The Inventory Management Dilemma: a Diagnosis Managerial Tool

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Abstract. Today manufacturing organizations are dealing with more complex competitive dynamics than those experimented in the recent years, because of the persistence of the financial crisis and the raising of some well known challenges, such as globalization, sustainability and a more sensitive consumer market. Some new general claims for an increased productivity, i.e. a high efficiency use of resources, are emerging. In the context above, the Inventory Management Dilemma stands for an extremely important matter that requires appropriate decision support tools, suitable and effective in providing meaningful data and models. This paper summarizes the most relevant results of a real case application of the Inventory Operating Curves model, here employed and developed as an Inventory diagnosis support tool. In addition, the demand pattern of the product investigated is affected by a seasonality trend.

Keywords: Inventory Management, Desk Simulation, Inventory Control

1. Introduction

The control of inventories has for a long time been a very classical Operations Research problem. As the general difficulties experienced by firms because of the financial crisis and the subsequent budget restrictions can have far-reaching effects on their competitive advantage, a new interest have been aroused in this field of research by both, the industrial practice and the academia. Although a prominent focus on the Inventory Management policies (i.e. Stock Replenishment Policies) is the primary result of the literature analysis [1], two general conceptual streams can also be recognized. On the one hand, the Inventory Optimization stream includes studies aimed to identify the optimal operating point, i.e. the specific value set for the inventory parameters, which lead a firm to achieve at the same time; a fixed service level and a certain performance of efficiency. On the other hand, the Inventory Management stream provides many methods and studies based on a modelling approach. In these works, the basic inventory parameters, such as the consumer demand (i.e. stochastic or deterministic), the time basis (i.e. continuous or periodic) and the performances of the inventory system (i.e. the logistic or financial perspective), are specified in a functional form, in order to describe the integration between the logistic activities and the traditional inventory control systems. In this context, the Inventory Dilemma problem lies not only in the traditional need to cut costs by reducing the quantities of materials stocked, but it rather evolved in the requisite to properly regulate and adjust the inventory levels, in order to target some fixed logistic performances [1]. Therefore, the design of the logistic parameters consistent with the manifold requirements of the downstream channel which requires appropriate decision support tools, suitable and effective in providing meaningful data and models.

This paper provides an original approach to the inventory stock diagnosis, in which the real application of the Inventory Operating Curves (IOC) model is considered. Specifically, the purpose of this research is to provide preliminary results of how the IOC model can be formalized [2] and employed in the actual business environment as a diagnosis tool, in order to support the inventory and stocks control process. The research is applicative in nature with the aim to contribute to the knowledge and diffusion of a well documented theory, i.e. the IOC model. Despite the descriptive validation provided by the author [2], practical implications and potential of the IOC model are still unexplored and highly unrealized. Therefore, a methodological approach is proposed, which clarifies how collect, treat and analyzed data from a real firm inventory system through multiple desk-simulation sessions.

2. Theoretical background

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The theoretical model of Logistics Curves, originally provided by Wiendahl *et al*. [3] and, in recent times, applied to the Inventory Management area [2] (i.e. the IOC model), is a framework which allows to derive the sufficient stock level to meet a certain customer demand in any given point in time. This method is proven to be an effective support to the inventory sizing decision. Therefore, after a categorization of the stocked items, it allows to analyze for each of the identified groups the relative relationship between the variable "delivery capability" (here deployed through two performance indicators such as "service level" and "average delay of delivery") and the average amount of material held in stock.

In particular, two types of curves are formalized in the IOC model:

- The Service Level Operating Curve (SLOC), that investigates values potentially achievable for the service level indicator, while considering different configurations of the input-output stock control system;
- The Delivery Delay Operating Curve (DDOC) that calculates the average delivery delay due to stock-outs, in the same input-output control configurations.

For some comprehensive considerations about the theoretical model, the reader is pleased to refer to the work of Nyhuis *et al*. [4], in which many relevant indications are provided as regard to the two operative forms taken by the model: the graphical method through the representation of the logistic variables above, based on the simulation of the logistic process for individual groups of stocked materials, and the approximate equations method, based on a deductive-experimental modelling of the logistics process. The advantage in applying the IOC model to the Inventory Management problems, compared to the traditional methods (e.g. the throughput diagram), results in the effective and simultaneous representation of the logistic variables and the performance objectives and their mutual interrelations [3].

As in the next sessions we are going to refer only to the SLOC curve, some essential notes on the formulas are cited, in order to facilitate the reading of this document. The approximate formula for the Service Level Operating Curves (SLOC) can be derived from the subsequent position:

$$SL = \sqrt{\frac{IL_m}{IL_1}}$$

where SL is the Service Level, which is at 100% in the limit condition of ILm = IL1.

Thus, the foregoing parameters can be calculated by the formula below:

$$IL_1 = \frac{Qin_m - Qout_m}{2} + \sqrt{\left(L^{+}_{\max} * RD_m\right) + \left(Q^{-}_{\max}\right)^2 + \left(\left(D_{\max} - D_m\right) * LTR\right)^2}$$

Symbols employed in the above equations and their meanings are shown in the Table 1.

Table 1: Summary of the approximate IOC model terms

Symbol	Measure unit	Description
L+max	days	Maximum delay in the delivery date as input in the inventory stock
L-max	days	Maximum advance in the delivery date as input in the inventory stock
Q-max	units	Maximum negative deviation in the output of finished goods
Q+max	units	Maximum positive deviation in the input volume of finished goods
Qoutm	units	Average lot size as output from the inventory stock
Qinm	units	Average lot size as input to the inventory stock
Dmax	units per day	Maximum Demand
LTR	days	Replenishment Lead time (i.e. the manufacturing lead time)
INm	units	Average input lot size (i.e. the production lot size)
Rm	units per day	Average Demand
Dmin	units per day	Minimum Demand

3. Methodology

The real application of the IOC model, in the form introduced in the previous section, may be based on historical data. Alternatively, if historical data is not available, the logistic parameters may be derived through a modelling analysis. The latter approach can be implemented with reference to the huge quantity of theoretical models provided by specific literature, such as Shapiro *et al*. [5]. We discuss here only the former approach, because it was the one applied in the case discussed below. This approach, which is general and repeatable, involved five major steps.

Step 1. All the materials stocked or Stock Keeping Units (SKUs), included and managed by the inventory system, have been classified through a logistic segmentation method. The most popular is the ABC analysis, which divides product based on some logistic characteristics. In this context, the selected variables should be relevant for the subsequent inventory diagnosis. Some general examples may include operative measures such as the product service goals, the product unit cost, the unit handling costs, the flow-through volume, the lead time, and others. Consistently with a recommended procedure [6], due to the IOC model applies to the individual product level, the desk-simulation below is performed on a single item or SKU, which has been identified as a representative sample.

Step 2. Since a SKU or a product family have been selected, according to the IOC model, the "service level" and "average delivery delay" parameters are extracted for inclusion in the segmentation process. Then, the target levels for the expected or the future state are specified and the corresponding operating points are plotted on the IOC figure.

Step 3. The actual operating points are then placed on the IOC curves, and the relative stock levels as currently set in the Inventory Control system, are identified. As reported above, the stock levels can be drawn from the IOC figures through a graphical approach or derived from the approximated equations. Generally, the simulation reflects the logistic activity realized at one specific instant in time, which can be assumed as "now", or can be placed in the past if the diagnosis of the logistic system is undertaken in order to give new insights over an experimented situation.

Step 4. After the parameters have been identified, the distance between the present and the future state is evaluated and analyzed. This could lead to an Inventory sizing problem. Therefore, because the IOC model employs the average amount of items stocked, the simulation may result in a reduction or an increase of the current stocked quantity for the selected SKU, according to the objectives on performances.

Step 5. Then, the appropriate actions to achieve the levels planned for performance are identified. The measures can range from the demand levelling to the improvement of forecasting techniques applied, from the reducing of lead times to the re-sizing of the input and output batches. Notice that, while considering and redefining this types of parameters or indicators, the simulative analysis remains at the operational level. Strategic issues about the logistic behaviour (actual or planned) of the investigated SKU, must be factored in, during the qualitative judgement phase of objectives setting.

4. Model setting

The product portfolio stocked by the selected company, consists of 102 items. The relative data base was first reviewed through an ABC cross-analysis, and secondly divided in three classes, while employing the "single item turnover" and the "inventory stock" as segmentation variables.

Table 2: Monthly amount of sales and inventory stock for the item FamA (e.g. peak seasonality data HS).

Month	February	March	April	May	June	July	August	Average
Turnover (Euros)	436.750	424.987	386.340	587.326	501.141	463.447	496.280	470.896
Inv_Stock (Euros)	1.908.635	1.867.253	1.533.552	1.629.102	1.542.406	1.550.840	1.453.930	1.640.817

In this step, the indicators are both assumed as monetary valued in Euros. Then, for the purpose of this work, a product belonging to the AA class was extracted. This item, hereinafter referred as FamA, is selected as representative of a product family within the AA class. The monthly averaged profiles of turnover and inventory stock for the selected product are reported in Table 2 and Table 3, for the peak season of sales and for the low one, respectively.

Table 3: Monthly amount of sales and inventory stock for the item FamA (e.g. low seasonality data LS).

Month	September	October	November	December	January	February	Average
Turnover (Euros)	339.927	391.216	422.536	214.723	273.078	436.750	346.372
Inv_Stock (Euros)	1.813.440	1.908.862	1.884.580	1.791.520	1.905.551	1.908.635	1.868.765

This phase of the real case application protocol required the definition and setting of the input parameters for the FamA product. The second column in the Table 4 reports the preliminary assumptions made in order to initialize the desk-simulation for the peak seasonality data, while the third column reports the values assumed for the low seasonality period. In the next sessions, findings of IOC model application are provided, in which the parameter "c" is assumed equal to 0.3. Notice that, this value has been assigned after trying many different values through iterative testing, anything else being the same.

Table 4: Model parameters assumptions to initialize the IOC application (e.g peak seasonality data HS).

Model Parameters	*FamA* (HS)	*FamA* (LS)
L^{-}_{max}	6,6	6,6
Q^{-}_{max}	2500	2500
D_{max}	26600	19850
LTR	66	66
INm	50000	50000
D_m	21400	15740
L^{-}_{max}	0	0
Q^{+}_{max}	0	0
D_{min}	17560	12400
OUT_m	1000	1000

Further setting values, such as Dmax, Dm, Dmin LTR, INm, were drawn from data relating to demand, production and picking lot size, production lead time[2].

5. Model desk-simulation

The analysis of the current situation resulting from the Inventory system truly adopted by the manufacturing organization, is provided in this session, which also reports the figures relating to SLOC functions for the FamA product (see Figure 1), as introduced in the approximate model.

The target or future state is fixed corresponding to a Service Level equal to 100%. In this case, the IOC model provides an average inventory stock equal to 395,000 units in the first period (HS), while in the second period the stock provided is 315,000 units (LS).If we consider a complete period (e.g. the sum of the two partial time horizons HS and LS), the IOC model provides an average stock level equal to (315.000 + 395.000)/2 = 355.000 units. Such a value is lower than the average quantity which can be calculated through the application of the IOC model on the year basis for the FamA item, without separate the diagnosis among different seasonality trends. The first finding is that accounting for seasonality effects with respect to the analysis on the complete period, may lead us to an inventory stock minimization approach, in order to draw some cost efficiency issues.

Moreover, on the same graphs, another scenario developed by the IOC model is depicted. If a Service Level of 98% can be accepted for the future state, the corresponding size of the inventory stock may be automatically fixed through the SLOC Curves. In the HS period, the minimum quantity may be equal to 150,000 units and in the LS period the volume may be 130,000 units. The second finding, is that the IOC model applications for both the periods under examination, result in a potential average stock reduction of the FamA item, while a good logistic performance (i.e. the Service Level) is assured.

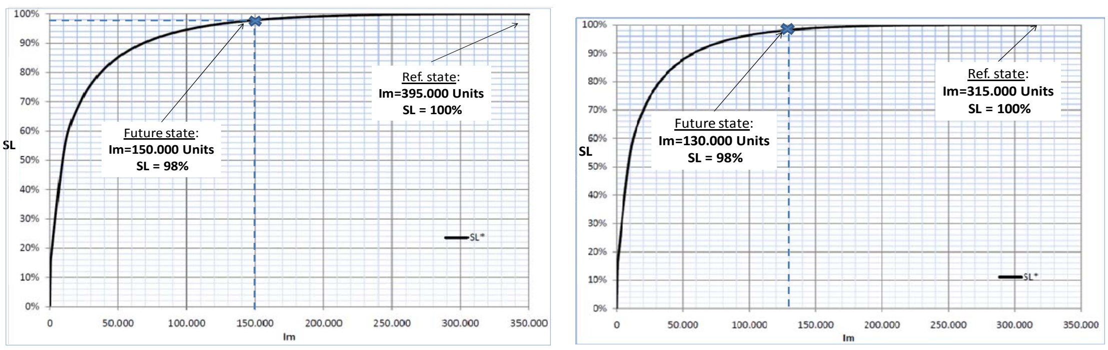

Fig. 1 SLOC Curves for the FamA item, in the peak and low seasonality period (HS and LS).

[2] For products labeled as FamA, the lead time is 3 months (i.e. 66 days); the production batch, which corresponds to the economic lot size, is fixed in 50,000 units. Moreover, further assumptions are made: Q-max=2,500 units, because a negative deviation of 5% on the replenishment lot size is accepted for the volume as input to the inventory stock; L+max=6.6 days, because a maximum delay in delivery date of 10% on replenishment lead time is assumed; OUTm=1,000 units, which is calculated for the volume of finished products as output from the inventory stock; L-max e Q+max are considered as negligible in the real case under investigation.

The main difference between the two periods is on the composition of the Safety Stock (SS). For instance, in the HS case, the fraction of the stock assigned to deal with delays in delivery date may be higher than in the LS case, and the IOC model application can support this intuitive assumption. By analyzing all individual components to the SS amount and the respective behaviour, we can identify all the variables to be controlled in order to limit the stock volume proliferation.

6. Conclusions

The objective of this paper was to introduce the formal model of the Inventory Operating Curves (IOC), in order to describe its potential application to a real case inventory system. The most important and original contribution is on the 5-step analytical method drawn from the IOC theory. Even if the setting phase is based on the availability of a considerable amount of input data relating to the inventory control system currently in use, the IOC model can lead to a suitable and effective method for the Inventory diagnosis. The real case application has some points of originality as well. The product family under examination was affected by a seasonality trend. Thus, the IOC model was iteratively applied to two sample of data, the first relating to the peak seasonality (HS) and the second relating to the low seasonality one (LS). The desk-simulations performed, allow identifying some typical problem in the Inventory Management area, which can be afforded through the IOC curves, such as the sizing of the Safety Stock held in inventory corresponding to a target Service Level (i.e. the SLOC curve). Although the method provided is still experimental, the analytical approach has been demonstrate as general as it may be used with benefit in many other circumstances.

7. References

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