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Increasing Efficiency in Inventory Control of Products with Sporadic Demand Using Simulation

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Abstract

The goal of this paper is to examine whether, in Q-system inventory control policy, a combination of the reorder point exceeding order quantity leads to minimal holding and ordering costs when dealing with sporadic demand. For this purpose, a past stock movement simulation is applied to a set of randomly generated data with different numbers of zero demand periods ranging from 10 to 90%. The outputs of the simulation prove that in situations where stock holding costs are too high, the simulation tends to reduce average stock by overcoming periods between two demand peaks with an increase in the numbers of small replenishment orders and reaches lower stock holding and ordering costs. Furthermore, the correlation analysis proves that there is a statistically significant relationship ($r = .847$, $p = .004$) between the number of time series that reach minimal holding and ordering costs under the control of reorder point (replenishment order) and the demand standard deviation affected by the evolving sporadicity. These findings can support decision making linked with inventory management of products with sporadic demand and contribute to development of business information systems.

Keywords

Sporadic demand; Inventory control; ERP; Enterprise resource planning; Simulation; Operations research.

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1 Introduction

Efficient inventory control has a direct impact on cost reduction, customer service levels and product quality, and so is critical to a company's economic and strategic success. In case demand is irregular and sporadic, inventory management becomes quite a challenging task. Sporadic demand represents an environment where demand patterns with very low demand frequency and demand size mean that very few items are required by customers (Gamberini et al., 2014). Examples of such demand can be found in car manufacturing (Do Rego & De Mesquita, 2015), maintenance (Zhu et al., 2022) or aviation (Şahin et al., 2021). It also occurs when products reach the end of their life cycle (Hur et al., 2018).

In inventory management literature, the three most common policies are fixed order quantity inventory control system (sometimes called Q-system or (R,Q)), periodic order up to policy (also known as P-system or (T,S)) and min/max (s,S) (Tao et al., 2017). These methods are frequently implemented in ERP systems, allowing businesses to provide automatic suggestions for what to order and when to order it. With an (R,Q) policy, a replenishment is requested for Q items when the inventory level drops below a threshold R (Dendauw et al., 2021). In a (T,S) policy, orders are placed periodically every T days and order quantity is calculated as the difference between order-up-to level S and the current inventory (Lagodimos et al., 2012). Finally, in min/max, orders are placed as soon as the inventory drops below the minimum and the order size varies and equals the gap between the maximum and the current inventory (Qiu et al., 2017).

To determine control variables in the Q-system, minimization of holding and ordering costs is usually applied (Chung & Cárdenas-Barrón, 2012). A frequent practice is to set the replenishment order as the economic order quantity (EOQ) and compute the reorder point accordingly (Vasconcelos & Marques, 2000). As the reorder point represents inventory for covering demand during the order lead time period, its calculation is often based on a forecast of average consumption. If the demand is regular, standard demand forecasting methods such as moving average or single exponential smoothing and its modifications for demand with trend and seasonality perform well (see, e.g., Chatfield, 1978). Croston (1972) pointed out that exponential smoothing is not appropriate for inventory control of products with sporadic demand and suggested a modification. This modification combines estimation of mean demand with estimation of mean interval length between two non-zero demands, whereas these estimations are updated only when demand occurs. Through the years, many researchers have concluded that Croston's method is robustly superior to traditional forecasting techniques and provides practitioners with significant benefits when dealing with sporadic demand (see, e.g., Willemain et al., 1994; Johnston & Boylan, 1996; Teunter & Duncan, 2009). Many researchers have also tried to improve the performance of Croston's method; well-known are the modifications proposed by Syntetos & Boylan (2001) or Levén & Segerstedt (2004).

Alternative approaches to obtain the reorder point when dealing with sporadic demand include mainly bootstrapping and also combinatorial optimization applied together with discrete-event simulation. The bootstrapping method developed by Willemain et al. (2004) samples from historical demand data to construct an empirical distribution of lead time demand using demand distribution over the replenishment lead time. Although the authors claim significant improvements in forecast accuracy over simple exponential smoothing or Croston's method, this is contradicted for example by Gardner & Koehler (2005) or more recently by Syntetos et al. 2015. Dyntar & Kemrová (2011) presented a past stock movement simulation and its application to inventory control of products with sporadic demand. The main idea of their approach is to discretize time in which historical demand observations are available to periods and simulate decrease (i.e., meeting the demand) and increase (i.e., arrival of replenishment order) of inventory level under control policy. Control variables of the selected policy are discretized too, combined with each other and total holding and ordering costs and service level reached are calculated for each combination at the end of the simulation run. The authors proved that the total enumeration used to calculate both control variables in selected stock control policy leads to lower holding and ordering costs than in the case of single exponential smoothing, Croston's method and its modification suggested by Syntetos and Boylan and Levén and Segerstedt, and also bootstrapping application. The most recent development and application of the past stock movement simulation method can be found in Dyntar (2018, pp. 119–138).

Inventory management policies based on EOQ usually assume that the order quantity is larger than demand during lead time, which means that order quantity is set to exceed the reorder point (Axsäter, 2000). The goal of this paper is to examine whether, in a Q-system, a combination of the reorder point exceeding order quantity leads to minimal holding and ordering costs when dealing with sporadic demand. For this purpose, a past stock movement simulation is applied to a set of randomly generated data with different numbers of zero demand periods ranging from 10 to 90%. The outputs of the simulation provide answers to two major questions:

- Does the extension of the number of simulated combinations of control variables lead to lower holding and ordering costs and at what cost in terms of computational time consumption?
- Is the changing variability of demand caused by the increase in the number of zero demand periods somehow related to the number of cases where a combination of the reorder point exceeding order quantity leads to minimal holding and ordering costs?

The answers to these questions can help increase efficiency in decision making linked with inventory management of products with sporadic demand and contribute to development of business information systems.

2 Research Methods

First, in the MS Excel environment, the RANDBETWEEN() function is applied to generate a data set consisting of 10,000 time series. Each series contains 50 periods with a demand ranging from 1 to 10 pieces. Then, using a macro (see Appendix A), the randomly selected demand values in the time series are replaced with zero so that the total number of zeros in the time series corresponds to the request (i.e., 10-90% with a step of 10%). The demand characteristics for 10-90% of the period with zero demand are shown in Table 1. For 10,000 time series with a certain proportion of periods with zero demand, two scenarios are simulated using past stock movement simulation in the form described by Dyntar (2018, pp. 125–128). The first scenario (Scenario 1) represents fixed order quantity inventory control system (i.e., Q-system), where the combination of the replenishment order (Q) and the reorder point ($Signal$) is not constrained by:

$$Q \geq Signal \tag{1}$$

Table 1. *Demand characteristics.*

Zero demand periods	Average demand [pcs]	Demand standard deviation
10%	4,945	3,184
20%	4,404	3,383
30%	3,846	3,481
40%	3,300	3,493
50%	2,745	3,414
60%	2,195	3,245
70%	1,646	2,966
80%	1,099	2,547
90%	0,549	1,882

This scenario in the form of an MS Excel macro is shown in Appendix B. The second simulated scenario (Scenario 2) includes only those combinations of Q-system control variables in which the replenishment order is greater than or equal to the reorder point. A total of 10,000 · 9 · 2 = 180,000 simulations are performed with the following parameters.

Table 2. *Simulation parameters.*

Price	185	€/piece
Holding costs	25%	% of average stock in €/period
Ordering costs	37	€/1 order
Required fill rate	98%	%
Lead time	3	Periods

To avoid a stock-out at the very beginning of a simulation run, the initial stock for each time series is set as:

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

where t represents a period. Multiple orders during the lead time are not allowed as well as back-ordering if the inventory level is insufficient to meet the demand during a period. In that case, the demand is satisfied partly and the missing quantity is recorded negatively affecting the reached fill rate. For a combination of a replenishment order and a reorder point that ensures at least the required fill rate, total holding and ordering costs (N_c) are calculated as:

$$N_c = AvgStock \cdot T \cdot c \cdot n_s + O \cdot n_o \tag{3}$$

where $AvgStock$ represents average stock, T the length of simulation, c is price, n_s is holding costs, O is the number of orders and n_o is ordering costs. At the end of the simulation, for each time series the combination of the replenishment order and the reorder point with minimal total holding and ordering costs is written down and becomes the subject of further processing and analysis. Together with the optimal combination of control variables for each time series, the consumption of computational time for the simulated scenario and the set of time series with a certain amount of zero demand periods (i.e., for 10,000 time series) is recorded with the help of MS Excel function NOW().

All experiments are carried out in the MS Excel 2016 environment using a computer with an Intel Core i7 7600U – 2.9 GHz processor, 16 GB RAM.

3 Solutions and Results

Based on the outputs of the simulation, the difference between best reached total holding and ordering costs for a time series in Scenarios 2 and 1 is calculated as:

$$Total\ cost\ difference = N_{c,Scenario\ 2} - N_{c,Scenario\ 1} \quad (4)$$

to find out the number of time series where the total cost difference is greater than 0 and therefore a combination of reorder point > replenishment order leads to minimal costs (see Figure 1).

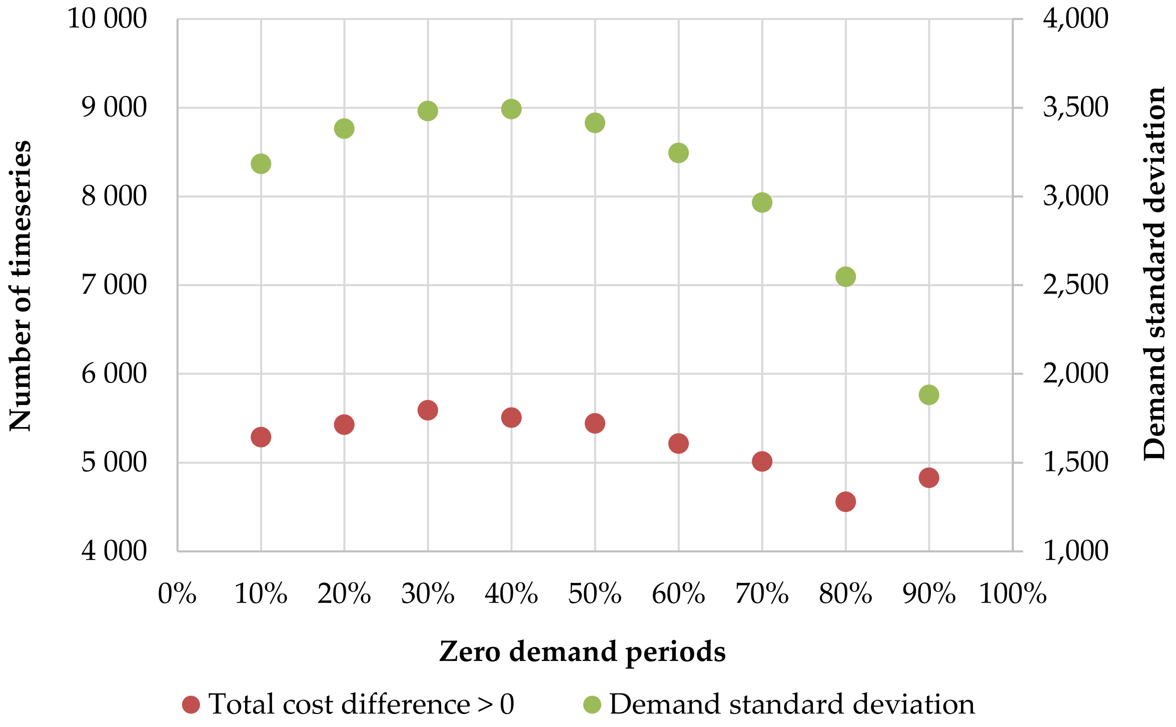

Figure 1. *Number of time series with total cost difference > 0.*

It can be seen in Figure 1 and also the correlation analysis proves that there is a statistically significant relationship (r = .847, p = .004) between the number of time series with total cost difference > 0 and the demand standard deviation affected by the evolving sporadicity. For data sets containing 10-90% zero demand periods, the number of time series with total cost difference > 0 ranges from 4,558 to 5,591.

For each time series, the percentage difference of best reached total holding and ordering costs in the Scenario 2 and Scenario 1 is calculated as:

$$\%\ difference\ in\ total\ costs = \frac{N_{c,Scenario\ 2} - N_{c,Scenario\ 1}}{N_{c,Scenario\ 2}} \cdot 100\% \quad (5)$$

The percentiles for % differences are shown in Table 3.

Table 3. *Percentiles for % differences in total costs.*

	Zero demand periods in time series								
Percentile	10%	20%	30%	40%	50%	60%	70%	80%	90%
10%	0%	0%	0%	0%	0%	0%	0%	0%	0%
20%	0%	0%	0%	0%	0%	0%	0%	0%	0%
30%	0%	0%	0%	0%	0%	0%	0%	0%	0%
40%	0%	0%	0%	0%	0%	0%	0%	0%	0%
50%	1%	2%	3%	3%	2%	1%	0%	0%	0%
60%	5%	6%	7%	7%	7%	6%	5%	3%	6%
70%	9%	10%	11%	12%	12%	11%	11%	9%	12%
80%	13%	15%	16%	17%	17%	17%	16%	15%	18%
90%	19%	20%	22%	24%	24%	24%	23%	23%	26%
100%	50%	55%	63%	53%	74%	59%	74%	62%	76%

For all data sets with 10-90% zero demand periods, the 50-90% percentiles involve a relatively stable 4-8% increase in total cost difference, while 10% of the time series show a significantly faster change ranging from 29 to 51%.

The main reason that there are so many time series with total cost differences > 0 is expensive stock holding when compared to ordering. In this situation, the simulation overcomes periods between two demand peaks with gradual increase of inventory based on small replenishment orders. This is shown in Figure 2.

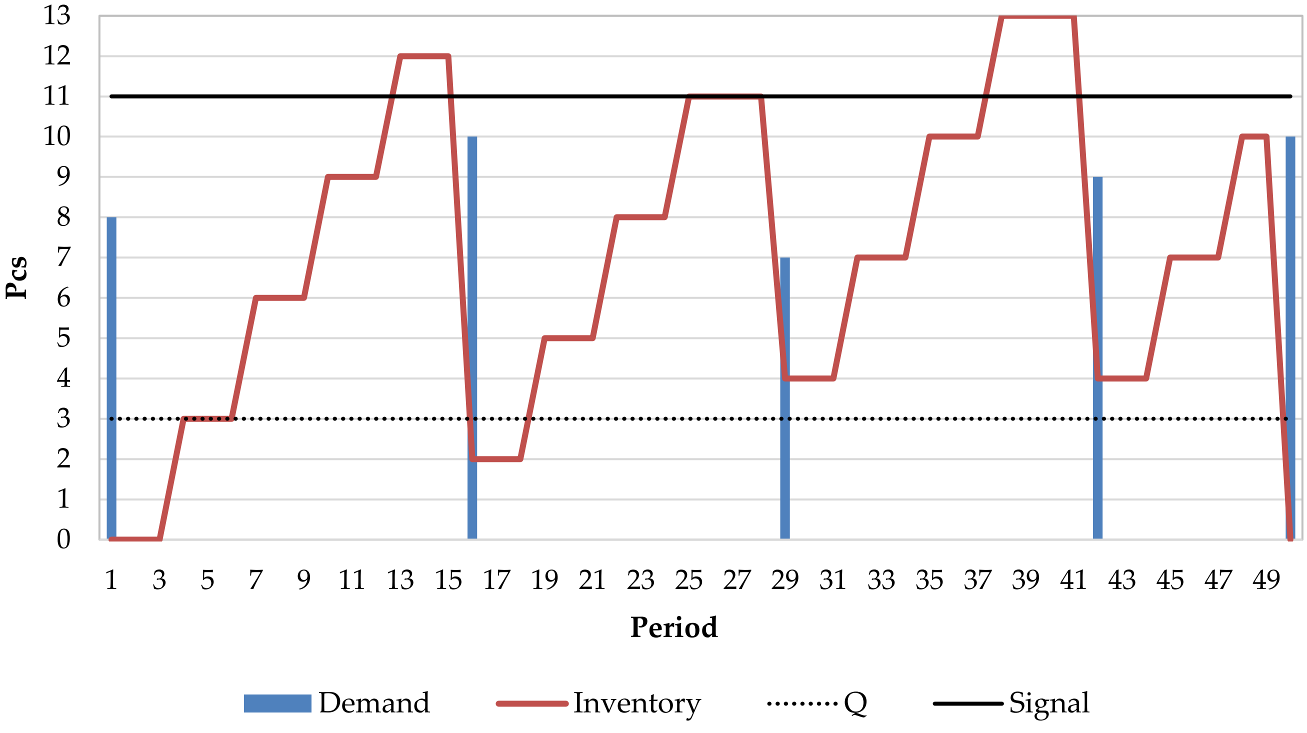

Figure 2. *Distribution of replenishment orders between demand peaks.*

The higher the number of zero demand periods, the more the simulation tends to compensate expensive stock holding with the increasing difference between reorder point and replenishment order (see Table 4).

Table 4. *Average reorder point – replenishment quantity difference.*

Zero demand periods	Average Signal - Q difference
10%	4.34
20%	4.71
30%	5.41
40%	5.76
50%	6.09
60%	6.25
70%	6.27
80%	6.46
90%	6.28

When compared to Scenario 2, the extension of the number of simulated combinations of reorder point and replenishment order in Scenario 1 also brings an up to twofold increase in computational time consumption, as shown in Figure 3. That is because the number of simulated combinations for a time series based on total demand for the entire length of the simulation (S) increases from $\frac{S\cdot(S-1)}{2}$ to S^2.

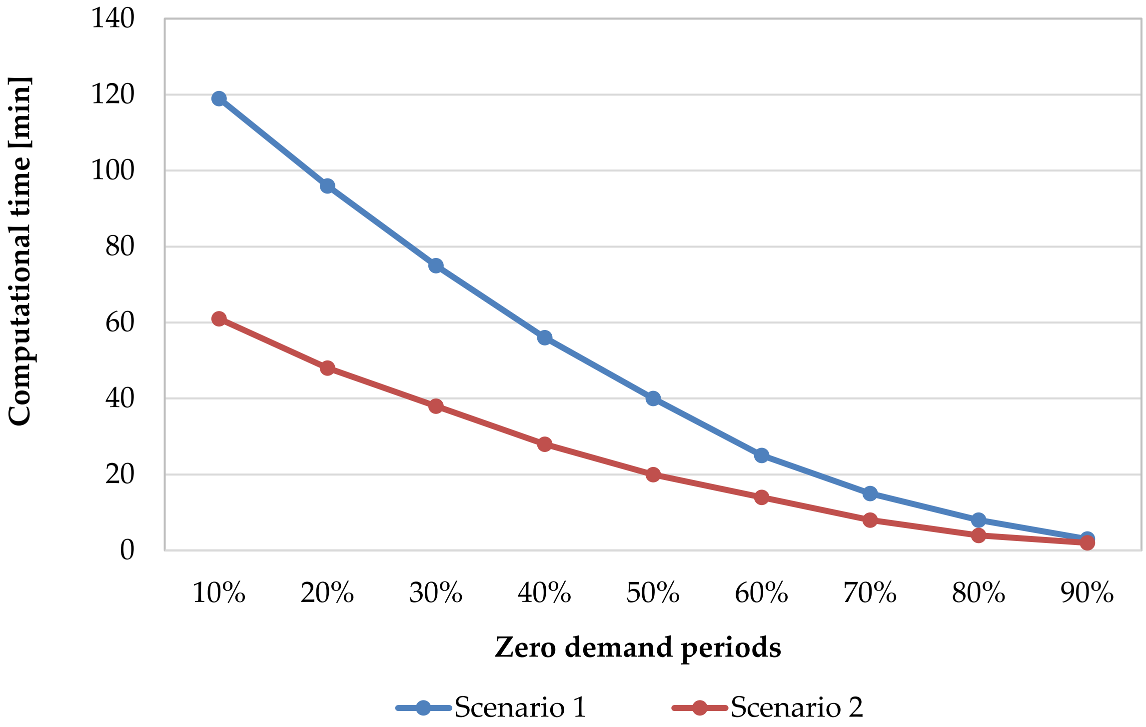

Figure 3. *Consumption of computational time.*

In both scenarios, the higher total demand for the entire length of the simulation that is linked with a lower number of zero demand periods in the time series also tends to cause exponential growth in the consumption of computational time.

4 Discussion

The outputs of past stock movement simulation prove that in a Q-system, under some circumstances the extension of the number of simulated combinations of control variables leads to lower holding and ordering costs. It is because the simulation tends to reduce average stock in situations where stock holding costs are too high by overcoming periods between two demand peaks with an increase in the number of small replenishment orders. For example, when simulating scenarios with stock holding costs at 1% of average stock in €/period and ordering costs of 370 €/order, no significant number of combinations of reorder point > replenishment order leading to minimal stock holding and ordering costs is observed no matter how many zero demand periods the time series contain.

The question therefore arises whether to include an EOQ-based procedure before the simulation itself, by means of which it would be possible to quickly compare the holding and ordering costs of the optimal order quantity and decide whether to devote additional computational time to verifying the extended number of combinations of control variables. This is important if a large number of simulated periods or too high demand will lead to the need to examine a large number of combinations of control variables. In the case of sporadic demand, the literature talks about lumpiness (see, e.g., Kukreja & Schmidt, 2005; Lowas III & Ciarallo, 2016). A more efficient examination or reduction of search space could then be achieved by combining past stock movement simulation with metaheuristics such as tabu search (Ghnatios et al., 2019), simulated annealing (Yuan et al., 2022) or an evolutionary algorithm (Pasandideh et al., 2011). This represents the direction for further development of our solution and challenges for future work.

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Conflict of Interests: The authors declare no conflict of interest.

Author Contributions: K.H.: Methodology, Conceptualization, Writing – Original draft preparation, Writing – Reviewing and Editing. J.D.: Data curation, Software, Writing – Original draft preparation, Supervision.

Data Availability: The data that support the findings of this study are available from the corresponding author.

Appendix A

```
Sub generator()
For aa = 1 To 10000
 Zeros = Round(Sheets("Timeseries").Range("B2") * 50, 0)
 While Zeros > 0
  Position = Round(1 + Rnd() * 49, 0)
  If Sheets("Timeseries").Cells(Position + 1, aa + 3) > 0 Then
   Sheets("Timeseries").Cells(Position + 1, aa + 3) = 0
   Zeros = Zeros - 1
  End If
 Wend
Next
End Sub
```

Appendix B

```
Sub Qsystem()
 Dim Demand(50)
'Set the length of simulation
 T = 50
 For xx = 1 To 10000
'Import timeseries with demand and set total demand
  For aa = 1 To T
   Demand(aa) = Sheets("Timeseries").Cells(aa + 1, xx + 3)
   S = S + Demand(aa) 'total demand
  Next
'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
 'Set initial stock level
  For aa = 1 To LT
   InitialStock = InitialStock + Demand(aa)
  Next
  Stock = InitialStock
  Ncbest = 1000000000 'best reached total holding and ordering costs
 'Past stock movement simulation
  For aa = 1 To S
  Signal = aa 'Set reorder point
   For bb = 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
 Sheets("Outputs").Cells(xx + 1, 2) = Ncbest
 Sheets("Outputs").Cells(xx + 1, 3) = Qbest
 Sheets("Outputs").Cells(xx + 1, 4) = Signalbest
 Sheets("Outputs").Cells(xx + 1, 5) = SLbest
 Sheets("Outputs").Cells(xx + 1, 6) = AvgStockbest
 Sheets("Outputs").Cells(xx + 1, 7) = Obest
 Sheets("Outputs").Cells(xx + 1, 8) = MQbest
 'Reset variables of simualtion
 S = 0
 InitialStock = 0
Next
End Sub
```

References

Axsäter, S. (2000) Exact Analysis of Continuous Review (R,Q) Policies in Two-Echelon Inventory Systems with Compound Poisson Demand. *Operations Research*, 48(5), 686-696. https://doi.org/10.1287/opre.48.5.686.12403

Croston, J. D. (1972). Forecasting and stock control for intermittent demands. *Journal of the Operational Research Society*, 23(3), 289-303.

Dendauw, P., Goeman, T., Claeys, D., De Turck, K., Fiems, D., & Bruneel, H. (2021). Condition-based critical level policy for spare parts inventory management. *Computers & Industrial Engineering*, 157, 107369. https://doi.org/10.1016/j.cie.2021.107369

Do Rego, J. R., & De Mesquita, M. A. (2015). Demand forecasting and inventory control: A simulation study on automotive spare parts. *International Journal of Production Economics*, 161, 1-16. https://doi.org/10.1016/j.ijpe.2014.11.009

Dyntar, J. (2018). *Návrh a optimalizace dodavatelských systémů s využitím dynamické simulace*. FinEco.

Dyntar, J., & Kemrová, E. (2011). Efficiency of Past stock movement simulation in intermittent demand stock control. *Scientific papers of the University of Pardubice. Series D,* 21(3), 31-42.

Gamberini, R., Lolli, F., Regattieri, A., & Rimini, B. (2014). Dynamic re-order policies for irregular and sporadic demand profiles. *Procedia Engineering*, 69, 1420-1429. https://doi.org/10.1016/j.proeng.2014.03.137

Gardner Jr, E., & Koehler, A. B. (2005). Comments on a patented bootstrapping method for forecasting intermittent demand. *International Journal of Forecasting*, 21(3), 617-618. https://doi.org/10.1016/j.ijforecast.2005.04.021

Ghnatios, C., Hage, R. M., & Hage, I. (2019). An efficient tabu-search optimized regression for data-driven modeling. *Comptes Rendus Mécanique*, 347(11), 806-816. https://doi.org/10.1016/j.crme.2019.11.006

Hur, M., Keskin, B. B., & Schmidt, C. P. (2018). End-of-life inventory control of aircraft spare parts under performance based logistics. *International Journal of Production Economics*, 204, 186-203. https://doi.org/10.1016/j.ijpe.2018.07.028

Chatfield, C. (1978). The Holt-Winters Forecasting Procedure. *Journal of the Royal Statistical Society, Series C (Applied Statistics)*, 27(3), 264–279. https://doi.org/10.2307/2347162

Chung, K. J., & Cárdenas-Barrón, L. E. (2012). The complete solution procedure for the EOQ and EPQ inventory models with linear and fixed backorder costs. *Mathematical and Computer Modelling*, 55(11-12), 2151-2156. https://doi.org/10.1016/j.mcm.2011.12.051

Johnston, F. R., & Boylan, J. E. (1996). Forecasting for Items with Intermittent Demand. *The Journal of the Operational Research Society*, 47(1), 113–121. https://doi.org/10.2307/2584256

Kukreja, A., & Schmidt, C. P. (2005). A model for lumpy demand parts in a multi-location inventory system with transshipments. *Computers & Operations Research*, 32(8), 2059-2075. https://doi.org/10.1016/j.cor.2004.01.007

Lagodimos, A. G., Christou, I. T., & Skouri, K. (2012). Computing globally optimal (s, S, T) inventory policies. *Omega*, 40(5), 660-671. https://doi.org/10.1016/j.omega.2011.12.008

Levén, E., & Segerstedt, A. (2004). Inventory control with a modified Croston procedure and Erlang distribution. *International Journal of Production Economics*, 90(3), 361-367. https://doi.org/10.1016/S0925-5273(03)00053-7

Lowas III, A. F., & Ciarallo, F. W. (2016). Reliability and operations: Keys to lumpy aircraft spare parts demands. *Journal of Air Transport Management*, 50, 30-40. https://doi.org/10.1016/j.jairtraman.2015.09.004

Pasandideh, S. H. R., Niaki, S. T. A., & Tokhmehchi, N. (2011). A parameter-tuned genetic algorithm to optimize two-echelon continuous review inventory systems. *Expert Systems with Applications*, 38(9), 11708-11714. https://doi.org/10.1016/j.eswa.2011.03.056

Qiu, R., Sun, M., & Lim, Y. F. (2017). Optimizing (s, S) policies for multi-period inventory models with demand distribution uncertainty: Robust dynamic programing approaches. *European Journal of Operational Research*, 261(3), 880-892. https://doi.org/10.1016/j.ejor.2017.02.027

Şahin, M., Eldemir, F., & Turkyilmaz, A. (2021). Inventory Cost Minimization of Spare Parts in Aviation Industry. *Transportation Research Procedia*, 59, 29-37. https://doi.org/10.1016/j.trpro.2021.11.094

Syntetos, A. A., Babai, M. Z., & Gardner Jr, E. S. (2015). Forecasting intermittent inventory demands: simple parametric methods vs. bootstrapping. *Journal of Business Research*, 68(8), 1746-1752. https://doi.org/10.1016/j.jbusres.2015.03.034

Syntetos, A. A., & Boylan, J. E. (2001). On the bias of intermittent demand estimates. *International Journal of Production Economics*, 71(1-3), 457-466. https://doi.org/10.1016/S0925-5273(00)00143-2

Tao, Y., Lee, L. H., Chew, E. P., Sun, G., & Charles, V. (2017). Inventory control policy for a periodic review system with expediting. *Applied Mathematical Modelling*, 49, 375-393. https://doi.org/10.1016/j.apm.2017.04.036

Teunter, R. H., & Duncan, L. (2009). Forecasting intermittent demand: a comparative study. *Journal of the Operational Research Society*, 60(3), 321-329. https://doi.org/10.1057/palgrave.jors.2602569

Vasconcelos, B. C., & Marques, M. P. (2000). Reorder Quantities for (Q, R) Inventory Models. *The Journal of the Operational Research Society*, 51(5), 635–638. https://doi.org/10.2307/254194

Willemain, T. R., Smart, C. N., Shockor, J. H., & DeSautels, P. A. (1994). Forecasting intermittent demand in manufacturing: a comparative evaluation of Croston's method. *International Journal of Forecasting*, 10(4), 529-538. https://doi.org/10.1016/0169-2070(94)90021-3

Willemain, T. R., Smart, C. N., & Schwarz, H. F. (2004). A new approach to forecasting intermittent demand for service parts inventories. *International Journal of Forecasting*, 20(3), 375-387. https://doi.org/10.1016/S0169-2070(03)00013-X

Yuan, Y., Tole, K., Ni, F., He, K., Xiong, Z., & Liu, J. (2022). Adaptive simulated annealing with greedy search for the circle bin packing problem. *Computers & Operations Research*, 105826. https://doi.org/10.1016/j.cor.2022.105826

Zhu, S., van Jaarsveld, W., & Dekker, R. (2022). Critical project planning and spare parts inventory management in shutdown maintenance. *Reliability Engineering & System Safety*, 219, 108197. https://doi.org/10.1016/j.ress.2021.108197

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