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Gaining competitive advantage in spare parts logistics through inventory control based on optimization via simulation and data aggregation

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Abstract

In this paper, we examine how a demand data aggregation affects the consumption of computational time in sporadic demand inventory control based on a past stock movement simulation (PSMS). PSMS represents a data-driven approach, which instead of estimating order lead time demand with help of a forecasting method rather focuses on a combinatorial optimization using an evolution of a replenishment process over a time. We simulate an all combinations search, a local search and modified local search together with (s, S) inventory control policy and a demand data aggregation ranging from 1 to 40 days using real daily demand data for 12,374 spare car parts covering a one-year period. The outputs from PSMS prove that an increasing data aggregation significantly shortens the time of searching for an s, S combination, ensuring the optimal trade-off between the fill rate and holding and ordering costs. However, the level of aggregation has to be set carefully, because once the positive effect of the aggregation is depleted, holding and ordering costs tend to increase rapidly according to growing average inventory. Acceleration through the data aggregation brings PSMS nearer to applications in extensive supply chain management real life tasks dealing with inventory control of products with sporadic demand.

Keywords: *supply chain management, inventory control, sporadic demand, demand data aggregation, optimization via simulation*

JEL Classification: M21, L62, C61, C63

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1 INTRODUCTION

Supply chain inventory control is a multifaceted and complex area that requires the integration of various optimization techniques, technologies, and risk management strategies to ensure efficient and cost-effective inventory management across the supply chain. As the demand in supply chains inherently fluctuates there is a high potential for a bullwhip effect to reduce the competitiveness of supply chains globally (Trapero & Pedregal, 2016). A bullwhip effect refers to the amplification of demand variability as information in the form of orders moving from lower echelons to higher echelons of the supply chain. It is driven by various factors, including demand signal processing, order batching and price variations (Lee et al., 2004). Moreover, several authors have examined different demand forecasting techniques and their impact on demand variability and the subsequent bullwhip effect (see, e.g., Ma & Ma, 2013; Michna et al., 2020; Yuan et al., 2020).

This phenomenon is also evident in the parts after sales market, also known as the aftermarket. The aftermarket encompasses a wide range of activities and services related to the sale of spare parts, maintenance, and customer service after the initial sale of a product. It is a strategic tool used in various industries to enhance sales, revenue, and profit (Kurata & Nam, 2013). In the automotive industry, the aftermarket is particularly profitable and crucial for maintaining an ongoing relationship with customers, as it includes the provision of spare parts, customer service, and accessories sales (Eslava et al., 2020). After-sales service is also an integral part of marketing activities, contributing to customer satisfaction and loyalty (Peng et al., 2020). The after sales market refers to markets for complementary goods and services such as maintenance, upgrades, and replacement parts used in conjunction with durable goods, emphasizing the interconnected nature of the aftermarket with the primary product market (Domazet & Stošić, 2018). Furthermore, the aftermarket is a critical component of supply networks, providing spare parts to fulfil after-sales commitments and contributing to the overall reliability of the supply chain (Rezapour et al., 2017). In the automotive industry, the aftermarket serves as a principal approach for enterprises to achieve more profits, with spare part logistics management being a crucial area of research and development (Wankhade & Kundu, 2020; Li, 2015). In many cases, aftermarket profits surpass those from selling the product itself, highlighting its significance in overall industry margins (Atefi et al., 2020). The aftermarket also presents challenges, such as demand forecasting influenced by economic factors, customer preferences, and environmental conditions (Chen et al., 2010). Moreover, the use of big data and product-in-use data has the potential to impact aftermarket demand planning and enhance aftermarket supply chain operations (Andersson & Jönsson, 2018).

For many products appearing in the aftersales market, as well as for parts used in maintaining a production equipment to operate smoothly, a typical demand pattern is called sporadic demand (Fan et al., 2023). Sporadic demand is characteristic by a frequent occurrence of zero demand periods as well as by a high variability of nonzero demand (Yuna et al., 2023). Single exponential smoothing-based parametric time series forecasting is regarded as a mainstream method in the scientific literature. With the aid of a time-series forecasting technique, it is necessary to estimate the mean and variance of lead time demand. These characteristics are then used as input to stock management, which typically aims to achieve the minimal inventory costs while reaching the required service level. However, the primary limitations of parametric techniques lie in their reliance on a predetermined demand distribution and the view that demand forecasting and inventory management are distinct processes (Huskova & Dyntar, 2023). That creates a research gap for novel nonparametric approaches to be developed, encompassing, for example, bootstrapping or simulation via optimization. In this paper, we further develop the original idea of past stock movement simulation (PSMS) and combine this technique with a data aggregation. While in the parametric time series forecasting the data aggregation is originally applied to reduce variability in optimization via PSMS, we rather see the potential to accelerate this modelling approach and to use the time savings to reach additional economic efficiency through inventory costs reduction. This additional efficiency can significantly enhance the competitive advantage of companies involved, for example, in spare parts logistics.

The rest of this paper in organized as follows: In section 2, we map the traditional parametric methods used for sporadic demand forecasting and inventory control, and we compare them to emerging non parametric approaches. In section 3, we summarize basic features of simulated demand data, and we show how the aggregation affects these features, including a modification of order lead times. We also describe PSMS of (s, S) inventory control policy, including a flowchart, and provide information on the organization of simulation experiments. Then, in section 4, we present the outputs from simulation experiments, and we discuss the benefits and drawbacks of combining demand data aggregation with PSMS. Finally, in the last section, we conclude.

2 THEORETICAL BACKGROUND

In the literature, estimating mean and variance of lead time demand with the help of a time-series forecasting method is usually considered to be an input to inventory control aimed at reaching a required service level or minimizing inventory costs (Pinçe et al., 2021). The irregular and erratic nature of sporadic demand makes time-series forecasting hard, and together with the development of appropriate forecasting techniques leads to the creation of strategies improving forecasting and inventory control performance. These strategies represent mainly the adoption of demand classification schemes (Boylan et al., 2008) and a demand data aggregation (Li & Lim, 2018). The demand data aggregation includes, for example, an aggregation of daily demand data for weeks or months (Willemain et al., 1994), temporal aggregation-disaggregation frameworks such as ADIDA (Spithourakis et al., 2014) or inverse ADIDA (Petropoulos et al., 2016) and hierarchical forecasting (Rehman et al., 2023).

In this paper, we focus on a non-overlapping demand data aggregation (Babai et al., 2012), which reduces the number of zero demand periods and the demand variability through the grouping together of daily demands into more extensive time intervals. Based on Rostami-Tabar et al. (2023), this approach increases the performance of parametric forecasting techniques that are usually used to estimate the demand over a lead time period. Among these techniques, Croston’s method (Croston, 1972) and its modifications (see, e.g., Levén & Segerstedt, 2007; Boylan & Syntetos, 2007) are considered to outperform traditional moving average or exponential smoothing by incorporating the occurrence of zero demand periods into demand forecasts, making them smoother, with less error variance, and therefore more stock friendly (Boylan & Syntetos, 2010). As the parametric approaches based on single exponential smoothing are easy to update, they have become an integral part of commercial software developed for sporadic demand forecasting and inventory control.

On the other hand, there are some disadvantages of parametric forecasting methods, including mainly an assumption on a standard demand distribution that supports the development of more data driven and assumptions free non-parametric techniques (Huskova & Dyntar, 2022). These techniques represent bootstrapping (see, e.g., Hasni et al., 2019a, 2019b), an empirical method (see, e.g., Van Wingerden et al., 2014; Zhu et al., 2017) and also recently applications of neural networks to learn demand patterns directly from the data (see, e.g., Guo et al., 2017; Abbasimehr et al., 2020; Lei et al., 2023; Mendizabal et al., 2023; Shafi et al., 2023; Belmiro & Oktariani, 2024). In our opinion, however, the major problem with both parametric and non-parametric approaches that focus on an estimation of the demand during an order lead time period is that they usually perceive demand forecasting and inventory control to be two separated stages. More precisely, when speaking about sporadic demand, many scientific studies have compared the performance of forecasting methods based on a forecast accuracy measure, but the number of studies measuring a forecasting method’s impact on inventory performance is surprisingly low (Pinçe et al., 2021). Moreover, a forecasting method that for a certain time series emerges to be the best, for example, in terms of root mean squared error, is not necessarily the best when either a different type of forecast error is applied or when the demand during order lead time period based on this method is used in a selected inventory control policy aimed at optimizing the trade-off between holding and ordering costs and a service level.

Dyntar and Kemrova (2011) proposed an alternative combinatorial approach to inventory control of products with sporadic demand that, instead of estimating order lead time demand, rather focuses on a simulation of replenishment process as it evolves over time. In their data-driven past stock movement simulation (PSMS), a period is separated into time intervals of the same length, and a demanded quantity for each interval is assigned based either on historic real demand data or data coming from a generation procedure. For each interval, there are three events such as a replenishment, a demand satisfaction directly from available inventory, and an ordering to be simulated. The ordering is controlled by a selected inventory control policy involving continuous or periodic review and constant or variable order quantity. In-depth discretization of time and the repetitive run of PSMS for all combinations of controlled variables lead to the optimal trade-off curve and surely outperform statistical forecasting techniques as well as other nonparametric approaches that determine order lead time demand independently. However, too-detailed discretization in PSMS leads to the excessive consumption of computational time (Huskova & Dyntar, 2023). Benefiting from the drawbacks of linear regression and bootstrapping when dealing with sporadic demand (Ye et al., 2022), Huskova and Dyntar (2023) suggest accelerating the original PSMS by bounding the searched solution space with a minimal and a maximal reorder point (i.e., the local search). When simulating continuous-review, fixed-order quantity inventory control policy using randomly generated sporadic demand data, the local search brings significant savings of the consumption of computational time while maintaining a decent ability to reach the best possible holding and ordering costs.

In this paper, we accelerate PSMS in a different way. The goal is to make it more suitable for applications in large-scale, real-life problems. Thus, we examine how a different level of the demand data aggregation affects both the consumption of computational time and the trade-off between a service level and total holding and ordering costs. We simulate one-year real-demand data for 12,374 items provided by a distributor of spare car parts operating at a local aftersales market in the Czech Republic. For each item, we simulate an all combinations search (AC), local search (LS) and modified local search (MLS), together with reorder point (*s*), order-up-to-level (*S*) inventory control policy [i.e., (s, S)] and a demand data aggregation ranging from 1 (i.e., no aggregation) to 40 days. We propose MLS in a way to further underestimate the minimal reorder point obtained with linear regression, ensuring an additional improvement of holding and ordering costs. This further underestimation includes 10, 50 and 90 % off the LS minimal reorder point.

3 RESEARCH OBJECTIVE, METHODOLOGY AND DATA

3.1 Demand data aggregation

Apart from daily demand observations for 12,374 items covering a one-year period, the original data set consists of purchasing prices of items ranging from 8 to 124 €/piece and lead times ranging from 2 to 45 days. For each item, with respect to the lead time range, we perform 8 different levels of non-overlapping demand data aggregation > 1 day that ranges from 5 to 40 days with a regular step equal to 5 days. Then, based on Syntetos et al. (2005), we calculate, for each level of aggregation, the average demand interval of k^{th} item (*ADI*) using Eq. 1:

$$ADI = \frac{Number\ of\ intervals\ in\ aggregated\ time\ series}{Number\ of\ non\ zero\ demand\ intervals\ in\ aggregated\ timeseries} \quad (1),$$

where number of intervals in aggregated time series is calculated as the nearest rounded up integer of $\frac{365}{Level\ of\ aggregation}$ and for non-zero demands in aggregated time series also the squared coefficient of variation (CV^2) using Eq. 2:

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

We summarize basic characteristics of original and aggregated demand data including minimal ($S_{t,min}$) and maximal non-zero demand per simulated time interval ($S_{t,max}$) in Table 1:

Tab. 1 - Basic characteristics of original and aggregated demand data

Level of aggregation **[days]**	**Average *ADI***	**Average CV^2**	**$S_{t,min}$ [pieces]**	**$S_{t,max}$ [pieces]**
1	4.94	0.31	1	13
5	1.51	0.37	1	55

10	1.17	0.31	1	92
15	1.08	0.27	1	99
20	1.05	0.23	1	137
25	1.02	0.19	1	156
30	1.03	0.19	1	174
35	1.01	0.16	1	186
40	1.03	0.18	1	196

Based on a recommended *ADI* cut-off value equal to 0.49 and CV^2 cut-off value equal to 1.32, we employ a demand classification scheme proposed by Syntetos et al. (2005) to sort items into 4 groups: smooth, erratic, intermittent and lumpy demand (see Table 2):

Tab. 2 - Items assortment based on the demand classification scheme proposed by Syntetos et al. (2005)

	Number of items in a group			
***Level of aggregation* [days]/Demand pattern**	Smooth	Intermittent	Erratic	Lumpy
1	0	10 561	0	1 813
5	6 090	4 199	765	1 320
10	9 415	1 671	702	586
15	10 883	597	675	219
20	11 428	341	511	94
25	11 796	143	404	31
30	11 936	53	374	11
35	12 052	41	270	11
40	12 135	23	211	5

As the *Level of aggregation* increases, we calculate modified lead time of k^{th} item (MLT_k) using Eq. 3 and subsequent rounding up to the nearest integer.

$$MLT_k = \frac{LT_k}{Level\ of\ aggregation} \quad (3),$$

where LT_k represents the lead time of k^{th} item in the original non-aggregated dataset. We further analyse modified lead times in term of percentiles and record the results in Table 3:

Tab. 3 - Modified lead times percentiles

***Level of aggregation* [days]/Percentile [%]**	**10**	**20**	**30**	**40**	**50**	**60**	**70**	**80**	**90**	**100**
1	4	6	8	9	11	14	21	24	29	45
5	1	2	2	2	3	3	5	5	6	9
10	1	1	1	1	2	2	3	3	3	5
15	1	1	1	1	1	1	2	2	2	3
20	1	1	1	1	1	1	2	2	2	3
25	1	1	1	1	1	1	1	1	2	2
30	1	1	1	1	1	1	1	1	1	2
35	1	1	1	1	1	1	1	1	1	2
40	1	1	1	1	1	1	1	1	1	2

3.2 Past stock movement simulation

We continue with loading demand data, purchasing prices (p_k) and modified lead times to PSMS of (s, S) inventory policy. Together with the data related to an individual item, we use holding costs (c_h), ordering costs (c_o) and required fill rate (FR) as the parameters that are common for all items (see Table 4):

Tab. 4 - Parameters of simulation

c_h	34	% from average inventory in € per 1 year
c_o	27	€ per 1 order
FR	95	%

In PSMS, a backordering as well as a placement of more than one order during the lead time is forbidden for an individual item. On the other hand, a partial demand satisfaction in a simulated interval right from an available inventory is enabled, which means that an occurrence of a missing quantity is written down, becoming a part of the calculation of achieved fill rate (AFR) for a simulated combination of s, S (see Eq. 4):

$$AFR \ = 1 - \frac{Total\ missing\ quantity}{Total\ demand} \qquad (4),$$

where *Total demand* in t = 1,2…..T simulated time intervals for k^{th} item is calculated as:

$$Total\ demand \ = \sum_{t=1}^{T} S_t \qquad (5),$$

where S_t represents a demand in a simulated interval. In the case that $AFR \geq FR$ for a simulated combination of s, S, total holding and ordering costs (C_t) are calculated with help of Eq. 6:

$$C_t = AI \cdot p_k \cdot c_h + N_o \cdot c_o \qquad (6),$$

where AI represents average inventory and N_o number of orders. As we do not want to commit a stock out in the very beginning of the simulation run, we set an initial inventory (II) for k^{th} item according to Eq. 7:

$$II \ = \sum_{t=1}^{MLT_k+1} S_t \qquad (7).$$

The flowchart of the simulation of (s, S) inventory policy for k^{th} item displays is in Figure 1:

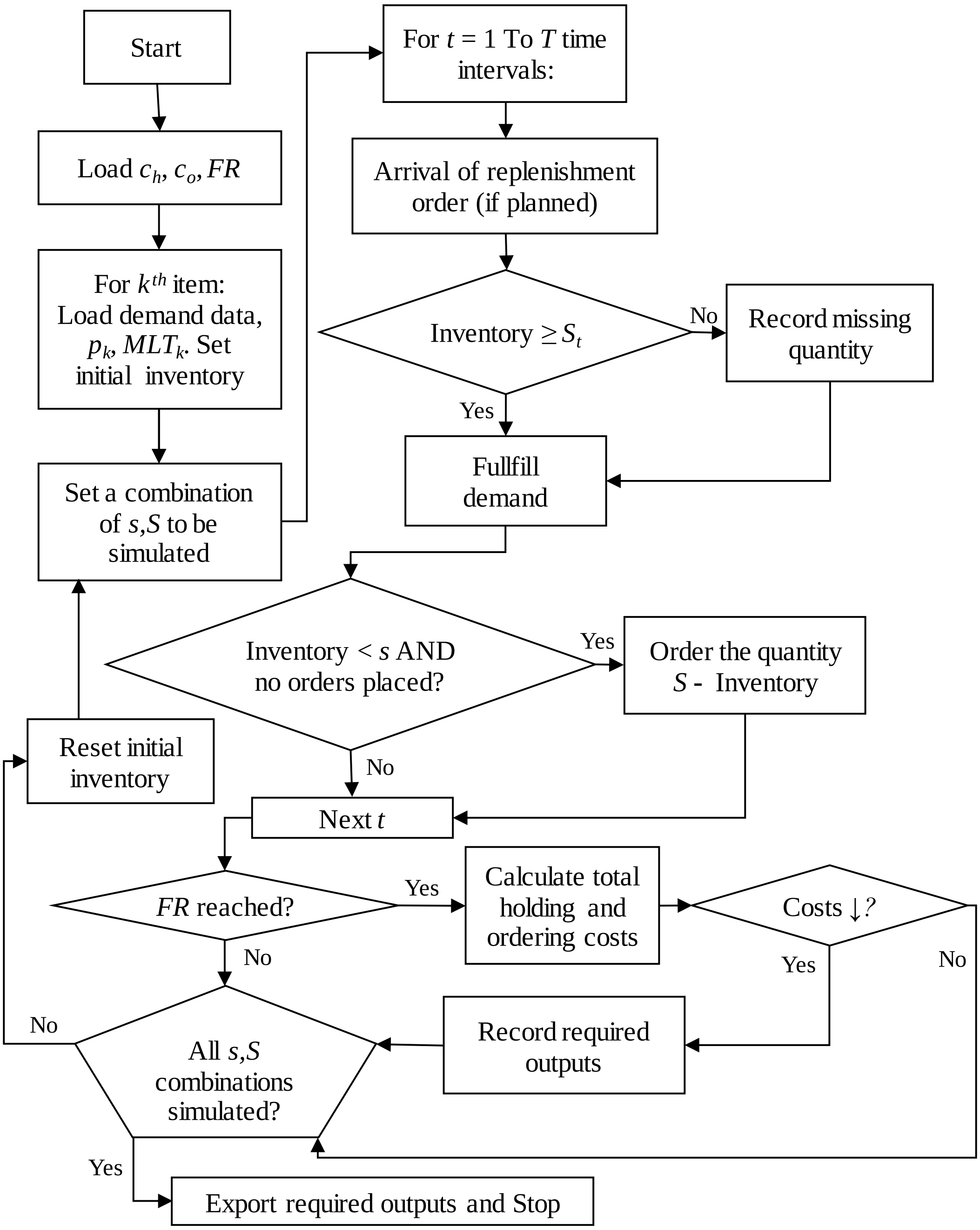

Fig. 1 - Flowchart of the simulation model of (s, S) inventory policy for k^{th} item

3.3 Simulation experiments

Simulation experiments are organized as follows: First, we simulate AC + PSMS and LS + PSMS for each item with 9 scenarios differing in demand data aggregation. In simulation experiments, we examine only such s, S combinations where $S > s$. We compare AC + PSMS and LS + PSMS in terms of the consumption of computational time and the trade-off between the fill rate and the minimal holding and ordering costs ($Ct_{best,k}$). Then, we simulate MLS + PSMS for each item, with 9 scenarios differing in demand data aggregation and 3 arrangements of LS minimal reorder point decrease. Finally, we compare MLS + PSMS and LS + PSMS with AC + PSMS again in terms of the consumption of computational time and the difference between $Ct_{best,k}$.

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All simulation experiments are performed in MS Excel on a computer with the processor Intel Core i7 – 2.8 GHz, 16 GB RAM. To record the consumption of computational time, we use the MS Excel function NOW() in the beginning and at the end of the simulation of a scenario.

4 RESULTS AND DISCUSSION

The consumption of computational time for simulated scenarios of AC + PSMS and LS + PSMS is displayed in Figure 2:

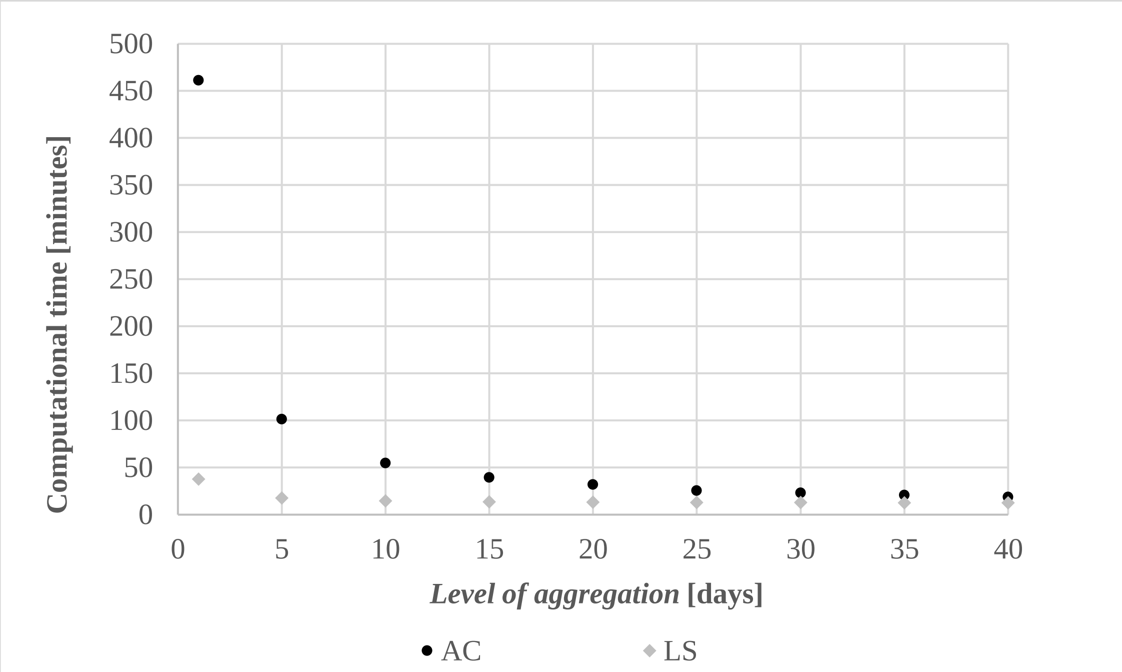

Fig. 2 - Consumption of computational time for different levels of demand data aggregation

The outputs from simulation experiments prove that an increasing data aggregation significantly shortens the time of searching for an *s*, *S* combination, ensuring the optimal trade-off between a fill rate and holding and ordering costs. While for the original data set with no aggregation, it takes AC + PSMS almost 8 hours to carry out the simulation of the scenario, in case of, for example, monthly aggregated demand data, it lasts only 23 minutes. The outputs from simulation experiments also prove that LS + PSMS is significantly faster than AC + PSMS mainly for a low level of demand data aggregation.

However, the decrease in the consumption of the computational time needs to be judged in conjunction with the evolution of optimal holding and ordering costs. Thus, based on the minimal holding and ordering costs coming from simulation experiments, we calculate total minimal holding and ordering costs for each scenario using Eq. 8:

$$\Sigma C_{t,best} = \sum_{k=1}^{12\,374} Ct_{best,k} \quad (8).$$

These costs for AC + PSMS and LS + PSMS are shown in Figure 3:

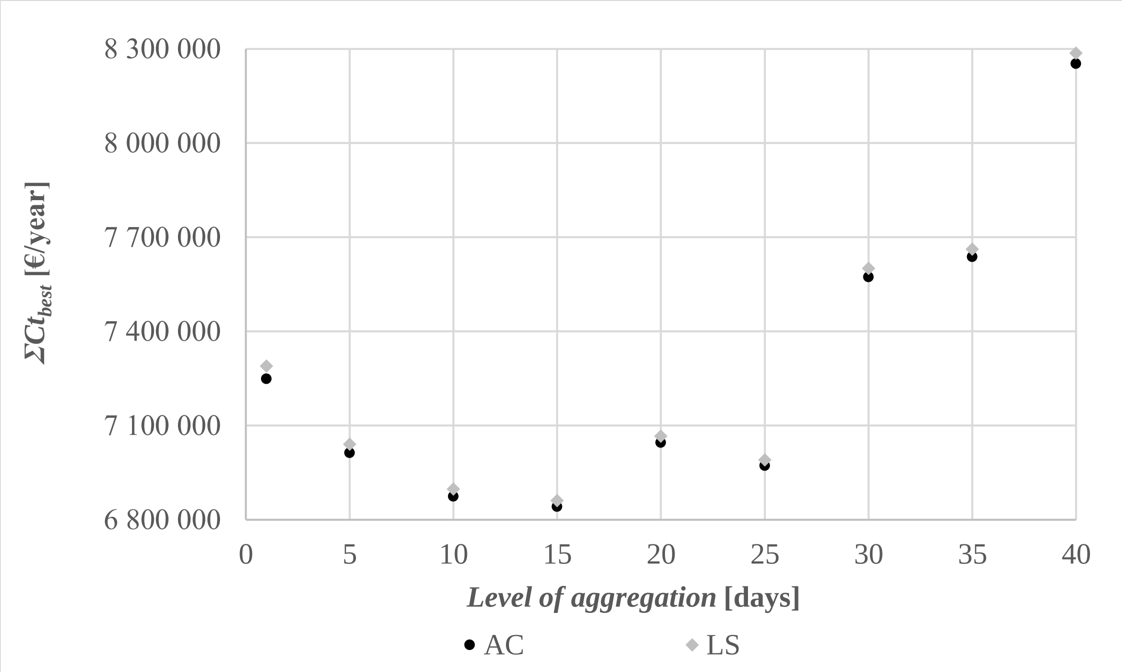

Fig. 3 - Total minimal holding and ordering costs

It can be seen in Figure 3 that there is a moderate decrease in total minimal holding and ordering costs for the level of aggregation 5, 10 and 15 days, reaching for AC + PSMS the lowest costs equal to approx. 6.8 million € compared to 7.2 million € for the original data set with no aggregation. For the level of aggregation 20 and 25 days, total minimal holding and ordering costs still hold below the value for non-aggregated data, while for the level of aggregation ≥ 30 days there is a steep increase. The described behaviour of holding and ordering costs is similar for AC + PSMS and LS + PSMS, and also AC + PSMS slightly outperforms LS + PSMS in terms of holding and ordering costs in each simulated scenario. LS + PSMS find no solution for a certain amount of simulated time series (see Table 5) as we use only 100 sampling runs in bootstrapping:

Tab. 5 - Number of simulated items with no solution found by LS + PSMS

Level of aggregation [days]	1	5	10	15	20	25	30	35	40
No solution found with LS	8	9	1	2	1	0	0	0	0

It can be seen in Table 5 that the number of simulated items with no solution found by LS + PSMS decreases with an increasing level of aggregation. This is because through the aggregation, the demand intermittency decreases (see Tables 1 and 2), which is in accordance with findings of Huskova and Dyntar (2023).

To analyse the evolution of optimal holding and ordering costs closely, we use average inventory linked with minimal holding and ordering costs and calculate total average inventory for each scenario, using Eq. 9:

$$\Sigma AI_{best} = \sum_{k=1}^{12\,374} AI_{Ct_{best},k} \qquad (9).$$

Similarly based on the number of orders linked with minimal holding and ordering costs, we calculate the total number of orders for each scenario using Eq. 10:

$$\Sigma No_{best} = \sum_{k=1}^{12\,374} No_{Ct_{best},k} \qquad (10).$$

Total average inventory and total number of orders linked with minimal holding and ordering costs for AC + PSMS and LS + PSMS are shown in Figures 4 and 5:

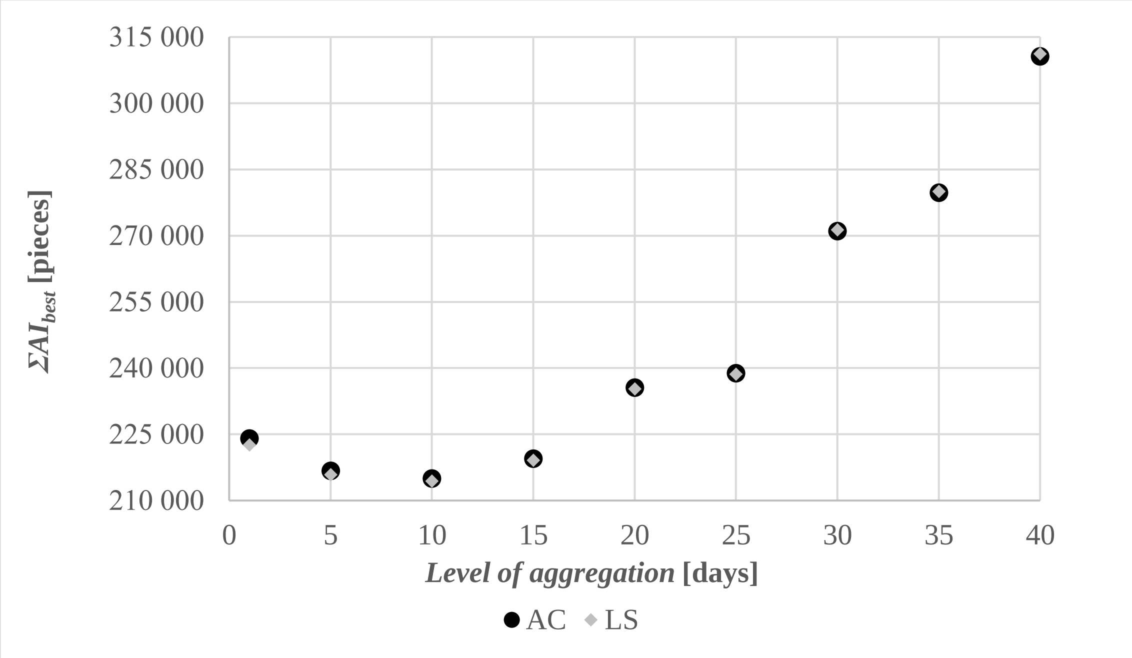

Fig. 4 - Total average inventory linked with minimal holding and ordering costs

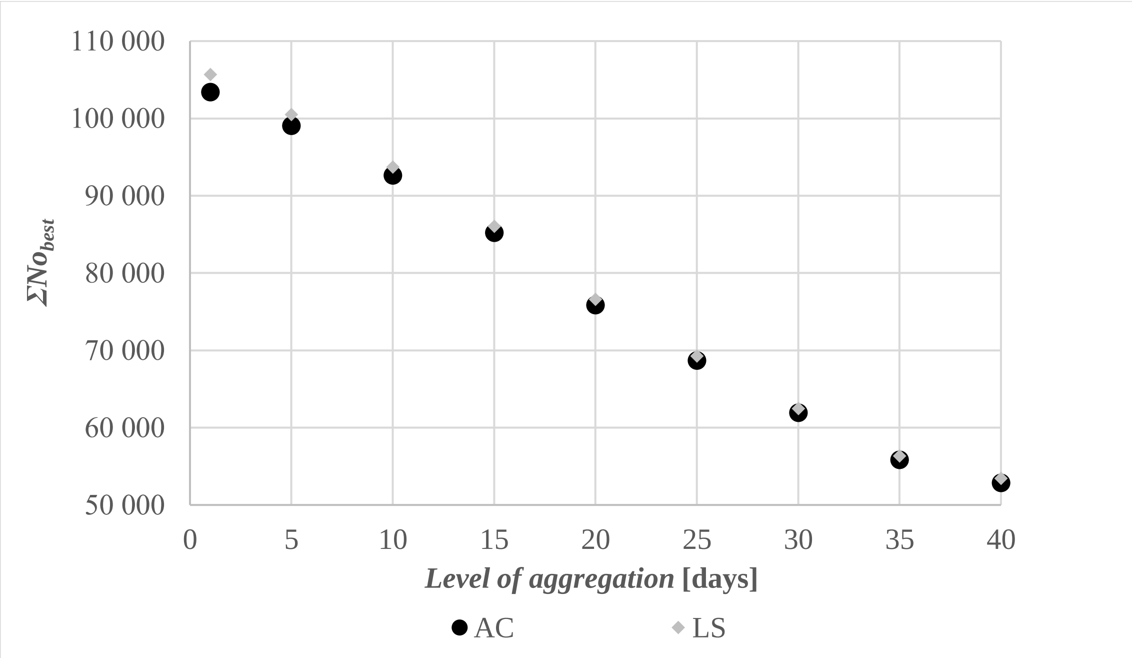

Fig. 5 - Total number of orders linked with minimal reached total holding and ordering costs

The evolution of optimal holding and ordering costs in Figure 3 follows the evolution of total average inventory linked with minimal holding and ordering costs in Figure 4 relatively closely. This means that holding costs represent the major part of total inventory costs, as the decreasing total number of orders in Figure 5 confirms. To put the evolution of total average inventory into context, we refer to the characteristics of aggregated data summarized in Tables 1, 2 and 3. More specifically, as long as there is enough potential to reduce demand variability and irregularity (see Table 1) and turn intermittent and lumpy demand into something more smooth (see Table 2), the simulation handles average inventory successfully until the modified order lead times (see Table 3) moving away from originals and covering longer time periods cause excessive initial inventory and inventory fulfilling the demand during the order lead time period.

After the LS + PSMS and AC + PSMS results, we also provide outputs for MLS + PSMS. Based on $Ct_{best,k}$. we calculate cost differences Δ using Eq. 11:

$$\Delta = \frac{Ct_{best,LS\ or\ MLS_k} - Ct_{best,AC_k}}{Ct_{best,AC_k}} \cdot 100\ \% \qquad (11).$$

For each level of aggregation and each level of LS minimal reorder point decrease, we calculate 10 to 100 % Δ percentiles and put these percentiles together with the number of time series, with no solution found by LS to Table 6:

Tab. 6 - Δ percentiles for LS + PSMS and MLS + PSMS

	Δ percentiles [%]												
***Level of aggregation* [days]**	**10**	**20**	**30**	**40**	**50**	**60**	**70**	**80**	**90**	**95**	**100**	**LS Min Reorder point off [%]**	**No solution found with (M)LS**
1	0 %	0 %	0 %	0 %	0 %	0 %	0 %	1 %	3 %	6 %	41 %	0	8
	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	2 %	4 %	36 %	10	8
	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	18 %	50	8
	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	9 %	90	8
5	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	2 %	5 %	36 %	0	9
	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	3 %	36 %	10	9
	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	27 %	50	9
	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	27 %	90	9
10	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	1 %	4 %	42 %	0	1
	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	2 %	36 %	10	1
	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	29 %	50	1
	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	2 %	90	1
15	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	4 %	43 %	0	2
	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	1 %	42 %	10	2
	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	29 %	50	2
	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	5 %	90	2
20	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	3 %	66 %	0	1
	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	66 %	10	1
	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	36 %	50	1
	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	8 %	90	1
25	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	2 %	65 %	0	0
	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	65 %	10	0
	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	46 %	50	0

	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	90	0
30	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	3 %	55 %	0	0
	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	53 %	10	0
	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	41 %	50	0
	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	2 %	90	0
35	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	2 %	86 %	0	0
	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	84 %	10	0
	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	62 %	50	0
	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	3 %	90	0
40	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	4 %	123 %	0	0
	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	123 %	10	0
	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	59 %	50	0
	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	9 %	90	0

Together with Δ percentiles, we are also interested in the consumption of computational time for LS + PSMS and MLS + PSMS. This consumption is shown in Table 7:

Tab. 7 - Consumption of computational time for LS + PSMS and MLS + PSMS [min]

	LS Min Reorder point off [%]			
***Level of aggregation* [days]**	**0**	**10**	**50**	**90**
1	38	42	56	71
5	18	19	23	26
10	15	15	18	20
15	14	14	17	18
20	13	14	16	18
25	13	14	15	17
30	13	14	15	16
35	13	13	15	16
40	13	13	15	16

Δ percentiles in Table 6 prove that an extension of reorder point interval with the further underestimation of LS minimal reorder point brings improvements in holding and ordering costs. For example, when speaking about a level of aggregation equal to 15 days, where AC + PSMS reaches absolutely minimal holding and ordering costs for all simulated scenarios, the original LS + PSMS reaches these costs only for 90 % of the simulated time series, and Δ for the rest of the simulated items is up to 43 %, while for MLS + PSMS with 90 % off LS minimal reorder point, absolutely minimal holding and ordering costs are reached for 95 % simulated time series, and Δ for the rest of simulated items is only up to 5 %. Furthermore, this cost improvement is at a reasonable price in terms of additional time consumption because there is just a moderate increase in this time from 14 to 18 minutes (see Table 7, level of aggregation equal to 15 days, and LS minimum reorder point off equal to 90 %). Besides the relatively stable consumption of computational time, MLS + PSMS behaves stably also in terms of number of time series for which no solution is found.

Based on the best-achieved costs and computational time consumption, we summarize the relative advantages of three methods within the PSMS framework in Table 8:

Tab. 8 – Comparison of relative advantages of methods within the PSMS framework

Method	Costs	Computational time
AC + PSMS	minimal	maximal
LS + PSMS	higher than AC+PSMS; higher than MLS+PSMS	lower than AC+PSMS; lower than MLS+PSMS
MLS + PSMS	higher than AC+PSMS; lower than LS+PSMS	lower than AC+PSMS; higher than LS+PSMS

As LS+PSMS excels in the consumption of computational time compared to AC+PSMS, this opens a possibility to invest some additional time to search for more extensive solution space and reach additional cost savings, which is a major idea of MLS+PSMS.

5 CONCLUSION

In this paper, we examined how a certain level of demand data aggregation affects the performance of sporadic demand inventory control based on a past stock movement simulation (PSMS). PSMS represents a data-driven approach that, instead of estimating order lead time demand with the help of a forecasting method, rather focuses on a combinatorial optimization using an evolution of a replenishment process over a time. We simulate reorder point/order-up-to-level inventory control policy with the demand data aggregation ranging from 1 to 40 days using the real daily demand data for 12,374 car spare parts covering a one year period. For each item, we perform PSMS with an all-combinations search, the local search (LS) proposed by Huskova and Dyntar (2023), and also with the newly designed modified local search (MLS), which further underestimates the minimal reorder point.

The outputs from the simulation experiments prove the positive impact of demand data aggregation on reducing demand variability and frequency of occurrence of zero demand periods, leading to the improvement of sporadic demand inventory control. These findings are in accordance, for example, with Willemain et al. (1994). Our results also confirm the findings presented by Nikolopoulos et al. (2011) that the level of aggregation has to be set carefully because too small or too extensive aggregation leads potentially to poor inventory control performance.

Our major contribution is that demand data aggregation combined with PSMS leads to the significant reduction of the consumption of computational time, bringing this data-driven approach nearer to applications in large scale real life problems dealing with sporadic demand inventory control. These savings are reached through the shortening of time series in PSMS as well as through the decrease of order lead times in LS and MLS.

However, we are also aware of some limitations connected with our work. First, while our dataset includes 12,374 spare parts, it is based on a single dataset, and its generalizability to a broader market remains an open question. Future research should explore whether similar findings hold across different industries, product categories, or datasets from multiple companies. Additionally, the total one-year demand for items in the simulated data set ranges from 14 to 1,391 pieces. In case that this total demand is, for example, a hundred times higher, searching through the more extensive solution space definitely requires a more efficient approach. There is also space to carry out a detailed sensitivity analysis of lead time and safety factor impact on underestimating the minimal reorder point in LS, or to even consider a replacement of linear regression in estimating mean and variance of lead time demand with a more reliable method.

Beyond the theoretical implications, our findings have practical significance for supply chain management. In industries such as automotive aftermarket services, aerospace, and medical equipment, where sporadic demand is common, the proposed approach could help companies optimize inventory control while reducing computational costs. For example, a spare parts distributor could use demand aggregation strategies to stabilize replenishment planning, minimizing the risk of stockouts while avoiding excessive inventory. Similarly, manufacturers dealing with highly variable component demand could integrate PSMS-based approaches to enhance their supply chain resilience. These insights highlight the potential for real-world applications and encourage further research into practical implementation strategies.

To successfully integrate this method into inventory management systems, companies can adopt PSMS-based decision-making modules into their existing ERP or inventory management software, allowing for automated optimization of reorder point. Furthermore, collaboration with AI-driven analytics platforms could enhance the efficiency of parameter improving in PSMS, ensuring that reorder points and stock levels remain dynamic and responsive to changes in demand patterns.

One possible direction for future research is the integration of artificial intelligence (AI) and neural networks into PSMS to enhance inventory optimization. AI-driven heuristics might also help to control the solution space more efficiently in large-scale datasets, reducing computational demand while maintaining high-quality results. Exploring these advanced techniques could further bridge the gap between theoretical inventory control models and practical applications in dynamic, high-uncertainty environments. These are the challenges for our future work.

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