IMPROVING FORECASTING CAPABILITIES IN THE 3PL INDUSTRY

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Summary

Most logistics companies rely on their customers' inventory to make money – the more inventory their customers have, the more warehouse storage space the third party logistics providers can sell. Inventories constitute financial resources that are tied up and cannot be used (invested) elsewhere. The case organization involved in this project, a logistics and freight forwarding company, decided that this was not the best approach for their customers. This motivated the launch of a research project with Cardiff University, to develop an approach to help customers better manage and if possible reduce inventory levels in their supply chains.

An inventory planning and optimization modeling tool has been developed to help the company's customers classify their products, forecast their demand and optimize their inventory levels subject to service level considerations.

Forecasting and inventory control should be directly integrated for avoiding major issues that current supply chains are facing (i.e. over-stocking, associated with unnecessary financial commitments, or under-stocking, associated with poor service levels offered to the customers). The project consists of two phases, reflecting current priorities of the case organization: i) spare parts forecasting and inventory control; ii) new products forecasting and life cycle management.

The implementation and evaluation of the current state-of-the-art in inventory forecasting and stock control provides stakeholders with the opportunity to reduce holding costs whilst having the right product at the right level of inventory at the right time.

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This thesis would have not been accomplished without the love and spiritual support of my parents and close-by friends and family. Despite the distance, they have tried very hard to make me feel close to them by giving me strength, courage and motivation to carry on.

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Table of Contents

List of Figures

List of Tables

PART A: PROJECT INTRODUCTION

A project has been launched between Cardiff University and a case organization to find ways to meet customers' requirements to forecast their demand and optimize their inventory levels in the supply chain whilst improving service levels. The project consists of two phases: i) spare parts forecasting and inventory control; ii) new products forecasting and life cycle management. The project was formalized as a Knowledge Transfer Partnership (KTP) between Cardiff University (Cardiff Business School) and the case organization. A detailed explanation of what a KTP is and what are the benefits for all its stakeholders are included in the first chapter of this thesis.

The first part of this thesis includes a project overview chapter (Chapter 1), which is providing a summary of the project's context, rationale, background and objectives. It offers a brief summary of the case organization's background and what their vision and mission are. More importantly, it refers to the project's initiation, what the need of launching such a project was and what needed to be achieved.

A detailed structure of the thesis follows in the last section of Chapter 1. More detailed information on the actual project and solution(s) adopted follows in parts B (spare parts management) and C (product life cycle management).

1. PROJECT OVERVIEW

1.1 Introduction

A logistics and freight forwarding company operating in more than 70 countries worldwide, was looking for ways to meet customers' requirements to optimize inventory levels in the supply chain and increase service levels, by means of introducing some major innovative operational improvements in the company's inventory system. Such improvements would relate to building and applying alternative forecasting and stock control procedures as suggested in the latest academic research. This would then result in considerable financial gain and the provision of an important competitive advantage. The areas of interest and focus were *spare parts* and *fashion goods*. The former are known to be characterized by intermittent demand patterns. The latter are associated with short life cycles and new products that are introduced on an ongoing basis.

1.2 Context

The case organization is one of the world's leading providers of end-to-end supply chain solutions. The company combines its core products of Air Freight, Ocean Freight and Logistics to deliver globally integrated, tailor-made end-to-end solutions. The range of supply chain solutions can vary from transport or storage up to complex operations. The company operates a global network with 500 offices in more than 70 countries, and it works with partner companies in a further 90 countries offering employment to over 16,000 people world-wide. The company's vision is to be the most customer focused global provider of freight forwarding and logistics solutions – a trusted, valued and respected partner. Their mission is to leverage global presence and competence in Air and Ocean Freight (by collaborating with their customers to unlock value in their supply chains and together build smart and efficient end-to-end logistics solutions) and to increase the range of integrated logistics and manufacturing services (LMS) offered to their customers. The project described in this thesis was undertaken under the company's LMS umbrella of activities and constitutes a collaborative work between Cardiff University and the case organization.

1.3 Background And Objectives

The 3PL (Third Party Logistics) industry has proved to be very important around the world as the global 3PL market reached $750 billion in 2014 [1]. Inventories in all industries represent around $12 trillion of cash. The US alone is currently sitting on more than $2 trillion worth of goods held for sale [2]. Any small improvements in inventory management translate to big amounts of money that can be released back to the economy, reducing inflation, creating new jobs and eliminating waste.

The initial contact between Cardiff University and the case organization was through an exploratory meeting organized by the Cardiff Lean Enterprise Research Centre (LERC) that took place at Cardiff Business School, with the presence of a couple of academics and company representatives. The purpose of this meeting was for the company to present their current challenges and for the academics to explore whether they could come up with some new ground breaking ideas that the company could utilize for further development. During this meeting, one of the major topics discussed was the need for inventory reductions in the company's customers businesses. Traditionally, most 3PL companies rely on their customer's inventory to make money - the more inventory their customers have, the more warehouse storage space the 3PLs can sell. The focus on filling warehouse space, is actually the opposite of what the customers need. Inventories constitute money that is tied up and cannot be used elsewhere.

Straight away the need was established to introduce a project that would aim at the reduction of the customers' inventory with great benefit for them, e.g. cost reductions (financial sustainability), reduced obsolescence and thus a reduced need to discard obsolete products (environmental sustainability) and, through reduced costs, reduced prices to be offered ultimately to end consumers (societal sustainability). The major rationale behind this project was the lack of any forecasting capability from the company's perspective as well as a limited knowledge of scientific inventory control.

As discussed above, the project's motivation was to challenge the traditional third-party logistics (3PL) approach to Logistics. 3PL providers seem not to be concerned with forecasting or inventory control on behalf of their customers. It is worth noting that there are actually 3PLs that are offering forecasting and inventory services to their customers. However, they operate in a way that does not add value (inventory wise) to their customers; customers also do not typically insist that 3PLs sort out their inventory problems. Such forecasting and inventory services are not value adding as far as it is concerned due to the fact that as already mentioned before, most logistics companies rely on their customers' inventory to make money (the more inventory their customers have, the more warehouse storage space the third party logistics providers can sell) and not helping customers better manage inventories or even reduce their inventory levels. What this project resulted to, a unique offering in the Third-Party Logistics (3PL) industry, is the case organization being the first provider that proactively helps customers to reduce inventory levels in the supply chain by developing its own inventory forecasting application. This development has been added to the LMS offerings of the company to their customers. As mentioned earlier on in this chapter, the company's first mission is to leverage global presence and competence in Air and Ocean Freight. However, apart from that, they would like to increase the range of integrated logistics and manufacturing services (LMS) offered to their customers. The offering of such services would position the case organization in a competitive advantage. The application developed in the project described here was given the name 'Demand Driven Inventory Dispositioning (D^2ID)' to reflect the effort to use (forecasted) demand to drive inventory decisions, and a concern with moving inventories out of the customers' warehouses. It was envisaged that the application would lead to sound forecasting and inventory decisions [3].

However, the title, D^2ID, does not reflect 100% accurately the work conducted during the project. "Dispositioning" is something that has not been looked at and considered in this work, but rather it reflects plans of the case organization to further develop the tool by means of integrating its functionality with location study services and network optimization solutions already (separately) offered by the company. It is also important to note that the case organization is very much interested in relocating inventory levels to different channels. Inventories being at the right place is an important aspect in supply chain management but this issue does not constitute part of the project.

The formalization of the project took place through a Knowledge Transfer Partnership (KTP) application between Cardiff University (Cardiff Business School) and the case organization. KTP programmes provide financial support (of up to 50% of the total cost of a project) to facilitate knowledge transfer from a knowledge base (typically a University) to a commercial (or, rarely, a public) organization. This UK government initiative aims to help businesses develop innovative solutions and benefit from the latest research in an area of interest, as well as improve their competitiveness and productivity through the better use of knowledge, technology and skills that reside within the UK knowledge base. KTPs are currently funded by the Technology Strategy Board (Innovate UK) with the occasional contribution of an appropriate research council; in this particular case, the Engineering and Physical Sciences Research Council (EPSRC) co-funded the project [4].

KTP projects are executed by an Associate who is employed by the University but is based in the company. The projects have been shown over many decades to be beneficial for all the stakeholders (KTP associate, University, company, UK government) with the most critical benefit relating to the effect of cooperation. The KTP associates benefit through the knowledge they get from the academic experts whist transferring such knowledge to practice. They are also typically offered the opportunity to pursue a research degree (MPhil), and the present thesis is submitted in partial fulfillment of the requirements for an MPhil degree at Cardiff University. (MPhil studies are different from Doctoral research in that the latter emphasize both the development and application of new knowledge, whereas the former are not associated with any expectation to produce new knowledge. The emphasis is on the rigorous implementation / application of existing knowledge in a practical setting.) The benefit for the University is that it has the opportunity to test and develop its research in a business environment, can demonstrate the impact of its research as well as create ideas for future research and enhance teaching with case studies. The advantage for the company is that it gets access to the latest research and the leading thinkers in a chosen field. Finally, the UK government benefits from increased productivity, increased employment and business growth.

In this particular case, the implementation and evaluation of the latest research in inventory forecasting and stock control would provide the company with the opportunity to reduce holding costs, have the right product at the right level of inventory, at the right time and keep products moving faster (higher turnover). Focus was given on two industries: spare parts (after sales industry) and fashion goods. As previously discussed, the former relates to inventory forecasting problems for intermittent demand items, and the latter to forecasting problems for new products and product life cycle management. At this point is worth mentioning that the original application to Innovate UK did not include any work in the fashion industry. This was added (upon approval from the KTP Adviser) to the KTP programme of work at a much later stage. The relevant work was successfully executed without of course any implications for the remainder of the deliverables (for spare parts management). However, the title of the project, (D^2ID), was retained only for the spare parts related part of the work. It is partly because of this considerable extra contribution (over and above the original objectives) that the KTP was very positively perceived both nationally but also internally, within Cardiff University (as discussed in more detail in the last chapter of the thesis).

Before closing this section, it should be noted that, in principle, the solution(s) developed through this work could be applied to other industrial inventory management settings. However, the data used to validate the models developed and assess their empirical utility came from the case organization.

1.4 Structure Of The Thesis

The remainder of the thesis is organized as follows:

PART B is about spare parts management and more specifically the development of the $\mathrm{D^2ID}$ tool. Some background information and a review of the literature are provided in the beginning (Chapter 2), followed by details on the analysis conducted, software development and implementation (Chapter 3). Then the implications of this work along with the next steps of research are discussed in Chapter 4.

PART C is about product life cycle management (PLC) and follows the same structure as part 2 including chapters 5 to 7.

PART D discusses the impact of this research for all stakeholders and summarizes its findings (Chapter 8).

References and Appendices follow at the end of the thesis (Chapter 9 and 10, respectively).

The structure of the thesis is presented graphically below.

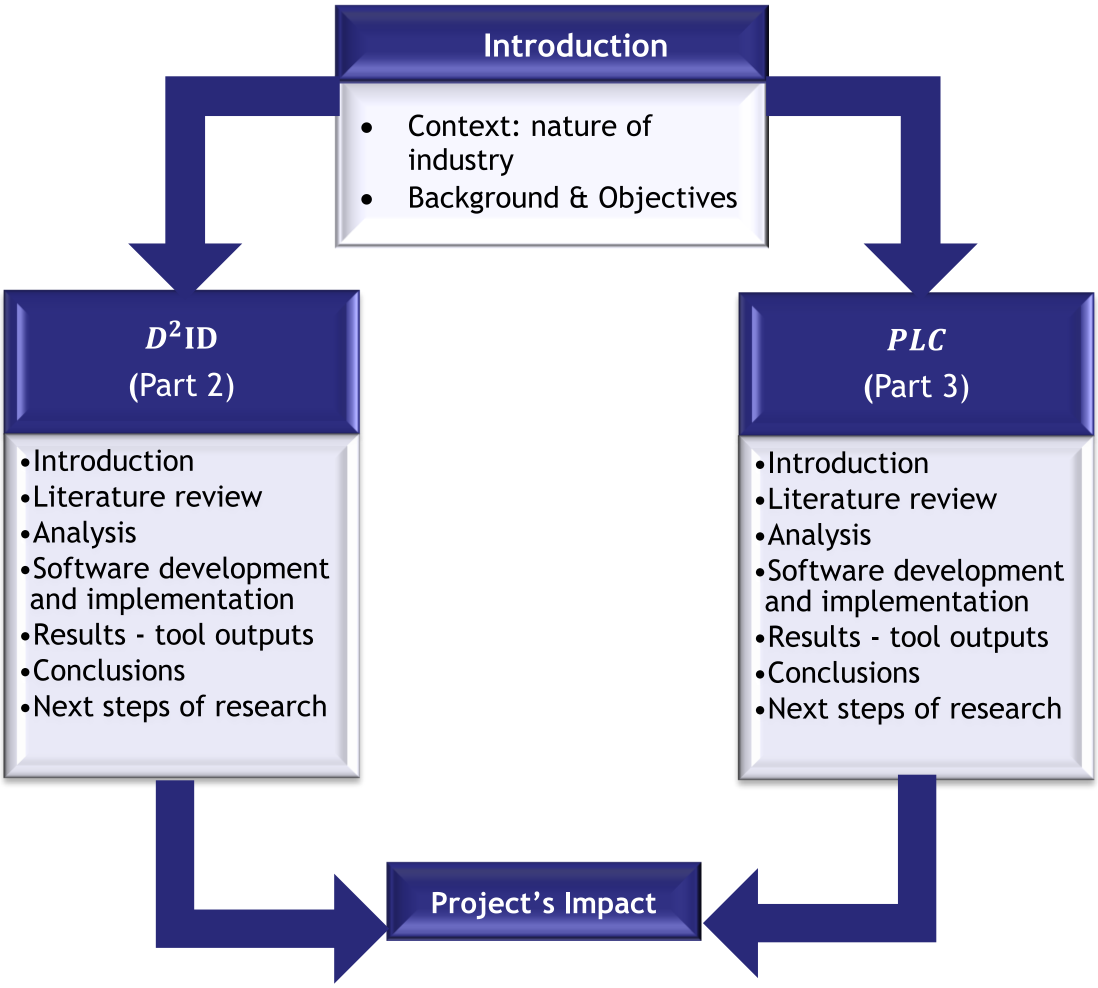


Figure 1: Structure of the thesis

1.5 Conclusion

In this chapter the main objectives of our work have been discussed along with the case organization's background and how this project has been set up. The structure of the thesis has also been presented along with a brief reference to the content of the ten chapters that follow this introductory part.

PART B: SPARE PARTS MANAGEMENT

This part is about spare parts management and more specifically the development of the $\mathrm{D}^2\mathrm{ID}$ tool. Spare parts inventory management has been proven to be very challenging both from academic and practitioner perspectives. It involves thousands of products whose demand is strangely varying over time which has as a result challenging complex demand patterns.[5] Such different demand patterns are essential to be categorized, as they are associated with different characteristics and therefore they require different forecasting and inventory control methods.

The D^2ID is an inventory forecasting tool, developed within the limits of a KTP project, using and combining methods that are published in the literature. Analysis was done on a SKU (stock keeping unit) by SKU level and the tool can provide demand classification, demand forecasts, optimized order levels, SKU fill rate specification, optimized inventory levels and a summary dashboard showing the inventory reductions and the cost savings (if any).

Spare parts management introduction together with some background information and a review of the literature are provided in the beginning (Chapter 2), followed by specific details on the analysis and methodology conducted, software development and implementation (Chapter 3) and the results–tool outputs (Chapter 4). Then the implications of this work are concluded together with the next steps of research (Chapter 4).

2. SPARE PARTS MANAGEMENT INTRODUCTION

2.1 Introduction

Spare parts inventory management is a very challenging exercise both from an academic and a practitioner perspective due to the fact that it involves thousands of products whose demand is 'strangely' varying over time [5]. Demand for such items is typically intermittent in nature, meaning that there are many zero demand observations interspersed with occasional (variable) demand occurrences (i.e. there is uncertainty governing both the arrival of positive demands and the size of the demand, when demand occurs) [6]. Beyond the spare parts industry, intermittent demand items may constitute up to 60% of the total stock value in very many contemporary industrial settings [7].

Spare parts management is an important issue for many companies that desperately want to reduce their holding costs while maintaining the same or even higher service levels and providing after sales support. Due to the increasing importance of the after sales industry, the interest of many companies in spare parts demand forecasting and inventory control has also dramatically increased over the recent years. This emphasis has also been facilitated by new solutions that have been developed specifically for intermittent demand series [8].

2.2 Spare Parts Issues

Spare parts forecasting and inventory control are affected by the intermittent nature of the demand data, the very large number of products available, the necessity to meet customers' requirements on time and maintain high service levels and the risk of obsolescence [9]. Therefore, any improvements in forecasting and thus in the management of spare parts items may lead to substantial cost savings, significant reduction of scrap and obsolescent items, and not unmet demand [10].

Accurate demand forecasting is very important for stock control purposes. However, when it comes to intermittent demand data (especially for spare parts) then it is very difficult to extrapolate requirements [10]. Intermittent demand series are very difficult to represent based on the standard time series structural components (level, trend, seasonality). This is because the limited number of positive observations makes it very difficult to observe any trend or seasonal components, even if those are present in the data. In addition, intermittent demand is usually not normally distributed, something that implies a deviation from the standard inventory theory that has been developed around the normality assumption [11][12]. An example of intermittent demand data is demonstrated in Figure 2.

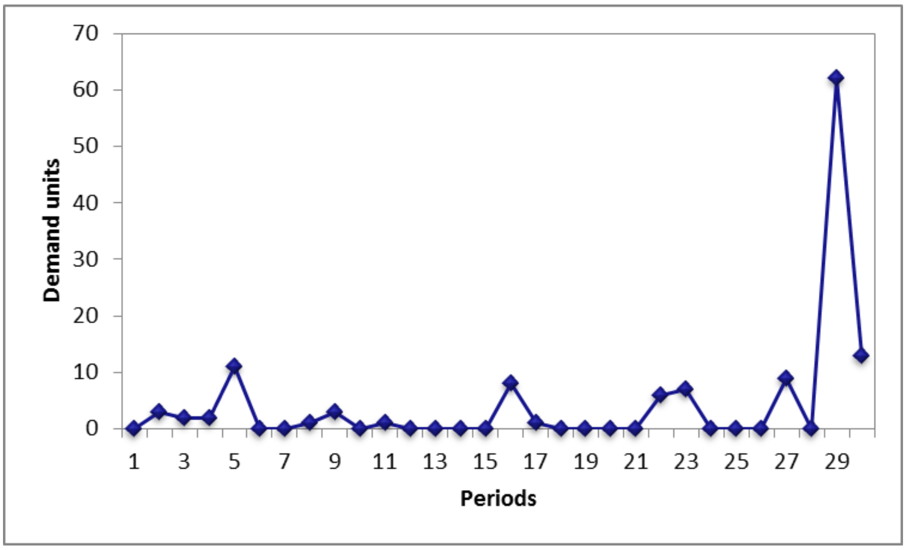


Figure 2: Intermittent demand data example

This is in fact a lumpy demand pattern. Intermittence relates to the presence of zeroes (regardless of the behavior of the demand when it occurs) and the fact that demand does not occur in every time period. Erraticness refers to the (high) variability of the demand sizes, when demand occurs. Lumpiness, is the combined effect of intermittent demand arrivals coupled with highly variable demand sizes. These terms will be explained in greater detail in the Analysis section. However, an important issue that emerges from this discussion is that of the need to classify / categorize demand patterns. Different demand patterns are associated with different characteristics and in turn require different forecasting and inventory control methods. Demand classification is a very important aspect of spare parts management [8][13].

2.3 Customers Inventory Management And Reduction From A 3pl Perspective

In the recent years, both the academic and industrial interest in the area of Third Party Logistics (3PL) has increased. 3PL rely upon a relationship between the logistic provider, the seller and the buyer [14].

Since the 1980s, 3PL providers have considerably increased their business and the reason is the increase in companies' need for outsourcing [15][16][17]. Over the years, companies are asking for more and more complicated, or even customized, logistics services from the 3PL providers which will be beneficial for their customers

[18][19]. Such customized services could relate to inventory management, product assembly, packaging, labeling, repairing, transportation, returns, customer service and order satisfaction or even consulting services [14][20]. Nowadays, 3PL companies, not only emphasize freight movements and all the aforementioned but also provide value added services, emphasizing manufacturing solutions and even offering services around personalization.

The need for a 3PL to sort out inventory issues of their customers has been recognized. However, as mentioned in chapter 1, 3PL providers seem not to be concerned with forecasting or inventory control on behalf of their customers. It is difficult to implement such services and add value inventory wise to the customers.

3PLs can contribute considerably to the effective inventory management on the part of their clients which has as a result increased customer satisfaction, reduction of inventory levels, increase of productivity and may also provide access to new innovative opportunities (such as use of manufacturing services and 3D printing of spare parts instead of storing large quantities of inventories which may become obsolete) or can create warehouse space for potential new customers [21]. It should also be noted that research around 3PL's and new logistic services will be further developed since 3PL is an emerging industry and a further increase of the outsourcing of logistic services is anticipated.

2.4 Conclusion

In this chapter, some background information and an overview of the literature around spare part management have been introduced and some key issues involved in this area have been discussed. All these issues are detailed in the next chapter along with their translation to practical applications.

3. METHODOLOGY

3.1 Introduction

Most logistics warehouses hold large amounts of spare parts in their stock (which implies automatically high storage costs) and at the same time are looking for ways to better manage their inventories, and eventually reduce them. As already discussed in chapter 1, the major rationale behind this project, was the lack of any classification/forecasting capability from the company's perspective as well as a limited knowledge of scientific inventory control systems.

3.2 D^{2}ID Capabilities

Inventories constitute one of the most important causes of waste, especially in modern business environments where product life cycles have been significantly reduced. Products are rapidly introduced in the market due to the recent fast technological developments. However, once a new or more updated model/product is introduced in the market, then the current one moves quickly to the decline phase. This translates to a very high risk of product obsolescence which is the toughest form of waste. The concept of product life cycle will be covered in more detail in the next part (Part C) of this thesis.

The project deals with inventory management, including statistical (and judgmental) demand forecasting and inventory control theory. It is based on simulation modeling. The next sections of this chapter will describe in more detail the methodological approach of the work conducted as well as in depth explanations of what the inputs are, the complete computations as well as the outputs of the tool together with the results of the empirical data used.

A key summary of what to be discussed next is pictorially presented below.

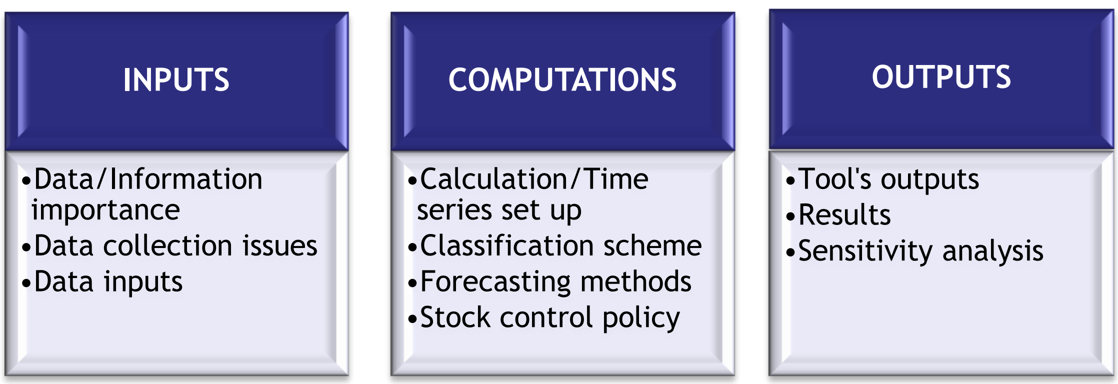


Figure 3: Key summary of inputs, computations and outputs

The empirical data was provided by an automotive spare parts customer (from the case organization) and is going to be discussed in more detail in the next section of this chapter. The key points of this project are as follows: first demand patterns are classified, then appropriate forecasting methods are used to estimate the parameters of a hypothesized demand distribution and then depending on what sort of inventory policy is used and what objectives or constraints are imposed on the system, the replenishment decisions are made. After that, it is simulated what would have happened if the proposed methodology were used in practice instead of what is currently being used and finally the differences are evaluated in terms of units, cost and service. At this point, it should be also noted that the inventory policy adopted is the order-up-to level policy (OUT) where the inventory levels are reviewed after a fixed period of time. An order is placed such that the current inventory position (actual stock on hand + on order – any backorders) plus the replenishment lot size equals a pre-specified level called the order-up-to level (OUT).

3.3 Inputs

3.3.1 Data/Information Importance

It is always very hard to collect data and more specifically the data that are particularly necessary and important for a specific project. The accomplishment of this project was heavily dependent upon the availability of clean inventory related information. The data was retrieved from the company's clients and this turned out to be far more challenging than expected due to the fact that the data needed was not available in the needed format. Appropriate collection of relevant historical data was an important part of this project. No empirical analysis can be conducted unless appropriate data is available.

3.3.2 Data Collection Issues

As in many projects, difficulties were encountered during the data collection process. An important constraint was the unwillingness to share any data until some tangible benefits could be demonstrated. But to demonstrate tangible benefits empirical data is of course needed. An equally important constraint was the fact that there wasn't a 'clean' database for extracting the data needed, even though all the data and information needed were in principle stored in the company's systems – however, not in a format that would be sufficiently convenient to use in this project.

As such, and in the process of building the empirical database needed, the tool was initially built and run on theoretically generated data. Demonstration of the benefits using theoretical data led to the provision of some empirical data which in turn facilitated the demonstration of further benefits and eventually led to a virtuous cycle of data accumulation.

Eventually, the real data provided by an automotive spare parts customer (of the case organization) covered the history of 9952 SKUs over a period of 24 months. This length is the minimum needed to deal with seasonality. Also, any less data make it very difficult to conduct proper initialization and then build the model or evaluate forecasting performance. Due to the nature of the data, some assumptions are needed to be made to fit our requirements and this issue is discussed next.

3.3.3 Data Input

The data available for experimentation purposes (along with necessary assumptions that needed to be made) can be summarized as follows.

- The tool's input, computations and outputs are on a monthly basis and the inventory is reviewed every month.
- 1 month review interval. The data was collected on a monthly basis so that one month can be viewed as the inventory review interval period ($T = 1$) and consequently at the end of every month the stock status is reviewed and decisions are made on replenishment.
- 24 demand data periods history per SKU.
- 24 purchase orders (receipts per period) history per SKU - for the same SKUs that their demand is provided (the inbound information is important due to the fact that the calculations are working backwards for calculating the initial inventory levels (the stock on hand at the end of period 1) for each SKU. It is important to note that this was not available initially – only the inventory levels at the end of the 24th period were available as an input to the tool. Both, the inbound information as well as the inventory levels at the end of each period are needed in this analysis due to the fact that when calculating the inventory position of each period in the out-of-sample block, it is necessary to know the quantity ordered in $t - L$ (where t is the current period and L is the lead time).
- Lead time (inbound) per SKU. **Constraint**: 1 month for all the SKUs. Provided by the customer. Lead time is the time between placing an order and the products being available to meet customer demand. It is assumed to be constant.

- Target service level for all the SKUs provided. **Constraint**: 95% service level for all the SKUs. After discussions with management this was judged to be the most appropriate (collectively) service level target.
- End stock levels at the end of the 24th period for all the SKUs provided. It is assumed that the stock on hand at the end of period 24 is equal to the end stock provided as an input to the tool.
- Unit cost per SKU. **Assumption:** No unit cost per SKU was provided by the company's clients as this was treated as confidential information. Given the lack of cost information, equal costs were assumed across all SKUS; the unit cost per SKU was standardized to $10. This will result in the summary volume differences being exactly the same as the cost differences when comparing the current inventory state with the optimized one. The D^2ID analysis was then repeated after generating randomly varying costs in order to show what could have happened in a more realistic setting. However, it is acknowledged that there are limitations of potentially associating expensive SKUS with a low cost and vice versa. Both cases are reported in section 3.5.1
- Overall target fill rate across all the SKUs. **Constraint**: 95% overall target fill rate across the whole collection of SKUs (without implying that the service level for each SKU is the same). After discussions with management this was judged to be the most appropriate (collectively) overall target fill rate across all the SKUs. Following that, fill rates per SKU are varied in a cost optimal manner based on some recent research in this area [22].

It is important to note, that the CSL measure has been used for optimizing the inventory levels as it was more intuitively appealing to the case organization, better understood by management and easier to implement. The fill rate has partial expectations as it is not an effortless procedure to calculate the individual service level targets based on an overall target fill rate across all SKUs. Despite the fact that the individual target fill rates have been calculated, they are not part of the solution itself. The aim was to show an indication of what could be done at the next phase of the project in terms of expanding the capabilities of the tool. Therefore the inventory optimization could be done using the individual target fill rates. Product fill rate is equal to the percentage (%) of customer demand satisfied directly from stock on hand and it translates directly to the customer service level achieved [23]. Cycle service level (CSL) is equal to the percentage (%) of replenishment cycles (or orders) in which no stock-outs occur. Replenishment cycle is the interval between two successive replenishment deliveries. In other words, it indicates how good is the inventory management system in avoiding stock outs so that the customers do not experience any delays.

It is also assumed that quantities to be ordered are placed at the end of the review period and are going to arrive after L (lead time) months and that the purchase orders are received at the start of each period.

It is also important to note the fact that service levels, lead times and cost figures (unit cost) can be treated as user inputs (i.e. can be altered to whatever value may be perceived as appropriate). Having said that the review interval (i.e. 1 period) and the total length of demand history (i.e. 24 periods) are hard-coded at the moment, although it is planned to relax this constraint in the next version of the tool.

3.4 Computations

3.4.1 Calculation/Time Series Set Up

The discussion starts with initialization related details. The given historical dataset is split into two equal blocks (of 12 periods each); the in-sample and out-of-sample blocks, respectively. The in-sample block is used for initialization purposes (parameter initial estimations and model selection). The out-of-sample block is used to evaluate the forecasting performance and conduct inventory calculations. However, it should be noted, that the evaluation conducted is not ex-ante but rather is ex-post: data used for classification, and thus for selecting appropriate methods, is then used for the evaluation of such methods. Although the value and realism associated with the former is recognized, it would not have been possible to further consider it due to lack of data availability. If the alternative was conducted (an ex-ante evaluation), then classification and forecasting would not be possible at all – since seasonal components cannot be captured from 12 months' worth of data.

Optimization of the (smoothing) parameters does not take place at the current stage of the tool; however, it is one of the areas of focus for further development of the tool's capabilities. Any initialization decisions for forecasting purposes are discussed in 3.4.3.4 Forecasting Solution where the forecasting methods used are explained along with the notation, whereas any decisions in terms of initialization for inventory purposes are discussed in 3.4.4.5 Simulated Solution.

3.4.2 Classification

3.4.2.1 Introduction

Companies use classification analysis to support any operational decisions that they need to undertake. Some of the most important decisions that they need to take are where to position the fast and slow moving items based on their picking frequency and/or quantity and where to locate the items based on their volume and/or weight. They are also interested in the price and annual usage of the items.

Nowadays, most companies are using the well-known ABC classification scheme (based on the Pareto rule analysis, 80-20% rule). ABC classification is a categorization analysis and it is commonly used by many organizations due to the fact that they deal daily with a very large number of SKUs so it is easier to control inventories by classifying the SKUs into groups [24][25][26]. The ABC inventory classification system can be used to separate out the few important items from the many trivial items. Typically, three categories are used to control the stock base: A (most important), B (intermediate importance) and C (less important); however, the analysis could be extended up to six classes [27][28]. Categorization could be done either by using single criterion or multi-criteria classification, using e.g. unit cost, demand volume, demand value, demand variability, order frequency, supply characteristics (e.g. replenishment lead time) or a combination of the aforementioned characteristics [9]. In practice, the most common approach is the single criterion classification, by considering the *volume* or *value* (volume multiplied by cost or price) criterion. Multi-criteria classifications can be challenging in terms of implementation.

The first step of the ABC classification is to deciding on the criterion to be applied, then ranking based on that criterion and then introducing arbitrarily categories to separate between the classes. ABC classification though, cannot be recommended for forecasting classification purposes. Neither the demand value nor the demand volume criteria are relevant for this kind of purpose as they do not indicate anything beneficial regarding the item's demand pattern (e.g. intermittence and lumpiness) and/or the customer characteristics generating the demand. Of course, there are alternative classification solutions that might take for example velocity (number of times a product was ordered in a defined period of time) into account. This solution might capture intermittence but not lumpiness [26]. The demand volume is not suitable due to the fact that it cannot provide any valuable information for choosing the best forecasting method to be used and demand value is not appropriate as the item's price has nothing to do with forecasting. In the case of this work, classification serves the purpose of distinguishing between alternative demand patterns and selecting the most appropriate forecasting method for each category [13]. The issues discussed in this paragraph are resolved through the classification solution adopted for the purposes of this work. This will be discussed in the next sub-section.

Demand forecasting and stock control have different requirements with regards to classification. The development of a multi-criteria classification scheme that would take stock control (e.g. price, lead time) and forecasting factors (e.g. intermittence and lumpiness) into account is of course an option. However, and as previously discussed, implementation related considerations mean that this would be a challenging exercise, in addition to no relevant solutions having been proposed in the literature.

3.4.2.2 Classification Solution

In this work, the 4 quadrant classification scheme [6] was adopted where classification takes into account the intermittence and lumpiness of demand apart from the non-intermittent demand data as well, as this method serves the purpose of selecting the most appropriate forecasting methods for managing better the spare parts inventory levels [6]. By first comparing alternative estimation procedures for the purpose of identifying regions with superior performance, then based on the results the demand patterns will be categorized. More details on the scheme and how it works are followed.

The scheme is based on the work conducted by Johnston and Boylan (1996). The researchers compared alternative forecasting methods with respect to their simulated mean squared error (MSE) for the purpose of identifying regions of superior performance. Classification then followed based on the comparative results. They compared Croston's method with Simple Exponential Smoothing (SES) on a wide range of theoretically generated data. (Both methods are going to be discussed later on in this sub-section, but briefly, SES is a robust estimator for fast demand items whereas Croston's method has been used and applied for intermittent demand items.) After comparing the results, they concluded that Croston's method performs better than SES when the average inter-demand interval (the inter-demand interval (p) is the gap between two consecutive demand occurrences (how large is, on average, the interval between successive demands)) is greater than 1.25 forecast review periods and thus the categorization was formalized under that one classification parameter (i.e. inter-demand interval). When the average inter-demand interval is less than 1.25 then demand patterns could be defined as fast whereas when it is greater than 1.25, then the demand patterns could be defined as intermittent [13].

Syntetos, Boylan and Croston (2005) extended the work described above to consider theoretical rather than simulated MSEs and introduced one more method into the evaluation process: the Syntetos – Boylan approximation (SBA) [6][29]. As discussed above, the approach relies upon first comparing alternative methods for establishing regions of superior performance followed by the classification of the demand patterns based on the results. The outcome was an approximate 2x2 matrix that classified demand based on the squared coefficient of variation of the demand sizes and the average inter-demand interval. The former is an additional parameter introduced to the work conducted by Johnston and Boylan (and is formally defined in the next paragraph). As a result, the categorization takes into account the erraticness of demand (how variable the demand is when it occurs) and the level of intermittence (how frequently demand arrives, or what the average inter-demand interval is) [25][26].

It is important to note that the coefficient of variation may be used instead of the squared coefficient of variation. The coefficient of variation (CV) is a relative measure of dispersion. It measures and indicates the volatility of the demand data [6][30][31]. The squared coefficient of variation is calculated as the standard deviation of the demand sizes over the mean squared (when demand occurs only), as follows:

$$\mathrm{C}V^2 = \frac{\sigma^2}{\mu^2}$$

where:

μ: the mean demand size

σ: the standard deviation of the demand sizes.

As Figure 4 demonstrates, the classification solution has two dimensions. The one dimension results in intermittent versus non intermittent (the latter termed also as Normal for the purposes of this work) and the other one into variable versus not variable. The end result is 4 categories; the erratic (the item’s demand size is highly variable) and fast (the item’s demand is pretty smooth) categories fall in the normal demand data division and the lumpy (intermittent and erratic demand item) and slow (the item's average demand per period is low) categories in the intermittence.

For the purposes of this work, the scheme was further amended in order to account for SKUs with no, or insufficient, demand observations. There might be cases when no positive demand observations are available in the out-of-sample (or in both sample blocks), in which case no performance evaluation may be conducted. Further, if there are less than 2 periods with positive demand in the initialization sub-sample then initial estimates of inter-demand intervals or demand sizes (both of which rely upon straight averages) cannot be calculated. The former case is classified as "evaluation constrained" and the latter as "calculation constrained".

These two categories are not forecasting applicable. However they are included in the output part of the tool and, based on the priorities of the KTP, they are not completely ignored due to the fact the company did not wish to exclude any data from the final presentation of the output. During implementation, they are obviously excluded from the forecasting related calculations, but can be easily identified if case the company wishes to deal with them in a judgmental manner.

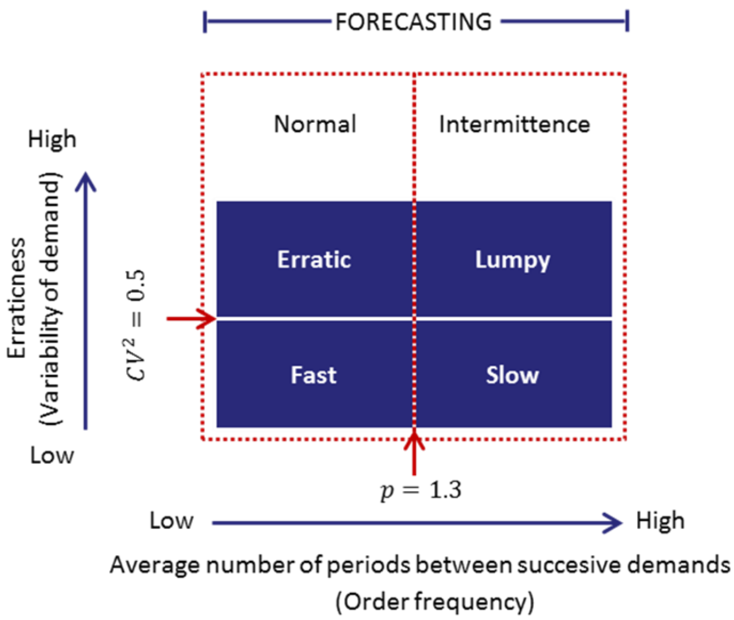


Figure 4: Classification scheme applied to D^2ID

The pseudo code for the classification solution is presented in Figure 5 and all the above information is graphically depicted in Figure 6**Error! Reference source not found.** and Table 1 below:

If $p \leq 1.3$ And $CV^2 \leq 0.5$ Then
Category="Fast"
If $p \leq 1.3$ And $CV^2 > 0.5$ Then
Category="Erratic"
ElseIf $p > 1.3$ And $CV^2 \leq 0.5$ Then
Category="Slow"
Else
Category="Lumpy"
End if

Figure 5: Classification scheme's solution pseudocode

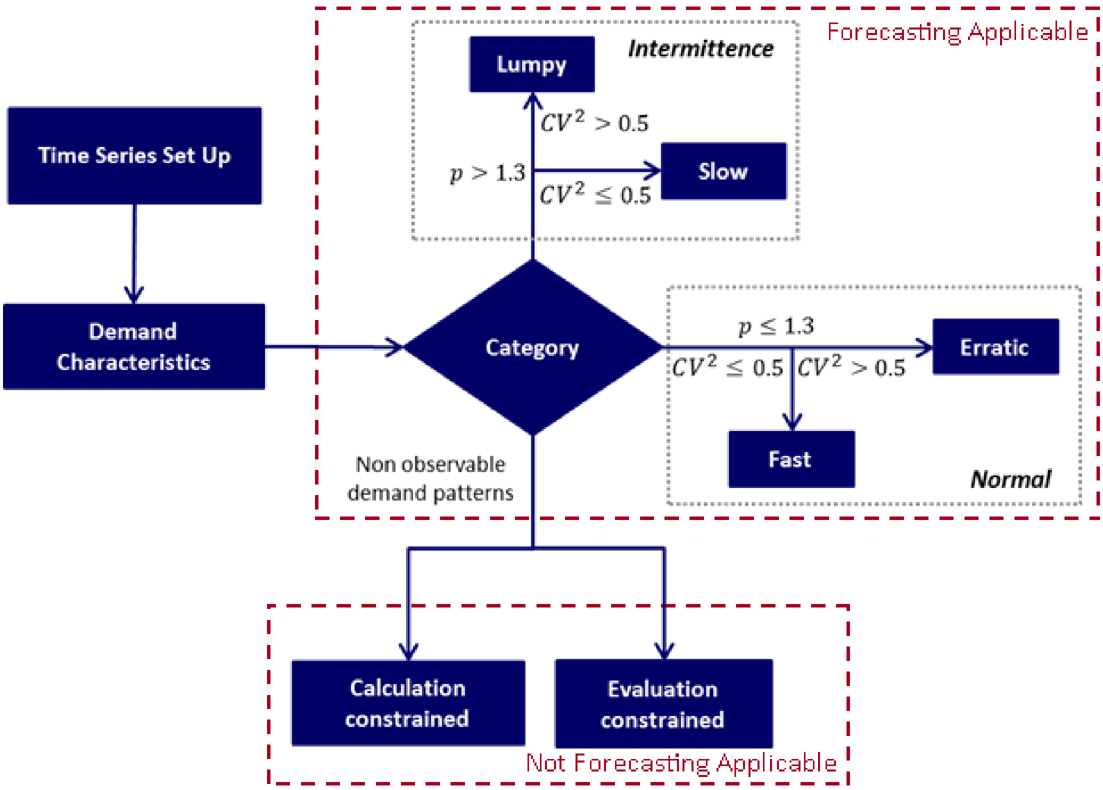


Figure 6: Detailed classification process adopted

Classification Categories			
	CATEGORIES	DESCRIPTION	
Normal	Erratic	The item's demand size is highly variable	Forecasting Applicable
	Fast	The item's demand is smooth	
Intermittence	Lumpy	Intermittent and erratic demand item	
	Slow	The item's average demand per period is low	
	Calculation constrained	No demand pattern on the history data	Not forecasting Applicable
	Evaluation	No demand at all	

Table 1: Classification categories in detail

3.4.3 Forecasting

3.4.3.1 Introduction: Forecasting In The Supply Chain

Demand forecasting plays a significant role in supply chain management as it forms the basis for most planning and control activities [30][32]. It is essential for the planning and allocation of the total inventory investment and subsequently for the evaluation of short term inventory requirements, the placing of replenishment orders and the satisfaction of customer needs [27][33]. Transportation requirements are also determined based on demand forecasting as, at the strategic level, the optimized location of warehouses and distribution centers is determined based on long term demand forecasts [33]. In general, forecasting is key to effective inventory management, production and operations planning, transportation and warehousing optimization. It also spans various levels of decision making, from strategic planning decisions (new products), to finance (costs, budgets), to marketing (sales, new products), to capacity planning and human resource decisions (manpower decisions, hiring, training needs) [27][34].

Demand forecasting in the supply chain has been studied by many academic researchers. Their research covers both fast and slow (intermittently) moving items. Forecasting for fast moving items covers the greatest part of relevant research [35], although forecasting for items with intermittent demand has been receiving increasing attention in recent years due to the fact that relevant items account for substantial proportions of stock value [11][36].

Forecasting is not a straightforward and effortless procedure. In contrast (and depending on the demand characteristics) it can become a very involved exercise [32][37]. Forecasting is based on the assumption that the past predicts the future therefore a forecast is only as good as the information included in the forecast (historical data). Nobody can tell if a forecast is right unless demand is realized. For every forecast there is a forecast error (the difference between the actual value and the forecasted value) [27]. There will be a different part explaining the measuring of forecast errors below.

Because of a typically large number of SKUs demand forecasts tend to be statistically derived (i.e. relying upon an automated procedure). However, statistical forecasts are then often judgmentally adjusted by managers to reflect information that may not be included in the historical data.

The comparative performance of judgmental and statistical forecasting also relates to the forecast horizon and the demand history. Judgmental forecasting is generally useful for strategic, long term decisions and quantitative forecasting preferred for operational, short terms decisions. The longer the forecast horizon, the better the use of judgmental forecasting due to the fact that it is highly probable that the series will experience some structural changes (eg. factors not considered in the past should be considered in the present). Of course this is not always exactly like that due to the nature of the decisions need to be taken. Long term quantitative inputs are also needed for strategic forecasting, and judgmental adjustments take place for short term operational forecasts. The longer the demand history, the more effective the use of quantitative forecasting is as for short demand histories, statistical methods cannot be implemented thus the need of judgmental forecasting is calling. For short time series, the forecasting performance may be improved if quantitative forecasting will be combined with judgmental forecasting [38]. Further discussion around the different types of forecasting is followed in this sub-section.

3.4.3.2 Links Between Inventory And Forecasting

Both demand uncertainty and inaccuracy of forecasts lead to the holding of higher inventory levels [30][39][40][41]. Over-forecasting or under-forecasting may cause major issues at the customer’s businesses. Over-forecasting could cause excessive inventory levels, high storage costs, obsolete stock and non-organized warehouse operations. On the other hand, under-forecasting could cause insufficient inventory levels, loss of sales, unsatisfied customers (poor customer service levels), backorder costs and excessive costs due to overtime.

Forecasting and inventory control should be integrated for avoiding major issues that current supply chains are facing. Forecasting links directly with inventory replenishment decision making since demand forecasts are translated into inventory related decisions. These are decisions on whether to replenish stock or not and if so by how much under the constraint that an item should be kept in stock. Before deciding the stock levels, a decision should be taken as to whether the item should be stocked or not by evaluating the historical demand pattern of the item and forecasting the mean demand. This work, is not looking at stock-non stock decision at the moment. More details are included in 3.4.4.2 Role Of Stock Control In The Supply Chain.

Forecasting approaches may be largely classified as parametric and non-parametric, the former being what is considered in this work. Parametric forecasting relies upon the estimation of the parameters of a hypothesized demand distribution. Key quantities of the distribution are then used depending on the inventory policy used and what it is trying to achieve (eg. the percentile for a CSL target). Non parametric forecasting (especially in the context of intermittent demand) takes the form of bootstrapping, i.e. reconstruction of the empirical distribution without any assumptions as to how that distribution may look like theoretically. The only assumption is that whatever was observed in the past will also persist into the future [42].

In summary, forecasting is the base of demand planning and therefore of the setting of inventory levels [43].

3.4.3.3 Categorization Of Forecasting Methods

Forecasting methods are generally categorized into qualitative and quantitative.

Qualitative forecasting methods are based on qualitative data (e.g. subjective opinions from one or more experts, educated opinions/guesses, surveys) [44][45]. People are the information processors for this type of forecasting as the forecast is made subjectively by the forecaster [46][47]. Due to the fact that qualitative methods are made by people they are often biased as the outcome may be related to personal opinions and motivations [48].

- **Executive opinion:** Combines managerial experience with statistical models and is a relatively quick process. Decisions are taken from a group of high level executives (e.g. managers). This method could be also used for adjusting a current forecast based on unusual events (e.g. promotions, strikes). From one side, this is good for strategic (or new product) forecasting however on the other side, this could be biased as people's opinion may dominate the quality of the forecast [44][48].

- **<u>Market research:</u>** A method that uses interview sessions or surveys with the help of questionnaires to identify any customer's preferences and new product ideas. This is a good determinant of customer preferences; however, a good questionnaire is difficult to be developed to cover and capture exactly what is needed. Sometimes a question may be interpreted differently by different people [45][48].
- **<u>Delphi method:</u>** It is an iterative group process with three types of participants: decision makers, staff and respondents, involving the development of questionnaires (by staff), and their sending to the respondents. As soon as the findings are summarized (by the decision makers), then an updated questionnaire will be resent to the respondents. This procedure continues until an agreement is reached. This method is trying to capture certain things that the respondents agree on and use that as the forecast. With this method, individual opinions are collected and considered but they are anonymously shared among a group. This is a time consuming method but is good for forecasting long term demand or identifying any long term technological changes [45][48].
- **<u>Sales force composite:</u>** This method captures information and opinion from the sales representatives due to the fact that each sales representative estimates the sales of a product for a given future period as it is this person who knows more than anyone else the customer's needs. What the forecaster does next, is to take these estimations into account and get the sales force composite forecast for the given time period [49].

Quantitative forecasting methods are based on mathematical modeling and rely on historical data/information. The forecast in this case is only as good as the information included in the forecast (historical data).

- **<u>Time series:</u>** Time series forecasting methods are based on historical demand data assuming that this is a good indicator for the future demand. A time series is a set of observations on a variable that occur across time [27][45][50]. The observations are collected at equally discrete time intervals over a specified period of time [30]. The setting of time buckets is very important. They could be daily, weekly, monthly, quarterly, annually etc. However, there has not been sufficient research to explore the issue of what constitutes the right length of a time period. This will vary depending on the nature of the industry, the length of historical data, the volume of demand, the information systems in place etc. The demand pattern of a specific product or a group of associated products could be considered as a time series of separate values (e.g. the total demand arising day by day) [27]. The series are broken down to its components which are level, trend, seasonality, cyclical patterns etc. [44].

Elements of Time Series Forecasting

The possible components of any time series (demonstrated also in Figure 7 are as follows:

- Level (α) – the scale (average) of the time series. Data fluctuates around a constant mean [30].
- Trend (β) – the increase or decrease in the level over time of the time series (upward or downward pattern) [27][45].
- Seasonal variations (γ) – A seasonal pattern exists when seasonal factors such as time/day of the week, month etc. influence the time series. Existence of patterns that repeat over known, fixed periods of time [30][27][45].
- Cyclical movements (C) – consequence of business cycles – fluctuation of data (increase, decrease) in a non-fixed period of time [50].
- Irregular random fluctuations (ε) – the remaining variation once the above have been accounted for. Irregular random fluctuations could be caused from uncertainty that is inherent in any time series. Uncertainty that simply cannot be explained otherwise. Erratic, unsystematic fluctuations due to unforeseen events (eg. weather) [27].

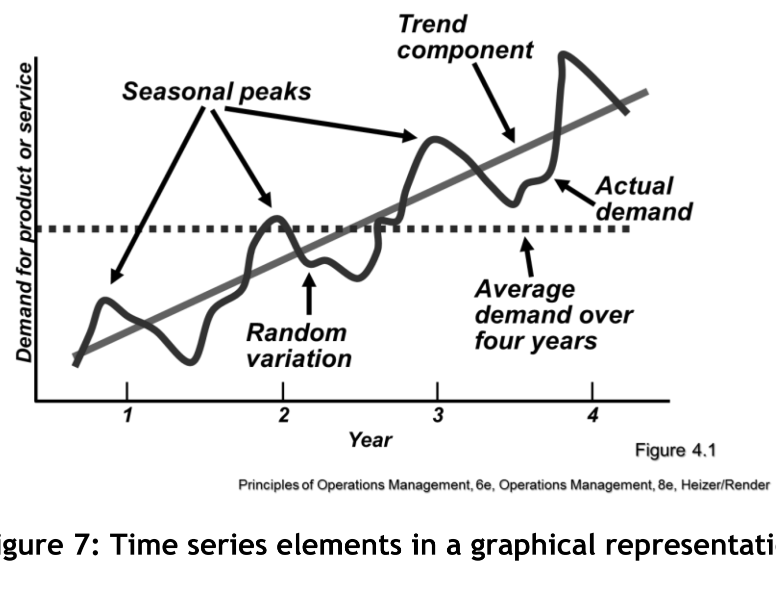


Figure 7: Time series elements in a graphical representation

[51]

Demonstration of trend and seasonality effects based on Pegel's (1969) classification:

Pegels (1969) has provided a useful framework for separating trend and seasonality effects in additive (linear) and multiplicative (non-linear) models. Different exponential smoothing methods are optimal for the below 9 scenarios, taking into account all combinations of trend and seasonal effects in additive and multiplicative form (eg. Simple exponential smoothing (SES) applies to scenario A1, additive Holt-Winter's applies to scenario B2 and multiplicative Holt-Winter's applies to scenario B3) [47][52].

In a multiplicative model, the magnitude of the seasonal pattern in the data depends on the magnitude of the data (eg. the magnitude of the seasonal pattern variation increases as the data values increase, and decreases as the data values decrease and the season is becoming wider) whereas in an additive model, the seasonal variation is independent of the level and the amplitude of the seasonal effect is the same each year (eg. the difference between the June values is approximately the same each year) [52].

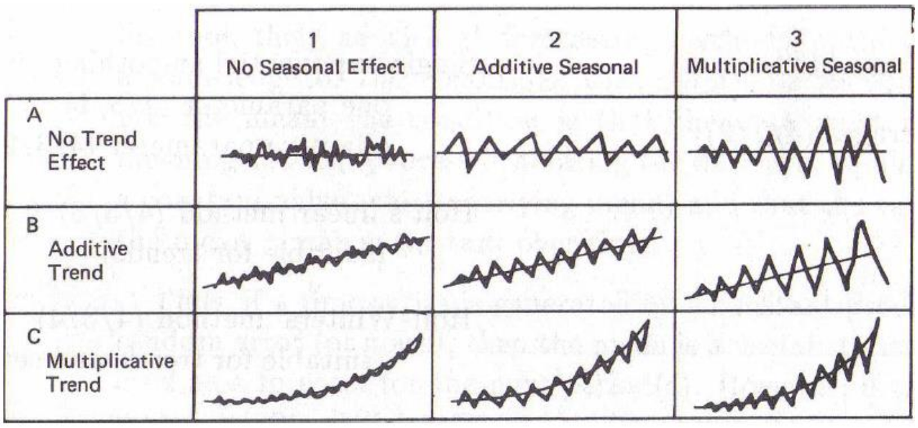


Figure 8: Patterns based on Pegels' (1969) classification

[52]

- **<u>Causal:</u>** Explores cause and effect relationships. Causal forecasting methods may determine the correlation (if any) between demand and other internal or external factors and the explanatory effect of these factors to the demand [30] [45][44]. However, causal methods can be challenging and complex if it comes to consider the relationships among many variables [48].
- **<u>Simulation:</u>** Simulation methods usually combine both time series and causal forecasting techniques together [30]. Simulation forecasting methods, imitate

and take into account the consumer choices that have already given rise to the demand which in turn will help to generate the demand forecast. Simulation is a powerful tool due to the fact that it provides the opportunity to apply hypothesis, alternative planning and policies with no need for experimentation on the actual system. For example, simulation could be used to find out the impact of a price promotion or the impact of a new competitor opening store nearby [30].

However, this work emphasizes time series forecasting which is common for spare parts demand. Time series forecasting, relies on past historical demand data (understanding the underlying demand pattern structure identifying growth pattern and/or seasonal patterns) to forecast future demand. However, explanatory/causal forecasting can also be used if there is a plethora of explanatory variables. Apart from the past historical demand data, some more related information is needed in order to associate their influence on the volume of the demand [48]. This is very common in maintenance for example where say number of flight hours or information on the condition of the equipment may determine the demand for a spare part. Due to the lack of data on explanatory variables (that may affect demand) and the nature of the specific problem needed to address, time series forecasting was adopted.

The aim of this work was to provide demand forecasts from month to month for particular products. Every year, the demand is likely to be increased (this is true in the growth stage of the life cycle, demand is not going to increase in the maturity stage and it will then decline (negative trend) in the decline stage); however, this upward trend will slowly disappear (damped) due to the fact that the market becomes saturated. Apart from the trend, it is highly likely that there is a seasonal component reflecting the seasonal changes from month to month in the customer's demand. The multiplicative method was applied in this work assuming that the seasonal and other effects act proportionally on the time series. For example, in seasonal data, it might be useful to assume that the June's value is the same proportion higher than the January's value in each year, rather than assuming that their difference is constant.

3.4.3.4 Forecasting Solution

A sound classification solution should determine the 'correct' forecasting method to pick up. In this case, the classification solution previously discussed is applied to select a method and produce one step ahead forecasts. The below figure shows the forecasting process in summary.

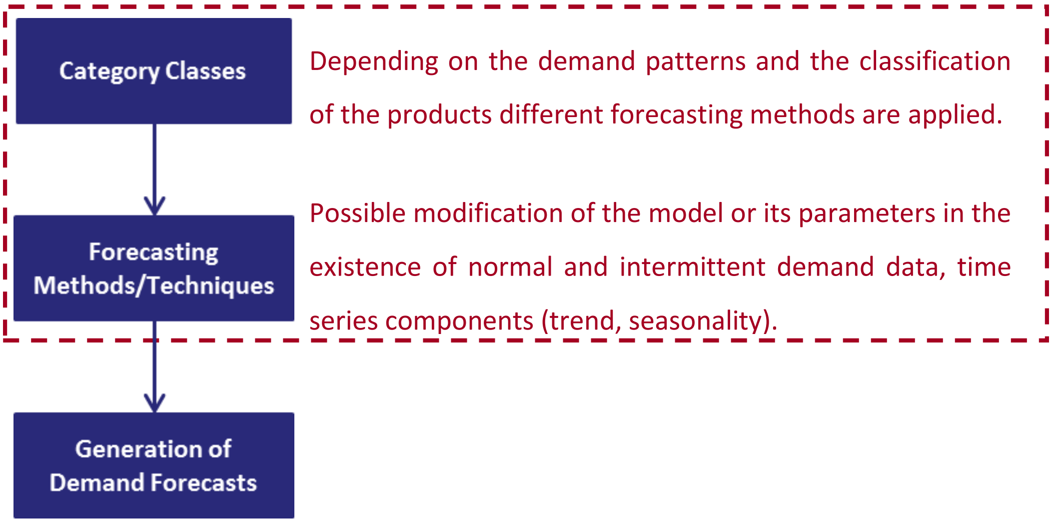


Figure 9: Forecasting process in summary

Simple exponential smoothing (SES) and Croston's method (1972) are generally used by many practitioners and academics to forecast intermittent demand data. SES forecasts the mean level of demand treating in the same way both zero and non-zero demand periods. However, Croston recognizes that demand sizes and demand intervals need to be treated and forecasted differently so separate forecasts of the mean level of non-zero demand and the mean inter-demand intervals are being made according to the method he proposed in 1972 [11][53]. Croston's method (1972) has become the standard estimator used in industry for forecasting intermittent demand data. However it has been found to be biased immediately after a demand occurrence (it consistently overestimates mean demand). There have been many attempts in the literature to improve on the performance of Croston's method (eg. Johnston and Boylan (1996), Snyder (2002), Syntetos and Boylan (2005), etc.) [11]. The Syntetos-Boylan Approximation (SBA) corrects for Croston's bias and is the method with most empirical evidence in its support. There have been many empirical studies demonstrating the very robust performance of that method [10][13]. Croston's method is gradually being replaced by the SBA, both as a benchmark in academic studies and as the suggested procedure in software packages. SBA applies a very simple correction factor to correct the inversion bias associated with Croston's estimator and improve its performance [6][29]. More details on SES, Croston' method, Croston's inversion bias and SBA follow below.

Simple Exponential Smoothing (SES)

Simple Exponential Smoothing is used for fast demands when demand has no trend or seasonality in order to forecast the next value of the time series [35]. The robustness and simplicity of SES have resulted in its wide implementation even when these assumptions are violated.

Let:

n: The forecast horizon

D'_t: The estimate of demand (forecast) at time t for the period $t+1$

L_t: Estimation of level of the time series at time t

L_0: The initial estimation of the level.

L_{t+1}: Estimation of level of the time series at time $t+1$ for the period $t+2$

D_i : All the historical data from period 1 to n

D_t: Demand observation at time t

D_{t+1}: Demand observation at time $t+1$

α: Smoothing constant value for the level, $0 < \alpha < 1$

Due to the fact that demand is assumed to have no trend or seasonality then the initial estimate of level L_0 is the average of all the historical data.

$$L_0 = \frac{1}{n}\sum_{i=1}^{n} D_i$$

Estimation of level at time t:

$$L_t = \alpha D_t + (1-\alpha)L_{t-1}$$

which is a weighted average of the observed value D_t at time period t and the old estimate of the level L_{t-1} at time period $t-1$.

Estimation of level at time $t + 1$:

$$L_{t+1} = \alpha D_{t+1} + (1 - \alpha)L_t$$

which is a weighted average of the observed value D_{t+1} at time period $t + 1$ and the old estimate of the level L_t at time period t.

The forecast at time t for the period $t + 1$ and at time $t + 1$ for the period $t + 2$ which cannot be negative:

$$D'_t = L_{t-1}$$

$$D'_{t+1} = \alpha D_t + (1 - \alpha)D'_t$$

D'_{t+1} is a weighted average of the current observation, D_t, with the forecast, D'_t, made at the previous time point $t - 1$.

[30][45][54]

The smoothing constant value represents a percentage of the forecast error. A disadvantage of single exponential smoothing is the difficulty of choosing a suitable smoothing constant value α. The selection of the smoothing constant plays an important role in determining how responsive the forecast is to the historical data available. The values could be controlled according to the actual underlying demand pattern and could vary between 0 and 1. When α takes values close to 1 then the forecast is more responsive to the recent observations and can cope quicker with any mean demand changes (if any) in the underlying demand pattern that varies little over time. However, a high smoothing constant value may cause an over response (yielding of erratic results with significant increases and decreases), if there are not changes in the mean demand and the error is simply the outcome of the fact that demand naturally varies over time. Therefore less smoothing is needed. When it is close to 0, the forecast will probably be stable and less responsive to recent observations (eg. the forecasted mean does not change quickly over time). The selection of the smoothing constant value to be close to 0 or as low as possible would be suitable when the mean demand is almost the same over time (small variations in the time series). However, a low smoothing constant value, may lead to under reaction, if there are changes in the mean demand (from the previous period) and the error is the outcome of such a change [55][56][57][58][59].

Following the discussion around the range of values that the smoothing constant value α can take, it is worth noting, that, the value of α could be decided even by reviewing the data or by optimizing the parameter.

SES is also widely used for intermittent and lumpy demand data. Croston examined the application of SES in an intermittent demand context and showed that it is biased for issue points in time only (focus is given on the time periods just after a demand occurrence)[53]. SES is biased high when the forecasts made at the issue points only are isolated. The forecasts are at their highest just after a demand occurs since every time a demand occurs it is assigned to a smoothing constant value α thus the increase, whereas when no demand occurs, the forecasts are decreasing exponentially in every following period with no demand until the next positive demand (which is going to start increasing again). This is also shown graphically in Figure 10 below. This implies that it is not a good estimation, as it is overestimating the mean demand. This is often the point at which the forecast triggers the stocking decision. The issue of overestimating the mean demand is also known as the decision point bias which causes overstocking. Croston proposed another method for addressing this bias problem associated within the intermittent demand context. [60]

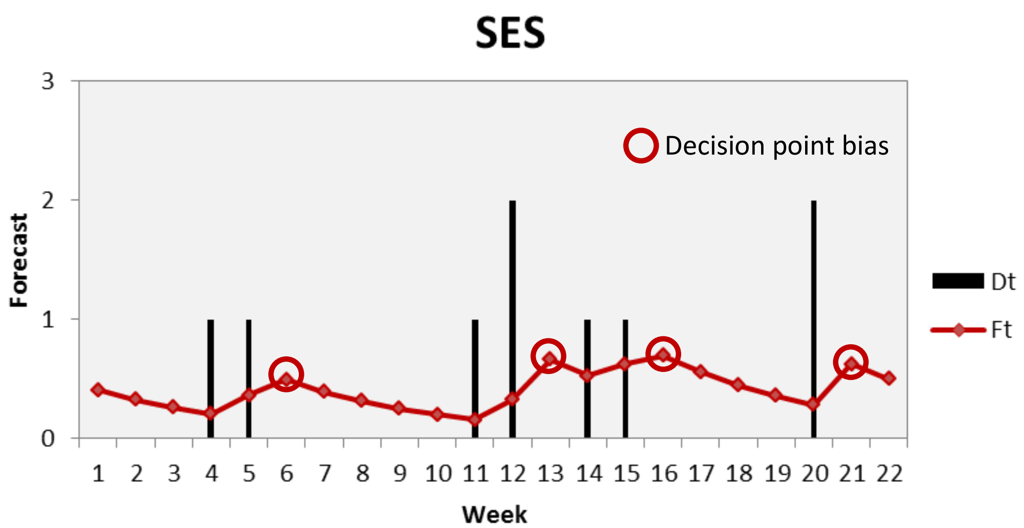


Figure 10: Graphical representation of bias in SES

Croston's Method

In 1972, John Croston proposed a forecasting method specifically developed for dealing with intermittent demand data and as mentioned before, the method recognizes that mean demand sizes (when demand occurs) and mean inter-demand intervals need to be treated and forecasted differently. Forecasts are produced, in both cases, using simple exponential smoothing (SES) and using the same smoothing constant value. If no demand occurs, then the estimates remain the same as before and do not re-estimate [53][60].

Croston's method, assumes that the distributions of non-zero demand sizes and inter demand intervals are normal and geometric respectively, and that the demand sizes and inter demand intervals are mutually independent (the length of the demand intervals does affect the demand sizes) [11]. The normality assumption does not make any difference in the formulation of Croston's method. The distribution of the demand sizes, could be in fact any other distribution. It also further assumes that the demand sizes are independent (a demand size is not correlated with previous demand occurrences) and inter-demand intervals are independent as well (as the probability of a demand occurrence is independent of the time and not correlated to the previously demand occurrence). Stationary mean is supported in the literature as the one describing the underlying intermittent demand pattern [29]. However, these assumptions have been challenged by Shenstone and Hyndman (2005) due to the fact that intermittent demand data are often non-stationary. The demand sizes are updated using SES, which implies actually non-stationarity and here is the inconsistence between Croston's model and method. However, the model is developed based on the stationary assumption, the method implies non stationarity. The same is the case for SBA which is going to be discussed next. Furthermore, the underlying model must be defined on a continuous sample that can take on either negative or positive demand values, something that is inconsistent with the reality that demand is always non-negative. However, these are theoretical limitations which have been shown not to affect the method's results in practice. Croston's method is widely used in practice and has received tremendous attention in the academic literature [11][12].

Croston's forecasting method is described below in summary, followed by a more detailed presentation.

Separate forecasts for the mean demand-size and mean demand-interval

If **demand occurs** then

Update the mean demand size (S_t) using exponential smoothing

Update the inter - demand interval (I_t) using exponential smoothing

Estimate the demand per period as: $D'_t = \frac{S_t}{I_t}$

Else If **no demand occurs** then

Do not re-estimate, forecasts remain the same as before

End if

Figure 11: Croston's method

In addition to the previous notation:

Let:

S_t : The smoothed estimate of the mean demand size (when demand occurs) at period t

I_t : The smoothed estimate of the mean inter-demand interval at period t

q : The time interval since the last non zero demand occurrence

The value of the smoothing constant is the same when forecasting both mean demand sizes and mean inter-demand intervals.

Regarding the initialization, the first estimate of the demand size is the average of the non-zero demand sizes in the in-sample demand data and the first estimate of the mean inter-demand interval is the average of the non-zero inter-demand intervals.

If $D_t > 0$ then

$$S_t = \alpha D_t + (1-\alpha)S_{t-1}$$

$$q = 0$$

$$I_t = \alpha q + (1-\alpha)I_{t-1}$$

$$D'_t = \frac{S_t}{I_t}$$

ElseIf $D_t = 0$ then

$$S_t = S_{t-1}$$

$$q = q + 1$$

$$I_t = I_{t-1}$$

$$D'_t = \frac{S_t}{I_t} = \frac{S_{t-1}}{I_{t-1}} = D'_{t-1}$$

End if

It is important is to note that when demand occurs every single period, then the Croston method generates the same forecasts as conventional SES. Therefore the same method could be used for both intermittent and non-intermittent demand series [11][10][61].

As discussed above, Croston's method, has been found to be upwardly biased (it consistently overestimates the mean demand by overestimating the probability of a demand occurrence) but not as high as with SES. The inversion bias (the use of the inverse of the inter-demand interval to estimate the probability of a demand occurrence causes the overestimated probability) associated with Croston's estimator has been identified by Syntetos and Boylan in 2001. With Croston's method, there are no updates when there is no demand but only when there is a demand occurrence. All of these are displayed graphically in Figure 12 below. It has to also be noted that the bias occurs not only in issue points in time only but for all points in time as well [60][62].

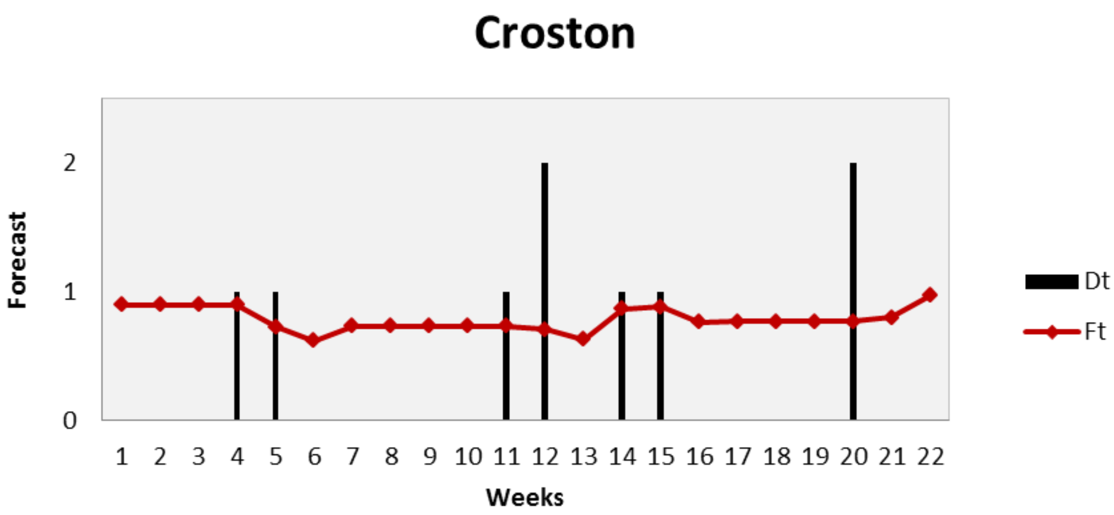


Figure 12: Graphical representation of bias in Croston's method

SBA Method

It was in 2001, when Syntetos and Boylan showed that the Croston's method is biased and in 2005 they proposed the Syntetos-Boylan Approximation (SBA) [62]. As previously discussed, Croston's method is gradually being replaced by the SBA, which applies a very simple correction factor to correct for the bias and improve performance [6][29]. The SBA's updating algorithm is as follows:

Bias correction of Croston's method

$$D'_t = (1 - \frac{\alpha}{2})\frac{S_t}{I_t}$$

Figure 13: SBA method

The value of α is the same smoothing constant value used for forecasting the mean inter-demand interval. The bias correction multiplicative factor reduces the Croston's forecast by $100\frac{\alpha}{2}$ %. SBA has been shown in a number of empirical case studies to perform very well [13].

Implementation

The decision whether to use Croston or SBA depends on the classification solution described above. Both the pseudo code and figure below shows that SBA is assigned to slow, lumpy and erratic items whereas Croston's method is assigned to the fast classification category.

```
If p > 1.3 Then
        Method="SBA"
ElseIf p ≤ 1.3 Then
    If CV^2 > 0.5 Then
            Method="SBA"
    End if
Else
        Method="Croston"
End if
```

Figure 14: Croston's method and SBA in pseudocode

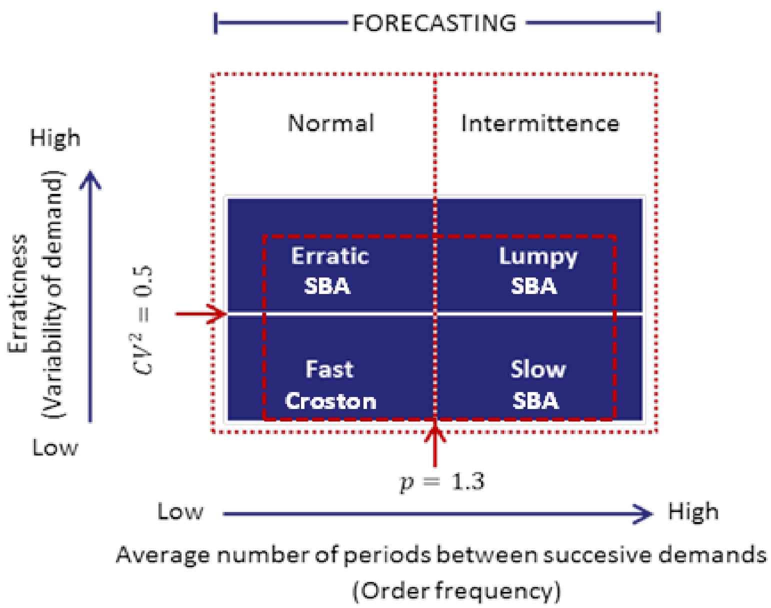


Figure 15: Linkage of forecasting methods to the classification scheme adopted

Croston's method and SBA are level related methods, i.e. they do not account for, and they have not been developed to cater for, trend or seasonality. Their operation implies that the forecast produced at the end of period 24 for period 25 is also the forecast produced for period 26 and indeed for any other future time period. That is to say, the forecast produced at the end of time t is the same for $t+1, t+2, t+3$ etc.

Further analysis for erratic and fast items

After checking if the demand data are non-intermittent or intermittent, assign each SKU to its classification category and apply the most appropriate forecasting method based on the classification criteria, further analysis is applied to the erratic and fast categories in order to check whether there is trend or seasonality to the normal data. As explained earlier on in this chapter, the term normal does not imply normality assumption. Rather, it is used conveniently to distinguish between patterns that are intermittent and patterns that are non-intermittent (whether or not they resemble the normal distribution). As can be seen in the diagram below, different forecasting methods are applied in these particular cases. If there is trend, then Holt’s method is used; if there is seasonality, Winter’s method is employed; and if both trend and seasonality exist, then the Holt Winter’s method is applied. Finally as mentioned earlier on, based on the performance measure adopted (an issue that is discussed later on this chapter), the best forecasting method predominates.

The classification and forecasting solution adopted can be seen graphically below:

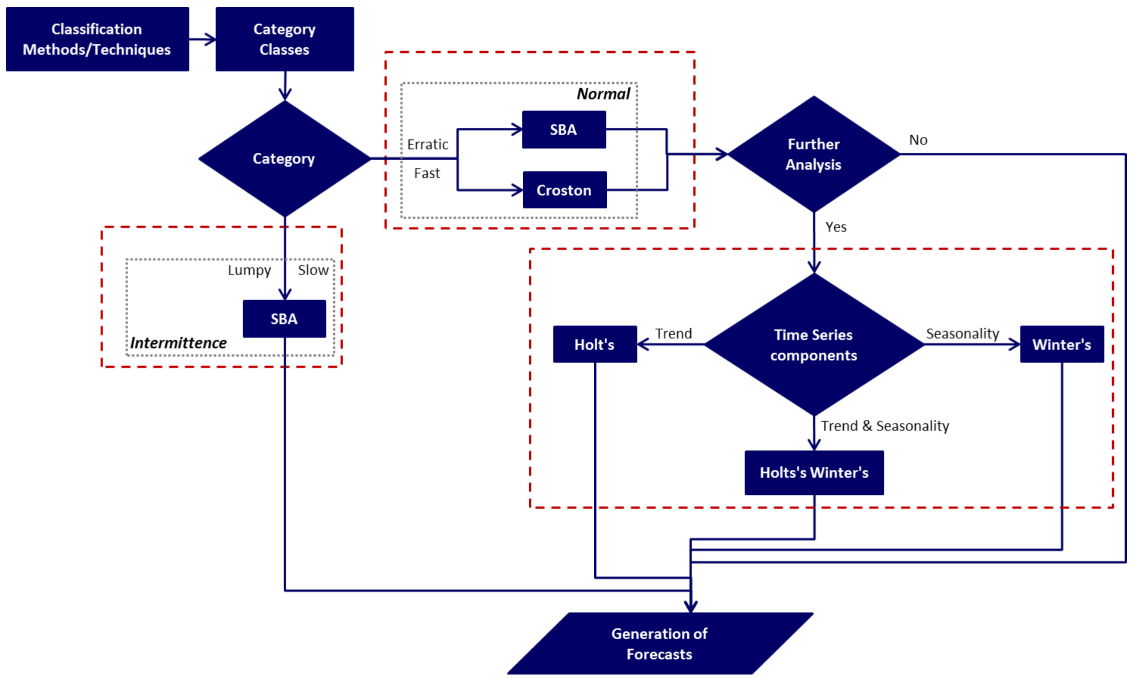


Figure 16: Classification and forecasting processes in detail

Holt's Linear Exponential Smoothing (H)

Holt's Linear Exponential Smoothing method is an extended version of exponential smoothing with two smoothing constants α and β. It takes account of both the level and the trend in a time series. The trend factor is added to the smoothing equation in order to allow for changes over time [30][54]. Holt's allows for different rates of smoothing for level and trend. It has to be noted, that no seasonality is relevant in this case.

In addition to the previous notation:

Let:

T_0: The initial estimation of the trend. The slope measuring the rate of change of demand level per period t.

L_0 : The initial estimation of the level. It measures also the estimation of demand at the period $t = 0$.

D_{t+1}: Demand observation at time $t + 1$

D'_{t+1}: The estimate of the demand (forecast) at time $t + 1$ for the period $t + 2$

D'_{t+n}: Forecast at time $t+n$ for the period $t+n+1$

T_t: Estimation of the trend of the time series at time t

T_{t+1}: Estimation of the trend of the time series at time $t+1$

β: Smoothing constant value for the trend, $0 < \beta < 1$

<u>For the initial estimation of the level and trend assume:</u>

$T_0 = 0$

$L_0 = Average\ of\ the\ in - sample\ demand\ data$

<u>Estimation of level at time t:</u>

$$L_t = \alpha D_t + (1-\alpha)(L_{t-1} + T_{t-1})$$

<u>Estimation of level at time $t+1$:</u>

$$L_{t+1} = \alpha D_{t+1} + (1-\alpha)(L_t + T_t)$$

<u>where:</u>

$$D'_t = L_t + T_t$$

is the forecast at time period t for the period $t+1$, which cannot be negative.

And when the actual values are not known and trying to find the future ones then:

$$L_{t+1} = \alpha D'_t + (1-\alpha) D'_{t+1}$$

<u>Estimation of trend at time t:</u>

$$T_t = \beta(L_t - L_{t-1}) + (1-\beta)T_{t-1}$$

<u>Estimation of trend at time $t+1$:</u>

$$T_{t+1} = \beta(L_{t+1} - L_t) + (1-\beta)T_t$$

The estimation of trend is a weighted average of the observed value and the old estimate.

The forecast at time $t + n$ for the period $t + n + 1$, which cannot be negative:

$$D'_{t+n} = L_{t+n} + nT_{t+n}$$

Following the discussion around the smoothing constant values from single exponential smoothing, the same happens here as well. Smoothing constant values close to 0.2 and 0.3 are more reasonable, produce more accurate predictions and signify that the current forecast should be adjusted 20-30% for error in the previous forecast [27][57][59][63][64]. As already mentioned, smoothing values close to 1 are more responsive to the recent observations and due to the nature of the data analyzed, lower smoothing values would be more reasonable - in an intermittent demand context, low smoothing parameter values are recommended in the literature in the range of 0.05-0.2 [6][53]. That is why, for the whole model, the smoothing constant values used at each method (SES, H, HW, W, Croston, SBA) were 0.2. However, this is a bit restrictive, and that is why it has been already decided to optimize the forecasting parameters in the next development phase of the tool. All the development plans are summarized together in the 4.5 Next Steps Of Development.

Holt - Winter's Exponential Smoothing (HW)

Holt-Winter's Exponential Smoothing method is an extended version of the Holt's linear exponential smoothing with three smoothing constants a, β and γ. It takes account of the level, trend and seasonality potentially present in a time series. It allows for different rates of smoothing for level, trend and seasonality.

In this work, Winter's Exponential Smoothing is an extended version of single exponential smoothing. The same process as in the Holt Winter's method is followed here, but with the exception that there is no trend at all, only seasonality and it allows again for different rates of smoothing for level and seasonality.

In addition to the previous notation:

Let:

D_i: The actual observation of demand at time period t

p: The periodicity of the demand (the number of periods after which the seasonality pattern is repeated).

S_i: Estimation of seasonality factor of the time series at time t, $1 \leq i \leq p$

S_{t+1}: Estimation of seasonality factor of the time series at time $t+1$

S_{t+1-p}: Estimation of seasonality factor of the time series at time $t+1-p$

S_{t+n-p}: Estimation of seasonality factor of the time series at time $t+n-p$

γ: Smoothing constant value for the seasonality factor, $0 < \gamma < 1$

<u>The estimation of seasonality factors:</u>

$$S_i = \frac{D_i}{mean(D_1,\dots,D_p)}, \qquad 1 \le i \le p$$

<u>For the initial estimation of the level and trend assume:</u>

$T_0 = 0$

$L_0 = average\ of\ the\ in - sample\ demand\ data$

The estimation of level (L_0), trend (T_0), and seasonality $(S_1, \dots, S_p)$, is based on historical data and these estimations will be used for all the future forecasts.

After obtaining the initial estimations of level (L_0), trend (T_0), and seasonality $(S_1, \dots, S_p)$, the level, trend and seasonality factors estimations as well as the forecasts are calculated.

<u>Estimation of level at time t:</u>

$$L_t = \alpha\left(D_t/S_{t-p}\right) + (1-a)(L_{t-1} + T_{t-1})$$

The estimation of level is a weighted average of the observed value and the old estimate.

<u>Estimation of level at time $t+1$:</u>

$$L_{t+1} = \alpha\left(D_{t+1}/S_{t+1-p}\right) + (1-a)(L_t + T_t)$$

<u>Estimation of trend at time t:</u>

$$T_t = \beta(L_t - L_{t-1}) + (1-\beta)T_{t-1}$$

The estimation of trend is a weighted average of the observed value and the old estimate.

Estimation of trend at time $t+1$:

$$T_{t+1} = \beta(L_{t+1} - L_t) + (1-\beta)T_t$$

Estimation of seasonality factor at time t:

$$S_t = \gamma(D_t/L_t) + (1-\gamma)S_{t-p}$$

Estimation of seasonality factor at time $t+1$:

$$S_{t+1} = \gamma(D_{t+1}/L_{t+1}) + (1-\gamma)S_{t+1-p}$$

The estimation of the seasonality factor is a weighted average of the observed value and the old estimate.

The forecast at time t for the period $t+1$, which cannot be negative:

$$D'_t = (L_t + T_t)\, S_{t+1-p}$$

and

$$D'_{t+n} = (L_{t+n} + nT_{t+n})\, S_{t+n-p}$$

[30][27][56][59][64]

Following the discussion around the smoothing constant values from the exponential smoothing and the Holt's method, the same happens here as well. When the smoothing constants take values close to 1 then a rapid response is happening and the forecast is more responsive to the recent observations. When they are close to 0, the forecast will be more stable and less responsive to recent observations. If however, any of the smoothing constants is 1 then more data are needed for the initialization step [54][55][65].

3.4.3.5 Performance Measurement For Intermittent Demand Items

The nature of intermittent demand data and in particular the existence of a substantial proportion of zero values (no demand), causes difficulties in selecting appropriate accuracy measures [29]. Thus, all relative to the series accuracy measures (the forecast error calculated for a particular time period is related to either the actual demand in the time period reviewing, the forecast itself or the arithmetic (equal weight) average of both) eg. MAPE (mean absolute percentage error) or MdAPE (median absolute percentage error – instead of taking the mean it takes the median) are not suitable in an intermittent demand context due to the fact that the actual demand may be zero and thus a division by zero error results [29]. Symmetric MAPE could be used though, but it is known that it suffers from asymmetry problems.[66] Relative to a base measures, could not be used for intermittent demand data as well due to the fact that the forecast error produced is usually related to a benchmark and in most cases the naïve 1 method for the same time period and most often is zero [29].

However, absolute error measures (where the forecast error in a particular time period is expressed in a square or absolute form) like mean squared error (MSE) or mean absolute error (MAE) are relevant to intermittence and are both scale dependent metrics. They are solely related to the forecast errors, not related to other forecasting methods or to ratio calculations [29]. When the MSE is used, greater errors are penalized more heavily.

As discussed before, MAPE is one of the forecast error measures related to the series which is the average of the absolute error (E_t) expressed as a percentage of the actual demand. It is the most widely used metric in most of the companies. It takes into consideration the unit of measurement and the scale of the data (scale independent metric) and it measures deviation as a percentage of actual data [67]. Actually, this is its principal advantage as it allows to average all MAPEs associated with a particular forecasting method across several time series. It does not have any linkages to inventory control, it suffers from asymmetry problems (MAPE gives smaller percentage errors when the actual demand is larger than the forecast than the opposite case and this can create issues when the actual demand is really small and the forecast very big since the APE will become very large and this leads to the symmetric MAPE), and in general is not natural for method optimization and selection purposes. It also suffers from a main drawback related to over penalizing for over-forecasting rather than under-forecasting. It puts a heavier penalty on negative errors than on positive errors. In addition, the MAE itself optimizes on the median, rather than the mean, and as such, for any series with 50% or more zeroes, a zero forecast would end up being the "optimum". Similar problems emerge for any metric that relates to absolute errors (such as the MAPE). Further, MAPE cannot be defined in an intermittent demand context due to the fact that zero observations may yield division by zero problems. However, and despite all the constraints, it was decided to be used in this work since it is the most intuitively appealing metric and one that can be directly understood by management [68]. It is the latter that influenced the actual decision of using this metric in the first stages of the tool. It should be noted that an alternative formulation has been used here to make sure this metric is defined in an intermittent demand context. The error statistic used in the out-of sample block is a ratio estimate, the numerator being the sum of absolute errors over every time period and the denominator being the sum of only the actual positive demands (since there might be cases when no positive demand observations would be available in the out-of sample block, in which case no performance evaluation may be conducted). This formulation guaranteed a non-zero denominator together with the constraint included in the classification solution described earlier on in this chapter, that the items with no positive demand observations in the out-of sample block will be categorized as "evaluation constrained" and they are not forecasting applicable [29].

Based on the development of the tool and the selection of this metric, it has to be noted, that this is not constraining in terms of further amendments that need to be introduced to cover other metrics in the tool as this can happen very easily. In the next steps of developing the tool a range of other appropriate metrics will be considered and this is to be combined with the fact that focus will be given to optimizing the smoothing constant values (something that is going to be further discussed in Chapter 4) and the fact that there are already plans of expanding the tool (and its functionality).

Formulation of MAPE:

$$MAPE_n = \frac{\sum_{t=1}^{n} \left| \frac{E_t}{D_t} \right| 100}{n}$$

[30]

where:

$$E_t = D'_{t-1} - D_t$$

In addition to the previous notation:

Let:

E_t: Forecast error at time period t

D'_{t-1}: The estimate of demand (forecast) at time period $t-1$ for period t

Alternative formulation of MAPE:

$$MAPE_n = \frac{\sum_{t=1}^{n} |E_t| 100}{n \sum_{t=1}^{n} |D_t|}$$

D_t: Actual positive demand at time period t

[30][32]

As discussed before, by adopting the mean absolute percentage error (MAPE), the best forecasting method (Croston, SBA, H, HW, W) for the fast and erratic items will be dominated and then the forecasts for all the categories will be generated.

3.4.4 Stock Control

3.4.4.1 Introduction

In most industrial environments inventories is a term used to describe any goods or products or services a company holds on stock for future sale or use. Inventories could also be work in progress or partial finished goods (materials or components that are in the production process but are not yet a complete finished product), raw materials (unprocessed material used to produce finished products), finished goods (complete products waiting to be sold and shipped to a potential customer), repairs (inventories used for maintenance/repair keeping equipment and processes productive) or spare parts. Inventory could be used or sold in the manufacturing procedure, industry market or sold to and/or managed by third parties as well [69][70][71] and is one of the major sources of cost in the supply chain.

Inventory control is a field that attracted interest around the start of the 20th century and more particularly, the issues of optimal stock management. Before the beginning of the previous century, scientists studied the issue of optimal stocking with stochastic demand. Also with the increase of interest rates in the 1970s, the significance of inventory control in the businesses increased as well [72]. Inventory control is the process that relates to the supervision, use, holding, storage, handling, supply, accessibility and selling of inventories in order to make sure that the right level of inventory is available at the right time at the right place (not covered in this work as discussed in chapter 1) and if possible at the right and lower cost [69][73]. More generally, planning, storing, moving and accounting aspects of the inventory are forming the basis for the entire logistics process [74][86]. Logistics, traditionally consisted of two things: Inventory Control and Transportation.

Inventory control is being used by many businesses for an improved monitoring, planning and scheduling of the inventory stock levels [75]. In the past, businesses were not using and applying inventory control. It was believed that having excess levels of inventory was a wealth sign. In contrast, nowadays, an effective and efficient inventory control is what every business requires [76]. Business's necessity of inventory control has to do with the reduction of any kind of cost around inventory in order to be able to compete across the market and increase profitability [76][77].

Inventory control is necessary for every business that wants to prevent stock outs, excess inventory stock levels, poor customer service levels, loss of sales-customers, shortages and high inventory holding costs. Organizations cannot also ignore the slow moving items which cost a fortune for keeping them without being demanded [3]. The excess inventory increases the risk of obsolescence and disposal [72][78]. Obsolescence is a major issue in the slow moving inventory context. It is necessary to find a balance between demand and supply for preventing stock-outs, excess inventory stock levels (obsolescence), poor customer service levels, loss of sales and customers and high inventory holding costs [79].

The figure below shows the balance between demand and a supplier.

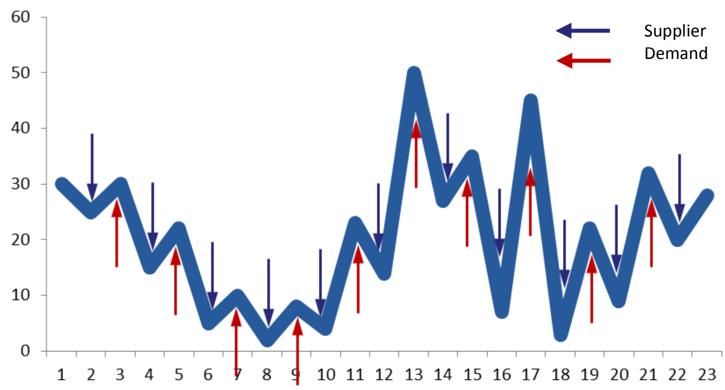


Figure 17: Balance between supplier and demand

The figure below summarized the most important reasons for companies keeping inventories in a more graphical way by categorizing them into forecasting (grey color), costs and times (blue color), and others related (white color). The most important ones is the uncertainty and erraticness of demand patterns in order to be prepared for customers' demand, meet customers' requirements and achieve on time delivery as well as be ready for any seasonal periods due to high seasonality. These are forecasting related reasons. By having larger shipments there will be a tradeoff between transport and shipping costs and by having discount via bulk buying meaning moving larger quantities of stock will reduce the transit times and at the same time lower the cost per unit. The distance between the manufacturer and the end customer is another reason for keeping inventories, since by storing larger amounts of inventories the lead time will thus be reduced. Although, if these products are stored for longer time then the value of some of them will be increased (investment stocks). In addition, by increasing the production runs and consequently storing more quantities, the production cost per unit will be reduced (when the production run is taking longer) as well as by producing products in advance saves time (work in progress storage). The large amount of stock availability could also cover for production shutdowns. Spare part storage is another reason for storing inventories as it could be used for repairing any defective/faulty items when needed without having to wait for the spare part order to arrive. Furthermore, vital stock equipment is stored in order to be prepared for any potential natural disasters (third sector storage).

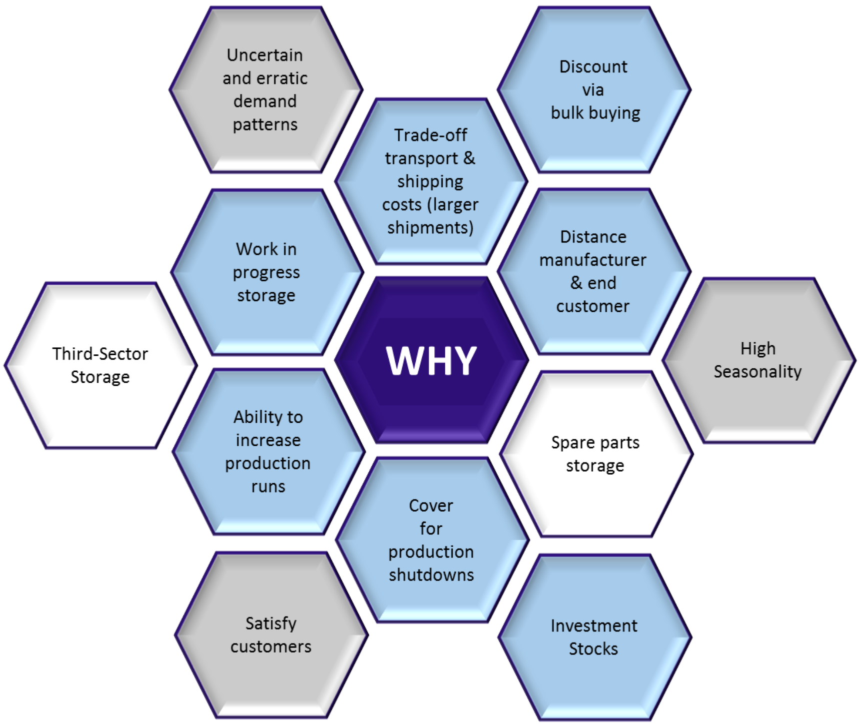


Figure 18: Reasons for keeping inventories

3.4.4.2 Role Of Stock Control In The Supply Chain

Inventories play a significant role in supply chains; the gap between demand and supply justifies their existence. Inventories are being kept for satisfying the customers' needs by having their orders/products ready for delivery when they asked for [80].

By proper planning, controlling and forecasting of demand, the optimal level or at least the reduction of inventory could be achieved and the above issues could be mitigated. However as already mentioned, the aim is not only the reduction of inventory levels but the balance and control of inventory between demand and suppliers [69]. Also important is that for every business the ideal inventory level will be different and unique due to the fact that each company follows different strategies and have different products, customers and suppliers.

Inventory control could be divided into stochastic or deterministic [81]. The work conducted in this thesis is based on a stochastic inventory control formulation problem. The demand is stochastic rather than constant or known (as in the deterministic model), due to the fact that is not fixed but rather varies over time thus it is not easy to decide how much it is needed to keep in stock to satisfy the customers' needs and their future demands (as it would be in the deterministic model). Also, the lead time for replenishment is taken to be constant and positive as if it was zero then there would be no need to have anything on stock [82]. There is also the case where the lead time varies over time as with the case of the demand, however, in this work, it is assumed that the lead time is constant.

Inventory control can be achieved by the application of continuous and periodic review policies. These two types of policies will be discussed in great detail later in this chapter. In summary, in the continuous policy, there is a continuous monitoring of the inventory levels and when the stock level drops at, or below, a reorder point (ROP – level that indicates the need to order) then an order is placed [40][69] [70]. In contrast, in periodic review applications, the inventory is tracked on regular, fixed, time intervals [40].

The two main issues involved in inventory management are how much and when to order conditioned to whether an item should be kept in stock or not. In this particular project, the work is focused on replenishment decisions (when and how much to order) given that an item should be kept in stock (not looking at stock-non stock decisions; extensions of the tool can cover the stock-non stock decisions as well) using the periodic review policy. Forecasting and inventory control are directly integraded for avoiding the major issues that current supply chains are facing (eg. over-stocking, under-stocking and poor service levels offered to the customers).

It should be also noted that this work is referring to make to stock environments – environments where it is expected to have things in stock ready for dispatch. The make to order environment (assemble to order) or any other environment are not covered in this project.

Keeping in mind the aforementioned issues, in most industrial applications they typically employed the minimization of the total inventory cost (further discussion below) subject to satisfying a particular service level objective (service level definition has been discussed earlier in this chapter in the data input sub section). However, the problem can also be formulated differently; eg. by maximizing the service level achieved subject to a specific inventory investment. Total inventory costs are costs associated with the holding, maintaining, ordering and backordering (the costs of not meeting a demand) costs of the product [83]. For the backordering costs, there are two possible formulations. One refers to backorders and the other to lost sales. In a business to business setting, backorders, are typically covered because the customers are willing to wait, if the product is not available in stock. In retailing though, lost sales models need to be employed. Holding costs includes the costs occurred when holding inventory over a period of time. Ordering cost involves the costs of placing, receiving and sending of the orders and inspection as well [69][70][84]. In this work, the backorders are taken into consideration.

The purpose of this project was not to solely improve inventory control or classification or forecasting but by combining all these three areas together so that each one to be dependent to each other and thus better managing the inventory levels which is the purpose of this work. The way these are combined will be revisited later in this chapter and also through the demonstration of the outputs of the tool in the Output section.

To conclude, in this work, a stochastic model is formulated using the periodic control policy and more specifically the OUT taking into account any backorders which may occur. More specific details to follow in the next sections.

3.4.4.3 Stock Control Policies

Continuous Review Policies: Under a continuous review policy, inventory levels are tracked continuously and when the inventory level drops at, or below, a reorder point (ROP), then automatically an order is placed [70][24][85]. Following such review policy, and depending on the demand, the time between consecutive orders may fluctuate whereas the size of the order depends on the system to be adopted.

Two of the most commonly used continuous review policies are the (s, Q) and the (s, S) systems. After each transaction, the stock status (i.e. inventory position – more details on the inventory position are discussed in 3.4.4.5 Simulated Solution part) is compared with a control parameter (s), called either the base stock or minimum or the re-order point. If then, the inventory position is less (or equal) than (s), then the replenishment order is triggered which could either be of a fixed order quantity (Q) for the (s, Q) policy or the size of the order may fluctuate depending on the transaction in order to raise the inventory position up to the OUT level (S) value. If the demand sizes vary then the replenishment quantity in the $(s,\ S)$ system will also vary, whereas if the demand sizes do not vary and are unit sized (ie. each time demand occurs is for a single unit only) then the two systems will be identical as the replenishment order will be made when the inventory position will exactly be at (s), so that the order will always be $Q = S - s$. The figure below, presents graphically the above two systems (s, Q) and $(s,\ S)$ (when unit sized transaction occur). Figure 19 shows that when the inventory position (IP) drops at the order point (s), then an order is placed (and received after the lead time (L) with a fixed quantity (Q) in order to raise the inventory position up to the OUT level (S) value. The (S), (s), (Q) values are fixed over time in the following graph, which is not the case in reality; the values are updated when reviewing the stock levels.

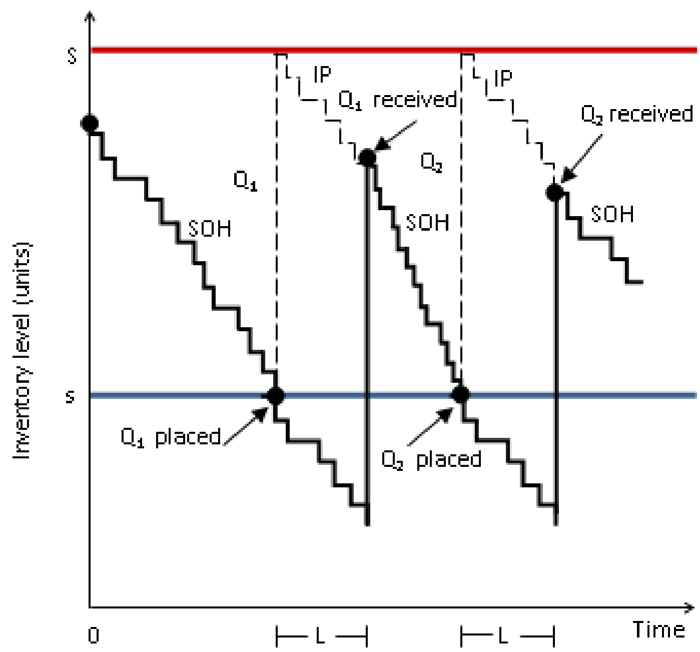


Figure 19: Continuous review policy

Periodic Review Policies: Under a periodic review system, inventory levels are reviewed after a fixed period of time [70][24][85].

Two of the most commonly used periodic review policies are the (T, S) and the (T, s, S) systems. For both systems, an order is placed in order to raise the inventory position up to the replenishment level. For the (T, S) system, an order is placed such that the level of current inventory plus the replenishment lot size equals a prespecified level called the order-up-to level (OUT). Simply, the inventory position is contrasted to the OUT level and if it is found to be less than that then an order is being placed to raise up to the OUT level. For the (T, s, S), the inventory position should be less than (or equal) to s before placing any order. Depending on the demand, the time between the orders will be constant in contrast with the size of the order which will fluctuate [30][86][40].

Figure 20, shows graphically the (T, s) system assuming that the lead time is greater than the review interval period. The OUT level (S) is fixed over time in the following graph, which is not the case in reality, the OUT level (S) is updated at every review interval period. At the review interval, the inventory position is compared with the OUT level (S) and if it is less than that, then an order is placed to raise it up to the OUT level (S).

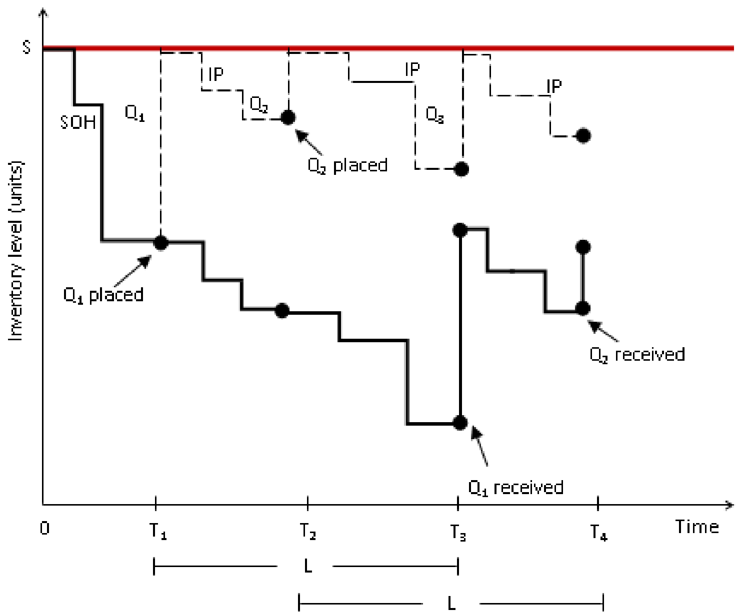


Figure 20: Periodic review policy (OUT)

The periodic review policy has been adopted instead of the continuous review policy since it is mainly used for spare parts demand data and also for maintaining continuous track of inventory would cost more (computer systems, bar code scanners, inventory software, etc.) [28][87][88]. The main disadvantage of the continuous review policy is its cost of implementation. Periodic inventory review also reduces the time a manager spends analyzing inventory counts which allows more time for other aspects of running the business. Important also is the fact that products in that existing warehouse may be purchased from the same supplier or transported in the same way, therefore they will be in the same review interval and ordered at the same point of time [88].

Even though, the application of the periodic review system in an intermittent demand context is theoretically justified and supported from many cases in the literature, the type of data available for simulation purposes are also triggering and supporting this decision [28][87][88]. The data was collected on a monthly basis so that one month to be viewed as the inventory review interval period ($T = 1$) and consequently at the end of every month to review the stock status and take decisions on the replenishment order levels. More particularly, the order-up-to-level (T, S) is being adopted in this work. It is a simple model to use, that could be computationally more appealing to practitioners than the (T,s,S) system for example as has already been applied to many real world cases. Apart from that, the optimization of the control parameter values (eg. T, S) was under the main objectives of this project. The T value was decided from the beginning due to the nature of the data as already discussed and the S value will be calculated during the simulation procedure [88]. At the end of every period $T(= 1$ month), the stock status is reviewed, the inventory position is raised to the replenishment level S and decisions on the replenishment order levels are being taken. More details are followed in the 3.4.4.5 Simulated Solution part.

3.4.4.5 Simulated Solution

Simulated solution

As already mentioned before, in this work, a stochastic model is formulated using the periodic control policy and more specifically the OUT taking into account any backorders which may occur. The input data are collected on a monthly basis and the review interval period is assumed to be one month. At the end of each review period (T), the forecast is updated, the stock levels are reviewed and the OUT is calculated. An order is being raised such that what is currently on stock (stock on hand) plus what is expected to receive/pending orders minus what it is owed (backorders) plus the new replenishment order to give the OUT level (what is currently on stock (stock on hand) plus what is expected to receive/pending orders minus what it is owed (backorders) gives the inventory position). It is assumed that the quantity to be ordered (order levels) is placed at the end of the review period and is going to arrive after the L (lead time) periods. It should be also noted that the purchase orders are received at the start of each period. Because of this, the uncertainty of the demand over the review period needs to be accounted for as well. The replenishment orders should be able to meet the customers demand during the $L+T$ periods (lead time plus one review period) taking into account that the order placing is not due until the end of each period (month in this case). It is also assumed that in practice, the lead time is greater or equal than the one review period. If the lead time was zero, then there would be no reason of storing inventories [89].

For continuous review systems, if the lead time is for example 3 months, then the uncertainty needed to be taken into consideration for every order placement is the amount of the demand over the following 3 months. However for this project (application of the periodic review system), the uncertainty of the demand over the one review period needs to be taken into account as well. For example, if the review interval is one month (as happens in this project) and the lead time is 3 months, then the order placement is going to arrive at the very beginning of the 3+1 months. The next review of the inventory and the quantities to be orders are not going to be placed until the end of the 3+1 (4^{th}) month. Therefore the uncertainty of the demand over that month (the one month review interval), should be taken into consideration when deciding the quantities to be ordered 4 months earlier [89].

By having already the demand per period, the purchase orders (receipts) per period and the end stock (stock on hand at the end of the 24^{th} period), it is fairly easy to calculate the initial inventory levels (stock on hand at the end of 1^{st} period of the in-sample data). This is needed because only the stock on hand at the end of the 24^{th} period (month) is available and the calculations of the inventory levels are going back to the 1^{st} period due to the fact that when calculating the inventory position of each period in the out-of-sample block, it is necessary to know the quantity ordered in $t-L$ (eg. where t is the current period).

It is assumed that the stock on hand at the end of period 24 is equal to the end stock provided as an input to the tool. By moving backwards, the stock on hand at the end of each period equals the stock on hand at the end of the next period plus the demand during the next period minus any purchase order (receipts) arrived on the next period. For example , if the stock on hand at the end of the 24^{th} month is 100 units, its demand was 50 units, and the receipts 30 units then the stock on hand at the end of the 23^{rd} month is 120 units(100-30+50) which equals the stock on hand at the very beginning of the 24^{th} month. Thus the stock on hand at the end of a period equals the stock on hand at the beginning of the next period. If the stock on hand is negative then backorders are allowed to be $(-1)stock\ on\ hand$. Therefore the net stock at the end of the period equals the stock on hand minus the backorders (where stock on hand equals zero) of that period. In the case that there are no backorders, then the net stock at the end of the period is the same as the stock on hand of that period. The relationships discussed above are now presented below in a more formal way.

In addition to the previous notation:

Let:

ES_t : End stock at the end of period t, as provided by the user in the Input Demand tab

SOH_t : Stock on hand at the end of period t is the end stock at the end of period t

POR_t : Purchase orders receipt at period t, ordered at $t-L$

B_t : Backorders at period t

NS_t : Net stock at the end of period t

IP_t : Inventory position at the end of period t

RC_t : Receipts that are going to arrive during the forthcoming $L+T$ periods (i.e. within t+L+T)

S_t : Order-up-to level (OUT) at the end of period t

O_t : Optimized order level quantity (calculation of the replenishment order level) at the end of period t

$OSOH_t$: Optimized stock on hand (calculation of what the stock should be following the whole simulated solution) at the end of period t

$$SOH_{24} = ES_{24}$$

$$SOH_t = SOH_{t+1} + D_{t+1} - POR_{t+1}$$

By moving backwards (from 24th period to 1st) to calculate the initial ending inventory levels – the stock on hand at the end of period 1 per SKU:

If $SOH_t < 0$ then

$$B_t = (-1)\, SOH_t$$

$$SOH_t = 0$$

$$NS_t = SOH_t - B_t$$

Else

$$B_t = 0$$

$$NS_t = SOH_t$$

End if

Initialization is again conducted in the in-sample period data (first 12 months) and the simulation and optimization of the order levels and OUT levels starts on the 12th period. For the last period of the in-sample data (12th period), if the lead time is equal to 1 ($L = 1$), then the inventory position at the end of the 12th period equals the net stock at the end of the previous period minus the demand of the 12th period plus the receipts arrived on the 12th period. In this case the receipts pending to arrive during the next $t + L$ periods are simply the receipts of the period t. However, due to the fact that those receipts have been ordered during the $t - L$ period (eg. where t=12 in this case is the current period), before the simulation starts (before the 12th period), therefore the actual receipts of the period t used as input to the tool have been used for this case. In summary, before the first optimized order level will arrive (which is placed at the end of the last period of the in sample data and is going to arrive after the L period), the actual receipts of each period are taken into account in the calculations.

In the case that the lead time is greater than 1 and $t - L > 12$ then the inventory position at the end of the 12th period equals the net stock at the end of the previous period minus the demand of the 12th period plus the receipts arrived on the 12th period plus any receipts pending to arrive during the next $t + L$ periods. However, in every case that $t - L < 12$, then the actual receipts used as input in the tool, are going to be used in the calculation of the inventory position of the 12th period due to the fact that no orders have been simulated before the 12th period). In summary, before the first optimized order will arrive (which is placed at the end of the last period of the in sample data and is going to arrive after the L period), the actual receipts of each period are taken into account in the calculations. The receipts arrived on the 12th period equal the actual receipts of the period t used as an input to the tool. Therefore the inventory position of any period before the 12th period, for example the inventory position of period $t-L$ equals the net stock of the previous period $(t-L-1)$ plus the actual receipts of the period t minus the demand of the period $t-L$. Having already calculated the inventory position and having the actual receipts, the theoretical OUT of the period $t-L$ could be calculated as the sum of the inventory position of the period $t-L$ plus the receipts of the 12th period.

For periods 13-24, if the lead time is greater than 1 and if $t-L<12$ then the calculations for the receipts during the period, the inventory position and the OUL are calculated as above (due to the simulation starting on the 12th period) whereas if the lead time is greater than 1 and if $t-L>12$ then the optimized order levels, the inventory positions and the OUL are calculated as follows:

$$IP_t{=}IP_{t-1}+POR_t-D_t+RC_t-RC_{t-1}$$

In the case that the lead time is equal to 1, then the inventory position of period t could be calculated as the inventory position of the previous period $(t-1)$ minus the demand of period t plus the receipts of the period t. In this case the receipts pending to arrive during the next $t+L$ periods are again simply the receipts of the period t. The optimized order level that is going to be placed at the end of each period, equals the OUT at the end of the period minus the inventory position at the end of the period as well. However, if the OUT minus the inventory position is negative then no replenishment order will be placed at the end of the period.

If $S_t-IP_t<0$ then

$O_t=0$

Else

$O_t=S_{t_t}-IP_t$

End if

Lastly, the optimized stock on hand level at the end of each period will be equal to the inventory position at the end of that period. If there is a case, where the inventory position is negative, then the optimized stock on hand will be equal to zero.

If $IP_t < 0$ then

$OSOH_t = 0$

Else

$OSOH_t = IP_t$

End if

The whole simulated stock control solution is adopted in a dynamic manner. As soon as the backward calculations have been completed, then it is needed to calculate the order levels and the OUT level quantities. The lead time forecasts and the calculation of the lead time variance are needed as well. Then a distribution is needed for demonstrating the demand over the lead time plus the review interval (the parameters of which have been calculated through the lead time mean demand and lead time variance). Below there is a more detailed discussion on what is the distribution used and why, how the forecasts are calculated (details back to the forecasting section), how the variance is being calculated and how everything is being put together to optimize the OUT level quantities at each period.

In 1997, Boylan proposed three criteria for assessing the suitability of the demand distributions (empirical evidence, flexibility of the distribution to represent different types of demand and a priori grounds for modeling demand)[90]. The distribution used for demonstrating the demand over the lead time plus the review interval and the one chosen to be used for computation purposes is assumed to be the negative binomial distribution (NBD) as it has been found to meet all the above criteria [91]. The NBD is a compound Poisson distribution with the variance greater than the mean. Although, the normal and gamma are the distributions mostly used for inventory control purposes, the NBD is the one mostly used and recommended in the literature because there is empirical evidence in its support - in its good fit for spare parts demand and intermittent demand in general [87][91]. These are valid for parametric approaches to inventory forecasting. For non-parametric approaches, no distributional assumptions need to be made. As mentioned before, the NBD is a compound Poisson distribution whereby demand arrives according to a Poisson process and the demand sizes follow a logarithmic distribution. Although there is empirical evidence in it support, it is also recognized that other compound Poisson distributions may be also appropriate as they are also associated with empirical support (like the stuttering Poisson, for example) (see, e.g. Lengu et al., 2014) [92].

Below it is discussed in detail the process of adopting the NBD along with how the probabilities of demand will be calculated and how the OUT levels are calculated.

$$p(0) = \left(\frac{1}{Z}\right)^{\frac{\mu_{L+T}}{Z-1}} \quad , \quad p(x) = \frac{\left[\left(\frac{\mu_{L+T}}{Z-1}\right) + x - 1\right]}{x} \frac{Z-1}{Z} p(x-1)$$

$$Z = \frac{\sigma^2{}_{L+T}}{\mu_{L+T}}$$

In addition to the previous notation:

Let:

$x = 1,2,3, \ldots$

$\mu_{L+T} = D'_{L+T}$: The expected mean demand over $L+T$ periods updated at the end of each period

D_t : The demand at period t

D'_t: The estimate of demand (forecast) at period t for period $t+1$

The mean demand over $L+T$ periods, is estimated based on the generated forecasts (not the mean of the demand data) as:

$$\mu_{L+T} = D'_{L+T} = (L+T)D'_t$$

The initialization of the forecasts and the forecasts produced over the in-sample data (the forecasts for each individual period made from the end of period 12th (estimate for period 13) until period 24th (estimate for period 25)) have already been calculated and discussed back to the 3.4.3.4 Forecasting Solution part. However, for the calculations of the MSE forecasts it is necessary to have some mean demand forecasts over the in-sample data and for that purpose the straight average method has been used. More specifically, in order to calculate the initial estimate of the MSE, we may need the forecasts from $t-T-L+1$ until the end of period 11. Therefore, from the end of period 1 (for period 2) until the end of period 11 (for period 12), the straight average method has been adopted for generating the forecasts.

$$D'_t = mean(D_1, \ldots, D_t) \quad , \quad 1 \leq t \leq 11$$

As discussed at the beginning of the 3.4.4.5 Simulated Solution, the variability of demand over $L+T$ periods, is estimated based on the smoothed mean squared error (MSE) (not the variability of the demand data) as [87][89]:

$$\sigma^2{}_{L+T} = MSE_{t,L+T}$$

$$MSE_{t,L+T} = \alpha \left\{ \sum_{i=t-T-L+1}^{t} \left(D_i - D'_i\right) \right\}^2 + (1-\alpha) MSE_{t-1,L+T}$$

<u>where:</u>

$\sigma^2{}_{L+T}$: The variability of demand over $L+T$ periods updated at the end of each period

Regarding the calculation of Z, then it is obvious that μ_{L+T} should be greater than zero.

The NBD simply necessitated the the variance of the demand over $L+T$ has to be greater than the estimation of the mean demand over $L+T$ when the probabilities that a demand size will be calculated [91].

$$\sigma^2{}_{L+T} > \mu_{L+T}$$

If there is a case where $\sigma^2{}_{L+T} \leq \mu_{L+T}$ then $\sigma^2{}_{L+T} = (1.05)\mu_{L+T}$ [91]

By using the NBD and each time that the mean and variance described above are updated at the end of each period then the optimal OUT is calculated.

$$\sum_{i=0}^{S} P(x=i) \leq Target\ CSL \quad and \quad \sum_{i=0}^{S+1} P(x=i) > Target\ CSL$$

3.4.4.6 SKU Service Level Specification

An alternative SKU service level method developed by Teunter, Syntetos and Babai (2017), was adopted in order to calculate the optimal targeting service level for each SKU individually by having the overall target fill rate (for all the SKUs). The target fill rate level, is taken to be that across the whole collection of SKUs, which does not imply that the service level for each SKU is the same, as also discussed in the data input sub section. Rather, the latest thinking in service level target specification is employed here, by varying (in a cost optimal manner) the target per SKU. More specifically, calculating the individual service levels, based on a collective constraint across all SKUs for a particular fill rate. As discussed earlier on this chapter, fill rate is equal to the % of customers demand satisfied from the available stock and it translates directly to the customer service level achieved. A higher fill rate is obviously associated with higher customer satisfaction. Many companies are assigning the same service level target either to all the SKUs or to SKUs belonging to the same class (say A items in an ABC classification – please refer to section 4.2 of this chapter) [22].

For calculating the optimal target fill rate for each SKU individually, given the overall target fill rate:

$$FR_i = 1 - (1 - FR)RCP_i$$

where:

$$RCP_i = \frac{c_i}{\frac{\sum_{i=1}^{n} c_i D_i}{\sum_{i=1}^{n} D_i}}$$

FR : Overall fill rate

FR_i : Fill rate of SKU i

c_i : Cost price of SKU i

D_i : Demand of SKU i

n : Total number of SKUs provided

ACP : Average cost price of all purchased SKUs that are weighted by their demand volumes

$$ACP = \frac{\sum_{i=1}^{n} c_i D_i}{\sum_{i=1}^{n} D_i}$$

RCP_i : Relative cost price of SKU i

An implicit assumption made, is that the SKUs resulted with a negative fill rate value, are set automatically to zero. This could happen due to exceptionally expensive SKUs (with extremely high cost price) and not so high overall target fill rate [22]. The most expensive an SKU is, the less stock is trying to be kept, whereas the less cheap it is, the more stock is trying to be stored.

In this tool, having already as an input the customer's target service level of each individual SKU (not the service level that the company believe that is offering to the customers) and calculating the optimal targeting service level for each SKU individually (thus the achieved ones), it is feasible to make comparisons and see how far the target ones are from the achieved ones.

3.5 Outputs

3.5.1 Introduction

The D^2ID is a fully automated, user friendly, VBA (Visual Basic for Applications) based tool, built in Microsoft Excel. The only thing needed on the part of the user is to input the necessary data and then by clicking the appropriate buttons, the applicable analysis is conducted and the results are generated. The tool was piloted using empirical data coming from the case organization; the details of the relevant procedures adopted to reflect the nature of such data was discussed before in this section. In addition, the tool was also tested and built around other datasets as well that were not coming from the case organization but turned out to be available through the University. Analysis was done on a SKU (stock keeping unit) by SKU level and the tool can provide demand classification, demand forecasts, optimized order levels, SKU fill rate specification, optimized inventory levels and a summary dashboard showing the inventory reductions and the cost savings (if any).

The tool provides clear visibility of the classification, forecasting, optimized order levels, optimized stock levels (how much stock they currently have at the end of the 24th month and how much they should have had based on the methodology described earlier in this chapter) for all the SKUs. Calculation of the optimized inventory levels (at a SKU level and on an aggregate level), gives the opportunity to make comparisons with the actual inventory and identifying any excess or insufficient units. With the appropriate inputs (discussed at the beginning of this chapter) the user can see the resulting performance from the suggested procedures against what the current performance is. This allows a direct appreciation of the impact of the tool and intervention when the users feel that the results are not encouraging enough. All the calculations have been done on an SKU by SKU level analysis. The tool can be used either by performing all the steps of the analysis or can be used solely as a classification and forecasting tool for the purpose of product groups visualization and operational and replenishment planning. The input data needed for conducting the analysis are referred to 3.3.3 Data Input and below all the outputs are discussed together with the results in detail. The below figure, demonstrates graphically the high level structure of the tool (what inputs are needed, what is calculated and what the benefits could be).

All the results below are under the assumption of randomly varying costs across the SKUs unless stated otherwise (eg. standardized cost across the SKUs).

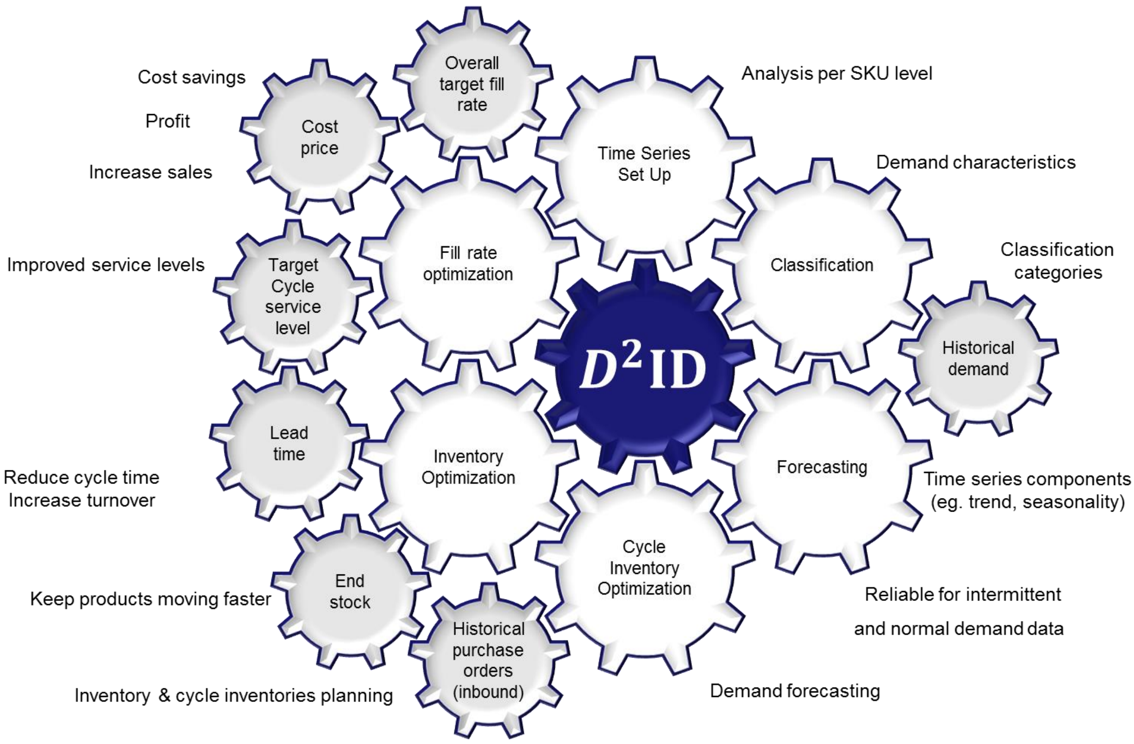


Figure 21: D^{2}ID – a high level structure of the tool

The interface of the tool is presented below along with a tool guide referring to the most important information that renders the use of the tool very straightforward. The “Clear Data” button, deletes all the data/information that have been input into the tool as well as the analysis conducted in order to be in the position to start a new piece of analysis. The tool includes two major sections, the input and the output. The input part consists of the “Input Demand” and “Input Purchase Orders” while the output part consists of the “Classification Forecasting”, the “Order Levels”, the “Inventory Checking” and the “Output Summary” sections reflected in relevant buttons.

Figure 22: D²ID tool's interface

The Tool Guide is as follows:

PROCESS	INSTRUCTIONS
Clear Data	Go to "D2ID_Tool" sheet and clear old data by clicking on the *Clear Data* button.
Input Demand	Enter Demand history (24 periods), lead time (not >3), target service level (<1), end stock, cost price per sku and overall target fill rate. Please note that periods with no demand should be entered as "0".
Input Purchase Orders	Enter Purchase orders (24 periods) depending on the demand history for the same SKUs. Please note that periods with no purchase orders should be entered as "0".
Classification Forecasting	Gives the classification and forecasts per SKU level. Please note that cannot be calculated without the Input Demand data.
Order Levels	Please note that cannot be calculated without the Input Demand and Input Purchase Orders data.
Inventory Checking	Shows the difference between the provided stock on hand and the optimized one.
Output Summary	Gives the output summary (eg. inventory reduction, savings, etc.)

Table 2: D²ID tool's guide

3.5.2 Analysis On An Individual SKU Basis

3.5.2.1 SKU Classification And Forecasts Per SKU Level

The snapshot presented below Table 4 indicates the initial output generated through the tool, containing the classification and forecasting results per SKU. The SKUs presented below, were chosen randomly from the list of SKUs analyzed. Apart from the classification category, it is also observable for every SKU whether there was/wasn't an observable trend or/and seasonality and in each case the appropriate forecasting method that was applied (all of which may be printed in the output). Based on the forecasting results it is possible to compare forecast accuracy between what the tool suggests, what the customers forecasted and reality. Classification could be also useful for better management of inventories (visualize the different groups of products in the warehouse according to their sales/demand variability and the order frequency).

The same could happen with the order levels discussed next. For the SKUs that were deemed to be not 'forecasting-applicable' based on the classification solution employed (either evaluation constrained or calculation constrained) their output is associated with blank lines.

SKU	MAPE	Overall MAPE across all SKUs
2233	92.20	61.94
14600	59.45	
17146	35.78	
24099	86.29	
24157	45.86	
41056	29.14	
41181	57.44	
808299	12.50	
815498	10.15	
815891	32.21	
1309051	21.04	
1309570	16.59	
1310116	52.66	
1907422	15.86	
1907734	29.04	

Table 3: MAPE results for spare parts

The above table demonstrates forecast accuracy results for spare parts forecasting. An arbitrary selection of SKUs are presented along with their related MAPE. The overall MAPE, across the whole list of SKUs (ignoring the evaluation and calculation constrained categories) is also provided.

3.5.2.2 Optimized Order Levels And Order Up To Levels And Calculation Of The Recommended Service Level Per SKU

The Table 5 (OUT results) below, is a snapshot from the actual tool, showing the suggested (by the tool) OUT while Table 6 (order level results) shows the proposed stock quantities that should be ordered at the end of each period and should have been ordered at the end of each month individually. Again the analysis has been done on an individual SKU basis. Other than that, the optimized service level per SKU (fill rate) is also calculated here and it is very easy to make comparisons with the customers target service levels (used as an input in the beginning). Table 7 below, shows with orange colour (indicated as service level) the customers target service levels and the light blue colour (indicated as fill rate) demonstrates the calculated achieved ones.

SKU	Classification	Trend	Seasonality	F13	F14	F15	F16	F17	F18	F19	F20	F21	F22	F23	F24	F25	F26	F27	F28	F29	F30	F31	F32	F33	F34	F35	F36	Forecast Method
6	No demand pattern																											
1015	No demand pattern																											
14600	Lumpy	No	No	7.91	7.12	5.46	5.80	6.33	5.80	6.79	7.59	7.59	7.59	6.43	7.31	8.03	8.03	8.03	8.03	8.03	8.03	8.03	8.03	8.03	8.03	8.03	8.03	SBA
15323	No demand																											
31025	No demand pattern																											
174947	Lumpy	No	No	0.64	0.62	0.62	0.62	0.62	0.62	0.62	0.62	0.62	0.40	0.72	0.72	0.72	0.72	0.72	0.72	0.72	0.72	0.72	0.72	0.72	0.72	0.72	0.72	SBA
177655	Erratic	No	Yes	6.00	10.27	12.01	9.65	11.42	14.85	19.42	9.37	7.70	16.90	11.49	0.82	5.98	12.97	10.39	10.45	12.42	19.44	14.82	8.73	9.39	23.93	24.30	1.25	Winter
177943	Erratic	No	No	25.42	20.10	18.24	18.24	14.26	14.26	14.26	9.93	9.80	10.88	10.86	10.86	9.08	9.08	9.08	9.08	9.08	9.08	9.08	9.08	9.08	9.08	9.08	9.08	SBA
180435	Slow	No	No	0.91	0.82	0.82	0.61	0.61	0.61	0.61	0.61	0.46	0.49	0.49	0.49	0.49	0.49	0.49	0.49	0.49	0.49	0.49	0.49	0.49	0.49	0.49	0.49	SBA
182927	No demand																											
182929	Fast	No	No	346.00	312.40	310.12	290.50	323.40	338.92	311.13	309.91	315.73	289.38	315.10	292.08	294.67	294.67	294.67	294.67	294.67	294.67	294.67	294.67	294.67	294.67	294.67	294.67	Croston
182931	Lumpy	No	No	5.33	5.47	5.24	5.24	5.07	4.88	4.88	4.88	4.88	3.33	5.90	5.90	5.90	5.90	5.90	5.90	5.90	5.90	5.90	5.90	5.90	5.90	5.90	5.90	SBA
184417	Slow	No	No	1.08	0.98	0.87	0.87	0.79	0.80	1.03	1.13	1.13	1.30	1.24	1.45	1.51	1.51	1.51	1.51	1.51	1.51	1.51	1.51	1.51	1.51	1.51	1.51	SBA
184418	Slow	No	No	0.33	0.30	0.30	0.30	0.30	0.26	0.26	0.35	0.35	0.35	0.34	0.34	0.42	0.42	0.42	0.42	0.42	0.42	0.42	0.42	0.42	0.42	0.42	0.42	SBA
184419	Lumpy	No	No	0.58	0.53	0.52	0.52	0.51	0.54	0.54	0.59	0.59	0.59	0.59	0.59	0.52	0.52	0.52	0.52	0.52	0.52	0.52	0.52	0.52	0.52	0.52	0.52	SBA
184821	No demand pattern																											
184912	Fast	No	No	2.83	2.83	2.41	2.18	1.98	1.81	2.56	2.64	2.34	2.08	1.88	2.67	2.74	2.74	2.74	2.74	2.74	2.74	2.74	2.74	2.74	2.74	2.74	2.74	Croston
1905884	Fast	Yes	No	28.42	35.28	32.51	31.68	29.39	31.78	34.50	39.62	47.61	50.21	55.09	54.87	56.82	59.14	61.46	63.78	66.10	68.42	70.74	73.07	75.39	77.71	80.03	82.35	Holt
1906013	No demand pattern																											
1906068	Slow	No	No	0.50	0.45	0.45	0.41	0.46	0.46	0.46	0.46	0.46	0.46	0.45	0.45	0.45	0.45	0.45	0.45	0.45	0.45	0.45	0.45	0.45	0.45	0.45	0.45	SBA
2113903	Fast	Yes	Yes	11.00	2.41	6.94	0.37	1.18	0.37	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	Holt Winter
2113904	Fast	No	No	3.58	3.47	4.37	5.10	5.68	4.94	4.95	5.36	4.69	4.55	4.44	4.55	5.04	5.04	5.04	5.04	5.04	5.04	5.04	5.04	5.04	5.04	5.04	5.04	Croston

Table 4: D^2ID tool's classification & forecasting output

SKU	P12	P13	P14	P15	P16	P17	P18	P19	P20	P21	P22	P23	P24
6													
1015													
1126													
1146													
1165													
2233	73	73	67	61	233	95	95	95	95	273	230	219	209
6100													
11442													
11443													
82346	2	2	2	2	2	2	2	2	2	2	2	2	2
82347	3	2	2	2	2	2	2	2	2	2	2	2	2
82349	5	4	4	4	3	3	3	3	3	3	3	3	3
87015													
87075	2	2	2	2	2	2	2	2	2	2	2	2	2
87089	1	1	1	2	2	3	4	4	4	4	4	4	4
87125	3	2	2	2	2	2	2	2	2	2	2	2	2
87153													
87203	7	6	6	5	5	5	5	5	5	5	5	5	6
87204	3	3	3	3	3	3	3	3	3	3	3	3	3
87223													
87224	3	2	2	2	2	2	2	2	2	2	2	2	2

Table 5: D^{2}ID tool's OUT optimized output

6													
1015													
1126													
1146													
1165													
2233	0	0	0	0	0	0	0	0	0	0	0	0	0
6100													
11442													
11443													
82346	0	0	0	0	1	0	1	0	1	0	0	1	0
82347	3	0	0	0	0	0	0	0	1	0	0	0	0
82349	7	0	0	0	0	0	0	0	0	0	0	0	0
87015													
87075	0	0	0	0	1	0	1	0	1	0	0	1	0
87089	0	0	0	0	0	0	0	0	1	1	0	0	0
87125	4	0	0	0	0	0	0	0	1	0	0	0	0
87153													
87203	10	0	0	1	1	0	0	0	3	1	3	0	1
87204	2	0	0	0	1	0	0	0	2	0	0	0	0
87223													
87224	0	0	0	0	0	0	0	0	0	0	0	0	0

Table 6: D^{2}ID tool's order level optimized output

SKU	Fill Rate	Service Level
6	0.99	0.95
1015	0.99	0.95
1126	0.93	0.95
1146	0.95	0.95
1165	0.99	0.95
2233	0.92	0.95
6100	0.90	0.95
11442	0.93	0.95
11443	0.90	0.95
82346	0.96	0.95
82347	0.92	0.95
82349	0.90	0.95
87015	1.00	0.95
87075	0.92	0.95
87089	0.90	0.95
87125	0.95	0.95
87153	0.94	0.95
87203	0.90	0.95
87204	0.99	0.95
87223	0.99	0.95
87224	0.97	0.95

Table 7: D^{2}ID tool's fill rate optimized

3.5.2.3 Optimized Inventory Levels Per SKU Level

The table below shows the optimized inventory levels (at a SKU level basis) and it clearly indicates any excess or insufficient units of stock. A summary of this could be also seen in **Error! Reference source not found.** and Table 13 demonstrating any reductions in inventory levels in terms of both units and costs between the current and the optimized solution.

SKU	End Stock	Stock on hand new
6	50	
1015	0	
1126	2800	
1146	0	
1165	600	
2233	756	756
6100	2900	
11442	5920	
11443	0	
82346	1	2
82347	1	2
82349	3	4
87015	0	
87075	1	2
87089	2	4
87125	1	2
87153	0	
87203	1	5
87204	1	3
87223	0	
87224	2	2

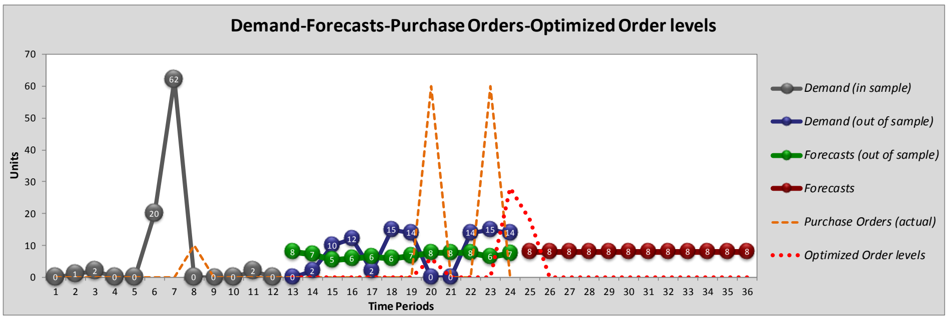
Table 8: D^{2}ID tool's optimized inventory levels output

3.5.2.4 Chart Output And Summary Dashboard

The output summary dashboard and the chart output are displaying clearly the forecasts, the proposed optimized solutions and any differences between what is currently being done with what is simulated. Any reductions on inventory levels in terms of units and cost (if any) or cases where more stock is needed to satisfy the customers' needs and improve their performance (when there are poor customer service levels achieved) are also indicated in the summary dashboard.

The chart output below, shows the actual demand (which is separated into the in-sample and out-of-sample demand), the out-of-sample forecasts, the forecasts for the next period, the actual purchase orders (receipts) for all the months and the optimized receipts from month 13th onwards (which is the first month that the optimized order level is going to arrive – after L period). From this graph, it is clearly demonstrated the overall behaviour of the demand and the receipts in the particular warehouse as well as the differences between the real and the optimized simulated solution. The visibility of the forecasts might be valuable for operational planning and replenishment management.

Dropdown SKUs list
14600



Selected Row	16

Column number	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
14600																		
Period	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
Demand (in sample)	0	1	2	0	0	20	62	0	0	0	2	0						
Demand (out of sample)													0	2	10	12	2	15
Forecasts (out of sample)													8	7	5	6	6	6
Forecasts																		
Purchase Orders (actual)	0	0	0	0	0	0	0	10	0	0	0	0	0	0	0	0	0	0
Optimized Order levels													0	0	0	0	0	0

Column number	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36
14600																		
Period	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36
Demand (in sample)																		
Demand (out of sample)	14	0	0	14	15	14												
Forecasts (out of sample)	7	8	8	8	6	7												
Forecasts							8	8	8	8	8	8	8	8	8	8	8	8
Purchase Orders (actual)	0	60	0	0	60	0												
Optimized Order levels	0	6	0	0	0	28	18											

Figure 23: D²ID tool's chart output

3.5.3 Analysis Across SKUs

Below are demonstrated the results from the case organization and more specifically the overall classification results as well as demand and inventory contribution to each category individually.

Category	*SKUs*	*% SKUs*	*Demand (units)*	*% Demand (units)*	*Current Inventory (units)*	*% Current Inventory (units)*
Erratic	380	4%	175,969	16%	71,074	16%
Fast	737	7%	655,952	60%	194,194	44%
Lumpy	766	8%	75,618	7%	55,431	13%
Slow	2,681	27%	61,623	6%	39,500	9%
Calculation constrained	2,907	29%	118,111	11%	54,360	12%
Evaluation constrained	2,481	25%	9,937	1%	27,351	6%
Total	**9,952**		**1,097,210**		**441,910**	

Erratic	380	8%	175,969	18%	71,074	20%
Fast	737	16%	655,952	68%	194,194	54%
Lumpy	766	17%	75,618	8%	55,431	15%
Slow	2,681	59%	61,623	6%	39,500	11%
Total	**4,564**		**969,162**		**360,199**	

	Total	*D2ID Applicable*
SKUs	9952	4564
Demand	1097210	969162
Inventory	441910	360199

Table 9: D²ID tool's classification summary output

The total number of SKUs provided was 9952; 4% were classified as erratic, 7% as fast, 8% as lumpy, 27% as slow, 29% as calculation constrained and 25% as evaluation constrained items. Due to the fact that the last two categories are non-forecasting applicable, they were excluded from the calculations.

The whole analysis was applied to the 4 classification categories (erratic, fast, lumpy and slow) with a total of 4,564 SKUs. By excluding the non-forecasting applicable categories, the lumpy and slow demand items constituted 76% of the SKUs together and 26% of all the units kept in stock (inventory level at the end of the 24th month) across all SKUS, relate to these two categories. However as it was expected, they do not contribute considerably to the total demand. Only 14% of the total demand across the time period examined relates to the lumpy and slow demand items, which is a big difference comparing to the % of the SKUs that are associated with these demand levels. By separating these 2 categories, the lumpy items constitute 17% of the SKUs, 8% of the total demand and 15% of the total inventory on hand, while at the same time, the slow movers constitute 59% of the total SKUs (more than the half products that are stored in the particular warehouse), 6% of the total demand and 11% of the current inventory levels. The fact that they do not contribute much to the inventory levels might look strange; however, it can be supported from the fact that these items suffer from backorders - a consequence of very poor customer service levels. Around 4,476 units of demand from the slow movers and 6,813 from the lumpy items were not satisfied on time, a fact that supports the above statement. If no action is going to be taken then customers might leave the particular organization and look for companies that could offer higher and on time service levels (for the percentage of the demand that was not satisfied on time).

There is no reason holding and storing so many SKUs (referring to lumpy & slow) that are not demanded very often or may become obsolete (leading to the risk of disposal with high costs from the customer's perspective) might be out of the market and they are covering almost the 26% of the current inventory. It is not an extremely large number but by even reducing the inventory levels of these two categories and consequently the warehouse space used for storing these inventory levels by only 1%, the probability of getting new customers into the warehouse will increase.

On the other hand, only 16% of the SKUs constitute fast moving items with an incredibly high % of demand and current inventory associated with that class, of 68% and 54% respectively. Also 8% of the SKUs are erratic, worth 18% of the total demand

and 20% of the current stock levels. It is clearly noted that only 16% of the SKUs are driving most of the warehouse operations. However, it should be also noted, that there are backorders in this category as well and also that the non-demanded and slow moving items could be reduced.

If the replenishment level decisions are taken without taking into consideration all the above steps described earlier in this chapter, then it is highly likely to end up with either excess or insufficient inventory levels into the warehouse. Regarding the former one, there is a high probability of ending up with a warehouse full of stock (that is not moving) and only a very small amount of SKUs will be demanded (still in "life" in the market). Storing large amount of inventories that are either not demanded became already obsolete or are particularly demanded very infrequently will be causing high storage costs from the customer perspective high risk of obsolescence which will be increasing day by day, non-organized warehouse operations (non-effective, damages on products, time consuming operations etc.) and unsatisfied customers as a consequence. By keeping the company's warehouse space occupied, reduces any opportunities of getting any new potential customers within the business environment. However, one cannot also disregard the fact, that the service levels the customer wants to achieve has a substantial effect on the optimization of the inventory levels since the higher the service level the higher the stock needed will be, and the lower the reduction of the inventory levels. The objective is not solely to reduce the inventory levels, but sometimes to increase them while always ensuring though the satisfaction of customers' needs, the availability and storing of the right level of inventory at the right time and the appropriate decision planning in the first place. On the other hand, insufficient inventory levels may lead to unsatisfied customers due to poor customer service levels, loss of sales-customers as a consequence, backordering costs and excessive costs due to overtime.

On the graphs below is clearly demonstrated the demand and product categorization as described and explained above before ignoring the two categories (evaluation constrained and calculation constrained) as well as the demand and product classification of the 4 most important categories.

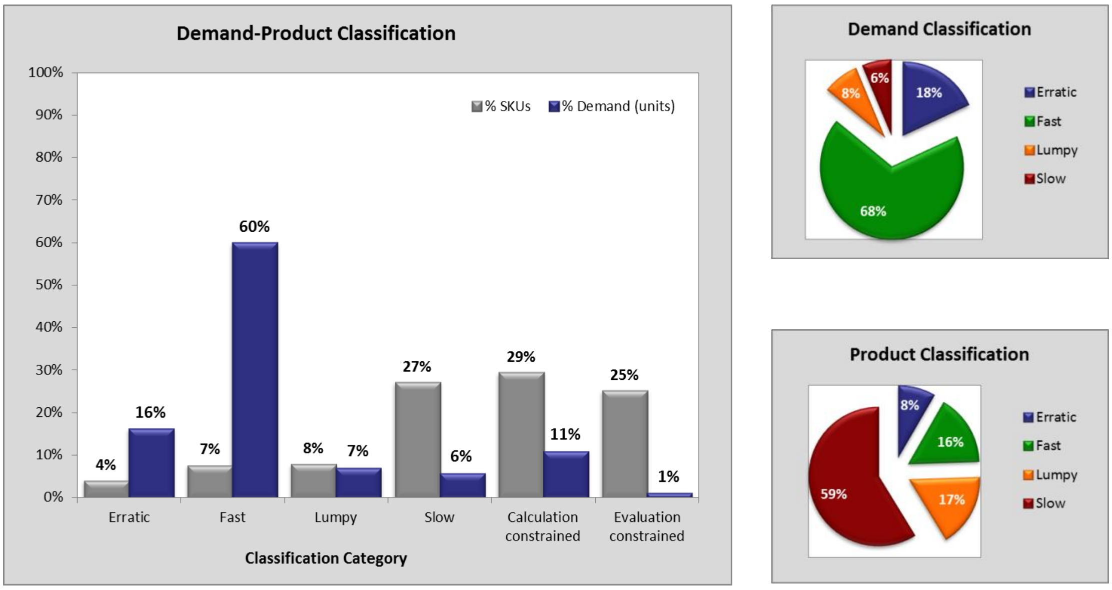


Figure 24: D²ID tool's demand-product summary output

Table 11 presented earlier on and **Error! Reference source not found.** presented below are going into even more detail dividing the erratic and fast items into 8 subcategories indicating for example how many SKUs are fast movers but having/not having trend/seasonality. The level of demand/inventory level and cost that are associated with each subcategory is presented in the summary Table 10 as well. Table 10 demonstrates the results given a standardized cost of $10 across all SKUs and Table 11 the results under randomly varying costs across the SKUs.

The figures and the tables below show how much the overall inventory as well as the inventory levels for each of the four categories should be. It has to be noted that the results will change if the lead time or the service level that the customer wants to achieve will be altered.

The snapshot table below is included in the summary output of the tool and could be also found in Appendices 10.1 for a clearer demonstration of the results.

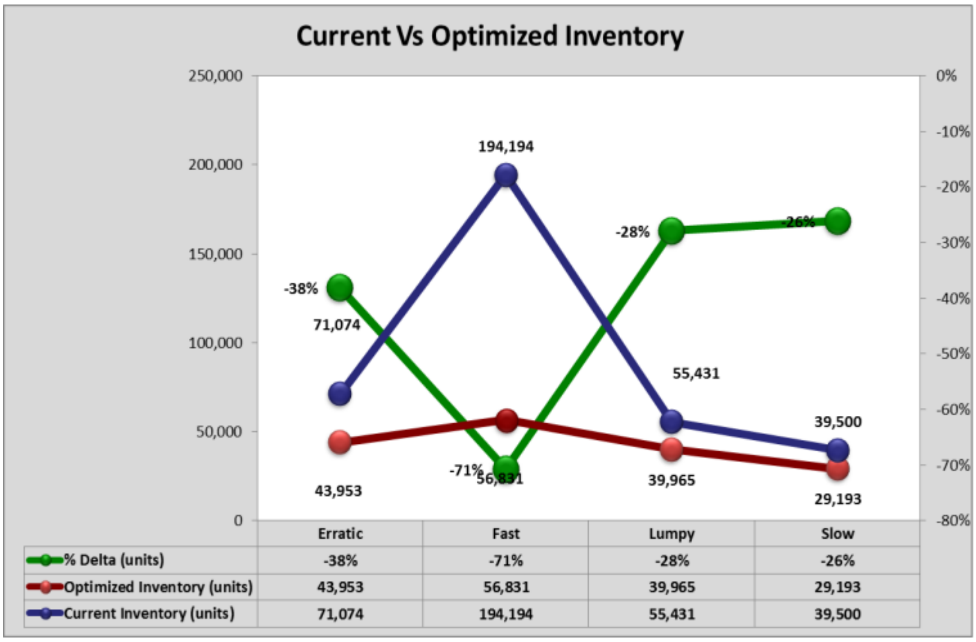


Figure 25: D²ID tool's current and optimized output in terms of inventory levels under the assumption of randomly varying costs across the SKUs

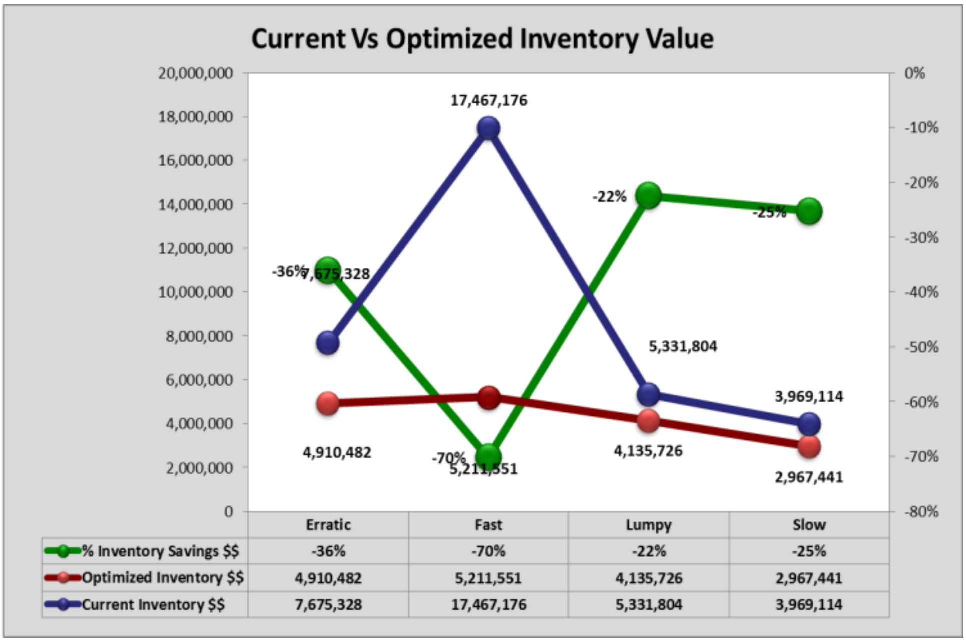


Figure 26: D²ID tool's current and optimized output in terms of inventory value under the assumption of randomly varying costs across the SKUs

Category	Trend	Seasonality	SKUs	% SKUs	Demand (units)	% Demand (units)	Current Inventory (units)	% Current Inventory (units)	Current Inventory $$	% Current Inventory $$	Optimized Inventory (units)	% Optimized Inventory (units)	Optimized Inventory $$	% Optimized Inventory $$	Delta (units)	% Delta (units)	Inventory Savings $$	% Inventory Savings $$
Erratic	No	No	268	6%	128,297	13%	49,889	14%	498,890	14%	28,745	17%	287,450	17%	-21,144	-42%	-211,440	-42%
		Yes	4	0%	2,334	0%	712	0%	7,120	0%	181	0%	1,810	0%	-531	-75%	-5,310	-75%
	Yes	No	99	2%	36,988	4%	17,488	5%	174,880	5%	14,208	8%	142,080	8%	-3,280	-19%	-32,800	-19%
		Yes	9	0%	8,350	1%	2,985	1%	29,850	1%	819	0%	8,190	0%	-2,166	-73%	-21,660	-73%
Total			380		175,969		71,074	20%	710,740	20%	43,953	26%	439,530	26%	-27,121	-38%	-271,210	-38%
Fast	No	No	519	11%	298,053	31%	90,552	25%	905,520	25%	30,366	18%	303,660	18%	-60,186	-66%	-601,860	-66%
		Yes	13	0%	8,262	1%	2,067	1%	20,670	1%	499	0%	4,990	0%	-1,568	-76%	-15,680	-76%
	Yes	No	202	4%	348,747	36%	101,281	28%	1,012,810	28%	25,873	15%	258,730	15%	-75,408	-74%	-754,080	-74%
		Yes	3	0%	890	0%	294	0%	2,940	0%	93	0%	930	0%	-201	-68%	-2,010	-68%
Total			737		655,952		194,194	54%	1,941,940	54%	56,831	33%	568,310	33%	-137,363	-71%	-1,373,630	-71%
Lumpy	No	No	766	17%	75,618	8%	55,431	15%	554,310	15%	39,965	24%	399,650	24%	-15,466	-28%	-154,660	-28%
Slow	No	No	2,681	59%	61,623	6%	39,500	11%	395,000	11%	29,193	17%	291,930	17%	-10,307	-26%	-103,070	-26%
Grand Total			**4,564**		**969,162**		**360,199**		**3,601,990**		**169,942**		**1,699,420**		**-190,257**	**-53%**	**-1,902,570**	**-53%**

Table 10: D^2ID tool's current and optimized summary output under the assumption of standardized cost across the SKUs

Category	Trend	Seasonality	SKUs	% SKUs	Demand (units)	% Demand (units)	Current Inventory (units)	% Current Inventory (units)	Current Inventory $$	% Current Inventory $$	Optimized Inventory (units)	% Optimized Inventory (units)	Optimized Inventory $$	% Optimized Inventory $$	Delta (units)	% Delta (units)	Inventory Savings $$	% Inventory Savings $$
Erratic	No	No	268	6%	128,297	13%	49,889	14%	5,094,950	15%	28,745	17%	3,089,474	18%	-21,144	-42%	-2,005,476	-39%
		Yes	4	0%	2,334	0%	712	0%	63,378	0%	181	0%	17,260	0%	-531	-75%	-46,118	-73%
	Yes	No	99	2%	36,988	4%	17,488	5%	2,046,261	6%	14,208	8%	1,683,959	10%	-3,280	-19%	-362,302	-18%
		Yes	9	0%	8,350	1%	2,985	1%	470,739	1%	819	0%	119,789	1%	-2,166	-73%	-350,950	-75%
Total			380		175,969		71,074	20%	7,675,328	22%	43,953	26%	4,910,482	29%	-27,121	-38%	-2,764,846	-36%
Fast	No	No	519	11%	298,053	31%	90,552	25%	9,009,157	26%	30,366	18%	3,060,405	18%	-60,186	-66%	-5,948,752	-66%
		Yes	13	0%	8,262	1%	2,067	1%	240,909	1%	499	0%	47,045	0%	-1,568	-76%	-193,864	-80%
	Yes	No	202	4%	348,747	36%	101,281	28%	8,175,420	24%	25,873	15%	2,096,436	12%	-75,408	-74%	-6,078,984	-74%
		Yes	3	0%	890	0%	294	0%	41,690	0%	93	0%	7,665	0%	-201	-68%	-34,025	-82%
Total			737		655,952		194,194	54%	17,467,176	51%	56,831	33%	5,211,551	30%	-137,363	-71%	-12,255,625	-70%
Lumpy	No	No	766	17%	75,618	8%	55,431	15%	5,331,804	15%	39,965	24%	4,135,726	24%	-15,466	-28%	-1,196,078	-22%
Slow	No	No	2,681	59%	61,623	6%	39,500	11%	3,969,114	12%	29,193	17%	2,967,441	17%	-10,307	-26%	-1,001,673	-25%
Grand Total			**4,564**		**969,162**		**360,199**		**34,443,422**		**169,942**		**17,225,200**		**-190,257**	**-53%**	**-17,218,222**	**-50%**

Table 11: D^{2}ID tool's current and optimized summary output under the assumption of randomly varying costs across the SKUs

	Total current inventory (units)	Current inventory	Optimized decrease	%	Current inventory	Optimized increase (units)	%	Optimized inventory (units)	% Delta (units)
Erratic	71074	70116	42680	-39%	958	1273	33%	43953	-38%
Fast	194194	194073	56054	-71%	121	777	542%	56831	-71%
Lumpy	55431	53953	36442	-32%	1478	3523	138%	39965	-28%
Slow	39500	38706	27180	-30%	794	2013	154%	29193	-26%

Table 12: Increase/decrease of inventory levels after applying the D2ID procedure

	Total SKUs	Stock decrease (SKUs)	%	Stock increase (SKUs)	%
Erratic	**380**	362	**95%**	18	**5%**
Fast	**737**	716	**97%**	21	**3%**
Lumpy	**766**	652	**85%**	114	**15%**
Slow	**2681**	2146	**80%**	535	**20%**

Table 13: Number of SKUs with increase/decrease of stock levels after applying the D^2ID procedure

It is obvious, from the analysis above, that there should be reductions in inventory levels in terms of both units and costs between the current and the optimized solution.

When the same standard cost is assumed across all the SKUs, the tool obviously results in summary volume differences being exactly the same with cost differences. It suggests a reduction of 53% of the inventory levels (in terms of both volumes and costs). Inventory levels are reduced from 360,199 to 169,942 units in total, and from $3,601,990 to $1,699,420 (a reduction of $1,902,590). At the same time, in terms of the calculation of the fill rate per SKU level, the cost price is a major driver in the calculation of the fill rate per SKU thus the results would differ in the case of having a standardized cost across all the SKUs.

When randomly varying costs are used across the SKUS, the tool suggests a reduction of 53% of the inventory levels, which is associated with savings of 50% of the current inventory cost ($17,218,222 out of $34,443,422). By looking into each category separately it suggests a reduction (in volume) of 38% for the erratic items, 71% for the fast, 28% for the lumpy and 26% for the slow moving items. The higher the targeting service level, the less reduction is achieved. In the case of the fast moving items, it is not strange that the tool recommends a reduction of 71% since it is not always necessary to be full of stock to cover the customers demand on time; this could be controlled with the replenishment orders as well. Higher service levels can be achieved by reducing their current stock. Judging exclusively from Table 11 it is obvious that the simulated solution suggests stock levels reduction in all 4 categories. However, by looking into each category separately it can be seen that for some SKUs it suggests a stock reduction and for some other SKUs a stock increase. For example, in the slow items category, it can be seen that in 80% of the SKUs fall in this category there is a suggested stock level reduction whilst in the 20% of the SKUs a suggested stock increase (as can be seen from Table 12 and Table 13). This translates to 30% reduction and 154% increment in the inventory levels respectively.

3.5.4 Sensitivity Analysis

As already discussed in the previous sub-section of this chapter, the target service level has a significant effect on the optimization of the inventory levels (the higher the service level - the higher the stock needed will be, and the lower the reduction of the inventory levels).

The target service level has a significant implication on the optimization results of the inventory levels. Table 14 below demonstrates how the inventory levels are affected by the modification of the service level.

	Total current inventory (units)	Optimized inventory (units)			
		CSL=70%	CSL=80%	CSL=95%	CSL=99%
Erratic	71,074	39,496	40,238	43,953	50,559
Fast	194,194	46,067	48,141	56,831	66,096
Lumpy	55,431	35,093	35,622	39,965	51,496
Slow	39,500	25,660	26,201	29,193	35,015
Total	**360,199**	**146,316**	**150,202**	**169,942**	**203,166**

Table 14: Differences in inventory optimization results affected by alternative service levels

Overall, the tool suggests a reduction of 59%, 58%, 53% and 44% of the inventory levels given that the service levels were 70%, 80%, 95% and 99% respectively. The results validate the fact that the higher the service level the higher the stock needed (and the lower the reduction of the stock levels suggested by the tool). As can be clearly seen there is a stock increase of about 3% from 70% to 80% service level, 13% from 80% to 95% and a 20% increase from 95% to 99%.

The results for each service level target are demonstrated in detail in Appendices 10.1.

3.6 Conclusion

In this chapter, the methodological approach to meeting the objectives of this work has been introduced along with the inputs, computations and outputs/results of the tool developed for the purposes of this work. More specifically, the capabilities of the tool have been presented with detailed discussion around the solutions adopted. The nature of the data provided by the case organization together with the initial difficulties faced during the data collection phase, have also been discussed.

4. CONCLUSIONS

4.1 D^2ID Applicability

This kind of analysis is applicable on existing warehouse operations upon the availability of historical information. A forecast is only as good as the information included in the forecast (historical data). It is focused on intermittent demand data and thus is relevant in any context where such data prevail (e.g. automotive and telecom industries, military sector, etc.). Although the tool does handle both trend and seasonal components, it has not been developed to manage fast demand items but rather to distinguish between such items and intermittent SKUs. In addition please note that the operation of the tool is also condition to context associated with "sufficient" historical demand information, as discussed in 3. METHODOLOGY.

4.2 D^2ID Limitations And Strengths

The D^2ID is an inventory forecasting tool, developed within the limits of a KTP project, using and combining methods that are published in the literature. It has been developed and wrapped as a tool in VBA (visual basic application) in Microsoft Excel.

At the moment, the tool is built to run on a monthly basis (with the use of monthly data) by having a fixed length of historical data (24 months) and a review interval of 1 period. The optimization of the smoothing parameters is not something that was looked at during this project.

The tool provides fully automated output without any human manual intervention. D^2ID is very easy to be rolled out across the case organization, very transparent and could be easily adjusted to customer specific requirements.

The $\mathrm{D}^2\mathrm{ID}$ analyzes supply chain data to assess and optimize existing inventory levels. It helps with inventory planning and forecasting decisions, helps customers manage and forecast their demand, keep products moving faster, optimize inventory levels in their supply chains, improve service levels, increase sales as a result of improved customer service levels and product availability and finally reduce costs and generate a potential profit. As discussed in chapter 1, the tool aims at the reduction of the customers' inventory with great benefit for them e.g. cost reductions (financial sustainability), reduced obsolescence and thus a reduced need to discard obsolete products – items that otherwise would have to be rejected (environmental sustainability) and, through reduced costs, reduced prices to be offered ultimately to end consumers (societal sustainability).

4.3 Judgmental Related Aspects

As already discussed earlier in this chapter, the D^2ID is a fully automated and VBA (Visual Basic for Applications) based tool, built in Microsoft Excel. The user-friendly interface, allows the user to easily appreciate and understand that all the steps of the analysis are 8 (clear data, input demand data, input purchase orders data, classification-forecasting results, order levels results, inventory checking results and output summary results) including the tool guide button. All the required guidelines that the user needs to know in advance before running the tool and conducting the analysis are included in the Tool guide button. The only thing needed on the part of the user is to input the necessary data and then by clicking the appropriate buttons, the applicable analysis is conducted and the results are generated. The only human intervention needed from the user for the purposes of running the tool and getting the results/outputs, is to input the data required where indicated. The results/outputs are generated and presented for each SKU individually as well as aggregated together and presented in the output summary tab indicating clearly the differences between the current and the optimized state.

At this point it should be noted that in some cases the statistical forecasts generated through the classification procedure discussed earlier on (for any of the categories), could be subject to judgmental adjustments by management. This may be due to SKUs with lack of historical information (eg. typo mistakes in the datasets), or due to SKUs with unique conditions (eg. new products, new competitor in the market, changes in planning strategies etc.) where for example the final forecast is adjusted based on these changes [93]. Therefore the final forecast is the one produced once the statistical forecast has been judgmentally adjusted, i.e. following the intervention of a relevant manager into the system. One cannot also disregard the fact that judgmental adjustments need to be made only when there is significant evidence that an adjustment is needed (e.g. more timely, up-to-date information or domain knowledge) and when relevant information is not incorporated in the statistical model. Apart from adjusting the statistical forecast it is also important to note that the demand/inbound data used as an input in the tool, could be also adjusted from a relevant manager if there are any already known typo mistakes in the datasets. Then the order levels and inventory checking buttons could be recalculated. The users do have the opportunity to alter forecasts and/or replenishment quantities, but no facilities are provided at the moment to record the rationale behind such potential interventions.

The simplicity of the tool and the intuitive appeal of the output, facilitates in fact the effective human intervention since managers know where the suggested quantities come from and may adjust them appropriately.

4.4 Conclusion

The D^2ID tool allows the case company to analyse supply chain data to assess existing inventory levels, identify opportunities for reducing such stock levels through improved forecasting and stock control, free up cash and maintain or even improve customer service levels. Excess inventory and obsolescence constitute two of the most important issues faced in modern business environments. Such issues are very important for all the industries served by the case organisation, although the developments presented here refer to a spare parts environment.

By the time the project was completed, for the purposes of the KTP work, the company had started to investigate ways of extracting the data necessary for this kind of analysis and appreciate the importance of collecting and maintaining large datasets. This is viewed as an important implication of the project; the need to maintain large amounts of relevant information is not necessarily apparent in industry. Retrieving and putting relevant data in a format appropriate for the purposes of this work constituted an unexpectedly large amount of effort on the part of the researcher. The existence of a more comprehensive database right at the start of the project would have saved an enormous amount of time. Yet, all the deliverables were met and planned extensions of the current form of the tool are discussed in the next section.

The company has successfully used this tool to strengthen its relationships with the spare parts organisation that provided the empirical data used. The tool facilitates intelligent inventory related evaluations and has been very well received. It is the proprietary nature of the tool and the fact that has been developed by a 3PL for the benefit of their customers that has attracted considerable attention. It is clear that inventory forecasting off-the-shelf software packages are collectively at a very advanced stage and may offer considerable value to companies. However, with 3PLs looking increasingly more after their clients' inventories, the 3PL companies themselves need to advance to a stage that they appreciate the importance of scientific inventory forecasting. That is, they need to appreciate themselves the principles of inventory forecasting before attempting to help other companies benefit from it. This is what was achieved through this project.

The case company is now looking to implement the tool (and obtain feedback on its functionality and interface) across multiple sites by offering the opportunity to the customers to check if they can reduce their inventories through a simple, easy to use and transparent Excel based application (i.e. the tool). With this development the company can work together with their customers to reduce their inventory levels, better understand their business and essentially form strategic collaborations with them. It should also be noted that the company was heavily involved during the development and design of the tool to ensure that the system can be understood by everybody and is associated with an intuitively appealing interface (as far as the company is concerned).

4.5 Next Steps Of Development

Following the successful KTP project, the KTP Associate was offered a permanent job at the company. At the same time, the company invested in a new Research Centre at Cardiff University. This is where the Associate resides, facilitating continuing collaboration with the academic team and enhancement and expansion of the functionality of the tool. First, it is discussed below the next steps in terms of enhancing the current functionality and then it is considered the immediate actions for expanding the functionality of the tool.

In terms of enhancing the already existing functionality of the tool, some further development of the tool will be needed in terms of the smoothing parameters, the forecast accuracy measures used, the length of the historical data used as an input to the tool, the stock control policies used, the cost price of the SKUs, the opportunity to keep a record of any judgemental changes in the forecasts or replenishment quantities, the distribution used for approximating the demand over the lead time plus the review interval, the forecasting methods used and the lead time variability.

In terms of expanding the functionality of the D^2ID tool, first of all it is planned that another promising forecasting method (the Teunter, Syntetos, Babai (TSB) method) will be added on slow methods, for the purpose of identifying obsolescence and being able to provide advice as to when an item should be discontinued [94]. This links to the important issue of whether an item should be kept in stock at all. This has not been considered in the original version of the tool where the assumption was that everything should be stocked. In the next steps rules along the lines suggested by

Johnston, Shale, Kapoor, True and Sheth (2011) and Tavares and Almeida (1983) will be considered to decide on whether an item should be stocked or not based on the number of movements of the item over a particular time interval and the volume of the demand. [95][96]

It is also possible to extend the work discussed in this thesis, to cover Pegels' classification (and the use of all the methods suggested here) on fast moving methods. As discussed earlier in this chapter, in 3.4.3.2 Links Between Inventory And Forecasting, Pegels has provided a framework for separating trend and seasonality effects in additive and multiplicative models. Different exponential smoothing methods are optimal for the 9 resulting scenarios, taking into account all combinations of trend and seasonal effects in additive and multiplicative form [47][52].

In addition, and with regards to possible extensions on the forecasting methods, the damped trend is also planned to be added to the next phase of development of the tool. Garden and McKenzie (1985) examined Holt's linear method, and suggested a more generalized version of the method by adding an autoregressive damping parameter to give more control over the trend extrapolation [97][98].

In theory, there is also some opportunity for further extending the classification scheme adopted in this work. The difference between the original SBC scheme and the extension proposed by Kostenko and Hyndman (2006) (see also Petropoulos and Kourentzes, 2015) lies in the correctness of the delineation of the bottom left quadrant [99][100][101]. The construction of the original scheme reflects an emphasis on operationalization. The revised scheme reflects an emphasis on theoretical correctness, and it leads to marginal forecast accuracy improvements. However, is more complex to apply in practice. The trade-off between ease of use and forecast accuracy improvements favor the original scheme. This is demonstrated for example by the use of the original scheme by such software manufacturers as JDA. It is for this reason that the original SBC scheme has been employed for the purposes of this work [99][100][101].

As previously discussed in this chapter, the current version of the tool, adopts an alternative formulation of the MAPE metric as it is the most intuitively appealing metric and one that can be directly understood by management. The usage of this metric, is not constraining in terms of further amendments to the tool. When further improving the tool, a range of other appropriate metrics will be considered and this is to be combined with the fact that focus will be given also to optimizing the smoothing constant values used when applying the selected forecasting methods.

The consideration of other inventory policies, like (T,s,S), which bear considerable relevance to spare parts will be taken into consideration, as well as optimizing the inventories using the fill rate measure and applying the stuttering Poisson distribution for intermittent demand data.

At the moment, the tool only accepts 24 months of historical data (eg. demand data, inbound – receipts). The plan is to further adapt the input part of the tool and make it even more flexible by accepting the handling of any number of demand data periods available, of course under some logical constraints (eg. given the fact that there should be a minimum number of months for capturing seasonality, more than 1 periods for calculating the mean or variance) etc.

Obviously, the importance of ensuring appropriate input data to the tool cannot be ignored. Cost information has not been made available thus far for the purposes of the tool development. Incorporation of cost information to the tool would considerably improve the value of its output. Further, it would be very useful if the customers were in a position to provide their own forecasts, something that would enable comparisons to be made also at the forecasting level.

As mentioned before, the users do have the opportunity to alter forecasts and/or replenishment quantities, but such adjustments cannot be recorded in the current version of the tool. Doing so, would imply progressively turning the tool into a full forecast support system (FSS) whereby users can learn by their past behaviour, see analogies etc. This is a possibility that will be looking at in the next phase of development of the tool.

The current version of the tool can handle lead time variability across the SKUs but it cannot process variable lead times per SKU. This is something that will also be looked at in the future.

The next area of interest to the case company is product life cycle forecasting, specifically for their fashion industry clients, and developments related to this issue are going to be discussed in detail in the next Part (Part C) of the thesis (Product life cycle management). What this part of the work aims to achieve is to be in a position to identify the product’s life cycle stage (even for completely new products) and map the inventory needs across the life cycle. The latter objective is something that will be not explicitly covered in this thesis. However, there are plans to link product life cycle forecasting with inventory optimization in the near future.

PART C: PRODUCT LIFE CYCLE

In this part of the thesis (Part C), the work conducted on Life Cycle forecasting is discussed. As mentioned in Part A, the original objectives and deliverables of this project, did not include any work in the fashion industry. However, due to the fact that from the very first year of the KTP, customers from the case organization, showed a particular interest in product life cycle forecasting, it was decided that this topic, should be added to the KTP programme.

The focus was given on calculating the initial monthly forecast of a completely new product before even being introduced in the market by not having any information about the product but relying on the history of similar products (that are no longer in the market and have already completed their life cycle).

Product life cycle management introduction together with some background information and a review of the literature are provided in Chapter 5, followed by the work conducted on life cycle forecasting, the methodology used, software development implementation and the results–tool outputs (Chapter 6). Then the implications of this work are discussed along with the next steps of research (Chapter 7).

5. PRODUCT LIFE CYCLE MANAGEMENT

5.1 Introduction

In the progress of the KTP project, discussions with the company's clients from the fashion industry revealed a tremendous interest in product life cycle forecasting. Despite the initial problems faced in the KTP in terms of empirical data acquisition, considerable progress was achieved in the first year of work, over and above what should have been delivered by that point in time. Given the perceived slack, discussions were initiated between the supervisory team and the KTP Associate on whether the deliverables could be possibly expanded to cover life cycle forecasting as well. Upon agreement that this was both desirable and achievable this issue was taken to the Local Management Committee and the expansion of the project's deliverables was agreed by the KTP Adviser. In this part of the thesis (Part C) the work conducted on Life Cycle Forecasting is discussed.

5.2 Introduction – Product Life Cycle

The Product Life Cycle (PLC) is a very well recognized concept that is associated with a possible explanation or anticipation of the expected life cycle of a product or service from design to obsolescence. It could indeed also refer to a product category or to a market as a whole [102]. The PLC curves may be different for products belonging to a particular brand than the PLC of the brand at its own [103]. A life cycle could last from a few days (eg. fashion items) only to a few months (eg. a new mobile phone) or to a century (eg. coca cola drink). However, technological developments and competitive pressures have resulted in the PLCs being constantly reduced, regardless of the context [105]. Each product or service has its own life cycle which denotes the particular period from the very first entry of the product/service into the market until its removal [102][106].

The PLC is divided into several stages which can vary in number between four and six as proposed in the literature depending on the industry [107]. The product life cycle curve shows the product unit sales performance across time (in the market) and comprises the most well-known stages; introduction, growth, maturity and decline [107][108]. However, depending on the purposes of using or applying the product life cycle concept, these stages may be further divided into other sub-stages such as the addition of the development stage (before the introduction – starting point of the PLC, when the idea has been found and started to be developed) or the saturation stage (the company no longer invest in this product but rather focus on the development of new products as the sales are starting to decline) which follows the maturity stage.

5.2.1 PLC Literature

The PLC concept was originally proposed in the 1950's by Joel Dean [109]. However, Belville (1966) & Rink and Swan (1979) argued that even through Dean did introduce the idea of PLC he did not necessarily refer to what the concept is associated with nowadays [110]. Dean was mainly concerned with changing of strategies (e.g. pricing) [111]. The PLC concept as it is established nowadays, it was proposed by Jones in 1957 and had a length of five stages; introduction, growth, maturity, saturation and decline [110][112]. The period from the end of 1950s till the mid-1970s was more about the announcement and promotion of the PLC theory. The empirical analysis of the concept took place from the end of 1970s until nowadays [111][113]. The logic of the PLC concept originates from diffusion theory and adoption of innovation models and more information is included in 5.3.3 New Product Life Cycle Forecasting Literature [102][109].

The most common form of PLC, is the classical S-shaped curve [102][108] and is demonstrated in Figure 27 below (Adopted from marketing strategy on different Stages PLC and its marketing implications on FMCG products p.126):

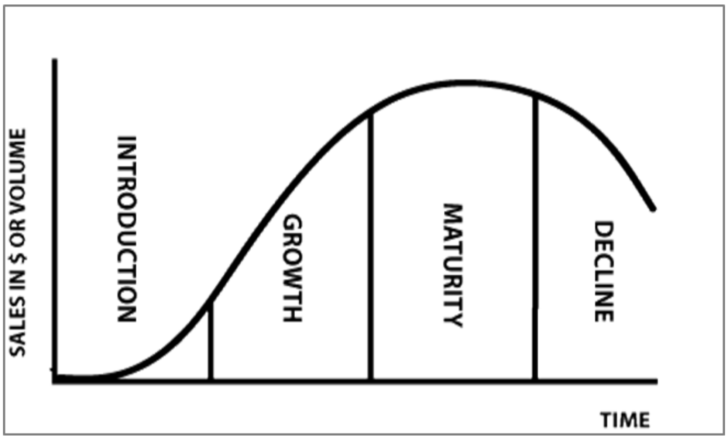


Figure 27: Product life cycle classical S-shaped curve

[102]

Each single product has its own limited life cycle and depending on the needs and requirements of that product, different strategies (marketing, manufacturing, purchasing, financial and human resource) are used at each distinct stage of the PLC.

The most extensive theoretical contribution related to the PLC that clearly affects relevant businesses strategies, has been developed by Hofer in 1975. He argued that "the most fundamental variable in determining an appropriate business strategy is the stage of the product life cycle" and that the “major changes in business strategy are usually required during three stages of the life cycle: introduction, maturity and decline”(p.6) [114]. Despite the relevance for many business areas (including inventory management), the PLC concept was initially predominantly associated with, and had a central role in, marketing theory and practice. In 1981, the PLC concept was judged by Biggadike to be one of the five most significant contributions of marketing when influencing strategic management [110].

5.2.2 Description Of The PLC Stages

The PLC measures the customer’s demand during the whole life cycle of the product showing the variation of the customer’s needs (sales data) at each stage separately [106]. The slope of the PLC curve is illustrative of the rate of diffusion of the particular product within the market [108]. Every single organization should have a full appreciation and understanding of the PLC before taking any decisions related to strategy, planning, control and forecasting [115].

There are several types of PLC curve, however the classical four stage cycle (introduction, growth, maturity and decline) will be considered as it is demonstrated in Figure 27. However, it has to be noted that while some products do go through all the four stages of the PLC, some others don’t. Some of them may go straight from the introduction to the decline phase or from introduction to maturity and then decline. Having said this, it is important to appreciate the fact that the profit of the company (if any) after selling the products will vary between the different stages [102].

The **introduction** stage of a product consists of the initial time the product first enters a market. Usually the product’s sales are rather low at this stage of the PLC due to the fact that the market is not yet familiar with the new product and only a few customers are aware of this new entry [107]. During this introductory stage, organizations should appreciate the fact that launching a new product into the market requires substantial investment for distributing the product and making potential customers aware of it [116]. Promotion and advertising expenses are typically very high but of course there is no guarantee that the product’s sales will be high too [106]. Despite the aforementioned challenges, a significant advantage of limited competition will occur when the product is completely new or different than any existing products in the market. This benefits the organization by giving the opportunity of capturing a large amount of market share before competing products enter the market [116]. Also, organizations that are introducing new products have the capability of charging higher prices than competitive products due to the fact that some customers are willing to pay more in order to get the newest product first even if the price is higher. In contrast, occasionally, organizations may prefer to motivate the market and potential buyers to buy the new product by offering lower prices than the competitors [102]. The aforementioned benefits, may allow the organization to recover some of the investment costs caused when launching the new product [116].

If the product is successfully accepted and recognized by the market then the unit sales will be increased and the introductory stage gives way to the **growth** stage [107]. The transition from the first stage to the second one and the expected increase of sales and profits are different for each market [116]. During this growth stage, the sales are rapidly increasing and the development and distribution of the product are also increasing without taking into consideration the presence of other products' offers or deals in the market [115]. Essentially, this is the crucial stage for market acceptance, recognition, awareness and increasing sales and profits. Once the demand is met by the increase of production then the manufacturing cost may be reduced due to the economies of scale (the more the production, the less the unit cost) [116]. One cannot also disregard the fact that all of the above may only be achieved by means of continuous promotion and advertisement of the new product [116][117]. During the growth stage, several challenges could be faced like the abrupt increase of the market competition. This happens when the demand of the new product increases dramatically while at the same time new (competing) manufacturers are looking for ways to take advantage of this new product in the market.

The decision of the competitors to introduce their products during the growth stage may have significant effects on the new product and the sales-profits of the particular organization. Consequently, the organization may possibly need to reduce its prices in order to achieve the planned increase of sales and profits [106][116]. If there is a small 'local' decline in the sales during the growth stage and the company misinterprets that as a 'global' decline and stops or even reduces the advertising and promotion this may cause a further decline and discontinue the natural development of the growth stage [118][119][120][121][122].

When new competitors with new products enter the market then the sales are influenced. They may remain at a stable level or even decrease [107]. Apart from the competitive market, the sales may be decreased since the product has been already accepted by the potential buyers in the market. Then it can be said that the product is in a **maturity** stage (the longest phase in the PLC) [115]. At this phase, the competition in the market will be really strong; the competitors are using strong advertising and promotional strategies to increase their sales and this is really challenging for the organizations that have already introduced new products in the market since they have to attempt to maintain the market share. The market share could be improved by the offering of new and different product features and advanced marketing strategies. The production developments and the manufacturing of larger quantities of the new introduced product has a consequence the reduction of the manufacturing costs [102].

The organization that has managed to achieve its target market share has nothing to worry about since this phase would be the most profitable. In contrast, organizations that did not achieve that have to develop an optimized marketing strategy.

The next and last stage of the PLC is the **decline** phase which is the beginning of the end life of the new product. Most of the consumers have already bought and become aware of the new product and now they are interested in newer products that are about to enter the market. This has as a result the reduction in both sales and profits of the already introduced product. The organizations support the sales until simply there is no demand at all anymore. Even though the product is about to be removed from the market, there are still some possibilities for the organization to make profit. This could be achieved by reducing the costs; moving the production to a cheaper location or by using other manufacturing options [107][116]. However, there are some cases where the organizations prefer to remove the product from the market before they make a loss. One cannot disregard the fact that the removal of a product from the market is not an easy decision. Spare parts availability and maintenance are some of the issues that the organizations are facing when they need to take such an important decision.

The table below is an overview of what has been already discussed earlier in this sub-section and summarizes the four stages accordingly to the product, price, distribution, advertising and promotion of each stage separately. Adopted from Kotler, Marketing Management, 9th Edition, p. 363.

	Introduction	Growth	Maturity	Decline
Product	Offer a basic product	Product extensions	Diversify brands	Phase out weak items
Price	Try to use price/value	Price to penetrate	Price to match competition	Cut price
Place/Distribution	Selective distribution	Intensive distribution	More intensive distribution	Selective. Phase out weak channels
Advertising	Build awareness among early adopters	Build awareness in mass market	Build preference	Reduce to level needed to retain loyals
Promotion	Heavy promotion	Reduce to take advantage of heavy consumer demand	Increase to encourage brand switching	Reduce to minimal

Table 15: PLC four stages accordingly to the product, price, distribution, advertising and promotion of each stage

[123]

Table 16 below summarizes the challenges and benefits of each of the four stages of the PLC.

	Challenges	Benefits
Introduction	Small market or no market at all High costs (investment, promotion, marketing etc) Low sales, No profits (not awareness of product)	No competition (large market share) Interest of buying a newest product (with high price) High product price
Growth	Increasing competition in the market Alternative promotion and marketing strategies Lower product price	Acceptance and recognition Reduction of manufacturing costs Increase in sales and profits
Maturity	New competitors in the market Decrease of market share Decrease of sales and profits	Reduction of manufacturing costs Increase market share (innovation marketing strategies, different product features)
Decline	Product removal No product interest Decrease of sales and profits	Profit by reduction of manufacturing costs Profit by change of production location Profit with the use of alternative manufacturing options

Table 16: Challenges and Benefits of the PLC for each stage separately

[116]

5.3 Introduction – Product Life Cycle Forecasting

The use of forecasting in the fashion industry is a difficult task. Fashion goods are associated with highly volatile demand, seasonal sales patterns, limited or no historical sales/demand data availability, short life cycles and fluctuating consumers' behavior (fashion trends, product attributes etc.). More detailed discussion about the forecasting issues in the fashion industry follows.

5.3.1 Forecasting Issues In Fashion Goods

The fashion market could be divided into three categories, fashion products with short life cycles, segasonal products with slightly longer life cycles and continuous products that are sold throughout the whole year [124].

The fashion industry has always been linked directly with products that are related with short life cycles. However, the rapid evolution of technology coupled with an increased market focus on innovative and complex solutions has resulted in a very fast pace of introducing new products that are associated with even shorter life cycles. The continuous design, differentiation and diversity of improved or entirely new products and services in a systematic manner affect the customers' requirements and behavior as well as the businesses strategies. This competitive market change, together with the high speed product development are resulting in challenging demand patterns and shortened lifetimes in many industry sectors. The management of such fast pace of new products with short product life cycles is challenging when it comes to demand forecasting. Demand uncertainty, short demand history and innumerable products increase remarkably the inventory levels.

Fashion products may have life cycles that last from a couple of months to a couple of years. A typical demand pattern for such kind of products could be described by rapid growth, maturity and decline phases as well as seasonal variation which could be caused by external market factors or a firm's internally factors.

Generating forecasts is a challenging and difficult task especially when products have short life cycles. When it comes to new product forecasting where limited or no data are available, the PLC forecasts rely on a group of historical products that had the same characteristics as the new one (more information is followed in this chapter). Historical data though may be limited or products may have short life cycles. Thus traditional methods will hardly take the product's characteristics into account. Due to the lack of historical data and such uncertainty in the demand pattern, traditional forecasting methods are not intended to be used for products with short life cycles. Forecasting methods that rely on historical data would fail in the context of forecasting the future and life cycle of a new product that has no history at all. Smoothing methods for example such as moving average or exponential smoothing are designed and best applied to steady trends [125]. Even by moving from one stage to the other and using different traditional forecasting methods at each stage, then this would fail as well due to the aforementioned reasons and due to the fact that even the historical products may have shortened life cycles thus no history to rely on.

5.3.2 Impact Of PLC Forecasting On Supply Chain Strategy

The current fashion industry market is under intense pressure of introducing new products to the potential buyers which shortens the life cycle of the products. Product life cycle forecasting, could be beneficial for supply chain decisions, satisfaction of customers' needs, using alternative operational strategies, increase or decrease of product's prices to achieve target sales as well as facilitation of planning and allocation processes of the total inventory investment. By examining the behavior and the stage of the future life cycle of a product, a company would be in the position to better understand the market needs and make appropriate plans for dealing with the competitive market. Therefore, they will be in the position to formulate not only their supply chain strategies but sales and marketing strategies as well.

The product life cycle concept offers the opportunity for important contributions in the area of forecasting and is currently attracting considerable interest from major companies and academic institutions due to its importance. It has been categorized as one of the most significant contributions of marketing when influencing the strategic management [110][114].

5.3.3 New Product Life Cycle Forecasting Literature

Nowadays, new product life cycle forecasting appears to attract considerable interest from businesses and especially from the fashion industry market. They are very much looking forward to be in the position to have PLC forecasts for completely new products as well as stock level requirements for precise operational and replenishment planning.

New product forecasting often appears in the literature to be covered by the use of diffusion models. As has been already mentioned in the PLC theory chapter, the logic of the PLC concept originates from the diffusion theory and adoption of innovation models [102]. Since its introduction around the 1960s to marketing, innovation diffusion theory has generated great research interests among consumer behavior and marketing management and especially the development of marketing strategies aimed at potential adopters for new products prospects [126]. Diffusion models have approximately the same concept like growth phenomena (e.g. from transition of disease to publicizing awareness). They try to estimate the transition disease within a population or information spread. But in this case a new product will be introduced into the market and the adoption procedure will start gradually, comes to peak point and then decrease (withdrawing) [105][127]. The very first steps on diffusion modeling have been introduced by Fourt and Woodlock, Mansfield, Floyd and Rogers, Chow and finally Bass whose relevant proposition is the most widely accepted and used one. Following these initial contributions, diffusion modeling has attracted a considerable amount of academic research and industrial attention [105][128]. In 1969, Bass developed the popular diffusion model of a single product while in 1987 with Norton, they used the Bass curve to present the procedure when an old product (the existing one) is being replaced by a new one [129][130]. After that, there was the Fisher and Pry development in 1971 as mentioned earlier in which the Bayesian priors are more straightforward to use than the Bass model for real data application [131]. The use of logistics curves in both industrial and commercial markets was originated with the Fisher and Pry development. In 1984, Meade examined growth curves for forecasting market development. He also studied several conditions (e.g. statistical and model validity and demonstrable forecasting validity and ability) for assessing the growth curves performance [132]. In 1990, Mahajan, Muller and Bass provided a research agenda for the better understanding of diffusion methodologies, for modeling and forecasting the transitional stages of the product, use of different forecasting methods and comparisons with diffusion methodologies based on empirical studies etc. [126]. Lenk and Rao in 1990 combined and applied hierarchical Bayesian principles with diffusion forecasting model [133]. Similar works have been carried out by Neelamegham and Chintagunta (1999 and 2003) and many other researchers whose point of interest was the diffusion methodologies [134][135].

5.4 Conclusion

In this chapter, there was a discussion around product life cycle management, with some background information and a review of the literature. The product life cycle concept has been introduced together with a detailed explanation of each of the product life cycle stages. Product life cycle forecasting and the forecasting issues in fashion good have been presented as well. This initiates what will be discussed in the next chapter along with the methodological approach followed.

6. METHODOLOGY

6.1 Introduction

As already mentioned, forecasting for fashions goods, is a challenging exercise due to the fact that the sales are volatile, there is limited or no historical data availability, the life cycles are short, there are many seasons etc. These make things even more difficult when it comes to capture the seasonality or when forecasting for the next couple of months, but it is already known that the specific product will no longer be in the market or become obsolete. The availability of this type of data will allow better estimates of model parameters.

Following the above, it was decided, that in this work, the statistical techniques developed by Abbas A. Kurawarwala and Hirofumi Matsuo (2014) are being adopted and used for forecasting demand in the fashion industry [125]. Real data coming from a case organization are utilized to assess the empirical validity and utility of the proposed solutions.

6.2 Capabilities

The solution developed is offering the possibility of handling the issues of no data availability, the short life cycles and the introduction of new products, the calculation of PLC forecasts and description of transit stages.

A non-linear least squares estimation (LSE) for a seasonal trend model has been used to represent the life cycle pattern of peak, growth and decline phases and also to use the peak timing month, month of introduction and total life cycle sales of prior similar products to estimate the parameters (the slopes of the line in the growth and decline phases as well as the 12 seasonal components) and generate the initial monthly forecasts between discrete time periods [125]. More details follow in this chapter.

The tool’s inputs, computations and outputs are on a monthly basis. The aim of the tool is to calculate an initial monthly forecast of a completely new product before even being introduced in the market by not having any information about the product but relying on the history of similar products (products that have the same characteristics, could be either provided by the company or by creating clusters based on their different attributes (eg. month of introduction, peak time, total sales, product color, type of fashion item etc.), that are no longer in the market, have already completed their life cycle and their seasonality can be captured. These initial monthly forecasts could be of great importance for operational and marketing purposes.

The product life cycle forecasting methodology discussed here could be applied to other industries products as well (e.g., technology, automotive, telecom, food). The decision to focus only on fashion goods was mainly because the case organization was particularly interested in that. There was great interest from its fashion customers around PLC forecasting and the empirical data came from that industry.

6.3 Inputs

Initially, it was considered the application of the method suggested in "Forecasting Demand for Fashion Goods: A Hierarchical Bayesian Approach" of Phillip M. Yelland and Xiaojin Dong [124]. It is a theoretical approach using Bayesian statistics; an agent-based simulation to reconstruct relevant demand data and Markov chain Monte Carlo techniques to make predictions and generate the PLC forecasts. In particular, it generates simulated demand (number of times the product was purchased from a consumer) which is motivated by exogenous or endogenous influences, e.g. mass media, advertising, people's choices etc. using demand information from previous periods. It also uses demand data from prior similar products that are no longer in the market, e.g. quantities purchased, life cycle curve, seasonality.

This method is, theoretically, very promising but very difficult to implement as it is extremely computationally intensive. It runs in Linux instead of Windows and although the key principles are comprehensive and it was actually possible to run it, a decision was made to not consider it further for practical purposes. Given its computational intensity and the huge number of parameters that need to specified, it was decided that it wouldn't be useful in a real world context [124]. The communication with Phillip Yelland was more than great and I would like to thank him very much for his devoted time, effort and contribution to this work. Although his method was not finally used in this work, his contribution was invaluable. Without actually using the method, but based on the paper, it seems that the Bayesian model proposed by Phillip Yelland, offers, better forecasting performance particularly early in the PLC [124].

The first trial and interaction in this project with new product forecasting was using a hybrid model combining diffusion theory (to describe transitional sales) linked with dynamic linear models (DLMs) (for seasonality and trend identification) and Bayesian statistics (for the better incorporation of judgmental information related to forecasting elements with real sales data statistics and for the use of historical sales data of already existing products for predicting sales information of a new product) due to the fact that the case organization was more interested in methods founded around new product life cycle forecasting. This has been examined by Philip M. Yelland in 2004 in his paper "A Model of the Product Lifecycle for Sales Forecasting". [105] As many researchers support and more specifically, Yelland and Lee in 2003, the product life cycle forecasting and more specifically the transitional sales are impossible to be calculated using the classic time series forecasting techniques [83]. However, it was decided that it was not very easy and practicable to be adapted in a real world context due to the many parameters needed to be specified. Undoubtedly, there are some other methods used for new product forecasting like different modifications of the Bass model, fuzzy piecewise regression analysis methods, Bayesian statistics, marketing models, etc. [136][137][138][139]. Since the above methods are difficult to implement due to their computational intensity, the fact that many parameters needed to specified, more input data were necessary, different operating systems would be needed and the fact that the empirical data provided from the case organization wouldn't fit in these methods, it was decided to use the method (described below). The data could then be fitted in the method explained below, would be an easy to understand method, adapt and implement by practitioners and grounded around PLC forecasting.

The inputs, computations and outputs are described and explained below in detail.

6.3.1 Data Collection

As with D^2ID, difficulties for collecting all the required data for the purposes of conducting empirical analysis were encountered in this case too, despite the fact that fashion customers seemed to be more keen in appropriate forecasting solutions, than the case organisations' clients in the spare parts industry. Eventually, a company operating in the fashion industry provided their empirical monthly data. The analysis was applied to 9 SKUs (8 of them acting as the prior similar products and 1 of them as the new product (ignoring the demand history that was provided which is only used for validation purposes)) with 24 months of historical demand observations. It has to be noted that analysis was conducted on an SKU by SKU basis and under the assumption that demand can be reasonably approximated by sales – which is admittedly a bit constraining in this industry. Not all the required data/information was available necessitating various assumptions to be made. The data required along with the assumptions made when needed will be discussed below in detail.

6.3.2 Data Input

This analysis captures seasonality and growth patterns using the facts and assumptions stated below. The prior similar products' demand history availability is of duration of 24 months. It is assumed that the demand of the new product will follow the same cycle pattern as well (in terms of demand volume, duration in the market, seasonality). The prior similar products could be either provided by the company or by creating clusters based on their different attributes (e.g. month of introduction, peak time, total sales, etc.). In this case a product list has been provided by the case organization but data was not available on which products are similar between them. The data were separated into divisions, by separating the fashion products into categories. For example all the shoes rely on a different division than the belts but it doesn't mean that all the shoes in that division are similar between them. Therefore, the decision on which products are similar between them has been reached during this work based on the following attributes the products have in common as discussed earlier in this chapter. All of them are categorized into the A41 division where the peak timing month is in December. Another common attribute which is very important for these models and it is based on a purely theoretical assumption (as the similar products were not provided by the customer, only their divisions), was that these 9 SKUs have similar total life cycles behaviour. The month of introduction (the point in time when the product is introduced in the market) and the peak timing month (the point of time where the sales peak) for products that have already completed their life cycle are important attributes to characterize the PLC of a new product similar to them and for generating the PLC forecasts but these can be easily captured purely from the total life cycle curve (the historical information available for them). Also the peak month is helpful for the calculation of the fraction of total sales (m) achieved by the theoretical peak time and consequently necessary for calculating the trend parameters of the new product. The peak timing month and the expected total life cycle sales are key aspects of the life cycle curve and vital requirements for the generation of the initial monthly forecasts of the new product. For the new product, this information could be collected from the sales and marketing department (either from consumer surveys they are conducting, market research analysis or from the discussions they have with the customers) or could be based on assumptions. It has to be noted that the month of introduction is also vital for the successful exploration of the model as it helps in determining the slopes for growth and decline phases of the new product. Information of the peak month, on the other hand, is necessary for the calculation of the theoretical peak time and consequently for determining the trend parameters. It is also assumed that the pattern of seasonal variation in demand is assumed to be the same across similar products and seasonal components from prior similar products will be used to forecast the new product as well [125].

All of the above can be seen in Table 18, Table 17 and Table 19.

Information needed for the new product

- Expected total life cycle sales (the expected life cycle sales in terms of volume (an aggregate estimate of how much this product will sell in total over its life time) of the new product is assumed to be the average sales of its similar ones).
- Month of introduction in the market (This is known, provided by the sales and marketing department or directly from the customer. In this case it wasn't known so it was assumed to be August, concluded purely from the data analysed and the similar products).
- Peak month timing (be collected from the sales and marketing department (either from consumer surveys they are conducting, market research analysis or from the discussions they have with the customers. In this case, the peak timing month is assumed to be December as it happened in all the similar products).

Data needed for the (8) prior similar products

- Complete product life cycle demand history
- The information below can be explicitly calculated upon the availability of the complete demand history of the product
    - Total product life cycle sales
    - Month of first positive demand (assumed to be the month of introduction)
    - Month of last positive demand
    - Peak timing month

6.4 Computations

The analysis, reflects cases where an initial forecast is generated following which a PLC is built for a completely new product (before even being introduced in the market) by not having any information about the product itself, but rather relying on and extracting the relevant data/information from the prior similar products.

This information is supplemented by key information on the product to be introduced in the market [125]. Such information is the expected total life cycle sales of the new product (e.g., from marketing department, market research analysis, consumer surveys, competitive analysis, expert opinion), the month of introduction in the market and the peak month timing (e.g. provided by the marketing department, or depending on the prior products and month of introduction). The approach used relies upon a medium term forecasting method based on life cycle growth and seasonality.

As already mentioned earlier in this chapter, a non-linear least squares estimation (LSE) for a seasonal trend model has been used to represent the life cycle pattern of peak, growth and decline phases and also to use the peak timing month, month of introduction and total life cycle sales of prior similar products to estimate the parameters (the slopes of the line in the growth and decline phases as well as the 12 seasonal components) and generate the initial monthly forecasts between discrete time periods [125]. The main steps of implementation are discussed in detail below. The pattern of seasonal variation in demand is assumed to be the same across similar products. This assumption practically holds in reality due to the fact that the primary causes of seasonal variation in demand are the weather, holidays, sales etc. that take place in a specific market channel. The estimation procedure described below is used to overcome the problem of little or no data availability for products with short life cycles that may prevent the calculation of the 12 seasonal components, by calculating the common seasonal component (from the prior similar products). Apart from the seasonal component, it is estimating the product's trend parameters as well [125]. The fact that this forecasting method uses information, growth and seasonality patterns from past products to generate initial monthly forecasts of the overall sales projections and builds the PLC curve for a completely new product constitute how valuable method is while at the same time other forecasting methods tend to be very volatile when it comes to new product life cycle forecasting.

1. Perform the non-linear LSE procedure for the 8 prior products to calculate the seasonal components and the slopes in growth and decline phases (product's trend parameters).

Let:

n : Denote the number of products

i : Index for the products $i = 1,2, \ldots, n$

s_i : First positive demand (in units) for product i

l_i : Last positive demand (in units) for product i

L : Last month in the horizon (the life cycle length)

D_{it} : Demand for product i in month t

a_t : Seasonal component for month t where $a_t = a_{t-12}$

p_i, q_i : Slopes for growth and decline phases for product i

N_{it}: Cumulative demand of product i by time (month) t

m: Expected/actual total life cycle sales (in units) for new/current product respectively

F_t: Forecast for time period (month) t

The cumulative demand and minimization of the sum of squared error are expressed as follows. The cumulative demand is an integration of a modification of the underlying differential equation of the Bass model as stated in the paper of Abbas A. Kurawarwala and Hirofumi Matsuo (2014).

$$N_{it} = m_i \left[\frac{1-exp\left[-(p_i+q_i)\sum_{t=s_i}^{t} a_t\right]}{1+\left(\frac{q_i}{p_i}\right)\exp\left[-(p_i+q_i)\sum_{t=s_i}^{t} a_t\right]} \right]$$

The simultaneous non-linear least squares estimation of the growth and decline parameters and the common seasonal components are calculated for the n products by minimizing the sum of squared errors:

$$\min_{p_i,q_i,\alpha_t} \sum_{i=1}^{n} \left\{ \sum_{s_i \leq t \leq l_i} \left[D_{it} - \left(N_{it} - N_{i,t-1}\right)\right]^2 \right\}$$

where $F_t = N_{it} - N_{i,t-1}$

subject to

$p_i > 0; \quad q_i, m_i \geq 0 \quad i = 1, \ldots, n$ (the growth parameters to be greater than zero and the decline parameters to be greater than or equal to zero. The expected/actual total life cycle sales (in units) for new/current product respectively cannot be negative)

$a_1 = 1.0; \quad a_t \geq 0 \quad t = 2, \ldots, L$ (first seasonal component equals 1 and all the remaining cannot be negative)

$a_t = a_{t-12} \geq 0 \quad t = 13, \ldots, L$ (for a seasonal effect of a constant period length 12 months, the seasonal component at time t would be the same as the seasonal component at time $t - 12$)

$\sum_{t=1}^{12} a_t = 12$ (the sum of all the seasonal components should be 12)

2. Perform the non-linear LSE procedure for the new product, using the output of step 1 as input to calculate the seasonal components and the slopes in growth and decline phases (product's trend parameters).
3. Calculate the theoretical peak time and the fraction of total sales (m) achieved by the theoretical peak time for the prior similar products using the p, q obtained from step 1.

In addition to the previous notation:

<u>Let:</u>

X: Fraction of total sales (m) achieved by the theoretical peak time

T^*: Theoretical peak time for prior similar products

$$T^* = \frac{1}{p+q} ln\left(\frac{q}{p}\right) \quad and \quad X = \frac{1}{2} - \frac{p}{2q}$$

where $X \geq 0 \quad and \quad T^* \geq 0$

4. Calculate the theoretical peak time of the new product

In addition to the previous notation:

<u>Let:</u>

${T^*}_n$: New product's theoretical peak time. Products with similar time to peak sales lie on the same T^* curve.

For example, products x and y are introduced in September and have their peak time in December. Products z and w that are introduced in June and July, respectively, they achieve peak time sales in December. Therefore, their parameter values are similar. Product k though is introduced in April and thus has a *T** value in between the two. The month of introduction determines the *p* and *q* values on a *T** curve.

t^*: New product's month to peak provided by the company (can be collected from the sales and marketing department (either from consumer surveys they are conducting, market research analysis or from the discussions they have with the customers) or could be based on assumptions)

t_n: New product's month of introduction

The theoretical peak time for the new product is calculated as the sum of the seasonal components (a_t) – those obtained from step 2, from the month of introduction to the peak time as stated in the paper of Abbas A. Kurawarwala and Hirofumi Matsuo (2014).

$$T^*{}_n = \sum_{t=t_n}^{t^*} a_t$$

5. For the prior similar products, calculate the X fraction of total sales (m) achieved by the theoretical peak time and the range in which this value lies.

This range is necessary for the calculation of the alternative forecasts. In this case, it was decided to provide 5 alternative PLC forecasts for the new product therefore 5 equally spaced values of X are needed *and* within each of these a specific number of X value ranges would exist (if the prior similar products were only introduced in May, July, September and November then only 4 value ranges would exist since they are based on the month of introduction). The ranges are calculated based on the month of introduction of the prior similar products and their fraction of total sales. For example if there are only 2 products introduced in August and their fraction of total sales is 0.495 and 0.513 respectively then this is the range of the X values for August. Products with same month of introduction lie in between the same range. These X values are necessary for the calculation of the new product's trend parameters and thus for the 5 alternative PLC forecasts. The five X values are equally spaced values calculated based on the minimum of the range of each month and all the 5 values should lie in between this range. Having all the above, the new slopes (p, q) for the new product could be calculated.

If there are no prior similar products introduced in the market the same month as it the new product is planned to, then the X value of the new product's is used for the calculation of the range intervals.

6. Calculate the theoretical peak time for the prior similar products and using the intervals calculated above – find the new slopes (p, q) for the new product.

Based on the month of introduction, the X values and the new slopes for the new product are calculated.

From $$T^* = \frac{1}{p+q} ln\left(\frac{q}{p}\right) \quad and \quad X = \frac{1}{2} - \frac{p}{2q}$$

the new p, q equations are obtained:

$$p = \frac{ln\left(\frac{1}{1-2X}\right)(1-2X)}{T^*(2-2X)} \quad and \quad q = \frac{p}{1-2X}$$

Having already calculated the theoretical peak time of the new product and already executing all the previous steps, then the new p, q values can be calculated.

7. Initial monthly forecasts are generated along with building the PLC of a completely new product using the the seasonal components (a_t) obtained from step 2 and the overall projections for the new product.

$$N_{it}{=}m_i \left[\frac{1-exp\left[-(p_i+q_i)\sum_{t=s_i}^{t} a_t\right]}{1+\left(\frac{q_i}{p_i}\right)\exp\left[-(p_i+q_i)\sum_{t=s_i}^{t} a_t\right]} \right]$$

$$F_t = N_{it} - N_{i,t-1}$$

Therefore 5 alternative PLC forecasts are then calculated based on the month of introduction, the 5 different values of X and the new p, q values for each X. The resulting forecasts are then validated with the actual data that was provided by the case organization.

As soon as this initial monthly forecast is generated, the PLC for the new product is then built (prior to introduction) and as new actual demand data arrives, then the product will then converted to a current product in the market. The PLC forecasts could be updated as the new actual demand data comes in. However, a major review of the initial forecast may not be warranted based on only one month’s data. The actual data coming through are then replacing the corresponding values obtained in the start-up forecast from step 1 (scenario 1), and by running a least-squares estimation procedure on the resulting data series, the PLC forecasts could be updated.

6.5 Outputs

The procedure and results are explained in more detail below.

Data collected for all the 9 SKUs

In Table 18, the historical demand data, the total PLC sales and information about the SKUs' similarity as provided by the case company are presented.

The following table includes the expected total life cycle sales, the month of introduction and the peak month of the potential new product, individually. The expected life cycle sales of a new product is assumed to be the average sales of its other 8 similar ones (excluding itself).

New product	Similar to Group	Expected Total PLC sales	Intro month	Month to peak
98686360563	A41	174	9	12
98686376120	A41	153	8	12
98689264974	A41	139	8	12
98689534336	A41	159	7	12
98689560373	A41	183	7	12
98689561431	A41	157	10	12
716453407289	A41	185	7	12
716453407296	A41	184	7	12
98686416451	A41	155	1	12

Table 17: Expected total life cycle sales, month of introduction and peak month of the potential new product, individually

SKUs	Jan-13	Feb-13	Mar-13	Apr-13	May-13	Jun-13	Jul-13	Aug-13	Sep-13	Oct-13	Nov-13	Dec-13	Jan-14	Feb-14	Mar-14	Apr-14	May-14	Jun-14	Jul-14	Aug-14	Sep-14	Oct-14	Nov-14	Dec-14	Total PLC sales	Similar Groups
98686360563	0	0	0	0	0	0	0	0	7	7	0	33	22	3	0	0	3	4	0	15	2	0	0	0	96	A41
98686376120	0	0	0	0	0	0	0	32	8	57	7	88	29	5	4	27	0	3	0	0	0	6	0	0	266	A41
98689264974	0	0	0	0	0	0	0	26	2	35	0	128	18	0	15	12	15	0	16	5	106	0	0	0	378	A41
98689534336	0	0	0	0	0	0	20	20	9	0	0	90	0	46	0	0	3	0	0	0	26	0	0	0	214	A41
98689560373	0	0	0	0	0	0	4	2	4	0	0	14	0	0	0	0	0	0	0	0	0	0	0	0	24	A41
98689561431	0	0	0	0	0	0	0	0	0	51	41	58	29	0	19	9	9	0	0	0	20	0	0	0	236	A41
716453407289	0	0	0	0	0	0	3	0	0	0	0	6	0	0	0	0	0	2	0	0	0	0	0	0	11	A41
716453407296	0	0	0	0	0	0	3	0	1	0	0	8	0	0	0	0	0	2	0	0	0	0	0	0	14	A41
98686416451	1	1	2	2	3	4	5	32	13	23	0	45	15	13	26	29	0	0	10	0	18	4	2	1	249	A41

Table 18: Historical demand data, total PLC sales and group similarity of the 9 SKUs provided

SKUs	Jan-13	Feb-13	Mar-13	Apr-13	May-13	Jun-13	Jul-13	Aug-13	Sep-13	Oct-13	Nov-13	Dec-13	Jan-14	Feb-14	Mar-14	Apr-14	May-14	Jun-14	Jul-14	Aug-14	Sep-14	Oct-14	Nov-14	Dec-14	Total PLC sales	Similar Groups
98686416451	1	1	2	2	3	4	5	32	13	23	0	45	15	13	26	29	0	0	10	0	18	4	2	1	249	A41
98686360563	0	0	0	0	0	0	0	0	7	7	0	33	22	3	0	0	3	4	0	15	2	0	0	0	96	A41
98689264974	0	0	0	0	0	0	0	26	2	35	0	128	18	0	15	12	15	0	16	5	106	0	0	0	378	A41
98689534336	0	0	0	0	0	0	20	20	9	0	0	90	0	46	0	0	3	0	0	0	26	0	0	0	214	A41
98689560373	0	0	0	0	0	0	4	2	4	0	0	14	0	0	0	0	0	0	0	0	0	0	0	0	24	A41
98689561431	0	0	0	0	0	0	0	0	0	51	41	58	29	0	19	9	9	0	0	0	20	0	0	0	236	A41
716453407289	0	0	0	0	0	0	3	0	0	0	0	6	0	0	0	0	0	2	0	0	0	0	0	0	11	A41
716453407296	0	0	0	0	0	0	3	0	1	0	0	8	0	0	0	0	0	2	0	0	0	0	0	0	14	A41

Table 19: Prior similar products, historical demand data and total PLC sales of the 98686376120 new product

Assume that the product 98686376120 is a new product that will be introduced in the market in July and has its peak timing in December. The 8 remaining products are assumed to be products similar to the pending new one that have already completed their life cycles and thus are no longer in the market. The input data for the 8 prior similar products are displayed in Table 20. For those products, a complete history of 24 months is provided. As already mentioned earlier on in this chapter, all 9 products come from the A41 division, have similar PLC and they are associated with the same peak timing month (December). The new product's 98686376120 expected total life cycle sales is assumed to be on average 153 units (average sales of the 8 similar products).

The analysis for all products is as follows.

The first step is to perform the non-linear LSE procedure for the 8 prior similar products in order to calculate the seasonal components and the slopes in growth and decline phases (product's trend parameters). The results are summarized in Tables 19 and 20, where the grey highlighted areas indicate the constraint estimation variables; slopes for growth and decline phases for each product i (Table 20) and the discrete seasonal components for month t where $a_t = a_{t-12}$ (Table 21).

SKUs	pi	qi	si	li	mi	t*	MinZ
98686416451	0.016	0.220	1	24	249	12	11985
98686360563	0.002	0.612	9	21	96	12	
98689264974	0.004	0.469	8	21	378	12	
98689534336	0.004	0.535	7	21	214	12	
98689560373	0.002	0.749	7	12	24	12	
98689561431	0.176	0.001	10	21	236	12	
716453407289	0.057	0.001	7	18	11	12	
716453407296	0.074	0.001	7	18	14	12	

Table 20: Slopes in growth and decline phases (product's trend parameters) after applying the non-linear LSE procedure for the 8 prior similar products

a1	a2	a3	a4	a5	a6	a7	a8	a9	a10	a11	a12	a13	a14	a15	a16	a17	a18	a19	a20	a21	a22	a23	a24
1	0.336	0.349	0.292	0.228	0.000	0.256	0.154	3.454	1.505	0.899	3.526	1.000	0.336	0.349	0.292	0.228	0.000	0.256	0.154	3.454	1.505	0.899	3.526

Table 21: Seasonal components after applying the non-linear LSE procedure for the 8 prior similar products

The non-linear LSE procedure is performed again, but this time for the new product, using as an input the seasonal components already obtained in step 1, in order to calculate the seasonal components and the slopes in growth and decline phases (product's trend parameters). Table 22 and Table 23 display the outcome of this LSE procedure.

SKUs	pi	qi	si	li	mi	t* & month to peak	MinZ
98686416451	0.007	0.008	1	24	153	12	0.0002097141

Table 22: Slopes in growth and decline phases (product's trend parameters) after applying the non-linear LSE procedure for the new product 98686376120

a1	a2	a3	a4	a5	a6	a7	a8	a9	a10	a11	a12	a13	a14	a15	a16	a17	a18	a19	a20	a21	a22	a23	a24
1.000	0.337	0.349	0.293	0.228	0.000	0.256	0.154	3.453	1.504	0.899	3.526	1.000	0.337	0.349	0.293	0.228	0.000	0.256	0.154	3.453	1.504	0.899	3.526

Table 23: Seasonal components after applying the non-linear LSE procedure for the new product 98686376120

The above parameters, will be necessary for the calculation of the theoretical peak time and the fraction of total sales achieved by the theoretical peak time for the prior similar products using the p, q obtained from step 1 and using the p, q obtained from step 2 to calculate the theoretical peak time of the new product. The results are presented inTable 24 and Table 25 below.

SKUs	T*	X	Intro month
98686416451	10.97337	0.462783	1
98686360563	9.192523	0.498239	9
98689264974	10.36612	0.496258	8
98689534336	9.261097	0.496596	7
98689560373	7.771907	0.498548	7
98689561431	0	0	10
716453407289	0	0	7
716453407296	0	0	7

Table 24: Theoretical peak time and fraction of total sales achieved by the theoretical peak time for the prior similar products using the p,q obtained from step 1.

New SKU	Tnew	Intro month
98686376120	9.536639	8

Table 25: Theoretical peak time of the new product 98686376120

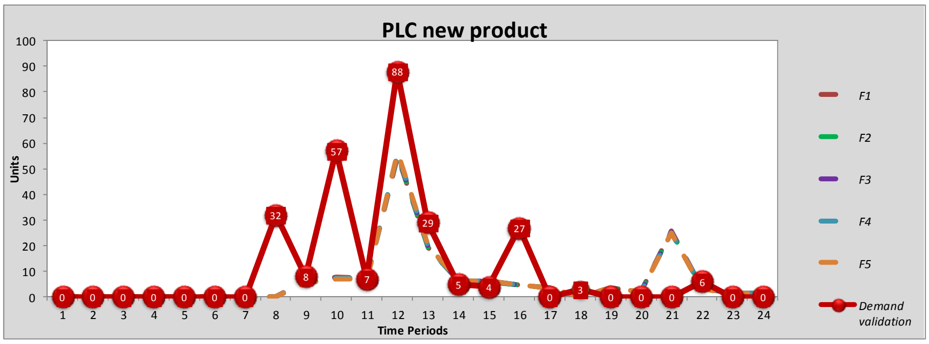
By having the X fraction of total sales achieved by the theoretical peak time for the new product and for the prior similar products then the ranges in which these values lies could be calculated as described in step 5 in 6.4 Computations and thus the new slopes (p, q) for the new product could be calculated as well.

Month intro		X1	pnew	qnew	X2	pnew	qnew	X3	pnew	qnew	X4	pnew	qnew	X5	pnew	qnew
January	1	0.46248	0.01895	0.25261	0.46268	0.01890	0.25322	0.46288	0.01884	0.25384	0.46308	0.01879	0.25447	0.46328	0.01873	0.25509
February	2	0.00010	0.00001	0.00001	0.00020	0.00002	0.00002	0.00030	0.00003	0.00003	0.00040	0.00004	0.00004	0.00050	0.00005	0.00005
March	3	0.00010	0.00001	0.00001	0.00020	0.00002	0.00002	0.00030	0.00003	0.00003	0.00040	0.00004	0.00004	0.00050	0.00005	0.00005
April	4	0.00010	0.00001	0.00001	0.00020	0.00002	0.00002	0.00030	0.00003	0.00003	0.00040	0.00004	0.00004	0.00050	0.00005	0.00005
May	5	0.00010	0.00001	0.00001	0.00020	0.00002	0.00002	0.00030	0.00003	0.00003	0.00040	0.00004	0.00004	0.00050	0.00005	0.00005
June	6	0.00010	0.00001	0.00001	0.00020	0.00002	0.00002	0.00030	0.00003	0.00003	0.00040	0.00004	0.00004	0.00050	0.00005	0.00005
July	7	0.09981	0.01038	0.01297	0.19962	0.02005	0.03338	0.29943	0.02742	0.06836	0.39924	0.02817	0.13980	0.49905	0.00125	0.65561
August	8	0.49596	0.00405	0.50114	0.49616	0.00389	0.50662	0.49636	0.00373	0.51239	0.49656	0.00357	0.51848	0.49676	0.00340	0.52492
September	9	0.49794	0.00236	0.57347	0.49814	0.00217	0.58436	0.49834	0.00198	0.59648	0.49854	0.00178	0.61013	0.49874	0.00158	0.62578
October	10	0.00010	0.00001	0.00001	0.00020	0.00002	0.00002	0.00030	0.00003	0.00003	0.00040	0.00004	0.00004	0.00050	0.00005	0.00005
November	11	0.00010	0.00001	0.00001	0.00020	0.00002	0.00002	0.00030	0.00003	0.00003	0.00040	0.00004	0.00004	0.00050	0.00005	0.00005
December	12	0.00010	0.00001	0.00001	0.00020	0.00002	0.00002	0.00030	0.00003	0.00003	0.00040	0.00004	0.00004	0.00050	0.00005	0.00005

Figure 28: Generation of initial monthly forecasts together with the PLC building of the new product 98686376120

After all, the initial monthly forecasts are generated together with the PLC of a completely new product along with the seasonal components (a_t) obtained from step 2.

Dropdown SKUs list
98686376120



Selected Row	1																							
Column number	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
98686376120																								
Period	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
F1	0	0	0	0	0	0	0	0	6	8	7	55	19	6	6	5	3	0	4	2	26	4	1	2
F2	0	0	0	0	0	0	0	0	6	7	7	55	19	6	6	5	3	0	4	2	25	3	1	2
F3	0	0	0	0	0	0	0	0	6	7	7	55	19	6	6	5	3	0	4	2	25	3	1	2
F4	0	0	0	0	0	0	0	0	6	7	7	56	20	6	6	5	3	0	4	2	25	3	1	2
F5	0	0	0	0	0	0	0	0	5	7	7	56	20	6	6	5	3	0	4	2	25	3	1	1
Demand validation	0	0	0	0	0	0	0	32	8	57	7	88	29	5	4	27	0	3	0	0	0	6	0	0

Table 26: Slopes for each of the 5 alternative forecasts for the new product 98686376120

The table below demonstrates the forecast accuracy results for new product forecasting. MAPE has been adopted in this case as well in order to have a consistency between the presentation of the results for the two tools. MAPE has been calculated for the five alternative forecasts and it can be concluded that the alternative F2 performs better.

	MAPE
F1	73.320
F2	55.794
F3	55.803
F4	55.811
F5	55.819

Table 27: MAPE for new products forecasting

6.6 Conclusion

In this chapter, the methodological approach followed to meet the extended objectives (product life cycle forecasting for fashion goods) of this work has been introduced together with the inputs, computations and outputs/results of the developed tool. The scenario considered has been presented in detail together with the empirical data provided by the case organization has also been discussed.

7. CONCLUSIONS

7.1 Applicability

As already mentioned above, the method discussed, is applicable to new products before even being introduced to the market and it is based on prior similar products that are no longer in the market and have already completed their life cycle (historical data/information needed for the prior similar products).

However, it has to be noted that the product life cycle concept does not apply effectively to cases associated with product redesign. If a product is further developed or redesigned then it should be considered as a different product as its product's characteristics will not be the same and thus the demand for that product will be affected (either increased or decreased). It is also possible that the product might go back from one stage to the previous one e.g. from maturity to growth stage due to a promotion or indeed redesign and further developments of the tool. Therefore the demand for that product before and after the redesign will not match as it will refer to actually two different products.

7.2 Limitations And Strengths

The PLC forecasting tool has been developed within the limits of the KTP project, using methods that are published in the literature. As mentioned in the beginning of this chapter, there are also methods that deal with (new) product life cycle forecasting but are very computational intensive and thus difficult to implement. The PLC tool, had been developed in VBA (Visual Basic for Applications), Microsoft Excel.

The case organization is in a competitive advantage as they now have their own PLC forecasting tool to be able to advise their customers on relevant matters. The tool provides an automated output with only some minor human intervention needed. As the tool had been built and developed in Excel, there are some limitations with the execution of the LSE procedure using VBA since solver in VBA could be only linked to cells in Excel but not linked to dynamical coding or parameters. Therefore it needs some minor manual intervention for the tool to run. The tool however, is very easy to use, very transparent and could be adjusted to specific customer requirements (historical demand availability, number of products, horizon of forecasts etc.).

The tool may be used as a planning or forecasting tool [140]. As a planning tool, it would be beneficial for helping the management towards a better characterization and understanding of the market needs. By the use of PLC concept, the main marketing challenges at each single stage (and more importantly the decline stage) could be addressed by the use of some alternative marketing strategies. The aim is to maximize their sales (and profits as well) by trying to minimize the unnecessary and costing expenses. Having in mind that almost all products that enter the PLC will be removed or replaced at some point of time then it is essential to give more attention on the product innovation, marketing and promotion. The allocation of advertising and promotion funds at each stage of the PLC separately could be easier with the introduction of new or alternative marketing strategies. As a forecasting tool, it gives the opportunity to the managers to forecast the product behavior and thus make plans for dealing with the competitive market. It helps with forecasting decisions, by helping customers manage and forecast their demand easily. However, it has to be noted that this does not constitute always essentially a good forecasting tool due to the fact that it is not always possible to accurately forecast the life cycle of the product. Companies do need the expected PLC length in advance in order to plan the production and marketing strategies that they are going to follow. As an explanatory tool its use is important since it helps with the better understanding of historical, current and future demand patterns [103].

Moving now to the limitations, at the moment, the tool is built to run on a monthly basis (with the use of monthly data) with a single peak (in a month) when it comes to the prior similar products. If there are products that have peak timing months more than once where the peak demand number is exactly the same, then this is something that is not covered in this study and needs to be deliberated in the future.

The new product forecasting has been applied to a small number of products. This limitation is recognized but it is important to note that this was the very best that could have been done given the lack of appropriate data and data/information sharing related difficulties with the company's clients. It should be also pointed out that empirical evidence in the area of PLC forecasting is generally lacking. Therefore, and despite this obvious limitation, this work can be viewed as a small step towards expanding the empirical knowledge base in this area.

The length of time each product spends at each stage separately and the length of its PLC is not fixed and the same is true for the time period of moving from one stage to the other (transitional time). This is because products, brands, organizations and industry markets are different. Therefore this may complicate matters when trying to identify which stage of the PLC the product is at and cause confusions on marketing strategic decisions. However, it has to be mentioned that a new product does not always pass through all the stages (introduction-growth-maturity-(saturation)-decline). The product may not even pass from the introduction stage to growth and rather go straight to the decline stage (e.g. DVDs, CDs, video games etc.) [103][118][119][120][121][122]. Therefore when calculating the PLC forecasts of a new product it would be better to have as many prior similar products as possible. Also when generating the initial monthly forecasts of the new product it is logical that the longer the forecast horizon is, the less reflection it will have in reality. Thus for making sure that the PLC forecasts are consistent, as soon as the actual data arrives the PLC forecasts could be reflected and regenerated for making comparisons with the initial guesses.

Despite these limitations, PLC has been judged by the case organization to be a useful tool since they can use it as a solution offering to current and potential new customers. It helps them to see how the product will behave in the future so that to check if they have sufficient stock levels to cover the forthcoming demand.

7.3 Conclusion

Part C of the thesis included the work carried out around product life cycle forecasting. As mentioned in Part A, this topic was not included in the original objectives and deliverables of this KTP. However, due the fact that company's customers were extremely interested in product life cycle forecasting, it was decided that this topic, should be added to the objectives of the KTP.

The forecasting scenario associated with cases where initial (monthly) forecasts for completely new products are needed and such forecasts are generated by means of using data/information from similar products previously available in the market was presented. The method proposed along with the assumptions made and the empirical data used for the purposes of this analysis have been discussed and an automated tool has been developed to allow experimentation on the part of the case company with real data.

This tool allows the case organisation to be in the position to make tangible suggestions to their clients on matters associated with product life cycles. The entire development was a by-product of the KTP project discussed in this thesis and further developments to the tool are planned. These are discussed in the next section.

7.4 Next Steps Of Development

Regarding the product life cycle forecasting, it would be very useful and beneficial if the customers could provide their forecasts in order to be in the position to make comparisons and evaluate the forecast accuracy of the above results.

At the moment, the tool is built to run on a monthly basis (with the use of monthly data) with a single peak month. If there are products that have peak timing months more than once and the peak demand number is exactly the same, then this is something that is not covered in this study and needs to be reflected in the near future.

The next step of research is to see how the product life cycle forecasting in the fashion industry could be linked with inventory and replenishment management to better help customers optimize their inventory levels and also help them with operational planning. However this linkage between PLC forecasting and inventory control has not been touched upon yet and it will addressed later on in the year as it is highly demanded from the case organization's customers.

Another area of focus could be to identify ways to group the products that are similar between them by clustering methods instead of waiting from the customer to provide this kind of information. This experimentation will start by focusing on the paper "Formation of seasonal groups and application of seasonal indices by JE Boylan, H Chen, M Mohammadipour and A Syntetos, 2014". This paper addresses how to form/cluster the seasonal groups and how to improve forecast accuracy at the item level.[141] This would be useful for the tool since it is highly likely that the customer may not have the products clustered into groups as in the case of this project (where the decision on which products are grouped together has been reached after consideration of the division of the product, the peak timing month, the life cycle behaviour), do not know any similar attributes that the products may have between them or the grouping criteria are confidential and could not be shared.

PART D: KTP'S PROJECT IMPACT

The work presented in this thesis has been presented in multiple internal and external (customer) workshops and seminars of the case organization as well as in academic workshops, posters and in a conference. It is also important to note, that this partnership motivated further collaboration between the case organization and the University with the establishment of a double KTP around 3D printing, involving not only the Cardiff Business School but also the Cardiff School of Engineering. Very importantly, this KTP led to a permanent appointment of the KTP Associate in the company. In this last part of this thesis, the impact of the work on all relevant stakeholders is discussed and its exposure to academic and practitioner communities is summarized (Chapter 8).

8. PROJECT'S IMPACT

8.1 Introduction

According to the company, the knowledge base partner and Innovate UK (along with EPSRC), the outcome of the project exceeded the original expectations. The reason was two-fold: i) the objectives of the original application to Innovate UK were not only successfully met but even exceeded in terms of what was offered to the company and what the knowledge base accomplished through the project; ii) the initial set of deliverables was considerably expanded to include what was essentially one more project on product life cycle forecasting. In the remainder of the chapter, the awards received for the KTP work, professional publications that resulted from it and the project's impact for both the company and knowledge base partner are discussed. Such information does not relate necessarily to the MPhil work (which describes the application of scientific knowledge into practice) but rather its implications and how it was perceived. However, it was judged important and suggested by the University to present such information for completeness (with regards to the KTP).

8.2 Presentations, Publications And Awards

The work presented in this thesis has been presented in multiple internal and external (customer) workshops and seminars of the case organization, as it also formed the basis of a presentation to the Advisory Board of the Logistics and Operations Management (LOM) Section of Cardiff Business School. It was also disseminated to academic audiences in the form of a guest lecture in the 'Logistics Modeling' and 'Operations Analytics' MSc modules at Cardiff Business School, at the Logistics and Operations Management Section Annual Conference (LOMSAC) 2016, and the EURO (2015) conference in Glasgow, UK (27th European Conference on Operational Research, University of Strathclyde, Glasgow, UK).

The project was awarded the highest grade of "Outstanding" by the KTP Grading Panel for its achievement in meeting the KTP's Objectives [142].

Following the above award, the KTP project entered the 2016 Innovation and Impact Awards Competition (Innovation Network, Cardiff University). Projects are evaluated under 5 main categories (Business Innovation, Innovation in Heath Care, Innovation in Policy Making, International Impact, Social Impact) It won the *Business Innovation* Award as well as the People's choice award. The latter is offered to the one of the five award winners receiving most preferences from the public (with participation though social media channels). This is important external validation of the application of knowledge to practical situations which is reassuring given these are the requirements of an MPhil.

Finally, this work was published in two practitioners articles, in the Lean Management Journal 2015 [143] and the IMPACT Magazine 2016 [144].

8.3 Impact On Case Organization

The work conducted in this project was encouraged by the company and finally reached the implementation stage due to the fact that the company and more specifically the top management were heavily involved during both the design and development of the tools. However, data acquisition has not been easy. This raises some interesting issues with regards to data sharing for every empirical project. Without data is impossible to demonstrate the practical implications of a solution but in order to convince an organization to provide data it is always expected to demonstrate the practical usefulness of a solution! This is an issue faced in this project too. The start was made by simulating performance using theoretical generated data reaching eventually a point where enough confidence had been generated in the tool to stimulate the release of empirical data. After demonstrating the empirical implications, more data became available and then finally the tool was developed by demonstrating its full implications. This process is graphically depicted in Figure 29. The good communication between the associate, the University and the company, and the commitment from top management received were of crucial importance towards the success of this project.

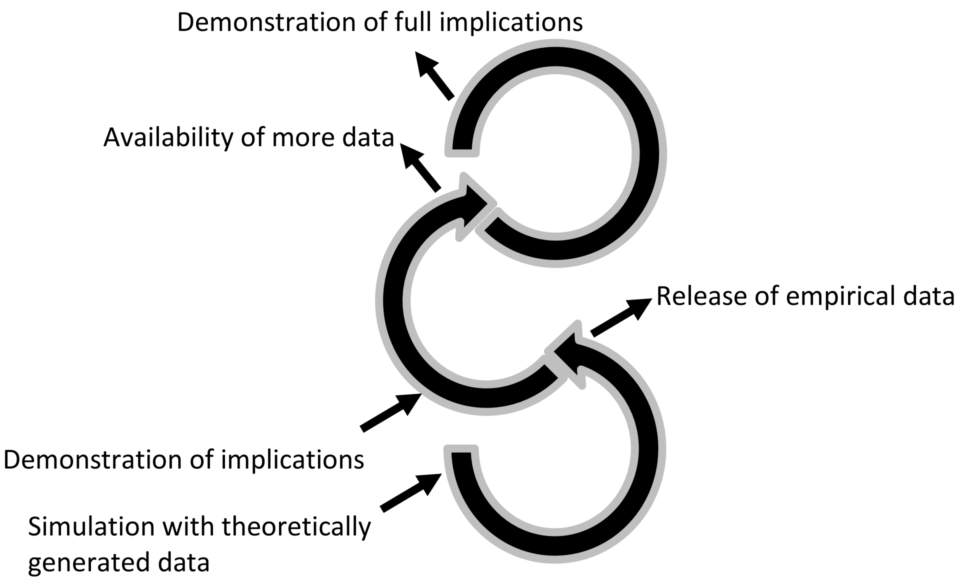


Figure 29: Data Availability- Demonstration of Implications

New knowledge was gained and transferred in the case organization on inventory control and supply chain forecasting as a direct result of the KTP. The work conducted has been showcased in external sales material as well as on the internal website of the company together with a sales brochure that includes what the tool can do. People in the company can have access to the tool and play with it, after a short training session. Also, the work was mentioned on the highlights part of the company's annual report in 2014, in addition to its inclusion into the company's newsletter and in several press releases.

More importantly though, the KTP had a major impact in terms of the overall approach of the case company to research and innovation. They organized their 2016 Innovation Board at Cardiff University seeking closer linkages with an academic institution and input from academics into their innovation strategy. As previously discussed, the company operates under three main pillars: Ocean Freight, Air Freight and Logistics Management Services (LMS). The LMS operates under: i) Spares and Repairs, ii) Reverse Loops, iii) Postponement Strategies iv) 3D printing and v) Data Analytics (broadly defined). Following the successful completion of the project, Supply Chain Forecasting became the dominant concern in the Data Analytics stream of activities.

Finally, and through the successful collaboration between the case company and the University, the former introduced an annual award offered to the MSc students in the LOM Section of Cardiff Business School. The nature of the task changes every year depending on research priorities. The company was also invited to give various guest lectures in the LOM Section offering them exposure to the University's student base. A considerable number of appointments of LOM students to the company have taken place over the last three years.

8.4 Impact On Cardiff University

Research is increasingly being measured not only in terms of relevant scientific excellence but also in terms of the resulting impact. Through this KTP, research previously conducted by members of the LOM faculty was successfully implemented, resulting into the production of an automated solution. Due to the nature of the company partner which is a 3PL serving very many industrial clients (ranging from multi-national corporations to SMEs), the solution has been exposed to a considerable number of companies.

Moreover, senior members of staff from the company have been invited (and they currently contribute) to the Advisory Board of the Logistics and Operations Management (LOM) Section of Cardiff Business School (CARBS) – the Board meets quarterly and offers strategic advice to the Section in terms of relevance of their research and reflection of Industry needs into the curriculum.

The company and Cardiff Business School have eventually embarked into a strategic relationship as an outcome of this KTP project. As previously discussed, the company has successfully introduced a company award offered annually to LOM students, offered very many MSc student placements, contributed with guest lectures in many modules offered by the LOM section, and most importantly have employed many of the LOM MSc and BA graduates with plans for further recruitment. Other Sections within CARBS (e.g. Marketing and Strategy) but also other Schools as well (e.g. Engineering) have also benefited from this strategic collaboration.

The successful completion of the KTP project was the starting point of some research expansion to new manufacturing technologies (such as 3D printing) and their implications for forecasting and inventory management. A new double KTP around 3D printing has started in January 2016 (reflecting a collaboration between Cardiff Business School and Cardiff School of Engineering), funded by Innovate UK, EPSRC and the case organization.

Most importantly, the company has also decided to further invest into academic collaboration, by means of funding a new Research Centre and sponsoring an existing Chair at Cardiff Business School for 5 years, starting in September 2016.

8.5 Impact on KTP associate

The KTP project has been a very challenging and intensive journey, as well as a highly rewarding one. I had the opportunity to attend a lot of trainings and thus progress my personal and professional development. Some of them were the lean six sigma yellow and green belt trainings as well as the forecasting and predictive analytics course of NATCOR (National Taught Course in Operational Research). VBA training course helped me with improving my programming skills in Microsoft Excel and allowed me to build both the D^2ID and new PLC forecasting tools. My attendance in workshops and trainings company related also helped me to improve my business mind-set, communication and presentation skills. Following the completion of the project I was offered a permanent job at the company and I have also pursued a research degree (MPhil) at Cardiff University.

8.6 Research Contribution Beyond The Implementation Aspects

A very important aspect of this project is the development of the idea that 3PLs should take ownership of their customers' (inventory) forecasting processes. The value of the D^{2}ID and PLC work is not associated only with the (fully/semi) automated solutions developed, but also with the suggestion of a new business model (one according to which 3PLs can be more actively involved in managing their customers' inventories rather than rely on customers' inventory to make money). There are other 3PLs that can also accommodate inventory forecasting requirements of their clients but only in a reactive way. The forecasting capabilities developed through this project enable the company to proactively help their customer to better forecast demand. The logistics product of the company is organized around 5 areas: Distributed Manufacturing, Product Life Cycle Extension, Additive Manufacturing, Installations and Inventory Management. The last one (Inventory Management) has been explicitly evolved around the work conducted in this research.

8.6.1 D^{2}ID

For the purposes of this work the SBC classification scheme was modified in order to account for SKUS with no, or insufficient, demand observations. There might be cases when no positive demand observations are available in the out-of-sample (or in both sample blocks), in which case no performance evaluation could be conducted. Therefore a new category was added to the scheme, called "Evaluation constrained". Further, there were also cases with less than 2 periods with positive demand in the initialization sub-sample, a case where initial estimates of inter-demand intervals or demand sizes (both of which rely upon straight averages) are impossible to be calculated. This latter case was classified as "Calculation constrained".

Some more adjustments needed to be done on the linkage of forecasting methods to the modified classification scheme due to the fact that the company was also interested in the seasonal and trend elements of spare parts. The right hand side of the scheme remains the same; however, the left hand side is appropriately modified with further analysis being applied to the erratic and fast categories in order to check for trend or/and seasonality for the non-intermittent items. If there is trend, then the Holt's method is being used; if there is seasonality, Winter's method is employed; and if both trend and seasonality exist, then the Holt Winter's method is applied. Finally, if there is seasonality, trend (or both), comparisons (based on a selected performance metric) determine which forecasting method is to be used.

8.6.2 PLC

The work conducted by Phillip M. Yelland and Xiaojin Dong (Forecasting Demand for Fashion Goods: A Hierarchical Bayesian Approach; Handbook on Intelligent Fashion Forecasting Systems: Models and Applications, 2014) on PLC forecasting for new products was also applied after consultation with the first author himself. However, and despite the fact that this is theoretically a very promising method, it is admittedly very difficult to implement, and very computationally intensive with a prohibitively large number of parameters that need to be specified. Therefore, the decision taken was that, for the purposes of this work, and more specifically for the case organisation, this method would not be taken further in terms of implementation.

The work conducted by Abbas A. Kurawarwala and Hirofumi Matsuo (Product growth models for medium-term forecasting of short life cycle products; Technological Forecasting and Social Change, 1998) on PLC forecasting for existing products was also applied. However, it was decided not included in this thesis due to space limitations.

8.7 Conclusion

The last chapter of this thesis, summarized the work done within the limits of the KTP and discussed the impact of this research on all its stakeholders. More precisely, it presented the project's impact on the case organization and Cardiff University as well as briefly introduced the awards received along with some practitioner articles published.

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10. APPENDICES

10.1 Sensitivity Analysis Supporting Results

Category	Trend	Seasonality	SKUs	% SKUs	Demand (units)	% Demand (units)	Current Inventory (units)	% Current Inventory (units)	Current Inventory $$	% Current Inventory $$	Optimized Inventory (units)	% Optimized Inventory (units)	Optimized Inventory $$	% Optimized Inventory $$	Delta (units)	% Delta (units)	Inventory Savings $$	% Inventory Savings $$
Erratic	No	No	268	6%	128,297	13%	49,889	14%	5,094,950	15%	25,139	17%	2,708,054	18%	-24,750	-50%	-2,386,896	-47%
		Yes	4	0%	2,334	0%	712	0%	63,378	0%	121	0%	10,559	0%	-591	-83%	-52,819	-83%
	Yes	No	99	2%	36,988	4%	17,488	5%	2,046,261	6%	13,723	9%	1,617,942	11%	-3,765	-22%	-428,319	-21%
		Yes	9	0%	8,350	1%	2,985	1%	470,739	1%	513	0%	67,275	0%	-2,472	-83%	-403,464	-86%
Total			380		175,969		71,074	20%	7,675,328	22%	39,496	27%	4,403,830	30%	-31,578	-44%	-3,271,498	-43%
Fast	No	No	519	11%	298,053	31%	90,552	25%	9,009,157	26%	24,254	17%	2,381,288	16%	-66,298	-73%	-6,627,869	-74%
		Yes	13	0%	8,262	1%	2,067	1%	240,909	1%	308	0%	24,043	0%	-1,759	-85%	-216,866	-90%
	Yes	No	202	4%	348,747	36%	101,281	28%	8,175,420	24%	21,467	15%	1,669,957	11%	-79,814	-79%	-6,505,463	-80%
		Yes	3	0%	890	0%	294	0%	41,690	0%	38	0%	1,887	0%	-256	-87%	-39,803	-95%
Total			737		655,952		194,194	54%	17,467,176	51%	46,067	31%	4,077,175	28%	-148,127	-76%	-13,390,001	-77%
Lumpy	No	No	766	17%	75,618	8%	55,431	15%	5,331,804	15%	35,093	24%	3,666,666	25%	-20,338	-37%	-1,665,138	-31%
Slow	No	No	2,681	59%	61,623	6%	39,500	11%	3,969,114	12%	25,660	18%	2,610,362	18%	-13,840	-35%	-1,358,752	-34%
Grand Total			4,564		969,162		360,199		34,443,422		146,316		14,758,033		-213,883	-59%	-19,685,389	-57%

Category	Trend	Seasonality	SKUs	% SKUs	Demand (units)	% Demand (units)	Current Inventory (units)	% Current Inventory (units)	Current Inventory $$	% Current Inventory $$	Optimized Inventory (units)	% Optimized Inventory (units)	Optimized Inventory $$	% Optimized Inventory $$	Delta (units)	% Delta (units)	Inventory Savings $$	% Inventory Savings $$
Erratic	No	No	268	6%	128,297	13%	49,889	14%	5,094,950	15%	25,716	17%	2,770,863	18%	-24,173	-48%	-2,324,087	-46%
		Yes	4	0%	2,334	0%	712	0%	63,378	0%	128	0%	11,486	0%	-584	-82%	-51,892	-82%
	Yes	No	99	2%	36,988	4%	17,488	5%	2,046,261	6%	13,802	9%	1,629,553	11%	-3,686	-21%	-416,708	-20%
		Yes	9	0%	8,350	1%	2,985	1%	470,739	1%	592	0%	81,167	1%	-2,393	-80%	-389,572	-83%
Total			380		175,969		71,074	20%	7,675,328	22%	40,238	27%	4,493,069	30%	-30,836	-43%	-3,182,259	-41%
Fast	No	No	519	11%	298,053	31%	90,552	25%	9,009,157	26%	25,763	17%	2,550,005	17%	-64,789	-72%	-6,459,152	-72%
		Yes	13	0%	8,262	1%	2,067	1%	240,909	1%	345	0%	28,264	0%	-1,722	-83%	-212,645	-88%
	Yes	No	202	4%	348,747	36%	101,281	28%	8,175,420	24%	21,986	15%	1,733,075	11%	-79,295	-78%	-6,442,345	-79%
		Yes	3	0%	890	0%	294	0%	41,690	0%	47	0%	2,814	0%	-247	-84%	-38,876	-93%
Total			737		655,952		194,194	54%	17,467,176	51%	48,141	32%	4,314,158	28%	-146,053	-75%	-13,153,018	-75%
Lumpy	No	No	766	17%	75,618	8%	55,431	15%	5,331,804	15%	35,622	24%	3,725,855	25%	-19,809	-36%	-1,605,949	-30%
Slow	No	No	2,681	59%	61,623	6%	39,500	11%	3,969,114	12%	26,201	17%	2,667,678	18%	-13,299	-34%	-1,301,436	-33%
Grand Total			4,564		969,162		360,199		34,443,422		150,202		15,200,760		-209,997	-58%	-19,242,662	-56%

Table 28: D2ID tool's current and optimized summary output given target service level is 70% (left table) and 80% (right table)

Category	Trend	Seasonality	SKUs	% SKUs	Demand (units)	% Demand (units)	Current Inventory (units)	% Current Inventory (units)	Current Inventory $$	% Current Inventory $$	Optimized Inventory (units)	% Optimized Inventory (units)	Optimized Inventory $$	% Optimized Inventory $$	Delta (units)	% Delta (units)	Inventory Savings $$	% Inventory Savings $$
Erratic	No	No	268	6%	128,297	13%	49,889	14%	5,094,950	15%	28,745	17%	3,089,474	18%	-21,144	-42%	-2,005,476	-39%
		Yes	4	0%	2,334	0%	712	0%	63,378	0%	181	0%	17,260	0%	-531	-75%	-46,118	-73%
	Yes	No	99	2%	36,988	4%	17,488	5%	2,046,261	6%	14,208	8%	1,683,959	10%	-3,280	-19%	-362,302	-18%
		Yes	9	0%	8,350	1%	2,985	1%	470,739	1%	819	0%	119,789	1%	-2,166	-73%	-350,950	-75%
Total			380		175,969		71,074	20%	7,675,328	22%	43,953	26%	4,910,482	29%	-27,121	-38%	-2,764,846	-36%
Fast	No	No	519	11%	298,053	31%	90,552	25%	9,009,157	26%	30,366	18%	3,060,405	18%	-60,186	-66%	-5,948,752	-66%
		Yes	13	0%	8,262	1%	2,067	1%	240,909	1%	499	0%	47,045	0%	-1,568	-76%	-193,864	-80%
	Yes	No	202	4%	348,747	36%	101,281	28%	8,175,420	24%	25,873	15%	2,096,436	12%	-75,408	-74%	-6,078,984	-74%
		Yes	3	0%	890	0%	294	0%	41,690	0%	93	0%	7,665	0%	-201	-68%	-34,025	-82%
Total			737		655,952		194,194	54%	17,467,176	51%	56,831	33%	5,211,551	30%	-137,363	-71%	-12,255,625	-70%
Lumpy	No	No	766	17%	75,618	8%	55,431	15%	5,331,804	15%	39,965	24%	4,135,726	24%	-15,466	-28%	-1,196,078	-22%
Slow	No	No	2,681	59%	61,623	6%	39,500	11%	3,969,114	12%	29,193	17%	2,967,441	17%	-10,307	-26%	-1,001,673	-25%
Grand Total			4,564		969,162		360,199		34,443,422		169,942		17,225,200		-190,257	-53%	-17,218,222	-50%

Category	Trend	Seasonality	SKUs	% SKUs	Demand (units)	% Demand (units)	Current Inventory (units)	% Current Inventory (units)	Current Inventory $$	% Current Inventory $$	Optimized Inventory (units)	% Optimized Inventory (units)	Optimized Inventory $$	% Optimized Inventory $$	Delta (units)	% Delta (units)	Inventory Savings $$	% Inventory Savings $$
Erratic	No	No	268	6%	128,297	13%	49,889	14%	5,094,950	15%	34,006	17%	3,616,917	18%	-15,883	-32%	-1,478,033	-29%
		Yes	4	0%	2,334	0%	712	0%	63,378	0%	258	0%	24,560	0%	-454	-64%	-38,818	-61%
	Yes	No	99	2%	36,988	4%	17,488	5%	2,046,261	6%	15,003	7%	1,782,449	9%	-2,485	-14%	-263,812	-13%
		Yes	9	0%	8,350	1%	2,985	1%	470,739	1%	1,292	1%	184,338	1%	-1,693	-57%	-286,401	-61%
Total			380		175,969		71,074	20%	7,675,328	22%	50,559	25%	5,608,264	27%	-20,515	-29%	-2,067,064	-27%
Fast	No	No	519	11%	298,053	31%	90,552	25%	9,009,157	26%	35,016	17%	3,563,349	17%	-55,536	-61%	-5,445,808	-60%
		Yes	13	0%	8,262	1%	2,067	1%	240,909	1%	659	0%	66,408	0%	-1,408	-68%	-174,501	-72%
	Yes	No	202	4%	348,747	36%	101,281	28%	8,175,420	24%	30,275	15%	2,515,680	12%	-71,006	-70%	-5,659,740	-69%
		Yes	3	0%	890	0%	294	0%	41,690	0%	146	0%	13,095	0%	-148	-50%	-28,595	-69%
Total			737		655,952		194,194	54%	17,467,176	51%	66,096	33%	6,158,532	30%	-128,098	-66%	-11,308,644	-65%
Lumpy	No	No	766	17%	75,618	8%	55,431	15%	5,331,804	15%	51,496	25%	5,232,961	25%	-3,935	-7%	-98,843	-2%
Slow	No	No	2,681	59%	61,623	6%	39,500	11%	3,969,114	12%	35,015	17%	3,561,583	17%	-4,485	-11%	-407,531	-10%
Grand Total			4,564		969,162		360,199		34,443,422		203,166		20,561,340		-157,033	-44%	-13,882,082	-40%

Table 29: D2ID tool's current and optimized summary output given target service level is 95% (left table) and 99% (right table)

	Total current inventory (units)	Current inventory	Optimized decrease (units)	%	Current inventory	Optimized increase (units)	%	Optimized inventory (units)	% Delta (units)
Erratic	71074	71020	39415	-45%	54	81	50%	39496	-44%
Fast	194194	194153	45667	-76%	41	400	876%	46067	-76%
Lumpy	55431	55215	34601	-37%	216	492	128%	35093	-37%
Slow	39500	39457	25419	-36%	43	241	460%	25660	-35%

Table 30: Increase/decrease of inventory levels after applying the D^2ID procedure given CSL=70%

	Total current inventory (units)	Current inventory	Optimized decrease (units)	%	Current inventory	Optimized increase (units)	%	Optimized inventory (units)	% Delta (units)
Erratic	71074	70968	40090	-44%	106	148	40%	40238	-43%
Fast	194194	194121	47636	-75%	73	505	592%	48141	-75%
Lumpy	55431	55176	34898	-37%	255	724	184%	35622	-36%
Slow	39500	39384	25775	-35%	116	426	267%	26201	-34%

Table 32: Increase/decrease of inventory levels after applying the D^2ID procedure given CSL=80%

	Total SKUs	Stock decrease (SKUs)	%	Stock increase (SKUs)	%
Erratic	380	375	99%	5	1%
Fast	737	724	98%	13	2%
Lumpy	766	719	94%	47	6%
Slow	2681	2562	96%	119	4%

Table 31: Number of SKUs with increase/decrease of stock levels after applying the D^2ID procedure given CSL=70%

	Total SKUs	Stock decrease (SKUs)	%	Stock increase (SKUs)	%
Erratic	380	373	98%	7	2%
Fast	737	721	98%	16	2%
Lumpy	766	709	93%	57	7%
Slow	2681	2508	94%	173	6%

Table 33: Number of SKUs with increase/decrease of stock levels after applying the D^2ID procedure given CSL=80%

	Total SKUs	Stock decrease (SKUs)	%	Stock increase (SKUs)	%
Erratic	**380**	342	**90%**	38	**10%**
Fast	**737**	706	**96%**	31	**4%**
Lumpy	**766**	496	**65%**	270	**35%**
Slow	**2681**	1764	**66%**	917	**34%**

Table 34: Number of SKUs with increase/decrease of stock levels after applying the D2ID procedure given CSL=99%

	Total current inventory (units)	Current inventory	Optimized decrease (units)	%	Current inventory	Optimized increase (units)	%	Optimized inventory (units)	% Delta (units)
Erratic	71074	68305	45988	-33%	2769	4571	65%	50559	-29%
Fast	194194	193813	64749	-67%	381	1347	254%	66096	-66%
Lumpy	55431	48476	36111	-26%	6955	15385	121%	51496	-7%
Slow	39500	36141	27678	-23%	3359	7337	118%	35015	-11%

Table 35: Increase/decrease of inventory levels after applying the D^2ID procedure