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SPEEDING UP PAST STOCK MOVEMENT SIMULATION IN SPORADIC DEMAND INVENTORY CONTROL

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Abstract
This paper is aimed at speeding up past stock movement simulation in sporadic demand inventory control making it more suitable to deal with large scale real life problems connected for example with stock management of spare parts used in the maintenance of production equipment. Thus, in continuous review, fixed order quantity inventory control policy, we suggest reducing number of simulated combinations of reorder point and replenishment order quantity replacing all combinations search with the local search. The local search is based on minimal and maximal reorder point coming from linear regression and bootstrapping. When simulating randomly generated intermittent data with increasing nonzero demand quantities the significant savings of computational time are reached while bringing up to 50 % of simulated timeseries to reach the best possible holding and ordering costs and another 40 % to reach the maximal deterioration of these costs up to 15 %. Upgraded simulation represents efficient, data driven and assumptions free approach to the sporadic demand stock management outperforming individual application of parametric forecasting methods.
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Key Words: Spare Parts, Sporadic Demand, Inventory Control, Continuous Review, Fixed Order Quantity, Simulation

1. INTRODUCTION

For most of the manufacturing and service companies, efficient control of spare parts inventory is essential for the product and equipment maintenance [1]. However, sporadic demand patterns represented by a significant amount of periods with zero demand and high variability of nonzero demand, substantially complicates forecasting [2] and inventory control [3]. The examples of such demand can be found for example in car manufacturing [4], aviation [5] or healthcare [6].

In many inventory control policies described in the literature a replenishment order is placed when the stock level drops below a reorder point [7]. The reorder point represents the amount of stock that prevents a company running out of stock during an order lead time period and its calculation is usually based on a forecast of average consumption [8]. Traditional forecasting techniques like exponential smoothing or regression work well if the demand is regular but with the growing occurrence of zero demand periods these methods suffer from inaccuracy as pointed out by Croston [9], who suggests a modification of single exponential smoothing and proves it to be more suitable when dealing with sporadic demand. Croston‘s method becomes a cornerstone for many researches trying to improve its performance throughout the years. We recommend examining for example the modification of Croston‘s method proposed by Syntetos and Boylan [10], Levén and Segerstedt [11], Teunter and Duncan [12] or Teunter et al. [13] who propose an estimator that is updated in every period rather than only after a demand occurrence. Based on the demand variability and the frequency of demand occurrence several classification schemes for the sporadic demand are also designed providing practitioners with the information which of these methods is the most suitable for a certain demand pattern (see e.g. [14-16]).

As the exponential smoothing and its modifications for sporadic demand represent parametric methods, their performance is affected by an assumption on a standard demand distribution and finding optimal value of smoothing constants in conjunction with the selection of an appropriate accuracy metric [17]. On the other hand, nonparametric approaches don't make any demand distributional assumptions and therefore they appear to be more flexible when dealing with highly irregular demand. An example of such nonparametric method represents bootstrapping proposed by Willemain et al. [18]. This approach samples from the historical demand data to create an empirical distribution of lead time demand using the demand distribution to set the reorder point for a required service level. Similarly to Croston's method bootstrapping becomes a subject to several improvements (see e.g. [19]). However, an essential problem with this resampling technique is that the representation of the distributional properties of the observed data may become poor due to the demand irregularity which generally leads to the significant oversizing of lead time demand [20].

Another nonparametric, data driven and assumptions free approaches represent neural networks [21] and also the past stock movement simulation [22].

The main idea of past stock movement simulation is to discretize time in which historical demand observations are available and to simulate 3 subsequent and interrelated events in each discrete time period. These events include:

- the arrival of replenishment order if planned,
- meeting the demand and
- placing replenishment order if necessary.

Whether the simulation run is repeated under the control of a selected inventory policy for a sufficient number of combinations of the control variables (e.g. reorder point/replenishment order quantity in continuous review, fixed order inventory control policy) reaching the best possible solution is certain. On the other hand, in case of increasing total demand, too detailed discretization of control variables leading to the all combinations search means excessive consumption of computational time and limits the method to be more widely used in practical applications [8].

The goal of this paper is to speed up past stock movement simulation in sporadic demand inventory control making it more suitable to deal with large scale real life problems. Thus, in continuous review, fixed order quantity inventory control policy, we suggest reducing number of simulated combinations of reorder point and replenishment order quantity replacing all combinations search with the local search. The local search is based on the determination of the minimal reorder point coming from the linear regression and the maximal reorder point which is obtained with bootstrapping. To prove significant savings of the computational time spent on the local search compared to all combinations search we randomly generate demand data with level of intermittency ranging from 20 to 70 % of zero demand periods and with nonzero demands ranging from 1 to 100 pieces per period. Together with the consumption of computational time we are also interested in the comparison of the best reached holding and ordering costs ensuring required service level represented by the fill rate.

The rest of this paper is organized as follows. In section 2 we provide information on the past stock movement simulation, the design of simulation experiments including the random generation of intermittent demand data and the description of the outputs coming from the simulation experiments. In section 3 we conclude this paper emphasizing our contribution to the development of sporadic demand inventory control theory and practice.

2. PAST STOCK MOVEMENT SIMULATION

2.1 Model description

As a starting point for the simulation experiments we use past stock movement simulation controlled by the continuous review, fixed order quantity inventory policy where a simulated combination of a reorder point (*Signal*) and a replenishment order quantity (Q) returns certain total holding and ordering costs and a service level in the form of fill rate (see MS Excel VBA code in [8], Appendix B). In the first step, we upgrade the model taking into account solely the combinations where Q > *Signal*. Total holding and ordering costs (N_c) are calculated as:

$$N_c = AvgStock \cdot T \cdot c \cdot n_s + O \cdot n_o \tag{1}$$

where *AvgStock* represents average stock, T the length of simulation, c price of the item, n_s holding costs, O number of orders and n_o ordering costs. Fill rate refers to the percentage of customer demand that is met by immediate stock availability. No backordering as well as multiple orders during the lead time are permitted. On the other hand, partial satisfaction of a demand during a period is allowed, in which case the missing quantity is recorded. To prevent getting out of stock in the beginning of a simulation the initial stock is calculated using Eq. (2):

$$Initial\ stock\ = \sum_{t=1}^{Lead\ time} S_t \tag{2}$$

where t represents a period and S_t represents a demand in a period. Whereas the default model covers all possible combinations of *Signal* > Q given by the total demand (S) during T (i.e. $\frac{S\cdot(S-1)}{2}$ combinations), the consumption of the computational time can easily become unacceptable if the total demand is too high. Thus we suggest replacing all combinations search (AC) with the local search (LS) in which simulated reorder point range is given by the linear regression (LR) and by the bootstrapping (BT). Based on [9] we select LR because we expect this method to underestimate average demand during a lead time when dealing with sporadic demand and therefore to provide LS with an estimation of the minimal reorder point. Similarly, based on [20] we expect BT to overestimate the reorder point providing LS with an estimation of the maximal reorder point. Unlike the methods considered to be suitable for sporadic demand that are based on exponential smoothing (i.e. Croston and the modifications) both LR and BT are not dependent on the optimization of smoothing constants and the selection of an appropriate performance metric. Furthermore, LR smoothing and subsequent *Signal* calculation can be realized directly and efficiently in a MS EXCEL sheet using *LINEST( )* function and Eq. (3):

$$Signal_{LR} = \bar{S}_{t,LR} \cdot Lead\ time + \ k \cdot \sigma_{S_{t,LR}} \cdot \sqrt{Lead\ time} \tag{3}$$

where $\bar{S}_{t,LR}$ and $\sigma_{S_{t,LR}}$ are mean and standard deviation of demand in each unit time period. When assuming that demand during successive unit time periods are independent and identically distributed random variables drawn from a normal distribution the safety coefficient k for a service level can be easily calculated in Excel using *NORMSINV( )* function. The calculation of maximal reorder point based on BT is incorporated to the VBA code of the original model including For/Next cycles and *Rnd( )* function for random selection of a demand from timeseries and *PERCENTILE( )* function to determine the reorder point (*ROP*) for a certain service level (see Appendix 1).

2.2 Simulation experiments

To assess the performance of LS compared to AC we generate 15 scenarios each consisting of 10.000 timeseries of the length of 50 periods. First, we use *RANDBETWEEN( )* function to generate non zero demand in a period ranging from 1 – 5; 1 – 25; 1 – 50; 1 – 75 and 1 – 100 pcs. Then, in each timeseries we replace randomly selected non zero demands with zeros using MS Excel VBA code described in [8], Appendix A. Timeseries in scenarios 1 – 5 contain 20 % zero demand periods, timeseries in scenarios 6 – 10 50 % zero demand periods and timeseries in scenarios 11 – 15 70 % zero demand periods. We use the Average Demand Interval (*ADI*), the square of the Coefficient of Variation (CV^2) to evaluate the demand regularity and variability. *ADI* is calculated as:

$$ADI = \frac{T}{Number\ of\ non\ zero\ demand\ periods} \quad (4)$$

CV^2 is calculated just for nonzero demand periods as:

$$CV^2 = \left(\frac{Demand\ standard\ deviation}{Average\ demand}\right)^2 \quad (5)$$

Based on *ADI* and CV^2 we employ demand classification scheme proposed in [15] to sort timeseries in each scenario into 4 groups. These include smooth demand ($CV^2 < 0{,}49$; $ADI < 1{,}32$); erratic demand ($CV^2 \geq 0{,}49$; $ADI < 1{,}32$); intermittent demand ($CV^2 < 0{,}49$; $ADI \geq 1{,}32$) and lumpy demand ($CV^2 \geq 0{,}49$; $ADI \geq 1{,}32$). Demand characteristics for each scenario are summarized in the following Table I.

Table I: Demand characteristics.

Scenario	***ADI***	$S_{t,min}$ [pcs]	$S_{t,max}$ [pcs]	***S*** [pcs]	CV^2	**Demand type**
1	1,25	1	5	86 - 154	0,08 - 0,43	Smooth (100 %)
2	1,25	1	25	350 - 675	0,09 - 0,64	Smooth (99 %); Erratic (1 %)
3	1,25	1	50	631 - 1359	0,09 - 0,64	Smooth (98 %); Erratic (2 %)
4	1,25	1	75	966 - 2020	0,12 - 0,75	Smooth (98 %); Erratic (2 %)
5	1,25	1	100	1230 - 2691	0,11 - 0,75	Smooth (97 %); Erratic (3 %)
6	2,00	1	5	47 - 101	0,05 - 0,51	Intermittent (100 %); Lumpy (0 %)
7	2,00	1	25	189 - 470	0,06 - 0,79	Intermittent (97 %); Lumpy (3 %)
8	2,00	1	50	351 - 874	0,07 - 0,84	Intermittent (95 %); Lumpy (5 %)
9	2,00	1	75	509 - 1354	0,06 - 0,90	Intermittent (94 %); Lumpy (6 %)
10	2,00	1	100	694 - 1768	0,07 - 0,89	Intermittent (94 %); Lumpy (6 %)
11	3,33	1	5	25 - 66	0,03 - 0,60	Intermittent (100 %); Lumpy (0 %)
12	3,33	1	25	87 - 290	0,04 - 0,90	Intermittent (93 %); Lumpy (7 %)
13	3,33	1	50	155 - 580	0,04 - 1,02	Intermittent (91 %); Lumpy (9 %)
14	3,33	1	75	262 - 905	0,05 - 1,33	Intermittent (90 %); Lumpy (10 %)
15	3,33	1	100	373 - 1219	0,04 - 1,06	Intermittent (90 %); Lumpy (10 %)

For each scenario we simulate 4 arrangements of past stock movement simulation encompassing AC and LS search for both optimal reorder point and replenishment order quantity and also the individual search for optimal replenishment order quantity in situation when reorder point comes from LR and BT. To obtain BT reorder point 100 calculations of the demand during lead time period are processed for each timeseries. Parameters of the simulation used in all experiments are summarized in the following Table II.

Table II: Parameters of simulation.

Price	150	€/piece
Holding costs	28 %	% of average stock in €/period
Ordering costs	35	€/1 order
Required fill rate	95 %	%
Lead time	3	Periods

To carry out simulations MS Excel 16 and a computer with the processor Intel Core i7 – 2,8 GHz, 16 GB RAM are used.

2.3 Simulation results

Based on the optimal reorder points coming from AC and reorder points set by LR and BT in individual search for optimal order quantity we evaluate the potential of LS to capture best possible solution (see Table III). As we expect in all scenarios for all timeseries reorder point obtained with BT is greater or equal to reorder point coming from LR. Moreover for almost 100 % of timeseries in all scenarios BT reorder point is greater than best possible solution coming from AC search. The small number of timeseries with $Signal_{AC}$ > $Signal_{BT}$ is, in our opinion, caused by the low number of calculations of the demand during lead time period in BT. Thus we consider BT reorder point to be the reliable estimation of the maximal reorder point for LS.

Table III: Reorder points comparison.

Scenario	$\boldsymbol{Signal_{BT} \geq Signal_{LR}}$	$\boldsymbol{Signal_{AC} > Signal_{BT}}$	$\boldsymbol{Signal_{AC} < Signal_{LR}}$
1	100 %	0 %	11 %
2	100 %	0 %	51 %
3	100 %	0 %	60 %
4	100 %	0 %	63 %
5	100 %	0 %	64 %
6	100 %	0,2 %	9 %
7	100 %	0,1 %	35 %
8	100 %	0,1 %	42 %
9	100 %	0,1 %	44 %
10	100 %	0,2 %	45 %
11	100 %	0,4 %	12 %
12	100 %	0,5 %	37 %
13	100 %	0,5 %	42 %
14	100 %	0,5 %	44 %
15	100 %	0,4 %	45 %

On the other hand when comparing AC reorder points to these coming from LR there is the significant amount of timeseries where $Signal_{AC}$ < $Signal_{LR}$. In case of scenarios with the demand per period ranging from 1 – 5 pcs (i.e. scenarios 1; 6 and 11) this amount fluctuates around 10 %. It is getting rapidly worse with increasing demand when in case of scenarios with smooth/erratic demand (i.e. scenarios 2 – 5) this amount increases gradually from 51 – 64 % and despite a partial improvement for scenarios with intermittent/lumpy demand (i.e. scenarios 7 – 10 and 12 – 15) which is caused by the increasing number of zeros, this amount still ranges from 35 – to 45 %. That means when replacing AC search with LS bounded by LR and BT reorder points, there exists the uncertainty of reaching the best possible solution.

Based on the best reached holding and ordering costs for 4 simulated arrangements we calculate cost differences (Δ) for each timeseries in each scenario between LS and AC search, between individual search of optimal order quantity with LR reorder point and between individual search of optimal order quantity with BT reorder point as:

$$\Delta = \frac{N_{c,LS\ or\ LR\ or\ BT} - N_{c,AC}}{N_{c,AC}} \cdot 100\ \% \tag{6}$$

Table IV shows 10 – 100 % percentiles of cost differences for each scenario.

Table IV: Cost differences.

	Cost Δ - percentile											
Scenario	**10 %**	**20 %**	**30 %**	**40 %**	**50 %**	**60 %**	**70 %**	**80 %**	**90 %**	**100 %**	***ROP* by**	**No solution**
	0 %	0 %	0 %	6 %	12 %	18 %	27 %	39 %	57 %	373 %	LR	2
1	50 %	60 %	68 %	76 %	83 %	91 %	100 %	111 %	128 %	266 %	BT	0
	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	63 %	LS	0
	0 %	1 %	4 %	7 %	9 %	12 %	16 %	22 %	32 %	247 %	LR	24
2	68 %	81 %	91 %	101 %	111 %	120 %	130 %	144 %	164 %	308 %	BT	0
	0 %	0 %	0 %	0 %	0 %	1 %	4 %	8 %	13 %	54 %	LS	0
	0 %	2 %	4 %	7 %	9 %	12 %	16 %	21 %	31 %	241 %	LR	30
3	71 %	84 %	95 %	104 %	113 %	123 %	134 %	148 %	168 %	369 %	BT	0
	0 %	0 %	0 %	0 %	0 %	3 %	5 %	9 %	14 %	69 %	LS	0
	0 %	3 %	4 %	7 %	9 %	12 %	16 %	21 %	30 %	190 %	LR	14
4	71 %	84 %	95 %	105 %	114 %	124 %	136 %	150 %	171 %	315 %	BT	0
	0 %	0 %	0 %	0 %	1 %	3 %	6 %	9 %	15 %	75 %	LS	0
	0 %	3 %	4 %	7 %	9 %	13 %	16 %	20 %	29 %	223 %	LR	28
5	70 %	85 %	95 %	104 %	114 %	124 %	134 %	149 %	171 %	373 %	BT	0
	0 %	0 %	0 %	0 %	1 %	4 %	6 %	10 %	15 %	69 %	LS	0
	0 %	2 %	10 %	18 %	26 %	35 %	46 %	61 %	84 %	381 %	LR	777
6	31 %	43 %	54 %	63 %	73 %	83 %	94 %	109 %	132 %	294 %	BT	13
	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	53 %	LS	13
	0 %	4 %	8 %	12 %	16 %	22 %	30 %	40 %	57 %	265 %	LR	530
7	46 %	62 %	74 %	85 %	96 %	108 %	122 %	138 %	165 %	493 %	BT	11
	0 %	0 %	0 %	0 %	0 %	0 %	0 %	4 %	11 %	63 %	LS	12
	0 %	3 %	7 %	11 %	15 %	21 %	27 %	37 %	54 %	272 %	LR	506
8	48 %	63 %	75 %	87 %	98 %	110 %	124 %	142 %	170 %	540 %	BT	14
	0 %	0 %	0 %	0 %	0 %	0 %	2 %	6 %	12 %	75 %	LS	16
	0 %	3 %	7 %	10 %	15 %	20 %	27 %	36 %	52 %	230 %	LR	479
9	47 %	64 %	75 %	86 %	98 %	110 %	125 %	142 %	169 %	355 %	BT	13
	0 %	0 %	0 %	0 %	0 %	0 %	2 %	6 %	12 %	82 %	LS	13
	0 %	3 %	7 %	11 %	15 %	20 %	27 %	37 %	54 %	282 %	LR	530
10	47 %	63 %	75 %	87 %	99 %	112 %	126 %	144 %	171 %	429 %	BT	12
	0 %	0 %	0 %	0 %	0 %	0 %	3 %	6 %	13 %	95 %	LS	8
	0 %	0 %	8 %	17 %	25 %	35 %	46 %	62 %	86 %	328 %	LR	955
11	21 %	35 %	47 %	57 %	67 %	79 %	92 %	110 %	138 %	456 %	BT	34
	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	118 %	LS	33
	0 %	3 %	8 %	12 %	18 %	25 %	34 %	46 %	67 %	252 %	LR	739
12	31 %	47 %	60 %	72 %	84 %	98 %	113 %	134 %	166 %	492 %	BT	37
	0 %	0 %	0 %	0 %	0 %	0 %	0 %	6 %	13 %	164 %	LS	35
	0 %	3 %	7 %	12 %	18 %	25 %	33 %	45 %	65 %	257 %	LR	636
13	30 %	47 %	60 %	73 %	86 %	100 %	117 %	137 %	172 %	488 %	BT	32
	0 %	0 %	0 %	0 %	0 %	0 %	1 %	7 %	15 %	104 %	LS	32
	0 %	3 %	7 %	12 %	18 %	24 %	33 %	45 %	63 %	254 %	LR	674
14	30 %	46 %	59 %	72 %	85 %	99 %	116 %	137 %	171 %	582 %	BT	32
	0 %	0 %	0 %	0 %	0 %	0 %	2 %	7 %	15 %	144 %	LS	37
	0 %	3 %	7 %	12 %	17 %	23 %	32 %	43 %	63 %	279 %	LR	656
15	30 %	46 %	59 %	72 %	85 %	100 %	117 %	138 %	173 %	548 %	BT	34
	0 %	0 %	0 %	0 %	0 %	0 %	2 %	7 %	15 %	181 %	LS	34

It can be seen in Table IV that systematic overestimation of BT reorder point in the individual optimization of order quantity simulation arrangement leads to the significantly higher holding and ordering costs when compared to AC. There is the tendency for BT cost differences to decrease in case of growing demand intermittency. Contrarily increasing non-zero demand quantity and variability leads rather to the cost difference enhancement. On the other hand BT reorder point enables past stock movement simulation to almost certainly find a feasible solution from required service level point of view (see Table IV, maximal number of timeseries with "No solution" for BT is 37 in scenario 12) even if the number of calculations of the demand during lead time period executed in BT is very low. It can be further seen in Table IV that LR reorder point in the individual optimization of order quantity simulation arrangement leads to more accurate solution in term of Δ than BT. As the demand intermittency grows LR tends to underestimate reorder point substantially causing increase in cost differences as well as increase in number of timeseries for which no feasible solution meeting required service level is found at all. Increase in non-zero demand quantity and variability helps LR reorder point simulation arrangement to reduce the cost difference. Finally, the outputs in Table IV shows that despite LS simulation arrangement does not guarantee reaching best possible solution in most cases it can get very close with maximal 90 % percentile for all scenarios equal to 15 %.

Together with the best reached holding and ordering costs the consumption of computational time is also recorded during the simulation of each scenario in a simulation arrangement. Obtained computational times are shown in Table V. It can be seen in Table V that computational times for the arrangements with LR and BT reorder points are in all simulated scenarios relatively stable ranging from 6 to 7 minutes and from 20 to 26 minutes respectively. As these arrangements represent individual optimization of order quantity and number of past stock movement simulation runs is consequently quite low we consider the sum of these times to be a reasonable estimation of minimal (and fixed) time spent on LS for given lead time (i.e. 3), number of calculations of the demand during the lead time in BT (i.e. 100), number of timeseries in a scenario (i.e. 10.000) and used hardware and software equipment. When compared LS to AC we reach no savings of computational time in scenarios 1; 6; 11 and 12. In these scenarios AC search lasts from 2 to 17 minutes which is well below of LS's fixed time.

Table V: Consumption of computational time.

	Reorder point obtained with	**AC**	**LR**	**BT**	**LS**
Scenario	**1**	7	7	25	31
	2	110	7	25	38
	3	397	7	25	62
	4	889	7	25	100
	5	1548	7	25	150
	6	4	6	20	29
	7	45	6	24	37
	8	163	7	24	53
	9	356	7	25	74
	10	622	7	23	115
	11	2	6	23	30
	12	17	6	23	32
	13	59	6	26	41
	14	129	6	23	54
	15	226	6	23	74

With increasing total demand AC search becomes more time demanding namely taking 110 – 1548 minutes in scenarios 2 – 5 compared to LS's 38 – 150 minutes; 45 – 622 minutes in scenarios 7 – 10 compared to LS's 37 – 115 minutes and 59 – 226 minutes in scenarios 13 – 15 compared to LS's 41 – 74 minutes.

3. CONCLUSION

The outputs coming from the simulation experiments prove that replacing all combinations search with local search bounded by the linear regression minimal reorder point and bootstrapping maximal reorder point bring significant savings of the consumption of computational time when nonzero demand per period increases from units of pieces to dozens of pieces in timeseries containing 20 %, 50 % and 70 % zeros. This time reduction means up to 50 % of simulated timeseries with such nonzero demand pattern to reach the best possible holding and ordering costs and another 40 % of simulated timeseries to reach the maximal deterioration of these costs up to 15 %. In fact, to set the minimal and maximal reorder point in local search we benefit from the negative features of linear regression (i.e. underestimating average demand per period) and bootstrapping (i.e. oversizing the demand during order lead time period) when dealing with sporadic demand. On the other hand both linear regression and bootstrapping are easy to be programmed, do not require the optimization of smoothing constants based on the selection of an appropriate accuracy metric and bring stable and relatively low consumption of computational time when used to calculate a reorder point.

The past stock simulation modified with local search is now more suitable for a real application in inventory control of large portfolios, where intermittency is a common pattern of behaviour. These are mainly portfolios of spare parts in the field of maintenance across various sectors, not only secondary sector as automotive, aviation or chemistry industry, but for example also in the field of healthcare, where it would be possible to manage the supply of non-standard medicines and medical equipment in this way. Due to the significant savings in computational time, it is realistic to include this method in the corporate ERP, whereas the latest inventory movements are taken into account with each planning run, and therefore the control variables are optimized according to the current state. This should subsequently bring savings in the ordering and holding costs compared to the individual application of a parametric forecasting method in the reorder point calculation.

Speeding up the past stock movement simulation also brings an opportunity to incorporate it as an agent into the next generation of discrete event simulations changing the traditional offline and standalone modelling tool to interactive and live facility connected to online data streams coming for example from a production process [23]. There are numerous benefits that such a live simulation could provide to practitioners. The idea of a digital twin offers one specific way to frame this benefit as a digital twin links a physical entity with a digital representation for the entirety of the physical entity's lifespan [24] providing for example a communication of the live state of a monitored asset, automatic adjustment of a parameter of a monitored asset or creating a prediction to guide suggestions that are either automatically implemented or sent to a human supervisor [25].

To further increase the ability of local search to reach the best possible holding and ordering costs we consider examining a reduction of the minimal reorder point that lies in the removal of safety stock. In addition, more effective examining of the search space could bring a combination of past stock movement simulation with a metaheuristic such as simulated annealing [26] or an evolutionary algorithm [27]. Application of metaheuristics could be essential mainly in case of constrained multi item inventory control (see e.g. [28, 29]). Last but not least, we are going to examine how a certain level of the discretization of control variables affects the efficiency of the past stock movement simulation in term of the consumption of the computational time and the best reached holding and ordering costs. These are the challenges for our future work.

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Appendix 1

```
Sub Qsystem_LocalSearch()
 'Set time of start
 Sheets("Outputs_LocalSearch").Range("J2").Select
 ActiveCell.FormulaR1C1 = "=NOW()"
 Sheets("Outputs_LocalSearch").Range("J2").Select
 Selection.Copy
 Sheets("Outputs_LocalSearch").Range("J2").Select
 Selection.PasteSpecial Paste:=xlPasteValues
 Application.CutCopyMode = False
 Dim Demand(50)
'Set the length of simulation
 T = 50
'Import parameters of simulation
 c = Sheets("Timeseries").Range("B8") 'price
 ns = Sheets("Timeseries").Range("B9") 'holding costs
 no = Sheets("Timeseries").Range("B10") 'ordering costs
 SL = Sheets("Timeseries").Range("B11") 'required fill rate
 LT = Sheets("Timeseries").Range("B12") 'lead time
'For each generated timeseries
 For xx = 1 To 10000
'Import timeseries with demand
  For aa = 1 To T
```

```
  Demand(aa) = Sheets("Timeseries").Cells(aa + 1, xx + 4)
 Next
'Set total demand and initial stock level
 S = Sheets("Timeseries").Cells(56, xx + 4) 'total demand
 InitialStock = Sheets("Timeseries").Cells(57, xx + 4)
 Stock = InitialStock
'LinRegr
 Sheets("Timeseries").Select
 Sheets("Timeseries").Cells(2, xx + 4).Select
 Range(Selection, Selection.End(xlDown)).Select
 Selection.Copy
 Sheets("Outputs_LocalSearch").Select
 Range("N2").Select
 ActiveSheet.Paste
'Bootstrapping
 Range("T5").Select
 Selection.ClearContents
 For aa = 1 To Sheets("Outputs_LocalSearch").Range("S5")
  Btrap = 0
  For bb = 1 To LT
   Position = Round(1 + Rnd() * 49, 0)
   Btrap = Btrap + Demand(Position)
  Next
  Sheets("Outputs_LocalSearch").Cells(aa + 1, 17) = Btrap
 Next
 Range("T5").Select
 ActiveCell.FormulaR1C1 = "=ROUNDUP(PERCENTILE(C[-3],RC[1]),0)"
'Past stock movement simulation
 Ncbest = 1000000000 'best reached total holding and ordering costs
 SignalLinRegr = Sheets("Outputs_LocalSearch").Range("X2")
 SignalBtrapping = Sheets("Outputs_LocalSearch").Range("T5")
 'Local search
 For aa = SignalLinRegr To SignalBtrapping
 Signal = aa 'Set reorder point
  For bb = Signal + 1 To S
   Q = bb 'Set replenishment order quantity
    For cc = 1 To T
     'Replenishment order arrival
     If cc = Ointransit Then
      Stock = Stock + Q
      Ointransit = 0 'order in transit
     End If
     'Demand satisfaction
     If Stock >= Demand(cc) Then
      Stock = Stock - Demand(cc)
     Else
      MQ = MQ + (Demand(cc) - Stock) 'missing quantity
      Stock = 0
     End If
     'Replenishment order placement
     If Stock < Signal And Ointransit = 0 Then
      Ointransit = cc + LT
      O = O + 1 'number of orders
     End If
     'Add inventory level in average stock
     AvgStock = AvgStock + Stock
    Next
   'Calculate total holding and ordering costs
   If 1 - (MQ / S) >= SL Then
    AvgStock = AvgStock / T
    Nc = AvgStock * T * c * ns + O * no
    'Improve the best reached solution
    If Nc < Ncbest Then
     Ncbest = Nc
     Qbest = Q
     Signalbest = Signal
     SLbest = 1 - (MQ / S)
     AvgStockbest = AvgStock
     Obest = O
     MQbest = MQ
    End If
   End If
   'Reset variables of simualtion
   Stock = InitialStock
   AvgStock = 0
   O = 0
   MQ = 0
   Ointransit = 0
  Next
 Next
 'Export the best reached solution if there is some
 If Ncbest < 1000000000 Then
  Sheets("Outputs_LocalSearch").Cells(xx + 1, 2) = Ncbest
  Sheets("Outputs_LocalSearch").Cells(xx + 1, 3) = Qbest
  Sheets("Outputs_LocalSearch").Cells(xx + 1, 4) = Signalbest
  Sheets("Outputs_LocalSearch").Cells(xx + 1, 5) = SLbest
  Sheets("Outputs_LocalSearch").Cells(xx + 1, 6) = AvgStockbest
  Sheets("Outputs_LocalSearch").Cells(xx + 1, 7) = Obest
  Sheets("Outputs_LocalSearch").Cells(xx + 1, 8) = MQbest
 End If
 'Reset variables of simualtion
 S = 0
 InitialStock = 0
Next
 'Set time of finish
 Sheets("Outputs_LocalSearch").Range("K2").Select
 ActiveCell.FormulaR1C1 = "=NOW()"
 Sheets("Outputs_LocalSearch").Range("K2").Select
 Selection.Copy
 Sheets("Outputs_LocalSearch").Range("K2").Select
 Selection.PasteSpecial Paste:=xlPasteValues
 Application.CutCopyMode = False
End Sub
```