EFFICIENCY OF PAST STOCK MOVEMENT SIMULATION IN INTERMITTENT DEMAND STOCK CONTROL

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Abstract: *In this paper we present the efficiency measurement study of past stock movement simulation designed for the stock management of products with intermittent demand. The proposed simulation is able to provide the 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 and the required fill rate. To obtain reorder stock level single exponential smoothing, Croston's method, the modification of Croston's method made up by Syntetos&Boylan and Levén&Segerstedt, the method of Smart and the total enumeration are considered. When tested on 5730 real intermittent demand series from automotive industry we conclude that the total enumeration used in the past stock movement simulation to calculate reorder stock level leads to the lowest stock holding and ordering costs and represents robust approach in intermittent demand stock control in term of increasing intermittence and lumpiness.*

Keywords: *Inventory, Intermittent Demand, Dynamic Simulation.*

JEL Classification: *C61***.**

Introduction

Croston's method is considered to be an appropriate approach for intermittent demand stock control. This method eliminates the drawbacks of single exponential smoothing and leads to the results guaranteeing sufficient stock level during order lead time period. With help of the Croston's approach it is possible to determine the reorder stock level but this method does not solve the problem of reorder size or mechanism of reordering. Therefore it is necessary to combine it with an additional procedure to assess how to reorder and how should be the reordering sizes set to ensure economical efficiency of stock replenishment.

As a perspective way of solving this problem we perceive the application of dynamic simulation. In Ekonomika a Management 3/2010 we suggest a solution, which uses dynamic simulation to determine the basic parameters of a stock management system on the basis of past stock movement (see [3]). This solution is able to provide precise answers for basic questions connected with the problem of effective stock management, which include:

- Reorder stock level assessment.
- Reorder size determination.
- The choice of an appropriate stock management policy.

The results of the suggested stock movement simulation model represent information of how reordering is generated and also a combination of control parameters such as reorder stock level and reorder size, which guarantees minimal stock holding and ordering costs, while maintaining the required service level. Our simulation model is able to work either with average demand provided by a forecasting method, which can be used to determine reorder stock level, or it converts the task of reorder stock level assessment to a combinatory optimization task. The aim of this article is to compare the efficiency of this solution in situations when different forecasting methods for reorder stock level assessment are applied or when reorder stock level is assessed using combinatory optimization. The efficiency measurement is realized with the set of real spare parts demand series coming from automotive industry. The rest of this paper is structured as follows. First, in Section 2, we provide the literature on intermittent demand forecasting and stock management. In Section 3 past stock movement simulation is described. In Section 4 basic features of tested demand series are given and the numerical study to assess the efficiency of past stock movement simulation is described. In Section 5 the outcomes of the simulation are discussed. Finally, the paper is summarised.

1 Intermittent demand forecasting and stock management

Single exponential smoothing is frequently used for forecasting demand in a routine stock management system. This procedure can be described by following equation [1]:

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

where y_t is the demand at time t, y'_t the estimate of mean demand per period made at time t and used as a one step ahead predictor of the demand at time $t + 1$, and α is a smoothing constant between zero and one. Reorder stock level r_t is then calculated as:

$$r_t = y'_t + k \cdot m_t, \tag{2}$$

where k is a safety factor dependent on the demand distribution type and m_t is the estimated mean absolute deviation of the errors of the predictor.

Croston pointed out that single exponential smoothing is not appropriate for stock management of products with intermittent demand and suggested a modification (see [2]). 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:

$$z'_t = \alpha \cdot z_t + (1-\alpha) \cdot z'_{t-1}, \tag{3}$$

$$p'_t = \alpha \cdot p_t + (1-\alpha) \cdot p'_{t-1}, \tag{4}$$

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:

$$y'_t = z'_t / p'_t, \tag{5}$$

Many researchers concluded that Croston's method is robustly superior to traditional methods such as moving average or exponential smoothing and can provide benefits to practitioners forecasting intermittent demand (see for example [12] or [5]).

A disadvantage of Croston's method is that it is positively biased, as it has been proven by Syntetos and Boylan (see [7]). These researchers modified Croston's estimate of mean demand per period y'_t in a way leading to (6):

$$y'_t = (1-\alpha/2) \cdot z'_t / p'_t, \qquad (6)$$

Better efficiency of this modification has been proven for example by Syntetos and Boylan (see [8]) or Syntetos, Boylan and Croston (see [9]). However, Teunter and Sani found that the modification of Syntetos and Boylan over-compensates positive bias of Croston's method and leads to a negative bias instead [10]. 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 modified Croston's method in an attempt to obtain a universal method for both slow and fast moving items (see [6]). Their estimation of mean demand per period y't is updated as follows:

$$y'_t = \alpha \cdot z'_t / p'_t + (1-\alpha) \cdot y'_{t-1}. \qquad (7)$$

However, their modification is even more positively biased than Croston's method [10].

Willemain, Smart and Schwarz introduced a fully new approach in intermittent demand stock management (see [13]). Their bootstrapping method 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 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 [4]. 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.

Teunter and Duncan 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 exponential smoothing (see [11]).

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 (AO_t; 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* $t = 1 \rightarrow \mathrm{AO}_{1 + LeadTime + 1}$) 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* $t = 1 \rightarrow \mathrm{AO}_{1 + LeadTime + 1}$) 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* $t = 1 \rightarrow TOA = TOA + \mathrm{AO}_{1 + LeadTime + 1}$) 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 (xavg) as:

$$H = h \cdot x_{avg} \cdot p \cdot T, \tag{8}$$

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:

$$x_{avg} = \frac{\sum_{t=1}^{T} FS_t}{T} \tag{9}$$

The total ordering costs (O) are evaluated as:

$$O = o \cdot Number\ of\ Orders, \tag{10}$$

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:

$$TC = H + O. \tag{11}$$

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 (12):

$$FL = 1 - \frac{\sum_{t=1}^{T} MQ_t}{\sum_{t=1}^{T} Demand_t} \tag{12}$$

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 (xh). 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 or with help of the method of Smart (SM). 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 or by the method of Smart 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 ⟨1; ⟩. 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 efficiency

To assess the past stock movement simulation efficiency we compare 12 different scenarios in a numerical study. These scenarios differ in a way of searching for the optimal control parameter combination used in the stock management policies that are employed in the simulation. As it is pointed out in the previous section there are two stock management policies available in our simulation (Q-system, PQ-system) each with two control parameters (Q – system → reorder stock level + order quantity; PQ – system → reorder stock level + order-up-to level). Each tested scenario consists of one stock management policy whereas reorder stock level common to both employed policies is calculated by one of the forecasting methods available in the simulation (i.e. SES, CR, SB, LS) or by the method of Smart (SM) or by the total enumeration. The second control parameter that determinates the sizes of orders (order quantity or order-up-to level) is than calculated with help of the total enumeration for all scenarios. All tested scenarios are summarized in the following table:

Tab. 1: Scenarios tested in a numerical study

Scenario	Stock management policy	Reorder stock level	Order quantity/ order-up-to level
1	Q-system	SES	total enumeration
2	Q-system	CR	total enumeration
3	Q-system	SB	total enumeration
4	Q-system	LS	total enumeration
5	Q-system	SM	total enumeration
6	Q-system	total enumeration	total enumeration
7	PQ-system	SES	total enumeration
8	PQ-system	CR	total enumeration
9	PQ-system	SB	total enumeration
10	PQ-system	LS	total enumeration
11	PQ-system	SM	total enumeration
12	PQ-system	total enumeration	total enumeration

Source of data: authors

Each scenario is tested on 5730 real intermittent demand series coming from automotive industry. Each demand timeline consists of 63 time periods/months. These timelines are divided into groups according to the probability that non-zero demand occurs and according to the standard deviation of these non-zero demands (see Table 2).

Tab. 2: Non-zero demand probability and variability of available time series

Stdev $Demand_t > 0$ [Pieces]	Probability $Demand_t > 0$ [%]							
	5-15	>15-25	>25-35	>35-45	>45-55	>55-65	>65-75	>75-85
0-1	1309	633	285	93	19	8		
>1-2	423	412	277	166	80	21	6	3
>2-3	129	199	153	81	53	26	6	2
>3-4	136	86	83	46	30	26	7	2
>4-5	59	43	65	36	34	15	7	3
>5-6	31	69	37	21	17	13	9	1
>6-7	55	38	33	17	15	12	9	1
>7-8	29	37	21	19	13	8	4	2
>8-9	21	27	11	9	9	15	1	1
>9-10	10	15	3	9	11	7	7	1

Source of data: authors

The set of the timelines tested in a numerical study contains for example 1309 items with the probability that non-zero demand occurs between 5 and 15% and the standard deviation of these demands between 0 and 1 piece as it is stated in Table 2. The absolute demand size, when demand occurs, ranges from 1 to 57 pieces and the total demanded quantity in all 63 months ranges from 4 to 717 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 0.04 € per piece to 4795 € per piece. Based on the agreement with demand time series provider which is the spare parts distributor in the Czech Republic the fixed ordering costs are set to 20 € per order, the holding costs are set to 30% of average stock in € per year and the required fill rate for each item to 98%. The starting stock of each item is set to $\sum_{t=1}^{LeadTime+1} Demand_t$ which ensures for each item that no stock out occurs in the first *LeadTime + 1* periods and that a combination of controlled parameters of the selected stock management policy which achieves required fill rate is always found at least with help of scenarios number 6 and 12.

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 [2] or [9]). The safety factor (k) is set equal to 3. The bootstrapping method of Smart (SM) approximates the distribution function of possible demands during the lead time period with help of 10 000 demand evaluations per item.

At the end of the simulation run 12·5730 combinations (i.e. number of scenarios· number of items) of control parameters involved in employed stock management policies are obtained. Each combination is assessed by the lowest total cost and required (or higher) fill rate. For each combination of control parameters assessed by the lowest total cost and required (or higher) fill rate the time spent on the computation is monitored as well. In case of the scenarios which consist of a forecasting method or of the method of Smart (i.e. the scenarios 1-5 and 7-11 from Table 1) the time spent on computation consists of the time spent on reorder stock level calculation with help of this method and the time spent on past stock movement simulation which is repeated for all possible combinations of reorder stock level and order quantity/order-up-to level. In this case the number of possible combinations for an item equals to the total demanded quantity of this item in all 63 periods. It is because the order quantity/order-up-to level can theoretically be an integer ranges from 1 to $\sum_{t=1}^{T} Demand_t$. In case of the scenarios which consist of the total enumeration method designated for both reorder stock level and order quantity/order-up-to level calculation (i.e. the scenarios 6 and 12 from Table 1) the time spent on computation consists only of the time spent on past stock movement simulation. This simulation is repeated according to a number of possible combinations of reorder stock level and order quantity/order-up-to level which is in this case equal to $(\sum_{t=1}^{T} Demand_t + 1) \cdot \sum_{t=1}^{T} Demand_t$ for an item. It is because the order quantity/order-up-to level possibly ranges from 1 to $\sum_{t=1}^{T} Demand_t$ and reorder stock level possibly ranges from 0 to $\sum_{t=1}^{T} Demand_t$ for an item.

4 Numerical study outcomes

First the total costs that assess 5730 optimal combinations of controlled parameters are summed up for each scenario ($\sum TC$) as well as the time consumptions spent on their computation ($\sum TimeConsumption$). These sums for each scenario are stated in the following table:

Tab. 3: Optimal total costs and time consumptions summed up for each scenario

Scenario	Stock management policy+r+Q/x_h	∑TC [€]	∑TimeConsumption [min]
6	Q_{system}+total enumeration+total enumeration	3 375 184	44.8
12	PQ_{system}+total enumeration+total enumeration	3 498 144	44.8
1	Q_{system}+SES+total enumeration	4 305 157	1.5
3	Q_{system}+SB+total enumeration	4 360 612	1.5
4	Q_{system}+LS+total enumeration	4 369 485	1.5
2	Q_{system}+CR+total enumeration	4 374 842	1.5
9	PQ_{system}+SB+total enumeration	4 394 491	1.5
10	PQ_{system}+LS+total enumeration	4 405 904	1.5
8	PQ_{system}+CR+total enumeration	4 406 942	1.5
11	PQ_{system}+SM+total enumeration	4 425 401	130.0
5	Q_{system}+SM+total enumeration	4 519 666	130.0
7	PQ_{system}+SES+total enumeration	4 531 705	1.5

Source of data: authors

As it is seen in Table 3 the most successful scenario is the one with Q-system stock management policy and with the control parameters (reorder stock level and order quantity) calculation realized by the total enumeration. This scenario as well as the scenario number 12 which is the one with PQ-system stock management policy and with the control parameters (reorder stock level and order-up-to level) calculation realized by the total enumeration highly outperforms all scenarios where a forecasting method (SES, CR, SB, LS) or the method of Smart (SM) is involved. However, when compared to other scenarios the efficiency of scenarios 6 and 12 is at the expense of longer computation time except the scenarios that consist of the method of Smart. It is because the number of repetitions of past stock movement simulation is for these scenarios (i.e. 6, 12) significantly higher. The high time consumption in case of scenarios where the method of Smart (SM) is involved is caused by the time spent on the construction of the distribution function of demands during lead time. This time depends on the number of demands that the distribution function consists of (in our study 10 000) and the lead time of an item. The higher the lead time and the higher the required number of demands involved in the distribution function construction, the longer the time spent on computation. Among the scenarios which consist of a forecasting method or of the method of Smart the scenario number 1 which includes single exponential smoothing is the one with the lowest costs but there are not such the big differences.

The interesting outcomes are summarized in Table 4 and Table 5. These tables are based on the grouping of all tested demand series according to the probability that non-zero demand occurs and according to the standard deviation of these non-zero demands (see Section 4, Table 2). To obtain the values in Table 4 the lowest total costs for each scenario are summed up for all items contained in a group. Then the scenario with the minimal sum of the total costs is placed in the table. For example the value 447 348 represents the minimal sum of the lowest total costs for 1309 tested items with the probability that non-zero demand occurs between 5 and 15% and the standard deviation of these demands between 0 and 1 piece achieved by the scenario number 6.

In accordance to the outcomes stated in Table 3 only scenarios 6 and 12 occur in Table 4. To obtain the values in Table 5 the lowest total costs for each scenario except scenarios 6 and 12 are summed up again for all items contained in a group. Then the scenario with the lowest sum of the total costs is placed in Table 5 and the difference between the minimal sum of the lowest total costs of this scenario and the minimal sum of the lowest total costs of the scenario placed in Table 4 at the same group is calculated. This difference represents how much (in €) is the best scenario 1-5 or 7-11 (i.e. the scenarios with SES, CR, SB, LS and SM) worse than the scenario placed in Table 4 (i.e. 6 or 12) at the same group. When divided by the minimal sum of the lowest total costs of the scenario placed in Table 4 at the same group the difference in € is recalculated to the difference in % (Δ). For example the value 15% achieved by the scenario number 3 in the group that contains 1309 tested items with the probability that non-zero demand occurs between 5 and 15% and the standard deviation of these demands between 0 and 1 piece means that the scenario number 3 reached the minimal sum of the total costs among scenarios 1-5 and 7-11 and that this sum is 15% higher than the sum of the total costs reached by the most effective scenario within the same group (i.e. 447 348 € achieved by the scenario number 6 in Table 4). The outputs stated in Table 5 show that the difference Δ between the scenarios 6 or 12 and the scenarios which consist of a forecasting method or the method of Smart increases with decreasing probability of non-zero demand occurrence. In the other words the more intermittent demand the higher the difference in total costs achieved by past stock movement simulation without application of SES, CR, SB, LS or SM and past stock movement simulation which uses these methods to calculate reorder stock level as a part of selected stock management policy. Similarly, the difference Δ between the scenarios 6 or 12 and the scenarios which consist of a forecasting method or the method of Smart increases with increasing variability of non-zero demands. The outputs stated in Table 5 also show that when applied in past stock movement simulation the forecasting methods considered to be appropriate for intermittent demand forecasting and stock management can achieve the lower total cost in case of the smooth demand as well as the forecasting methods considered to be appropriate for the smooth demand can achieve the lower total cost in case of the intermittent demand. It means that in situation when the past stock movement simulation is applied (for example if the short computation time is available) and the only scenarios used to calculate reorder stock level are SES, CR, SB and LS (i.e. scenarios 1-4 and 7-10) no forecasting method emerges as the best overall.

Conclusion

In a numerical study the past stock movement simulation efficiency was assessed. We proved 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, LS and SM application. However, this better performance is at the expense of longer computation time when compared to SES, CR, SB and LS application. This can be a problem mainly if the total demanded quantity in all observed periods for an item is very high because the higher the total demanded quantity the higher the number of possible combinations of reorder stock level and order quantity/order-up-to level that has to be evaluated by the past stock movement simulation. 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. It is however possible only if the method is significantly accelerated. Therefore, the acceleration of the past stock movement simulation is the next objective of our research team.

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