Inventory management in a multi-echelon spare parts supply chain

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Abstract

In many industrial sectors, firms are dealing with a demand which is more and more uncertain often due to the supply chain structure. One of the most critical effects of demand uncertainty is the simultaneous increase of inventories and decrease of customer service. This work describes an integrated system for managing inventories in a multi-echelon spare parts supply chain, in which customers of different size lay at the same level of the supply chain. The differences in size generate demand peaks and thus a very variable and lumpy demand pattern. The analysis presented in the paper stems from a case study in the field of durable goods spare parts. The paper contributes in three ways: on the one hand, it shows that consistency between managerial solutions and supply chain structure enables to enhance operative performances. On the other hand, it provides a new solution to a problem that characterises several different industrial contexts. Eventually, it highlights that the exploitation of a larger and more reliable set of information dramatically improves performance.

Keywords: Demand management; Lumpy demand; Supply chain heterogeneity; Spare parts

1. Literature analysis

In many industries demand is becoming more and more variable and uncertain. Such fluctuations of demand are sometimes due to quick changes in the final customer’s preferences and taste (e.g., in the fashion industry demand for a given colour can change dramatically from year to year), but quite often the supply chain is an important source of demand uncertainty (e.g., think about the well known Barilla case in the food industry). Literature has discussed and analysed this phenomenon called the Bullwhip Effect (e.g., Forrester, 1961; Inger et al., 1995; Lee et al., 1997), observing that, while moving towards the higher levels of the supply chain, orders show a more variable and uncertain pattern. The causes of this behaviour are several: erroneous demand forecasting, supply shortages, long lead times, batch ordering, price variations and inconsistency of the customers located in the lower levels of the chain. This phenomenon is quite well known and a quite large body of literature has focused on the multi-echelon supply chain management (Lee, 1987; Axsäter et al., 1994; Clark, 1994). So far literature has devoted major attention, from one side to the forecasting of lumpy demand, and from...
another to the development of stock policies for multi-echelon supply chains. In this framework, minor attention has been devoted to the case of a central warehouse that on the one hand serves several end-consumers and on the other hand serves few intermediate and independent warehouses when no information is provided along the supply chain. In this work we argue that the complex structure of this supply chain is sometimes one of the causes of demand variability and poor inventory performances. So we argue that, even if the central warehouse has no control of the reorder policies of the other entities in the supply chain, some clues may be drawn by modelling the supply condition it has to deal with.

The tools proposed for forecasting very uncertain demand can be classified in two main streams: on the one hand there are methods based on traditional tools, as exponential smoothing and ARIMA techniques, formally developed for uncertain demand (Croston, 1972; Johnston and Boylan, 1996). Empirical use of these techniques has shown that the more uncertainty rises, the more the performance of these tools worsens.

On the other hand, there are techniques based on a much wider spectrum of information. This information is obtainable from the demand process generation and lets achieve better future estimations. Chen et al. (2000) have analysed the effect of forecasting systems and information sharing through the supply chain. They have shown that providing each stage of the supply chain with complete information on customer demand can reduce the bullwhip effect.

Other papers focus on specific industries and specific pieces of information and show that additional information can enhance the performance of the planning process (Kekre et al., 1990; Fisher et al., 1994; Bartezzaghi and Verganti, 1995). A few studies show that as uncertainty and demand variability increase companies should devote more attention to the demand generation process and understand the process that generates the order (Bartezzaghi and Verganti, 1995). In addition in these situations collecting additional information about future demand tends to pay-off: in other words the value of information increases as demand gets more and more variable and uncertain.

The role of information is also critical in the inventory management literature. Papers regarding inventory management in multi-echelon supply chains can be classified according to whether information is globally spread or locally managed and control is centralised or decentralised. Local information implies that each location sees demand only in the form of orders that arrive from the locations it directly supplies. Also, it has visibility of only its own inventory status and cost structure. Global information implies that the decision-maker has visibility on demand, costs and inventory status of all the locations in the system. Centralised control implies that attempts are made to jointly optimise the entire system, while decentralised control implies that decisions are made independently by separate locations. This classification is summarised in Table 1.

In particular the most discussed approaches are from one side Installation Stock Policies and, from the other, Echelon Stock ones. For a general description and review of these approaches we refer to Axsäter (1993), Federgruen (1993), Van Houtum et al. (1996), Diks et al. (1996).

A different classification can be derived according to the assumptions made on demand. In particular literature can be clustered in two main classes: analytical-deterministic models (Williams, 1982; Cohen and Lee, 1989) where demand structure is given and optimisation systems are developed; analytical-stochastic models (Cohen and Lee, 1988; Svoronos and Zipkin, 1991) in which, given a particular demand distribution, are

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<th>Table 1</th>
<th>Adapted from Silver et al. (1998)</th>
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<td></td>
<td>Centralised control</td>
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<tr>
<td>Global information</td>
<td>Echelon stock</td>
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<tr>
<td>Local information</td>
<td>Does not make any sense</td>
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developed methods to minimise the expected costs of orders management. For a detailed description of these approaches see Beamon (1998).

This work focuses on a situation where no information is provided along the supply chain and inventory control at the various echelons of the chain is completely decentralised. Also we focus on a condition where demand shows particular uncertainty mainly due to the supply chain structure considered. In fact, this paper presents data from a rather complex supply chain where a central warehouse serves both end-customers and intermediate warehouses thus making demand rather composite. The paper shows how the combined development of the two activities can guarantee a substantial improvement of performance. In particular the paper shows how both traditional and innovative forecasting approaches can be combined as an input to an analytical-stochastic inventory management model.

2. Objectives and methodology

This section presents the general framework of the research developed. This paper stems from a joint research project with the spare parts business unit of a major white goods manufacturer located in Northern Italy. The general objective of the research was to develop new approaches to manage demand in that industry. While designing the solution we found out that some features of the problem are not specific to the white goods spare parts industry but rather typical in those sectors where demand is extremely variable and the supply chain is rather complex. Thus, while the data used in this paper refer to a single firm in the white goods industry, we believe that the findings (at least partially) apply to other industries as well. Thus objectives are:

1. Show the relationship between the supply chain, the demand patterns and a managerial solution.
2. Develop a solution for a specific supply chain.

The solution described and tested in this paper stems from the characteristics of the problem we are facing. Thus the research and the paper consist of three major phases:

(i) Analysis of the problem. It is worth noticing that this analysis enables the reader and potential users to evaluate to which extent the solution described in this paper can be applied in other firms. Indeed, one should expect that a similar problem should ask for a rather similar solution.

(ii) This body of knowledge enabled us to design a solution that fits the demand characteristics and the supply chain structure and is specific not to the company considered but to the features of the problem (in terms of structure of the supply chain and characteristics of demand).

(iii) Finally the alternatives designed in the paper have been tested and compared by simulating their performance with real demand data.1

The remainder of the paper is organised as follows: Section 3 analyses the supply chain and the demand patterns for the real case we considered, Section 4 describes in detail the solution proposed, Section 5 validates the results with a larger set of data and Section 6 draws some conclusions and sets guidelines for future researches.

3. Analysis of supply chain and demand

The first step towards the development of the system was the analysis of the supply chain structure that is rather complex. Indeed, the company we co-operated with is restructuring the supply chain to reduce the stock holding cost (in the spare parts business the number of SKUs is quite high—the warehouse holds about 96,000 different spare parts—and inventory turns few times a year, thus making the holding cost substantial). This suggested the company to reduce the number of intermediate warehouses and

1The firm we co-operated with provided us with daily demand and number of order lines during a 209 days period for 1,214 different SKUs.
launch the so-called direct delivery project. This trend seems to be widespread in many industries where companies try to reduce the logistic cost. As a result of this project national warehouses in most European countries were closed and the central European warehouse located in Northern Italy ships directly to end-customers. However, the European central warehouse also serves European countries that are too far from Italy (e.g., Sweden) and to non-European countries. In these cases the national warehouses were not closed. Hence the central warehouse serves, on one side, a one-echelon chain and, on another, a two-echelon supply chain.

In this situation various numbers of echelons co-exist in the same supply chain, thus making “pure” solutions (i.e. solutions designed for a given number of echelons) perform poorly (see Fig. 1).

Important is to consider that the central warehouse previously introduced has no control of the other warehouses belonging to the supply chain. So, the only variable the firm can control to adjust its inventory performances is its own stock level. Moreover, no information is available to the forecasting managers regarding the number of customers at each echelon, nor their specific reordering policies. In these terms both installation and echelon stock systems are not applicable in this situation, as not enough information is available.

The second step towards the design of the solution was the analysis of demand, using data regarding 200 SKUs. The company stores data at daily level, so we were not able to analyse transactional data. We considered both the demand and the number of order lines to understand if demand variability is due to changes in the number of orders received per day or in the orders size. We analysed the mean, the standard deviation and the coefficient of variation of these variables. Table 2 shows the values of these parameters for the SKUs in analysis.

Table 2 suggests that daily demand is 2.58 (3.89/1.54) times more variable than the number of order lines. This suggests that changes in order size rather than in the number of orders lead to the very high demand variability the company is facing. Quite interestingly this is closely related to the supply chain structure: indeed, the company receives orders of very different sizes because on the one hand it serves small customers that receive direct deliveries and, on the other hand, it serves large customers and national warehouses that place batch orders. More in-depth graphical analyses confirmed that the root cause of demand variability is the overlap of two phenomena: a “regular” pattern consisting of many small orders
by many small customers and an “irregular” pattern generated by few huge orders from the largest customers. Fig. 2 shows this phenomenon.

This analysis of demand, together with the analysis of the demand management process the firm uses, let us understand the causes of inefficiency. In particular, the firm uses only one demand management process for the two rather different sources of demand (see Fig. 3) thus adopting a solution that, at least partially, does not fit with demand characteristics. This is partially due to the fact that though managers recognised conceptually that demand has two modes, they were not able to analytically separate the two demand series. Moreover, the forecasting and inventory management systems the firm uses are incapable of good performances when dealing with variable and composite demand.

4. Solution design

This section describes the four alternatives considered through a stepwise process.

4.1. Alternative (a): Current solution

The actual system the firm uses is built up of two phases. First, the Whybark system, based on the exponential smoothing, is used to forecast future demand on the basis of past data. Then, orders are emitted using the order up-to policy, according to the forecast the system produces. Fig. 3 describes this process.

Although this is a specific solution used in a single firm, it is quite representative of a great number of different solutions applied in real contexts: many firms adopt simple demand
management (i.e. forecasting and inventory management policies), so we think that this alternative is rather representative of many real situations.

Improvement in performances can be gained using the knowledge on demand bi-modality (see alternative (b)).

4.2. Alternative (b): Literature model

Given the bi-modality of demand, the first solution we propose is based on the separation of demand in two series (further called “stable” and “irregular” and respectively built up of many small orders and few huge ones) and on the adoption of two ad hoc forecasting techniques, that better fit the two patterns. Fig. 4 shows the scheme of alternative (b).

This solution is based on a three-step process: a filtering procedure to separate the two demand series, the forecasting of the two components and their aggregation, and finally the inventory management.

4.2.1. Filtering

To properly manage the two series previously described we had to develop a filtering system capable of separating peaks from the more “stable” demand. The idea is to build a threshold that separates what should be considered “stable” from what should be considered “irregular”. Every demand observation lower than the threshold is considered “stable”, otherwise it is considered irregular (Fig. 5 exemplifies the filtering process). A similar application of this approach, developed in the food industry, can be found in Cachon and Fisher (1997).

To properly estimate the threshold, we have to evaluate precisely the even pattern of the stable series and its natural variability. So the problem of estimating correctly this threshold is split into two sub-problems: estimate the mean behaviour of the stable series and its variability.

One might think of using the average of past demand to estimate the mean of stable series, but this estimator is deeply influenced and biased by the demand peaks. On the contrary, we have to use an estimator of the mean stable demand that is not influenced by the peaks. The median of demand is only shortly influenced by the large peaks, and so seems to be a much better metric since it estimates much more correctly the even behaviour of the stable series.

To evaluate precisely the standard deviation of the stable series, we could not use standard deviation of the total demand as the peaks made total demand variability very much different from the stable series one. So, we developed a two-phase filtering system, aiming at better estimating the standard deviation and the median of the stable pattern. In the first phase the system eliminates the most variable phenomena using the median and standard deviation of the total demand series. The new series obtained is much less variable and it’s closer to the real stable pattern. In particular, its median and standard deviation are closer to that of the stable series. Applying the second filtering system, using the new series as input, evaluates correctly the stable part of demand.
The output of the filtering system is made of two demand series which appear more internally consistent, and for which two separated forecasting techniques can be developed.

To measure the effective results of the filtering process, we compared the volume-weighted coefficients of variation of total demand and of the stable series. This comparison is summarised by Table 3.

This comparison shows that the filtering system described is capable of identifying the causes of demand inconsistency quite well, as it reduces stable series variability of 2/3 than total demand one.

4.2.2. Forecasting

To properly forecast the two series, we had to find two particular methods that fit with the series...
they are supposed to manage. In particular the stable series is generally quite even, so it seems reasonable to use an exponential smoothing-based system, which performs well when facing low variability patterns. In particular, the system here adopted is the Whybark Method that is the actual forecasting system the firm uses.

On the contrary, as the irregular series has typically a strong *lumpy* pattern, we adopted a specific method built to manage such demand. In particular we considered the Croston method to evaluate future requirements. The Croston method is based on the exponential smoothing, but it has two main peculiarities that distinguish it from simple smoothing techniques. First of all, it splits the forecasting problem in two sub-problems: it estimates separately the mean demand size per period and the inter-arrival time between orders. The objective is to evaluate demand forecast as product of the mean size of orders and of the number of orders during the planning period. Second, forecasts are updated only when demand shows. This particular procedure allows forecast not to be too much influenced by a great number of days with no demand, as, for example, exponential smoothing does. The criticality of this technique lays in the estimation of “when” the peak will occur. Moreover, after the occurrence of an order, the system pushes inventory management systems to reorder thus accumulating parts right after demand has occurred. This, due to demand sporadicity, generates high inventory level for a long time.

We believe, and further show, that a different system to evaluate when the order will show up should guarantee better performances.

4.3. Alternative (c): Ad hoc model

We developed a solution that uses the filtering system introduced in alternative (b) to evaluate the two series (stable and irregular). Moreover, solution (c) uses two separated forecasting and inventory management systems for each of the two series. Fig. 6 shows the scheme of solution (c).

4.3.1. Forecasting

As in cases (a) and (b), we use the Whybark method for the stable series, while for the irregular series, a deeper analysis is needed.

The problem of forecasting a peak of demand can be divided in two sub-problems: first of all one must estimate when the peak will occur, then how many parts will be ordered (see Fig. 7 for an example). The analysis of demand allows to separate the two constituent phenomena and so

### Table 3

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<tr>
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<th>Total demand</th>
<th>Stable series</th>
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<td>Weighted coefficient of</td>
<td>3.73</td>
<td>1.15</td>
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Fig. 6. Alternative (c) scheme.
to evaluate separately the inter-arrival time between peaks and the ordered quantities. By observing the characteristics of the irregular series it is notable that even if the peaks are the major cause of the great variability demand has, they show some regularity. In particular, it is notable that both the inter-arrival time between two successive demand peaks and the number of parts ordered are even. This feature is related to the supply chain structure and reordering processes of large customers: we expect that many customers use reorder systems based on the economic order quantity or fixed reorder period, as the demand they manage appears relatively stable. So they will reorder relatively stable quantities with a relatively even frequency. The forecasting algorithm can exploit these regularities to achieve good performance.

Literature has devoted a major attention to evaluate which statistical distribution fits better to the problem we are looking at. The major part of the literature considers demand of spare parts modelled according to a Poisson or Compound Poisson process\(^2\) (Friend, 1960; Hadley and Within, 1963). Other authors have analysed when other distribution may be adopted (Vereecke and Verstraeten, 1994). We analysed the demand data provided to evaluate which distribution fits better and we discovered that the SKUs under consideration could be clustered according to two main distributions. Some SKUs fit very well the Poisson assumption, while for others, the Normal distribution appears to be better. We argue that this distinction is mainly due to how the demand peaks are generated: when many customers are responsible for these phenomena the Poisson assumption tend to perform better, as the process of peak generation is memory-less. Instead, when a single customer is the source of the demand peaks the process tends to have memory and so the regularities in the customers’ reorder process tend to outperform the Poisson model; in this situation the Normal assumption is likely to perform better. In the development of this solution we adopted these two distributions according to how they fit to the data in analysis.

The proposed method updates the mean and variance of inter-arrival time daily and considering both the occurrence and the absence of a peak. Indeed a few codes, after showing a few peaks in the first months, have no peaks for the rest of the simulation run. So, the updating procedure keeps on estimating that the peaks will occur with the initial frequency. Actually this intuitive solution disregards an important piece of information: the
time since last peak has occurred. The solution we adopted was of integrating into the updating system also the information that a peak hasn’t shown up in a long time. Thus the inter-arrival time estimate is updated regardless of whether the peak has occurred or not. In particular, if at time $T$ no peak is observed, the estimate is updated considering that it will occur from $T$ on. The better way to make this estimation would have been to use a survival analysis technique (Kleinbaum, 1996); to simplify the solution we used an approximated estimate, which, in fact, doesn’t consider the censored distribution of the last peak. In particular, the forecasting for the inter-arrival mean during the $t$ period is equal to

$$
\hat{\mu}_t = \max\{\mu_t(1 - x_1) + \mu_1 \delta_i; \mu_t(1 - x_1) + \mu_1 \delta_i(1 - x_2) + \mu_2 \delta_i\},
$$

where $\mu_t$ is the estimate of mean till the $t$ period, $\delta_i$ is the inter-arrival time between the last two peaks, $i_i$ the inter-arrival time since the last peak, and $x_1, x_2$ are two smoothing constants.

The first part of the formula updates the mean whenever a peak is observed at time $T$, while the second one when a peak is not observed at time $T$. The two smoothing constants are used to weight how much a peak occurrence and delay influence the actual estimate. A similar updating process is applied to the standard deviation of the inter-arrival times.

The estimated parameters (mean and standard deviation) are used to evaluate the probability distribution of the peak occurrence. To evaluate the probability of occurrence of future orders we have to consider (a) the information available regarding the time elapsed since last peak and (b) the possibility that more than one peak will occur over the planning period.

We will discuss the two issues separately.

(a) Whenever a forecast is produced, we have to consider whether the process of generation of a peak is memory-less or not; so if the normal assumption is considered for a particular SKU we can add the information that till today a peak hasn’t occurred yet. To do so we have to compute the probability of occurrence of a peak given that it hasn’t already shown up, using a conditioned probability. Fig. 8 exemplifies this process.

(b) If more than one peak occurs over the planning period, we have to evaluate the cumulative probability of more events. If on day $T$ a peak occurred, the expected date of the $n$th peak is $T$ plus $n$ times the expected inter-arrival time. Nevertheless, these distributions will show different variances, as the number of possible events (the days in which a peak may occur) rises. In particular we assume inter-arrivals not to be auto-correlated. Thus the standard deviation of the second peak will be equal to $\sqrt{2} \sigma$, as the number of possible events is double than the first peak ones, for the third peak will be $\sqrt{3} \sigma$, for the $n$th will be $\sqrt{n} \sigma$ and so on, where $\sigma$ is the estimated standard deviation of the inter-arrival period. Fig. 9 exemplifies this process.

Given the probability of occurrence of one or more peaks during the planning horizon, it is also necessary to evaluate the mean size of the huge

![Fig. 8. Evaluation of the probability of peak occurrence.](image-url)
orders, which lets forecast the total number of parts expected to be ordered. We did not assume any distribution for this dimension but we estimated the mean order size using an exponential smoothing to avoid distortions caused by contingent events. Each time a peak occurs, the estimate of mean size order is updated as follows:

$$\hat{m}_{q,t} = \hat{m}_{q,t-1}(1 - \alpha) + D_t \alpha,$$

where $\hat{m}_{q,t}$ is the estimate at time $t$, $D_t$ is the peak size at time $t$, and $\alpha$ is the smoothing constant.

So the system here described every day of the simulation calculates the probability of occurrence of one or more peaks in the lead-time and, according to the mean order size, forecasts the total number of parts that are expected to be ordered.

4.3.2. Inventory management

The forecasting system feeds probabilistic forecasts (i.e. distributions) into the inventory management system. An inventory management system based on a simple technique as order-up-to policy perfectly fits the stable series patterns. This is not true for the irregular series; furthermore, we think that an inventory management that fully exploits the probabilistic information produced by the forecasting system can deeply rise process performances.

This sounds reasonable also for the differences among the two kinds of orders, concerning the inventory management. First of all the two series are associated to different economic value. The huge orders size, very much bigger than the small ones, involves that the economic effect of their lost sale or long time stock keeping is particularly critical. Additionally, the huge orders management has a particular impact on the firm reputation. Arranging a huge order reduces significantly the supply availability, which affects the opportunity of accepting future orders from smaller customers. On the contrary, if the huge order is backlogged, although stock is available to many small customers, this has a critical impact because service is not granted to an “important” customer. Although the described trade-off exists also for the stable demand, its relevance is much less critical.

For the irregular series, the order management system we propose tries to balance the backlog and stock holding costs, evaluating when it is convenient to place an order. As the expected cost is a function of the probability of occurrence of a peak, the idea is to bind the emission of an order to a minimum probability of occurrence (MPO), estimated by the forecasting system. If the probability of occurrence of demand peaks over the planning horizon is lower than MPO, no orders are placed, otherwise the system releases an order.
If the MPO value is low, the system will place orders even when the likelihood that it will actually occur is quite low. On the contrary, if this value is high, the system places purchasing orders only when it is extremely likely that at least a large customer will place a big order.

Whenever an order has to be placed, it is convenient to reorder a number of parts equal to the mean peak dimension, estimated by the forecasting system. Fig. 10 shows the Service Level/Inventory Level trade-off curves, built for two different values of MPO.

Consider the lines plotted for a high value of MPO (i.e. 0.95) and for a low one (i.e. 0.10). The comparison shows that high MPO values perform better than low values for low SL, while this result is turned over for high SL. This is due to the fact that high MPO values stop not-likely orders reducing stocks, but backordering few orders, while low values of MPO catch more orders while increasing stocks.

The global performance curve can be plotted by interpolating the lines that represent the performance trade-off for any given threshold value of MPO, as Fig. 11 shows. The particular MPO should be chosen according to the target SL the company wants to achieve.
4.4. Alternative (d): Improving performances through information

Solutions b and c are based on an internally consistent demand management process that fits demand and supply chain characteristics. They use a given set of information (in this case the number of units requested and the number of orders per day in the past) to improve operational performance. On the other hand, past literature suggests that a company might collect a larger set of information to further improve performance. Such a collection of additional information might require organisational efforts, both from the supplier and the buyer side. This paper, like others in the past, deliberately does not consider the organisational costs given that they are quite hard to model and firm specific. Thus organisational cost can be better estimated through case studies and gut-feel rather than through management science models. On the other hand, a model can quite precisely show the potential benefits of a given amount of information, in terms of service level/inventory level improvements. In particular, we assume that the company should focus its efforts on the irregular portion of demand. Peaks are generated by a small number of large customers and thus the cost of collecting that information should be relatively low. In addition, usually salespeople by default devote a large portion of their time to key accounts and thus can forecast future orders quite precisely with a very limited additional effort. On the other hand, those few customers create a significant variability in demand and thus tend to reduce the service level and increase stocks. This makes the information about their future demand extremely useful for forecasting and planning purposes and relatively cheap.

We built a model that simulates such asymmetric collection of information. The model, like in cases b and c manages the stable and irregular series separately. In particular, for the stable series an exponential smoothing forecasting system is used, while, for the irregular series, a different approach is considered. The simulation model assumes that the large customers provide the company with some information about how many units the single customer is going to order in the future. Obviously, the information the company collects is probabilistic rather than deterministic. Thus we assume that both the timing and the size of forthcoming peaks are normally distributed.

To properly use real demand data, the model starts from the real timing and real size of the peak and simulates the forecasted timing and size as the actual figures plus a normal error with a zero deviation. This technique, on the one hand, enables us to describe the effects of information collection and, on the other hand, does not alter the real demand time series. The more company’s information and predictions are reliable, the lower is the variance of the two distributions and the better the system performs. Fig. 12 shows the scheme of alternative (d).

5. Performance

The four alternatives presented in the previous section are compared through IL/SL trade-off curves. In particular, for each alternative we run simulations using 1,214 codes over 209 days. For a given alternative (e.g., alternative (a)), a point on the trade off curve represents the IL and the SL the company can gain with a given hedge (i.e. with a given parameter that influences the level of safety stocks). Thus a trade-off curve represents all the mixes of performances a company can gain with a given alternative by changing the amount of inventories kept in the warehouse. Fig. 13 shows, as one would have expected, that the alternative d is the best while a performs poorly.

To make the comparison easier we consider the amount of inventories the four solutions require to gain a 83% SL and a 95% SL. Table 4 and 5 describe the savings alternative x (in the columns) can gain as compared to alternative y (in the rows). A stepwise analysis that compares each solution to the next one might better show the additional benefits of the features of each single solution.

- a vs. b. Solution b reduces the inventory investment by 49% as compared to the base case of solution a. Thus solution b guarantees
a substantial cost reduction. Hence, the filtering algorithm and adoption of two different forecasting approaches for the two different time series does add value to the company. More in general, this result suggests that when demand and supply chain are composite, companies should identify the different demand management problems they are facing to choose specific solutions.

- \( b \) vs. \( c \). Solution \( c \) performs far better than solution \( b \) (50.6% stock reduction). Both \( a \), \( b \) and \( c \) rely on the same information (i.e. past orders and demand), thus the comparison seems quite fair. Solutions \( b \) and \( c \) share the same
filtering algorithm thus differences in performance are due to the forecasting and inventory management. However, it is quite interesting to notice that the accuracy of this new forecasting approach is only slightly better than the forecasting approach suggested by Croston, while the operational performance differs substantially. We actually think that this is due to the fact that \( c \) is an integrated solution where the forecasting and inventory management are consistent. We believe that what really makes the difference is that the solution fits with the features of the supply chain and demand and is internally consistent. This, together with decision making theory, suggests that the forecasting solution is not supposed to reduce forecasting errors but rather to support decision making processes (in this case inventory decisions).

- \( c \) vs. \( d \). Solution \( d \) reduces inventory investment by 81.9% as compared to the base case \( a \) and by 28.2% as compared to solution \( c \). Solutions \( c \) and \( d \) rely on a significantly different set of pieces of information, so we can not conclude that \( d \) dominates \( c \); we can just conclude that \( d \) performs better, but it might well be too expensive (in terms of effort required to collect the information from the customers and to deliver such information to planners). Nevertheless the results seem to be quite interesting since they suggest that forecasting is not just a matter of developing algorithms to fully exploit past data, but can involve organisational processes even in the spare parts business. It is worth saying that the company we co-operated with has used these quantitative analyses to support an effort to collect information from key customers.

Finally, we can compare Tables 4 and 5. This comparison tells us the impact of service level on differences in performance. As one would have expected the inventory investment increases for all alternatives. In addition, the absolute differences among the four solutions increase thus suggesting that from a business perspective the importance of choosing the right approach to the management of demand grows as the target service level is more and more challenging and the inventory investment enlarges. Though, quite interestingly, percentage differences among solutions are reduced (for example savings of solution \( b \) vs. \( a \) drop from 49.0% to 43%). At a close look it seems rather intuitive: as the company targets extremely high SLs and faces extremely variable demand, it should be capable of meeting the huge maximum potential demand at all times. Regardless of the solution (\( a, b, c \) or \( d \)) this requires to keep a very high inventory all the time just in case a huge (though very unlikely) peak occurs. Thus for high SL targets absolute differences increase but percentage differences tend to decrease given that all solutions will always require very high inventories.

6. Conclusion

This paper contributes to knowledge in inventory management in two rather different ways.

First, the paper discusses the rather unexplored problem of managing supply chains with a various numbers of echelons, multi-modal and extremely variable demand, and with lack of visibility over
the distribution channel. The paper provides an algorithmic solution that, through the comprehension of the sources of demand variability and through a probabilistic forecast and inventory management, leads to performance improvement as compared to current solutions adopted by the firm and proposed by the literature. In addition, the paper shows that a proper collection of information regarding the purchasing plans of few large customers (that usually significantly contribute to the total variance of demand) can improve the performance of the supply chain substantially.

Second, the paper contributes to the more general problem of how to design a solution to manage uncertain and extremely variable demand.

(a) The paper clearly shows the close relationship between supply chain structure, demand patterns and the characteristic of the demand management solution. In particular, in the case discussed in the paper, a supply chain with different numbers of echelons generates a multi-modal demand that asks for a composite managerial solution (compare solutions $b$ and $a$ in Section 5).

(b) The paper shows that integrated and consistent solutions can outperform classical solutions based on a stepwise process (compare solutions $c$ and $b$ in Section 5).

(c) Finally, the paper adds to the literature debate on the value of information in supply chain and inventory management. Clearly the model presented is not the solution itself (which relies on organisational processes and exchange of information about inventory levels etc.) but can estimate its benefits (compare solutions $d$ and $c$ in Section 5). Such model was adopted by the firm we co-operated with to justify organisational efforts in the area of collaborative planning.

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