Management of a high mix production system with interdependent demands: simulation of proposed policies

by

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B.E. Mechanical Engineering (2008)
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Submitted to the Department of Mechanical Engineering
in Partial Fulfillment of the Requirements for the Degree of

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Abstract

The finished goods inventory management in the accessories area of a material testing company is complex. There is interdependence between the demands of products and they can be sold both as part of systems and as individual after sales items. Besides, there is uncertainty in determining replenishment lead times. An optimization problem is formulated considering customer satisfaction, inventory holding costs and correlation between demands. To ascertain its validity, a discrete event simulation is executed over historical demand. Simulation also helps to check the solution robustness by executing the proposed inventory levels over statistically generated demands. The result provides the right mix of finished products which should be stored on the shelves. 90% reduction in lost sales and 35% in inventory value on hand have been projected. The results have been further implemented at the part level inventory.

Thesis Supervisor: Dr. Stanley B. Gershwin

Title: Senior Research Scientist

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1. Introduction

1.1 Instron Corporation as a Research Environment

Founded in 1946, Instron® is the recognized worldwide market leader in the materials testing industry, holding more than 50% of the market share. The company has various products with all of them sharing production lines. The products cover the following areas of testing: fatigue, tension, compression, flexure, hardness, impact, torsion, spring, test analysis, structural and custom testing. Within each of these categories, many combinations of machines and accessories (hereafter called systems) are possible according to the customer's requirement. That is, all the testing equipment can be customized by the customer. Thus, even the same requirement of two customers may not result in the same order.

Such market behavior forces Instron to keep multiple product lines which further translate into a high inventory, low output factory floor. Thus, Instron serves more than a 'job-shop' volume but at the same time maintains a flexible manufacturing facility to produce highly customized products in minimum time. This issue is clearly visible in the accessories business of the electromechanical division. This area of the production line has the maximum variability and hence is an effective bottleneck. It is well known in the inventory management industry that rather than high demand, it is the variability that is the real reason behind the difficulty in managing service levels [1]. Thus, it is very important to make this area ready for such variability. This can only happen if the right mix of accessories is available at the right time, in the right quantities and at the right place.

Variability is not the only concern while dealing with the inventory in the EM accessories business. There are other intricacies involved which make the problem more challenging. For example, not only can the finished goods be sold as part of a system but they can also be sold as individual after sales parts (hereafter called as OTC - Over The Counter products). Secondly, each system has to wait until all the items in it are available and only then it can be shipped. Thus, in the case of a system order, there is dependence of demand between these items, and they cannot be viewed as separate entities.

Figure 1.1 5800 Series System

Figure 1.2 AWedge Action Grip

The figures above show some products offered by the Electro-Mechanical business. Figure-1.1 shows a 5800 Series System. It includes a double column machine with accessories- grips and computers. Orders comprising this whole package i.e. machine with accessories is called a system order.Figure-1.2 shows a similar grip. These grips (and other accessories) can also be sold separately from the whole system and such orders are the Over the Counter (OTC) orders. Figure 1.3 shows different accessories that can be a part of the system.

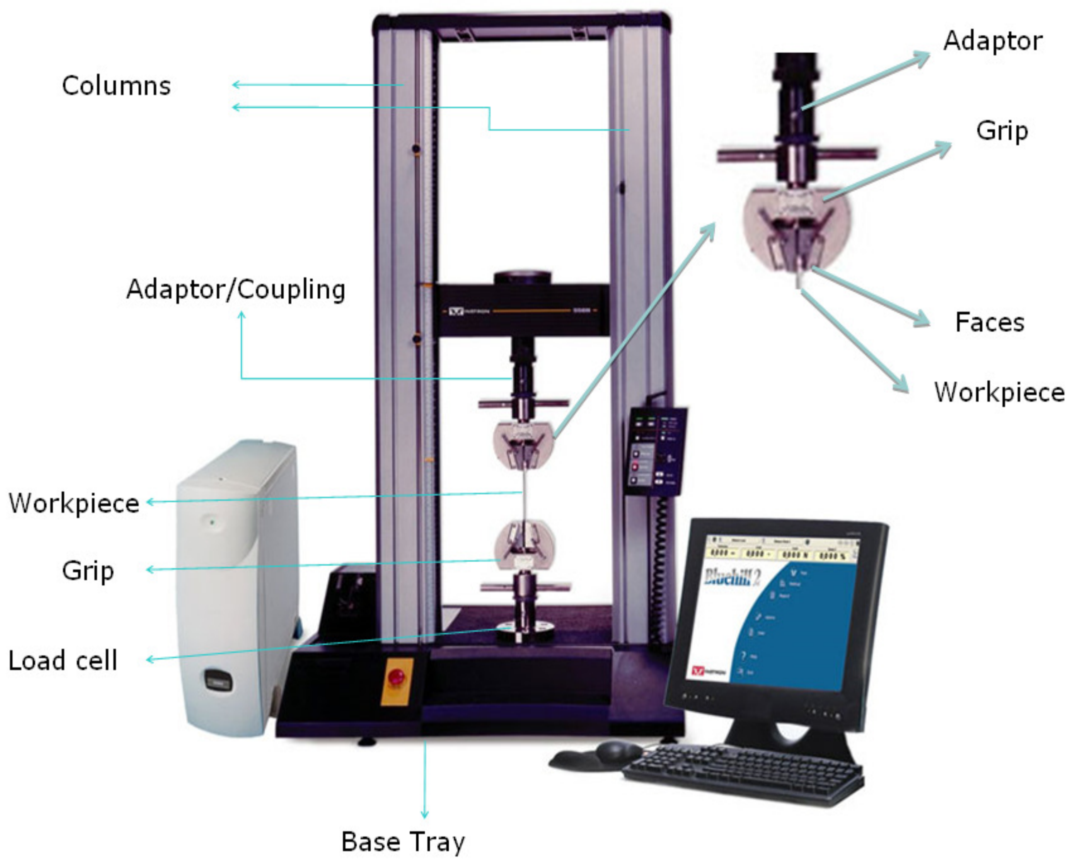

Figure 1.3 An Instron Two Column Machine with Accessories

Currently, Instron holds an inventory value of $4million in the EM area with inventory control based on Distribution By Value (classifying products into categories A, B, C and D according to their cost) and ITW's policy of having a maximum of 2 months-on-hand demand. However, many aspects are neglected while determining their inventory policy- such as demand variability, percentage of lost sales, holding costs and customer expectations. Thus, there is a certain opportunity to scientifically determine the inventory levels taking all the significant factors into account and improving the customer satisfaction by fulfilling more orders as well as minimizing inventory levels.

1.2 Background

Generally, Instron's finished products can be classified into two categories: systems and OTC. In the electromechanical division, both of these categories exist and share a common inventory. Due to the demand variability, the management has decided not to base the inventory control on predicted demand but to switch to a pull production strategy in order to allow production to reorder parts only when finished goods are "pulled" away from the system. The physical implementation of pull production is achieved through the use of Kanban[2] cards for some of the purchased parts and components, and by not stocking some inventory items at all. However, Kanban is not available at the level of final finished goods level yet and has been implemented only 40% at the part level. Some finished goods are currently being replenished according to minimum level reports being generated through the internal inventory management system. This means that the goods are replenished only when a report is run and hence they are more prone to inaccuracies. Some other goods are being replenished by visually seeing on the floor if the quantity drops below a minimum mark, triggering a development order by the area manager. This method too can be inaccurate.

No records for lost orders are kept. Thus, it becomes difficult to determine which item causes the order to be lost. The available data shows only the orders which were fulfilled and hence, it acts as a barrier in determining the optimum inventory level since the actual demand will be underestimated.

The suppliers can also overlap i.e. one item can be bought from two different suppliers. This complicates the case further since there will be two lead times for the same product.

Finally, the final lead time to customer is also hard to determine due to a system audit which takes place on certain products and takes about a day to complete.

Figure 1.4 Current Finished Goods Inventory Storage

Currently, sometimes during peak demand, the factory floor gets clogged with the unfinished machines. Also, occasionally, when a whole order is made to wait longer, it gets cancelled, even if just one item was not available.

The markets of OTC and system orders have their own special requirement. While on the system side, the customers are more relenting and are willing to accept larger lead times, the OTC market is more demanding. The customers prefer expedited delivery since they are just waiting for one component in their system. Hence, the OTC market is very competitive.

The system market is usually more relaxed as Instron machines are expensive and they come as a capital purchase for their customers. Hence, the customers understand the large lead times for the machines. For a capital purchase, customers themselves need time to get the money sanctioned from their own organization. This too helps to mitigate the dissatisfaction due to high lead times.

For the same reason, Instron starts building the product as soon as it gets an order. However, it does not ship it until all the bills have been cleared.

The systems market helps the OTC market by ensuring that customers buy only Instron accessories which are specifically designed for their machines. Easily available cheaper duplicates require extra adaptors and are not backed up with warranty. Despite this, customers want lowest possible lead times in the OTC products.

1.3 Significance of the Problem

The significance of the project for Instron and the contribution of this study to the literature in the field of inventory management are shown in the following paragraphs.

1.3.1 Significance of the Project

The number of items and parts concerning the Assembly Department is around 1000. In this situation, a great waste of time and money can easily be caused by overstocking. On the other hand Instron's responsiveness to customer demand is identified as an important goal in order to maintain competitive advantage. The optimization of the control parameters is thus critical at the accessories area at Norwood. In order for the strategy to remain optimal in the future, the control parameters must be adjustable accordingly to variations in the product line and in the demand. It is also important that the proposed inventory strategy is easy to apply for the planners and the workers of the facility to properly control the stocking of so many items. The impact of proposing an effective inventory control strategy consists in improved production efficiency and better competitiveness on waiting times which is especially important for the OTC market.

1.3.2 Significance of the Study

This work considers the case of low-volume high-mix inventory systems where customer orders may require several different products (i.e., high customization between products and hence demand between different products is correlated) and the shipment of those items cannot be split. The time delay seen by the customer is the performance measure of concern and the customer impatience is modeled and taken into account: whenever one or more items belonging to an order are backlogged, the customer is quoted a waiting time which is as long as the slowest item's lead time. As the waiting time increases, a customer is less prone to make the order. A continuous review model is proposed using historical sales data rather than using forecasted demand.

Interdependent demands frequently arise in real life multi-item inventory systems. The dependencies of demands for different inventory items may be implied by product options or kits. When the manufacturing lead times for some accessories are long or when customer order assembly time is small, the configuration of a proper mix of items is critical to ensure their availability with the desired probability and avoid order fulfillment delays. Ignoring correlation in the demand when present may lead to two possible consequences: stocking more than necessary or not being able to provide the desired service level. It is demonstrated by R. Zangh that this assumption leads to an overestimate of the total time delay when items are actually correlated[2].

Unfortunately most inventory models on time delay in the literature assume one-item orders. The resources available in the literature which consider interdependence in the inventory planning can be split in two main categories:

- Studies about joint replenishment take advantage of the correlation of the demand to minimize the ordering or setup costs and transportation costs. Unfortunately these techniques are not useful when items are provided by many suppliers. As described in the Introduction, for what concerns the case studied here, accessories are both manufactured in-house as well as ordered from a large number of outsider suppliers.
- A small number of studies describe similar problems but under different conditions. In particular some of them assume that parts belonging to the same order can be shipped separately to the customer if some item is not immediately available. Other works consider other inventory control models.

1.4 Review of Prior Instron projects

In the past ten years three MIT graduate students have completed research internships at Instron working on inventory control and operations management. The theses of D. Wheeler, G. Caterino and H.T.Nguyen are outlined below.

The purpose of Wheeler was to optimize the EM grip inventory by applying queuing theory, optimization techniques, supply chain rationalization and simulation models[3]. In particular the author, together with a project improvement team, achieved a thirty-percent reduction of the inventory for the 56 EM grips belonging to the Instron product line at that time. They implemented a pull production in the grip assembly job shop by setting up stock shelves for finished goods and components within the shop from which the parts were removed to fill the orders. When the level of finished goods drops below a specified quantity (the reorder quantity) the mechanic is signaled to replenish it. Moreover as the components to build the grips, which are drawn from the bins on the shelves, drop below the reorder point, the planner receives a signal and replenishment orders are placed. Reorder quantities and lot sizes for the finished grips and some components were provided by the Economic Order Quantity (EOQ) and the continuous review (Q,r) models. These models were applied on the most significant components which had been identified by applying the Distribution By Value (DBV) technique[4]. Items were classified as belonging to three different Classes (A, B and C). The most valuable components (Class A and B) were placed under the Q,r control policy, while reorder quantities and reorder points for items belonging to Class C were set respectively to one year's supply and six months' supply for each item.

The second thesis objective was to improve the responsiveness and flexibility of the assembly process applying elements of Lean Manufacturing[5]. With the use of Kanban control in assembly, daily production schedules based on demand rate and decision rules to guide the work process, the assembly throughput times have been reduced by 40% on average in the final assembly operations. Changes to the physical assembly environment have been made in order to increase flexibility of the output. The author proposes an inventory policy to coordinate in-house inventory levels with manufacturing demand and improve the coordination with external suppliers. The policy, similarly to Wheeler's work, is based on a (Q,r) model and DBV and is tailored on a small number of finished good items (three selected product families). Its application on a pilot process showed a 15% reduction in the required floor space for an equivalent manufacturing output.

Nguyen in his work has tried to improve the service level by implementing lean initiatives in the plant[6]. Root cause and Value chain analysis were carried out in the plant to find opportunities for improvement. A material replenishment model was proposed that would help the company effectively pull parts from the suppliers. Lot sizes were determined according to extended economic order model quantities adjusted using Lagrange multiplier to account for multiple parts being manufactured at the same time. For the inventory control, continuous review policy is proposed for the EM business so that low safety stock can be kept and probability of stock out can be reduced.

In the next sections, the problem has been cleared defined qualitatively and quantitatively. Literature review for the work has been summarized in the next section. It highlights all the text that was helpful in understanding and interpreting the problem better. Next, the methodology to study the problem has been introduced which introduces the thought process used to develop the approach and then the steps that were followed, how data was collected and how it was interpreted. Finally, the problem was solved using the method highlighted in the above mentioned section and results obtained. These results after proper validation are discussed in the results section with some recommendations.

2. Problem statement

The project goal, shared among the four group members' theses, is the definition and implementation of an inventory control framework for the EM accessories stored in the Norwood facility. The result of this work is enabling the inventory planners of the Configuration Department to stock the optimal mix of accessories in order to guarantee a satisfactory service level to the customers and minimize the inventory cost.

2.1 Project Objectives

The project specifications provided by Instron are listed below:

1) Analyze the accessory level offerings based on customer demand and sales volume.
2) Determine finished goods inventory level for each accessory.
3) Develop and implement an internal finished goods replenishment model based on a *pull* strategy.
4) Coordinate with Supply Chain group to insure Kanban quantities support for the finished goods model.
5) Identify and procure any needed tooling.
6) Determine and implement any layout changes.
7) Measure and monitor results.
8) Make it visual and involve factory employees.
9) Identify key performance indicators.

2.2 Designing the Optimal Inventory Policy

In order to meet the specifications, the problem has been modeled and its critical elements have been identified.

A first challenge for this project comes from the large amount of accessories to control: more than 800 finished goods concern the Configuration Department and include grips, fixtures, faces, extensometers, couplings, adaptors, computers etc.

Some of them are assembled in the Norwood facility, while some of them are purchased parts or assemblies. The large number of components that constitute each finished item and the large number of vendors that supply Instron represent a further source of complexity for the analysis.

In the previous theses performed at Instron, a simplification of the large amount of parts considered was provided by Distribution By Value (DVB) and 80/20 techniques, which are described in Chapter 4, allowing the authors to focus on the most significant ones in terms of value or profitability. Since the 80/20 analysis is a currently widely used and appreciated tool within the company, the team decided to adopt it to perform an analysis of the demand, measuring volumes and profits.

As described in the Introduction, demand has two components: Systems and OTC. This allows the problem to be split in two separate analyses.

For OTC accessories customers expect immediate shipment. Since the OTC market is more sensitive to competitiveness, an effective control strategy is critical to provide customers with a satisfactory service.

The Systems market, instead, is characterized by longer waiting times expected by the customers and less external competitiveness. However all the parts of the machine must be shipped together, with rare exceptions, and if a part is missing the order is delayed. In fact most of the times customers cannot perform their tests if a part is missing, and in every case splitting the shipment of an order is costly and not desired by the company. In 2008 no more than 4% of the Systems orders got split and this percentage is meant to decrease.

While the OTC market can be analyzed considering individual profits and volumes for every item, an accurate model of the Systems demand should take into consideration the inter-correlation among products. This suggests that the demand analysis for systems should also account for the importance of an accessory as purchased together with critical items. The *Virtual Profit* is an index based on combined profits developed by the team to model the inter-dependence of the demands and it is presented in the paragraph 4.3.2.

Since the waiting time expectations for the two markets are different, the inventory levels for the same items must satisfy the two demands. The problem can be thus decomposed in two analyses for the different markets. Once both the stocking quantities are set for both demands a risk pooling strategy can be implemented by aggregating those results.

For both the markets, once the 80/20 analysis has provided a measurement of the criticality of the items within the product list, the proper inventory control policy for the items must be identified. Constraints to this project are given by the fact that the Norwood stocking capacity is limited and the inventory allowed by the Instron management is less than 2 MOH[1] (Months on Hand) for every item. Thus in order to maximize the customer satisfaction and so the profit, the basic strategy is implementing two different control policies for two different classes of accessories:

- The most critical items will be assembled or purchased to stock so that high service levels will be achieved.
- The less profitable items will be assembled or purchased to order, minimizing their inventory costs.

However the optimal division between items deserving to be stocked and items that will be made to order needs to be found. Another parameter to be set is the desired *Type I service level*, or percentage of customers that will be immediately served, for the first class items. Wheeler [3] suggests to favor the "80" items (those items that concur to the 80% of the total profit/volume or Correlation) and provide them with 0.95 Type I service level. Unfortunately there are two reasons why this is only a suboptimal solution:

[1] Months on Hand = 12 (Average Inventory Value on Hand / COGS)

- The 80/20 curves usually show one or more steps in the distribution of volumes or profits, so that the division between most important and less important items is quite clear. This is also valid if the quantity measured is the Correlation. However the step does not necessarily occur at the 80% of the cumulative profit: its position can vary depending on the situation. Setting the threshold at 80% would lead only to a suboptimum.
- The 0.95 Type I service level was set accordingly to the Instron management which found it reasonable. However assigning a constant service level for all the make to stock parts is certainly not the optimal strategy.

This issue can be addressed designing an optimization problem which would allow splitting the items in the two classes in an optimal manner, setting at the same time the service levels for the for the first class items.

There are several factors that the problem must take into account. Firstly storing parts has a cost in terms of space, handling and cash blocking, in general referred to as *holding cost*, which has to be minimized. Moreover there are items which are more worthy to be stored than others because give a larger profit (on their own or being sold with other items). In order to consider the described issues the stock level for each item i will be determined by maximizing the expected total profit generated by that item. A model of the expected total profit is given by the expected revenue minus the expected total costs.

The expected revenue for each product can be found by multiplying its unit cost by its expected sales $E(S_i)$, which are a function of the demand rate and the number of items in stock. Note that the past and future expressions of the demand are not available since the sales lost because of the waiting time quoted are not registered and forecast is not used at Instron. Historical sales are the only information that can be found. For the purpose of this project we assume that the expected demand is equal to the past sales. The effects of this assumption are mitigated by the pull strategy that (Q,r) represents causing the actual demand to drive the inventory control once the control parameters are chosen.

Moreover, since customers are willing to wait a variable amount of time if the parts are not immediately available, sales are also function of the *delay acceptability* w_i, or the percentage of customers that would still buy the item if it is not in stock.

Currently, the production lot sizes or reorder quantities are determined based on their value and historical demand without taking into consideration the lead times. Though suppliers have a negotiated contract with the company, they are usually supportive of the lot size requirements. In order to guarantee the selected service levels to the customers, one of the components of the solution consists in making sure that these quantities are enough to satisfy the demand over lead time with satisfactory probability.

Finally, the raw materials control is evaluated. Based on the finished goods production, the raw materials inventory control has to be synchronized and the parts have to be available with high probability. An optimized policy is proposed in order to guarantee the necessary support to the finished goods replenishment model. The optimized policy requires knowing the suppliers' replenishment lead times; this requires data collection and accuracy. The raw materials control is evaluated by comparison with the current policy.

The resulting optimal strategy is evaluated in its costs and benefits: a simulation tool is designed in order to test and validate the control policy and compare it with the current situation.

In order for the finished good inventory policy to be implemented and utilized by the Instron workers in the future, the control parameters must be periodically computed and adjusted. For this reason the analytical tools used for this work are designed for reusability and robustness, as well as easiness of use and compatibility with the data and tools available at Instron. The tools must take into consideration adjustments for new products introduced in the product line and for dismissed ones. In fact the introduction of a new series of accessories with a partial substitution of some old one has occurred this year and can occur again in the future. The implementation of the strategy in the Configuration Department, including the physical arrangement of the stock bins and the Kanban cards, and the training of the workforce are part of this work, are part of this work, in order to guarantee that the strategy is correctly understood and continued.

3. Literature Survey

3.1 Introduction

Since our first contact with the problem, it was clear to us that its set of features and objectives made it a very particular challenge. The theory we learnt from classes and from Simchi-Levi et al. 2000 [7] guided us to the choice of a (Q,r) policy but the standard set of assumptions used to determine the parameters Q and R did not fit our problem. In particular the correlation between the demand of the various products, the fact that many items could be sold both alone and in a system order, the fact that a system order cannot be shipped unless all the items are available and the fact that customers have different expectations on acceptable lead times for different items required a new approach to solve the problem. Many of these challenges are somehow considered in literature but often with a different objective and anyway, to our best knowledge, they have been never considered together. In 3.2 we briefly discuss the vast literature about the (Q,r) policy which constitutes the basis of our work; in 3.3 we present papers which faces the demand correlation issue; in 3.4 we argue about the usage of some papers regarding the customers' expectation issue; in 3.5 some references about simulation are presented.

3.2 The (Q,r) Policy

In those cases in which the inventory is reviewed continuously (in opposition to periodically) a heuristic control policy which has been well-studied in the last several decades is the so called "Q,r" (sometimes also named r,Q or in other ways). The basic idea is that whenever the number of items held in inventory drops to or below r an amount of Q units of goods is issued to replenish the system. Hadley and Whitin 1963 [8] present an exact solution to the problem when there is a known penalty cost assessed on each unit backordered and they provide, under some assumptions, two approximate iterative heuristic solutions.

During the following decades the Q,r policy has been extensively explored in literature, many of the original assumptions have been relaxed and many of its properties proved.

In particular important convexity results are given in Zipkin 1986 [9] and Federgruen and Zheng 1992 [10] and the existence of such results justify the research of optimum values. Also, interesting convexity results are proved in Wang and Li 2007 [11] for the discrete demand and inventory case.

3.3 Correlated demand and inventory management problem

3.3.1 Correlated demand and job-fill rate

Demand correlation among different items and its effect on inventory policies is a key aspect of this work. Even though it is common in real-life multi-item inventory systems, this phenomenon has not received a large attention in the existing inventory literature. We were able to find some papers related to the problem we are facing but none of them could directly be used in this case either because they pose different objectives or they are firmly based on a set of assumptions which does not apply to Instron case.

One of the first papers to focus on similar problems is Smith and Chambers 1980 [12]. In such work in fact it is introduced for the first time the concept of "job-fill" (in opposition to "part-fill") rate criterion in this context. The paper deals with the determination of the appropriate collection of parts to be carried out to repair a machine. As in our case if only one part is missing the order cannot be completed (the machine cannot be repaired). In that case the cost associated with not being able to complete a given job due to unavailable parts is related to a longer downtime for the machine (the repairer has to go back to the warehouse and return on site again), in our case it is tied to the customer unsatisfaction and the resulting risk of losing the order. Such problem was already known at the time as the "fly away kit problem" or the "submarine provisioning problem", however these previous papers traded off shortages against part-fill rate instead of order-fill rate. Smith and Chambers is then an interesting article but doesn't consider all the issues present in our case because the correlation is not considered as the failures of different part types is assumed to be independent [12]. However, other than for the "job-fill" rate criterion, is very useful to us also for a theorem about the importance of ranking the items before considering an optimization problem [12].

Using Smith and Chambers' "Job-fill" rate criterion, Zhang 1999 [13] studies the expected time delay in multi-items inventory systems. In such paper the demand is assumed to be correlated across items and customer satisfaction is measured by the time delays seen by the customers. As a result, an exact expression for the expected total time delay is derived. Also, it is shown that when items are actually correlated, assuming items are independent leads to an overestimate of the total time delay. This however assumes that the parts can be sold separately if some of them are not in stock. In this sense it is shown that demand correlation is in fact an opportunity that should be exploited. In our case, because an order cannot be shipped unless all the parts are available, the demand correlation is an issue.

3.3.2 Correlated demand and joint replenishment

The point of view presented in [13] is common to many other papers that deal with correlated demand. In fact many papers who consider demand correlation are focused on joint replenishments policies such as Liu et Yuan 2000 [14], Feng et al. 2007 [15] and Tsai et al. 2009 [16]. In particular [14] specifically considers the can-order policy for a two-item inventory system with correlated demands. Unfortunately joint replenishment doesn't specifically help with the problems that Instron want to solve in its EM department and, even though it can still be beneficial, its usage would add a large amount of complexity and would allow very small benefits, if any. In fact, as regards items manufactured outside the company Instron has a very large number of suppliers and buys from each of them a very small amount of different products. Moreover, as regards items manufactured inside the company, very small setup costs are involved and the assembly is mostly make-to-order. In other words in the papers which focus on joint replenishment the objective is reaching a balance between ordering costs, storage costs and stockout costs while in our case ordering costs are not significant. The same considerations about joint replenishments also apply to [15] and [16]. Specifically, [15] formulates the problem as a Markov Decision Process and focuses on joint replenishment and correlated demand, proposing a moving boundary based policy and comparing it to other control policies. Tsai et al. [16] instead propose a clustering algorithm to deal with demand correlation which is similar to a first possible solution, later abandoned, that we considered to solve our problem. Such paper claims that it is difficult to define the demand correlation between items, especially when the number of items increases and for this reason a clustering algorithm is proposed. Such algorithm is used to find an optimal clustering result which is used to determine the parameters of a can-order policy in presence of joint replenishment. The result is then tested through simulation and sensitivity analysis, two steps that are fundamental also in our approach.

3.3.3 Previous work with different assumptions

As said the literature which deals with correlated demand is relatively small and a good part of it is focused on joint replenishment which is not useful in our case. However, some papers are closely related in their intent to our work, although not directly applicable due to different assumptions. Hausman et al. 1998 [17] has very similar problem statement to our as it is said that the objective is to "configure a proper combination of component item inventories so that availability of component items is ensured at pre-specified levels to avoid order fulfillment delays". Unfortunately this paper considers a periodic review order-up-to policy and so is not compatible with continuous replenishment. Anyway the paper contains some very interest ideas and some theorems and lemmas which can be considered also in our case. Very close to our objective is also Wang et Hu 2008 [18] which studies the application of a (Q,r) policy with budget constraints and optional components. The budget constraints, at least in the way they are formulated in [18], are not of primary concern in our case but the approach proposed is still very interesting. Unfortunately two of their assumptions are not verified in our case: it is not true that the payment is due at the time an order is placed (but this problem could be overcome) and most importantly it is not true that the customer will purchase a system without optional components when the optional components are out of stock. Optional components are in fact, in the majority of cases, necessary to use the Instron machine and no one would buy a machine without them.

3.4 Customer defection

In this work, the effect of customer impatience (or *defection*) on the inventory performance is studied. Two main contributions on this field are used as references: Gershwin et al. 2009 [19] and Veatch [20]. The main reason why this work investigates the customer impatience is that the number of orders filled (in literature *Type II Service level*) depends on how many customers would wait for a product if it were not in stock. In particular, the number of filled orders is the sum of the number of orders filled immediately plus the number of orders completed because the customers decided to wait and not to cancel the order once they were quoted a lead time.

In [19], a manufacturing firm that builds a product to stock in order to meet a random demand is studied. If a product is not in stock and orders cannot be met, customers are quoted a lead time that is proportional to the backlog, based on the production time. In order to represent the customers' response to waiting, a *defection function* - the fraction of customers who choose not to order as a function of the quoted lead time - is introduced. The defection function is then used to obtain the optimal production policy, which results in a hedging point form. One family of defection functions is studied, a sigmoid function of the form:

$$B(x) = \frac{1}{1+e^{\gamma(x-\eta)}} \tag{3.1}$$

This expression for the defection function is then used to model the system behavior, and will also be used in this work. However, an additional important conclusion is that numerical results suggest that there is limited sensitivity to the exact shape of B(x). Furthermore, the precision of the defection function is limited by the intrinsic approximate nature of what it models, i.e. the customer impatience.

In [20] the same production model, in which the customer is quoted a lead time depending on production time and backlog, is presented as a "nuanced model" of customer behavior, compared to the two extreme models of complete backordering and lost sales, where all the customers either wait or not. One particular production model is considered: a continuous one-part-type, single machine model with Markov modulated demand and deterministic production is considered. Using this particular model, the impact of customer impatience is shown to be captured by one quantity, the mean sojourn time in the backlog states. As in [19], the optimal quantity has hedging point form.

Based on the particular model considered, Veatch shows that the effect of customer impatience can be captured by the only mean sojourn time in backlog, and this simplifies the problem of obtaining an optimal production policy. Given that the effect of customer impatience is captured by the above mentioned quantity, in fact, other simpler customer behavior models can be used, and still the optimal policy is reached.

This thesis analyzes a different model: only some of the products are produced in the factory floor, while most of them are ordered from suppliers. Moreover, the replenishment lead time is random and constraints on the reorder quantities have to be considered. Thus, the assumptions made in [19] and [20] are not valid any more, and the optimization problem is different. Moreover, the two papers do not present any attempt to shape the defection function in the actual industrial application. However, the analyzed work gave some useful insight into the modeling of customer impatience. The suggested sigmoid form is used in this work, and the limited sensitivity to the exact shape of the function is considered. Finally, this thesis considers the use of company-wide surveys in order to shape the defection function to the needed precision level.

3.5 Simulation

Simulation has been used as a validation tool in this work. Monte Carlo is one of the simulation techniques used to validate our results. The principle behind Monte Carlo simulation is that the behavior of a statistic in random samples can be accessed by the empirical process of drawing lots of random samples and observing the behavior [21]. However, care has been taken while generating customer demand. Truncated normal distribution is used to generate demand since it should not go negative in the cases when the coefficient of variation is high [22]. Coakley and Carpenter 1983 [23] have used Monte Carlo simulation to predict final system behavior when it cannot be directly predicted from the inventory models. They validate the model before running the simulation using constant values and matching them with theoretical results. Finally, they use the simulation results to analyze different conditions such as relaxing theoretical constraints and getting the inventory levels.

Jung et al. 2004 [24] have presented a method to determine safety stock levels, which further effect the customer satisfaction levels (service levels), using a computational framework for planning scheduling applications in realistic supply chains. They use simulations to optimize their results when faced with improving customer satisfaction, holding costs and production constraints. Inside the computation for optimization, repeated simulation of the supply chain takes place over the planning horizon, each with given Monte Carlo demand samples. Then, within each of these simulations, a series of planning and scheduling optimization problems are solved.

Grange [25] in his paper pays particular focus to demand distributions of slow moving items. He finds out the misidentifying demand distributions can have a detrimental effect on the fill rate leading to high and lower rates depending on over and under estimation of right tails. He also adds that multi-SKU inventory compensates misidentification by reallocating investment relative to the costs and expected demands of all the SKUs. We have thus, taken particular care in finding out the demand distribution in our case, as highlight in the methods section.

3.6 Conclusion

The problem this work deals with is a particular one and a solution tailored for this case cannot be found in literature. Not many authors focused on demand correlation in multi-items inventory systems and many of them consider a rather different set of assumptions thus being allowed to see it as an opportunity to be exploited using joint replenishment. A few papers which consider a similar problem statement are still not applicable to our case because they differ in some fundamental assumption such as periodic inventory review and optional nature of accessories. Also as regards the customer impatience issue the papers analyzed do not provide a univocal methodology to be used in our practical case but they contain very interesting ideas and results. Simulation was also found to be frequently used both as tool to find a solution and as tool to validate the result found with another method.

In conclusion our problem requires a new solution in order to deal with all its features but the existing literature constitutes a fundamental basis to our work with its ideas, theorems, reasonings and methods.

4. Methods

4.1 Choosing the right methods

The goals of this project are described in detail in chapters 1 and 2. One sentence summarizes them effectively: "having the right mix of products on the shelves at the right time". As mentioned before, this involves searching an optimal inventory control and production policy by considering all the products together, especially taking into account the system orders, thus the correlation among items' demands.

The significant number of items involved and the differences in their supply chains added high levels of complexity to the project. Not only do we want to have the correct "mix" on the shelf, but the implementation of the derived policies will differ depending on the product's type and supply chain. Furthermore, using one's own judgment on each SKU would not provide the company with a repeatable strategy. For these reasons, general and parametric methods always have to be used.

In addition to the optimal policies, important results of the project come from the analysis phase (demand analysis, correlation analysis, customer defection, 80/20). The produced documents, indeed, are important in providing the manufacturing, sales and marketing departments with sources of data which allow effective strategic planning. As an example, knowing which products are often sold together in the last two years, could suggest marketing already customized systems (composed of the products often sold together); if this operation is successful, the company could focus its investment in the inventory for a limited number of products, holding less risk associated with other products. Moreover the results of the analysis performed by the team and provided to the company find an application in the identification of products to discontinue because of their scarce profitability and importance within the product list.

What is more, in each sub-issue addressed by this thesis, the purpose is not only identifying the optimum (optimal inventory control policy, optimal replenishment levels) but also proposing the so called *"good enough"* solution. As widely happens in manufacturing and operations management, in fact, the application of systematically searched optimal policies holds a level of complexity that is not worth the investment. For instance, considering the optimal replenishment methods, agreeing with the suppliers on the optimal reorder quantities for a product could not be feasible or could involve additional investment, and using a QR policy implemented with Kanban cards, that are already used, would be more easily and quickly implementable than different policies that could guarantee a relatively small increase in expected profit.

In conclusion, the work described in this thesis is meant to produce data analysis reports and suitable solutions for the inventory control policies of a significant number of products. This chapter describes the steps that are undertaken in building the analysis reports, in designing the control policies and in collecting the necessary data for the policies to be implemented. The methods used in each step are briefly described in the following paragraphs and then explained in more details in the following chapters.

4.2 Main steps followed

Figure 4.1 shows the main steps involved in the project. Every independent task is represented by a blue filled circle, while the developed software tools are represented by smoothed rectangles. The arrows indicate task scheduling requirements. As an example, let us consider the following tasks: comparison, individual demand analysis and correlated demand analysis. In order to perform the comparison task, the results from the individual and correlated demand analysis are necessary; thus, these two tasks need to be finished in order for the comparison task to be performed. The diagram is a modified version of the PERT diagram which does not show the duration of the tasks.

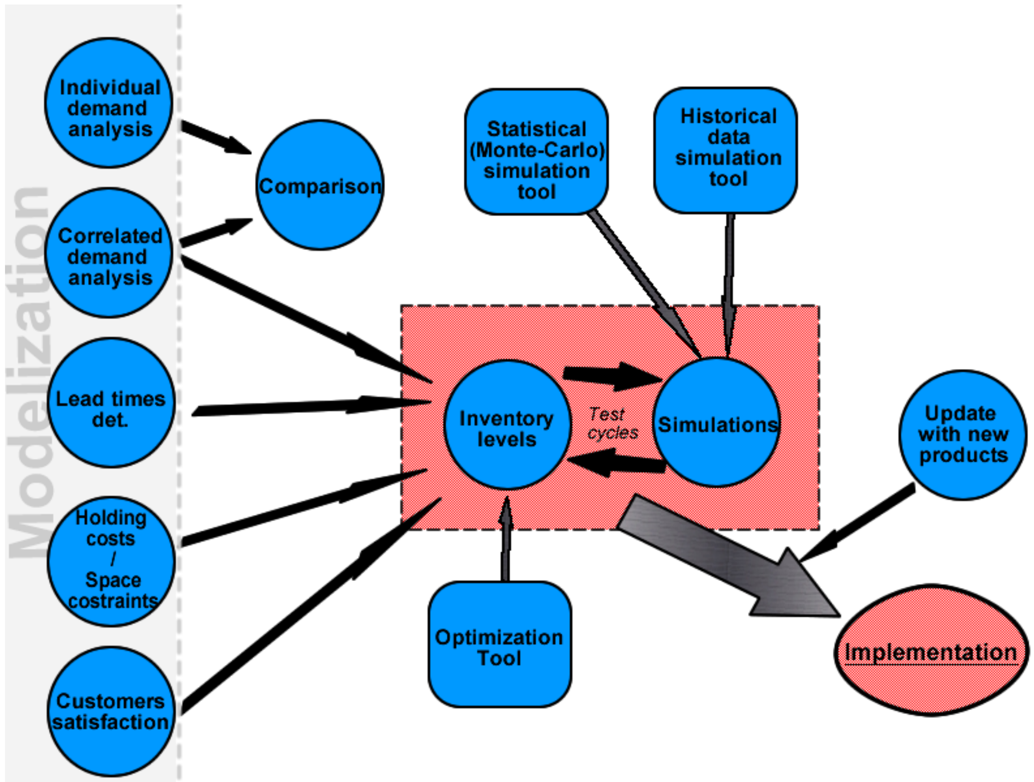

Figure 4.1 Main Project Steps

As previously mentioned, the main outcome of the project consists in data analysis reports and recommendations for inventory control policies. The most important reports are obtained in the steps *Individual demand analysis*, *Correlated demand analysis* and *Comparison*. In these three steps, demand analysis of all the involved products is performed, at first simply by volume and profit, and then considering how they correlate to each other. Finally the results are collected in a Comparison report, meant to underline the importance of the correlation. The step *Inventory level* involves designing the control policies, while the performance of these policies are estimated in the step *Simulations* and implemented in the step *Implementation*. The importance of these two final steps is highlighted by the orange box in the diagram.

The left side of the diagram shows the steps needed in modeling the system. In order to design the inventory control policies, the following information is needed: lead times for each product, profit and correlation analysis, holding costs, space constraints and a model of the customer satisfaction. All this information builds the model of the system, used to find the optimal solutions.

The remaining part of this chapter describes the goals of each task, the approach to it and the methods used.

4.3 Explanation of the tasks

4.3.1 Individual demand analysis or Pareto analysis

This task involves analyzing the orders placed in 2008 and 2009. The list of orders, together with the associated quantities and prices, is used to perform a demand analysis based on both profit and volume. The purpose of this analysis is to find the most important products and the least profitable ones. The results are useful to the company in showing the updated data on volume and profit made by the products during the last two years.

The *Pareto principle* (also called *80/20 principle*) is a heuristic principle that is often applied in analyzing profit and volume in operations management (the Pareto analysis). Applied to profit, it states that about 80% of the profit of a company is made by only 20% of the products it sells. The products belonging to that 80%, which are the most profitable ones, are called the *80s*, while the remaining products are the *20s*.

For the purpose of this analysis, the products are divided in six different categories: grips, fixtures, faces, coupling and adapters, compression anvils and anvil sets and other accessories. The first step of the analysis involves summing up the profits made by each product in all the orders and determining the total quantity shipped in each year. A report has been given to the supervisor, in which the most profitable items were identified through the Pareto analysis. In addition to this, the least profitable items were highlighted in the report: all those products which belong to the bottom 1% of the profit or were sold at most twice. This result is important to identify items eligible to be discontinued. However it does not provide a measurement of their criticality within the product list. The Correlation analysis, described in 4.3.1, provides a more accurate result.

An expanded discussion of the Pareto analysis has been carried out in Palano, Ch-5 [26].

4.3.2 Correlated demand analysis and Comparison

As mentioned earlier, the design of the optimal policy is complex because it has to encompass a very high number of different accessories that are often sold together in the system orders (when customers buy a machine and choose a set of accessories with it). Moreover, the above mentioned individual demand analysis is less accurate than necessary because it does not take into account the system orders.

As an example, two products X and Y can be considered. If X is an “80” item and Y is one of the lowest profit items, the individual demand analysis would suggest holding less inventory for item Y or even making it to order. By considering the system orders, however, we could find out that product Y is often sold together with X, and is less profitable because it is discounted or relatively less important. Holding lower inventory levels for item Y would then be a losing strategy, because it would block the orders of X and create additional profit loss.

In this project, the correlation between different products is considered in designing the control policies. The goal is obtaining a profit indicator which quantifies the profit made by each product if in stock, or quantifies the loss realized by not having it in stock for a given period of time. A MATLAB function, using the IBS reports with all the orders of 2007 and 2008, calculates how many times each product is sold with any other item and quantifies this expected profit.

New profit indicators were obtained considering the correlation, and a new analysis report was generated (step *Comparison*). This report shows what are the most profitable items and what are the ones which are still in the bottom 1% of the profit after considering the correlation. As mentioned in paragraph 4.3.1, this report completes the analysis of the items to be discontinued, together with the 80/20 report.

An expanded discussion of the correlation analysis has been carried out in Serra [27].

4.3.3 Lead time, holding costs and space constraints

These three steps involved data collection, which is necessary to design the control policies. The data collection methods, including holding costs and space constraints, are further explained in chapter 4.4 of this thesis.

By working with the supply chain managers and using the IBS tracking system, at first we tried to obtain a list of lead time values for all the products involved in the project. The term "lead time" was used in a more general sense, indicating replenishment lead times for purchased parts, manufacturing run time for manufactured or assembled parts, and collecting time for catalog numbers that actually are a kit of items. In general, the term, lead time, indicated the total time needed for a product to be again on the shelf when required.

4.3.4 Customer satisfaction

In order to maximize the expected profit, the loss for a part not being on the shelf has to be quantified. Let consider the case, however, in which one particular SKU is not on the shelf. The customer would learn that a particular product was not on the shelf and that the total waiting time would be n weeks. Would he still go on with the order? And what if the order request was actually for a system including that product?

In general, there will always be a number of customers who will still buy a product even if the order cannot be fulfilled from stock and a longer waiting time is quoted. This percentage depends on the product and on the type of order, and is a function of the quoted waiting time. This function is referred to as "customer defection". The literature background about customer defection is discussed in chapter 3.

Obtaining this quantity from the data or in any rigorous way is not feasible due to the following reasons:

- Lack of hard data about lost sales
- Customers have different interests, priorities, concerns
- Other reasons (human behavior, complex products interdependence)

Thus, a reasonable estimate is obtained through a survey directed to the sales people, who work on orders with the customers. The starting expression of the customer defection function is a sigmoid, as discussed from the literature, and the function is further shaped by asking general questions and looking for ranges of values through the survey. This function represents the percentage of customers still willing to wait depending on the waiting time that can be offered on one particular item.

An expanded discussion of the customer defection analysis has been carried out in Palano, Ch-6 [26].

4.3.5 Inventory levels

This task involves designing the production and inventory control policies for both finished goods and raw materials.

Two main types of policies are used: make to stock and make to order. The less profitable items will hold lower service levels or be made to order, while for the remaining products stock levels are determined. The choice of the MTO or MTS policy for each item is based on optimizing the profit, and is described in *4.3.6*.

The most suitable make to stock inventory control policy is the QR policy (or *reorder quantity*). One reason is that the inventory at Instron has always been managed through two quantities: the so called *minimum quantity*, corresponding to the safety stock, and the reorder quantity. Even if these quantities were obtained with rules of thumb, they are used to set a safety stock level and reordering when the levels go below the minimum quantities. Moreover, an increasing number of parts are being managed by *Kanban cards*, which is an automatic inventory replenishment method. When the inventory level reaches a minimum quantity, the corresponding card is put on a board and it will automatically trigger the order of a predetermined release quantity from the suppliers. This system is easily updatable once the new optimal values for Q (reorder quantity) and R (reorder point) are derived.

The reorder quantities are determined in such a way that they cover the demand over lead time with a probability of 99.87%, still satisfying eventual constraints on the lot sizes. The optimal reorder points, on the other hand, are calculated from the lead times, the average demand, the values of Q and the desired service levels. While lead times and average demand are obtained in the data collection phase, the service levels represent our degrees of freedom in designing the policy. For the finished goods inventory, these levels were chosen by optimizing the profit, as described in *4.3.6*. The raw materials inventory control, instead, is designed in such a way that the service levels are always high, in order to support the finished goods production.

An expanded discussion of the raw material inventory control has been carried out in Palano, Ch7 [26].

4.3.6 Optimization

The available degrees of freedom in designing the FG inventory control policy are given by the service level corresponding to each item (Type I service level, defined as the percentage of time the inventory for a certain item will not be empty, thus being able to meet demand) and whether each product will be made to stock or made to order (MTS or MTO).

These choices are determined by solving an optimization problem. The goal function is the total expected profit, defined as total expected profit coming from sales minus the inventory holding costs. The total expected profit coming from sales is calculated considering the correlation between products in the same orders (as described in *4.3.2*), while the inventory annual holding costs per item are multiplied by the expected inventory levels in the QR policy.

The result of the optimization tool, implemented in Matlab, is a list of optimal service levels for all the items. If the optimal service level for a particular product is lower than a certain limit than the final suggestion for it will be a make to order policy.

An expanded discussion of the finished goods policies optimization has been carried out in Facelli, Ch5 [28].

4.3.7 Simulation

An important step in studying the optimal control policies is the simulation phase. It allows us to test the designed strategy in order to check its feasibility and to estimate its performance measures (actual service level obtained, months on hand of average inventory).

The simulation tools are used both as design aid and as final performance measurement that helps in selling the proposed recommendations. The simulations are implemented in two different ways: at first simulating random demand with a discrete probability distribution with the actual mean and standard deviation (plus intra-quarter growing average), then by using the actual historical data. The former tests the policy for robustness with a more general background; the latter shows a comparison between the results of the proposed policy and the current one.

The simulation has been discussed in detail from ch-5 onwards.

4.4 Data collection methods and IBS

Most of the tasks undertaken in modeling the system involved hard data collection from the databases of the company. Referring to the diagram in picture 1, these tasks are:

- Individual demand analysis;
- Correlated demand analysis;
- Lead times determination;
- Holding costs / Space constraints;
- Customer satisfaction;
- Historical data simulation tool;
- Update with new products.

The holding costs are obtained from the operations manager and head of manufacturing and through some financial research on cost of capital; the space constraints are estimated talking to the managers and exploring the factory floor. The information about the new products (new item numbers, discontinued items, updated demand forecast) was obtained from to the engineers in charge of the corresponding projects.

The model of customer satisfaction is firstly defined based upon literature and suggestions from the operations management. Then, the model is shaped and refined through a company-wise survey, filled by the sales department and the field engineers, who are the ones involved in the customer satisfaction aspect of sales.

All the remaining tasks involve collecting data from Instron's databases:

- previous years' sales
- product types
- inventory locations
- costs and prices
- replenishment lead times
- manufacturing run times and set-up times
- current reorder points and quantities

The necessary information is collected through IBS. IBS is an Instron database management system that tracks all the information associated with orders and products. For each order placed by customers, IBS contains order number, dates, quoted lead times, standard costs, gross price, discounts and a number of other entries. For each product, IBS contains item number, bill of materials, information about suppliers and planners, current inventory levels and limited inventory level history, lead time and a number of other entries.

IBS is used in all the departments in the company. The sales people, when dealing with customers, use IBS to get the expected lead times, to check what is available in stock, to check prices and costs and to handle orders. The employees working in the factory floor update it when parts arrive from suppliers, when products are shipped, when changes are made to the orders, when WIP inventory is used and a part is assembled and in several other cases. Moreover, all the other employees often use IBS to get required information for analysis purposes or to update it.

In order to collect the needed data, reports are automatically generated by IBS. IBS can be queried with a list of items or orders, and the required information is written on Excel spreadsheets. The result is that every analysis or manipulation which starts from the generated spreadsheets can be easily repeated and updated by using the same type of queries.

4.5 MATLAB implementation and reusability

4.5.1 The need for a tool

The goal of the project at Instron is not only to provide a numerical solution to the problem of which control policy and which parameters should be used. Also, a fundamental goal is to provide a long term solution framework, so that, year after year and quarter after quarter, a new numerical solution can be computed and used. In fact one has to consider that every product has a certain life cycle and that the demand for each of them changes over time. Therefore, it is clear that the "determination of the right mix" is not something that can be determined once. On the contrary, a regular update of the safety stocks levels and inventory control policies parameters is necessary.

For this reason, since the beginning of the project the research team focused on creating a tool that could be used in the research and that then Instron could use in the future to make the calculations and update the policies regularly.

4.5.2 Reusability

The way we see the solution framework is depicted in *Table 1*. On a periodic basis (the choice of the frequency is discussed briefly in the next paragraph) Instron personnel will update the inventory levels. In order to do this, they will export all the relevant past sales data from IBS (the ERP software they are currently using) to an Excel file using a template that we built in IBS. Then, in a similar way, a list containing the lead times, the lot sizes and other information regarding the items will be extracted from IBS. Finally these XLS files will be put into the same folder as our software tool (an EXE file) and by just running it a solution will be computed.

The output will be composed of three files. The first one is an Excel file containing the information that should be used for the Kanban cards, that is to say the reorder quantities and the reorder point that has just been determined. The second file is a *Correlation report* that is to say a description of the items that were most often sold together which is useful for Instron personnel to understand the demand and what drove the suggested inventory levels. Finally, the third output is an *80/20 report* in which the items are divided by category and ranked by their virtual profit. Also this report will help to explain to the people the re-order quantities determined by the tool and it will also suggest which items can be suppressed without losing, both directly and indirectly, much profit.

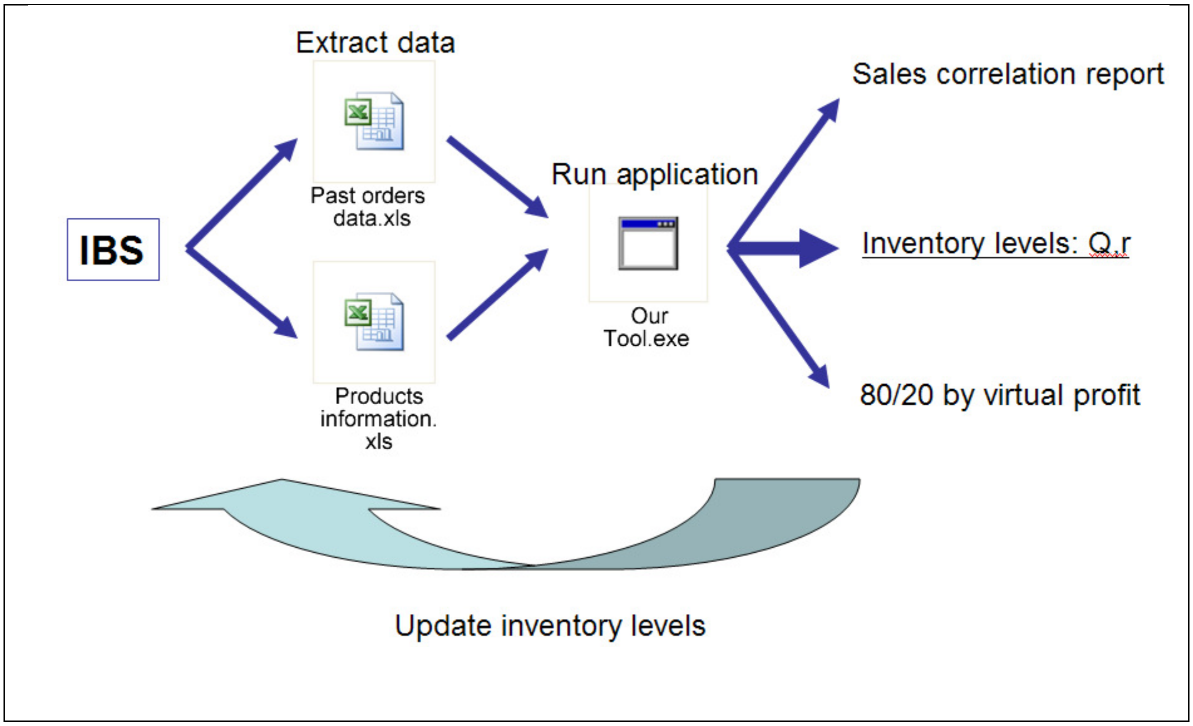

Figure 4.2 Tool Reusability Framework

4.5.3 Frequency of stock determination

There is a trade-off in the frequency with which the inventory levels should be re-computed. In fact, on one hand the higher the frequency with which the inventory is re-determined, the best the inventory levels will theoretically perform because they will use the most recent demand information. On the other hand, re-determining the levels involves a certain effort from Instron staff and represents a cost that can balance the advantage of using more recent data. To determine the new levels in fact some data has to be gathered as described above and the computation has to be started. Then the resulting suggested reorder quantities has to be compared with the ones currently in use. If an "R" needs to be updated, then the Kanban card currently used for that item must be reprinted and substituted on the bin.

As seen, a trade-off exists and the correct time does determine new levels depend on the effort necessary to physically update the inventory levels. As a first guess, we think a frequency of 3 or

6 months seems reasonable, unless some of the determining factors (the demand or the lead times for example) will at some point drastically change.

4.5.4 Matlab implementation, reusability and flexibility

The tool described above is built in the Matlab environment and then compiled as an executable file. The choice was suggested by our familiarity with such environment and its power and abundance of mathematical functions. As regards the part of the code which deals with data crunching a C code would have probably been faster but in such a language the optimization part would have been harder to code and, overall, the time required to build the tool and test it would have been much longer. Because in our case the quickness with which the tool was to be built is very important while the computation time required for every run is not particularly significant (as seen the tool is going to be run a few times per year), the choice of Matlab seems to be the best one.

Moreover, Instron owns many Matlab licenses for other reasons so such software is and will be available to the company without any added cost. This is an important issue because, even though we want to give an “easy to use” – “black box” solution, we also want to provide the source code that could be checked and modified in the future and while to run the exe file Matlab is not necessary, to modify the source code is.

5. Simulation Introduction

Simulation has been used as a validation tool in this work. A simulation contains a set of mathematical models of one or more dynamic systems and the interactions between those systems and their environment [29]. Generally, when a simulation is executed, it moves through time and the system is solved at each time step. This monitoring of the system being modeled using virtual techniques is termed as simulation. Since, the system involved in our case is very complex, simulation is the only way to validate our results.

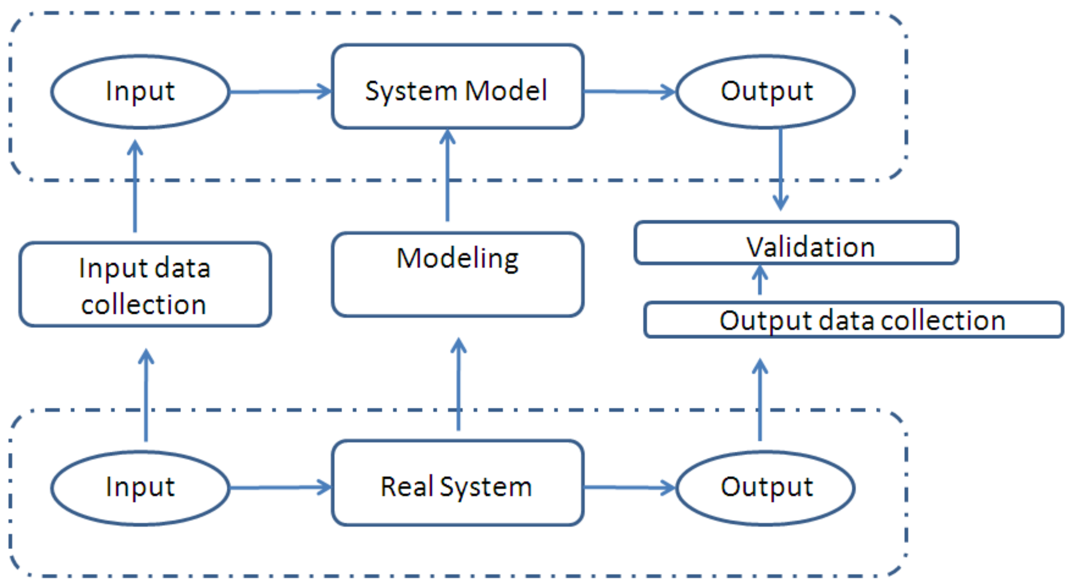

Figure 5.1 Simulation-Real World Interaction (source: Gallien[30])

As shown above, simulation is a representation of the real world and has three main components: input, system model and the output. Input into the simulation is extracted from the real input data. System model is developed from the real system by making some simplification assumptions so that the simulation can be mathematically implemented. After running the simulation, outputs are obtained which can be validated from the results of the real system.

Since simulation is a recreation of a specific activity in the universe, one should be sure that the virtual model created is a true representation of the system. Also, a model should be created which is easily implementable in a computer code but at the same time it should not be so simple that it deviates from reality. Thus, it is essential to understand the problem before undertaking any simulation activity. Gallien recommends the following steps as a systematic approach to start a simulation activity [30]. These steps if followed correctly and in order will lead to beneficial and believable results for the factory floor.

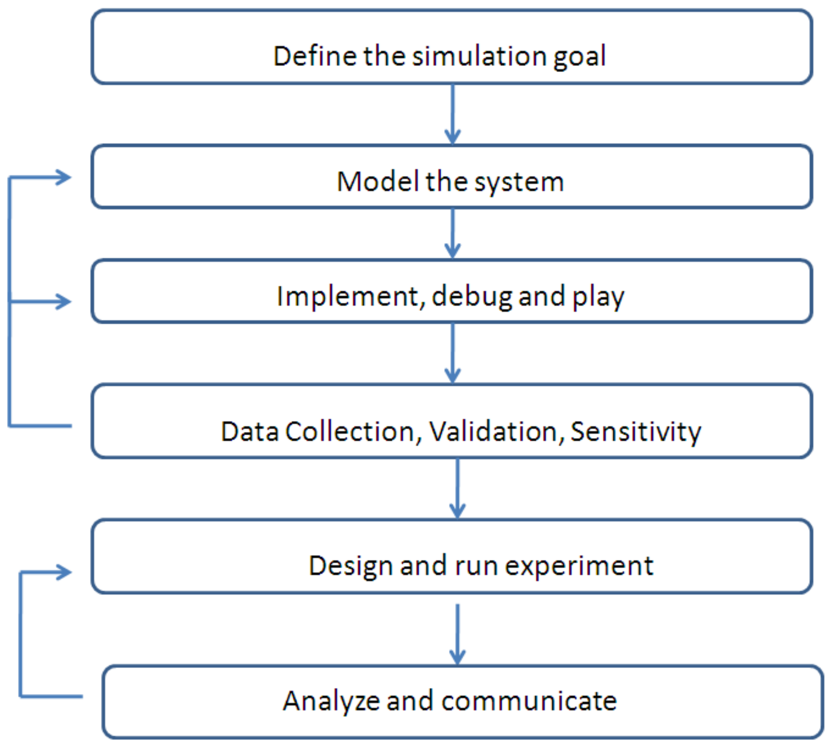

Figure 5.2 Simulation Process Flowchart

It is essential to define the goal of the simulation before working ahead on it. Creating a correct simulation is a very work intensive process. Thus, it is important to start with a vision of what one wishes to achieve from the activity. This also helps in pointing out that area of the universe which needs to be recreated. After identifying the problem and goal the simulation should achieve, the developer can model the system. It is vital to debug it by carrying out validation tests and some sensitivity analysis, before running the simulation for real data. If errors are found, the system needs to be remodeled. After building enough confidence about the simulation, experiments can be performed and results analyzed. In all the above steps, it is essential to keep on getting customer feedback. This helps in making sure that a correct representation of the real system is being recreated.

5.1 Simulation in a Manufacturing Industry

5.1.1 Challenges in mathematical modeling

Uncertainties in the product demand and supply chain increase the likelihood of reduction in profits. Variable demand can be met by storing excess inventory, but high inventory holding costs will be incurred. Likewise, if low inventory is kept, more customers will be lost. Thus, to hedge against these uncertainties safety stocks and effective supplier contracts are established. However, establishing these stock levels and policies is not an easy task. There are many reasons which attribute to this problem: Firstly, in the real world, the number of variables involved is very high. This makes the problem very difficult to solve by incumbent mathematical formulas since assumptions are made to simplify the calculations which only provide approximate solutions. Secondly, most of these variables cannot be determined easily and do not follow any exact distribution. Such as, product demand depends on market conditions, which itself is dependent on many other variables. Also, sometimes demand of one product is dependent on other products. Similarly, lead times can vary due to supplier or transportation errors or even natural calamities. Thirdly, most supply chains are multiple products sharing multiple manufacturing plants. Thus, it is not easy to represent such variables mathematically since traditional inventory models do not accommodate such detailing. Thus, it is very unlikely to get deterministic mathematical solutions and hence practical alternatives are used.

5.1.2 Simulation as an Inventory management tool

Manufacturing and material handling systems are extremely complex and difficult to understand. Intricacies such as queuing, down time and random consumer behavior cannot be modeled completely using other methods such as spread sheets and linear programming [31]. Simulation, on the other hand, is a tool which can recreate complex systems with very high detail. Also, any manufacturing initiative has high capital costs and organizations need to be completely sure before implementing any new proposal.

Monte Carlo is one of the simulation techniques used to validate our results. The principle behind Monte Carlo simulation is that the behavior of a statistic in random samples can be accessed by the empirical process of drawing lots of random samples and observing the behavior [32]. However, care has been taken while generating customer demand. Distributions used to generate demand must be always positive since it should not go negative in the cases when the coefficient of variation is high [33].

5.2 Problem Description and Goal

As discussed in the problem description and methods section the factory floor has been modeled into an optimization problem to include the effects of lead time, customer satisfaction, capacity constraints and inventory holding costs. However, solving this is not easy since much of the above data is either inaccurate or unavailable. It is not possible to reach a confident solution by just solving the optimization problem alone and hence simulation is used as a validation tool to confirm if the solutions obtained from the optimization do create a positive impact i.e. low inventory and better customer satisfaction. Thus, a discrete variable dynamic simulation is developed. Broadly, the goal of the simulation is to validate the results from the optimization and perform a robustness analysis on the final results.

The simulation recreates the orders executed by the manufacturing floor using the proposed inventory management policy. Thus, in order to model the manufacturing floor, its critical elements need to be identified. Since all of the departments on the floor work in coordination, the interconnections must be highlighted beforehand. This helps to better understand the constraints of the configuration department.

5.2.1 Material Flow

The flow of the product on the factory floor is shown in Figure 5.3 which is further explained below:

Receiving Area

In this area, all parts are received from the suppliers by the department leader and his helpers. They receive the parts from the suppliers and count everything. If the count matches with the quantity mentioned, the parts are entered into the IBS system (internal inventory management software). The system then generates receiving tickets, which are pasted on the carton containing those parts. After a day of collection, items are dispatched once a day to their respective departments.

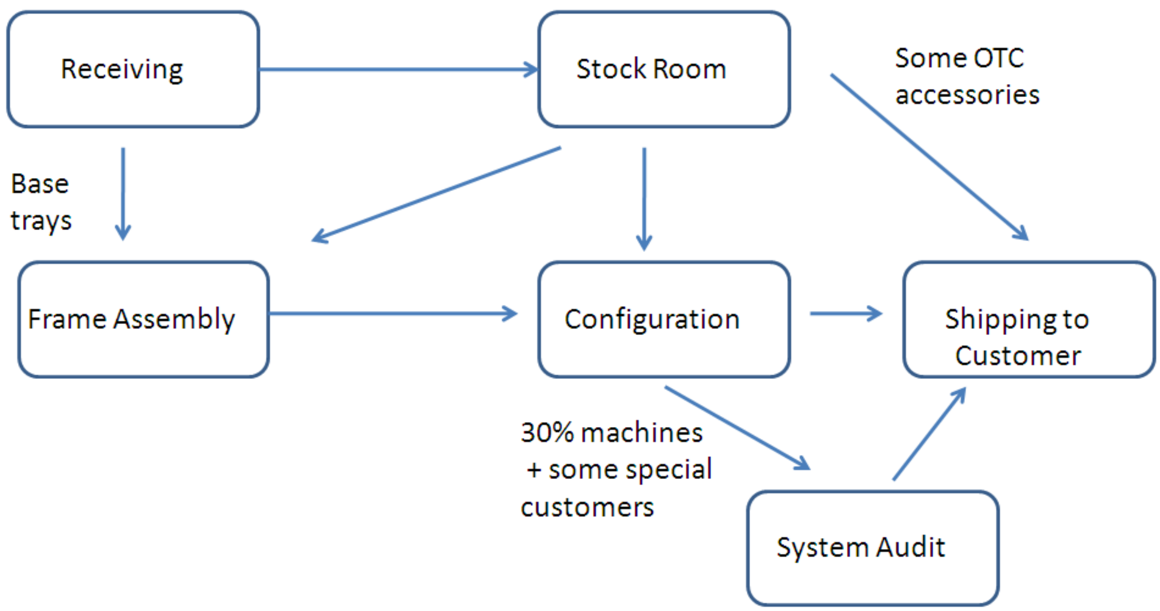

Figure 5.3 Flow of material on the factory floor

Stock Room

Stock room is the heart of the supply chain. All the inventory flows through it, except a few emergency items, which are taken directly to the required department. The stock room facility keeps the entire inventory at one place so that the factory floor does not get clustered. The OTC accessories are stored here.

Frame Assembly

In this area the different equipment are assembled on the base tray and fully assembled machines are given as output. However, the assembly line is not rigid. Two models are made in one assembly line: double column machines and single column machines. There is another assembly line which is dedicated to the floor models, since they have a very high lead time. The assembled machines are then marked as “Ready for configuration” and kept at the end of the assembly line

Configuration Area

This area deals with customizing the machines according to the wishes of each customer. The assembled machine from the frame assembly area is kept on a cart and brought to this area. Then, all the accessories requested by the customer are gathered and checked off from the list accompanying the machine. There are various accessories which can be requested by the customers such as extensometers, special softwares, grips, extra load cells and grip faces. All these items are either made in the configuration area – in the grip cell – or imported from the stock room in boxes named by the management as *tote boxes*.

System Audit

System audit means carrying out a complete assembly of all the accessories on the machine to see that they fit completely. This is carried out on 30% of the assembled machines randomly selected by the IBS system. Moreover all machines going to countries where Instron does not have customer support centers are audited.

Shipping

The shipping department packages the machines and the accessories so they can be carried by the freight carriers. The shipping department also functions as a final check-post for the machines. If the full payment has not been made, the machine is put on a *credit hold* and barred from leaving the facility.

5.2.2 Information Flow and Order Processing

In the flow diagram shown in figure 5.4, the information flow is represented in the color blue and the material flow in the color black.

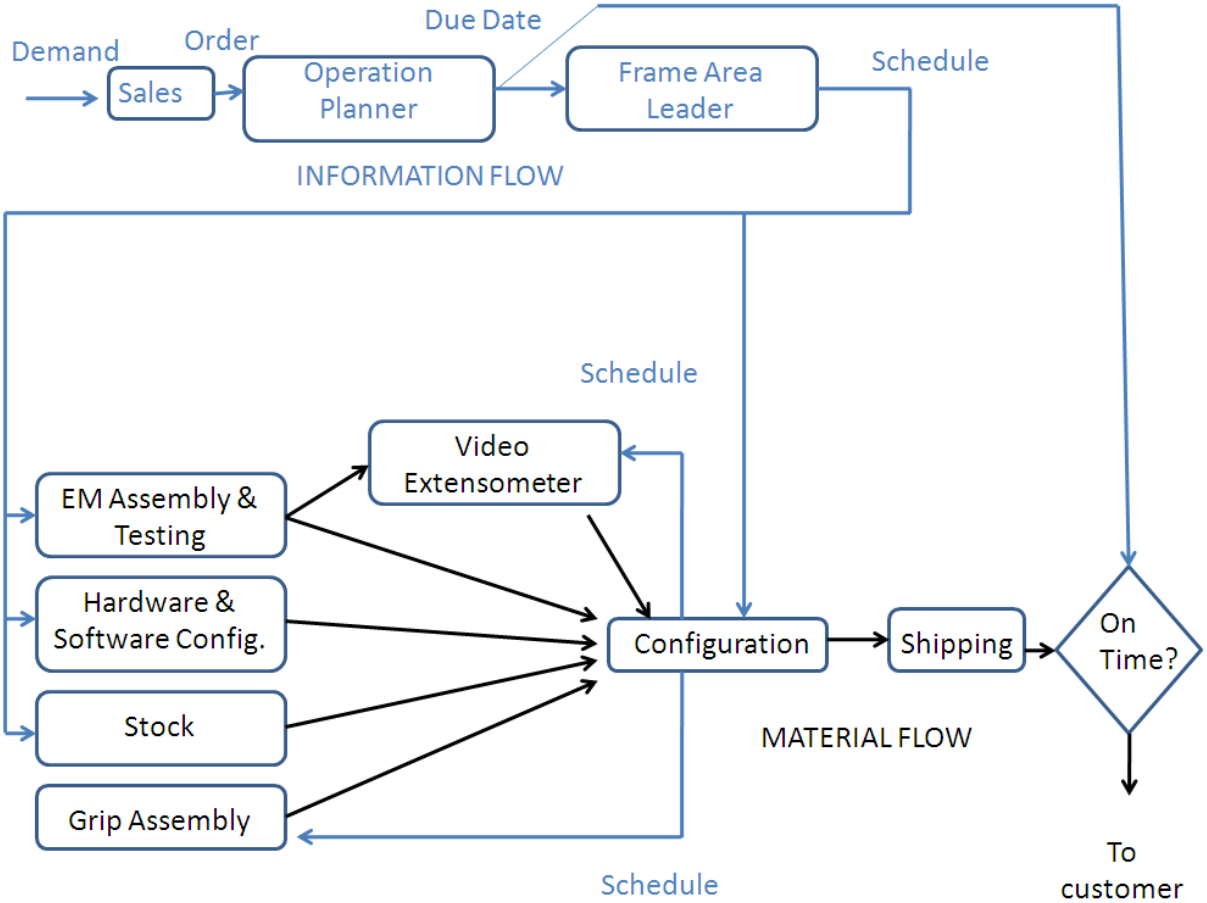

Figure 5.4 Material and Information flow

The diagram shows how a sales order inputted in the system by a sales representative flows through the factory floor. The operation planner receives these orders and determines the due date according to the availability of the inventory items, other order commitments during that period and capacity constraints. The sales representative then conveys this information back to the customer who accepts or rejects the proposal. The information is then sent to the leader of the frame assembly area. He disburses the information to the different departments, so that they can be ready with their respective parts. Then, finally, operation planner keeps a watch if the products are shipped by the due date.

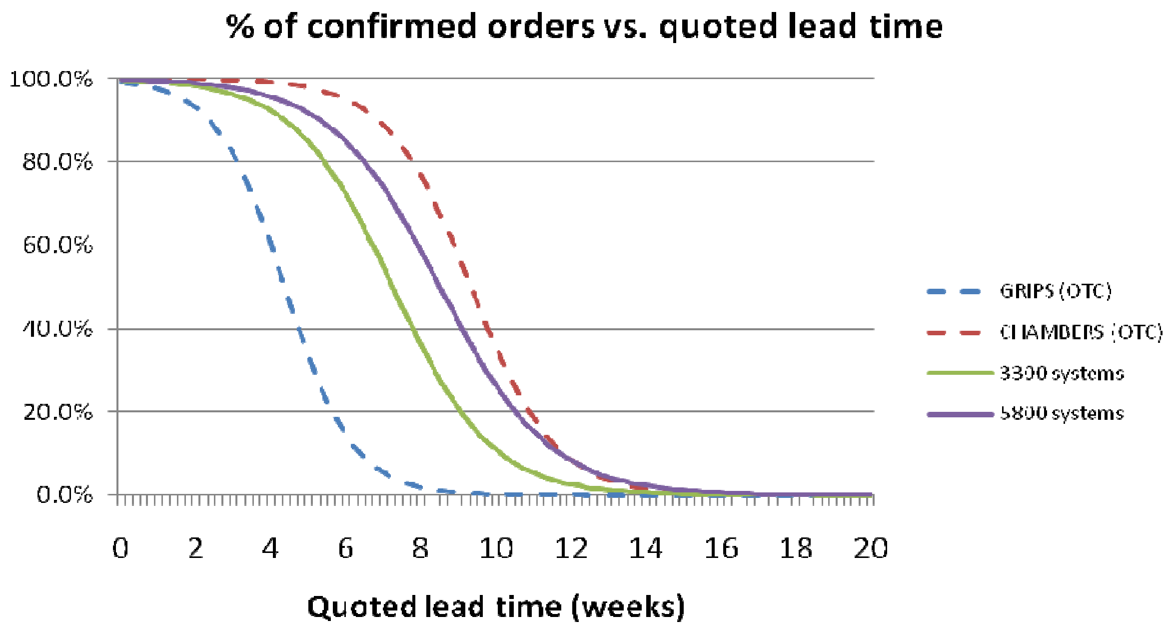

Figure 5.5 Customer Satisfaction: Customer's Willingness to wait

The acceptance or rejection of lead times by the customer has been modeled by Diego Palano[26]. Customer satisfaction over lead time can be approximated to fit a sigmoid function shown above. As we can see that customer's willingness to accept longer lead times is greater for systems order as compared to OTC items. If the customer accepts the proposal, 99% times he receives the orders when promised. Sometimes, the orders get delayed due to the fault of the manufacturing department or the customer's inability to mobilize financial resources to pay for this capital purchase. In any case, Instron keeps contact with the customer throughout the order and till the delivery phase and revises delivery dates if found wanting.

6. Simulation Model

As explained in the previous chapter, the manufacturing floor is very complex. It is very essential to model the system such that the goals of the simulation are met with minimum complexity; the goal being to check the result of the optimization, implement it over some generated demand and find out the change in profits. Thus, in the simulation, a demand had to be created which would run through the proposed inventory policy over a period of time. Results which predict the performance of the inventory policy were obtained in the end. These results were then compared with the incumbent inventory management policy and, if required, fed back to the optimization to obtain better results as shown in figure 6.1

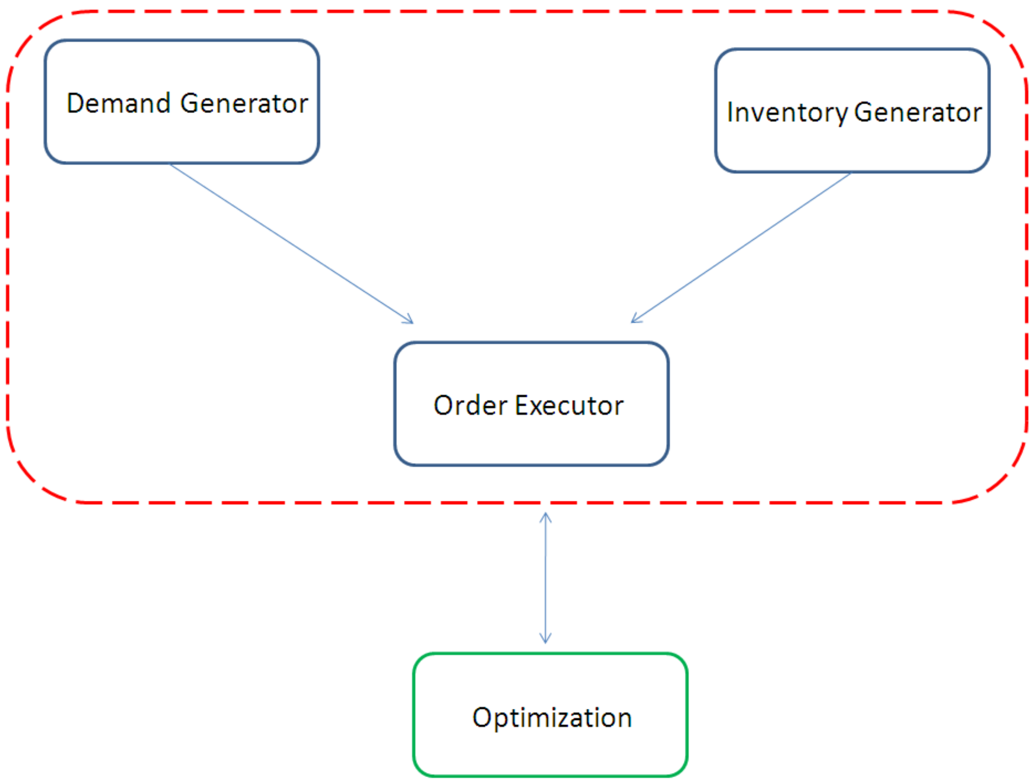

Figure 6.1 Simulation-Optimization Interface

Thus, various iterations were carried out between the optimization and simulation before a final result was achieved. Also, since, all digital simulations are long and complex computer codes, it is also essential to validate the simulation before using its solutions. Side by side, it is also a good habit to monitor the various validation parameters to get more depth on the results.

Effectively simulation can be broken down into the following big components:

a.) Demand Modeling

b.) Inventory Management

c.) Order Execution

d.) Outputs

e.) Validation

f.) Monitoring

Each of these components has been dealt with separately keeping the goal in mind and integrated into one final model.

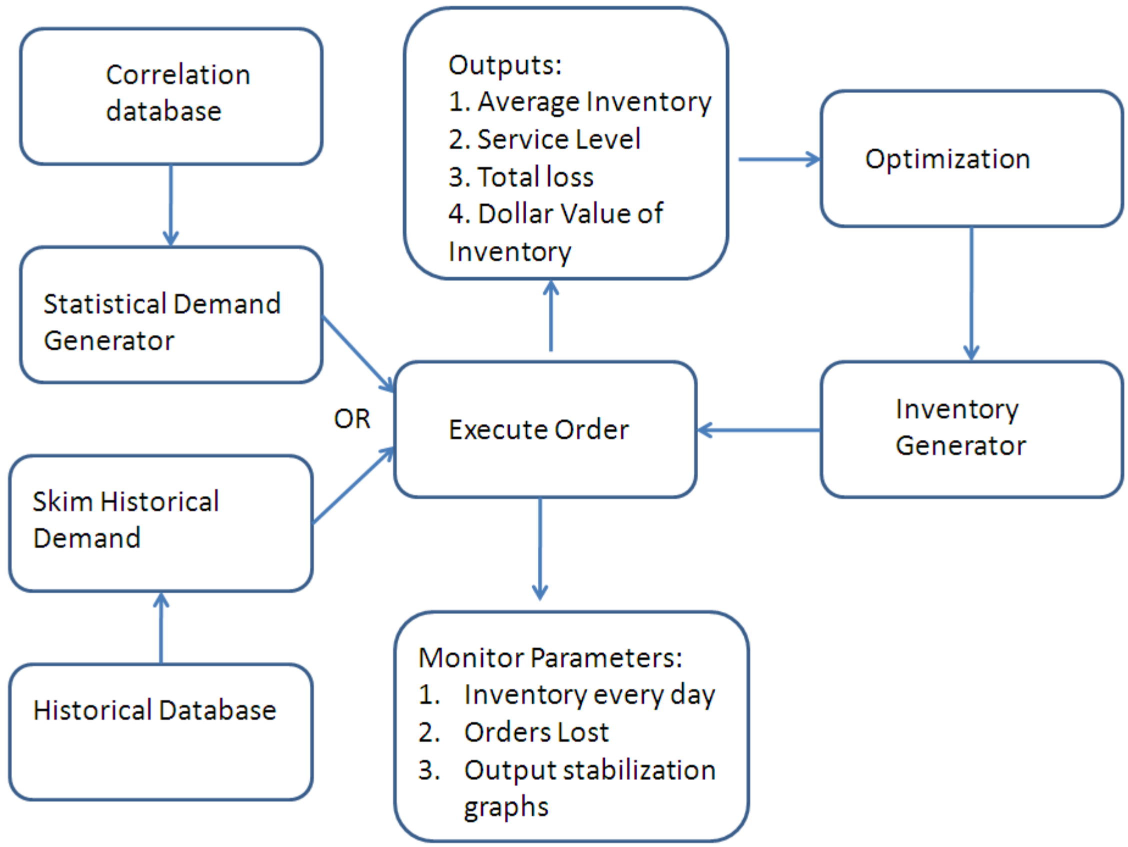

Figure 6.2 Simulation Structure

Two kinds of demand generators can be used- either statistically generated orders or historical orders. Historical demand needs to be cleaned ("Skim Historical Demand") before using it since it may contain some orders not required for the analysis. Demand modeling (Demand generator) creates demand and feeds it to the Order execution module ("Execute Order"). Order execution gets the inventory levels to operate on from the inventory management module ("Inventory Generator") and the inventory levels keep on changing as orders keep on getting placed during the simulation. Finally, after the simulation is over, the outputs are obtained which can be studied in depth to find out where potential improvements can be made and then, fed back into the optimization.

6.1 Demand Model

To execute the simulation, orders need to be created. By running orders with the inventory on hand, we can find out if the inventory levels are enough to support that demand. Thus, order generation is a critical phase of the simulation. As discussed in the previous sections, two kinds of orders can be placed- systems and Over The Counter (for spare parts ordering). These orders have different customer constraints as far as lead times demanded by customers are concerned [26]. There are also shipping constraints on the systems orders. All items in the order must be available before the order can be shipped. However, this constraint is not valid on the OTC orders.

Generally, demands for systems and OTC orders can be generated through two sources -

1. Historical Demand Modeling
2. Statistical Demand Modeling

Historical demand modeling recreates the electromechanical product orders placed with the company in the previous years (2007 and 2008). Statistical demand simulation generates random orders using a Poisson distribution keeping the correlation between different parts into consideration. Both these simulations can help in validating the proposed inventory levels.

Since, we can generate two types of demands; we can run two types of simulations on the same inventory policy and see results on both. The two types of demand modeling are explained in more detail below-

6.1.1 Historical Demand Model

Instron has demand for systems and OTC orders. They make profit not only by the products sold but also by selling features such as color, special configurations. In order to compare if the proposed policy is better than the current policy a simulation over the historical orders is essential. By executing the historical orders over the proposed and current inventory policies we can get a comparison of inventory holding costs and the losses made. This tool will thus be crucial in convincing the management if the proposed policy is better.

An historical order has the following information associated with it-

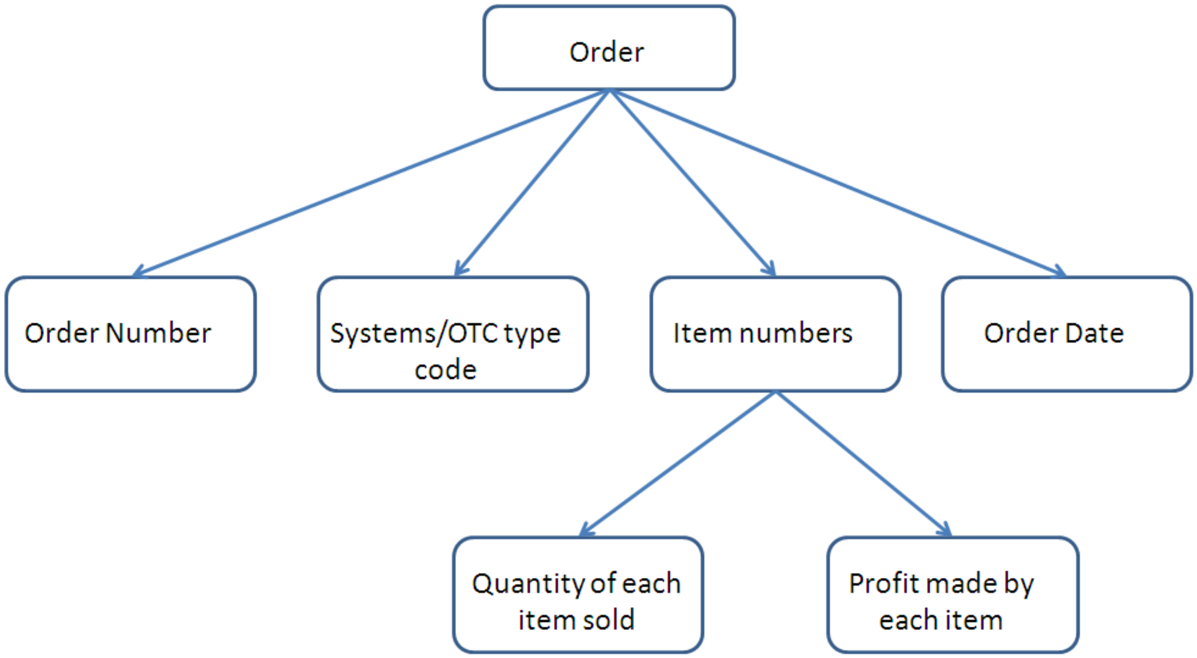

Figure 6.3 Information associated with a Historical Order

- An order number is assigned to it
- Each order has a code which tells if is it an OTC or a systems order
- Each order has the item-numbers sold in it ,their quantities and the profit that they make
- Each order has a order date- date on which the order was placed

This format of orders needs to be converted into a convenient format which can be easily applied in the simulation. A method was devised to convert this order data into a structured database which can be implemented in the simulation. This database is explained in detail in section 6.2

6.1.2 Statistical Demand Model

Historical Simulation can be used only once to find if the proposed policy is better than the current one. This is because only one set of data is available. Also, future demand will not be the same as the historical demand. Thus, the proposed inventory policy should be robust to future demands which might be more or less than the historical demand. Hence, a statistical demand is created which generates "artificial" orders [27]. The policies are then tested over this demand to see if they can bear the new distribution of orders. Many demands can be generated using this method and the performance of the proposed and current inventory models can be tested.

Since correlation between the demands of different items is an important factor for system orders, we need to include it while generating the artificial orders. We know the probability of each item being sold with a specific system from the correlation analysis. We can use this probability to assign an item to an order. These orders themselves have been seen to follow a Poisson distribution in the historical orders. Thus, they can be spread over time using this distribution. The figure below shows the distribution of the aggregate systems demand and the fitting of Poisson distribution over them.

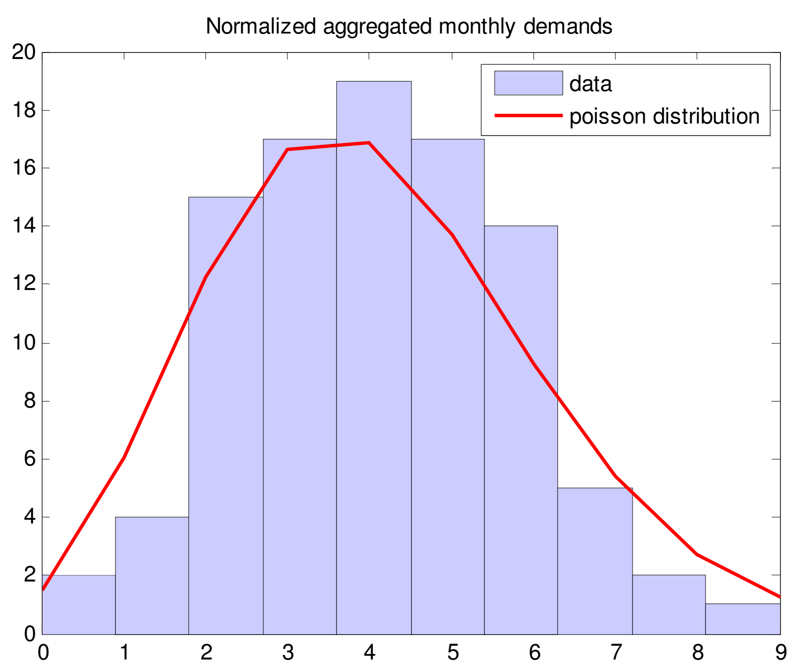

Figure 6.4 Aggregate Demand of Frame Orders (systems) (Serra [27])

The statistical OTC orders can be directly determined from the demand of each item as an OTC product and approximately distributed according to their historical distribution. The system and the OTC orders can then be combined to represent a statistical demand generator.

6.1.3 Demand Database

After creating orders from the demand modeling functions, we need to store them in a format which is easy to access using the simulation. Thus, a database is created which stores the orders in an easily retrievable format. A Matlab code is prepared to prepare this database. The code extracts the relevant quantities in the order and stores them in separate variables:

- N -contains the order numbers sorted according to when they were placed.
- D- contains the date on which the corresponding order from N was placed
- I- contains the item numbers of all the items that were sold with the corresponding order from N
- Q- contains the quantity each item is sold corresponding to I
- Profit- contains the profit each item makes corresponding to items in I
- T- indicates the type of order: system or OTC

Thus, the 5^{th} element of N will give the number of the fifth order placed. 5^{th} element of D will give the date on which this order was placed. 5^{th} element of I will give all the items which were there in this order. 5^{th} element of Q and Profit will give the quantity of each item and profits in this order. Finally, the 5^{th} element of T indicates the type of this order- OTC or system.

6.2 Order Execution and Inventory Management

After the demand database is ready, the inventory level for each item should be provided and the policy under which it will be replenished. Inventory replenishment and reorder levels are obtained from the optimization module developed by Facelli [28]. This is the optimum policy considering a certain holding cost. However, since the profit used in the function is the virtual profit, a direct holding cost cannot be used in the optimization problem:

max: $E[P_i] = \beta_i V_i - E[I_i]H$ (Decomposed Optimization-optimizing for each item) (6.1)

or more accurately,

max: $E[P] = \sum_i \beta_i V_i - E[I_i]H$ (Global Optimization-optimizing the whole factory) (6.2)

where, P_i = profit for item i

β_i = service level

V_i = virtual profit of item i

$E[I_i]$= expected inventory of item i

H= holding cost

To solve this issue, various holding costs are assumed and the optimization function solved giving different amount of inventory held by the manufacturing floor. The solution from the optimization i.e. the proposed inventory policy is then implemented into the simulation. The simulation presents results if the proposed inventory policy gives better results than the current policy. The simulations also helps to check if the proposed policy if feasible under capacity constraints. Thus, if it is ascertained that the proposed policy is not good enough, a new optimization solution is generated and simulated. Hence, various iterations of the optimization and simulation take place to reach the final level.

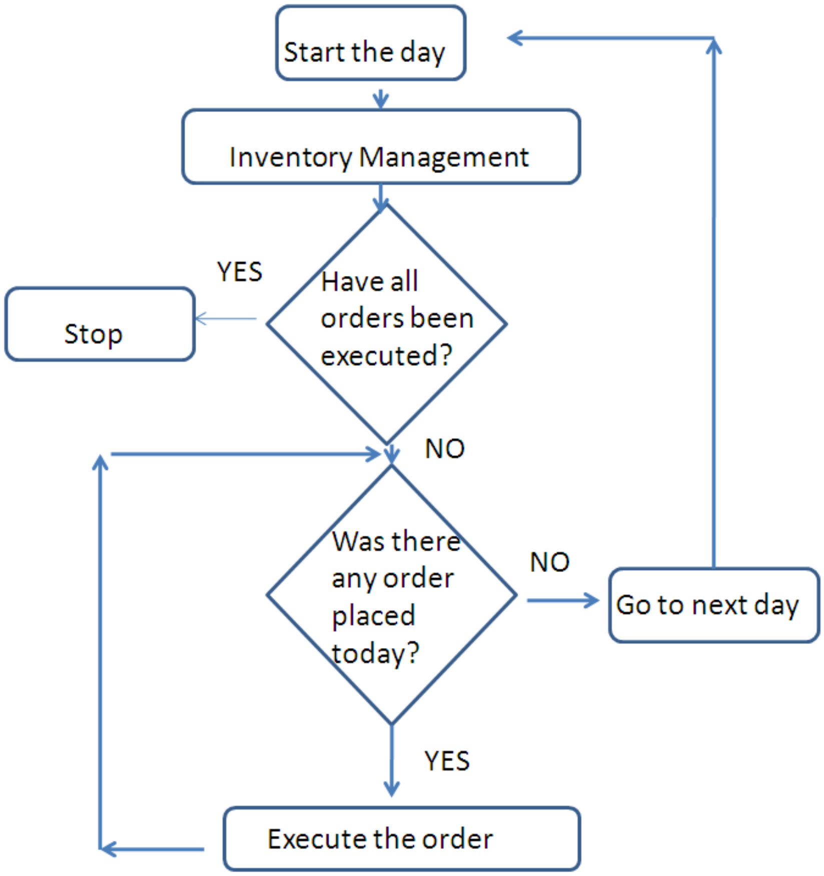

Figure 6.5 Inventory Management and Order Execution Flowchart

Fig. 6.5 shows order execution involves running through orders placed on each day. That is, we start the simulation from day-1 and check if any order was placed on day-1. If an order was placed we execute the order according to its type (system or OTC). The loop keeps on running until all the orders placed in the day are executed. Also, inventory management is done daily to make sure current inventory levels satisfy the incoming demand.

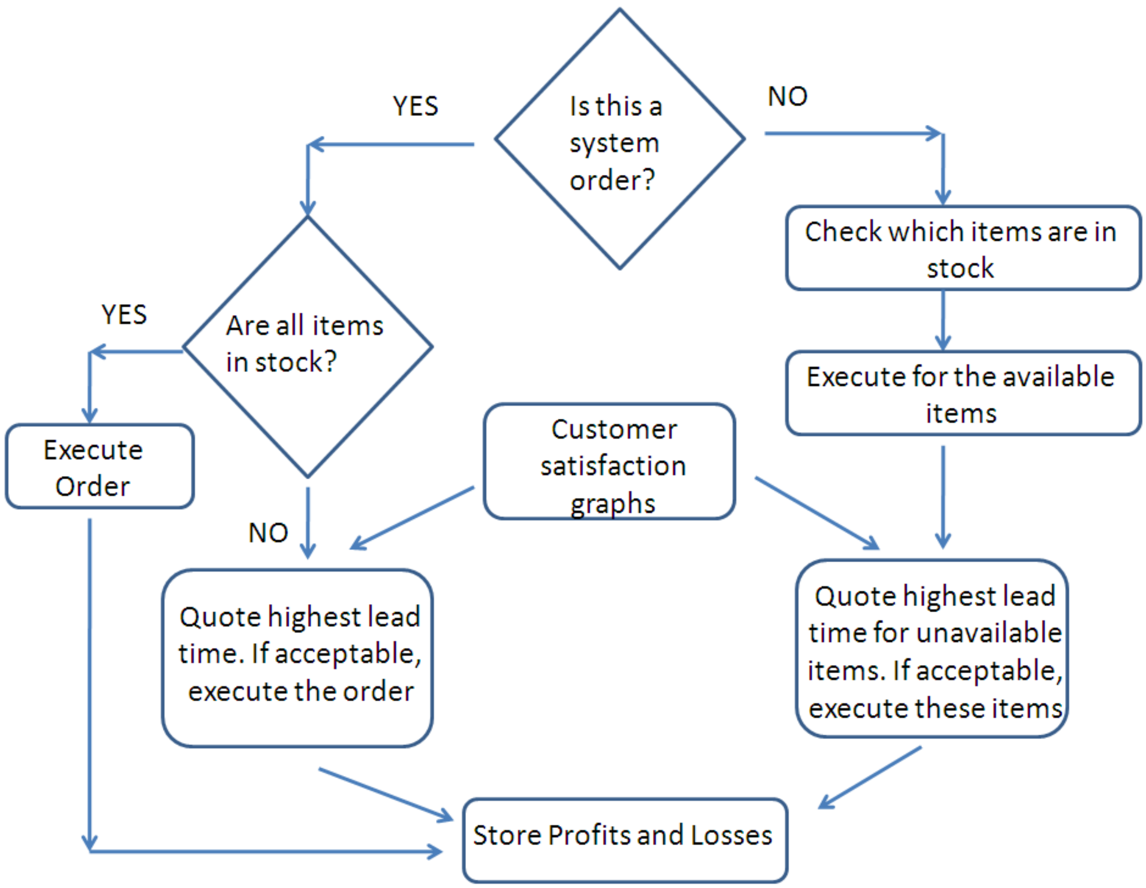

Figure 6.6 Order Execution Detailed Flowchart

If an order was placed, it is checked whether it is a system order or an OTC order. In a system order, it is checked if all the items in the order are available. If any of items is not available, it is checked according to the customer satisfaction graphs if the customer will accept a longer lead time for the order. If the customer is willing to accept the lead time, the order is executed. Otherwise, the order is lost.

In an OTC order the same procedure is followed as the system order. However, since, the OTC orders can be fulfilled partially, only those items are sold which are in stock and whose lead times the customer is willing to accept.

The factory floor follows the Kanban system of inventory management. Kanban is a visual replenishment method using the QR policy.

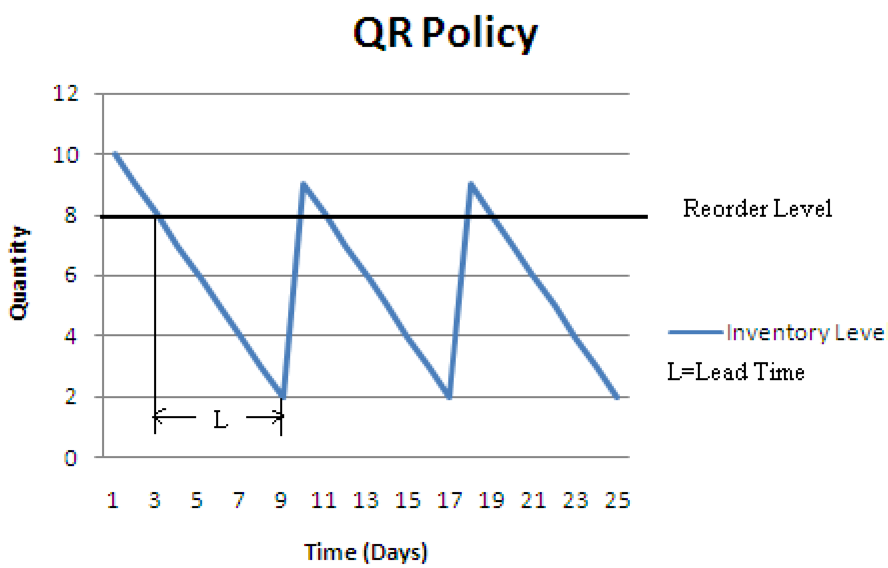

Figure 6.7 A typical QR Policy

In the QR model, a refill order is triggered as soon as a reorder level is reached (usually designated as R). After the lead time to procure that part is finished, the part is received and the current inventory is increased by the ordered amount (referred to as Q or the replenishment quantity). This quantity Q can be determined by Economic order quantity model or by supplier constraints. However, care must be taken to make sure that this amount at least covers the demand over the replenishment lead time. This is because if the replenishment quantity is not enough to make the inventory level to jump above the reorder level, the average inventory decreases leading to loss of orders.

Inventory is managed by the simulation by checking the inventory level everyday and replenishing it using a lead time counter (p). p is a variable assigned individually to every item number. It counts the number of days past from the day when the reorder level is reached to the time the inventory gets replenished.

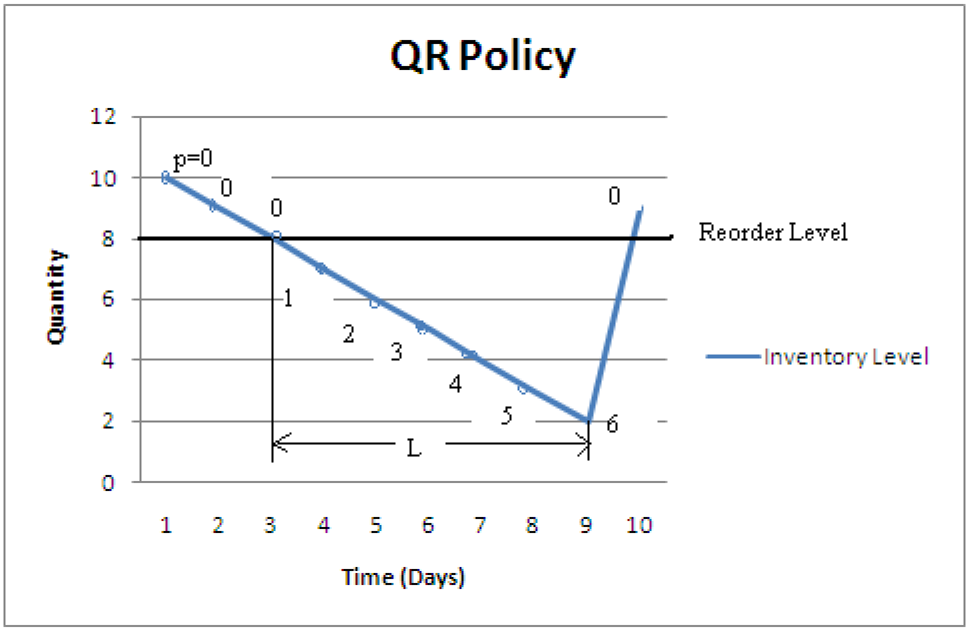

Figure 6.8 Lead Time Counter for Replenishment

For example, in the figure shown above, the counter is at zero on day 1 and on day 2. As soon as the inventory level drops to the reorder level 8, on day 3, the counter starts to increase by 1 everyday. On the 9th day when p becomes equal to the lead time to procure the part, the inventory increases by the replenishment quantity Q.

6.3 Customer Satisfaction (Random Number Generation)

In the case when an order cannot be fulfilled since one or more item is not available, we use the customer satisfaction data find out if the customer will be willing to accept a longer lead time. A random number is generated from a uniform distribution and is checked to be less than the probability of customer's acceptance from the customer satisfaction graphs. For example, say, for a particular order 3 items are unavailable. The lead time quoted to the customer is the highest of the lead time of all these 3 items not available in the order. Now, corresponding to this quoted lead time, there will be a probability that a customer will accept the lead time. A random number is generated for this purpose. If the random number is less than the probability from the customer satisfaction graphs, the order gets placed. Else, the order is lost.

rand() function from Matlab is used to generate the random number. Rand is based on the sequence of integers defined by the recursive formula-

$$x_{k+1} = remainder((cx_k + d) \ / \ a) \tag{6.3}$$

This method is known as Linear Congruential Generation. This number generation has a period of (a-1) since after (a-1) times the numbers will start to get repeated. Also, these numbers get uniformly distributed. With faster computational capabilities, 'a' is kept a high value-2^{31}

6.4 Simulation Output

Outputs are essential in this simulation since they give feedback into the optimization problem. Optimization function should know how the previous policy ferried and hence accordingly a new optimization problem can be formulated. Thus, some key performance indicators for the inventory policy are:

1. Number of orders lost (service level)

Number of orders lost gives the service level the policy offers. Type-II service level is given by-

$$Type - II \ Service \ Level = \beta = \frac{number \ of \ orders \ lost}{total \ orders \ placed} \tag{6.4}$$

Service level is used extensively in industry to indicate the ability of a firm to meet the needs of their customer. Instron strives to obtain above 95% service level on their products and thus, monitoring this effect is very essential.

2. Average inventory on hand in the simulation period

This indicates the average dollar value of inventory on hand over the whole simulation period in terms of the demand of every item. It is essential to know the average inventory on hand since inventory holding is a cost against free cash flow. Thus, it is essential that minimal inventory is kept. Inventory value can be calculated by simply using the cost of items or using months on hand of demand.

$$Months \ on \ Hand \ (MOH) = \frac{\sum_i E(I)_i . cost_i}{\sum_i \mu_i . cost_i} \tag{6.5}$$

where, E(I)= average inventory for every item

μ=monthly demand for each item

3. Total loss made by this policy in terms of the dollar value of orders lost

The total loss made by a policy gives the value of lost orders. If big orders lost, the policy should be revised to reduce the amount of total loss. A better policy should be able to fulfill large orders and have least amount of losses. This is however, not an indication of customer satisfaction. The aim of the optimization is to minimize the expected losses. Hence, it is possible that more orders are lost (and hence, more customers unsatisfied) but less loss is made.

6.5 Simulation Validation and Debugging

Before, noting down any results, it is essential that the simulation itself is validated and monitored during the process. This simulation has been validated using sensitivity analysis and solving the problem for one item and computing the simulation by hand. Also, inventory was observed for these items during the period of simulation to confirm if they are replenishing as expected.

Also, some monitoring of the simulation is done during every run. The orders which are lost are studied to see which item was the most critical component.

Finally, all results of the simulation are processed only if enough simulations have been carried out and the outputs have reached a cumulative average limit.

7. Simulation Results & Assumptions

7.1 Optimization Validation

The simulation module helps to validate the optimization model proposed by Facelli [28]. Optimization provides the right mix of products with some expected loss and months on hand of inventory. Several of these optimized mixes were obtained for different months on hand and compared with the simulation results over historical demand as shown in the table below

	Months on Hand Inventory		Expected Loss ($/year)		Value on Hand ($)	
	Optimization	Simulation	Optimization	Simulation	Optimization	Simulation
Mix 1	1.37	1.38	7075.62	10664	180661	170423
Mix 2	1.2	1.193	12452.5	12478	157411	148410
Mix 3	1.10	1.09	17452	19980	145310	136747
Mix 4	0.99	0.98	24338	22928	131131	122924

Table 1 Optimization validation using simulation

Table 1 proves that the optimization model predicts the critical parameters well. All parameter values are close and follow similar trends. These parameters have been discussed in detail below:

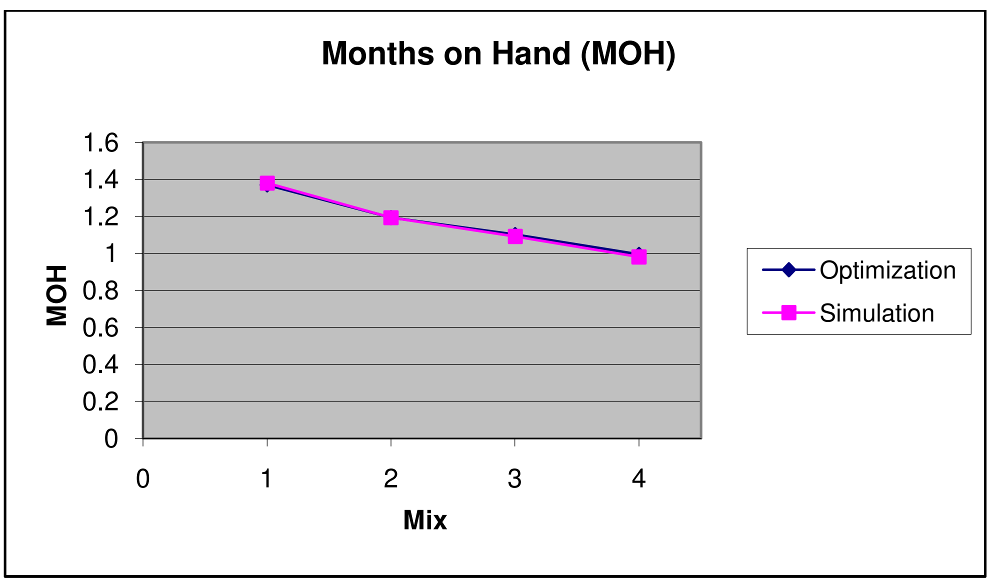

Figure 7.1 Comparison between MOH: Optimization and Simulation

From the Fig 7.1, we can see that the months on hand theoretically predicted from the optimization are similar to the simulation results. We also see that mix 4 has the lowest months on hand inventory (i.e. highest holding cost considered) and the inventory drops from mix 1 towards 4.

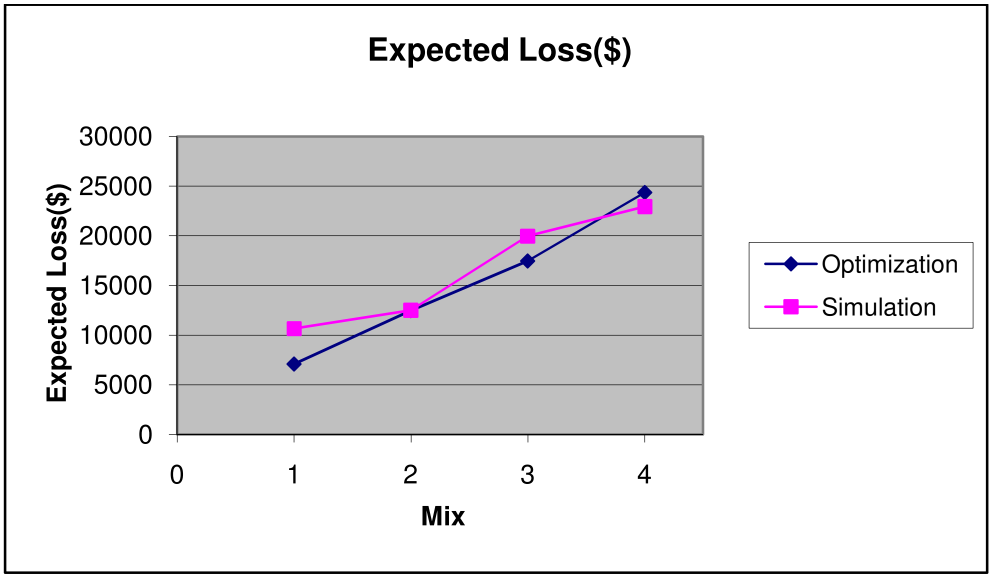

Figure 7.2 Comparison between expected loss: Optimization and Simulation

The above figure shows the expected loss made by 4 mixes as predicted by the optimization and validated using the simulation. As expected, mix 4 will have the maximum loss since it has the minimum inventory. Also, the expected loss values from the simulation hover around the optimization, indicating that the demand during the simulation period was expected.

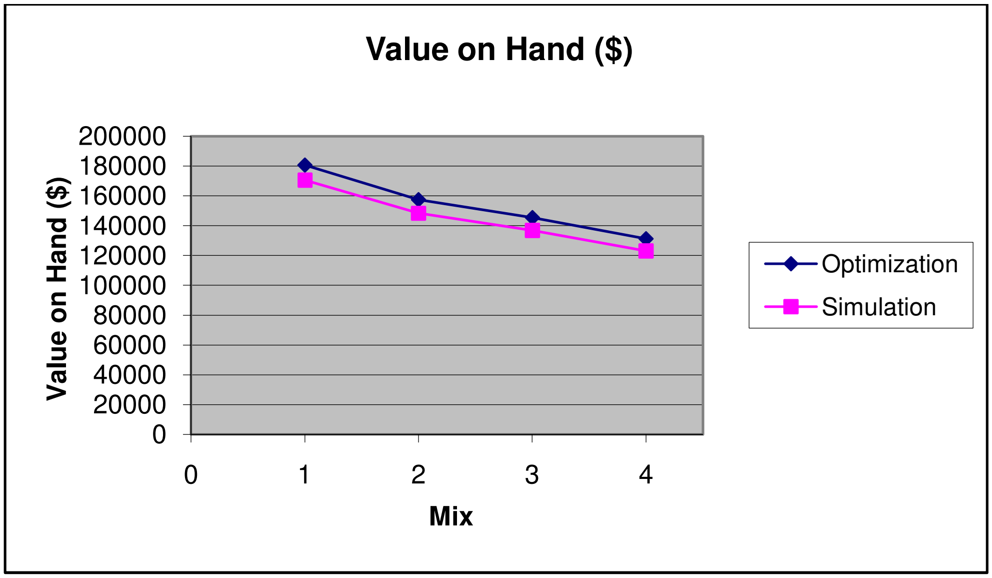

Figure 7.3 Comparison between value on hand: Optimization and Simulation

All simulations were performed 50 times to ensure a steady state result. As we can see, the optimization model predictions are similar to those obtained from the simulation. However, there seems to be a bias towards the lower side in the inventory value of hand graph (Fig 7.3). It can attributed to the assumption in the simulation that instantaneous execution of orders takes place and items get deducted from the inventory. However, in reality, they will sit through the build time before getting deducted from the inventory.

Thus, we can conclude that the optimization correctly models the floor.

7.2 Comparison with Current Policy

The simulation can also be used to compare between the proposed policy and the current policy. As an example, consider an optimized mix with 1.35 MOH simulated over the 2009 historical demand and compared with the current policy. From the simulation we find out that the inventory being held for the current policy is 3.32 MOH.

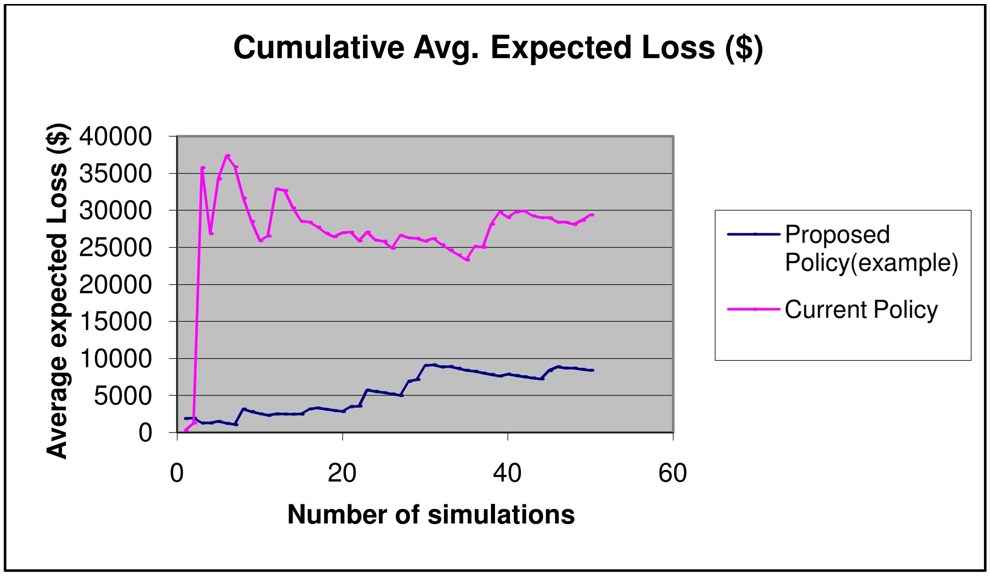

Figure 7.4 Proposed Policy and Current Policy expected loss comparison

As we can see, the steady state average loss of the proposed policy after 50 simulations is around $800 while for the current policy it is $30,000. An interesting behavior to study here is the consistency of maintaining expected losses. In the case of current policy, the expected loss is more disturbed and likely to show unexpected results.

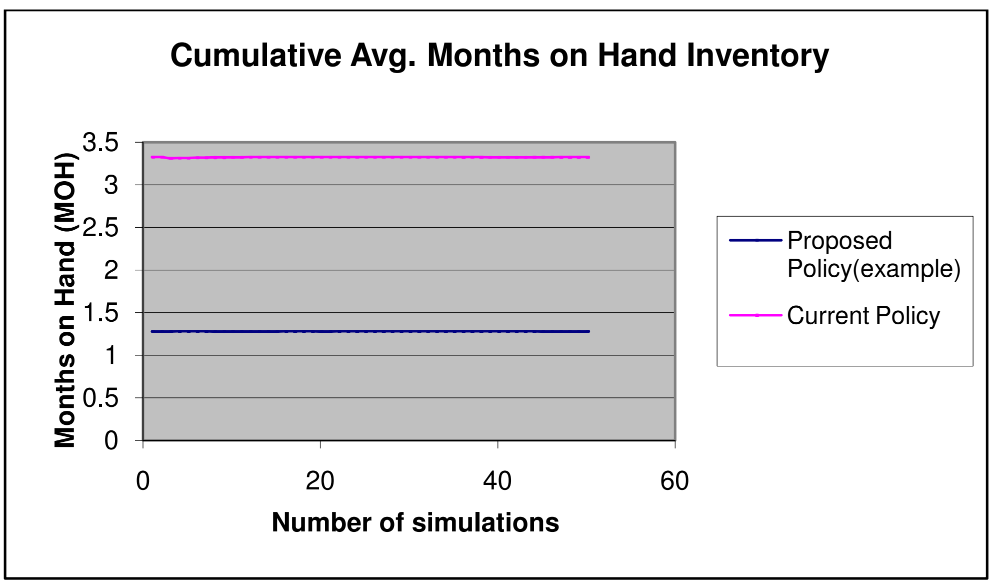

Figure 7.5 Proposed Policy and Current Policy MOH comparison

Fig. 7.5 and 7.6 show the cumulative average inventory based on demand (MOH) and inventory value on hand(VOH). The graphs are constant indicating that the simulation has stabilized and the resultant values are the steady state results.

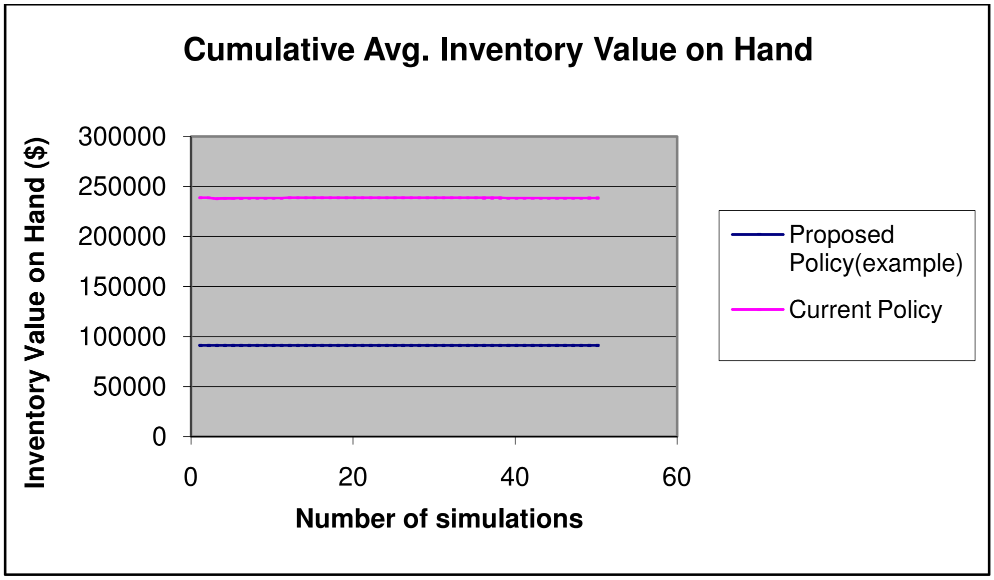

Figure 7.6 Proposed Policy and Current Policy value on hand comparison

We can see that by holding less inventory over this period this optimized mix still looses lesser orders. Savings in inventory value is approximately $150,000 and in lost sales around $20,000. This result brings confidence that optimizing the correct mix of products on the floor is essential to minimize the losses.

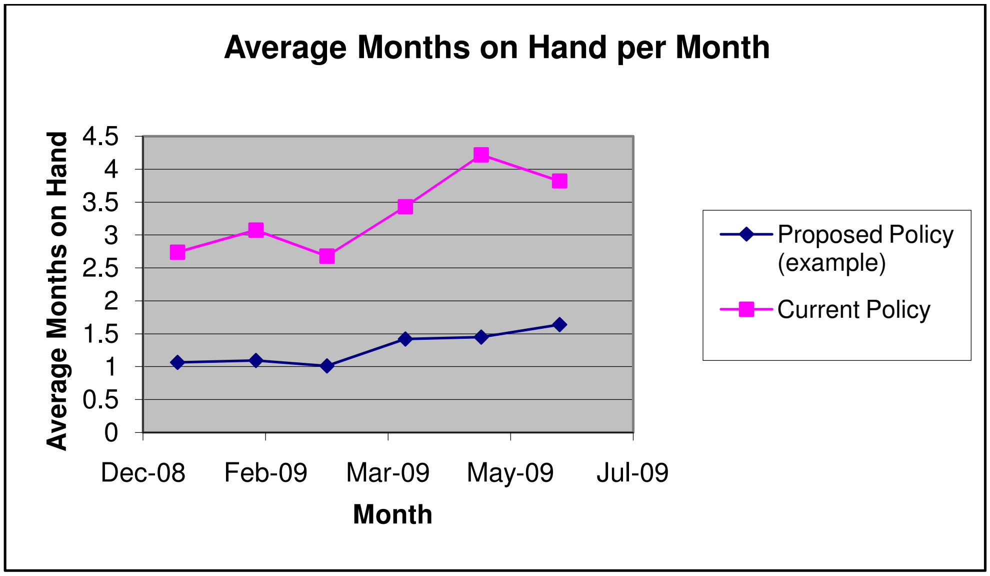

Figure 7.7 Proposed Policy and Current Policy MOH comparison for every month

An even more interesting observation comes from the average months on hand for every month of the simulation. We see that the inventory on hand has high variation in the current policy (2.5 to 4.5 MOH; variance is 0.38) while for the proposed, it stays stable between 1 and 1.7 MOH; variance is 0.06. Thus, having an optimized inventory policy helps in keeping the correct mix on the floor which makes sure that the floor is not flooded when demand decreases.

In the Project results section, we will see a similar comparison between the current policy and the final proposed policy based on future forecasted demand and with inclusion of new accessories which the company expects to start sell from the next quarter

7.3 Benefits of Considering Demand Interdependence

An interesting result to observe from the outputs is whether consideration of demand interdependence has any impact on improving the results or does it make the process more complex. Different optimum mixes were developed considering Virtual (Correlated) Profits and individual profits.

Serra (ch-7) shows that considering the virtual profit instead of individual profit improves the solution with expected losses always being lesser [27]. This effect is more visible at low inventory levels than at high inventory levels. At MOH less than 0.4, the difference can be as high as $50,000 while for 1.4 MOH and beyond it approaches zero. This can be attributed to the characteristic of the virtual profit which makes sure that the high value system orders are not lost by having a correct mix of items on the shelf.

7.4 Assumptions

The goal of the simulation is to achieve certain objectives by recreating a real system which cannot be either created physically or is too capital/labor intensive to pursue at an initial design stage. To achieve these objectives, it is not essential to reconstruct all the characteristics of the system and simplifying assumptions can be made until they do not hamper the results of the simulation. These assumptions are highlighted below-

- When the manufacturing planner receives an order for lead time quotation, he checks his current inventory, capacity constraints and the backlog of order

  In the simulation only the current inventory is checked. If items are in stock, the order is executed. No capacity constraints or backlog orders are considered. This is because implementing backlog orders is difficult and may not be required since all levels obtained from the optimization-simulation will be checked by the manufacturing managers for capacity constraints. Also, the customer satisfaction graphs have been used to determine the customer's willingness to wait for the extra lead time which gives the manufacturing floor enough time to get the order executed. In addition, the lead times for procurement of certain critical items were increased so that there is extra current inventory available.

- An order is executed if all items are available or in the case of unavailability the customer is willing to accept the lead time

  In the real case an order is not executed until it is built and shipped to the customer. Thus, in reality it is the inventory during the build process that makes the final decision on whether the order will be completely executed. Clearly, it is not possible to implement this in a simulation since some components may be built on one day and others on some other day. Such precise reconstruction of reality will require implementation of back orders and other manufacturing constraints. Executing an order at the same moment of receiving is equivalent to committing the inventory for that order. This actually does not happen in reality. However, Instron looses less than 1% of committed orders and is ready to flex order schedules to meet the customer promised lead time. Hence, this assumption is a fair recreation of the real inventory.

- At certain times, the demand is so high that the replenishment quantity is not enough and hence the average inventory decreases.

  This is an inventory management issue. To maintain a good QR policy, we propose that inventory be checked as soon as Instron receives replenishment from the supplier. If the replenishment quantity is below the reorder level, another replenishment should be triggered immediately. Failing this, orders can be lost since lower average inventory will be maintained.

- Simulation begins from Average Inventory levels (Initial Transience Problem)

  All simulations suffer from initial transience. Initial transience is a condition in which the initial values of determining parameters (in this case- the current inventory) lead to unsteady initial simulations giving unreliable results. After many simulations have been completed and the simulation has been sufficiently "warmed up", steady state values are obtained in output.

  There are two ways to deal with this problem. One way is to not consider the initial simulations and another way is to start with steady state inventory levels. Initial simulations cannot be neglected in historical simulations since the initial months have a definite weight age on final months on hand inventory. Also, the steady state values of inventory are easily available from the general QR policy. Thus, the second method has been used in this case.

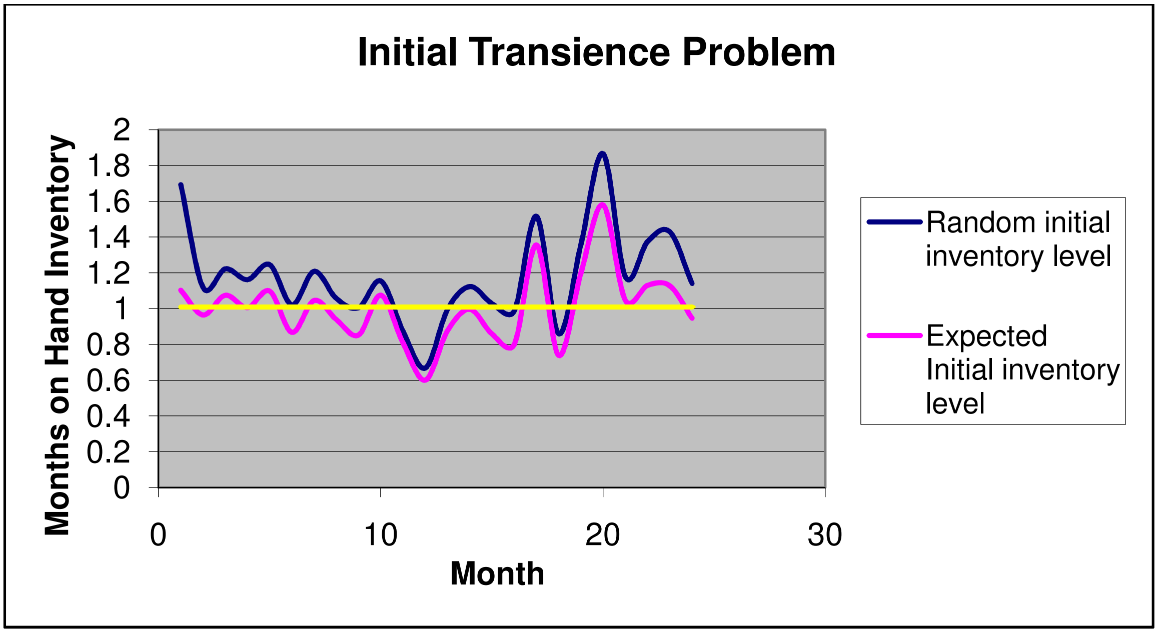

Figure 7.8 Initial Transience Problem for MOH

As shown in the above Fig. 7.8, the initial months have high months on hand inventory since the initial current inventory levels are selected randomly from a uniform distribution. The inventory comes down to the same level, had it been started from its expected level. Thus, we see that compensation of initial transience is essential to reach a stable simulation.

8. Project Results and discussion

8.1 Raw materials inventory

As introduced in chapter 4 and further described in Palano ch-7, purpose of the project was also to provide a raw materials inventory control policy supporting the finished goods inventory [26]. The current policy is value-based: the parts are classified by financial value to the company (classes A, B, C and D) and the reorder quantities and levels only depend on the class. A QR policy with fixed service levels is proposed; the results are here summarized and discussed.

8.1.1 Results

In order to implement the QR policy for the raw materials inventory, some information is necessary. In particular, knowing the replenishment lead times negotiated with the supplier is fundamental. In this paragraph, the results of the QR policy are presented by comparison with the current value-based control policy. Firstly, the importance of the lead time is shown through a parametric comparison; then, the two policies are evaluated with the best current estimate of the lead times.

Figure 8-1 shows the difference that could be made by having more accurate information about the lead times. The graph on the top shows the expected inventory value on hand, while the graph below shows the average service levels. For the sole purpose of showing the differences as the lead times vary, the graphs are based on the assumption that the lead time is the same, and constant, for all the parts. The blue lines represent the current value-based policy, which does not consider lead times or the demand variability. The red lines correspond to the QR policy, implemented using also the lead times and variability information. Two examples are highlighted with vertical lines: a lead time of 4 days and a lead time of 18 days.

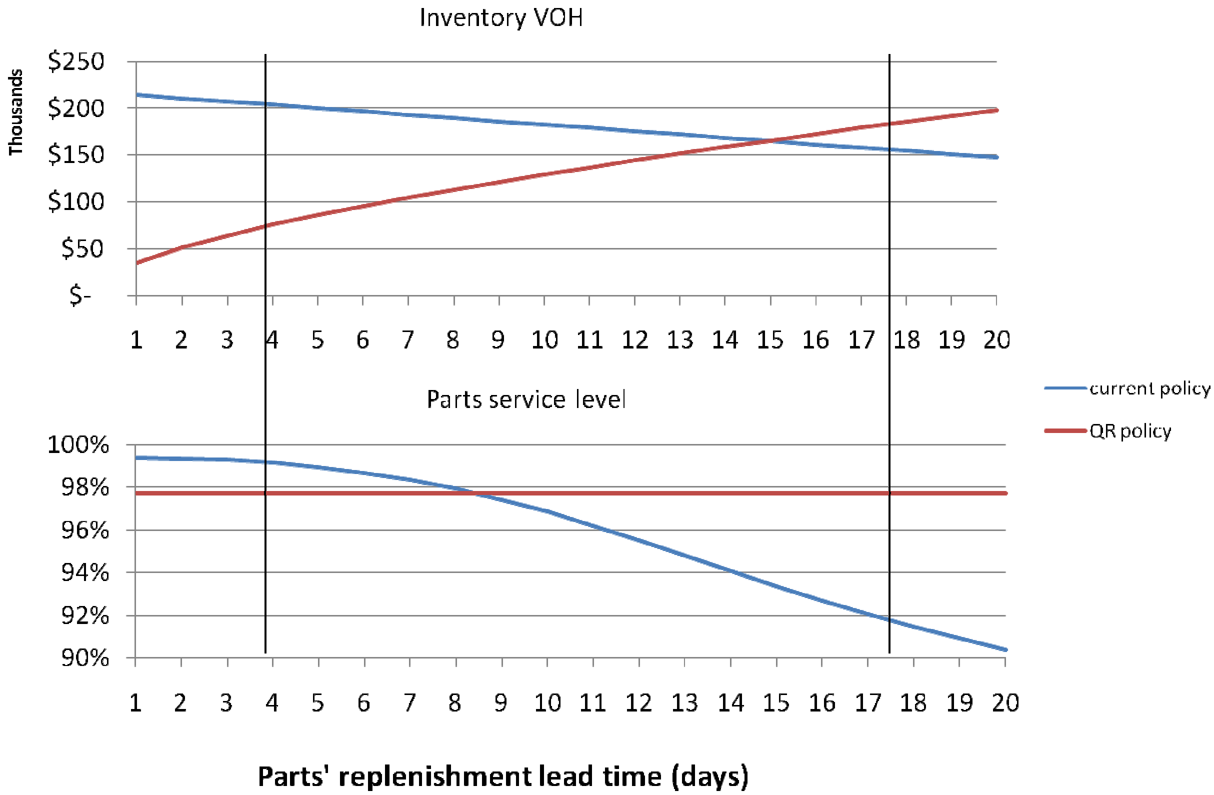

Figure 8.1 Service level and Inventory VOH vs. lead time

If the suppliers ship more quickly than expected, and the lead time is shorter, both policies have high service levels because the shelves are replenished quickly. Being designed upon the shorter lead times, however, the QR policy manages to accomplish high service levels with low inventories. In the first example, indeed, the value on hand is reduced by three times.

On the other hand, if the lead times are longer, the only way to achieve high service levels is to have higher inventories. Thus, the proposed policy suggests inventory levels that are comparable or even higher than the current ones. The QR policy, on one hand, uses the information about lead times in order to maintain high service levels; the current policy, on the contrary, does not consider them, causing a significant percentage of lost orders (orders meaning grips to be assembled), as shown in the second example.

An estimate of the actual supplier replenishment lead times is obtained by talking with the purchasing department and described in Palano ch-7.5 [26]. In this case, the lead times are different for each part. Table-2 shows a comparison of the results obtainable with the two policies based on this estimate. Moreover it provides an estimate of the savings that would be achieved by agreeing on shorter lead times with the suppliers.

Method	Average inventory VOH	Parts service level
ABCD - Division by value	$179,731	93.2%
QR – Knowing and using the lead times	$126,299 (-30%)	97.7%

Table-2 Comparison of raw materials inventory control policies

As table-2 shows, only as a result of improving the accuracy of lead times, the QR policy would allow achieving high service levels at the same time cutting the costs by 30%. If, in addition, the purchasers obtain agreements for shorter lead times for the most valuable parts, the costs would further decrease.

8.1.2 Discussion

Based on the analysis proposed in Palano and on the results here described, the current inventory policy, which is value-based and does not consider lead time and demand variability, can result in irregular inventory distribution, lower service levels and higher inventory value on hand [26]. A simple QR policy is proposed, which gives better and more regular results.

In designing and optimizing the finished goods inventory control, the assumption that all the raw materials are always available is made. The designed QR policy achieves service levels of about 98% for each part. Thus, the above mentioned assumption can be still considered valid.

However, in order to implement the QR policy, the replenishment lead times are necessary. As a general consideration, the lead times are necessary to make sure that the service levels are high without wasting inventory. Thus, the lead times of every part should be tracked in the way described in section 9.1, and accurate information should be kept on the company databases. In addition, if the suppliers are flexible on the lead times, the Excel spreadsheets can be used in the decision process to determine the correct tradeoff between lead times and inventory value on hand.

8.2 Finished goods inventory

The policy proposed shows potential for a significant improvement in inventory control. Figure 8.2 shows a comparison between the proposed policy, a simple QR policy and the values of Q and R currently in use. Note that the term "simple QR" refers to a QR policy with an equal safety factor z for all the products. The figure shows the expected lost sales, due to products unavailability, versus the total expected inventory held. The amount of inventory held is measured in months on hand (MOH) (eq. 6.5)

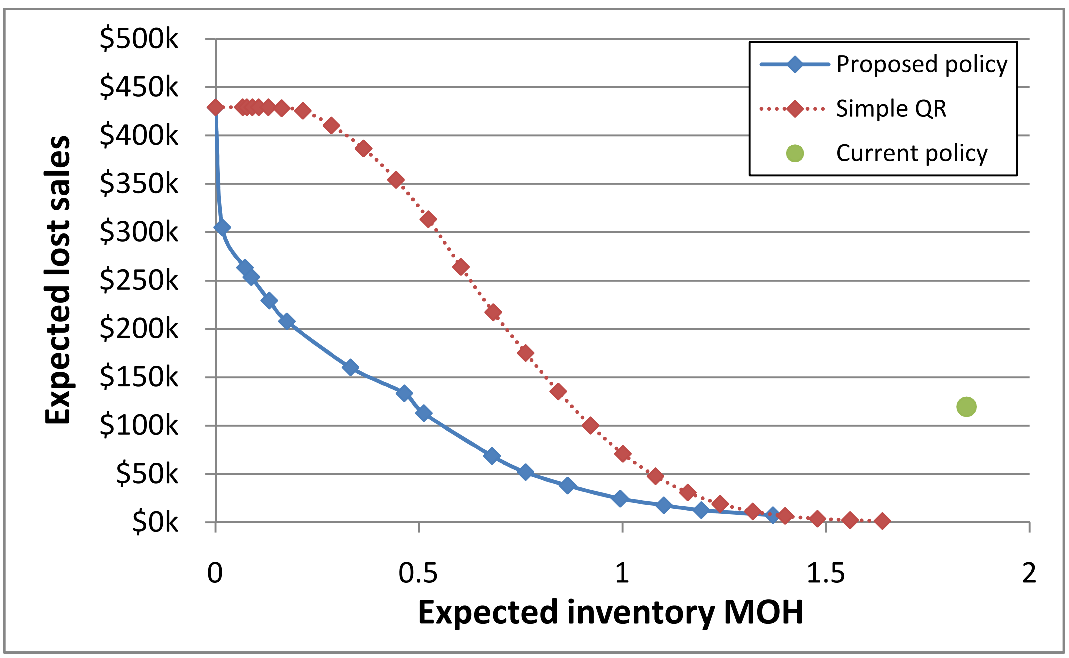

Figure 8.2 Expected lost sales vs. Inventory MOH

As figure 8.2 shows, the proposed policy outperforms both the simple QR and the current policy. In particular, at the same level of expected loss sales given by the current policy, the proposed policy allows reducing the inventory from about 1.8 MOH to 0.5 MOH. From another point of view, with the amount of inventory currently held, the proposed policy would allow reducing the expected lost sales from about $120,000 per year to nearly zero.

In addition, Figure 8.2 shows that the proposed policy outperforms the simple QR policy. As one might expect, the difference increases as the size of the inventory gets smaller, while it decreases as larger inventory is considered. As a limit case, the value of lost sales achieved by the simple QR with 0.15 MOH is the same that would be obtained by a complete make to order (MTO) policy. With the proposed policy, instead, 0.15 MOH of inventory can halve the expected loss as compared to an MTO policy.

Figure 8.3 shows the expected lost sales value versus the value of the inventory on hand. As one can see from the graph, if a solution with 1.2 MOH is chosen (the penultimate point on the purple line) the inventory could be reduced from $240,000 to $157,000.

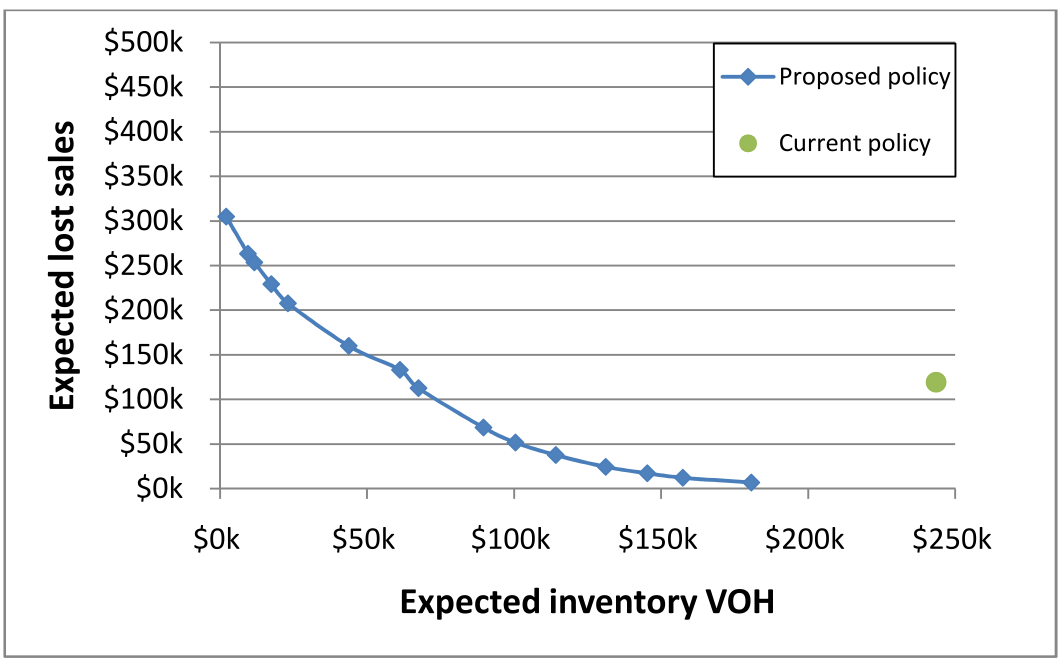

Figure 8.3 Expected lost sales vs Inventory VOH

Considering the trade-off between size of inventory and expected loss sales, a good compromise is a solution with an expected inventory of 1.2 MOH. This allows both reducing the amount of inventory and the expected loss sales. Moreover, a preliminary analysis of the maximum inventory levels shows that, with this solution, it is unlikely that the inventory levels measured at the end of one month will go above 2 MOH (considering the monthly demand variability). Table-3 shows a comparison between the proposed solution (with 1.2 MOH) and the current policy.

	Current Policy	Proposed Policy
Average value of Lost orders	$119,391	$12,453
Expected Inventory (MOH)	1.85	1.19
Expected Inventory (VOH)	$243,481	$157,411

Table 3 Current Policy Vs 1.2 MOH Solution

8.3 Simulation

The aim of simulation is to validate the results of the optimization module and to test the robustness of the proposed policy. The simulation also helps to determine the advantage of considering correlation between the demands of items sold in systems as compared to neglecting them in the analysis as explained by Serra [27]. The simulation estimates the following performance measures: number of orders lost, their value, months on hand of inventory for every month simulated and dollar value of inventory for each simulated day.

8.3.1 Validation

The optimization model provides the right mix of products that should be available on the floor. To validate these results, the levels were simulated 50 times over two years, 2007 and 2008, and then compared with the projected results from the optimization.

Figure 8.4 shows the losses made for different optimized inventory levels as predicted from the optimization and the simulation, versus the inventory months on hand.

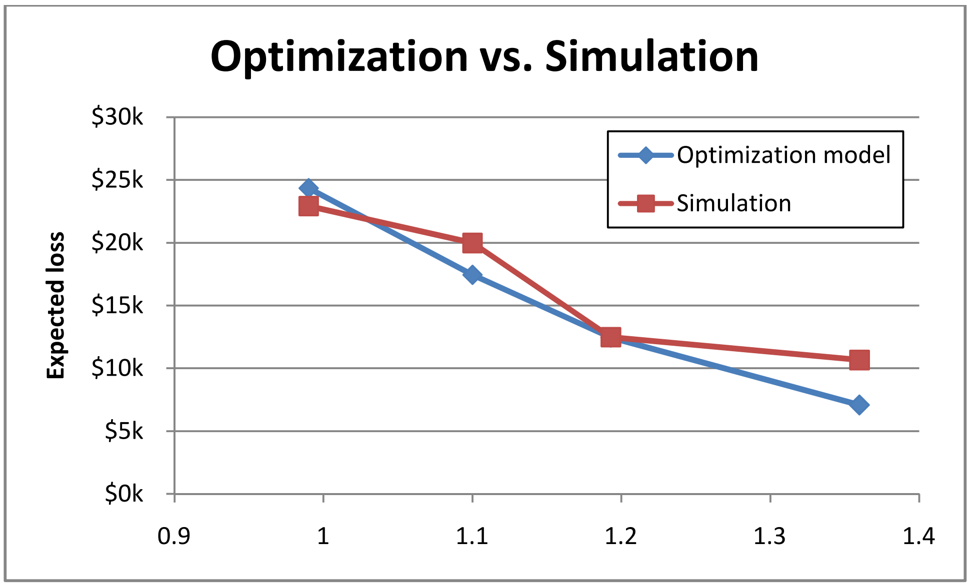

Figure 8.4 Comparison between theoretical and simulated loss for different solutions of the proposed policy

As it can be seen in figure 8.4, there is a small difference between the performance expected from the optimization model and the simulated one. This is because the optimization is based on the normal assumption, and because the simulation involves random sampling. However, the two graphs show a similar behavior and the difference looks relatively small, supporting the correctness of the optimization model.

This curve led to the selection of a solution providing an average inventory level of 1.2 months on hand, as described in section 8.2.

8.3.2 Robustness analysis

By running the proposed inventory levels over statistical demand, the robustness of the proposed policy can be tested, as described by [27]. The statistical demand is generated using the distribution of demand of each system and item over the previous two years. In the following example, the simulation is run 50 times for seven different values of shift in demand. The shift in demand, however, is not taken into account in calculating the proposed inventory levels. Figure 8.5 depicts the average inventory months on hand versus the shift in demand.

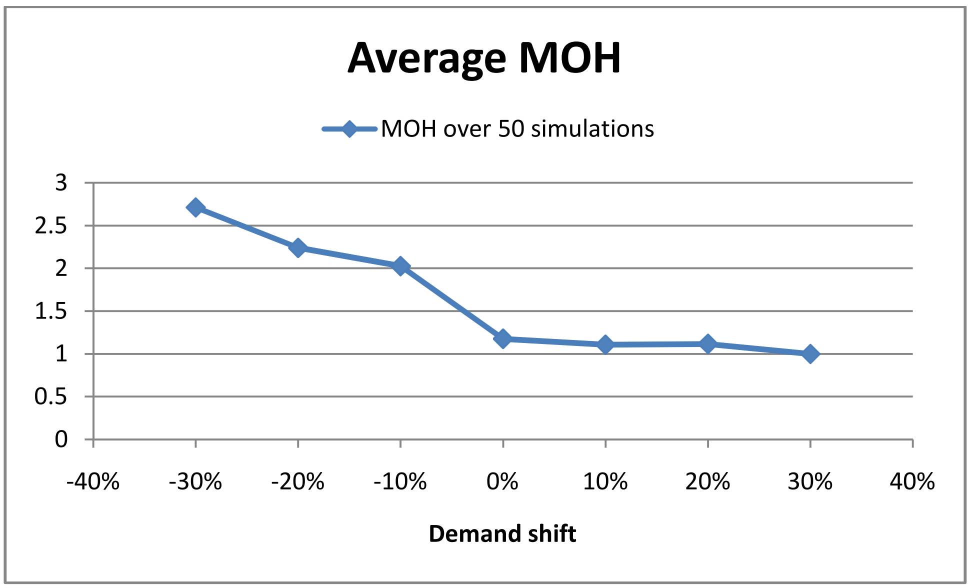

Figure 8.5 Simulated average MOH vs. demand shift

As the demand decreases the proposed policy shows a steep increase in the MOH (above the limit of 2), while, when there is an increase in the volumes, the months on hand remain substantially stable but there is a considerable increase in the lost sales. This suggests the need for the inventory planner at Instron to update the control parameters as soon as a shift in the demand is detected, using the provided tools.

9. Recommendations

9.1 Introduction

As showed in section 8,2, the optimized control parameters result in a decrease of 35% in the inventory MOH. Moreover, it is estimated that extending the optimization to all the accessories in the Configuration Department would reduce the MOH by a similar percentage. Finally, as mentioned in section 8.1, the raw materials inventory policy provided would cut the parts inventory value on hand by 30% (or even 46% if shorter lead times are agreed with suppliers).

This represents a substantial motivation to extensively use the software provided, which allows computing the replenishment parameters for all the Instron accessories both at the finished goods and part levels, and integrate it into the Manufacturing Department procedures.

The following recommendations are made to the Instron workers in order to properly implement the proposed policy and allow improvements in the future:

- Compute the inventory levels for the raw parts using the proposed tool as frequently as possible
- Compute the inventory levels for the finished goods using the proposed tool as frequently as possible
- Keep the data on IBS updated as the accuracy of the solutions depend on the quality of available data
- Keep track of the lead times for both raw parts and finished goods
- Use the provided tool to evaluate the benefits of negotiating better lead times from the suppliers

9.2 Discussion

9.2.1 Updating inventory levels

In order to guarantee that the optimal mix of accessories is on the shelves, the inventory planners of the Configuration Department should periodically update the proposed inventory control framework using the most recent sales records available. The computation of the control parameters can be performed with the provided software.

The rapid changes that can occur in the demand, in fact, dictate the need to update the replenishment quantities as frequently as possible. On the other hand, changing the parameters implies a cost in terms of time: the time required to gather the data, run the executable file and insert the new values in IBS. This might imply negotiating new quantities with the suppliers, when agreements exist. Since it is common practice at Instron to update the IBS records at the beginning of every quarter, there is the opportunity to combine these operations and perform the computation every quarter, in time for the data of last quarter to be fully available.

A further decision to be taken by the software operator concerns the quantity of sales data to include in the analysis, for the statistical characterization of the demand and the computation of the Virtual Profit. One year is the minimum time interval that should be considered to properly estimate the variations. As the considered time period increases, the computation time increases as well. Moreover, since there is continuous variation in the product list and in the market, including older data in the analysis implies greater differences between the historical data and the current situation.

In order to minimize the run time and achieve accurate results, the sales records of the last four quarters should be used. As an example, if the analysis is performed in July, the planner should collect the data for the third and fourth quarters of the previous year and for the first and second quarter of the current year.

9.2.2 Shift in demand

As mentioned in Chapter 4, historical sales are used to estimate the future demand. While it is reasonable to assume that the relationships among products (the correlation) and the variations in the demands resemble the ones of the previous year, shifts in the average volumes can occur from one year to another. When a forecast of the shift is available, it should be entered in the command shell of the software, which is able to take this factor into consideration and to provide control parameters that fit the actual situation.

9.2.3 Dividing the analysis

In order for the information involved to be easily managed, the control parameters should not be optimized for all the items at the same time. In fact, because IBS does not currently provide all the quantities needed for the analysis, a manual integration of data is required. For example, the operator has to manually enter lead times for the items considered when not available and check for the accuracy of other parameters, such as unit costs and lot sizes, when unexpected results are detected. Moreover, the optimization of the part level replenishment quantities involves downloading the bill of materials for all the considered products and the complexity of this operation increases with their number. Therefore the items should be divided into groups sized so that the operator is comfortable with their management.

The division of the analysis in groups of items allows focusing on the accuracy of the inputted data which is critical for the correct performance of provided software. As an example, the inaccuracy of the lead times data provided by IBS can lead to store inadequate quantity of items.

Similarly, even if the simulation would be a closer representation of the factory floor since more items will be simulated, the run time would become large and results difficult to interpret.

9.2.4 Lead times accuracy and negotiation

As demonstrated in section 8.1, the correct estimation of the replenishment lead times would lead to a saving of 30% in terms of VOH.

This suggests the need to improve the recording criterion for this type of data, which is currently based on many criteria. While for some of the items that are on Kanban and for the parts that come from Binghamton, another Instron facility, the values are known, for the majority of the items the lead time corresponds to the maximum lead time that can be tolerated from the supplier. As the cost and the yearly volume of one item increase, the less quantity can be stored for that item and the less time the company can wait for the supply to arrive. Also regarding the finished goods levels, lead times are missing on IBS for the parts assembled or reworked in the Norwood facility. For these parts, in fact, while setup time and run time are usually available, the time that elapses between the arrival of the order and the moment the product is ready is not recorded. The latter, however, is necessary for the computation of the optimal inventory levels.

Sufficiently accurate values can be obtained by using a new recording procedure and integrating it into IBS. Whenever an order is placed to the supplier, the purchasing agent should register the date and the supplier code, assigning a unique code to this record. The same identification number should be used in the receiving area to register the arrival date as soon as the order gets to the Norwood facility. This way, by comparing the records with the same identification numbers, it is possible to track the lead times for all the items and suppliers so that they can be used in the computation of the inventory control parameters. When variability is present, the statistical distributions of the lead times can be evaluated. The availability of this type of data would potentially allow an extension of the optimization tools which consider stochastic lead times.

As also showed in the raw materials control, a more drastic drop in the VOH can by achieved by negotiating shorter lead times with the suppliers. Whenever negotiation is possible, the supply chain planners should use the provided tool to evaluate the possible benefits of changing the lead times. In particular, they can compare the decrease in inventory value on hand with the eventual increase in purchasing cost.

9.2.5 Product categories

The category of a finished good (face, grip, fixture, etc.) is not stored by the IT system. However, as showed by Facelli and Palano, the customer expectations differ for items belonging to different categories, and this record becomes important for the optimization tool [28,26]. Right now such information can be found in the product catalog and in many other sources. However, keeping an updatable database or excel file with all the products divided by categories would help to easily identify this information and decrease the time necessary to gather the data needed for the finished goods optimization program.

9.2.6 Warning messages

For what concerns the information accuracy, the operator should take advantage of the warning messages displayed by the programs provided when unexpected results are detected.

The instruction to follow when such events occur and the operating procedure for the calculation of the inventory control parameters are presented by Serra, appendix [27].

9.2.7 New products and substitutions

Whenever new products are released and their replenishment quantities have to be calculated, the operator should provide a table containing information about the new items. Two cases can be considered:

- If the new products directly substitute one or more items in the product list, those item should be indicated as well as the fraction of demand of the old product that would converge into the new one. This allows the program to estimate the Virtual Profit and the statistical parameters of the new products demands based on the old sales data.

- If the new products are added to the product list and no old item is substituted, no historical sales data can be used to estimate the Virtual Profit, and the control parameters should be evaluated based on the simple QR model, without considering the correlation among the new items and the rest of the product list. In this case the operator is asked to provide a forecast of the future sales. This data is used to estimate mean value and standard deviation of the demand, and the z-factors are set by default to a high value which is not necessarily the optimal one, which cannot be estimated without knowing the Virtual Profit, but matches the need for the company to provide a high service level when the new items are introduced to the market.

9.2.8 Selecting the best solution

The final step of the computation of the control parameters involves the selection of the desired solution. Different solutions are provided, each one involving a different value of average MOH, and the operator is asked to choose one of them. A graph, similar to the one showed in figure 9.1, is displayed in order to aid the selection. For all the different solutions, the loss of sales profits and the MOH are plotted in the same graph and, as described in Facelli , the higher is the MOH, the smaller loss is achieved [28].

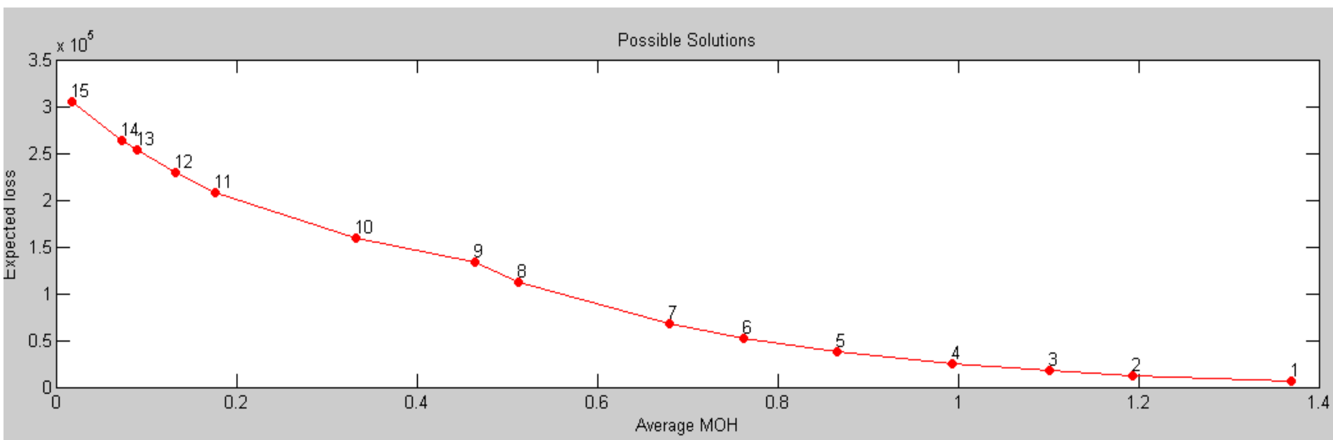

Figure 9.1 Picture displayed by the optimization tool for finished goods, comparing MOH and expected loss for different proposed solutions

When making this decision, the operator should consider that the displayed MOH is an average value and may fluctuate depending of the variability of the sales volumes. Because the Instron demand is subject to consistent fluctuations, the operator should not choose a value close to 2 MOH, which is the maximum value allowed at Instron. At the same time a small loss from sales should be achieved. This curve usually shows a flat tail, where for a little increase in the inventory cost only a little portion of sales is redeemed. The starting point of the flat tail can be considered a satisfactory solution.

9.2.9 Using and adjusting the recommended quantities

The output of this computation is a list of recommended minimum quantities and reorder quantities, which are the parameters used to build the Kanban cards. While the reorder quantity coincides with Q in the QR model, the minimum quantity is R+1. The reason for this is that the minimum quantity indicates the number of items contained in a bag; when the bag is opened to take one part the level R is reached and the order is placed.

At this point, the operator has the chance to modify the proposed quantities if constraints are present. For instance, constraints on the lot sizes exist. In addition, some items have to be ordered or assembled in lots that are multiples of some predetermined quantity. After the quantities are updated according to these constraints, a sensitivity analysis for the finished goods should be performed in order to evaluate the increase in the costs. The quantities can be directly modified in the Excel spreadsheet provided as output of the optimization tool, and the updated values of the theoretical MOH and VOH are showed. These quantities can be compared with the proposed ones and the choice must be taken accordingly.

A simulation can also be performed to observe the changes introduced by the adjusted quantities on the lost sales, value on hand and months on hand.

10. Future work

As discussed in the Results and Discussion section, Instron has potential for improving its operations management. The result of this work is reducing wastes in the inventory management. Some topics from this research, which can be further explored, are:

10.1 Lead time variability

Lead time variability is critical to every inventory policy. Variation in lead time can lead to unexpected stock outs or surges in inventory leading to increased costs and unsatisfied customers. This issue can be taken into account if the variation in lead time is known. If Instron Corporation keeps track of lead times as described in the recommendations section, the variability can be recorded and implemented inside the replenishment policy.

10.2 Manufacturing constraints

Manufacturing constraints are essential on a factory floor since mostly limited work force is available to accomplish tasks. Orders sometimes need to be rescheduled, or in the worst case lost, if manufacturing constraints and pending commitments are not taken into consideration while promising a lead time to a customer. Thus, while determining the finished goods and part levels, it is important to consider the manufacturing constraints since if these are not considered, unrealistic levels will be obtained. At the same time, the initial analysis has revealed that most of the manufacturing constraints are both independent and difficult to quantify.

Currently, final finished good levels are checked and compared by the inventory planning team before implementing. Also, the lead times have been increased to account for manufacturing constraints [28]. However, the optimum method to implement this would be to consider the constraints inside the optimization and simulation itself. This will make the new inventory levels faster to implement and easily reusable.

10.3 Include back orders in the simulation

As discussed in the above work, simulation has been developed on a simplified model of the manufacturing floor. Back orders have not been considered in the simulation and immediate order execution is being done. However, in reality, back orders will cause the orders to wait longer than required. Implementing back orders in the simulation is a complex process and needs the creation of a new database to keep track of them. Also, some orders are unexpectedly delayed due to incomplete payments, quality audits, etc. A more accurate picture can be obtained if back orders and manufacturing time is considered inside the simulation.

10.4 Include part level into the simulation

Currently the simulation tool only considers the finished goods level. The part level inventory has been determined directly under the condition that it has to be available with a very high probability whenever the finished goods need to be prepared. This, however, is an approximation and there is a miniscule probability that an order cannot be satisfied if a part level inventory is not available. Thus, it is required that a simulation be built which starts from the part level inventory, develops finished goods and finally executes the orders. This simulation will be a more accurate representation of the factory floor.

10.5 QR policy using Poisson distributed demand

As shown by Serra, Instron's monthly demand for frames can be better approximated with a Poisson distribution [27]. The assumption of normally distributed and continuous demand fits well the reality if the average demand is large enough. However for many products at Instron the sales volume is limited and it might then be interesting to perform a similar analysis with a QR policy assuming Poisson distributed demand. An in depth study can provide detailed results on whether changing the demand distribution can lead to increased profits.

10.6 Category-wise Optimization

Optimization is a complex process to run every time. It gives the service levels for each item such that an optimal mix is obtained. However, having different service level for every item can lead to confusion while undergoing policy revisions and corrections. Currently, the factory floor operates on dividing the products into categories based on values having very high service levels for each item in every category.

An optimization framework can be implemented which can present discrete service levels for such categories. The benefit of using such a method is that not only will the manufacturing planners will have easy control and understanding over such a system but, also that the correct mix of products will be available while working within the same framework. However, this solution would be less optimal than the solution proposed in this work and its implementation may still be complex.

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