Evaluating Inventory Management Performance: a Preliminary Desk-Simulation Study Based on IOC Model

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***Abstract*—The focus of this study is on preliminary use and implementation of an innovative stock performance evaluation procedure, based on the Inventory Operating Curves model. The evaluation of Inventory System performances is becoming a primary concern for senior managers in many sectors, due to the global financial crisis and the budget-cutting policies. However, traditional models require to simultaneously assess and monitor many interrelated parameters, in order to describe the logistic behavior of a huge quantity of items. In that sense, traditional tools are not very useful or effective for decision-making and managerial practice.**

The Inventory Operating Curves (IOC) model, based on an aggregate Inventory Level approach, can be successfully employed to perform an evaluation of the current Inventory System. In addition, it can support the re-design of the logistic parameters consistently with the manifold requirements of the downstream channel. The case study provided in this paper refers to a selected Italian pharmaceutical manufacturer. The evaluation of the real inventory data available, is developed around the seasonality issues which are expected to affect the demand pattern of a particular product family.

***Index Terms*—Inventory Management, Desk Simulation, Inventory Control.**

I. Introduction

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. Since inventories represent a significant investment by many firms, and with annual carrying costs typically ranging from 20 to 40 percent of inventory value, managing them well is a top-management priority.

In practice, while 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 several methods and studies based on a modeling 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 analytical formulas, in order to describe the integration between the logistic activities and the traditional inventory control systems.

In this context, the evaluation of the performance for an Inventory System currently in use, cannot be uniquely aimed to the traditional need to cut costs, by reducing the quantities of stocked materials. Therefore, it rather evolved in the requisite to properly regulate and adjust the inventory levels in their aggregate form, in order to achieve some strategic objectives.

As counterpart, it’s of primary importance that the design of the logistic parameters is realized consistently with the manifold requirements of the downstream channel.

This paper illustrates an original approach to the inventory management performance evaluation, by providing a IOC-model-based procedure, which can be developed from readily available company data.

Specifically, the purpose of this research is to introduce preliminary results of how the IOC model can be formalized [2] and employed in the actual business environment as an evaluation 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.

II. Theoretical background

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.

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In particular, two types of curves are formalized in the IOC model [2]:

- 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 modeling of the logistics process.

The advantage in applying the IOC model to the Inventory Management evaluation problem, 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 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 $IL_m = IL_1$.

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 I.

TABLE I: 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

III. METHODOLOGY

The practical 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 for the Inventory System of a company, the logistic parameters may be derived through a modeling 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 study developed below. This approach, which is general and repeatable, involved five major steps.

Step 1: Identification of the unit of analysis. All the materials stocked or Stock Keeping Units (SKUs), included and managed in the inventory system, should be classified through a logistic segmentation method. The most popular is the ABC analysis, which divides products based on some logistic characteristics. In this context, the selected variables should be relevant for the subsequent inventory evaluation. 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: Inference of the current performance. Since a SKU or a product family have been selected, according to the IOC model, the "service level" and "average delivery delay" parameters have to be extracted for inclusion in the segmentation process. This preliminary analysis can be derived from general stock status reports, which usually include inventory levels and shipping volumes. According to the stocking rules applied to them, SKUs which are similar, may be classified together and plotted as a group in the relative graphs. At this stage is important to define the time basis for the collection of data. If stock reports are available for periods of time less than a year, inventory levels should be averaged and the throughput should be summed, in order to refer them to the same time interval.

The IOC curves should be prepared for the items or SKUs families selected, on the time basis of interest. Then, the target levels for the expected or the future state should be specified and the corresponding operating points plotted on the IOC figure.

Step 3: Preliminary model setting. 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 evaluation of the Inventory System is undertaken in order to give new insights over an experimented situation.

Step 4: Analysis of deviations from the expected values. After the parameters have been identified, the distance between the present and the future state is evaluated and analyzed. A company may employ formal inventory management rules or informal judgments-based rules, or a combination of these. Inventory levels may deviate from those expected or planned based on the rules being applied. Even not grounded in a item-by-item analysis, the extent of the deviation, in terms of a benchmark against which current stocking levels may be compared, should be deducted from the IOC curves plotted at the previous step. This could lead to an Inventory sizing problem. Therefore, because the IOC model apply at an aggregate level and 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 established on logistic performances.

Step 5: Creation of an action plan. Then, the appropriate actions to achieve the levels planned for performance are identified. The measures can range from the demand leveling to the improvement of forecasting techniques currently 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 behavior (actual or planned) of the investigated SKU, must be factored in, during the qualitative judgment phase of objectives setting.

IV. The Case Study Performed

The procedure introduced above, and in particular the desk-simulation analysis, is performed with reference to the inventory data provided by a manufacturer in the pharmaceutical and biotech industry, which actually produces and distributes in the Northern Italy.

In recent years, this company experimented the aggressive requirements posed by the distribution channel, whose logistic performance must meet specific regulations and deal with new market dynamics.

Moreover, in this industry the inherent complexity of the downstream channel is exacerbated by instances of a very short fulfillment time in face of an extremely limited number of items per order, and by a regulation on the maximum delivery delay acceptable by the customer.

As a consequence, the competition results significantly affected by cost reduction programs, because of a current phase of market saturation and price pressure. Indeed, most available evidence has found the Italian demand for pharmaceuticals to be quite insensitive or even unresponsive to price policies.

Those factors led the top-management to redesign the current inventory stock system of the manufacturing company, in light of a more systemic efficiency achievable as regard to the logistic performance objectives.

In addition, some key product, even belonging to the A-class of an ABC classification, are characterized by a seasonality trend in the demand pattern (Fig. 1). The impact of seasonal variations and unrepresentative data shifts, which can occur in the short time periods, may be reduced by plotting annual data. Therefore, plotting the IOC logistic parameters on a monthly base may provide better insights, as the nature of deviations from the expected\planned performance.

The analysis reported below tried to gather all the suggestions here mentioned.

V. Preliminary 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.

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 II and Table III, for the peak season of sales and for the low one, respectively.

This phase of the real case application protocol required the definition and setting of the input parameters for the FamA products.

TABLE II: Inventory Stock and Sales for FamA Items (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

TABLE III: Inventory Stock and Sales for FamA Items (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

The second column in the Table IV 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.

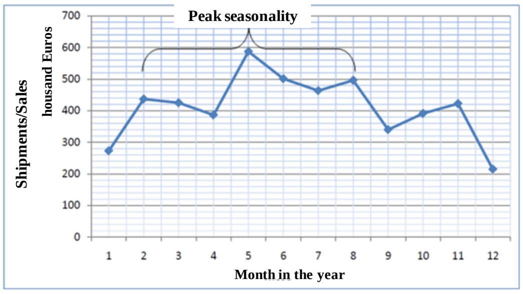

Fig. 1. Demand pattern on a monthly base

TABLE IV: INITIAL PARAMETER ASSUMPTIONS

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 D_{max}, D_m, D_{min}, LTR, IN_m, were drawn from data relating to demand, production and picking lot size, production lead time.

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; OUT_m=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.

VI. 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 Fig. 2 and Fig. 3), as introduced whit the approximate model.

The target or future state is fixed corresponding to a Service Level equal to 100%, because of the requisites of the downside channel. 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 (i.e. the sum of the two partial time horizons for 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 items, without separate the evaluation among different seasonality trends.

Consequently, the first finding is that accounting for seasonality effects with respect to the analysis on the complete period, may lead to an inventory stock minimization approach, in order to draw some cost efficiency issues.

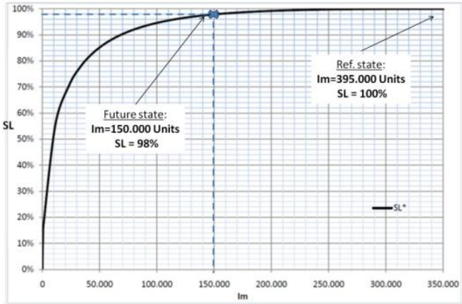

Fig. 2. SLOC curve for peak seasonality period (HS)

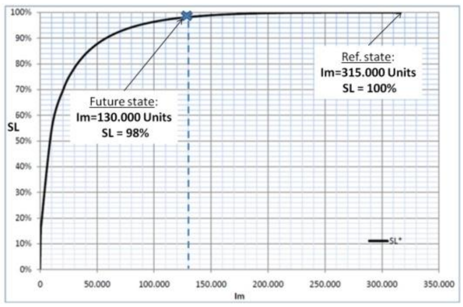

Fig. 3. SLOC curve for low seasonality period (LS)

Secondly, in order to proper understand the output of iterative simulations, it is important to separate inventories according to their function in the system. In particular, the main difference between the two periods, as emerging from the SLOC curve analysis, is on the composition of the Safety Stock (SS). The value of the safety stock (SS) maintained in the system is designed to compensate for deviations from the ideal situation, due to:

- Delays in delivery date (L + max);
- Negative variations in the quantity delivered from the production to inventory stock (Q-max)
- Variations in the downside demand (Dmax) and replenishment lead time (LTR).

The safety stock, as usual, is defined in order to guarantee the expected performance levels toward customers, even if some unexpected deviations occur from the ideal condition (i.e. the parameters above are not null in the approximate model). By assuming the three deviation effects to be statistically independent, the subsequent expression for the Safety Stock (SS) variable can be derived:

$$SS_{min} = \sqrt{(L^{+}_{max} * D_m)^2 + (Q^{-}_{max})^2 + \left((D_{max} - D_m) * LTR\right)^2} = \sqrt{(SS_{1,min})^2 + (SS_{2,min})^2 + (SS_{3,min})^2}$$

For instance, in the HS case, the fraction of the stock assigned to deal with delays in delivery date (SS_1) may be higher than in the LS case, and the IOC model application can support this intuitive assumption (see Table V).

TABLE V: COMPONENTS ANALYSIS FOR THE SAFETY STOCK

SS components	*FamA* (HS)	*FamA* (LS)
SS_1 (Delay in the delivery date)	29.01%	27.51%
SS_2 (Deviation in the quantity delivered)	0.51%	0.66%
SS_3 (Deviation in the demand for LTR)	70.48%	71.83%

Therefore, in the LS period, the component related to deviation in demand (SS_3) is increasing as percentage.

This trend shows a further reduction potential of the individual additional quantity, through the adoption of appropriate delivery strategy in first case and by improving forecast reliability in the second one.

Moreover, by analyzing the components of the SS variable and their respective behavior, the IOC model allows to identify all parameters to be controlled, in order to limit the stock volume proliferation.

VII. CONCLUSIONS

The objective of this paper was to introduce a formal procedure based on the Inventory Operating Curves (IOC) model, in order to discuss its potential application to a real Inventory System.

Through the case study conduct, some previous conclusions are given further credibility; specifically:

- that the IOC model can lead to a reasonable representation of the logistic performances, as alternative to the common inventory control policies;
- that the optimal "c" value included in the IOC equations can be adaptively set, maybe drawing upon many iterative desk-simulations;
- that the IOC model can be a reasonable predictor of the stock reduction potential, which will permit taking advantage of cost savings and providing rapid liquidity increases.

The most important and original contribution of this study is on the 5-step analytical procedure, 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 performance evaluation. 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 in parallel, 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 procedure provided stems for a preliminary study, the analytical approach has been demonstrate as general as it may be used with benefit in many other circumstances.

REFERENCES

[1] R. J. Tersine, *Principles of Inventory and Materials Management*, Prentice Hall PTR, 1993.

[2] S. Lutz, H. Loedding, and H. P. Wiendahl, "Logistic-Oriented Inventory Analysis," *Int. J. of Prod. Ecs*., vol. 85, no. 2, pp. 217-231, August 2003.

[3] H. P. Wiendahl and P. Nyhuis, "Performance Measurement of the Procurement Process on the Basis of a New Operating Curve of Stock-on-Hand," *Prod. Eng*., vol. 4, no. 1, pp. 105-108, January 1997.

[4] P. Nyhuis, G. von Cieminski, and A. Fischer, "Applying Simulation and Analytical Models for Logistic Performance Prediction," *Annals of CIRP–Manufacturing Technology*, vol. 54, no. 1, pp. 417-422, January 2005.

[5] J. F. Shapiro and S. N. Wagner, "Strategic Inventory Optimization," *J Business Logs*, vol. 30, no. 2, pp. Autumn 2009.

[6] J. D. Sterman, *Business Dynamics*, New York: McGraw-Hill Higher Education, 2000.

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