A DECISION SUPPORT SYSTEM FOR INVENTORY MANAGEMENT OF INTERMITTENT DEMAND

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ABSTRACT
Demand forecasting is one of the most crucial aspects of inventory management. For intermittent demand, i.e. demand peaks follow several periods of zero or low demands, forecasting is difficult. Furthermore, the choice of the forecasting method can have an impact on the inventory management policy that is best used. A simulation model is used to study a single-product inventory system facing demand of the intermittent type. In this paper, a decision support system is presented to choose between several forecasting methods and inventory management policies for intermittent demand.

Keywords: simulation-optimization, intermittent demand, forecasting, inventory management

1. INTRODUCTION

Inventory systems have to cope with uncertainty in demand. The inventory control literature mostly makes use of the Normal or Gamma distribution for describing the demand in the lead-time. The Poisson distribution has been found to provide a reasonable fit when demand is very low (only a few pieces per year). Less attention has been paid to irregular demand. This type of demand is characterised by a high level of variability, but may be also of the intermittent type, i.e. demand peaks follow several periods of zero or low demands. In practice, items with intermittent demand include service or spare parts and high-priced capital goods. A common example of such goods are spare parts for airline fleets.

Demand forecasting is one of the most crucial aspects of inventory management (Willemain et al. 2004). However, for intermittent demand, forecasting is difficult, and errors in prediction may be costly in terms of obsolescent stock or unmet demand (Syntetos and Boylan 2005). The standard forecasting method for intermittent demand items is considered to be Croston's method (Croston 1972). This method builds estimates taking into account both demand size and the interval between demand occurrences. Despite the theoretical superiority of such an estimation procedure, empirical evidence suggests modest gains in performance when compared with simpler forecasting techniques (Syntetos and Boylan 2001). Furthermore, the choice of the forecasting method can have an impact on the inventory management policy that is best used.

In this paper, a decision support system is presented to choose between several forecasting methods and inventory management policies for intermittent demand. Because of the uncertainty present in the inventory system, often mathematical models cannot accurately describe the system. Therefore, a simulation model is used. The simulation model is optimised to find the best strategy in combining inventory decision making and demand forecasting for intermittent demand. However, the best strategy depends on uncontrollable factors, i.e. the costs of the inventory system and the distribution of demand during lead time.

A good decision support system is necessary because there is a considerable increase in the total costs of the inventory system when not using the best strategy. The decision support system is presented as a decision tree where levels of the uncontrollable factors indicate which strategy in combining inventory decision making and demand forecasting is best chosen.

The organisation of the paper is as follows: in section 2 the simulation model and research approach are described; the experimental environment is described in section 3; section 4 discusses the results of the simulation model and presents the decision support system and in section 5 conclusions are formulated.

2. SIMULATION MODEL AND RESEARCH APPROACH

2.1. Simulation Model

The study focuses on a single-product inventory system facing demand of the intermittent type. The simulation model is developed in Microsoft Excel spreadsheets and uses VBA. The simulation model starts by generating intermittent demand as described in the previous section. Next, the inventory system is simulated for 52 periods. At each review-time, a demand forecast and an order decision are made. The total costs of the inventory system are determined. 10 replications are made for each simulation run.

To generate intermittent demand, demand occurrence and demand size are separately generated. The demand occurrence is generated according to a first-order Markov process with transition matrix

$$\mathbf{P}=\begin{pmatrix} p_{00} p_{01} \\ p_{10} p_{11} \end{pmatrix},$$

where p_{00} is the probability of no order in the next period when there has been no order in this period and p_{10} is the probability of no order in the next period when there has been an order in the current period. Individual order sizes are generated using a Gamma distribution with shape parameter γ and scale parameter β.

The standard forecasting method for intermittent demand items is considered to be Croston's method. However, in practice, single exponential smoothing and simple moving averages are often used to deal with intermittent demand. These three forecasting methods are compared.

In this research, two periodic review models are used. The first one is the (R, s, S) system. This means that every *R* units of time, the inventory level is checked. If it is at or below the reorder point *s*, a sufficient quantity is ordered to raise it to *S*. The second system (R, s, Q) is similar to the (R, s, S) system but uses a fixed order quantity *Q* instead of an order-up-to-level *S*.

A deterministic lead-time *L* is assumed. The following costs are considered: unit holding cost per period C_h, ordering cost C_o and unit shortage cost per period C_s. The simulation starts with an initial inventory level I_0.

2.2. Experimental Design

The parameters of the inventory system to optimise include both qualitative and quantitative factors. The experimental design includes two qualitative factors: the forecasting method and the inventory management policy. In addition, depending on the choice of the qualitative factors, a set of quantitative factors are part of the experimental design. If the (R, s, Q) inventory management policy is used, the safety stock SS and order quantity Q are the parameters to optimise. If the (R, s, S) inventory management policy is used, the safety stock SS and order-up-to-level S are the optimising parameters. For single exponential smoothing and Croston's method, the smoothing parameter α is optimised and for moving averages, the weights of the past values are optimised.

2.3. Research Approach

Because of the dependence of the quantitative factors on the choice of the qualitative factors, we use for the optimisation the research approach described in this section.

For every combination of forecasting method, inventory management policy and review period, the optimal values of the quantitative factors are determined. The total costs of the inventory system are optimised using tabu search. Tabu search is shortly described below. Once the optimal values are found, the best combination of forecasting method, inventory management policy and review period is chosen.

Tabu search uses a local or neighbourhood search procedure to iteratively move from one solution to the next in the neighbourhood of the first, until some stopping criterion has been satisfied. To explore regions in the search space that would be left unexplored by the local search procedure and escape local optimality, tabu search modifies the neighbourhood structure of each solution as the search progresses. The solutions admitted to the new neighbourhood are determined through the use of special memory structures. Tabu search uses both long-term and short-term memory, and each type of memory has its own special strategies (Dengiz and Alabas 2000, Glover 1989).

Tabu search is a heuristic optimisation technique developed specifically for combinatorial problems. Very few works deal with the application to the global minimization of functions depending on continuous variables. The method we propose in this paper is based on (Chelouah and Siarry 2000, Siarry and Berthiau 1997). The purpose in these papers is to keep as close as possible to original tabu search. Two issues must be examined: the generation of current solution neighbours and the elaboration of the tabu list.

To define a neighbourhood of the current solution, a set of hyperrectangles is used for the partition of the current solution neighbourhood. The *k* neighbours of the current solution are obtained by selecting one point at random inside each hyperrectangular zone.

Once a new current solution is determined, the immediate neighbourhood of the previous solution is added to the tabu list.

3. EXPERIMENTAL ENVIRONMENT

The experimental environment contains the uncontrollable factors of the inventory system: the costs of the inventory system and the parameters for generating intermittent demand. These factors can have an effect on the results that are obtained. The research approach described above, is executed using a single combination of the costs of the inventory system and demand. A fractional factorial design of 16 experimental points is set up for these factors and the optimisation phase is repeated for each experimental point.

Demand occurrence is generated using a first-order Markov process with transition matrices:

$$P_1 = \begin{pmatrix} 0.7875 & 0.2125 \\ 0.85 & 0.15 \end{pmatrix}$$

or

$$P_2 = \begin{pmatrix} 0.5667 & 0.4333 \\ 0.65 & 0.35 \end{pmatrix}.$$

They correspond with a probability of 20% to have demand in a certain period for the first matrix and a probability of 40% to have demand in a period for the second matrix. The *size of demand* is generated using a Gamma distribution with 4 different combinations of the scale parameter γ and the shape parameter β. These values are summarized in Table 1.

Table 1: Parameters of the Gamma Distribution

Level	γ	β
1	6	1
2	12	1
3	3	2
4	24	0.5

The levels of the *costs* of the inventory system are given in Table 2. The initial inventory level I_0 equals 5.

Table 2: Levels for the Costs of the System

Level	C_o	C_h	C_s
1	100	2	5
2	200	4	10

The fractional factorial design is shown in Table 3. This fractional factorial design makes it possible to determine the impact of uncontrollable factors as the cost structure and the demand during lead time.

4. RESULTS

Each run of a single experiment from the fractional factorial design leads to a best inventory policy, together with its set of optimal parameter values, and to a best forecasting method, together with its set of optimal parameter values (Table 4). This section aims to investigate which design factors have an influence on the choice of inventory policy and forecasting method. At first, a detailed study is made of the influence of each individual factor, and afterwards an attempt is made to simplify and structure these findings in a decision support system, which is generated using a classification tree.

Eight experimental points have the order-up-to-level (OUL) inventory management policy with S=1 as best strategy but with various best forecasting methods. For the other eight experimental points, the best strategy is an OUL-inventory management policy with S≥15 or a fixed order quantity (FOQ) policy with Q≥15. An FOQ-inventory management policy as best goes together with the moving averages (MA)-method as best forecasting

Table 3: Experimental Design

Exp	C_o	C_h	C_s	Freq	γ	β
1	200	4	10	0.4	12	1
2	100	4	5	0.4	12	1
3	200	2	5	0.4	24	0.5
4	100	2	10	0.4	24	0.5
5	200	2	5	0.4	3	2
6	100	2	10	0.4	3	2
7	200	4	10	0.4	6	1
8	100	4	5	0.4	6	1
9	200	2	10	0.2	12	1
10	100	2	5	0.2	12	1
11	200	4	5	0.2	24	0.5
12	100	4	10	0.2	24	0.5
13	200	4	5	0.2	3	2
14	100	4	10	0.2	3	2
15	200	2	10	0.2	6	1
16	100	2	5	0.2	6	1

method. Also in case the OUL-inventory management policy with S≥15 is best, MA shows to be the best forecasting method. In case the OUL-inventory management policy with S=1 is best, no specific forecasting method is preferred. The results also indicate that the parameters of the forecasting method have no significant impact on the results. In the next paragraphs, the influence of the uncontrollable factors on the results is examined in further detail.

When the *demand frequency* is generated using matrix P_1, corresponding to a probability of 20% of having demand in a certain period, an order-up-to-level S of 1 unit is optimal. When the demand frequency is generated using matrix P_2, which corresponds to a probability of 40% of having demand in a certain period, the order-up-to-level S or fixed order quantity Q is a value between 15 and 30. This can be explained because the intermittent character of demand is more distinct when the probability of demand is equal to 20%, leading to an optimal order-up-to-level S of 1 unit. When the intermittent character of demand is less distinct (40%), it is better to order a quantity of at least 15 units. The only exception to this order-up-to-level S of 1 unit for a demand probability of 20% can be found when both the ordering cost and the unit shortage cost are high and the unit holding cost is low. In these circumstances it is better to order a bigger quantity because it is less costly to hold inventory than to have a stock-out or to order a small quantity every time.

Table 4: Optimal Results based on Tabu Search

Exp	Best strategy
1	MA/FOQ; ROP=0; Q=25
2	ES/OUL; ROP=0; S=1
3	MA/OUL; ROP=0; S=30
4	MA/OUL; ROP=0; S=25
5	MA/FOQ; ROP=0; Q=20
6	MA/OUL; ROP=0; S=15
7	MA/FOQ; ROP=0; Q=15
8	ES/OUL; ROP=0; S=1
9	MA/FOQ; ROP=0; Q=20
10	ES/OUL; ROP=0; S=1
11	CR/OUL; ROP=0; S=1
12	ES/OUL; ROP=0; S=1
13	MA/OUL; ROP=0; S=1
14	MA/OUL; ROP=0; S=1
15	MA/OUL; ROP=0; S=15
16	ES/OUL; ROP=0; S=1

Inversely, when a demand probability of 40% is used, it is better to use an order-up-to-level S of 1 unit when both the ordering cost and the unit shortage cost are low and the unit holding cost is high.

When comparing results for changing the parameters of the *demand size*, no significant impact of these changes on the results can be detected.

Changes in the cost structure of the inventory system have a significant impact on the results. When the *ordering cost* is equal to 100, an order-up-to-level inventory management policy is used with the order-up-to-level S equal to 1, except when the unit holding cost is low, the unit shortage cost is high and the demand probability of a certain period is 40%. The level of these three factors all favour holding more units in inventory. The combination of these three levels therefore changes the best policy to a policy with an order-up-to-level or fixed order quantity between 15 and 30, although the order cost is low. When the ordering cost is equal to 200, the order-up-to-level S or fixed order quantity Q is between 15 and 30, except when the unit holding cost is high, the unit shortage cost is low and the demand probability of a period equals 20%.

When the *unit holding cost* is equal to 2, an order-up-to-level S or fixed order quantity Q between 15 and 30 is used, unless both the ordering cost and the unit shortage cost are also low and the demand probability of a period equals 20%. When this combination of factor levels occurs, an inventory policy with an order-up-to-level S equal to 1 is better used because all these factor levels give preference to a lower inventory level. When the unit holding cost equals 4, an order-up-to-level S of 1 is the best choice, unless the ordering cost and unit shortage cost are also high and the demand probability of a period is 40%. This combination of factor levels favours a higher inventory level and thus an order-up-to-level or fixed order quantity between 15 and 30 is better used.

A *unit shortage cost* of 5 implies an order-up-to-level S of 1 unit, except when the unit holding cost is also low and the probability of demand for a certain period equals 40%. When the shortage cost is low, it is not necessary to keep a lot of units in inventory. Therefore, an order-up-to-level equal to 1 is the best policy. However, if the holding cost is also low and the intermittent character of demand is not so distinct, it is better to have more units in inventory even though the shortage cost is low. Doubling the unit shortage cost leads to an order-up-to-level S or fixed order quantity Q between 15 and 30, except when the unit holding cost is high and the demand frequency is equal to 20%.

Overall, it can be concluded that the uncontrollable factors have an impact on the best strategy for combining inventory decision-making and demand forecasting for intermittent demand. Furthermore, there is interaction between these factors.

To structure these findings, a decision support system is developed using a classification tree. The classification tree is constructed using the C4.5 algorithm, a well-known algorithm in data mining (Quinlan 1993). The classification tree can be found in Figure 1. Using this tree, it can be decided which of the two strategies is best: an order-up-to-level inventory management policy with S=1 or an order-up-to-level inventory management policy with S≥15 or a fixed order quantity model with Q≥15. Three factors are needed to determine the best strategy in combining inventory decision making and demand forecasting: the frequency of demand, the order cost and the inventory cost. If one of these three factors is not known, the knowledge of the stock-out cost is also sufficient to make a classification. Summarizing, it can be said that if three factors of the four just mentioned (frequency of demand, order cost, inventory cost and stock-out cost) are fixed, the best strategy is presented.

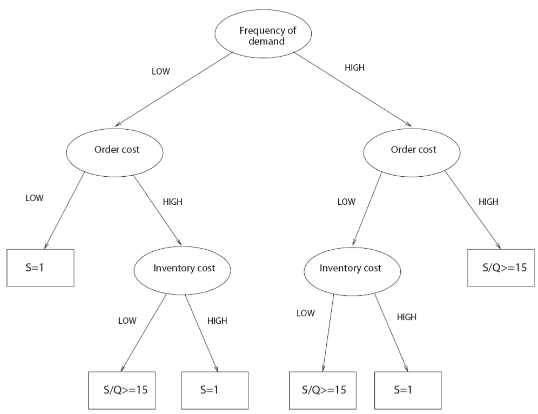

Figure 1: Classification tree

A good classification is necessary because there is a considerable increase in the costs of the inventory system when using the other strategy. When a fixed order quantity inventory management policy with Q=15 is used instead of an order-up-to-level inventory management policy with S=1, total costs are on average 20% higher. In the opposite case, when an order-up-to-level inventory management policy with S=1 is used instead of an order-up-to-level inventory management policy with S≥15 or a fixed order quantity model with Q≥15, total costs increase with more than 40% on average.

5. CONCLUSIONS

In this paper a decision support system is presented to choose between several forecasting methods and inventory management policies for intermittent demand. A best strategy in combining inventory decision making and demand forecasting is proposed, using a simulation model. An experimental design is set up to determine the impact of uncontrollable factors: the cost structure and the demand. Depending on the experimental environment, two options for optimal strategies can be distinguished: an order-up-to level inventory management policy with an order-up-to level equal to 1 and a reorder point equal to 0 or an inventory management policy with a fixed order quantity Q>1 or an order-up-to level S>1 and a reorder point equal to 0. Four factors of the experimental environment have an influence on which of the two strategies is best chosen: the frequency of demand, the inventory holding cost, the order cost and the stock-out cost. When the level of three factors out of these four are fixed, it is possible to determine the optimal strategy. To structure these findings, a decision support system is developed using a classification tree. It is important to know which of both strategies is best because there is a significant increase in total costs of the inventory system if the wrong strategy is chosen.

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BIOGRAPHY

Katrien Ramaekers graduated as Master of Business Economics at the Limburg University Centre in 2002. In 2007, she obtained her Ph.D. in Applied Economic Sciences at Hasselt University. Her Ph.D. research is on the integration of simulation and optimisation, especially as a support for complex logistics decision-making. Currently, she is a post-doctoral researcher at Hasselt University and is working on the modelling of freight transport. She is a member of the Transportation Research Institute of Hasselt University.

Gerrit K. Janssens received degrees of M.Sc. in Engineering with Economy from the University of Antwerp (RUCA), Belgium, M.Sc. in Computer Science from the University of Ghent (RUG), Belgium, and Ph.D. from the Free University of Brussels (VUB), Belgium. After some years of work at General Motors Continental, Antwerp, he joined the University of Antwerp until the year 2000. Currently he is Professor of Operations Management and Logistics at Hasselt University within the Faculty of Business Administration. He also holds the CPIM certificate of the American Production and Inventory Control Society (APICS). His main research interests include the development and application of operations research models in production and distribution logistics.