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The effect of demand aggregation on spare part supply chain planning: An empirical study of oil company

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Abstract

Spare parts with intermittent demand pose obstacles in forecasting and inventory decisions since the demand pattern does not follow a regular probability distribution. Therefore, the significant difficulties in planning regard to demand quantity and arrival time. A well-structured strategy is aggregating the demand in low-frequency time intervals to reduce the zero-demand occurrence. In this paper, we consider a planning model for a repairable spare part supply chain (SPSC) and examine the effect of aggregation on cost, stock level, and shortage. The planning model includes the repair and inventory decisions in an SPSC that uses the Multi-echelon Technique for Recoverable Item Control (METRIC) to formulate an inventory model. The empirical study from the Iranian Oil Company is used to evaluate the benefit of demand aggregation. The results show that choosing an optimal level of aggregation decreases the stock level and shortage. It also improves the demand estimation gap. The managerial insights help the practitioners make robust decisions since the coefficient of variation decreases.

Keywords: Supply chain, spare part, aggregation, planning, inventory

1-Introduction

Spare parts supply chain planning involves different repair and inventory decisions that significantly affect performance. Repairable spare parts are the primary resources used in repairing operations, accounting for about 80% of the spare parts' values (Driessen, 2018). Every industry considers profitability a major objective, so maintenance and repair should be set to achieve these goals by keeping resources such as equipment in acceptable working conditions to prevent possible shutdowns. Spare parts used in repairing equipment can be low-demand and high-value and may have a long supply time, so improving the planning reduces the shortages. Many companies hold spare part stocks to minimize downtime costs and ensure equipment availability. The main difficulty arises when we deal with low-demand spare parts since a high inventory level causes huge inventory costs while shortage imposes shutdown costs (Pinçe et al., 2021). The trade-off between the repair and inventory decisions gives the optimized stock level. Sherbrooke, (1968a) is the first researcher to develop a METRIC[1] model for optimizing the stock level of repairable spare parts with low demand to minimize cost. Spare parts with intermittent demand need a specific technique to prepare data for use in the METRIC model due to zero demand in irregular time intervals (Babai et al., 2012). Inventory control decisions for intermittent items are used to determine order planning. The related decision will be made more wisely if a more accurate demand estimation exists. Demand estimation and stock control improvements can be interpreted as prominent cost reductions. Demand estimations are usually related to high deviations due to the origins of variation, such as demand occurrence and quantity, so the aggregation approach affects the errors. A vendor may implement

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the point-of-sale data to forecast at the lower level, while the manufacturer may use the aggregated demand to forecast production planning (Chopra & Meindl, 2007). The aggregation, disaggregation, and levels can be affected over time, so the interaction between the planning and aggregation levels is noticeable to recognize the future structures (Babai et al., 2021; Mircetic et al., 2022).

The main problem happens when zero observations exist. A well-organized strategy to deal with unusual patterns is aggregating demand in lower-frequency intervals and eliminating zero observations. The literature review shows that aggregation is used in many fields such as financial, industrial, etc. while examining the effect of aggregation for intermittent demand is rarely discussed, especially when considering the planning decisions regarding the spare part supply chain. This paper analyzes the impact of aggregation levels on a mathematical model for the spare parts supply chain when intermittent demand exists, validated by a case study in an oil company. The benefit of using aggregation is to reduce zero-demand occurrences; thus, the planning decisions will be more reliable due to reducing variations.

The rest of the paper is structured in the following sections: First, section 2 provides the literature review. Then, the problem statement is explained in section 3. The model formulation is presented in section 4. The results are presented in section 5, followed by section 6, which describes the discussions. Finally, conclusions and future research opportunities are expressed in section 7.

2-Literature review

This section reviews the works regarding spare part supply chain planning and forecasting. Finally, the research gaps are presented. (Gross & Ince, 1978) considered the maintenance and repair planning of machines and specified the number of spare parts and repair channels for stochastic failure in an M/M/c queuing network. The model's objective function is to maximize the availability of spare parts. Walker, (1997) investigated the number of machines and to find the optimal inventory level of spare parts to achieve the expected reliability. Lapide, (1998) states that the percentage variations will be lower for the aggregated data than for individual items. Aggregation usually causes a cut down on variance since the fluctuations in the data of one item are affected by the other items, so the total variance of the aggregated data is reduced, thereby enhancing the forecasting accuracy (DeLurgio, 1998). Axsäter, (2003) presented a single-item and single-echelon model with a continuous review policy considering the unilateral transshipment between warehouses to reduce shortages. Moini et al., (2021) considered a spare part supply chain that considers the stochastic demand, but demand estimation is not discussed. Jain & Raghavan, (2009) published a paper regarding inventory planning in a multi-tier supply chain. In this network, manufacturers, warehouses, and vendors are considered. M/M/∞ model is used for a logistics hub and M/M/1 for manufacturing centers to assess performance. Nikolopoulos et al., (2011) examined the effect of aggregation levels for spare parts with intermittent demand. They considered the aggregation level equal to lead time plus review period (L+R) and compared the disaggregation results with aggregation. Farhadi, (2013) presented a mathematical model that maximizes the availability of spare parts considering redundancy and the number of parallel spare parts. Redundancy is analyzed by the K-out-of-N system considering different quality of spare parts. The model determines the number of orders and the quality, considering the budget and availability of the system. The model is formulated by the Markov process and tree diagram. van Jaarsveld et al., (2015) developed an integer programming model regarding a multi-location, single-echelon, multi-item spare parts supply chain that uses a continuous review policy. They analyzed lateral transshipment to assess the effect on performance. Keizer et al., (2017) developed a multi-item maintenance supply chain model to minimize the expected cost by formulating the uncertainty using the Markov process considering replenishment policy (s, S). M. Assadi et al., (2019) formulated queuing models at repair centers to obtain the optimal capacity and maximize availability. Qin et al., (2021) formulated two models with cost and profit objective functions for a repairable spare part supply chain that considers performance evaluation in servicing centers by implementing a new formulation of uncertain demand. The researchers focus on the repairable spare parts supply chain that considers various decisions such as lateral transshipment, inventory planning, and system performance measurement. They formulate the uncertain demand in the METRIC model using the Markov process, while low-demand spare parts planning problems are not well investigated.

Spare parts with intermittent demand are commonly discussed when zero demand happens. Many models are used to forecast this type of demand, such as (Croston, 1972), which considers demand quantity and inter-demand intervals. Also, Syntetos & Boylan, (2005) presented the Syntetos-Boylan approximation (SBA), and (Babai et al., 2019) developed a modified SBA (MSBA) by manipulating the smoothing parameters. Willemain et al., (2004) proposed a bootstrap method that forecasts the intermittent demand for spare parts by generating random data from historical data. This method obtains the demand quantity and occurrence, providing more accurate results. Amin-Naseri & Tabar, (2008) examined recurrent neural networks (NN) for forecasting the lumpy demand of spare parts. This method outperforms the parametric models such as Croston, SBA, and MSBA. Amirkolaii et al., (2017) analyzed the neural network for single- and multi-feature demand. The results show that adding higher features improves the forecasting accuracy for spare parts with intermittent demands. Dodin et al., (2021) used a machine learning (ML) method for aircraft spare parts with intermittent and non-intermittent demands when discussing the aftermarket. This method results in better accuracy and run time. The increasing trend of attention on well-balanced integration between planning and forecasting is under the focus of many researchers, as shown by (Basten et al., 2015; Driessen, 2018; Goltsos et al., 2022) since it highly affects the In this study, we contribute to the existing literature in repairable spare parts by presenting a model that considers planning decisions and examines the level of demand aggregation and integration of the decisions. Concerning the reviewed papers, the contributions of this study would be organized as follows:

- Considering the level of demand aggregation for the spare parts with intermittent demand
- Integrating the planning model concerning analyses of the integration of decisions
- Developing the METRIC model by considering the effect of intermittent demand and aggregation level
- Presenting a planning model concerning integrated repair and inventory decisions

3- Problem statement

The spare part supply chain is illustrated in figure 1. The developed model for the repairable spare part supply chain considers the planning decisions such as repair and inventory. The network consists of installation bases, inspection centers, repair centers, and warehouses. The failed equipment is transferred from installation bases to inspection centers, where the inspection team decides on repairing or disposing. The equipment which enters the repair centers is repaired by replacing the spare parts which are supplied by the central warehouses. As the equipment is repaired, it is stocked in warehouses or delivered to the installation base. Spare parts used in the equipment are high-value and low-demand, while they need high responsiveness. Hence, companies may hold massive inventories of spare parts to meet the demand, but the inventory costs may be too high because of the high value of these items. A well-organized inventory model with performance assessment is suggested that considers the queues in warehouses. METRIC is one of the models for this purpose which assesses the performance in the warehouses by formulating the queuing of order replenishment. A critical factor in planning, especially in the spare part supply chain, is the items' demand patterns directly affecting the uncertainty. The demand type of spare parts is divided into four main categories such as smooth, lumpy, intermittent, and erratic. This classification is determined based on the variation of quantity and demand inter-arrival. According to this definition, smooth demand has the lowest variation in demand quantity and inter-arrivals, while the lumpy type has a high value for both. The quantity variation for erratic demand is high, but the inter-arrival variation is low. The last one, the intermittent demand type, is against the erratic. We focus on intermittent demand and examine the effect of aggregation level on planning performance. The aggregation can be performed for a group of items, places, periods, and other possible criteria. In this study, the aggregation is examined over time. Considering the aggregation becomes essential since it reduces the variation by merging the multiple origins of data. The developed model discusses the planning decisions considering the effect of aggregation levels. The following list describes the details of the decisions made by the model:

- Stock level in central and local warehouses
- Expected waiting time for order replenishment
- The flows between the facilities
- The aggregation level for each spare part
- Repairing or not repairing the equipment
-

4- Mathematical model

The model is described in this section. First, we present the assumptions, then the parameters and variables are shown. Finally, the objective function and constraints are explained.

4-1- Assumptions

- The changes in cost will be subtle over the time
- Shortages will not happen in central warehouses
- Each equipment (LRU[1]) has several spare parts (SRU[2])
- LRUs’ demands depend on spare parts (SRUs)
- Each SRU lies only in one LRU
- (S-1, S) replenishment policy is implemented

Table 1. A brief of the literature review

Author	Year	Decisions			Aggregation strategy		Case study	Objective function		
		Repair	Inventory	Inspection	Aggregation	Disaggregation		Minimizing cost	Minimizing forecasting error	Maximizing availability
Gross & Ince	1978	✓	✓							✓
Axsäter	2003		✓							✓
Jain & Raghavan	2009		✓				✓	✓		
Nikolopoulos et al.	2011				✓	✓			✓	
Farhadi	2013	✓								✓
van Jaarsveld et al.	2015		✓				✓			✓
Keizer et al.	2017	✓	✓					✓		
M. Assadi et al.	2019	✓					✓			✓
Qin et al.	2021	✓	✓				✓	✓		✓
Amirkolaii et al.	2017		✓				✓		✓	
Dodin et al.	2021						✓		✓	
Goltsos et al.	2022		✓						✓	
Present paper	**2023**	✓	✓	✓	✓	✓	✓	✓		

[1] Line Replaceable Unit
[2] Shop Replaceable Unit

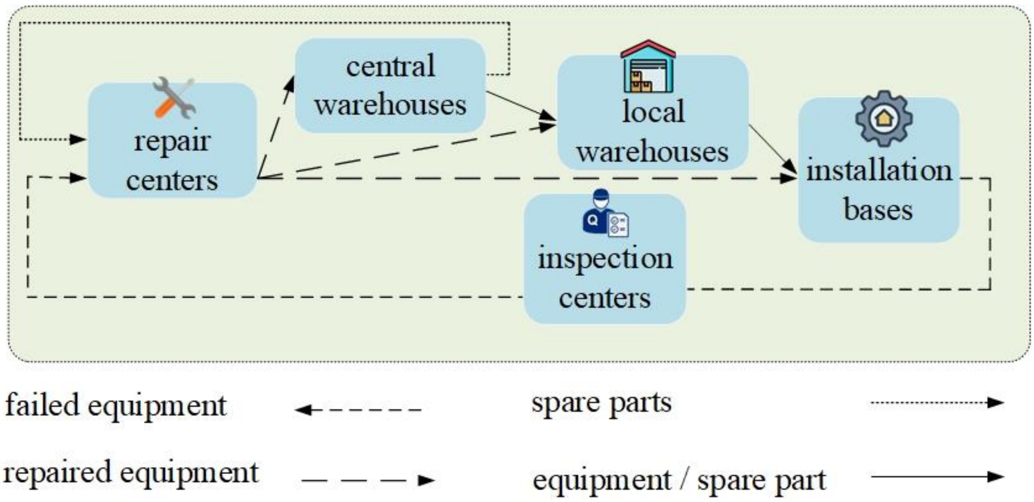

Fig 1. The perspective of the spare part supply chain

4-2- Indices and sets

$s \in S\,, s_1, s_2 \subseteq s$	Equipment / Spare parts
$j, j' \in J$ $w, r, i\,, c, s' \subseteq j, j'$	All nodes
$w, w' \in W$ $w_1 \subseteq w; w_2 \subseteq w$	Warehouses, Central and Local warehouses
$r \in R;\ r_1 \in r; r_2 \in r$	Repair centers; Inner-company; Outer-company repair centers
$i \in I$	Inspection center
$c \in C$	Installation bases
$t \in T$	Period (time interval)

4-3- Parameters

d_{sct}	Spare part s demand (failure) at installation base c in period t
$tc_{sjj'}$	Transportation cost from node j to j'
$pu_{s_1 s_2}$	Probability of demand for spare part s_1 in equipment $s_2 \in s$ in the repair center
⍰$_{sw}$	Spare part s holding cost in warehouse w
I^0_{swt}	Initial inventory of spare part s in warehouse w in period t
$\tau_{sw_1w_2}$	Traveling time of spare part s from central warehouse w_1 to local warehouse w_2
π'_s	Shortage cost of spare part s
$\tau_{sw_1} = \sum_{s'} \mu_{ss'w_1}$	Travel time of spare part s from supplier s' to central warehouse w_1
G_{si}	Probability of repairability of equipment s in inspection center i
rc_{sr}	Repair cost of equipment s in repair center r

4-4- Decision variables

x'_{scit}	Amount of equipment *s* from installation base *c* to inspection center *i* in period *t*
y'_{sirt}	Amount of equipment *s* from inspection center *i* to repair center *r* in period *t*
$x^{(2)}{}_{srw_1t}$	Amount of equipment *s* from repair center *r* to the central warehouse w_1 in period *t*
$y^{(1)}{}_{sw_1w_2t}$	Amount of equipment *s* from central warehouse w_1 to local warehouse w_2 in period *t*
$y^{(2)}{}_{srw_2t}$	Amount of equipment *s* from repair center *r* to local warehouse w_2 in period *t*
$z^{(1)}{}_{sw_2ct}$	Amount of equipment *s* from local warehouse w_2 to installation base *c* in period *t*
$z^{(2)}{}_{srct}$	Amount of equipment *s* from repair center *r* to installation base *c* in period *t*
wa_{sw_1t}	Spare part *s* replenishment waiting time in the central warehouse w_1 in period *t*
ws_{sw_1rt}	Amount of spare part s from central warehouse w_1 to repair center *r* in period *t*
I^+_{swt}	Average on-hand inventory of spare part *s* in warehouse *w* in period *t*
I^-_{swt}	Average shortage of spare part *s* in warehouse *w* in period *t*
st_{swt}	Stock level of spare part *s* in warehouse *w* in period *t*
λ_{swt}	Demand rate of spare part *s* in warehouse *w* in period *t*
a_s	Number of periods for aggregating spare part *s* demand
u_{a_s}	Aggregated demand of spare part *s* over a_s period(s)

4-5- Objective function and constraints

The objective function aims to minimize total cost, which is presented in equations (4-1-1) to (4-1-11). Transportation costs are presented in equations (4-1-1) to (4-1-8). Equations (4-1-1) - (4-1-3) respectively show the transportation costs from repair centers to central warehouses, local warehouses, and installation bases. The transportation costs between the warehouses are presented in equation (4-1-4). Equation (4-1-5) computes the traveling cost from local warehouses to installation bases. Equations (4-1-6) expresses the transportation cost from installation bases to inspection centers and equation (4-1-7) calculates the transportation costs from inspection to repair centers. The traveling cost of spare parts used in repairing the equipment, from central warehouses to repair centers, is defined in equation (4-1-8). The repair cost is presented in equations (4-1-9). Equations (4-1-10) and (4-1-11) calculate holding and shortage costs.

$$Min\ Z_t = \sum_t \sum_s \sum_r \sum_{w_1} tc_{srw_1} x^{(2)}{}_{srw_1t} \qquad (4\text{-}1\text{-}1)$$

$$+\sum_t \sum_s \sum_r \sum_{w_2} tc_{srw_2} y^{(2)}{}_{srw_2t} \qquad (4\text{-}1\text{-}2)$$

$$+\sum_t \sum_s \sum_r \sum_c tc_{src} z^{(2)}_{srct} \qquad (4\text{-}1\text{-}3)$$

$$+\sum_t \sum_s \sum_{w_1} \sum_{w_2} tc_{sw_1w_2} y^{(1)}{}_{sw_1w_2t} \qquad (4\text{-}1\text{-}4)$$

$$+\sum_t \sum_s \sum_{w_2} \sum_c tc_{sw_2c}\, z^{(1)}_{sw_2ct} \qquad (4\text{-}1\text{-}5)$$

$$+\sum_t \sum_s \sum_c \sum_i tc_{sci}\, x'_{scit} \qquad (4\text{-}1\text{-}6)$$

$$+\sum_t \sum_s \sum_i \sum_r tc_{sir} y'_{sirt} \qquad (4\text{-}1\text{-}7)$$

$$+\sum_t \sum_s \sum_{w_1} \sum_{r_1} tc_{sw_1r_1}\, ws_{sw_1r_1t} \qquad (4\text{-}1\text{-}8)$$

$$+\sum_{t}\sum_{s}\sum_{i}\sum_{r} rc_{sr}y'_{sirt} \tag{4-1-9}$$

$$+\sum_{t}\sum_{s}\sum_{w} h_{sw}I^{+}_{swt} \tag{4-1-10}$$

$$+\sum_{t}\sum_{s}\sum_{w} \pi'_{s}\, I^{-}_{swt} \tag{4-1-11}$$

The balance between the reverse flow to the inspection center and demand is calculated by equation (4-2). Also, the flow from repair centers and warehouses should be equal to demand, as shown in equation (4-3).

$$\sum_{i} x'_{scit} = d_{sct} \qquad \forall s,c,t \tag{4-2}$$

$$\sum_{w_2} z^{(1)}{}_{sw_2c} + \sum_{r} z^{(2)}{}_{src} = d_{sc} \qquad \forall s,c \tag{4-3}$$

Equations (4-4) – (4-11) present the METRIC model constraints. The basic METRIC model is developed by (Sherbrooke, 1968b) for repairable items that is further extended from the aspect of planning and network design decisions, e.g., some researchers considered multi-item and location characteristics. Also, others added capacity limitations and lateral transshipments. The average on-hand inventory is shown in equation (4-4). Equation (4-5) is the demand of locals from each central warehouse. The average shortage in the central warehouse is computed by equation (4-6). The little law in equation (4-7) computes the average waiting time. The average replenishment time in local warehouses is presented in equation (4-8), which is the sum of average waiting time and constant travel time between central and local warehouses. The demand of each local warehouse is computed in equation (4-9). Then, the average on-hand and shortage inventory of local warehouses is shown in equation (4-10) and (4-11). The balance equations in central and local warehouses are presented in equations (4-12) and (4-13).

$$I^{+}_{sw_1t} = \sum_{j=1}^{st_{sw_1t}} j.P(X=j) = \sum_{j=1}^{st_{sw_1t}} j\frac{e^{-\lambda_{sw_1t}\tau_{sw_1}}(\lambda_{sw_1t}\tau_{sw_1})^{st_{sw_1t}-j}}{(st_{sw_1t}-j)!} \tag{4-4}$$

$$\lambda_{sw_1t} = \sum_{w_2} y^{(1)}_{sw_1w_2t} \qquad \forall s, w_1, t \tag{4-5}$$

$$I^{-}_{sw_1t} = I^{+}_{sw_1t} - (st_{sw_1t} - \lambda_{sw_1t}\tau_{sw_1}) \tag{4-6}$$

$$wa_{sw_1t} = \frac{I^{-}_{sw_1t}}{\lambda_{sw_1t}}, \lambda_{sw_1t} \neq 0 \tag{4-7}$$

$$\bar{\tau}_{sw_2t} = \sum_{w_1}(\tau_{sw_1w_2} + wa_{sw_1t}) \tag{4-8}$$

$$\lambda_{sw_2t} = \sum_{w_1} y^{(1)}_{sw_1w_2t} \tag{4-9}$$

$$\forall s, w_2, t$$

$$I^{+}_{sw_2t} = \sum_{j_s=1}^{st_{sw_2t}} j_s \times \frac{e^{-\lambda_{sw_2t}\bar{\tau}_{sw_2}}(\lambda_{sw_2t}\bar{\tau}_{sw_2})^{st_{sw_2t}-j_s}}{(st_{sw_2t}-j_s)!} \tag{4-10}$$

$$I^{-}_{sw_2t} = I^{+}_{sw_2t} - (st_{sw_1t} - \lambda_{sw_2t}\bar{\tau}_{sw_2t}) \tag{4-11}$$

$$I^0_{sw_1t} + \sum_{s'} x^{(1)}{}_{ss'w_1t} + \sum_r x^{(2)}{}_{srw_1t} = st_{sw_1t} + \sum_{w_2} y^{(1)}{}_{sw_1w_2t} + \sum_r ws_{sw_1rt} \qquad \forall s, w_1 \qquad (4\text{-}12)$$

$$I^0_{sw_2t} + \sum_{w_1} y^{(1)}{}_{sw_1w_2t} + \sum_r y^{(2)}{}_{srw_2t} = st_{sw_2t} + \sum_c z^{(1)}{}_{sw_2ct} \qquad \forall s, w_2 \qquad (4\text{-}13)$$

Inner-company repair centers use tools, budgets, materials, and energy, while outer-company repair centers operate independently. Equation (4-14) calculates the spare parts required in inner-company repair centers that the central warehouses supply them.

$$\sum_{w_1} ws_{sw_1r_1t} \geq pu_{ss_1} \times \sum_i y'_{s_1ir_1t} \qquad \forall s, r_1, t \qquad (4\text{-}14)$$

The amount of repairable equipment is computed in equation (4-15) based on the probability of repairability. equation (4-16) shows the flow balance in repair centers. Finally, the domains of variables are shown.

$$\sum_r y'_{sirt} = \sum_c G_{si} \times x'_{scit} \qquad \forall s, i, t \qquad (4\text{-}15)$$

$$\sum_i y'_{sirt} = \sum_{w_1} x^{(2)}{}_{srw_1t} + \sum_{w_2} y^{(2)}{}_{srw_2t} + \sum_c z^{(2)}{}_{srct} \qquad \forall s, r, t \qquad (4\text{-}16)$$

$$x'_{scit},\ y'_{sirt},\ x^{(1)}_{ss'w_1t}, x^{(2)}_{srw_1t},\ y^{(1)}_{sw_1w_2t},\ y^{(2)}_{srw_2t},$$
$$z^{(1)}_{sw_2ct},\ z^{(2)}_{srct},\ st_{swt} \in \mathbb{Z}^+ ;\quad I^+_{swt},\ I^-_{swt} \in \mathbb{R}^+$$

4-6- Aggregation formulation

The aggregation comes from minimizing the effect of variation on planning and forecasting. As an acceptable theoretical and practical concept, the variation decreases as the number of samples rises. u_{a_s} shows the aggregated demand and a_s is the number of aggregated periods, shown in equation (4-17). The estimated demand per period is calculated by $\frac{u_{a_s}}{a_s}$. First, we present the measures to evaluate the gaps between the aggregated demand, the forecasted demand, and real demand. The gap between the aggregated demand and real demand (ARG) is obtained by dividing the aggregated demand u_{a_s} by the number of aggregated periods a_s. Another measure is defined as the gaps between the aggregated demand and forecasted demand (AFG).

$$u_{a_s} = \sum\nolimits_{t=1}^{a_s} \sum\nolimits_c d_{sct} \qquad (4\text{-}17)$$

$$ARG_{st} = \frac{\left| \frac{u_{a_s}}{a_s} - \sum_c d_{sct} \right|}{\sum_c d_{sct}} \qquad (4\text{-}18)$$

$$AGF_{st} = \frac{\left| \frac{u_{a_s}}{a_s} - F_{st} \right|}{F_{st}} \qquad (4\text{-}19)$$

The introduced measures will assess the performance of the aggregation strategy. The forecasts are obtained by three methods which are used for intermittent demand. These approaches are Croston, Syntetos-Bolyan approximation (SBA), and Modified SBA. Croston's method considers the historical data and the intervals between demand. The estimated demand is shown by z_t and the estimate of the interval between demand by p_{st}. This method uses α_s as the smoothing factor. The interval between the last two periods with demand is denoted by q_s. Finally, the forecast is obtained in equation (4-22) by dividing z_{st} by ps_t which results in F_{st}.

$$z_{st} = z_{s\,t-1} + \alpha_s(\sum_c d_{sct} - z_{s\,t-1}) \quad (4\text{-}20)$$

$$p_{st} = p_{s\,t-1} + \alpha_s(q_s - p_{s\,t-1}) \quad (4\text{-}21)$$

$$F_{st} = \frac{z_{st}}{ps_t} \quad (4\text{-}22)$$

The SBA method uses the Croston formula and modifies bias yielded by multiplying $(1 - \frac{\beta_s}{2})$ to the basic Croston.

$$F_{st} = (1 - \frac{\beta_s}{2})\frac{z_{st}}{p_{st}} \quad (4\text{-}23)$$

Modified SBA, shown in equation (4-24), is an extension to SBA, improving this method by treating the zero-demand occurrences differently. The formula follows equation (4-23) when demand is positive, but if the demand is zero, the first term in equation (4-24) is the estimated demand, while the second term is the demand interval.

$$\begin{aligned} \hat{z}_t &= z_{t-1} \\ \hat{p}_{st} &= \begin{cases} p_{s\,t-1} & p_{st} \le p_{s\,t-1} \\ p_{s\,t-1} + \beta_s(p_{st} - p_{s\,t-1}) & p_{st} > p_{s\,t-1} \end{cases} \end{aligned} \quad (4\text{-}24)$$

The planning model is solved for each period by considering the aggregation or disaggregation strategy. The number of periods for aggregating the demand is called "aggregation level," which composes the demand data used to solve the planning model. ARG and AFG assess the model performance and the objective function to determine the optimal aggregation level. The case study and results are discussed in the next section.

5- Computations and results

Iran possesses about 9% of the global oil reserves worth 45.7 billion dollars, 4% of the world share. Spare parts are critical resources used in maintenance and repair operations. The National Iranian South Oilfields Company (NISOC) includes a region from Bushehr province to the north of Khuzestan, such as Ahwaz, Aghajari, Gachsaran, Kranj, Bibi Hakimeh, Marun, and Rag Sefid. Three central warehouses, six local warehouses, three repair centers, and ten installation bases are considered. The central warehouses are in Gachsaran and Ahwaz. The equipment is moved to the inspection center for technical inspection, where repairable items are assigned to repair centers. The data of spare parts are presented in table 2. The spare parts are divided into four categories in which spare parts with similar demand patterns lie in a category.

Table 2. Spare parts data statistics

	spare parts category			
	1	2	3	4
Mean	7.12	8.15	7.97	7.4
Std.	4.29	4.52	4.64	5.14
C.V.	0.36	0.31	0.34	0.48
Minimum	0	0	0	0
Maximum	15	25	19	24

The model is solved using GAMS by a PC with a CPU @ 2.5 GHz and 16 GB RAM. Table 3 and figure 2 show the cost for each aggregation level. It is observed that the cost decreases as the aggregation level increases. This trend continues until it reaches three levels, which means it is optimal to aggregate demand for three periods to reduce the possible errors. However, the cost tends to increase as the number of levels deviates from other values.

Table 3. Spare parts data statistics

Aggregation level	1	2	3	4	5
Cost ($\times \mathbf{10^6}$)	1.3	1.27	1.25	1.26	1.28

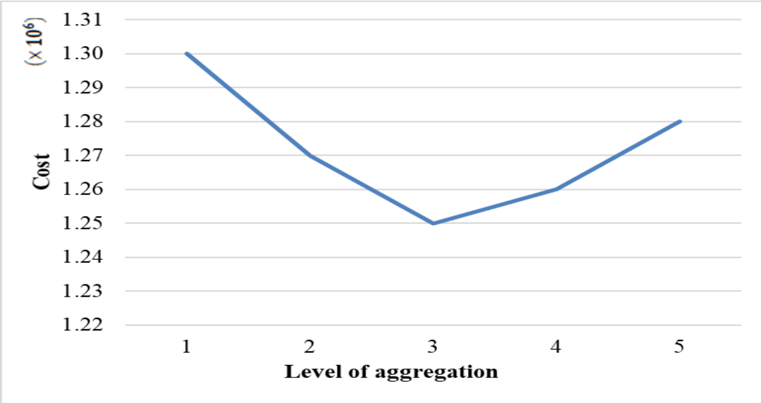

Fig2. MASE vs. aggregation level

The results for MASE of moving average (MA) are presented in table 4 according to aggregation levels. It can be seen that the minimum MASE is obtained when demands for three periods are aggregated. It can be interpreted as the minimum gaps between the MA and the real demand. Although aggregation can reduce MASE, it raises errors since the high level of aggregating does not accurately reflect the demand of each period.

Table 4. MASE for various aggregation level

level	MASE
2	0.71
3	0.69
5	0.7
7	0.73

6- Discussions and analyses

The results provided in the previous section give a perspective of the model's applicability. In this section, the results are discussed to obtain enriched insights.

6-1- MASE results for aggregation levels

The changes in MASE for MA are illustrated in figure 3. Another finding is the equal value of MASE for aggregation levels two and six, which points out the similar result for both levels. Therefore, they can be used interchangeably when the demand data is unavailable for other aggregation levels. This would be a valuable point since a lack of data can be a significant obstacle in many research so demand estimation can be important for this purpose.

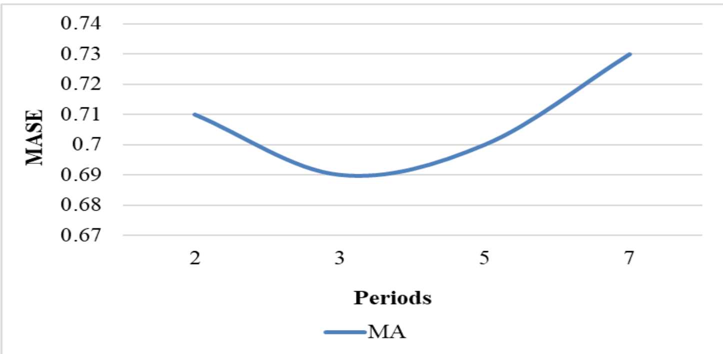

Fig 3. MASE vs. aggregation level

Different models are tested to examine the effect of smoothing parameters to tune these models. Following Croston's result, MASE decreases as alpha increases, and SBA confirms but rises in MSBA. This parameter affects the estimations by the weight it gives to quantity or time interval. A prominent perception is that historical data is not always compelling since the demand pattern may change over time due to working conditions, equipment lifetime, and other factors. The analysis for MSBA shows that weight to historical data is more critical due to conditional forecast for MSBA, which depends on positive and zero demand quantity.

Table 5. MASE for smoothing parameter

Alfa	Croston	SBA	MSBA
0.03	0.65	0.68	0.61
0.05	0.64	0.67	0.61
0.1	0.63	0.66	0.62
0.15	0.62	0.65	0.62
0.2	0.59	0.53	0.62

6-2- Results of model comparison and parameters

The effect of change in the smoothing parameter is also illustrated in figure 4. It can be seen that close MASE is observed for $\alpha_s = 0.15$, so the methods can be used interchangeably in this case. Additionally, MSBA outperforms other methods when the lowest value for the smoothing parameter is used. As we move to the right side, MSBA results in better MASE than other methods. These analyses can be used as a criterion for implementing various methods when the smoothing factor fluctuates. Another result that is analyzed in table 6 and figure 5 illustrates MASE by changing the aggregation levels, which is comparable with previous outcomes. The aggregation levels between three and five result in optimal MASE, which is close to MA. Considering figure 6, it is evident that SBA has the minimum MASE while MA gives the maximum value. Croston and MSBA have comparative results so that they can be implemented interchangeably.

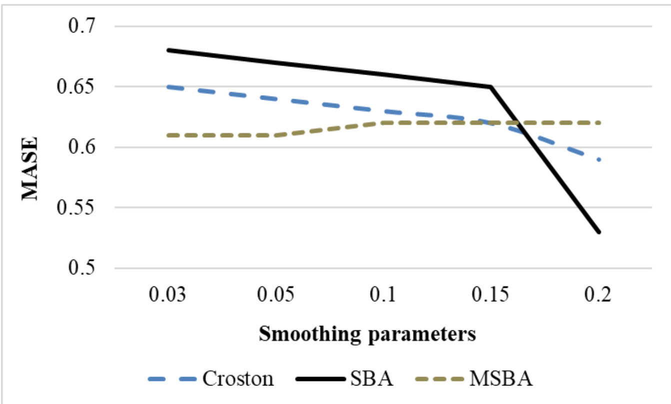

Fig 4. Effect of smoothing parameter on MASE

Table 6. MASE for aggregation levels

Aggregation level	MASE
2	0.71
3	0.68
5	0.67
7	0.68
9	0.69
10	0.7

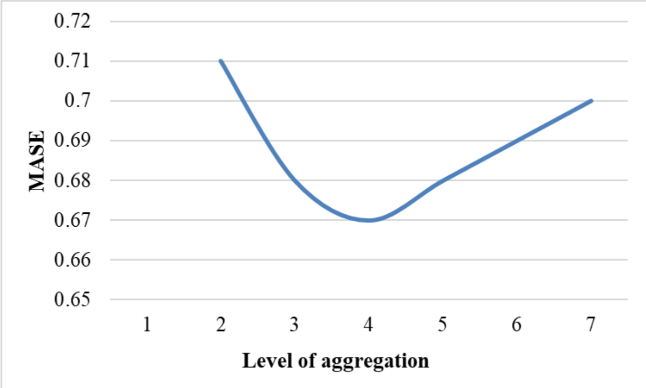

Fig 5. MASE vs. aggregation level

Table 7. MASE for aggregation levels

Model	SBA	Croston	MSBA	MA
MASE	0.53	0.59	0.61	0.69

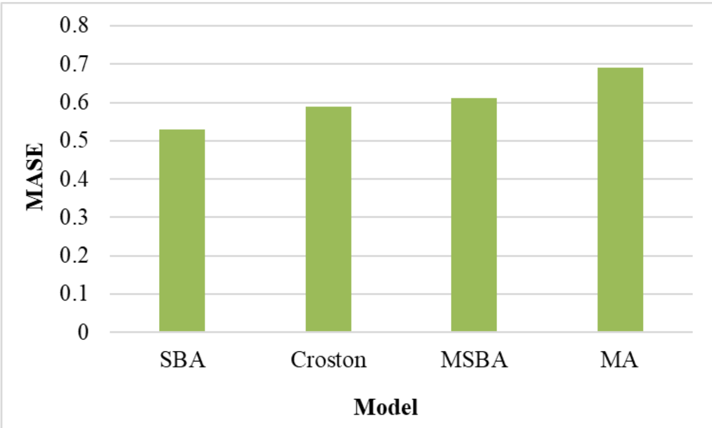

Fig 6. MASE for various models

6-3- Inventory performance

To evaluate the inventory performance of the developed model, we consider the stock level and shortage and trigger the changes. We assume that a shortage happens if the demand cannot be met from the stock. The expected shortage showed by $I^{-}_{sw_1t}$ for each period which is calculated in equations (4-6) and (4-11). To compare the methods, we vary the demand and aggregation levels to calculate the resulting stock level and shortage volumes. We depict the related curve for stock level and shortage versus the mentioned parameters. First, we focus on the stock level analysis versus demand shown in figure 7. The diagram depicts that the stock level increases by the demand since high shortage costs cause to increase in the stock level. This trend continues until a certain point, a trade-off between the cost, capacity, and stock level. In other words, increasing the stock level is not economical due to facility capacity, investment cost, or company policy. In this case, two options are recommended: cause and effect diagrams to justify the failures and the increasing trend. The other option is to update the planning policies by customizing the planning for each spare part according to demand patterns which highly affect subsequent decisions.

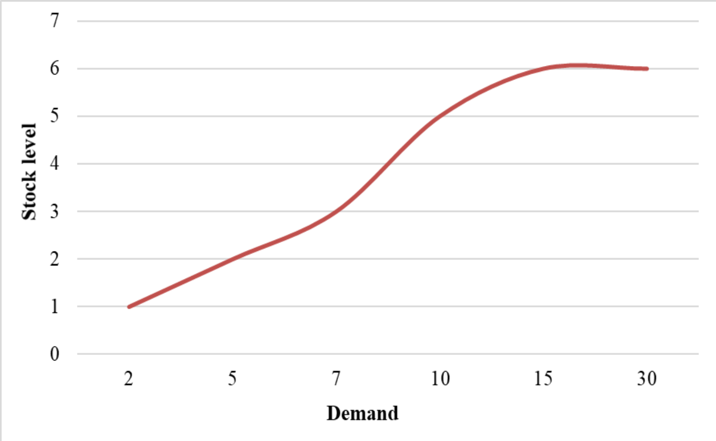

Fig 7. Stock level vs. demand

To shed light on the aggregation decisions, figure 8 is drawn, which shows the relation of stock level with aggregation level. The trade-off between the stock level and aggregation level reaches the minimum value when demands of three periods are aggregated. This behavior can be interpreted as the effect of aggregation level on planning accuracy since it can theoretically reduce the variance. In practice, the division of demand to different intervals increases error since new arrival for low-demand items does not happen in each period, so using the expected value can reduce possible errors. Additionally, considering weight for the share of each period can result in more accurate estimations.

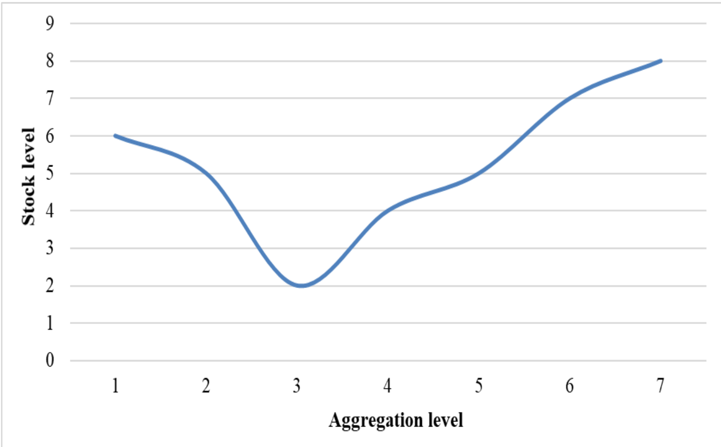

Fig 8. Stock level vs. aggregation level

Following the previous analysis of the stock level, the shortage decreases as the stock level increases, as shown in figure 9. The aggregation causes the planning to be more accurate, resulting in supply at the right time and quantity. As we deviate from the optimal aggregation level, the shortage increases since the forecasting error rises due to the high variation level. Therefore, we can conclude that the more sparsity of the observations causes less accurate planning. A good practice is eliminating the outlier points to control the disproportionate results that may eventuate in misleading interpretations.

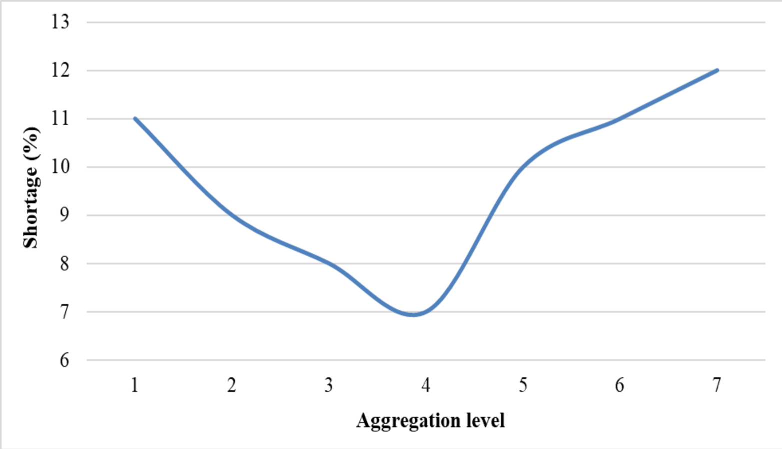

Fig 9. Shortage (%) vs. aggregation level

6-4- Performance evaluation

As stated earlier, we introduced two criteria for the gaps between the aggregated and real demand (ARG) and the gaps between the aggregated and forecasted demand (AGF). The aggregated demand which is denoted by u_{a_s} and the aggregation levels is signified by a_s. These variables directly impact ARG and AGF measures. The main difference between $\frac{u_{a_s}}{a_s}$ and d_{sct} comes from the concept of aggregation, which first computes total demand and then is divided by aggregation level. Indeed, this term calculates the expected demand, which estimates the real demand. We need to perform trial and error to obtain the optimal aggregation level that can be used for future estimation.

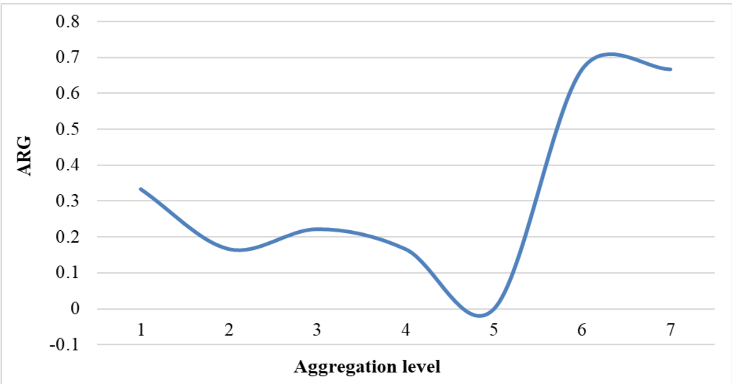

Fig 10. ARG as aggregation level changes

Figure 10 shows the ARG when the aggregation level changes. It is observed that ARG decreases as the aggregation level increases. This trend continues until aggregation level five but tends to increase afterward. This interpretation matches the previous analyses regarding aggregation; however, the trade-off between the costs and aggregation level may change the optimal level. So, we can conclude that the gap between the demand and estimation by aggregation deviates as the variation increases in comparison with the mean; in other words, the coefficient of variation (CV) increases.

AGF is another measure we considered to examine the gap between the forecast and aggregated demand. This measure is examined by two forecast estimations for positive and negative deviations, as illustrated in figure 11. An intersection occurs at level five, where AGF gives equal value for both deviations. This point of aggregation level matches the level for ARG.

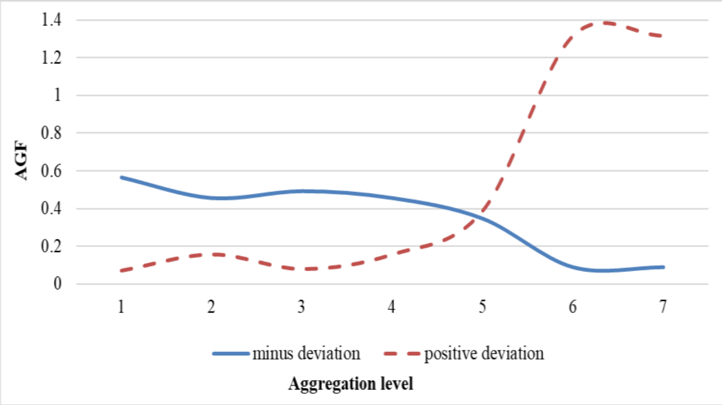

Fig 11. ARG and AGF as aggregation level changes

A prominent result of this analysis is that we can use AGF as a criterion for validating the forecast in which the aggregation level varies. In the next section, the conclusion and future research are presented.

7- Conclusion and further research

Spare parts play a critical role in operation since the continuation of production highly depends on maintenance and repair. Spare parts have particular demand patterns, which makes the planning techniques different. Among various demand patterns, intermittent demand is one category that involves spare parts with low demand quantity and high arrival variance. This paper develops a mathematical model for the repairable spare part supply chain in which the demand pattern follows the intermittent pattern. High variation in the arrival of this pattern necessitates using a technique to deal with the sparse demand. Aggregation is one of the techniques that can reduce the variance of the estimation, but the main question arises: what level of aggregation should we use. To answer this question, the aggregation effect is examined in the planning model to optimize the cost, stock level, and shortage. In this regard, two criteria are defined for computing the gaps between the aggregation, demand, and forecast. ARG obtains the gaps between the aggregation and demand, and AGF computes the gaps between the forecast and aggregation. A National Iranian South Oilfields Company (NISOC) case study is used to validate the model. The results of this study are concluded as the following:

- First, Aggregation analysis sheds light on the levels that can be used interchangeably for forecasting methods when the demand data is unavailable for all the levels. This is noteworthy when there is an obstacle to data gathering. Therefore, it is suggested that practitioners use aggregation analyses when they face the dilemma of finding the proper forecasting methods.
- Second, the Smoothing parameter affects the estimations by giving weight to quantity or time interval. A well-balanced trade-off between the aggregation level and smoothing parameter gives insight into extracting the demand pattern estimation, which may change over time due to different factors such as working conditions. Moreover, this parameter can affect planning accuracy since demand estimation is the basis of a robust planning technique.
- Third, the SBA forecasting method outperforms other models since it considers the interval of demand arrival.
- Fourth, Shortage and stock levels are optimized around a minimum aggregation level, but they increase when we deviate from this point.
- Fifth, ARG's diagram is a near-convex curve which confirms the validity of improvement in the estimation gap. Additionally, AGF matches ARG, which gives an influencing insight into choosing the optimal aggregation level and aggregating demand without any concern for selecting the level.
- Sixth, we can conclude that the gap between the demand and estimation by aggregation deviates as the variation increases in comparison with the mean; in other words, the coefficient of variation (CV) increases. This interpretation can be used to measure the performance of the other models when dealing with aggregation.
- Seventh, Aggregation reduces the variance of data which affects the bullwhip effect since the variance of orders to the variance of demand is optimized by tuning the aggregation level.

- Finally, we developed a planning model for the repairable spare parts supply chain of the Iranian oil company in which the effect of aggregation is analyzed. Several analyses are provided, which give managerial insights that practitioners can use.

  This work can be an avenue for other research for further studies. Using machine learning algorithms for parameter estimation can be advantageous. Also, using multivariate time series allows one to consider several attributes, giving more accurate results. Additionally, considering the supply chain's hierarchical decisions results in a more comprehensive planning model.

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