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Dynamic Re-Order Policies for Irregular and Sporadic Demand Profiles

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Abstract

Irregular and sporadic demand profiles frequently occur in different contexts characterised either by a large fragmentation of client requests within a broad product mix or when new products are introduced. Their optimal management often requires the definition of approaches based on Key Performance Indicators (KPI) other than costs, which in the aforementioned situations are characterised by uncertainty. Specifically, holding costs and stock-out costs are difficult to quantify. This paper examines 104 dynamic re-order policies in an environment where demand patterns with very low demand frequency and demand size equal to very few items are required by customers. Furthermore, the cost structure is uncertain. The aforementioned alternative management approaches are experimentally compared in terms of the average inventory level, average and maximum lost demand and average number of stock-out they can ensure.

Keywords: dynamic re-order policies; inventory management; irregular and sporadic demand profiles

Nomenclature

CSL	cycle service level, probability of not running out of stock in the period preceding the following replenishment cycle
D_i	average demand during time period i, for $i = 0,\dots,n$
$f(x)$	probability density function of x

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$F(x)$	cumulative distribution of x
I_i	inventory level at the end of period i, for $i = 0,\dots,n$
I_{tot}	expected sum of inventory levels at the end of each time period belonging to the planning horizon
LT	supply lead time
m	number of past time periods
n	number of time periods in the planning horizon
N_s	total number of units short
N_{si}	number of units short in time period i, for $i = 0,\dots,n$
Q_i	lot size in time period i, for $i = 0,\dots,n$
ROP_i	re-order point in time period i, for $i = 0,\dots,n$
SS	safety stock
x	demand during a single time period, which is the uncertain variable
z_i	number of units added to ROP_i in time period i, for $i = 0,\dots,n$

1. Introduction

Estimating a final customer demand profile is crucial for managing company processes and, in particular, for production planning and component purchasing. Irregular and sporadic demand profiles present discontinuous consumption in terms both of demand sizes and intervals between not-null demands. Forecasting is thus more difficult and the definition of optimal re-order policies is a significant management problem. Irregular and sporadic demand profiles appear in various production contexts, for example in mechanical spare parts [1], which are subject to stochastic and highly irregular demand, in start-up production or in multi-echelon supply chains. The case dealt with in this paper is the very recent online supermarket sector, where the high irregularity of demand and the need for immediate response to customer requests generate a trade-off between high service levels and curbing of stocking out events. In particular, registered demand profiles are characterised by demand events with very few items, often only one.

After a close examination in section 2 of the main approaches to the problem provided by the relevant literature, we shall proceed to analyse the method applied to the comparative evaluation of the various re-order policies proposed. The paper is organised as follows: definition of initial hypotheses and type of re-order policies applied (section 3), problem statement (section 4), solution method applied (section 5), a case study (section 6) and a conclusion (section 7) for decision makers.

2. Literature review

The main problem in production planning, which various authors have dealt with in recent decades, can be summarised by the questions of when and how much to order, both in terms of purchasing and production. The literature is therefore full of alternative re-order policy solutions; some based on mathematical models, others on heuristic models. As [2, 3] underline in their overview, the proliferation of alternative lot sizing policies derives from the complexity of the reference models, categorised in accordance with a framework of dimensions. The nature of demand is a factor included into it. Demand represents the input of the decision-making problem and can be deterministic rather than stochastic. It clearly depends on the productive model applied. In a Make To Stock (MTS) system, the demand is forecasted and therefore subject to stochastic errors, on the other hand an Engineering To Order (ETO) environment will present a deterministic demand and therefore the re-ordering policies do not include any forecasting techniques. However, the focus of the work is on a stochastic operative environment. Often, demand profiles following a Gaussian distribution function are hypothesised. Nevertheless, normal distribution is not a realistic choice for all operative fields. In the following paper, the case of irregular and sporadic demand profiles is analysed, where behaviour is not well represented by a Gaussian distribution function, but requires ad-hoc defined approaches [4].

Thus, in order to focalise the present short literature overview to the field to which the present paper refers, stochastic inventory control in the specific case of irregular and sporadic demand patterns is analysed. A classification of irregular and sporadic demand profiles is reported in [5]. In the case of demand profiles that are assumed to occur as a Bernoulli process and subsequently when inter-demand intervals and demand sizes are respectively geometrically and normally distributed, the authors propose a classification scheme obtained by evaluating the region of predominance of predefined forecasting methods (i.e. Croston's method and Syntetos-Boylan's approach).

Two main issues can be identified in irregular and sporadic demand pattern management. The first concerns the application of forecasting techniques in this context (for a more detailed discussion, see [6]), while the second specifically treats the evaluation of different inventory control models in the presence of irregular and sporadic demand profiles and is briefly dealt with below. In accordance with the framework applied by [7] in their literature review, two main streams in literature on the stochastic inventory control in the case of irregular and sporadic demand patterns can be detected, i.e. case studies of inventory control systems and modelling of irregular and sporadic demand patterns. The former concerns the comparative analysis of several inventory policies, rather than their introduction in practical operative environments, through appropriate case studies [8, 9, 10, 11, 12, 13 14, 15, 16]. The latter stream in literature on stochastic inventory control in the case of irregular and sporadic demand patterns is focused specifically on modelling variable and sporadic demand patterns and investigating the interaction between the hypothetical probability distribution functions and the parameters that characterise different re-order policies. The normality assumption is most often employed for modelling the demand but, if demand does not occur regularly and it is particularly variable, then such an assumption is judged to be far from appropriate [17]. This occurs in many practical situations; therefore, several authors have investigated this issue as crucial in irregular and sporadic demand management. Since the irregular and sporadic demand phenomenon is made up of two constituent elements, which are demand intermittence and demand variability, a compound demand distribution is often suggested. In this field, two demand generation processes have dominated literature. On one hand, if time is treated as a discrete and integer variable, then demand may be assumed to be generated based on a Bernoulli process, while, on the other hand, if time is treated as a continuous variable, then demand may be assumed to be generated based on a Poisson process. By combining Bernoulli or Poisson arrivals of demands with an arbitrary distribution of demand size, compound Poisson or compound Bernoulli total demand distributions are respectively obtained. However, compound Poisson demand processes have been more often preferred due to their theoretical advantages and simplicity. Moreover, such compound demand distribution may also be applied to modelling fast-moving items by considering very low time intervals. One of the early contributions on the application of this compound demand distribution in the inventory control theory is [18]. Other contributions are reported in [7, 19, 20, 21, 22, 23, 24] and in [25] for the case of non-stationary demand.

Nevertheless, the aforementioned contributions propose cost-oriented approaches, disregarding the fact that cost structures are not always known, e.g. in the case of new companies or new items introduced in the market. Moreover, unitary holding and stock-out costs, which often affect the decision of the best re-order policy and inventory management approach, are hardly quantifiable in a wide range of operative environments. Unitary holding costs are obtained by dividing annual holding costs among stocked items. Nevertheless, stocked items are strictly connected with the adopted re-order and inventory management approach. Hence, rather than the fixed value of the unitary holding costs registered in the past, approaches for selecting the best re-order policy and inventory management approach should adopt functions that describe the trend of unitary holding costs in accordance with the amount of stocked items registered. Otherwise, when a fixed value of the unitary holding cost registered in the past is adopted, a simplified model of the reality is implemented. Furthermore, stock-out costs are related to lost demand or customer dissatisfaction, which are hardly quantifiable in an economic parameter. Thus, this paper proposes many different heuristic re-order policies, applies them in the field of irregular and sporadic demand profiles and estimates their effectiveness using the following parameters: average inventory level, average lost demand, maximum lost demand and total number of stock-out.

Moreover, the aforementioned approaches achieve theoretical results that sometimes simply cannot be implemented in practice, i.e. long-term series are required. Nevertheless, again in the case of new companies or new items introduced in the market, such data is not available. Thus, in this paper, by taking data from the innovative field of the online supermarket, simple re-order policies and inventory management approaches are tested and compared.

In accordance with the aspects underlined in this section, this paper has to be framed in stochastic inventory control for irregular and sporadic demands (in particular referring to items recently introduced on the market and then characterised by low values of demand in not-null demand periods). It involves several dynamic heuristic re-order policies, whose performances are compared in terms of average values in a multi-criteria non-cost-based perspective through the simulative approach.

3. Initial hypotheses and type of re-order policy applied

The reference environment is related to emerging commercial sectors, i.e. the online supermarket. In this context, the following reasonable hypotheses are outlined:

- Stock-outs induce a lost demand rather than a backlog order. Customers familiar with e-tools simply verify the existence of alternative suppliers and contact them for similar products and services.
- In order to reduce the number of orders sent to suppliers, the solving approaches adopted do not allow the possibility of sending orders in two consecutive periods.
- The time period unit measurement is weeks. The inventory control is executed on a weekly basis.
- The supply lead time L is null. Since time periods are counted in weeks, it is reasonable to suppose that the order sent at the end of each time period i will be received during time period $i+1$. Thus, when calculating the inventory level at the end of time period $i+1$, supposing that the whole order is available at the beginning of the same time period, $i+1$ is possible without losing validity.
- The probability density function $f(x)$ is supposed constant for each time period.
- The re-order policies proposed are single-product. This choice is motivated by the fact that online supermarkets often offer niche products, e.g. characterised by high quality or social commitment. Hence, single-product orders occur more frequently than in traditional commercial channels.

As we shall see, initial hypotheses limit the field of applicability of the re-order policies but do not compromise the validity of the results.

Two main kinds of static multi-period re-order policies are used in the standard inventory theory: (*ROP, Q*) and (*T,S*). In the (*ROP, Q*) policy, the fixed quantity Q is ordered whenever the inventory level drops to the re-order point *ROP* or below (see fig. 1 (a)). Thus, this basic policy involves a continuous review of the inventory level. Instead, the control procedure in the (*T, S*) policy is such that every T units of time (review interval), a variable quantity Q_i is ordered to raise the inventory position to level S (see fig. 1 (b).

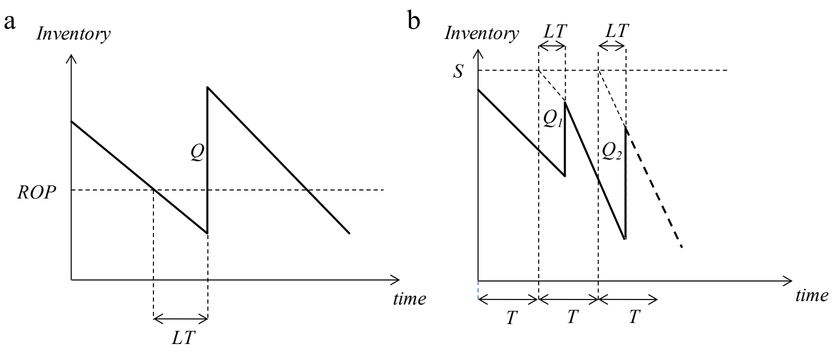

Fig. 1. (a) the (ROP, Q) policy; (b) the (T, S) policy.

This paper refers to dynamic lot sizing policies that belong to the (ROP_i, Q_i) approach with a periodic review of the inventory level, which will be briefly described below (see fig. 2). The quantity Q_{i+1} is ordered whenever the inventory level I_i drops to the re-order point ROP_i at the end of each time period i (periodic review), with Q_{i+1} and ROP_i depending on the specific time period i (dynamic policy). Supply lead time is null for the initial hypotheses, therefore the re-order quantity Q_{i+1} could be considered available at the beginning of time period $i+1$.

Note that the order of Q_{i+1} units is placed at the end of time period i because $I_i \leq ROP_i$, while the order of Q_{i+3} units is placed at the end of time period $i+2$ because $I_{i+2} \leq ROP_{i+2}$.

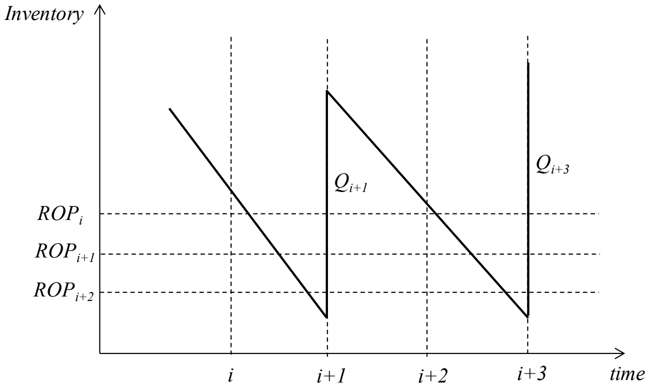

Fig. 2. The (ROP_i, Q_i) policy.

4. Problem statement

This paper deals with a stochastic dynamic lot sizing problem that is not cost-oriented and a minimal service level criterion, say *CSL*, that is used as the probability that at the end of every period the net inventory will not be negative. The demand x is considered as a random variable with a known probability density function $f(x)$ that may not vary from period to period. The model can be expressed as the minimisation of four expected sizes over the n-period planning horizon subject to the service level constraint, as follows:

- Minimise $E\{I_{tot}\} = \int_0^\infty \sum_{i=0}^{n} I_i f(x)dx = \int_0^\infty \sum_{i=0}^{n} (I_{i-1} + \delta_{i-1}Q_i - x_i) f(x)dx$ *(average inventory level)* (1)
- Minimise $E\{N_s\} = \sum_{i=0}^{n} \int_{(I_{i-1}+\delta_{i-1}Q_i)}^{\infty} |I_i| f(x)dx$ *(average lost demand)* (2)
- Minimise $E\{\max N_{si}$, for $i = 0,\ldots,n\}$ *(maximum lost demand)* (3)
- Minimise $E\{ \sum_{i=0}^{n} \beta_i \}$ *(total number of stock-out)* (4)

subject to:

$$ROP_i = D_i + SS + z_i \qquad i = 0, \ldots, n, \tag{5}$$

$$\delta_i = \begin{cases} 1 & \text{if } I_i \leq ROP_i \\ 0 & \text{otherwise} \end{cases} \qquad i = 0, \dots, n, \tag{6}$$

$$\beta_i = \begin{cases} 1 & \text{if } I_i \leq 0 \\ 0 & \text{otherwise} \end{cases} \qquad i = 0, \dots, n, \tag{7}$$

$$Pr\{I_i \geq 0\} = CSL \qquad i = 0, \dots, n, | \delta_i = 1, \tag{8}$$

$$0 \leq \delta_{i-1} + \delta_i \leq 1 \qquad i = 0, \dots, n, \tag{9}$$

$$Q_i, z_i \geq 0 \quad \text{(decision variables),} \qquad i = 0, \dots, n. \tag{10}$$

where Eq. (1) represents the expected sum of the inventory levels at the end of each time period belonging to the planning horizon, Eq. (2) represents the expected total number of units short, Eq. (3) and (4) represent the objectives of minimising the maximum lost demand and the total number of stock-out. Constraint (5) represents the re-order point in the (ROP_i, Q_i) policy (see fig. 2), with the dynamic quantity z_i added to ROP_i as a precautionary size against the high variability and uncertainty of the demand. Constraints (6) and (7) define two binary variables useful in the model. While (6) depends on the replenishment order placed in time period i, (7) depends on stock-out occurrences in time period i. Service level constraint (8) establishes that the probability of stock-out not incurring in periods preceding the receipt of the following replenishment is equal to CSL. For a more detailed discussion about the minimal service level criterion, see [26, 27, 28]. Finally, constraint (9) represents the condition that orders cannot be made to suppliers in two consecutive periods, in order to reduce the total number of emitted orders and constraints (10) assure the implementation of the solutions in real-life applications.

Thus, the stochastic dynamic lot sizing problem formulated above can be reduced to evaluating the two dynamic decision variables Q_i and z_i for each time period i, supposing that the probability density function $f(x)$ is known, after calculating the safety stock SS and the average demand D_i. In fact, all the results achieved depend on the probability density function $f(x)$ applied, which affects both the calculation of the sizes necessary for the application of the re-order policies (SS and D_i) and the experimental analysis conducted thorough the pseudo-random generation of series that follow the specific $f(x)$ chosen.

5. Solution method applied

The steps of the solution approach are listed below:

1. Search for the probability density function $f(x)$ that best represents real demand profiles and calculation of safety stock SS to guarantee a pre-defined cycle service level CSL.
2. Definition of re-order policies by different rules to calculate $ROPi$ and Qi.
3. Simulation of demand (1,000 runs) with $f(x)$ assigned at point 1. and evaluation of average values of the following quantities for each of the predefined re-order policies ($ROPi$, Qi):

    - average inventory level
    - average lost demand
    - maximum lost demand
    - total number of stock-out

The problem statement related to the adopted approach indicates that the decision variables are two dynamic sizes, Q_i and z_i, evaluated in each time period i. Investigating innovative heuristics to compute the two decision variables is therefore the main issue. Thus, the guideline adopted for the choice of re-order policies is to set simple rules to calculate both Q_i and z_i in order to generate alternative re-order policies that are immediate, easily automated and therefore applicable to small and medium-sized enterprises (SME).

Lot size Q_i could be computed by 13 different rules, divided into seven rules with variable lots numbered from Id 1 to Id 7 (see tab. 1) and six rules with lots that can have only two values, either *a* or *b*, numbered from Id 8 to Id 13 (see tab. 2), as follows:

Table 1. The variable lot size Q_i. Rules to calculate it.

Id	Notation	Rules
1	M2	Q_i = mean demand of last 2 periods (*i-2, i-1*)
2	M3	Q_i = mean demand of last 3 periods (*i-3, i-2, i-1*)
3	M4	Q_i = mean demand of last 4 periods (*i-4, i-3, i-2, i-1)*
4	M6	Q_i = mean demand of last 6 periods (*i-6,..., i-1)*
5	MX2	Q_i = max demand of last 2 periods (*i-2, i-1)*
6	MX4	Q_i = max demand of last 4 periods (*i-4, i-3, i-2, i-1)*
7	MX	Q_i = max demand until time period *i*

Table 2. The two-value lot size Q_i. Rules to calculate it.

Id	Notation	Rules
8	2M2	If mean demand of last 2 periods <= *d* then $Q_i = a$ else $Q_i = b$
9	2M3	If mean demand of last 3 periods <= *d* then $Q_i = a$ else $Q_i = b$
10	2M4	If mean demand of last 4 periods <= *d* then $Q_i = a$ else $Q_i = b$
11	2M6	If mean demand of last 6 periods <= *d* then $Q_i = a$ else $Q_i = b$
12	2MX2	If maximum demand of last 2 periods <= *d* then $Q_i = a$ else $Q_i = b$
13	2MX4	If maximum demand of last 4 periods <= *d* then $Q_i = a$ else $Q_i = b$

The values of *a* and *b* (see tab. 2) establish the only two possible lot sizes, hence they have to be fixed according to the specific case dealt with (i.e. in relation to demand pattern, supply condition and product characteristics) as well as *d*, which represents the boundary level needed to define the different rules.

Eight rules are used to calculate z_i (tab. 3), similar to the ones described above in tab. 1.

Table 3. Rules to calculate z_i.

Id	Notation	Rules
1	M2	z_i = mean demand of last 2 periods (*i-2, i-1*)
2	M3	z_i = mean demand of last 3 periods (*i-3, i-2, i-1*)
3	M4	z_i = mean demand of last 4 periods (*i-4, i-3, i-2, i-1)*
4	M6	z_i = mean demand of last 6 periods (*i-6,..., i-1)*
5	MO	z_i = mode of last 10 periods (*i-10, ..., i-1)*
6	MX2	z_i = max demand of last 2 periods (*i-2, i-1)*
7	MX4	z_i = max demand of last 4 periods (*i-4, i-3, i-2, i-1)*
8	MX	z_i = max demand until time period *i*

Every single re-order policy analysed in this work is obtained by combining the 13 rules to calculate Q_i with the eight rules to calculate z_i, so that 104 different re-order policies are obtained.

6. Case study

This case study deals with a pool of 500 demand profiles.

Stat-Fit for Simul8® is adopted to select the distribution function that best represents data. The geometric distribution is often chosen. In accordance with its characteristics, *SS* obtained by varying the required *CSL* are reported in tab. 4.

In this case study, a service level *CSL* equal to 99 % is given, whereby 4 units cover the role of *SS*.

Before testing and comparing the different re-order policies described in section 5 with the simulative approach, the values of *a*, *b* and *d* should be fixed, in accordance with the specifics of the analysed case study. The guidelines established in conjunction with managers are reported below:

Table 4. Calculation of safety stock.

x	f(x)	F(x)	CSL(%)	SS
0	0.60	0.60	60	0
1	0.24	0.84	84	1
2	0.10	0.94	94	2
3	0.04	0.97	97	3
4	**0.02**	**0.99**	**99**	**4**
5	0.01	≅ 1.00	≅ 100	5
6	≅ 0.00	≅ 1.00	≅ 100	6
7	≅ 0.00	≅ 1.00	≅ 100	7
8	≅ 0.00	≅ 1.00	≅ 100	8
9	≅ 0.00	≅ 1.00	≅ 100	9
10	≅ 0.00	≅ 1.00	≅ 100	10

Table 5. Final results achieved by the simulative approach.

	Q_i / ROP_i	*M2*	*M3*	*M4*	*M6*	*MX2*	*MX4*	*MX*	*2M2*	*2M3*	*2M4*	*2M6*	*2MX2*	*2MX4*	*Mean*
Average inventory level	***M2***	2.20	2.40	2.80	2.90	3.10	5.10	7.00	5.20	5.00	4.90	4.80	5.70	5.80	*4.38*
	M3	2.20	2.40	2.80	2.90	3.10	5.20	7.00	5.20	5.00	5.00	4.90	5.70	5.90	*4.41*
	M4	2.30	2.40	2.80	2.90	3.10	5.30	7.00	5.30	5.10	5.10	5.00	5.70	6.00	*4.46*
	M6	2.00	2.50	2.90	3.00	3.10	5.30	7.00	5.30	5.20	5.10	5.00	5.80	6.00	*4.48*
	MO	1.90	2.30	2.60	2.70	3.00	4.50	6.10	4.60	4.40	4.40	4.30	4.90	5.10	***3.91***
	MX2	1.90	2.40	2.90	2.90	3.10	5.30	7.40	5.20	5.10	5.00	4.90	5.90	6.00	*4.46*
	MX4	2.00	2.50	2.90	3.00	3.10	5.80	7.70	5.60	5.40	5.40	5.20	6.20	6.60	*4.72*
	MX	2.00	2.50	2.90	3.30	3.10	6.60	9.70	7.50	7.30	7.30	7.20	8.10	8.40	*5.84*
	Mean	***2.06***	*2.43*	*2.83*	*2.95*	*3.09*	*5.39*	*7.36*	*5.49*	*5.31*	*5.28*	*5.16*	*6.00*	*6.23*	
Average lost demand	***M2***	0.180	0.100	0.080	0.080	0.060	0.010	0.001	0.010	0.010	0.010	0.020	0.006	0.005	*0.044*
	M3	0.180	0.100	0.080	0.080	0.050	0.010	0.001	0.010	0.010	0.010	0.020	0.006	0.005	*0.043*
	M4	0.170	0.100	0.080	0.080	0.050	0.010	0.001	0.010	0.010	0.010	0.020	0.006	0.005	*0.042*
	M6	0.140	0.100	0.070	0.070	0.050	0.010	0.001	0.010	0.010	0.010	0.020	0.006	0.005	*0.039*
	MO	0.140	0.100	0.090	0.080	0.060	0.010	0.002	0.010	0.020	0.020	0.020	0.010	0.009	*0.044*
	MX2	0.140	0.100	0.070	0.080	0.050	0.010	0.001	0.010	0.010	0.010	0.020	0.005	0.005	*0.039*
	MX4	0.140	0.090	0.070	0.070	0.050	0.010	0.001	0.010	0.010	0.010	0.010	0.005	0.004	*0.037*
	MX	0.140	0.090	0.070	0.070	0.050	0.010	0.000	0.003	0.004	0.005	0.005	0.002	0.002	***0.035***
	Mean	*0.154*	*0.098*	*0.076*	*0.076*	*0.053*	*0.010*	***0.001***	*0.009*	*0.011*	*0.011*	*0.017*	*0.006*	*0.005*	
Maximum lost demand	***M2***	2.20	1.80	1.50	1.40	1.30	0.30	0.03	0.20	0.30	0.30	0.30	0.10	0.10	*0.76*
	M3	2.20	1.80	1.50	1.40	1.20	0.20	0.03	0.20	0.30	0.30	0.30	0.10	0.10	*0.74*
	M4	2.10	1.80	1.50	1.40	1.20	0.20	0.03	0.20	0.30	0.30	0.30	0.10	0.10	*0.73*
	M6	2.20	1.80	1.40	1.30	1.20	0.20	0.03	0.20	0.30	0.30	0.30	0.10	0.10	*0.73*
	MO	2.20	1.80	1.50	1.50	1.30	0.40	0.07	0.30	0.40	0.40	0.50	0.30	0.20	*0.84*
	MX2	2.20	1.80	1.40	1.40	1.20	0.20	0.03	0.20	0.30	0.30	0.30	0.10	0.10	*0.73*
	MX4	2.20	1.70	1.40	1.30	1.20	0.20	0.03	0.20	0.30	0.30	0.30	0.10	0.10	*0.72*
	MX	2.20	1.70	1.40	1.30	1.20	0.20	0.01	0.10	0.10	0.10	0.10	0.10	0.05	***0.66***
	Mean	*2.19*	*1.78*	*1.45*	*1.38*	*1.23*	*0.24*	***0.03***	*0.20*	*0.29*	*0.29*	*0.30*	*0.13*	*0.11*	
Number of Stock-out	***M2***	3.40	2.00	1.40	1.50	1.00	0.20	0.02	0.20	0.20	0.20	0.30	0.10	0.10	*0.82*
	M3	3.40	2.00	1.40	1.50	1.00	0.20	0.02	0.20	0.20	0.20	0.30	0.10	0.10	*0.82*
	M4	3.30	1.90	1.40	1.50	1.00	0.20	0.02	0.20	0.20	0.20	0.30	0.10	0.10	*0.80*
	M6	2.60	1.90	1.30	1.40	1.00	0.20	0.02	0.20	0.20	0.20	0.30	0.10	0.10	*0.73*
	MO	2.60	1.90	1.60	1.60	1.10	0.30	0.05	0.30	0.30	0.30	0.40	0.20	0.20	*0.83*
	MX2	2.60	1.90	1.40	1.50	1.00	0.20	0.02	0.20	0.20	0.20	0.30	0.10	0.10	*0.75*
	MX4	2.50	1.80	1.40	1.40	1.00	0.10	0.01	0.10	0.20	0.20	0.20	0.10	0.10	*0.70*
	MX	2.60	1.80	1.40	1.30	1.00	0.10	0.00	0.10	0.10	0.10	0.10	0.04	0.03	***0.67***

	Mean	*2.88*	*1.90*	*1.41*	*1.46*	*1.01*	*0.19*	***0.02***	*0.19*	*0.20*	*0.20*	*0.28*	*0.11*	*0.10*

- *a*, which is selected as the most frequent not-null value in the time series, i.e. $a = 2$
- *b*, which is set as the average peak of the demand in the time series, i.e. $b = 5$
- *d*, the boundary level in the two values lot sizing rules, is chosen equal to *a*, i.e. $d = 2$

Moreover, note that the mode of a geometrically distributed demand is zero, and thus all the policies with z_i equal to the mode (see tab. 3) do not provide for any precautionary size to add to ROP_i.

Results obtained by considering a planning horizon equal to 30 are reported in tab. 5.

At the end of each row and each column, the mean value of the performances achieved by each rule (i.e. average inventory level, average lost demand, maximum lost demand and number of stock-out) is reported. In particular, the minimum values obtained are in bold. Tab. 5 represents a useful tool for comparing the heuristic re-order policies in terms of the priorities given by the management when irregular and sporadic items have to be managed. In particular, when the cost structure is not known *a priori* or cost items are characterised by uncertainty and the demand patterns follow a specific distribution function (in this case the geometric distribution), then the achieved values guide the management towards the more effective re-order policy in terms of their needs. Thus, each heuristic can be evaluated in terms of the weighted average of the four aforementioned measures, with each weight affected by management considerations.

7. Conclusion

Managing irregular and sporadic demand profiles is a common issue in several real industrial environments. Nevertheless, the literature does not offer tools that are simply and effectively implementable in all kinds of company. Specifically, small and medium-sized enterprises are characterised by low resources dedicated to forecasting and managing items. Furthermore, in emerging economic sectors or in new companies, cost-oriented management approaches published in literature are difficult to implement, due to the uncertainty of the available data.

The present paper is focused on re-order policies and inventory management approaches for irregular and sporadic demand profiles. Specifically, 104 models are proposed and their performance is tested.

After an examination of a relevant real data set, the geometric distribution function, with a specific shape factor, is chosen as the one that best models these demand patterns. This result allows the simulative approach to be applied by a pseudo-random generation. In particular, the aforementioned 104 dynamic re-order policies (ROP_i, Q_i) are tested in a multi-criteria non cost-based perspective, in terms of average inventory level, average lost demand, maximum lost demand and number of stock-out. The wide set of solutions obtained is finally evaluated in accordance with weights affected by management considerations.

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