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SPARE PARTS DISTRIBUTION SYSTEM MANAGEMENT

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Abstract: *In this paper we present an application of past stock movement simulation in a task dealing with the stock control of spare parts. The spare parts demand is intermittent by nature as well as for example the special medicals or the special laboratory chemicals demand. We apply our simulation to set the stock levels of 7295 items represented by the real time series of historical demand observations. With help of the simulation experiment we prove that the past stock movement simulation leads to the lower stock holding and ordering costs in case of the total enumeration reorder stock level assessment then in case of forecasting methods considered to be particularly suitable for intermittent demand stock control such as Croston's method and its modifications made up by Syntetos & Boylan and Levén & Segerstedt.*

Key words: *Inventory, Intermittent Demand, Forecasting, Croston's method, Discrete-Event Simulation*

1 INTRODUCTION

Many products have the specific demand characteristics, which makes difficulties linked with their demand forecasting and the stock management. Experiences with problems of such products distribution have distributors or manufacturers of service or spare parts for cars, aircrafts, special equipment maintenance, capital goods, special medicaments etc. Figure1 displays the basic problem of such materials flow management from the supply chain point of view. On the one side customers call for the very short order lead time, the shorter the more valuable, and on the other side manufacturers lead times are very long. This situation force distributors to calculate the optimal stock and order level of these goods.

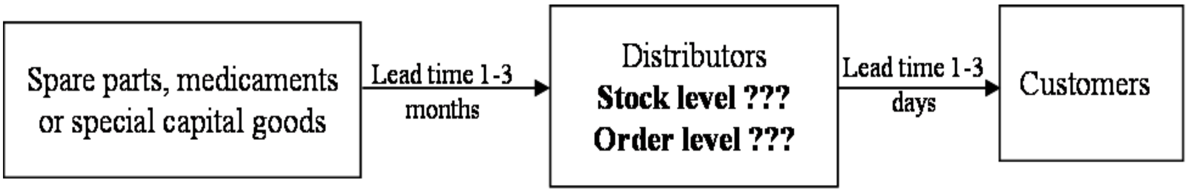

Fig. 1 *Supply system*

When the consumption is "normal", it means uninterrupted in time, with few time periods with zero consumption, classical methods of the flow management such as Customer Relationship Management (CRM) and Continuous Planning, Forecasting and Replenishment (CPFR) systems based on the demand forecast consolidation, the stock level data communication and on the reorder level basis stock replenishment are sufficient. But implementation of these modern methods in intermittent demand environment is very difficult. The typical features of intermittent demand represent relatively small demanded quantities with low variance but mainly the high percentage of periods when no demand occurs at all (see Figure 2).

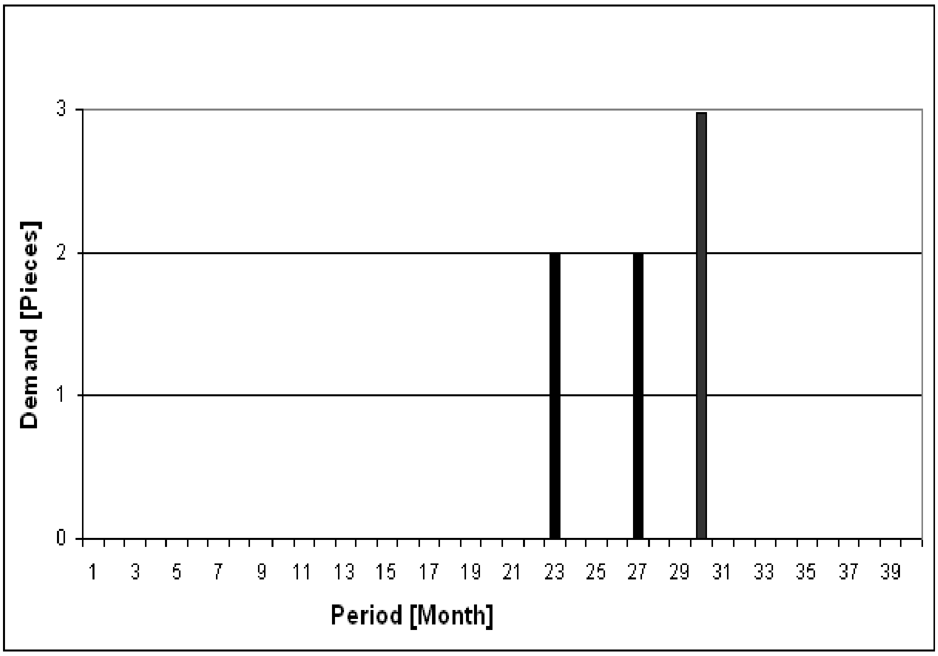

Fig. 2 *Intermittent demand*

In case of the demand intermittence connected with high variance of demanded quantities the demand is called “lumpy” (see Figure 3).

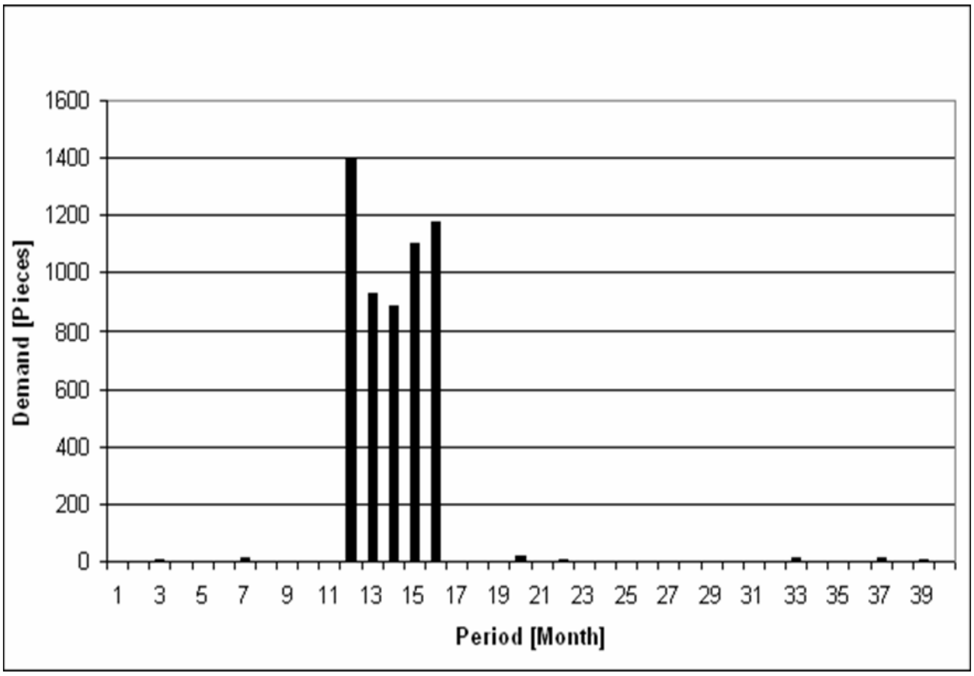

Fig. 3 *Lumpy demand*

Single Exponential Smoothing or its modifications designed for a demand with a trend (Holt, 1957) or seasonality (Winters, 1960) is frequently used for forecasting demand in a routine stock management system (see Brown, 1959). Croston (1972) corrected by Rao (1973) pointed out that Single Exponential Smoothing is not appropriate for stock management of products with intermittent demand and suggested a modification. His method is focused on the estimation of mean demand size z'_t, and also on the mean interval length between two non-zero demands p'_t:

$$z'_t = \alpha \cdot z_t + (1-\alpha) \cdot z'_{t-1}, \tag{1}$$

$$p'_t = \alpha \cdot p_t + (1-\alpha) \cdot p'_{t-1}, \tag{2}$$

where p_t is the time between consecutive transactions and z_t the magnitude of the individual transactions. These estimates are only updated when demand occurs. Croston’s estimate of mean demand per period y'_t is then described by following equation:

$$y'_t = z'_t / p'_t\ , \tag{3}$$

and reorder stock level r_t is then calculated as:

$$r_t = y'_t + k \cdot m_t. \tag{4}$$

Many researchers proved that Croston’s method performs better compared to traditional forecasting methods and can provide benefits to practitioners when dealing with intermittent demand stock control (see for example Willemain et al., 1994 or Johnston and Boylan, 1996).

A disadvantage of Croston’s method is that it is positively biased, as it has been proven by Syntetos and Boylan (2001). These researchers modified Croston’s estimate of mean demand per period y'_t in a way leading to (5):

$$y'_t = (1-\alpha/2) \cdot z'_t / p'_t. \quad (5)$$

Higher performance of their modification has been proven for example by Syntetos and Boylan (2005) or Syntetos, Boylan and Croston (2005). However, Teunter and Sani (2009) found that the modification of Syntetos and Boylan over-compensates positive bias of Croston's method and leads to a negative bias instead. They also pointed out that Croston's method provides better results in case of few zero demand periods, while the modification of Syntetos and Boylan performs efficiently in case of many zero demand periods.

Levén and Segerstedt (2004) modified Croston's method in an attempt to obtain a universal method for both slow and fast moving items. Their estimation of mean demand per period y'_t is updated as follows:

$$y'_t = \alpha \cdot z'_t / p'_t + (1-\alpha) \cdot y'_{t-1}. \quad (6)$$

However, their modification is even more positively biased than Croston's method (see Teunter, Sani, 2009).

Willemain, Smart and Schwarz (2004) introduced the bootstrapping method which is not aimed at the estimation of average demand, but approximates its distribution function. They compared their method with various forecasting techniques and found that the bootstrapping method outperforms both exponential smoothing and Croston's method.

The performance of methods put forward as particularly suitable for intermittent demand is usually compared using traditional measures of accuracy such as mean absolute deviation or root mean square error. Eaves and Kingsman (2004) showed that application of different measure of accuracy for intermittent demand forecasting leads to varying results and no single forecasting method emerges as the best overall. Their research even indicates that in some cases the simpler forecasting methods such as moving average or exponential smoothing can provide the best results for intermittent demand items, while Croston's method and its modifications can provide the best results in case of smooth demand. Thus, Eaves and Kingsman concluded that identifying the best forecasting method for use in a stock control environment is not objective when using the traditional measures of accuracy.

Teunter and Duncan (2008) used a new performance measure based on service level to compare various forecasting techniques. They showed that Croston's method and its modifications developed by Syntetos and Boylan and by Levén and Segerstedt all outperform moving average and Single Exponential Smoothing.

Dyntar, Gros, Kemrová (2010) present the idea to control the stock of products with intermittent demand by the past stock movement simulation. This simulation provides precise answers for basic questions connected with the problem of effective stock management, which include reorder stock level assessment reorder size determination and the choice of an appropriate stock management policy. The outputs of simulation are represented by a combination of controlled parameters (reorder stock level + order quantity/order-up-to level) included in two frequently used stock management policies (Q-system, PQ-system) which guarantees the minimal stock holding and ordering costs while maintaining the required service level. The proposed solution works with two basic ways of reorder stock level assessment. First, reorder stock level can be assessed with help of a forecasting method such as Single Exponential Smoothing (SES), Croston's method (CR) or the modifications of Croston's method made up by Syntetos & Boylan (SB) and Levén & Segerstedt (LS). Croston's method and its modifications are in contrary to single exponential smoothing the procedures considered to be particularly suitable for intermittent demand forecasting and can be found in many commercial software products. Second, reorder stock level can be obtained by a combinatory task solving using the total enumeration. Reorder stock level assessment plays the key role in the stock management system performance. It represents the ability to satisfy the demand occurring during the lead time period which means that it directly influences the service level required by customers. On the other hand reorder stock level itself doesn't solve the way of stock replenishment which is important to ensure the economical efficiency of stock management. Thus, the question is how to combine reorder stock level assessment with the stock replenishment to set the appropriate stock levels that ensure service level requirements as well as the economical efficiency of the stock control.

In this paper we present an application of past stock movement simulation in a task dealing with the stock control of spare parts. We applied this approach to set the stock levels of 7295 items represented by the real time series of historical demand observations. Our aim is to prove the past stock movement simulation to perform better in case of total enumeration application then in case of forecasting methods application considered to be particularly suitable for intermittent demand stock control. The spare parts demand is intermittent by nature as well as for example the special medicals or special laboratory chemicals demand.

2 PAST STOCK MOVEMENT SIMULATION

Our past stock movement simulation is based on the recapitulation of stock movements under the control of a certain stock management system. The inputs to the simulation model are represented by lead time (*LeadTime*), starting stock of a stored item (*StartingStock*) and historical demand observations of a stored item ($Demand_t$). These observations are collected for $t = 1, 2, .., T$ periods (for example months). In each *t-th* period stock movements are represented by met customer demands (stock decrease) and the arrival of replenishment orders (stock increase). Let the simulation starts in the period $t = 1$ and let the initial state of the period (IS_t) is represented by a starting stock (*StartingStock*). First, the current stock (*CurrentStock*) is set equal to the initial state of the period (i.e. for $t = 1 \rightarrow CurrentStock = IS_1 = StartingStock$). Then, the current stock is increased by the arriving order (*AOt*; i.e. *for* $t = 1 \rightarrow CurrentStock = CurrentStock + AO_1$) if there is some. Because there can be more than one delivery in the pipeline which is possible if lead time is longer than the time between two subsequent orders the total ordered amount (*TOA*) has to be decreased by ordered amount right after its arrival (i.e. for $t = 1 \rightarrow TOA = TOA – AO_1$). Then, the current stock is decreased by the demand (i.e. for $t = 1 \rightarrow CurrentStock = CurrentStock - Demand_1$). In case of insufficient current stock the demand is fulfilled only partially, missing quantity (MQ_t) is noted as a difference between the demand and the current stock (i.e. for $t = 1 \rightarrow MQ_1 = Demand_1 – CurrentStock$) and the current stock is set to zero ($CurrentStock = 0$). The simulation doesn't take into account the backordering which means that if the demand in *t-th* period is greater than the current stock there are the lost sales. In the next step, the simulation checks if it is necessary to place an order and its size. The order is placed whether the current stock increased by the total ordered amount is below or equal to the reorder stock level (*r*). The arrival of the order placed in the *t-th* period occurs in period $t + LeadTime + 1$ which means that the ordered amount is available in the beginning of the period $t + LeadTime + 1$. The reorder size depends on the selected stock management policy. The simulation works with the two basic stock management policies. If a reorder-point, reorder-quantity policy (Q-system) is employed the reorder size is constant and the order arriving in *period* $t + LeadTime + 1$(i.e. for $t = 1 \rightarrow AO_1 + LeadTime + 1$) equals order quantity (*Q*). If a reorder-point, order-up-to policy (PQ-system) is employed the size of the order arriving in period $t + LeadTime + 1$(i.e. for $t = 1 \rightarrow AO_1 + LeadTime + 1$) is the order-up-to level (x_h) decreased by the current stock and the total ordered amount. After the order is placed the total ordered amount is increased by the generated arriving order (i.e. for $t = 1 \rightarrow TOA = TOA + AO_1 + LeadTime + 1$) and the final state of the period (FS_t) is set equal to the current stock ($FS_1 = CurrentStock$). Then the simulation continues with the stock movements in the period $t = 2, 3, ..., T$. All

these periods start from the initial state ($IS_t>1$) equal to the final state of the previous period (FS_t-1).
The advantage of such simulation structure is the possibility to assess the economical efficiency of storing and ordering as well as the ability to satisfy the demand. To assess the economical efficiency of storing and ordering two types of costs are evaluated at the end of simulation run for each stored item. The total stock holding costs (H) are evaluated with help of the average stock (x_{avg}) as (see Winston, 1994):

$$H = h \cdot x_{avg} \cdot p \cdot T, \tag{7}$$

where h represents the holding costs stated as the percentage of average stock in Euros per one simulated period, p is the price of stored item and T is the number of simulated periods. The average stock is obtained from the final states of all simulated periods as:

$$x_{avg} = \frac{\sum_{t=1}^{T} FS_t}{T} \quad . \tag{8}$$

The total ordering costs (O) are evaluated as:

$$O = o \cdot Number\ of\ Orders, \tag{9}$$

where o represents fixed ordering costs and *Number of Orders* represents the number of orders placed during the simulation run. The total costs (TC) are then evaluated as:

$$TC = H + O. \tag{10}$$

The ability to satisfy the demand is evaluated in the form of the fill rate (FL). The fill rate represents the demand that can be satisfied right from the current stock. To evaluate the fill rate for the stored item the missing quantities obtained during the simulation run are used in a way leading to (11):

$$FL = 1 - \frac{\sum_{t=1}^{T} MQ_t}{\sum_{t=1}^{T} Demand_t} \tag{11}$$

With help of the fill rate it is possible to set different service levels for stored items according to their importance for example for revenue generating in case of the spare parts distribution. In this case ABC analysis is frequently used to set required fill rates. To achieve required service level in the form of the fill rate the past stock movement simulation has to run under the control of an appropriate combination of the control parameters that are available in the selected stock management policy. In the other words if for example the required fill rate for a stored item is 98%, the total demand in T periods is 100 pieces and the selected stock management policy in the simulation is Q-system, the appropriate combination of reorder stock level (r) and order quantity (Q) has to ensure that the total missing quantity in T periods is no more than 2 pieces. The same goes for PQ-system but for the combination of reorder stock level (r) and order-up-to level (x_h). For a stored item many combinations of the control parameters available in the stock management policies usually ensure the required fill rate. The question is which combination is the best. It is the one with the lowest total costs.

There are two basic ways how to search for the optimal combination of control parameters in our past stock movement simulation. First way is to calculate reorder stock level (r) with help of a forecasting method. In the simulation, forecasting methods such as single exponential smoothing (SES), Croston's method (CR), the modification of Croston's method made up by Syntetos and Boylan (SB), the modification of Croston's method made up by Levén and Segerstedt (LS) are considered. All these methods are summarized in Section 2. The second control parameter which is order quantity in case of Q-system and order-up-to level in case of PQ-system is calculated with help of the total enumeration. It means that for a stored items the past stock movement simulation creates all combinations of reorder stock level obtained by a forecasting method and order quantity or order-up-to level which is an integer from the interval $\langle 1; \sum_{t=1}^{T} Demand_t \rangle$. Than the simulation runs separately for each combination and the combination with both the lowest total costs and achieved required fill rate is obtained. The second way how to search for the optimal combination of control parameters in our past stock movement simulation is to apply the total enumeration on both reorder stock level and order quantity or order-up-to level. In this case the simulation creates all combinations of reorder stock level which is an integer from the interval $\langle 0; \sum_{t=1}^{T} Demand_t \rangle$ and order quantity or order-up-to level which is an integer from the interval $\langle 1; \sum_{t=1}^{T} Demand_t \rangle$. Than the simulation runs separately for each combination again and the combination with both the lowest total costs and achieved required fill rate is obtained.

3 PAST STOCK MOVEMENT SIMULATION EXPERIMENT

We apply the past stock movement simulation in the structure described in previous on the set of real time series. The absolute demand size, when demand occurs, ranges from 1 to 650 pieces and the total demanded quantity in all 40 months ranges from 2 to 799 pieces. Each tested item is except its timeline characteristic with its lead time and the price. The lead times range from 1 to 3 months and the prices range from 1 CZK per piece to 3576 CZK per piece. The fixed ordering costs are set to 500 CZK per order, the holding costs are set to 30 % of average stock in CZK per year and the required fill rate for each item to 98%. The starting stock of each item is set to order quantity/order-up-to level. To initialize the forecasting methods used for reorder stock level calculation in the past stock movement simulation the first 12-period demand data are used. The first SES estimate is taken to be the average demand over the first 12 periods. In a similar way, the initial mean demand size and the mean interval length between two non-zero demands for CR, SB and LS can be based on the average corresponding values over the first 12 periods. If no demand occurs in the first 12 periods, the initial SES estimate is set to zero, the initial mean demand size for CR, SB and LS to 1 and the initial mean interval length between two non-zero demands for CR, SB and LS to 12. Optimization of the smoothing constant is not considered and its value is set to 0.1 according to the recommendations in the literature (see for example Ward, 1963 or Harrison 1965). The safety factor (k) is set equal to 3. We try to decide whether the simulation provides better results when the total enumeration is used to set the reorder stock level instead of forecasting methods considered to be suitable for intermittent demand stock control. Our measurement is based on stock holding and ordering costs and on the required fill rate as well. We apply two stock management policies such as Q-system and PQ-system that together with the total enumeration, SES, CR, SB and LS create $2 \cdot 5 = 10$ different scenarios for reorder stock level assessment. The second controlled parameter (order quantity/order-up-to level) for each scenario is obtained by the total enumeration. With help of past stock movement simulation we minimize stock holding and ordering costs while respecting required fill rate for each item. The results of such experiment are summarized in following table:

Tab. 1: *Stock holding and ordering costs*

Scenario	Stock management policy	Reorder stock level assessment	Stock holding + ordering costs [mil. CZK]
5	Q-system	total enumeration	155.7
10	PQ-system	total enumeration	174.9
1	Q-system	SES	223.2
6	PQ-system	SES	230.4
3	Q-system	SB	231.9
2	Q-system	CR	232.6
4	Q-system	LS	233.3
7	PQ-system	CR	235.4
8	PQ-system	SB	235.4
9	PQ-system	LS	236.0

6 CONCLUSIONS

The outcomes of the simulation experiment prove that the total enumeration used to calculate both reorder stock level and order quantity/order-up-to level in selected stock control policy leads to the lower stock holding and ordering costs than in case of SES, CR, SB and LS application. The advantage of the past stock movement simulation with the application of the total enumeration in both reorder stock level and order quantity/order-up-to level assessment is that no initialize values have to be set as well as no smoothing constant has to be optimized. Another advantage is its robustness in term of demand variability as well as in term of demand intermittence. These properties together with the possibility to change the criteria of the performance assessment (for example the profit) determine the past stock movement simulation with the application of the total enumeration in both reorder stock level and order quantity/order-up-to level assessment to be used as the universal approach in the stock management of a large portfolio of items. However its application can be limited in situations when the total demanded quantity in all simulated periods is extremely high which may cause unbearable time consumption spent on the simulation run. Thus the simulation run has to be substantially accelerated. The simulation itself is also not able to take into account unexpected and rapid demand changes in a way leading to the risk reduction connected with the stock keeping of such item. Thus, we recommend to supplement the past stock movement simulation by the programming procedures for demand forecasting, Fill Rate assessment and risk reduction derived from the demand lumpiness.

Possible applications of past stock movement simulation in practical tasks lies not only in the field of spare parts or special medicals stock management but also in the field of supply chain modelling and optimization. When for example combined with algorithms suitable for logistics objects location and algorithms designed for vehicle routing, past stock movement simulation can serve to design distribution supply chain ensuring the minimization of costs spent on stock holding, replenishment, warehouses operation or customer serving. The application of past stock movement simulation in supply chain design and optimisation represents the next challenge for our research.

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