.972	0.987	360.68	0.968	0.989
Scenario 2	Negative biased	346.06	0.995	0.999	311.92	0.990	0.996	271.45	0.943	0.967
	Unbiased	67,585.39	0.929	0.948	66,348.49	0.910	0.930	65,453.68	0.861	0.888
	Positive biased	100.58	0.769	0.909	91.81	0.727	0.866	92.15	0.782	0.897

Table 5.19 The results of the biased on adjustments on the inventory performance analysis for B items

Scenario	Classification	System OUT replenishment level			Final OUT replenishment Level			SMA-based OUT replenishment Level		
		Total inventory investment (€)	Average CSL	Average fill rate	Total inventory investment (€)	Average CSL	Average fill rate	Total inventory investment (€)	Average CSL	Average fill rate
Scenario 1	Negative biased	475.18	0.990	0.946	461.94	0.990	0.946	437.83	0.990	0.946
	Unbiased	64,983.96	0.989	0.969	65,128.63	0.990	0.972	63,135.88	0.990	0.974
	Positive biased	1,341.89	0.968	0.927	1,427.67	0.968	0.933	1,549.38	0.973	0.942
Scenario 2	Negative biased	392.58	0.869	0.885	383.19	0.867	0.881	371.04	0.888	0.901
	Unbiased	57,021.83	0.904	0.911	57,029.50	0.902	0.910	56,619.65	0.900	0.904
	Positive biased	967.61	0.796	0.755	993.50	0.813	0.782	999.82	0.785	0.801

5.10. Learning effects of making adjustments on inventory performance

The analysis of learning effects is conducted in order to evaluate whether there are such effects in the process of superimposing judgement into inventory related decisions. The analysis is based on the number of adjustments to each SKU (assuming that there is only one person dealing with each SKU) followed by their grouping in three categories as follows:

i) Low: number of adjustments ≤ 13

ii) Medium: $13 <$ number of adjustments ≤ 21

iii) High: number of adjustments >21.

We then compare the inventory performance resulting in these three groups, assuming the more adjustments are associated with a higher learning effect (the more the process of adjusting is repeated, the more the individual who performs the adjustments learns and the better s/he performs.)

From Table 5.20 we can see that, for A-class items, judgemental adjustments generally lead to inventory investment reductions. The lowest inventory investment value resulted from the ‘medium adjustments’ category for both scenarios. In terms of CSL and fill rate, we may say that, for scenario 1, there is no difference between unadjusted and adjusted replenishment orders. For scenario 2, the CSL and fill rate of System OUT replenishment levels seems to have higher values as compared to the Final OUT replenishment levels for medium and high number of adjustments category. Since a high number of adjustments do not improve the inventory system performance, we may conclude that there is no learning effect taking place in A-class items.

Table 5.21 shows the simulation results for the B-class items. It can be seen that the inventory investment associated with the Final OUT replenishment levels is higher than that related to System OUT replenishment levels. For scenario 1, the CSL and fill rate of the former is also higher than that of the latter, whereas the opposite is the case for scenario 2. The medium and high numbers of adjustment categories seem to perform better than the small number of adjustment category. Thus, we may conclude that for B items there is an occurrence of learning effect.

In the comparison between the Final OUT replenishment levels and the SMA-based OUT replenishment levels for the A items, the inventory investment of the latter is lower than that of the former (except for the ‘low adjustments category’ in scenario 1). However, for B items, the same is the case for the low and medium adjustments categories in scenario 1, and also for the ‘low adjustment category’ in scenario 2.

Regarding the CSL and fill rate values, it can be seen that the highest value of CSL and fill rate for A items is found in the ‘low adjustment category’, whereas for B items this mostly occurs in the ‘high adjustment category’. As a result, we may say that there is no learning effect associated with A items since the high number of adjustments does not lead to a better performance. For instance, when considering the Final OUT replenishment level of scenario 1, as the number of adjustments increases, the CSL and fill rate decrease.

On the other hand, it does appear to be a learning effect when the manager makes adjustments on replenishment order decisions for B items, as shown by the increase in the value of SCL and fill rate as the number of adjustments becomes higher. From Table 5.21 we can see that the highest CSL and fill rate for both scenarios mostly results from the ‘high number of adjustments’ category. For example, in scenario 2 the fill rate increases from 0.830 in the low adjustments category to 0.931 in the high adjustments category.

Table 5.20 The results of learning-effects analysis based on number of adjustments for A items

Scenario	Classification	System OUT replenishment level			Final OUT replenishment Level			SMA-based OUT replenishment Level		
		Total inventory investment (€)	Average CSL	Average fill rate	Total inventory investment (€)	Average CSL	Average fill rate	Total inventory investment (€)	Average CSL	Average fill rate
Scenario 1	adjustment <=13	7,725.17	1.000	1.000	7,645.70	1.000	1.000	7,694.58	1.000	1.000
	<13adjustment <=21	67,902.07	0.993	0.992	66,749.48	0.993	0.992	65,205.44	0.993	0.992
	adjustment >21	1,897.00	0.981	0.992	1,962.90	0.982	0.993	1,918.91	0.982	0.994
Scenario 2	adjustment <=13	7,637.98	1.000	1.000	7,618.45	1.000	1.000	7,578.94	1.000	1.000
	<13adjustment <=21	59,134.21	0.933	0.947	57,890.62	0.913	0.928	57,080.39	0.863	0.887
	adjustment >21	1,259.84	0.870	0.942	1,243.15	0.852	0.924	1,157.95	0.828	0.894

Table 5.21 The results of learning-effects analysis based on number of adjustments for B items

Scenario	Classification	System OUT replenishment level			Final OUT replenishment Level			SMA-based OUT replenishment Level		
		Total inventory investment (€)	Average CSL	Average fill rate	Total inventory investment (€)	Average CSL	Average fill rate	Total inventory investment (€)	Average CSL	Average fill rate
Scenario 1	adjustment <=13	30,817.08	0.986	0.869	30,893.03	0.986	0.869	30,459.94	0.986	0.872
	<13adjustment <=21	32,837.03	0.987	0.967	32,917.83	0.988	0.970	31,298.49	0.988	0.971
	adjustment >21	3,205.38	0.986	0.980	3,264.94	0.987	0.984	3,421.88	0.988	0.988
Scenario 2	adjustment <=13	29,305.22	0.885	0.834	29,339.33	0.878	0.830	28,871.79	0.854	0.834
	<13adjustment <=21	26,495.99	0.870	0.876	26,444.98	0.867	0.873	26,504.54	0.867	0.871
	adjustment >21	2,631.02	0.910	0.922	2,670.48	0.916	0.931	2,670.99	0.915	0.930

The above findings indicate that demand characteristics may affect the presence of learning effects. The judgemental adjustments for A items, which are less intermittent than B items, do not improve over time. This result is consistent with the findings of studies of judgmentally adjusted forecasts where no learning effect is found in the forecasting function (Syntetos et al, 2009b). Moreover, Nikolopoulos et al. (2006) show that there are gaps in the learning loop in the forecasting systems (adjusted and unadjusted) since forecasters in companies are not trained sufficiently over time (Lim and O’Connor, 1996; Klassen and Flores, 2001).

The performance of the inventory system for A items does not improve over time most probably because of the inability of the managers to use contextual information and/or experience when making adjustments. In judgemental forecasting research, Nikolopoulos et al. (2006) state that forecasting error cannot be eliminated, because of specific reasons such as the inability of organisations to deal with the current information. This inability may be caused by certain characteristics embedded in a company. As proposed by Walsh and Ungson (1991), these characteristics include individuals, culture, structures and external sources. This inability may constitute the reason behind managers not learning from the past or taking into account the current information effectively when making decision on a stock control system.

The results for B items could be interpreted as the decision maker (we assume that there is only one decision maker making adjustments) learning how to use the causal information and how to avoid the wrong decision from analogies with past cases. The rationale behind these circumstances is mainly the fact the prices of B items are collectively higher than those related to A items. As a result managers tend to give careful attention on making adjustments. In addition, it might be due to the high intermittent nature of the B items that consequently are associated with higher obsolescence rates. As explained by Levitt and

March (1996), organisations can learn by accumulating and encoding experiences informally (culture, beliefs and paradigms) and formally (rules, procedures, policies and technologies). Further, this finding is in line with the forecasting study conducted by Lee et al. (2007) who reported that forecasters often apply information from analogous events to an anticipated special event. Thus, we may say that it is important to improve the process of documentation and the reasons claimed by managers when changing the OUT level produced by the software system. As suggested by Nikolopoulos et al. (2006), documentation of information should contain all relevant information, maintain its originality and its complete form, in order to avoid overlooked or forgotten information. In addition, access to such information should be straightforward. These explanations may be the answer to the research question about the learning effect in the process of adjusting stock control quantities (research question 5).

5.11. The combination methods of the OUT level

The analysis of the effect of combining different methods for the calculation of the OUT level also applies to the analysis of the inventory performance. To recap, we consider three methods of replenishing orders: System OUT replenishment level, Final OUT replenishment level, and SMA-based OUT replenishment level. For the purpose of combination analysis, we combine all three methods to obtain the total of inventory investment and the average of CSL and fill rate, first between System OUT replenishment level and Final OUT replenishment level, secondly between System OUT replenishment level and SMA-based OUT replenishment level, and finally between Final OUT replenishment level and SMA-based OUT replenishment level. The combination value is calculated by averaging (50%-50% weight) the OUT replenishment level resulting from each method and the results are shown in Table 5.22.

It can be seen from Table 5.22 that, although it is not very significant, mainly, the inventory investment resulting from all the individual methods seems to have a higher value compared to the inventory investment of the combination methods, whereas for CSL and fill rate, the individual and the combination methods seem to produce very close values. This is true of both scenarios for A and B items. Thus, we may say that the combination methods seem to make valuable contributions to improving the performance of inventory systems, especially for reducing the inventory investment. This finding is consistent with the results presented in most relevant studies in the forecasting field where evidence shows that forecast combinations are more accurate than the forecasts produced by individual methods (Clement, 1989; Makridakis, 1989).

Furthermore, if we analyse the three combination of replenishment order methods above, we find that the CSL and fill rate seem to have very close values for both scenarios of A and B items. Or we may say that there is no significant difference of CSL and fill rate values between the three combination methods. Mainly, the lowest inventory investment of A and B items results from the combination where there is an SMA-based OUT replenishment level method. This indicates that the SMA-based OUT replenishment level performs better when incorporated with the judgemental stock control method compared with other statistical methods (in this case is the System OUT replenishment level). This finding supports that of the next analysis (see section 5.12) regarding the explanatory power of SMA-based OUT replenishment level.

Table 5.22 The simulation results for A and B items

Combination replenishment order method	Scenario	A items			B items		
		Total Inventory Investment (€)	Ave. CSL	Ave. Fill Rate	Total Inventory Investment (€)	Ave. CSL	Ave. Fill Rate
System OUT replenishment level – Final OUT replenishment level	Scenario 1	1,065,855.13	0.991	0.993	131,766.12	0.987	0.965
	Scenario 2	730,134.82	0.905	0.938	107,034.69	0.885	0.888
System OUT replenishment level – SMA-based OUT replenishment level	Scenario 1	1,036,582.38	0.991	0.993	130,917.10	0.987	0.966
	Scenario 2	711,256.72	0.882	0.919	107,420.91	0.883	0.892
SMA-based OUT replenishment level – Final OUT replenishment level	Scenario 1	1,046,356.14	0.991	0.993	132,600.85	0.988	0.967
	Scenario 2	705,006.65	0.886	0.909	108, 285.80	0.890	0.894

The above findings indicate that a combination method in stock control seems to improve the performance of the inventory system. Goodwin (2000a) argued that forecast accuracy can improve when combination methods between statistical and judgemental methods are used, since the statistical method may be able to filter time-series patterns from noisy data, where the judgement can be used to anticipate the effects of special events that occur in the future. This rationale may exist on the judgementally adjusted stock control decision when statistical methods are incorporated into the process of decision making. This analysis answers our research question regarding the combination method of OUT level (research question 6).

5.12. Explanatory Power of SMA-based OUT replenishment level

In order to analyse the explanatory power of the SMA-based OUT replenishment level to the Final OUT replenishment level, we conducted regression analysis to find out the significance of the interaction between the former and the latter. The SMA-based OUT level is essentially utilized as a type of benchmark based on which decisions are being made for adjusting the System OUT replenishment level. It is therefore natural to expect that the SMA related OUT level should reasonably 'explain' the behaviour of the adjusted OUT level.

The SMA-based OUT replenishment level is considered as the independent variable, while the Final OUT replenishment level is treated as the dependent variable. We conducted the analysis solely for SKUs that have ten or more consecutive adjustments. The statistical significance (P-value) is calculated using simple regression analysis in Microsoft Excel. After calculating the P-value for each SKU, the results are analysed using descriptive statistics, and comparing the percentage of statistically significant SKUs and non-statistically significant SKUs. The level of confidence is assumed at 95%.

To get a better understanding of how we calculate the significant value of each SKU, a sample is described below. The example is taken from material XB0306001 in A items. The values of SMA-based OUT replenishment level and Final OUT replenishment level can be seen in Table 5.23.

Table 5.23 Data of SMA-based OUT replenishment levels and Final OUT replenishment levels for material XB0306001

Period	SMA-based OUT replenishment level	Final OUT replenishment level
1	212.17	250
2	205.04	250
3	250.96	300
4	326.79	300
5	306.53	300
6	280.11	300
7	213.16	225
8	236.06	225
9	238.71	225
10	250.16	225
11	309.17	280
12	280.11	280
13	298.60	280
14	273.94	280

Regression analysis in Microsoft Excel is then applied to the above data, and the output can be seen in Table 5.24.

Table 5.24. Summary output of regression analysis of material XB0306001

Regression Statistics	
Multiple R	0.7379
R Square	0.5445
Adjusted R Square	0.5066
Standard Error	21.906
Observations	14

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	6884.3	6884.3	14.346	0.0026
Residual	12	5758.5	479.88		
Total	13	12643			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	111.9	41.03	2.7272	0.0184	22.501	201.3	22.501	201.3
XB0306001	0.5849	0.1544	3.7876	**0.0026**	0.2485	0.9214	0.2485	0.9214

Column 5 shows that the P-value for material XB0306001 is 0.0026, which is smaller than 0.05. As a result, the null hypothesis is rejected, which means that there is a statistical significance between the SMA-based OUT replenishment level and the Final OUT replenishment level. This process is repeated for each SKU, and the results for A and B items are summarised in Table 5.25.

Table 5.25 The descriptive statistic of P value for A and B items

Descriptive statistic	**A ITEMS**	**B ITEMS**
Minimum	0.0000	0.0000
25% Percentile	0.0000	0.0000
Median	0.0000	0.0000
75% Percentile	0.0010	0.0031
Maximum	0.9546	0.9183
Average	0.0286	0.0340
Standard deviation	0.1281	0.1206
Statically significant (P value < 0.05)	93.78%	87.84%
Not statistically significant (P value ≥ 0.05)	6.22%	12.16%

The results from Table 5.25 show that the linkage between the SMA-based OUT replenishment level and the Final OUT replenishment level is very close, at 93.78% and 87.84% of SKUs for A and B items respectively, and shown to be statistically significant. This suggests that the company's approach (based on the SMA forecast) can explain the Final OUT replenishment level used for decision-making purposes. It means that the manager seems to consider the SMA-based OUT replenishment level before making an adjustment as the final decision. Managers trust the SMA-based OUT replenishment level as the benchmark method, most probably because they understand its procedure. In the forecasting area, many studies have reported institutions using the SMA method because they are familiar with the procedure and it is relatively easy to understand (Sanders and Manrodt, 1994). Moreover, in the context of intermittent demand, the SMA method reflects a popular industry approach in dealing with forecasting tasks (Sani, 1995; Syntetos, 2001; Syntetos and Boylan, 2005). Since many academic studies have found that the SMA method is robust (Sani and Kingsman, 1997; Syntetos and Boylan, 2005), this factor might be another reason why many organisations apply it in forecasting practices.

The SMA-based OUT replenishment level is based on the forecasting result calculated using the SMA method. The robustness of the SMA forecasting method, and its simplicity, may explain the power of the SMA-based OUT replenishment level. Similarly, the case organisation takes this approach as the benchmark method and seems to rely on it in making the final decision. This can be the answer to our research question in terms of the explanatory power of the SMA-based OUT replenishment level over the Final OUT replenishment level.

5.13. Framework for judgmentally adjusted orders

Following from the discussion conducted in the previous sections, a framework is presented below to facilitate the process of judgemental interventions in an inventory control system. Base on the analysis we recommend the adjustment framework for replenishment order decision which can be seen in Figure 5.19.

The first step of the process is to define the demand series characteristics (separate for example between fast and intermittent demand) that consequently will necessitate a different inventory policy. The policy itself will determine when and how much (time and quantity related requirements) to order. This is essentially the principle of inventory system regardless of whether adjustments are performed or not. The next step is to define the size and sign of the judgemental adjustment. This should be based on two factors. First, we have to consider any contextual information related to future events that may affect the demand, such as the promotion of new product. Second, we need to analyse any archived justifications of previous adjustments along with the performance of such adjustments in order to be able to judge on the effects and performance of previous interventions. Well documented and detailed justifications may enable managers to improve the performance of future interventions. In this study, we have found that SKUs associated with a higher number of justifications did relate to a better performance as compared to SKUS where fewer justifications were offered. Moreover, we have found that negative and large adjustment performed better than positive and small adjustment. Thus, in order to adjust the replenishment orders, particularly when small and positive adjustments are regularly taking place, we suggest to manager to give excessive consideration on the above factors.

In order to evaluate whether or not the adjustments may improve the performance of the inventory system, the measurement procedure (i.e. what constitutes good performance) has to be defined. We recommend that performance measurement is undertaken regularly. This would facilitate the process of providing feedback in order to further improve the process of judgemental interventions.

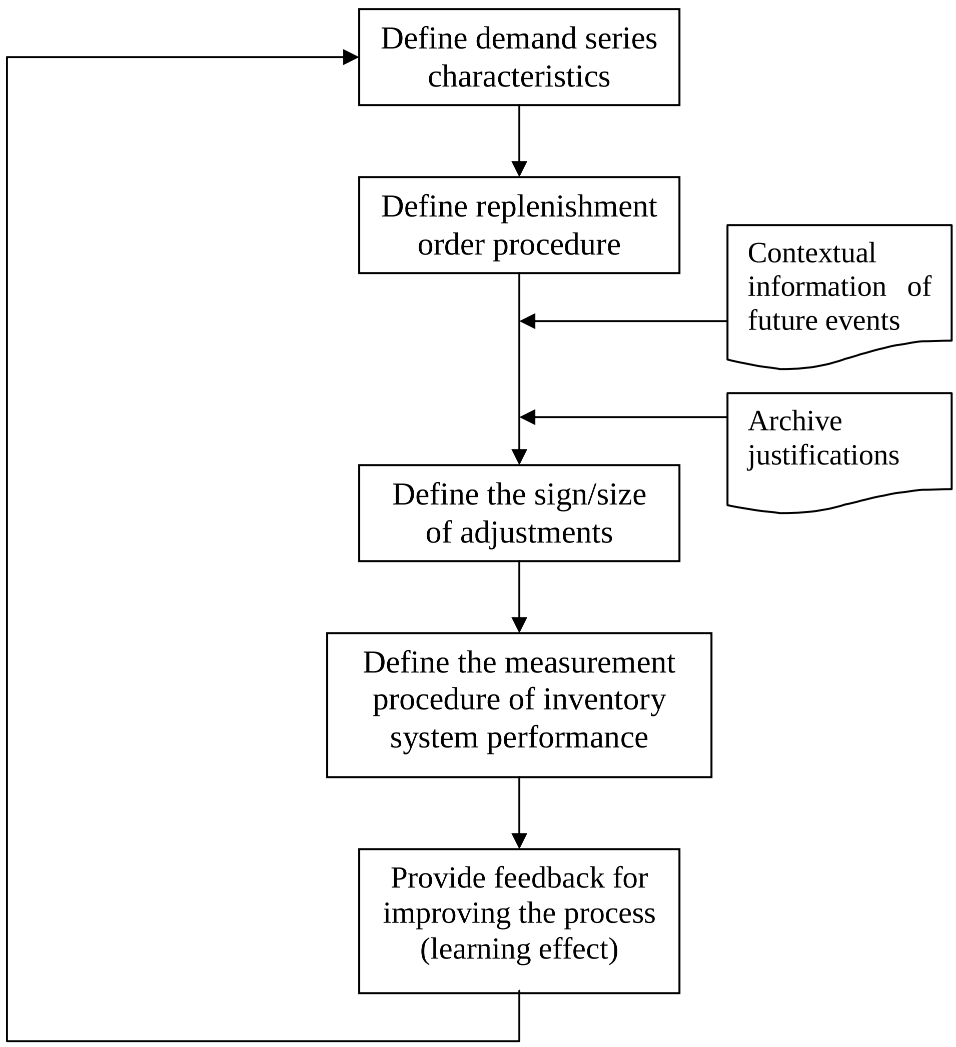


Figure 5.19 A framework to facilitate the process of judgemental adjustments

5.14. Conclusions

In this chapter, the empirical data analysis is discussed and the findings along with the insights for real world practices are presented. In total, 359 A-class and 1,454 B-class SKUs are considered for the purposes of this research. To develop an understanding of the nature of the demand and its characteristic, the analysis of demand descriptive statistics is conducted (in section 5.1) by considering demand per period, demand sizes, and inter-demand intervals of each SKU. The results of the analysis show that the demand sizes for A items are higher than for the B items, whereas the inverse is true with regards to the inter-demand interval. Moreover, the analysis of the price of the SKUs is also carried out in section 5.2, where we found that the range of prices for the B items is wider than that related to the A items. It also found that B items are associated with high prices. From above findings, we surmise that, although A-class items defined as the most important SKU category (based on the ABC classification approach), B items also need more attention from managers since this category, in this case organisation, is more intermittent in nature, resulting presumably in higher obsolescence and having a much greater impact on stock stock-holding costs.

The analyses have also been conducted on the adjustment distribution of the signed size of adjustments, absolute size of adjustments, relative signed size and relative absolute size, and found that adjustments may be fitted by some theoretical statistical distributions (see section 5.3). The information that we obtained from the distribution of adjustments (form and parameters) may be used as the control parameter (a minimum and a maximum allowance) when managers make an adjustment. This is also an important finding for the design of decision support systems.

Moreover, in analysis of the justification of adjustments presented in section 5.4, we have attempted to cluster all the justifications into conceptually uniform categories, resulting in

24 such categories. We found that managers claimed a 'decreasing demand' situation in the great majority of cases. This indicates that managers are indeed aware of important contextual information, but for convenience they always report the same justification. In addition, we found that the reasons for adjustments of the OUT level are mainly based on the information that the manager has regarding demand for spare parts, inventory position, or replenishment orders information, but are not based on the price of parts. Further, there is often a discrepancy between the sign of the adjustments and what the demand patterns indicate. The manager's decision to change the OUT level does not always reflect demand pattern changes. These findings indicate that managers still seem to make significant errors in making adjustments in inventory control decisions and in adjusting the OUT level. Adjustments are made in an arbitrary way and often reflect a sense of ownership on the part of managers.

Simulation experiments were conducted to evaluate the performance of the inventory system. The effect of adjustments was measured by reporting the implied inventory investment, the Cycle Service Level (CSL) and fill rate achieved. We consider the System OUT replenishment level (unadjusted OUT level), the Final OUT replenishment level (adjusted OUT level), and the SMA-Based OUT replenishment level. The simulation is carried out for A and B items and two scenarios are designed. We can see from the simulation results in section 5.5 that, although the effects are not significant enough to improve the performance of the inventory system, human intervention seems to offer a reasonable advantage in stock control decision making.

To obtain a better understanding of the effects of human judgement on the stock control decision, we evaluate the issues regarding the sign and size of adjustments, the bias and the learning effect on judgmentally adjusted stock control decision making (these analyses are presented in sections 5.6, 5.7, 5.9, and 5.10). The findings synchronize with what is found in the judgemental forecasting field where the negative and large adjustments seem to perform better in improving the inventory performance than the positive and small adjustments. Moreover, we also found that bias may be introduced into the entire observed system (System OUT replenishment level, the Final OUT replenishment level, and the SMA-Based OUT replenishment level) and the negative bias leads to better performance than does the positive one. In terms of learning effects, since the high number of adjustment categories did not improve the inventory performance, we conclude that there is no learning effect in A items. On the other hand, there is an occurrence of learning effects for B items. Furthermore, from the analysis of the combination methods of the OUT replenishment level (averaging 50%-50% weight of the OUT level) we found that that the combination method in stock control seems to improve the performance of the inventory system (see section 5.11).

In the analysis of the effects of justification of adjustments on inventory performance (see section 5.8) we found that the SKUs associated with more than 75% of justifications produce the highest stock control performance. This indicates that offering the rationale and reasons for making the adjustment, including its documentation, is an important factor that helps the decision maker to make adjustments. The justification for adjustments should be determined not only by when the decision maker makes an adjustment, but also by how, presenting the reason why the judgement is incorporated into the decision.

In addition, we attempted to investigate the explanatory power of the SMA-Based OUT replenishment order as the benchmark method utilized in this case organisation. The analysis result suggests that the company’s approach (based on the SMA forecast) can explain the Final OUT replenishment level used for decision-making purposes. It means that the manager seems to consider the SMA-based OUT replenishment level before making an adjustment as the final decision. Managers trust the SMA-based OUT replenishment level, most probably because they understand its procedure.

Based on all the findings above, we develop a framework for judgementally adjusted replenishment orders which is presented in Section 5.13.

Chapter 6. CONCLUSION, CONTRIBUTIONS, LIMITATIONS, AND FURTHER RESEARCH

6.1. Introduction

This chapter provides a brief discussion of the main issues addressed in our research. The implications of this research for the OM theory and practice are also presented. Moreover, the limitations of this research, theoretically and empirically, are identified and the next steps of the research are suggested.

This study aimed to explore the effects of incorporating human judgement into inventory decision-making.

The aim of the research was reflected in the following objectives:

1. To critically review the literature on how judgement relates to the main functions of an inventory system: demand categorisation, forecasting and stock control (Chapters 2 and 3).
2. To assess the implications of judgemental adjustments on real data, focusing on replenishment orders (Chapters 4 and 5).
3. To link the performance of adjustments with the managers' justification for introducing such adjustments in the first place (Chapter 5).
4. To understand for the first time how managers adjust inventory-related decisions (Chapters 4 and 5).

5. To evaluate the circumstances under which human judgement leads to performance improvement (Chapter 5).
6. To derive a number of insights with regard to practical applications and a number of suggestions for improving the functionality of software packages (Chapter 5).

All the objectives have been achieved and the summary and contributions of the thesis are outlined in the following section.

6.2. Conclusions

Physical inventories constitute a considerable proportion of companies' investments in today's competitive environment. The trade-off between customer service levels and inventory investments is addressed in practice by formal quantitative inventory management (stock control) solutions. The solutions need to be fully automated since, commonly, organizations deal with a tremendous number of SKUs. From the literature review we found that decision makers/managers tend to reflect (superimpose) their own judgment on the solutions resulted from specialized software systems.

This study was carried out in a single company representing the European logistics headquarters of a major international electronics manufacturer. In this research we are concerned with the value being added (or not) when statistical/quantitative output is judgementally adjusted by managers. Our work aims to investigate the effects of incorporating human judgement into such inventory-related decisions. In achieving the aim, first, a set of relevant research questions was developed based on a critical review of the literature. Then, an extended database of approximately 1,800 SKUs from the case study organisation was analysed for the purpose of addressing these research questions. In addition to exploratory empirical analysis, a simulation experiment was performed to evaluate in a dynamic fashion the effects of adjustments on the performance of a stock control system.

A computer simulation experiment was designed to quantify the inventory performance and evaluate the implications of judgemental adjustments in an inventory system, focusing on replenishment orders. For simulation purposes, the database was arranged in Microsoft Excel worksheets and then Visual Basic Application code was developed to measure inventory performance. The results on the simulation experiment revealed that, by considering the trade-off between inventory cost and service level, it seems that judgemental adjustments account for an improvement in inventory investment. However, the effects are not too prevailing in increasing the CSL and fill rate. Overall, the results indicate that human intervention seems to offer a ‘reasonable’ advantage in stock control decision making, important enough to offer a justification for these interventions in the first place. This result is in line with the previous empirical research in the area of demand forecasting conducted by Syntetos et al. (2009b) and Syntetos et al. (2010a) which shows that the inventory implications of adjusting demand forecasts are prominent. Moreover, the outcome of our empirical research shows (indirectly) that the effect of adjusting inventory decisions is less significant than that associated with adjusting forecasts. This finding confirms the previous study conducted by Syntetos et al. (2011) about the comparatively bigger importance of adjusting at the forecasting rather than at the inventory control level.

With regards to the characteristics of the adjustments, we have found that negative adjustments result in better performance than positive ones, and that adjustments of a medium/large size perform better than small ones. This is aligned with the main conclusions derived in the forecasting literature and it can similarly be explained in terms of: i) a sense of ownership associated with small adjustments, that do not necessarily reflect an important piece of information but rather a desire to merely intervene in the system; ii) the optimistic bias characterizing many individuals that leads to upward (positive) adjustments. Negative adjustments would typically result in a reduction of the service provision if things were not to change, so adjustments in that direction should typically be associated with some genuine knowledge about the underlying demand process. We have also explored this bias-related properties of judgemental adjustments and have found that indeed bias may be present in such a system. Furthermore, negative bias leads to better performance than positive. This indicates that, if the managers adjust the Order-Up-To (OUT) levels without any logical justification, the downward adjustments would seem to perform better than the upward ones. Some learning effect seems to take place in the process of adjusting stock control quantities, as it was found that SKUs associated with a high number of adjustments are indeed also associated with a better inventory control performance.

Since the justification of the adjustments was recorded, we attempted to assess whether offering a justification is associated with better performance. The association of judgemental adjustments with a justification provided can be viewed as a contribution in its own right, as no empirical studies have been previously conducted in this area, neither in the forecasting nor in the stock control field. From the simulation experiment results, we found that providing a justification for adjusting stock control quantities may lead to an improvement in inventory performance.

Justifications very often related to a perceived change in the underlying demand pattern, (recorded as ‘demand increasing’ or ‘decreasing’). An examination of the consistency between such justifications and the actual underlying demand movement was undertaken and it was found that in about 21% and 25% of the cases for A and B items respectively, adjustments were made in a different direction from that of the time series evolution. This indicates that managers may make significant errors in adjusting the OUT levels. They seem to make judgements in an arbitrary way, often reflecting the managers' sense of ownership. We clustered the justifications into 24 conceptually uniform categories, of which the 'decreasing demand' category accounted for 40.9% and 45.5% for the A- and B-class items. Also, we found that most of the reasons for adjustments made by the managers are merely related to the information that the managers have to hand, regarding the demand for spare parts, their inventory position, and/or replenishment order information, but not upon the prices of spare parts.

An analysis of combined methods (the combination of System OUT replenishment level and Final OUT replenishment level, System OUT replenishment level and SMA-based OUT replenishment level, and Final OUT replenishment level and SMA-based OUT replenishment level) for calculating the inventory performance was also conducted. The combination value was calculated by averaging (50%-50% weight) the OUT replenishment level resulting from each method. The findings indicate that the combined method of stock control seems to improve the performance of the inventory system, especially in reducing inventory investment. However, other additional combination methods need to be carried out in order to achieve a better understanding of this issue.

In making adjustments to the final decision of the replenishment order quantity, managers use the SMA-based OUT replenishment levels as their benchmark. By using regression analysis we find that the SMA-based OUT replenishment level (that is based on the SMA forecast) can explain the Final OUT replenishment level. This indicates that managers trust this method and rely on it in making the final decisions.

From the empirical analysis we found some theoretical distributions that fit the adjustments. The goodness-of-fit of theoretical statistical distributions on judgemental adjustments was analysed using the Kolmogorov-Smirnov (K-S) test. The results can be seen in Table 5.5. For the A items it is found that the Cauchy distribution provides a strong fit for most series of signed sizes of adjustments (80.0 %) and relative signed sizes of adjustments (83.8%), whereas the Gamma distribution provides a strong fit for the absolute size of adjustments (76.3%) and the relative absolute size of adjustments (88.8%). Similar results are reported for the B items, where the Cauchy is associated with a strong fit for 95.0% of the relative signed size of adjustments and the relative absolute size of adjustment (95.0%). The Gamma distribution offers a strong fit for the absolute size of adjustments (97.5%), whereas the Weibull distribution performs very well on the signed size of adjustments (95.0% cases of strong fit).

Knowing the distribution that resembles the range and shape of the relevant decisions made by humans is most important in terms of the design of support systems. A support system is any structured process that may facilitate decision making. It may be a well documented process, but mostly nowadays is a computerised solution (i.e. software package). A software package which is developed to support the inventory management function is called an Inventory Support System (ISS). ISS has not been discussed in the literature. From the goodness-of-fit tests, some theoretical distributions that fit the adjustment distributions were found. Based on that information, managers may define a specific percentile above or below which adjustments are permitted. For example, as we found that small adjustments are not performing well, managers may decide that there is no adjustment allowed below the fifth percentile. Moreover, since large adjustments are found to perform well, perhaps managers may want to have more information on the rationale behind large adjustments (exceeding say the 90^{th} percentile).

Based on the above findings obtained through the empirical analysis, we can make a number of suggestions (see Figure 5.19) for improving the functionality of software packages.

6.3. Implications

This research has generated a number of implications for the OM theory and practice. More specifically, it has contributed to the development of insights in managing intermittent demand inventories.

6.3.1. Implications for the OM theory

This research is the first study that investigates in an empirical way the effects of judgementally adjusting replenishment decisions. It analyses the way adjustments are made by humans and their effect on the performance of a stock control system in the context of intermittent demand. There is a substantial body of knowledge on the effects of judgment in the forecasting area, particularly on demand/sales forecasting. When it comes to the inventory area though there are only two studies that look at this issue. The first one is a presentation in the International Symposium of Forecasting by Kolassa et al. (2008) that offers some very preliminary empirical insights into this issue. The second is a study conducted by Syntetos et al. (2011) that relies upon the use of System Dynamics. There are no complete studies to date that look, empirically, at the implications of human interventions into an inventory system, particularly on replenishment order decisions. This study points out the need for more empirical work (rather than laboratory experiments) in the area of judgement and inventory control. It demonstrates the complications of real world inventory systems and the non-textbook behavior of such systems (both in terms of their actual operation and optimization) that call for more work with real data, and/or real situations. We return to this issue when we discuss the next steps of research.

Moreover, the forecasting literature suggests that judgemental forecasting is most useful in terms of potential amendments to Forecast Support Systems (FSS). For example, the study by Fildes et al. (2009) and Syntetos et al. (2009b) found that small adjustments do not perform well since they are known to simply reflect a response to noise, whereas the negative adjustments perform better than the positive ones as they reflect genuinely important information (Fildes et al., 2009). From the outcome of this research, a reference may now be made to Inventory Support Systems (ISS). Similarly, to Forecast Support Systems, systems that support the inventory function and provide guidance into how the inventory replenishment task may be improved should attract high attention in the academic community and research into both their functionality and implications for real world practices.

In addition, since the justifications of adjustments are provided by the case organisation, this research investigates the performance of stock control systems when justification of adjustments is offered as compared to those without a justification. This is also the first study that explicitly analyses in an empirical way the justification for adjustments. There is no previous study has discussed this issue, not only in the area of inventory, but in the area of forecasting as well.

Finally, since this research includes elements of Operation Management (OM)/Operational Research (OR) and behavioral aspects of decision making, it should contribute and advance knowledge in the field of behavioral operations.

6.3.2. Implications for the OM practice

This research provides the evidence of what is a standard practice in inventory systems where managers tend to adjust replenishment order decisions. As discussed before, there are only two studies (Kolassa et al., 2008 and Syntetos et al., 2011) investigating the effects of such adjustments and no empirical evidence has been put forward thus far in the literature with regards to this issue. The current research documented the process of adjusting the replenishment order decision as a standard practice in the real inventory world.

Furthermore, this research has some implications for the statistical analysis of the properties of the adjustments (i.e. formal distributions that fit the adjustments). The results of empirical analysis of this research may lead towards the improvement of the functionality of software packages, and further towards the development of more generic ISS.

These implications can be summarised on the following issues:

- Defining the demand series characteristics for the purpose of choosing an appropriate inventory policy. The policy itself will determine when and how much (time and quantity related requirements) to order.
- Deciding the size and sign of the judgemental adjustment. In this research, we found that the negative and adjustments perform better in improving the performance of the inventory system compared to the positive and small adjustments. The size of adjustments may be defined by using the parameters of the particular distributions that provide a good fit to the adjustments. For example, by knowing the mean and the variance of such distribution, managers may decide the specific percentile above/below which adjustments need to be authorized/or further debated.
- Considering any contextual information related to future events that may affect the demand, such as the promotion of new product in deciding the size and sign of adjustments.
- Evaluating any archived justifications of previous adjustments along with the performance of such adjustments is also important in order to review the effects and performance of previous interventions. Well-documented and detailed justifications may enable managers to improve the performance of future interventions.
- In order to evaluate whether or not the adjustments may improve the performance of the inventory system, the measurement procedure (i.e. what constitutes good

performance) has to be defined. We recommend that performance measurement is undertaken regularly. This would facilitate the process of providing feedback in order to further improve the process of judgemental interventions.

6.4. Limitations

In this section we summarise the limitations of the work conducted for the purposes of this research.

6.4.1. Generalisation of theory

The analysis in this research has been developed for a specific case originated from one organisation. As discussed in Chapter 1, the fact that this work is based on a single case can be justified by the lack of any previous research in this area, and even more so by the sensitivity of the information required in conducting such a study. Specificities related to the problem in hand may obviously differ from one situation to the other and in that respect generality may be questioned. Although we are concerned with a single organisation and essentially a particular case of SKUs (spare/service parts), this company could be viewed as a ‘good sample’ to be used for discussing the pertinent issues. First of all the demand for spare parts is predominantly intermittent in nature and intermittent demand patterns prevail in any organisational setting. In fact the vast majority of SKUs in any business setting are intermittent in nature. Second, and very importantly, we cover SKUs from two classes in an ABC classification by value and that also covers a big part of any company's investment in stock. Finally the company's practices are very typical (to the best of our knowledge) of what is happening in industry. That is people do not adjust replenishment orders (order quantities) but order levels (re-order points or Order-Up-To levels).

The general observations and associated learning should easily be transferred to other organisations as well. Moreover, the insights and discussions regarding the judgementally adjusted stock control decisions in this research should provide practical insights to many other industrial organisations. However, replications of our research on more cases definitely need to be conducted for the purpose of obtaining a better understanding of all pertinent issues.

6.4.2. Interviews with the manager

This research does not involve the collection of any qualitative information directly from the managers who conducted the actual judgemental adjustments. Interviews with these people would enable an understanding on ‘how’ and ‘why’ adjustments are performed. Further, they would also allow a direct linkage of such information with the quantitatively derived insights of our research and the actual performance of the adjustments. To the best of our knowledge, the linkage identified above is a missing one also in the forecasting, not only in the inventory control, literature.

6.4.3. Construction of the database and simulation experiment

A database was established in order to conduct the simulation experiment. In the process of construction (explained in section 4.3), the Visual Basic software (embedded in Microsoft Excel) was used. However, some steps of the process had to be done manually, for example entering all SKUs for every period in a single Excel worksheet (one SKU per row). This process might have been more effective and efficient if the VBA software had been used. Moreover, the simulation experiment looks only at one forecasting model, that is, a simple moving average. Although much of the academic literature states that this forecasting method is robust, several forecasting procedures are more suitable for intermittent demand, such as Croston’s method and the SBA (Syntetos-Boylan Approximation, Syntetos and Boylan, 2005.

6.4.4. Goodness-of-fit distribution tests

The Kolmogorov-Smirnov (K-S) test was deployed to determine the goodness-of-fit of the adjustments distributions, in Chapter 5. However, this test is not ideal since it relies upon continuous random variables to be tested. On the other hand, the sign and size of adjustments constitute the random variables in our analysis. These are discrete variables, since the value could be any integer between zero and plus infinity, and it conflicts with the theoretical cumulative distribution being tested in K-S. However, as pointed out in section 5.3, the K-S test was chosen as there is no requirement for grouping the data into categories, and it seems flexible. In addition, no more than two parameter statistical distributions were considered in our analysis.

6.5. Further research

Future steps of the research are intended to:

- Replicate the analysis in other datasets/organisations. As discussed above, empirical analysis on one case study seems insufficient for the generalisation of the concepts and the outcomes of this research. An extensive study of several cases in other organizations needs to be undertaken where human intervention is incorporated in stock control decision making. In addition, in order to further understand and clarify 'how' and 'why' managers perform adjustments in stock control, interviews are also highly recommended.
- Develop more suitable scenarios using more appropriate forecasting methods such as the SBA and stock control policies to investigate the effects of human intervention in an inventory control setting. Moreover, the study of a system where adjustments are performed at both the forecasting and inventory control stage, would allow developing

our empirical understanding on the progressive accumulation of the effects of adjustments in an inventory management context.

- Develop a Decision Support System (DSS) for stock control purposes (what may be termed as Inventory Support System - ISS). So far, to the best of our knowledge, there is not a single academic publication that discusses the features of computerized support systems for facilitating judgemental adjustments of inventory related decisions. Given the extent to which managers intervene into inventory applications, such a support system would be very welcomed by practitioners.

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APPENDICES

Appendix A: Forecasting methods for fast-moving forecasting

The items that need to be replaced frequently, compared to those that are usable for extended period of time, are known as fast-moving demand items. Commonly, these items category is characterised by smooth demand nature. Many forecasting methods have been established for this demand category. Some of these methods are discussed as follow:

a) Decomposition methods

The pattern in data series can be breakdown (decomposed) into sub patterns that identify each component of the time series separately. Decomposition assumes that the data are made up as follows:

$$\text{Data} = \text{pattern} + \text{error}$$

$$\text{Data} = f\,(\text{trend-cycle, seasonality, error})$$

Trend-cycle represents long-term changes in the level of the series. Seasonal factor relates to periodic fluctuations of constant length that are caused by such things and error assumed to be the difference between the combined effect of the two sub patterns of the series and the actual data.

Alternatives of decomposition forecasting methods are additive model (appropriate if the magnitude of the seasonal fluctuations does not vary with the level of the series), multiplicative model (appropriate if the seasonal fluctuation increase and decrease proportionally with increases and decreases in the level of the series), logarithms model (fit a multiplicative relationship by fitting an additive relationship to the logarithms of the data), and pseudo-additive decomposition (useful in series where there is one month or quarter that is much higher or lower than all the other months or quarters. For an additive decomposition, the seasonally adjusted data are computed by simply subtracting the seasonal component, whereas for multiplicative decomposition, the data are divided by the seasonal component to give seasonally adjusted data. The decomposition method seems not effective to be used in practice as this is not a dynamic method but rather what is called a static methodology.

b) Averaging methods

There are two general averaging methods. The first one relies upon a straight average of all historical information and it is typically termed as Total Average method. This method performs well only if the underlying demands process is stationary in nature. Another method is the Simple Moving Average (SMA) method. SMA is also an average but referring only to the n latest observation (where n >1). The term moving average is used because as each new observation becomes available, a new average can be computed by dropping the oldest observation and including the newest one.

c) Autoregressive Integrated Moving Average (ARIMA)

ARIMA models were popularized by George Box and Gwilym Jenkins. Box and Jenkins effectively put together in a comprehensive manner the relevant information required to understand and use univariate time series ARIMA models. The basis of the Box-Jenkins approach to modeling time series consists of three phases: identification, estimation and testing, and application.

The autoregression (AR) equation is developing by changing the explanatory variables of regression model with the previous values of the forecast variable. In autoregression the basic assumption of independence of the error (residual) terms can easily be violated. Just as it is possible to regress against past values of the series, there is a time series model which uses past errors as explanatory variables. Here, a dependence relationship is set up among the successive error terms, and the equation is called a moving average (MA) model. This model is called a moving average because it is defined as moving averages of the error series (e_t).

Autoregressive (AR) model can be effectively coupled with moving average (MA) models to form a general and useful of time series models called autoregressive moving average (ARMA) models. However, they can only be used when the data are stationary. This class of model can be extended to non-stationary series by allowing differencing of the data series. These are called autoregressive integrated moving average (ARIMA) models.

d) Causal methods

Causal method assumes that the variable to be forecasted exhibits an explanatory relationship with one or more independent variable. This method lies between long time horizon forecasting and short time horizon forecasting. The most useful technique of this method is a regression model. There are two type of regression model. The first is simple regression model which is assume that there is a relationship between the variable to be forecasted (the dependent variable) and another variable (the independent variable). Furthermore, the basic relationship is linear is assumed. The second one is multiple regressions. In this type of regression, there is one variable to forecasts and several explanatory variables and the objective will be to find a function that relates the variable to forecast with all of the explanatory variables.

Appendix B: ERP

1. The evolution of ERP

The ERP terminology was first proposed by the Gartner Group in the early 1990s (Mabert et al, 2003). According to Jacobs and Weston (2007) and Leon (2008) the evolution of ERP was started in the 1960s. Jacobs and Weston (2007) state that the primary competitive thrust in the 1960s was cost, which resulted in product-focused manufacturing strategies based on high-volume production and cost minimisation, and which assumed stable economic conditions. At this time, basic manufacturing planning and control was satisfied by the introduction of the computerised reorder point (ROP) system. Moreover, in the late 1970s, there was a shifted paradigm on primary competitive thrust towards marketing. It brought about the adoption of target markets strategies with an emphasis on greater production integration and planning. Material Requirement Planning (MRP) system successfully fulfilled this need because of the integration between forecasting, master scheduling, procurement, and shop floor control. In addition, major software companies which later become important ERP vendors were also established during this time, such as SAP in 1972 and the Baan Corporation in 1978.

The MRP II is the third stage of ERP evolution developed in the 1980s. It is an expansion of MRP into a company-wide system capable of planning and controlling virtually all the firm’s resources (Chen 2001). Leon (2008) adds that as compared to MRP, MRP II contains the following additional capabilities: sales and operational planning, financial enterprise and simulation capabilities for better decision making. Finally, in the 1990s, ERP was further expanded into ERP II and was intended to improve resource planning by extending the scope of planning to include more of the supply chain than MRP II (Chen, 2001) and since then it has become a popular information technology within the business environment (Chung and Snyder, 2000). Further, Chen (2001) describes the manner in which ERP links whole areas of an organisation including order management, manufacturing, human resources, financial systems, and distribution with external suppliers and customers into a single integrated system with shared data and visibility. Leon (2008) summarises the evolution of ERP from the 1960s to the 1990s as can be seen in Table 1. Moreover, Chung and Snyder (2000) investigate and compare the potential integration of some technology context in MRP, MRPII and ERP (Table 2). This table shows that the ERP system has a high potential for integrating all technology contexts.

Table 1 Evolution of ERP

Timeline	System	Description
1960s	Inventory Management & Control	Inventory management and control is the combination of information technology and business processes of maintaining the appropriate level of stock in warehouse.
1970s	Material Requirement Planning (MRP)	MRP utilizes software applications for scheduling production processes. It generates schedules for the operations and raw material purchased based on the production requirements of finished goods, the structure of production system, the current inventory levels and the lot sizing procedure for each operation.
1980s	Manufacturing Resource Planning (MRP II)	MRP II utilizes software applications for coordinating manufacturing processes, from product planning, parts purchasing, inventory control to product distribution.
1990s	Enterprise Resource Planning (ERP)	ERP uses multi-module application software for improving the performance of the internal business process. ERP systems often integrate business activities across functional departments, from product planning, parts purchasing, inventory control, product distribution, fulfillment, to order tracking. It may include application modules for supporting marketing, finance, accounting and human resources.

(source: Leon, 2008)

Table 2. Task-technology integration in MRP, MRPII and ERP

Technology context	Degree of potential integration		
	MRP	MRP II	ERP
Bill of materials	Low	High	High
Master planning schedule	Low	Medium	High
Capacity resource planning	Low	Medium	High
Value chain activities	Low	Medium	High
Customer demand forecast	Low	Low	High
Product development methodology	Low	Low	High
Data management	Low	Medium	High
Process repository	Low	Medium	High
IT connectivity	Low	Medium	High

(source: Chung and Snyder, 2000)

2. ERP modules and advantages

The ERP system consists of several modules, the names and numbers of which differ from one vendor to another vendor. Shehab et al. (2004) summarise some of the popular modules and functions in Figure 1. This figure shows that the ERP system has six modules, namely: Material Management, Quality Management, Human Resources, Project Management, Financial and Accounting, and Sales and Distribution.

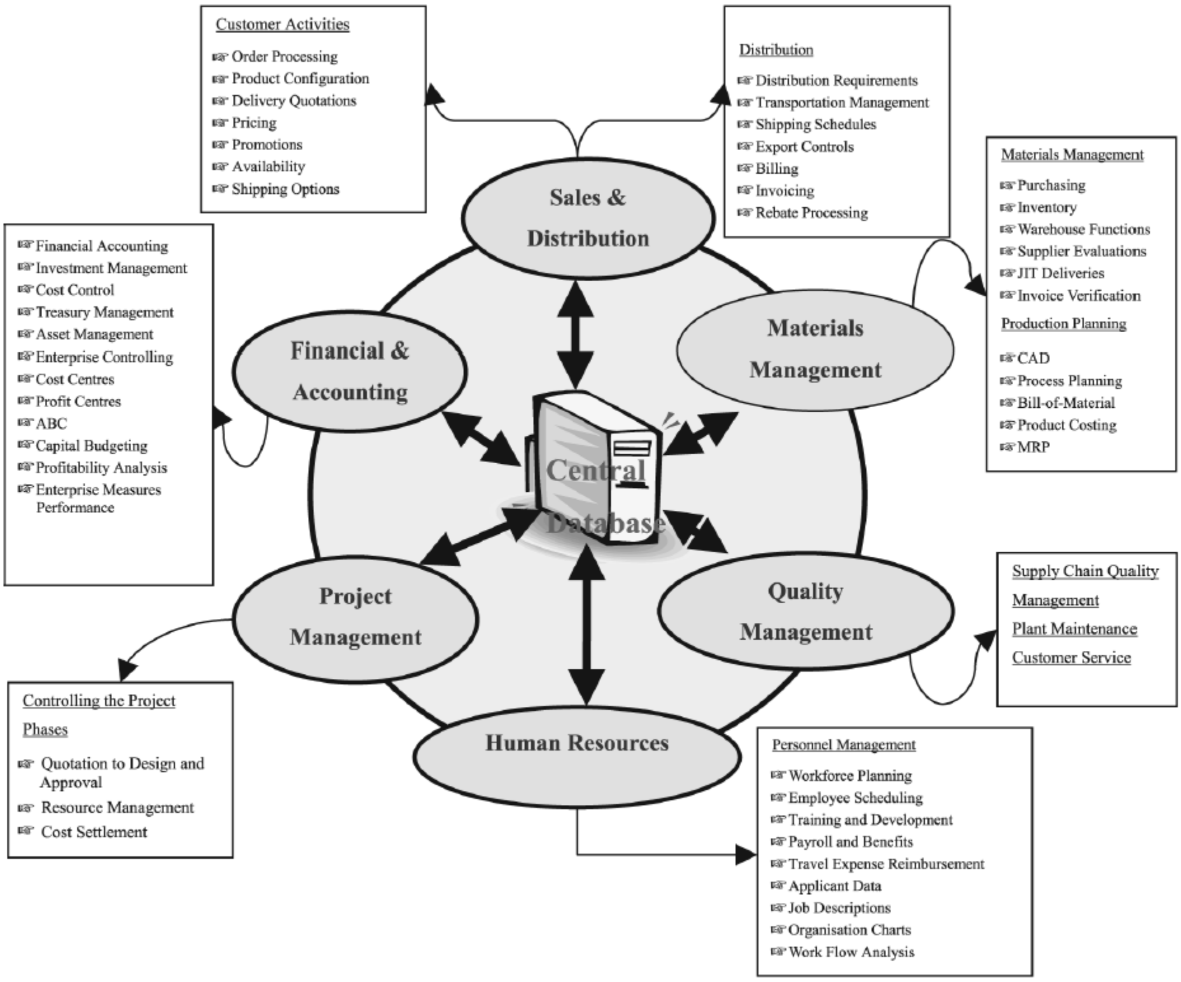

Figure 1. ERP system modules
(Source: Shehab et al, 2001)

Some of the SAP R/3 modules are described below (Mendelson, 2000):

SD – Sales and Distribution module supports sales and distribution processes, with functions for pricing, order processing and delivery quotation. It has a direct interface to the Materials Management (MM) and Production Planning (PP) modules.

MM – The Materials Management module is designed to support the procurement process and to optimise the logistics pipeline within the enterprise. It enables automated supplier evaluation and can lower procurement and warehousing costs with accurate inventory and warehouse management. It also integrates invoice verification. The module is additionally designed to support foreign trade processing, such as customs declarations. Tools for inventory control and purchasing information help to identify trends and developments.

PP – The Production Planning module supports production planning, manufacturing processes execution, analysis and production control. This application covers the production process from the creation of master data to production planning, MRP, and capacity planning, right down to production control and costing. It supports a variety of manufacturing processes including repetitive, make-to-order and assemble-to-order production. Quality management, laboratory information systems and data analysis functions are also available.

3. ERP Advantages

There are many advantages in the application of the ERP system within a company. Leon (2008) differentiates between direct and indirect advantages. The direct advantages include improved efficiency, information integration for better decision making, and faster response time to customer queries. The indirect benefits include better corporate image, improved customer goodwill and customer satisfaction. Further, Gargeya and Brady (2005) provide more detail on the benefits of the implementation of the ERP system in Table 3.

Table 3 Tangible and intangible benefit of ERP system

Tangible benefits	Intangible benefits
Inventory reduction Personnel reduction Productivity improvements Order management improvements Financial cycle improvements Information technology cost reduction Procurement cost reduction Cash management improvement Revenue/profit increase Transportation/logistics cost reduction Maintenance reductions On-time delivery improvements	Information visibility New/improved processes Customer responsiveness Cost reductions Integration Standardization Flexibility Globalization Supply/demand chain Business performance Dismantling inefficient legacy system

Unlike Gargeya and Brady (2005) and Leon (2008), Shang and Seddon (2000) use different perspective for analysing the benefits of the ERP system. They classified the benefits into five types:

- Operational benefits. Cost reduction, cycle time reduction, productivity improvement, quality improvement, and customer services improvement.
- Managerial benefits. Better resource management, better decision making, and planning and performance improvement.
- Strategic benefits. Supports business growth, supports business alliance, builds business innovations, builds cost leadership, generates product differentiation, and builds external linkages.
- It infrastructure benefits. Builds business flexibility, IT costs reduction, and increased IT infrastructure capability.
- Organisational benefits. Supports business organisational changes; facilitates business learning, encourages empowerment, and builds common visions.

Appendix C: WEEE Directive

According to the Eurostat (2012), the growth of waste electrical and electronic equipment (WEEE) in the European Union (EU) is at 3-5% and is growing exponentially. As WEEE puts health and the environment at risk, the EU has been promoting legislation for collecting and recycling WEEE since February 2003 (WEEE Directive 2002/96/EC). UK law introduced2006 WEEE Regulations in January 2007. The annual production of WEEE in the UK is around 2 million tonnes (EA, 2012).

The purpose of this directive is to increase the recycling and/or reuse of WEEE. Moreover, it also seeks to improve the environmental performance of all operators involved in the life cycle of electrical and electronic equipment (EEE), e.g. producers, distributors and consumers, and in particular those operators directly involved in the treatment of waste electrical and electronic equipment. Towards this aim, the WEEE Directive sets collection, recycling and recovery targets for all types of EEE goods and can be seen in below table.

Table 1. Minimum rates for separate collection of WEEE (source: Eurostat, 2012)

Date	Annual minimum collection rate
By 31 December 2015	At least 4 kg / inhabitant of WEEE from private households; ***OR*** the same weight as the average amount of WEEE collected in that Member State in the three preceding years; whichever of the two figures that is highest shall continue to apply.
From 2016 to 2018	45% of EEE put on the market, calculated on the basis of: - the total weight of WEEE collected; and - the average weight of EEE put on the market in the three preceding years.
As of 2019	65% of EEE put on the market, calculated on the basis of: - the total weight of WEEE collected; and - the average weight of EEE put on the market in the three preceding years. **OR** 85% of WEEE generated on the territory of that Member State. As of 2019 (Member States will be able to choose which one of these two equivalent ways to measure the target they wish to report.)

The EEE goods covered by the WEEE regulations are those which (EA, 2012):

- are dependent on electric currents or electromagnetic fields in order to work properly, including equipment for the generation, transfer and measurement of such currents and fields;
- are designed for use with a voltage rating not exceeding 1,000V for alternating current and 1,500V for direct current;
- fall into one of the 10 categories in Schedule 1 of the WEEE: Large household appliances; Small household appliances; IT and Telecommunications equipment; Consumer equipment; Lighting equipment; Electrical and electronic tools; Toys, leisure and sports equipment; Medical devices; Monitoring and control instruments; and Automatic dispensers.

Further, details of EEE under each category can be found at http://www.environment-agency.gov.uk/business/topics/waste/32120.aspx

The WEEE Regulations place legal obligations on the following types of organisations that handle EEE (EA, 2012): importers, rebranders and manufacturers; operators of producer compliance schemes; waste management industry; retailers; business users; householders; and local authorities.

There are two options for the retailer/distributor to comply with the WEEE regulations in the UK (DFT, 2012):

- Option A: Offer customers the opportunity to return their WEEE in store, free of charge when purchasing a similar item or an item for similar use as their old equipment. If customers wish the retailer/distributor to collect, then a reasonable fee may be charged. The retailer/distributor is required to record the amount of WEEE returned.

- Option B: Join the Distributor Take Back Scheme (DTS) which is run by an appointed company. Under this scheme the retailer/distributor does not have to take back any waste electrical and electronic equipment (WEEE); instead the company will supply the retailer/distributor with all the information needed in directing customers to their nearest recycling facility.

Moreover, regardless of business size and quantities of EEE placed on the market, producers (importers, re-branders or manufacturers) of EEE have responsibilities under WEEE Regulations and should be registered with an approved producer compliance scheme (EA, 2012). In addition, for the manufacturer of EEE, extra WEEE rules must be followed, including labeling products (e.g. use the crossed-out wheelie bin symbol), marking products (eg. use producer's identification mark), and producing products that are easy to repair and recycle (Gov. UK, 2012).

As a major international electronics manufacturer relies on service parts, the case study organisation made some changes for the purpose of facing this regulation. For example, the company managers had to rearrange their service parts management. Managers now need to give more attention to their stock control policy, especially for critical and obsolete items since the spare/service parts demand pattern is intermittent in nature (this introduces slow moving items). In addition, managers had to arrange the procedure of reuse, recycling, and waste collection of their products in order to show their responsibility as regards the environment.

Appendix D: RoHS Directive

Restriction of Hazardous Substances Directive (RoHS) 2002/95/EC is EU legislation restricting the use of certain hazardous substances in electrical and electronic (EEE) equipment. The directive has been in force since February 2003 (EC, 2012). This directive came into force in the UK on 1 July 2006 (NMO, 2012a). Currently, it has been recast and will be repealed by Directive 2011/65/EU (RoHS 2) with effect from 3 January 2013. The authorities responsible for enforcing the RoHS Regulations within the UK are the Department for Business, Innovation and Skills (BIS) and the National Measurement Office (NMO) (NMO, 2012b).

The objective of RoHS Directive is to prevent all new electrical and electronic equipment put in the European Economic Area from containing certain levels of hazardous substances. It restricts the use of lead (Pb), mercury (Hg), cadmium (Cd), hexavalent chromium (Cr6+), polybrominated biphenyls (PBB) and polybrominated diphenyl ether (PBDE). The weight of substance at raw homogeneous material must be less than 0.01% for cadmium and hexavalent chromium and less than 0.1% for lead, PBB, and PBDE. For mercury, any RoHS compliant component must have 100 ppm or less of mercury and the mercury must not have been intentionally added to the component. EEE that has to comply with the RoHS Directive also applies with the WEEE directive, except for medical devices and monitoring and control equipment (NMO, 2012c).

Under this regulation, EEE's producers must ensure that their products meet the requirement of the directive. As a result, producers have to retain technical documentation showing that their equipment complies with the RoHS Regulations. This documentation must be retained for inspection for four years from the date the equipment is put on the market. The producer can refer to the manufacturer, seller, reseller or importer/exporter of EEE.

As the case study organisation can be categorized as a producer of EEE, this regulation may have a considerable impact on service parts management. Several changes were implemented in order to face these regulations. For example, the spare parts managers in all European sites had to scrap parts that are used in new EEE as they may have contained hazardous substances. Consequently, the implementation of these changes may have an impact on their supply chain of spare parts.

Appendix E: The results of goodness of fit test of Final OUT replenishment level adjustment distribution across SKUs

A items

Significant level (α)	0.2	0.1	0.05	0.02	0.01
Critical value	0.28072	0.03199	0.03553	0.03971	0.04262

1. Signed size of adjustment

No.	Distribution	K-S statistic
1	Cauchy	0.05081
2	Error Function	0.21506
3	Gumbel max	0.27602
4	Gumbel min	0.23985
5	Hypersecant	0.19328
6	Laplace	0.16815
7	Logistic	0.20564
8	Normal	0.22109
9	Uniform	0.25375

2. Absolute size of adjustment

No.	Distribution	K-S statistic
1	Gamma	0.55447
2	Weibull	0.12364
3	Uniform	0.40768
4	Gumbel max	0.42906
5	Normal	0.37456
6	Logistic	0.35892
7	Cauchy	0.25043
8	Gumbel min	0.39951
9	Exponential	0.29863

3. Relative signed size of adjustment

No.	Distribution	K-S statistic
1	Cauchy	0.12128
2	Error Function	0.17219
3	Gumbel max	0.07229
4	Gumbel min	0.15403
5	Hypersecant	0.12301
6	Laplace	0.15139
7	Logistic	0.10961
8	Normal	0.09255
9	Uniform	0.12191

4. Relative absolute size of adjustment

No.	Distribution	K-S statistic
1	Weibull	0.07066
2	Gamma	0.07483
3	Gumbel max	0.07881
4	Gumbel min	0.19590
5	Logistic	0.12609
6	Normal	0.14199
7	Exponential	0.16516
8	Cauchy	0.13101
9	Uniform	0.17574

B items

Significant level (α)	0.2	0.1	0.05	0.02	0.01
Critical value	0.01973	0.02249	0.02497	0.02791	0.02995

1. Signed size of adjustment

No.	Distribution	K-S statistic
1	Cauchy	0.03298
2	Error Function	0.26504
3	Gumbel max	0.31353
4	Gumbel min	0.31991
5	Hypersecant	0.23728
6	Laplace	0.21199
7	Logistic	0.24711
8	Normal	0.26301
9	Uniform	0.30013

2. Absolute size of adjustment

No.	Distribution	K-S statistic
1	Gamma	0.30334
2	Weibull	0.17370
3	Uniform	0.37830
4	Gumbel max	0.38433
5	Normal	0.33767
6	Logistic	-
7	Cauchy	0.14382
8	Gumbel min	0.35941
9	Exponential	0.17086

3. Relative signed size of adjustment

No.	Distribution	K-S statistic
1	Cauchy	0.12718
2	Error Function	0.14914
3	Gumbel max	0.09489
4	Gumbel min	0.14876
5	Hypersecant	0.12668
6	Laplace	0.15216
7	Logistic	0.11126
8	Normal	0.13095
9	Uniform	0.18558

4. Relative absolute size of adjustment

No.	Distribution	K-S statistic
1	Weibull	0.12458
2	Gamma	0.13329
3	Gumbel max	0.21374
4	Gumbel min	0.31545
5	Logistic	0.24153
6	Normal	0.24931
7	Exponential	0.22385
8	Cauchy	0.09897
9	Uniform	0.26519

Appendix F: Results of fitting distribution test on Final OUT replenishment level across period

The results of fitting distribution test on Final OUT replenishment level across period for A items

Relative Absolute

	Cauchy		Exponential		Gamma		Gum Max		Gum Min		Logistic		Normal		Uniform		Weibull	
	Fit Test	Sig. Leve	Fit Test	Sig. Leve	Fit Test	Sig. Leve	Fit Test	Sig. Leve	Fit Test	Sig. Leve	Fit Test	Sig. Leve	Fit Test	Sig. Leve	Fit Test	Sig. Leve	Fit Test	Sig. Level
Strong Fit	85.00%	98.75%	31.25%	41.25%	88.75%	95.00%	86.25%	97.50%	52.50%	80.00%	72.50%	85.00%	75.00%	88.75%	76.25%	93.75%	86.25%	97.50%
Fit	12.50%		8.75%		5.00%		10.00%		18.75%		15.00%		13.75%		15.00%		8.75%	
No Fit	2.50%	1.25%	60.00%	58.75%	6.25%	5.00%	3.75%	2.50%	28.75%	20.00%	12.50%	15.00%	11.25%	11.25%	8.75%	6.25%	5.00%	2.50%

Size Absolute

	Cauchy		Exponential		Gamma		Gum Max		Gum Min		Logistic		Normal		Uniform		Weibull	
	Fit Test	Sig. Leve	Fit Test	Sig. Leve	Fit Test	Sig. Leve	Fit Test	Sig. Leve	Fit Test	Sig. Leve	Fit Test	Sig. Leve	Fit Test	Sig. Leve	Fit Test	Sig. Leve	Fit Test	Sig. Level
Strong Fit	72.50%	92.50%	42.50%	66.25%	76.25%	97.50%	73.75%	93.75%	35.00%	68.75%	61.25%	83.75%	61.25%	85.00%	63.75%	92.50%	68.75%	90.00%
Fit	12.50%		18.75%		17.50%		17.50%		28.75%		18.75%		21.25%		20.00%		18.75%	
No Fit	15.00%	7.50%	38.75%	33.75%	6.25%	2.50%	8.75%	6.25%	36.25%	31.25%	20.00%	16.25%	17.50%	15.00%	16.25%	7.50%	12.50%	10.00%

Relative Sign

	Cauchy		Error		Gum Max		Gum Min		Hypersecant		Laplace		Logistic		Normal		Uniform	
	Fit Test	Sig. Leve	Fit Test	Sig. Leve	Fit Test	Sig. Leve	Fit Test	Sig. Leve	Fit Test	Sig. Leve	Fit Test	Sig. Leve	Fit Test	Sig. Leve	Fit Test	Sig. Leve	Fit Test	Sig. Level
Strong Fit	83.75%	100.00%	17.50%	35.00%	68.75%	86.25%	42.50%	68.75%	53.75%	86.25%	48.75%	76.25%	57.50%	88.75%	58.75%	91.25%	63.75%	93.75%
Fit	13.75%		13.75%		13.75%		23.75%		23.75%		22.50%		20.00%		21.25%		22.50%	
No Fit	2.50%	0.00%	68.75%	65.00%	17.50%	13.75%	33.75%	31.25%	22.50%	13.75%	28.75%	23.75%	22.50%	11.25%	20.00%	8.75%	13.75%	6.25%

Size Sign

	Cauchy		Error		Gum Max		Gum Min		Hypersecant		Laplace		Logistic		Normal		Uniform	
	Fit Test	Sig. Leve	Fit Test	Sig. Leve	Fit Test	Sig. Leve	Fit Test	Sig. Leve	Fit Test	Sig. Leve	Fit Test	Sig. Leve	Fit Test	Sig. Leve	Fit Test	Sig. Leve	Fit Test	Sig. Level
Strong Fit	80.00%	97.50%	16.25%	42.50%	58.75%	78.75%	61.25%	82.50%	61.25%	92.50%	55.00%	83.75%	65.00%	96.25%	68.75%	97.50%	66.25%	98.75%
Fit	7.50%		20.00%		23.75%		18.75%		22.50%		20.00%		18.75%		17.50%		25.00%	
No Fit	12.50%	2.50%	63.75%	57.50%	17.50%	21.25%	20.00%	17.50%	16.25%	7.50%	25.00%	16.25%	16.25%	3.75%	13.75%	2.50%	8.75%	1.25%

The results of fitting distribution test on Final OUT replenishment level across period for B items

Relative Absolute																		
	Cauchy		Exponential		Gamma		Gum Max		Gum Min		Logistic		Normal		Uniform		Weibull	
	Fit Test	Sig. Leve	Fit Test	Sig. Leve	Fit Test	Sig. Leve	Fit Test	Sig. Leve	Fit Test	Sig. Leve	Fit Test	Sig. Leve	Fit Test	Sig. Leve	Fit Test	Sig. Leve	Fit Test	Sig. Level
Strong Fit	95.00%	97.50%	50.00%	52.50%	92.50%	95.00%	87.50%	87.50%	57.50%	65.00%	87.50%	87.50%	87.50%	85.00%	80.00%	87.50%	92.50%	95.00%
Fit	2.50%		30.00%		5.00%		7.50%		25.00%		2.50%		2.50%		10.00%		5.00%	
No Fit	2.50%	2.50%	20.00%	47.50%	2.50%	5.00%	5.00%	12.50%	17.50%	35.00%	10.00%	12.50%	10.00%	15.00%	10.00%	12.50%	2.50%	5.00%

Size Absolute																		
	Cauchy		Exponential		Gamma		Gum Max		Gum Min		Logistic		Normal		Uniform		Weibull	
	Fit Test	Sig. Leve	Fit Test	Sig. Leve	Fit Test	Sig. Leve	Fit Test	Sig. Leve	Fit Test	Sig. Leve	Fit Test	Sig. Leve	Fit Test	Sig. Leve	Fit Test	Sig. Leve	Fit Test	Sig. Level
Strong Fit	90.00%	92.50%	62.50%	62.50%	97.50%	95.00%	95.00%	95.00%	52.50%	57.50%	72.50%	77.50%	72.50%	82.50%	72.50%	82.50%	95.00%	95.00%
Fit	7.50%		12.50%		0.00%		2.50%		20.00%		20.00%		20.00%		22.50%		2.50%	
No Fit	2.50%	7.50%	25.00%	37.50%	2.50%	5.00%	2.50%	5.00%	27.50%	42.50%	7.50%	22.50%	7.50%	17.50%	5.00%	17.50%	2.50%	5.00%

Relative Sign																		
	Cauchy		Error		Gum Max		Gum Min		Hypersecant		Laplace		Logistic		Normal		Uniform	
	Fit Test	Sig. Leve	Fit Test	Sig. Leve	Fit Test	Sig. Leve	Fit Test	Sig. Leve	Fit Test	Sig. Leve	Fit Test	Sig. Leve	Fit Test	Sig. Leve	Fit Test	Sig. Leve	Fit Test	Sig. Level
Strong Fit	95.00%	100.00%	52.50%	57.50%	85.00%	92.50%	70.00%	77.50%	82.50%	87.50%	72.50%	75.00%	85.00%	90.00%	85.00%	87.50%	85.00%	90.00%
Fit	2.50%		27.50%		10.00%		17.50%		12.50%		17.50%		10.00%		10.00%		10.00%	
No Fit	2.50%	0.00%	20.00%	42.50%	5.00%	7.50%	12.50%	22.50%	5.00%	12.50%	10.00%	25.00%	5.00%	10.00%	5.00%	12.50%	5.00%	10.00%

Size Sign																		
	Cauchy		Error		Gum Max		Gum Min		Hypersecant		Laplace		Logistic		Normal		Uniform	
	Fit Test	Sig. Leve	Fit Test	Sig. Leve	Fit Test	Sig. Leve	Fit Test	Sig. Leve	Fit Test	Sig. Leve	Fit Test	Sig. Leve	Fit Test	Sig. Leve	Fit Test	Sig. Leve	Fit Test	Sig. Level
Strong Fit	85.00%	90.00%	57.50%	60.00%	75.00%	77.50%	85.00%	87.50%	70.00%	77.50%	70.00%	70.00%	80.00%	82.50%	85.00%	90.00%	95.00%	92.50%
Fit	12.50%		20.00%		12.50%		12.50%		27.50%		17.50%		17.50%		12.50%		5.00%	
No Fit	2.50%	10.00%	22.50%	40.00%	12.50%	22.50%	2.50%	12.50%	2.50%	22.50%	12.50%	30.00%	2.50%	17.50%	2.50%	10.00%	0.00%	7.50%

Appendix G: Explanation of reason categories

I-No reason, D-No reason:

Managers change the OUT level without having any reason. They simply intervene to the process regardless of whether they possess some important information or not. No justifications are recorded.

I-Backorder:

Managers make adjustment to increase the OUT level because current stock level is insufficient to satisfy demand.

I-Low stock, D-Over stock:

Managers adjust to increasing or reducing OUT level by considering current on-hand inventory.

I-Certain period:

Managers increase the OUT level based on past information in which demand increased in particular time.

I-Steady demand, D-Steady demand:

Although the demand is steady, sometimes managers make adjustments to increase/decrease the OUT level. It seems adjustments reflect a desire for a sense of ownership on the part of the managers.

I-Increasing demand, D-Decreasing demand:

Managers change the OUT level as the demand patterns which tend to increase or decrease over time.

I-Order spike, D-Order spike:

Managers make adjustment to increase/decrease OUT level based on past information regarding order spike.

I-Min ROP, D-Min ROP:

Managers increase/decrease OUT level up to minimal OUT level (Min OUT level is 3 units)

I-Large demand, D-Hardly demand:

The reason for changing the OUT level (increase/decrease) because the demand is very large or there is no demand on particular material.

I-ROP too low:

Managers adjust to increase OUT level because the current OUT level seems to low compare with demand on the past.

I-Flat average:

Managers decide to increase the OUT level based on the flat average forecasting information.

I-Replacement part, D-Replacement part:

Managers adjust to increase/decrease OUT level as the material is a replacement part.

I-Not classified yet, D-Not classified yet:

Managers increase/decrease the OUT level based on a very specific reason where researcher does not know yet in which category it for.

D-Slow demand:

Managers decided to decrease the OUT level as the item is categorised as the slow demand.

D-Bulk order:

Decreasing the OUT level because there is bulk order.

Appendix H – List of Code

```
Dim i As Long, t As Long, Positive_Inventory_Position As Single, Investment As Double,
Price As Double, Ave_Positive_Inventory_Position As Double
Dim NegativeStock As Long, Proportion_NegativeStock As Double, BackorderedDemand
As Long, TotalDemand As Long, FillRate As Double

For i = 1 To 1454
    'For t = 4 To 27
        'Worksheets("stock").Cells(i + 2, t) = Worksheets("stock").Cells(i + 2, t - 1) -
        Worksheets("Demand").Cells(i + 2, t) + Worksheets("Order").Cells(i + 2, t - 2)
        'If Worksheets("ROP").Cells(i + 2, t) > Worksheets("stock").Cells(i + 2, t) Then
            'Worksheets("Order").Cells(i + 2, t) = Worksheets("ROP").Cells(i + 2, t) -
            Worksheets("stock").Cells(i + 2, t)
            'Else
            'Worksheets("Order").Cells(i + 2, t) = 0
        'End If
    'Next t
    For t = 4 To 27
        Worksheets("stock").Cells(i + 2, t) = Worksheets("stock").Cells(i + 2, t - 1) -
        Worksheets("Demand").Cells(i + 2, t) + Worksheets("Order").Cells(i + 2, t - 2)
        If Worksheets("ROP").Cells(i + 2, t) > Worksheets("stock").Cells(i + 2, t) Then
          Worksheets("Order").Cells(i + 2, t) = Worksheets("ROP").Cells(i + 2, t) -
        Worksheets("ROP").Cells(i + 2, t - 1) + Worksheets("Demand").Cells(i + 2, t)
        Else
          Worksheets("Order").Cells(i + 2, t) = 0
    End If
  Next t

  Inventory_Position = 0
    For t = 4 To 27
     Inventory_Position = Inventory_Position + Worksheets("stock").Cells(i + 2, t)
  Next t
```

```
    Ave_Inventory_Position = Inventory_Position / 24
    Worksheets("stock").Cells(i + 2, 28) = Ave_Inventory_Position

    Positive_Inventory_Position = 0
    For t = 4 To 27
        If Worksheets("stock").Cells(i + 2, t) > 0 Then
            Positive_Inventory_Position = Positive_Inventory_Position +
Worksheets("stock").Cells(i + 2, t)
        End If
    Next t
    Ave_Positive_Inventory_Position = Positive_Inventory_Position / 24
    Price = Worksheets("Price").Cells(i + 2, 28)
    Investment = Ave_Positive_Inventory_Position * Price
    Worksheets("stock").Cells(i + 2, 29) = Investment

    NegativeStock = 0
    For t = 4 To 27
        If Worksheets("stock").Cells(i + 2, t) < 0 Then
            NegativeStock = NegativeStock + 1
        End If
    Next t
    Proportion_NegativeStock = NegativeStock / 24
    Worksheets("stock").Cells(i + 2, 30) = 1 - Proportion_NegativeStock

    BackorderedDemand = 0
    For t = 4 To 27
        If Worksheets("Demand").Cells(i + 2, t) > Worksheets("stock").Cells(i + 2, t) Then
            BackorderedDemand = BackorderedDemand + (Worksheets("Demand").Cells(i +
     2, t) -   Application.WorksheetFunction.Max(Worksheets("stock").Cells(i + 2, t), 0))
        End If
    Next t
        TotalDemand = 0
    For t = 4 To 27
        TotalDemand = TotalDemand + Worksheets("Demand").Cells(i + 2, t)
```

```
    Next t
        If TotalDemand > 0 Then
        FillRate = (TotalDemand - BackorderedDemand) / TotalDemand
    Else
        FillRate = 0
    End If
    Worksheets("stock").Cells(i + 2, 31) = FillRate
Next i
End Sub
```