Forecasting and stock control: a study in a wholesaling context

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Abstract

Wholesalers add value to the products they deal with, by essentially bringing them closer to the end consumers. In that respect, the effective control of stock levels becomes an important measure of operational performance especially in the context of achieving high customer service levels. In this paper, we address issues pertinent to forecasting and inventory management in a wholesaling environment and discuss the recommendations proposed in such a context in a case study organization. Our findings demonstrate the considerable scope that exists for improving current practices and offers insights into possible managerial issues.

Keywords: Forecasting, Inventory, Demand Categorisation; Wholesaling

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1. Introduction

Wholesalers add value to the products they deal with, by essentially bringing them closer to the end consumers or industrial clients. In that respect, availability becomes a crucial operational performance measure whilst at the same time inventory related costs constitute the main investment in this environment. Consequently, effective stock control represents the main opportunity for attaining high customer service levels and generating considerable cost benefits.

The academic literature that deals with inventory management related issues in the wholesaling context is rather extensive. The relevant literature extends back to the 1950’s and has considered many topics ranging from the strategic level decision making (such as network design and distributional strategies) to more ‘tactical’ issues such as demand forecasting, inventory level settings in the warehouses or stores and the replenishment coordination between them. Nevertheless, despite the huge literature dealing with this problem, very few papers are actually considering empirical solution implementation and case studies, that may also offer qualitative insight, are lacking.

In this paper, we explore forecasting and stock control related opportunities for increasing service levels and reducing costs in a wholesaling context. We analyse pertinent issues through a case study of a UK based wholesaler of engineering supplies. This research work has been launched along with the initiation of a project in the organisation under concern that aimed at increasing the service availability to consumers and reducing the overall stock levels. Our work has been conducted in collaboration with a dedicated
working group in that company. We will show, through this case study, that although a rather ‘basic’ (as compared to the theoretical advancements in this area) inventory control solution has been proposed, the projected organisational savings are substantial. This result is not surprising but rather it has been expected since practical in-house inventory management related applications lag considerably behind the corresponding theoretical propositions in this area. In that respect, our work can be seen as a contribution towards bridging the gap between the theory and practice of OR in the area of inventory management.

The remainder of this paper is organised as follows: in section 2, the case study organisation is presented along with a detailed discussion of the pre-project processes governing stock control. In section 3, the relevant literature is overviewed for the purpose of informing, where possible, our investigation. In section 4, we present the development of the proposed forecasting and stock control solution followed, in section 5, by details related to the experimental structure of our investigation. In section 6, the empirical performance of the proposed solution is evaluated against that of the system currently in place. The conclusions of our paper along with some natural extensions of the work presented here are given in section 7.

2. Case study organisation

Valves Instruments Plus Ltd. (VIP) is a wholesaler of engineering supplies stocking a wide range of valves and ancillary products and selling primarily to the construction sector. The company was founded in 1985 and it is situated just outside the Manchester
city centre boundaries. Its customers throughout the UK range from small to medium size companies to government funded bodies, universities and major engineering contractors. The company sells an extensive range of stock items which are primarily stored in the warehouse ready for dispatch; it also accepts ‘special’ orders which often involve highly complex equipment sourced from various suppliers. The company’s supply base is quite vast, given the wide range of items available in its catalogue. Currently, supplies are primarily sourced from within the UK; however, increasing numbers of items are sourced from Italy and Asia. This is more efficient from an economic standpoint, but the lead times can exceed in some cases 20 weeks rendering an effective forecasting and stock control strategy an immediate necessity.

2.1 Inventory management

Before our project was launched, the stock control process was managed manually (by the stock control officer) based, essentially, on a periodic re-order point method. The inventory positions (that comprised only stock on hand, without considering planned receipts) were reviewed weekly (every Friday); if stock on hand was below an arbitrarily specified re-order point, an order was placed for a quantity that represented the average demand over a certain number of previous weeks. The pre-specified re-order quantities were suggested years ago by the Managing Director and never updated since then. This means that recently introduced codes are not even associated with a suggested re-order level rendering the ordering process even more arbitrary in nature. In addition to the weekly re-ordering system, if stock is urgently needed for a particular item to facilitate an order, the corresponding transaction would occur on the day the problem was experienced. The process involved the use of a paper-based report generated by the data
system utilised by the company, called Opera. Opera also facilitates the company’s administrative and financial procedures and it supports the whole information related infrastructure. In terms of stock ordering, data on all transactions carried out against each item is available. Similarly, additional information like current stock levels, quantity on order, etc. may also become available, if necessary, in order to inform the ad hoc decisions made by the stock control officer when re-ordering items.

The details related to each item need to be checked against the system, as the re-order report contains various inaccuracies, such as obsolete (no longer traded) items appearing on the report. (Another software solution exists in the company that it could potentially offer reports that would be more useful in assisting the stock control officer in the re-ordering process. Such software though has not been utilised due to the lack of time available to personnel.) A purchase order is then raised within Opera for the necessary goods. Item prices are automatically entered by Opera; the stock officer just enters the quantity required and date.

In the past, staff felt reasonably comfortable with the ordering processes in place; in the presence of ‘unusual’ problems they resorted to internal communications in order to resolve them. That was feasible given the long service of particular individuals within the organisation and their acquaintance with the imperfections of the system. However, as the company recently started expanding with new staff being employed, the lack of transparency in the system became far more obvious and the need for increased levels of automation was exemplified. In addition, the lack of any degree of science behind that
process facilitated our demonstration, at the conceptual level, of the potential benefits that a well-informed system would offer to the company.

3. Literature overview

The academic literature that deals with inventory management related issues in the wholesaling context is rather extensive. The relevant literature has considered many topics ranging from the strategic level decision making (such as network design and distributional strategies) to more ‘tactical’ issues such as demand forecasting, inventory level settings in the warehouses or stores and the replenishment coordination between them (e.g. Das and Tyagi, 1999; Germain and Groge, 1999). Nevertheless, and as discussed in the previous section of our paper, the case study organisation serves mainly the construction industry rather than specific retail outlets. As such, theoretical advancements that relate to the typical configuration of the relevant systems (i.e. one wholesaler - many retailers) do not necessarily inform our empirical investigation and consequently they are not explicitly considered in this section.

3.1 Demand forecasting and stock control

Forecasting in a supply chain context has attracted a considerable amount of academic research. This is true both for fast moving items and, more recently, also for slow movers or intermittent demand Stock Keeping Units (SKUs) that are characterised by infrequent demand arrivals (see, for example, Altay et al., 2008; Gutierrez et al., 2008; Porras and Dekker, 2008; Syntetos et al., 2008; Teunter and Sani, 2009). Such studies are very relevant for the purposes of our investigation since the great majority of the SKUs in the
case study organisation are intermittent in nature. For a comprehensive review of advancements in the area of supply chain forecasting in general the reader is referred to Fildes et al. (2008).

Some recent research work in this area has also been focusing on new forecasting approaches that deal with demand aggregation and the use of combined forecasts, especially in the presence of demand intermittence, demand seasonality and trend (e.g. Chen and Boylan, 2007; Viswanathan et al., 2008). This need for forecasting methods that consider product aggregation has emerged from the growing assortments of products and the shorter product life cycles in the wholesaling environment. Moreover, this may be also due to demand data showing too high variation and/or other issues related to constructing reliable forecast models at the individual item level.

Typical stock control approaches discussed in the literature in the wholesaling context are relying upon traditional well-known methods such as the min-max (s, S) policy (e.g. Schneider and Rinks, 1991). Moreover, our experience indicates that in practical situations all too often managers resort to very basic inventory rules such as the reorder point methods where the control parameters are set arbitrarily. This is also true for the case study organisation.

Pearson (2006) looked at the newspaper wholesaler problem and investigated the relationship between the two main targets associated with the ‘optimal’ supply of newspapers (mean number of unsold newspapers/overage and probability of no stock-out/underage) and the forecasting method employed to predict demand as well as their
joint impact on the system’s performance through a case study. By considering the time series for newspaper demand over a 31-week period, he showed that the employment of a prediction method in conjunction with a new technique for adapting targets (that subsequently renders the prediction method capable of satisfying both targets) resulted in considerable improvements as compared to the previous situation according to which a forecasting method would not simultaneously achieve low overage and low underage.

The relevance of performance measurement in the wholesaling environment was also discussed by Ritchie and Kingsman (1985). They investigated a wholesaling stock system based on a periodic order-up-to-level policy with weekly reviews and replenishments. The authors studied the implications of various measures (such as Return on Sales, Return on Stock Investment, Stock Turn, etc.) for setting stock levels and they showed that some measures are very sensitive to the level of sales.

4. Solution development

In order to investigate the effectiveness of current practices in the company with respect to inventory management, empirical demand data was obviously required. As expected, data collection ended up being a rather complicated process due to the lack of integration of the relevant information and the lack of any previous attempts to collate data that collectively could be used for stock control purposes. Our objective was to retrieve a complete historical picture of how the system had been performing for as long a period as possible. Such a picture would comprise weekly information on demands received, orders placed and orders received, stock on hand and backordered as well as supportive information in terms of initial stocks, unit cost details etc. The recommended solution
could then be empirically assessed in a dynamic fashion, i.e. we would be able to evaluate how the new solution would have performed if it had been used in this situation.

In this section, the data collection process is first briefly described. Subsequently, issues related to classification of the SKUS are discussed followed by our proposed intervention in terms of forecasting and stock control modelling.

4.1 Data collection

As previously discussed, the company’s administrative and financial procedures as well as the whole information related infrastructure are controlled through Opera. The following information was extracted from the Opera system via the XRL software.

- Demand and sales histories (volumes of sales, returns)
- Timing of new codes being introduced and sales since their introduction
- Historical ordered quantities to the suppliers (quantities and timing)
- Actual weekly quantities in stock and initial quantities; information retrieval was feasible only from January 2005 onwards
- Costs and prices for all SKUs
- Actual lead-times (that were expressed in working days). This information was also retrieved in conjunction with estimation from purchasing staff.

A series of meetings took place to confirm the validity of this information. Lead-times constitute an approximate average of the time difference between placing orders and receiving them. Their expression in working days and the lack of compatibility with the
weekly time periods considered for our analysis introduced also a new problem; that of converting the relevant time periods into weekly ‘buckets’. A programme was written in Visual Basic to allow this conversion and the validity of the final outcomes was checked with the purchasing manager of the company. The data collection process resulted in 2,156 demand histories accompanied by all information needed for a stock control analysis.

At this point it is important to note that there is a number of items managed by the company but were not considered in our investigation. Such items relate to: i) SKUs that are never held in stock but which are on sale. If an order is placed for such items, they are purchased directly from the suppliers, on demand. Such a procedure reflects short lead times and beneficial contractual agreements with the relevant suppliers; ii) the company imports certain items in bulk getting special prices for doing so, given the large quantities that such items are being ordered. It was decided that these items would continue to be ordered in this fashion reflecting economies-of-scale considerations.

4.2 Demand classification

The above discussed data collection process resulted in a data set of 2,156 SKUs with accompanying information about the unit costs, the selling price per SKU as well as the actual replenishment lead times. Weekly demand information was made available for the period Jan. 2005 - Sep. 2007. Demand characteristics varied considerably amongst the SKUs with some being particularly slow moving, having only one or two demands recorded over the entire history. Some SKUs had not been moved at all.
The first stage of our analysis consisted of the classification of the SKUs for the purpose of developing our understanding regarding the relevant data and finding appropriate ways of communicating our ideas with management. No such analysis had ever been performed before and no formal records existed of, say which are the best sellers in the organisation and which is their contribution to the total turnover. Correspondingly, no attempts had ever been made to identify obsolete items or SKUs that are very slowly moving.

Several classification rules have been proposed in the academic literature to facilitate managerial decision making. It is common for organizations to classify their SKUs, assigning higher service-level targets to some segments than others and treating the different categories in distinct ways as far as forecasting and stock control are concerned. In particular, ABC (Pareto) type classifications are often used in practical applications. A Pareto report lists all SKUs in descending/ascending order, by either demand frequency, demand volumes, demand values or by demand profit (Silver et al., 1998) and relevant categories (A, B, C etc) are specified. Rules based on demand value (sales volumes $\times$ selling prices) are perhaps the ones most commonly encountered.

For the purpose of this project, a Pareto classification analysis has been conducted based on the contribution to profit (sales volumes $\times$ net profit, where the latter is calculated as the selling price minus the cost price). Management felt more comfortable with the idea of identifying contribution to net profit as apposed to gross sales for the purpose of identifying the best selling products. Moreover, it is important to note that frequency
based rules that have often been recommended for use in the context of slow moving or intermittent demands were also not perceived as informative by management. The results are presented in Table 1; the classes were constructed as to indicate percentage contribution to profit in increments of 20%.

The results were very surprising to the company; 20% of all profit comes from just 11 items. There are only 233 items (about 11% of the entire stock base) generating 80% of the net profit. There is a tremendous number of SKUs contributing literally nothing to the profit of the organisation. Please also note that in the majority of cases such SKUs were not even important in terms of complementing orders for a range of items. The analysis, despite its simplicity, was particularly effective in initiating managerial action: i) first, it was decided to look closely at the best sellers on a regular basis and introduce periodic updates of the Pareto scheme; ii) the analysis triggered an immediate response with respect to ‘clearing’ the stock base and discarding (in the majority of cases at a discounted price) obsolete items. That aggressive write-off strategy was perceived as one of the most important outcomes of our project.

Preliminary empirical analysis indicated a wide range of underlying demand patterns, most of which were intermittent in nature. Although management was convinced of the value of more advanced classification schemes that capture demand characteristics (e.g. Syntetos et al., 2005) and their potential value in facilitating a more effective approach to forecasting and stock control (in terms of treating in a different way the resulting
categories), the relevant implementation was decided to be excluded at that initial stage of intervention with the system. This issue is further discussed in section 7 of the paper where the natural next steps of research are outlined.

4.3 Forecasting methods

The stock base of the company consists of very few ‘fast’ and many intermittent SKUs, the latter being associated with sporadic arrivals of demands which are interspersed by some (many) time period where no demand occurs. The distribution of the average inter-demand intervals across all the SKUs considered in the sample, is indicated in Figure 1. Inter-demand intervals equal to 1 mean that demand occurs in every single period (week).

As the classification of the SKUs based on their demand pattern and the subsequent selection of different estimators was not feasible at this stage, we considered the implementation of estimators across the entire stock base. In particular two methods were evaluated: Simple Exponential Smoothing (SES) and an estimator specifically developed for intermittent demand patterns, the Syntetos-Boylan Approximation (SBA) (Syntetos and Boylan, 2005).

<<<Please insert Figure 1 about here>>>

The SBA is a bias deduction modification to Croston’s method and it has been shown to outperform this estimator both theoretically and empirically. Our decision for experimentation with these methods reflected a careful preliminary analysis of the demand data set as well as three main considerations: i) ease of application and
communication to management; ii) robustness and iii) statistical properties of the methods under concern.

When SES is used, the estimate of the demand level $F_t$ made at the end of period $t-1$ for the demand in period $t$ is as follows:

$$F_t = F_{t-1} + \alpha(D_{t-1} - F_{t-1})$$  \hspace{1cm} (1)

where: $D_{t-1}$ is the actual demand in period $t-1$ and $\alpha$ is a smoothing constant.

When the SBA method is used, the forecast is given by:

$$F_t = (1 - \frac{\delta}{2}) \frac{\hat{Z}_t}{\hat{T}_t}$$  \hspace{1cm} (2)

with $\hat{T}_t = \hat{T}_{t-1} + \delta(T_t - \hat{T}_{t-1})$ and $\hat{Z}_t = \hat{Z}_{t-1} + \lambda(Z_t - \hat{Z}_{t-1})$ being the estimates of the demand interval and size respectively updated by using SES at the end of the demand occurring periods only. If no demand occurs the relevant estimates remain the same.

In both cases, the variance of the forecast error is estimated through the smoothed Mean Squared Error (MSE) approach, so that:

$$MSE_t = \beta(D_{t-1}-F_{t-1})^2 + (1-\beta)MSE_{t-1}$$  \hspace{1cm} (3)
The parameters $\beta, \delta, \lambda$ are smoothing constants.

**4.4 Stock control modelling**

For stock control purposes, we proposed the application of the periodic reorder point $(T, r, Q)$ policy, with the review period $T = 1$. (For ease of presentation we will be simply referring to this policy as $(r, Q)$ for the remainder of the paper.). Periodic order-up-to level policies that, according to our opinion, would be far more suitable in such an environment were not further considered. This is because management opted for a policy that it would resemble to the greatest possible extent current practices utilised in the organisation. To recap, currently stock is being controlled by essentially a periodic reorder point policy albeit with a judgemental (arbitrary) setting of the re-order levels and order quantities and manual operation (please refer also to section 2).

Let us recall that under the periodic $(r, Q)$ policy, time is treated as a discrete variable. The system is controlled at the end of every review period, and if the inventory position falls below the reorder point $r$, a quantity $Q$ is ordered. The quantity ordered is received after the replenishment lead-time $L$. The reorder point is re-computed at the end of every period, whereas the ordering quantity is computed once and for all for each SKU.

The parameters of the $(r, Q)$ policy are computed by considering a Cycle Service Level (CSL) rather than a cost constraint in accordance with the company’s priorities and the

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1 The order of events in a period (week) is assumed to be as follows: a demand occurs (may be zero), net inventory levels are determined and holding/backorder costs are incurred (for each unit on hand or backordered, respectively), an order can be placed, and an order can arrive.
strong competition present in the market they operate in. The CSL is the probability of no stock-out during a cycle (the cycle is the time period between two successive demands). The re-order point computed for period $t$ (at the end of period $t-1$) is denoted by $r_t$ and is given by:

$$r_t = (L+1) F_t + \Phi^{-1}(CSL) \sqrt{MSE_t(L+1)}$$

(4)

where: $\Phi(.)$ is the cumulative distribution of the demand per period.

Naturally, an assumption of the probability distribution of the demand per period is needed in order to compute the inventory control policy parameters. For the purposes of our work, demand was assumed to be Gamma distributed. The Gamma distribution has been much used in the inventory control literature due to its high flexibility regarding the variance to mean ratio as well as empirical evidence in its support for both smooth and intermittent demands. In order to compute the ordering quantity $Q$, we use the EOQ formula:

$$Q = \sqrt{\frac{2A\mu_\rho}{h}}$$

(5)

where: $A$ is the ordering cost, $h$ the inventory holding charge and $\mu_\rho$ the mean demand over the within-sample initialisation period. For more details on the experimental structure of our investigation and the within and out-of-sample arrangements please refer to the next section of the paper.
5. Empirical Investigation

5.1 Empirical data

As previously discussed, the database consists of the individual demand histories of 2,156 SKUs covering 142 consecutive periods (weeks) from January 2005 to September 2007. Not all series were considered for experimentation purposes. A considerable number of SKUs were found to be obsolete without having moved at all in the last 3 years, since January 2005. In addition, 315 SKUs were associated with a considerable initial stock that resulted in no ordering at all during the demand history. These SKUs were also excluded from our empirical investigation. (Very high initial stocks constitute also the case for many other SKUs distorting somehow the empirical results of our investigation. This issue is discussed further in the next section.) The screening process resulted in 1,109 SKUs being considered for our simulation purposes. Descriptive statistics related to the demand data are given in Tables 2 and 3. The lead time (in days) distribution for all 1,109 SKUs is then presented in Figure 2. At this point we should note that some of the SKUs were ‘introduced’ at some point after January 2005 and consequently the starting period used for simulation purposes as well as the summary statistics and the performance evaluation related to these items refer to the corresponding time intervals.

<<<<<Please insert Table 2, Table 3 and Figure 2 about here>>>>

5.2 Experimental structure and simulation related details

We use the demand data set described above to empirically assess the performance of the approach we proposed to the case study organization, namely the classical reorder point
(r, Q) policy in conjunction with two possible estimators, against the performance of the arbitrary stock control related practices currently in use.

For the purposes of our empirical investigation, we split the demand history available for each SKU into two parts. The 1\textsuperscript{st} part (i.e. within-sample) represents the 40\% of the total number of periods and is used in order to initialise the estimates of level and variance of demand. The 2\textsuperscript{nd} part (out-of-sample) constitutes the remaining 60\% of the total number of periods and is used for the out-of-sample generation of results and evaluation of performance. Please note that the relative rather than absolute break-down of the demand time series is due to the differing number of periods available for the SKUs depending on their introduction in the stock base of the organisation. Moreover, and given that some of the lead times are very long (maximum lead time = 165 working days) the rule introduced ensures a reasonable within-sample length for initialisation purposes. Optimisation of the forecasting parameters (smoothing constants) has not been considered at this stage of our investigation. The smoothing constant values used are the following: $\alpha = \delta = \lambda = 0.05$ and $\beta = 0.25$ (reflecting the usual values of practical usage in such contexts of application).

\textbf{6. Implementation, empirical results and discussion}

Since no precise information about various inventory related charges was available, we resorted to discussions with the company for the purpose of approximating such figures that were essential for us in terms of the empirical investigation. This exercise was also perceived as very useful by the individuals participating in our meetings in terms of
developing their understanding on inventory related costs and the effect that they may have on the bottom line of the organization. Regarding the ordering costs, we decided to experiment with a figure that is proportional to the unit cost. For the case study organization, the ordering cost expressed in relative terms is between 50% and 400% of the SKU cost. As such, we experimented with the following proportions: 50%, 75%, 100%, 200% and 400% of the unit cost in order to analyze the effect on the results. At this point it is important to note that the company operates with very high margins (unit price – unit cost) to allow a profit to be made given the high ordering related expenses. The distribution of the ratio unit price/unit cost (%) across all SKUs is presented in Figure 3.

<<<Please insert Figure 3 about here>>>

Regarding the inventory holding \((h)\) and backordering \((b)\) charges the ratio \(h/b = 10\%\) was thought to accurately represent current business. The total inventory costs include the inventory holding cost, the backlog cost and the ordering cost. Results are generated by considering four target cycle service levels: 87%, 91%, 95% and 99%. For each of those targets we report (across all SKUs): i) the average achieved cycle service level, ii) the average inventory holding and backlog volumes, iii) the average number of orders placed, and iv) the total inventory cost. Results are presented for both forecasting methods we experimented with: SES (Table 4) and SBA (Tables 5) for the case of the ordering cost being 100% of the unit cost. (Please note that all other ordering cost related structures lead to similar insights.)

<<<Please insert Tables 4 and 5 about here>>>

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The results indicate that the very high initial stocking levels are carried forward affecting the outcome of our investigation. The aggregate achieved service levels appear to be very high (when compared against the target) as a result of this initial over-stock ing. Nevertheless, performance differences are still evident and they did allow a comprehensive assessment of the comparative merits of the new approach against that currently being used. In particular, the new approach results in considerably lower inventory costs whilst at the same time offering similar service levels. The superior stock control performance of the new approach is conclusive, being reflected on reduced inventories, reduced backlogs as well as a lower number of orders being placed.

The cost related benefits decrease with the target service level and increase with the ordering fraction (percentage of the unit cost). The aggregate service levels achieved when employing the SBA are always less than the ones induced by SES and this is in accordance with theoretical expectations. SES has long been shown to be positively biased in an intermittent demand context (Croston, 1972) with that bias obviously being translated in an inflated service level. SBA in contrast is approximately unbiased, with a little negative bias remaining (Syntetos and Boylan, 2005). In the case study data both methods over-achieve the target levels; the latter estimator though induces far lower inventory related costs at an aggregate level and as such it is preferred for practical implementation.

In summary, the company decided to adopt the proposed (s, Q) policy, in conjunction with the SBA, operating under a CSL target of 95%. (In this case, the cost related savings have been shown to be at least 40%.) Such a target reflected, according to management,
the best trade-off between costs and achieved service levels taking also into account the high stocking levels inherent in the current situation. At this initial stage of the intervention with the system, the above discussed solution would apply to all SKUs in a fully automated way with scope for managerial adjustments on the top 11% of the best selling items and continuation of the write-off strategy for those products that are obsolete. Periodic review of the Pareto classification scheme would also ensure that management retains an up-to-date summarized and comprehensive picture of the entire stock base.

7. Conclusions and way ahead

The area of inventory management in the wholesaling environment has attracted considerable attention from the academic community. However, case studies that consider a solution development and implementation in a real application are lacking. In this paper such a study has been performed on the system of a UK-based wholesaling company dealing with engineering supplies. The company serves mainly the construction industry, thus selling in large quantities without though necessarily having to deal with specific retail outlets. The company manages a wide range of products controlling their inventories through ad hoc arbitrary procedures.

Following a major intervention with the company’s system for the purpose of retrieving relevant data, a typical ABC classification revealed the tremendous scope for improving the system through an increased managerial attention to the best selling items and introduction of a write-off policy for obsolete SKUs. Subsequently, the performance of
the classical \((r, Q)\) policy in conjunction with two possible forecasting methods was compared against current practices. The findings were such, that management was convinced to move into a fully automated approach to stock control (that comprises the order-point policy and the use of an appropriate forecasting method, SBA) albeit with the possibility of overriding the system if necessary. The company retained previous policies with respect to some items that are associated with economies-of-scale purchasing procedures and special contractual agreements with specific suppliers.

The collaboration of the academic team with the company under concern will continue as part of a knowledge transfer programme subsidised by the UK government and a series of further modifications have already been planned for the next calendar year. At the operational level, the possibility of eventually introducing a more informative SKU classification scheme has already been discussed. Such a scheme would allow a more effective approach to inventory management by separating items into various categories and treating them differently for forecasting and stock control purposes. Moreover, performance measurement, and the way this is captured through appropriate metrics, constitutes one other important opportunity for advancing the operational efficiency and effectiveness of the company. At the strategic level, a complete back-to-back (customers to suppliers) alignment of information has been proposed for linking demand and supply in a more comprehensive manner.
References


List of Tables

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<th>Classes</th>
<th>Number of SKUs</th>
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<th>Cumulative percentage of SKUs</th>
<th>Cumulative Profit</th>
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Table 1. SKUs classification with respect to profit

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<td>Max.</td>
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<td>17056.333</td>
<td>102.000</td>
</tr>
</tbody>
</table>

Table 2. Demand data descriptive statistics (across SKUs, to the 3rd decimal place)

<table>
<thead>
<tr>
<th></th>
<th>Minimum</th>
<th>Maximum</th>
<th>Average</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lead-time (days)</td>
<td>1</td>
<td>165</td>
<td>14.474</td>
</tr>
<tr>
<td>Unit Price (£)</td>
<td>0.01</td>
<td>1639.680</td>
<td>47.229</td>
</tr>
</tbody>
</table>

Table 3. Lead-time and unit cost information

<table>
<thead>
<tr>
<th>1109 SKUs - VIP</th>
<th>Holding (volume)</th>
<th>Backlog (volume)</th>
<th>No of orders</th>
<th>Total cost</th>
<th>CSL</th>
</tr>
</thead>
<tbody>
<tr>
<td>VIP Approach</td>
<td>30.040</td>
<td>0.232</td>
<td>3.167</td>
<td>179.746</td>
<td>0.980</td>
</tr>
<tr>
<td>New Approach</td>
<td>CSL =87%</td>
<td>16.706</td>
<td>0.317</td>
<td>4.074</td>
<td>92.024</td>
</tr>
<tr>
<td></td>
<td>CSL =91%</td>
<td>19.843</td>
<td>0.267</td>
<td>4.162</td>
<td>97.368</td>
</tr>
<tr>
<td></td>
<td>CSL =95%</td>
<td>25.713</td>
<td>0.214</td>
<td>4.335</td>
<td>108.654</td>
</tr>
<tr>
<td></td>
<td>CSL =99%</td>
<td>45.144</td>
<td>0.132</td>
<td>4.986</td>
<td>147.865</td>
</tr>
</tbody>
</table>

Table 4. Empirical results (ordering cost: 100% of unit cost) – SES
<table>
<thead>
<tr>
<th>1109 SKUs - VIP</th>
<th>Holding (volume)</th>
<th>Backlog (volume)</th>
<th>No of orders</th>
<th>Total cost</th>
<th>CSL</th>
</tr>
</thead>
<tbody>
<tr>
<td>VIP Approach</td>
<td>30.040</td>
<td>0.232</td>
<td>3.167</td>
<td>179.746</td>
<td>0.980</td>
</tr>
<tr>
<td>CSL = 87%</td>
<td>15.354</td>
<td>0.391</td>
<td>3.843</td>
<td>84.227</td>
<td>0.975</td>
</tr>
<tr>
<td>CSL = 91%</td>
<td>18.076</td>
<td>0.333</td>
<td>3.867</td>
<td>85.224</td>
<td>0.979</td>
</tr>
<tr>
<td>CSL = 95%</td>
<td>23.524</td>
<td>0.257</td>
<td>3.941</td>
<td>88.977</td>
<td>0.984</td>
</tr>
<tr>
<td>CSL = 99%</td>
<td>44.559</td>
<td>0.138</td>
<td>4.698</td>
<td>128.648</td>
<td>0.991</td>
</tr>
</tbody>
</table>

Table 5. Empirical results (ordering cost: 100% of unit cost) – SBA

List of Figures

![Distribution of the demand intervals](image)

**Figure 1. Demand interval distribution**
Figure 2. Lead-time distribution

Figure 3. Relationship between unit price & unit cost