Inventory Modeling for Automotive Spare Parts with Probabilistic Demand by Considering an Integrated Cost and Filling Rate

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Abstract

The availability of spare parts for automotive products is one part of after-sales service, which is a critical factor that must also be considered to support customer acceptance and maintain the sustainability of the sales of these products. The fluctuating characteristics of demand for spare parts is a challenge for automotive manufacturers in preparing inventory levels so that they are always available in the correct quantity and time when customers need them. This study adds the objective function of profit and constraint of fill rate and costs in the calculation of the optimization model and is applicable for probabilistic demand characteristics. In addition, inventory classification based on the results of profit and fill rate optimization can be utilized as a reference for companies to prioritize and review the inventory management of existing SKUs.

Keywords
probabilistic demand, backorder, re-order point, eoq, inventory classification.

1. Introduction
Continuous improvement efforts carried out by a company in maintaining and improving product quality must also be supported by suitable after-sales service activities. After-sales service is one of the critical keys to improving marketing performance and can increase customer loyalty in the long term. The scope of after-sales service activities are vast and varied, and one of them is the availability of service parts (spare parts).

Spare parts inventory management is essential for every company in various sectors (Boylan & Syntetos, 2010). The characteristics of demand that have a high level of fluctuation in terms of type and quantity cause companies to have to prepare higher inventory levels to mitigate the risk of not meeting demand (Hu, Boylan et al., 2018). This high level of spare parts inventory, on the other hand, will have an impact on increasing the budget for inventory and inventory costs, and this will harm the company's profits and business continuity in the long term. Another problem that must be observed is the relatively large number of types of spare parts to control. With a tremendous amount of stock keeping unit (SKU) that has no proper inventory strategy, the company will find it difficult to determine which spare parts need to be prioritized and stay aligned with its business needs. Therefore, a grouping strategy is needed for the SKUs.

Research on spare parts inventory has developed quite a lot in optimizing the amount of inventory and inventory classification, but not many have integrated the two. Examples of such non-integrated research included Vaez-Alaei (2018), which focuses on optimizing inventory and fill rates for case studies of aircraft spare parts, and Chawla et al. (2019) in research which focuses on developing classification methods with multiple criteria. Teunter et al. (2010) were the first to integrate inventory optimization and inventory classification with service level criteria and cost minimization objective functions. Millstein et al. (2014) developed inventory classification with profit and cost optimization criteria, even Yang (2017) in his research with profit and cost optimization, with non-stationary demand characteristics. However, both the research of Millstein et al. (2014) and Yang et al. (2017) did not make the fill rate the target parameter to be achieved. The three studies have not been able to answer the problems faced by many manufacturers, which seek the maximization of profit, cost and at the same time fill rate, which will then be used as consideration for grouping inventory classification. Thus, by considering both cost and fill rate simultaneously and integrating it further with inventory classification using profit, cost and fill rate as the determining factors for classification, the decision to the highest profit of inventory policy will still be a challenging task.

2. Inventory Management Studies

Vaez-Alei et al. (2018) formulate a mathematical model for inventory optimization with stochastic demand characteristics, which offers two objective function options, namely TSL (Target Stock Level) optimization with cost minimization or FR (Fill Rate) optimization. However, in determining the optimal solution, the optimal solution cannot be determined precisely depending on the simulation of EBO calculations that use the assumption of a distribution probability, both continuous and discrete functions for each ROP as a decision variable. Therefore, a heuristic or metaheuristic approach can be applied to obtain a 'near optimal'.

Historically, in the later inventory classification development, using ABC Classification has added several criteria in the inventory classification so that the inventory classification process becomes more accurate and optimal according to the company's business needs. For example, Chawla and Macheli (2019) research have proposed six criteria in the inventory classification process. Those six criteria can be distinguished into two groups of indices, namely, direct index (Average Unit Cost, Annual Revenue, Lead Time) and indirect index (Ship Complete, Cost of Stock-out and Strategic Importance). with weighting for each criterion according to the level of importance or priority of the criteria. Determination of inventory classification based on score.

Several previous studies have tried to integrate inventory optimization and inventory classification simultaneously, as Teunter et al. (2010) did by optimizing inventory with a single criterion inventory classification, namely, cost minimization as the development of ABC Classification. On the other hand, Milstein et al. (2014) tried to add multicriteria in their inventory classification and optimization with the profit maximization objective function. Yang et al. (2017) further developed it by adding an objective function, namely minimizing inventory capital. In this study, what distinguishes it from previous research is the objective function of profit optimization, taking into account cost and fill rate simultaneously, and then used as a consideration in determining inventory classification.

Teunter et al. (2010) developed an inventory classification model for the ABC Classification model, generally based on the number of requests or the value of requests as ranking criteria, modified by using cost optimization (minimization) criteria. The output of Teunter's research is the ranking of SKUs based on cost criteria. The cost criterion can divide SKUs into three classes A, B, and C, with a composition of 20%, 30%, and 50%. It can also be divided into six classes with a composition of 4%, 7%, 10%, 16%, 25% and 38%. These classes may also have a predetermined service level.

Millstein (2014) optimizes the model to develop the quality of inventory grouping so that the expected output is the optimal number of classes or groups of an inventory system by considering profit, cost and service level factors. Formulation of model optimization using a mixed-integer linear program (MILP). Millstein's research prefers profit maximization, optimizing the trade-off between inventory costs and profit. However, this model still uses a oneperiodic static model that can be developed for multi periods in the future. Furthermore, the model optimization approach is still deterministic, which can still be developed through a simulation approach to accommodate demand problems whose characteristics are uncertain or uncertain.

Yang (2017) developed an Integrated Multi-Period DCIC (Dynamic Inventory Classification and Control) for an inventory classification system with the MILP (Mixed Integer Linear Programming) approach in finding optimal inventory solutions for non-stationary demand. The objective function of this research is the maximization of NPV (Net Present Value) of Profit based on the reduction of gross profit on storage costs. The limiting function of this model is that inventory costs do not exceed the inventory budget. The CSL (Customer Service Level) level or fill rate is not a target because it can be different for each SKU based on the inventory budget. It is then used as criteria for grouping/classifying inventory. The result of Yang's research is optimising the number of classes in the inventory classification system based on the CSL (service level) level to achieve maximum NPV Profit. One of the developments of this model is that it has not considered the costs incurred due to backorder/shortage (penalty cost or loss opportunity cost) so that in the future it can be included in the cost calculation component.

Previous research can be distinguished according to the objective function, for example, Teunter et al (2010) and Millstein (2014) groups inventory based on cost minimization or profit maximization, while Yang (2017) grouping inventory based on profit maximization by considering the target inventory budget, however all three have not considered the target fill rate in the research model. While in this study, the group of inventories is constructed by pursuing maximum profit while still considering the target cost and fill rate.

The inventory's parameters and characteristics determine the type and model of inventory that is appropriate to be implemented by the company. The most dominant characteristics are demand factors and inventory review. Demand characteristics are divided into deterministic and stochastic, where demand conditions are uncertain or probabilistic. Inventory review consists of periodic, i.e. the period of inventory review has been determined in the same period, for example, weekly or monthly, and continuous review, which is an unspecified period, which generally occurs in daily inventory systems. The continuous review model (r, q) approximates the operational system for the object of research on spare parts (Jin 2019). The notation q indicates the number of orders, and r is the 're-order point'. This inventory model has several possible conditions, as shown in Figure 1. Cycle 1 shows the inventory situation can meet demand, cycle 2 shows a backorder situation, while cycle 3 shows a surplus inventory situation.

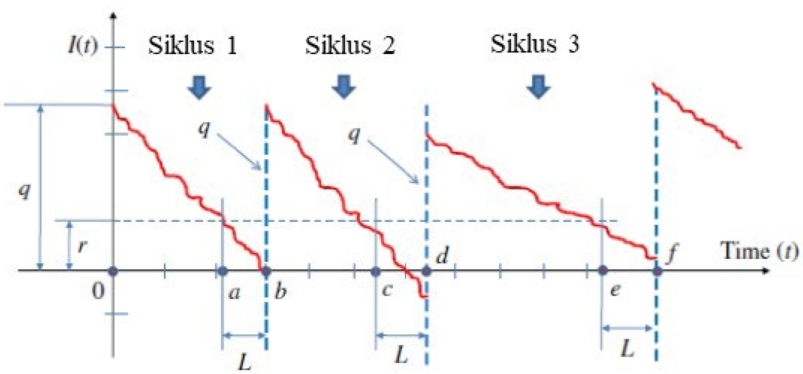

Figure 1. The basic cycle of inventory management.

3. Model Development

This research produces a mathematical model for inventory optimization and inventory classification in an integrated manner. To produce optimal profit, it determines the decision variables, namely re-order point and order quantity for each SKU. This research assumes that the demand data in this study is based on historical data. The lead time for fulfilling the demand has been determined (deterministic), and backorder is allowed, which is assumed to follow a normal distribution. After elaborating the theory of inventory optimization, the research of Rezaei et al. (2018) and Vaez-alaei et al. (2018) is used as a reference basis for development in this study. In this study, the backorder value was determined using the normal distribution function approach, so it required a heuristic algorithm approach to determine the model's optimal value. In contrast, the decision variables of this research model were ROP (Re-Order Point) and Safety Stock. First, for inventory classification theory, then for the integration model with inventory classification, referring to previous studies from Teunter (2010), Millstein (2014) and Yang (2017).

In this proposed model, the formulation integrates the objective function of profit maximization and fill rate in the form of inventory performance value (Performance Score), an aggregate of profit and fill rate criteria with a certain weight for each criterion. Profit parameters consist of total revenue and total costs. The demand calculation in this proposed model will use historical average data, while the probabilistic factor of fluctuating demand is represented by the calculation of EBO (backorder). The decision variables of this proposed model are the value of Q (order quantity) and ROP (re-order point), which are the determinants in calculating the EBO value and fill rate. The value of Q and ROP is the basis for determining the optimal inventory level because it is a function in the formulation of total cost and fill rate. The objective function of this research is the maximization of inventory performance score, which consists of several criteria parameters, namely profit, cost and fill rate. The limiting model is the cost and fill rate parameters. The cost limit is set following company policy, namely the total cost does not exceed 80% of the total revenue. Meanwhile, the fill rate parameter is set at a minimum of 95% for the total fill rate and each SKU.

<u>Index</u>

i indeks SKU (Stock Keeping Unit)

<u>Parameters</u>

PS_i Performance Score of each SKU
PR_i Profit of each SKU
TCi Total Cost of each SKU
FR_i Fill Rate of each SKU
TFR Total Fill Rate
EBO_i Expected Back Order of each SKU
D_i Demand (Permintaan) of each SKU
L_i Lead time of each SKU
Op_i Loss Opportunity Cost of each SKU
Oc_i Ordering Cost (biaya pemesanan) of each SKU
Hc_i Holding Cost (biaya penyimpanan) of each SKU
HJ_i Harga Jual of each SKU
HB_i Harga Beli of each SKU
W_j Weighted Ratio criterion of j[th]

<u>Decision Variables</u>

ROP_i Re-Order Point of each SKU
Qi Order Quantity of each SKU

The objective function is expressed in equation 1, which finds the maximum value of the performance score of each SKU.

$$Max\ PS_i = \sum_{j=1}^{k} Wj\left(\frac{PRi}{\sum_i^N PR} + \frac{FRi}{\sum_i^N FR}\right) \quad (1)$$

where the profit can be calculated by the difference of sales of SKU and the total cost, which is given in equation 2.

$$PRi = HJi \times Di - TCi \quad (2)$$

by substituting equation 2 to 1, the new objective function can be expressed as in equation 3.

$$Max\ PS_i = \sum_{j=1}^{k} W_j\left(\frac{HJ_i \times D_i - TC_i}{\sum_i^N HJ_i \times D_i - TC_i} + \frac{FR_i}{\sum_i^N FR_i}\right) \quad (3)$$

where TC_i (total cost) is a function of ROP_i and Q_i, which is given in equation 4, and FR (fill rate) is a function of Q_i given in equation 5.

$$TC_i = (\frac{Oc_i \times Di}{Q_i}) + Hci \times \left(\frac{Q_i}{2} + ROPi - D_L\right) + (\frac{Op_i \times EBOi \times Di}{Q_i}) + (HBi \times D_i) \tag{4}$$

$$1 - \frac{EBO}{Q_i} = FRi \tag{5}$$

where the FR_i value depends on the calculation of the EBO probability value (expected back order) as expressed in equation 6 for every discrete value of x.

$$EBO = \sum_{x=ROP+1}^{\infty} (x - ROP)p(x)dx \tag{6}$$

Constraints

1. The minimum fill rate for each SKU and Total Fill rate is 95% and meet the expression in equation 7 and 8.

$$1 - \frac{EBO}{Qi} \geq FRi \tag{7}$$

$$\sum_{i=1}^{N} (1 - \frac{EBO}{Qi} i) \geq TFR \tag{8}$$

2. Total Cost for all SKUs does not exceed 80% of Total Revenue (Selling Price × Total Request) as expressed in equation 9.

$$\sum_{i=1}^{N} TC_i \leq 0.8 \times \sum_{i=1}^{N} (HJ_i \times D_i) \tag{9}$$

3. Total Weighted Ratio should be equal to 1 as expressed in equation 10.

$$\sum_{j=1}^{k} Wj = 1 \tag{10}$$

In this development model there are only 2 weighted ratios, namely, to profit (W_1) and fill rate (W_2). The values for each weighting for example are 0.7 for W_1 and 0.3 for W_2. This value can be adjusted to the existing inventory policy in a company.

Determining the optimal solution depends on the simulation of EBO calculations that use the assumption of a discrete distribution of probability functions for each ROP as a decision variable makes it difficult to determine the optimal solution precisely. Therefore, a heuristic approach can be applied to obtain a 'near optimal'. After obtaining the optimal profit, cost, and fill rate, the PS (Performance Score) value is calculated and sorted from largest to smallest. The inventory classification will be divided into four groups with the rules of 60%, 20%, 15 and 5%, according to VaezAlaei (2018).

5. Results and Discussion

This research uses data taken from an actual manufacturer, which consist of 9050 SKU. Calculation was performed on the historical demand for the last 25 months period and optimization calculation for one month. The results of the calculation of the algorithm and development model using MATLAB as shown in Table 1. Table 1 shows data on some of the SKUs, which are the result of an integrated optimization between the optimization of the Performance Score (*PS*) value and the optimization of several other parameters in the form of income, profit, and costs as well as the decision variables (*ROP* and Q_i) for each SKU.

The optimal PS_i value for each SKU is obtained from the MATLAB calculation process with the total *PS* value for all SKUs, namely PS_i is 1.0. The calculation results have met the limits set in the model development, among others, for a minimum total *FR* and FR_i of 95% and for TC_i of USD 1,436,074, which is 79.3% of the total revenue below the maximum limit of 80%. The optimal profit calculation result is USD 376,049, or about 21% of the total revenue. The next step is to group/classify all SKUs which are divided into four groups based on the PS value, with a composition of 60%, 20%, 15% and 5%, as shown in Table.2

Table 1. Calculation Results.

No urut	Part No.	Average Demand	*Revenue*	*Total Cost (TCi)*	*Profit (PRi)*	*Qi (Qty Order)*	ROPi	FRi	Nilai PSi
1	04465BZ170	2592	85850	64900	20949	1996	3498	0,9742	0,03902
2	531110K700	156	32764	24805	7958	119	216	0,9547	0,01484
3	531000KD00	263	19534	14798	4736	221	346	0,9838	0,00884
4	670050K310	76	15102	11484	3618	68	137	0,9707	0,00676
5	044950K040	313	13724	10414	3310	272	456	0,9541	0,00619
6	533010K150	128	12514	9521	2994	108	222	0,9651	0.00560
7	670050D360	69	11849	8998	2851	59	92	0,9816	0,00534
8	04495BZ011	555	11111	8428	2683	444	683	0,9781	0,00502
9	04491BZ020	293	9624	7302	2322	264	363	0,9857	0,00435
10	811100KB90	39	9024	6858	2166	35	57	0,9574	0,00406
9047	64828BZ020	52	11,4	48,1	-36,7	40	90	0,9572	-0,000035
9048	90430T0010	62	4,1	41,5	-37,4	48	74	0,9801	-0.000036
9049	9004A20058	79	3,5	40,6	-37,1	62	152	0,9591	-0.000036
9050	462170B010	33	2,2	40,5	-38,3	25	56	0.9618	-0,000038
Total		111476	1812753	1436704	376049	125855		0,9510	1,00

Table 2. The SKUs grouping based on the calculated *PS*.

Group	PS	SKU (%)	*Profit* (USD)	*Profit* (%)	Income (USD)	Income (%)
G1	60%	1651 (18%)	370.274	98,5%	1.602.765	88,4%

G2	20%	2790 (31%)	35.077	9,3%	163.444	9,0%
G3	15%	3216 (36%)	-14.795	-3,9%	40.199	2,2%
G4	5%	1393 (15%)	-14.507	-3,9%	6.345	0,4%
Total	100%	9050(100%)	376.049	100%	1.812.753	100%

In Table 2, group 1 (G1), with a PS value of 60%, consists of 18% of the number of SKUs, contributing very dominantly to revenue of 88.4% and profit of 98.5%. On the other hand, group 2 (G2), with 20% PS value, consists of a larger number of SKUs, which is 31% contributing to the revenue of only 9.0% and profit of 9.3%. Meanwhile, groups 3 and 4 (G3 and G4) with a total of 51% SKU, only contributed 2.6% to revenue and scored a negative profit of -7.8%.

To show the improvements, several parameters of the optimization results are shown compared to the conditions before the optimization calculation as depicted in Table 3. Total costs increased by USD 177,208 (+14.1%) but could still be offset by an increase in income which had a larger nominal value, namely USD 221,435 or grew +13.9%, so it could still increase Profit by USD 44,227 (+13.3%). In addition, total Fill rate has increased from 76% to 95.1%, according to the targeted limit. The increased total costs arise from increasing stock levels consisting of the amount of ROP and Qi.

Table 3. Model result vs existing.

Parameters	Model Output	Existing	Difference (+/-)	%
Income (USD)	1.812.753	1.591.318	+221.435	+13,9%
Total Profit (USD)	376.049	331.822	+44.227	+13,3%
Profit Ratio (%)	20,7%	20,9%	-0,1%	-0,5%
Total Cost (USD)	1.436.704	1.259.496	+177.208	+14,1%
Cost Ratio (%)	79,3%	79,1%	+0,1%	+0,1%
Total *Fill rate* (%)	95,1%	76%	+19%	+25,1%

Table 1 sgiws that the total Qi of all SKUs for the one month of calculation is 125,855 pcs, or 113% compared to the total average demand (∑Di) of 111,476 pcs. Therefore, the number of orders to these suppliers, including inventory levels, increases supply to fluctuating demand and reduces the probability of backorders (EBO). Thus, even with increased costs due to increased inventory levels, it also increases revenue due to reduced backorders and ultimately increases company profits, as long as total costs are kept within the limit according to company policy, which is 80%.

Parameters and decision variables in the form of income, total costs, ROP and Qi response to changes in demand and costs. Demand change scenarios range from a -20% decrease to a +50% increase. Changes in income, total demand, ROP and Qi are directly proportional to changes in demand. For revenue, total costs and ROP, the amount of change almost follows the magnitude of the change in demand, except for the change in total Qi (order quantity), not as large as the change in demand. For example, a decrease in demand (-20%) resulted in a -20% decrease in revenue, a -19% decrease in total costs, a -21% decrease in total ROP, and a -15% decrease in total Qi. Vice versa for changes in demand increased by +50%, income increased +50%, total costs +52%, as well as total ROP increased by +53%, while total Qi only increased by +32%. From the calculation results of several scenarios, it can also be seen that the total Qi (order quantity) has the flexibility to meet an increase in demand of up to +3% without having to make changes or add orders.

Additionally, an inventory classification analysis was conducted to learn more about the results of grouping or grouping SKUs based on the optimization of the development model that can be used as a reference for decision making in inventory management. Table 2 shows that 9050 SKUs were divided into groups G1 to G4, with interesting data that only G1 and G2 contributed positive profits, while G3 and G4 generated negative profits. Furthermore, each group's characteristics will be analysed to get a reference in the formulation of inventory policies. The parameters to be analyzed are related to the number of requests and part prices. Therefore, the SKU characteristics of each group are mapped into 4 zones based on the number of requests and part prices, i.e. zone A (low demand, low price), zone B (high demand, low price), zone C (low demand, high prices), zone D (high demand, high prices). The mapping of each group is shown in Figure 2.

Figure 2 shows that the characteristics of SKUs in group 1 (G1) are dominant in zones B, C and D, which tend to have high demand and high prices, and almost none have low demand, low prices. These characteristics in G1 contributed greatly to income and profit. On the contrary, if we look at G3 and G4, they have the characteristics of low demand and low prices. The characteristics of the SKUs in G3 and G4 are low demand or slow-moving, which results in unfavourable profit conditions. By looking at this data, it can be used as a reference for company management to evaluate and improve SKUs in G3 and G4 to increase profits or at least reduce losses. The evaluation results can be in the form of a proposal to change SKUs with low demand/slow-moving from inventory items to non-inventory items (zero inventory) to reduce costs.

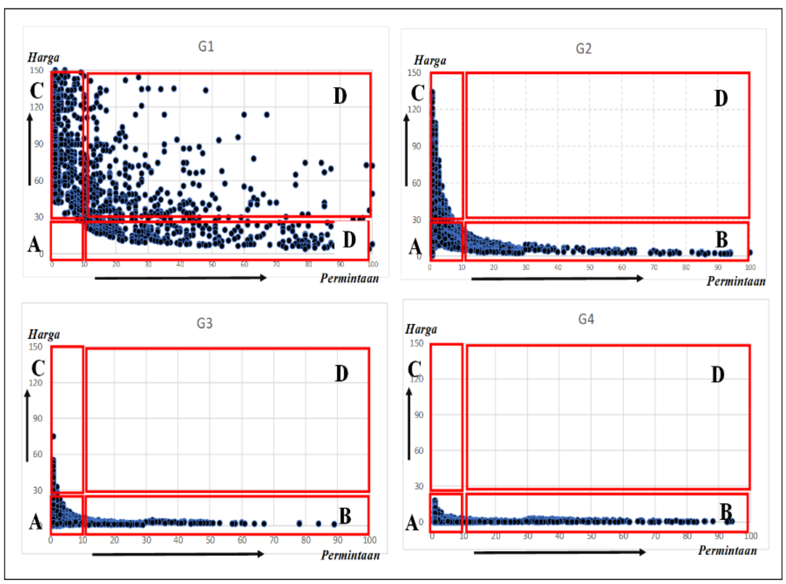

Figure 2. Mapping of SKUs within each group.

6. Conclusion

This research produces mathematical models and algorithms for inventory optimization and inventory classification in an integrated manner and can be implemented in general on inventory models with characteristics at PT X and other companies with the same characteristics. Fluctuations influence the re-order point and order quantity decision variables for each SKU in demand, although with different sensitivity levels. Meanwhile, changes in costs have no effect on the decision variables. Applying the proposed model and algorithm can improve the company's business performance by increasing the total profit by 13.3% and the fill rate from 76% to 95.1%. Inventory classification is divided into four groups sorted by the optimization value of PS (Performance Score), with the top 2 groups contributing positive profits and the other two groups contributing negative profits. In this study, improvements to the spare parts business operations were carried out on the 'supply' side, while from the 'demand' side, it was still wide open for development. In the future, the analysis can further elaborate on the demand patterns and very diverse characteristics of each SKU. Furthermore, the number and range of inventory classification groups can be studied further to obtain an optimal grouping or classification following the company's business needs.

References

Boylan, J. E., Syntetos, A. A., Spare parts management: a review of forecasting research and extensions, *IMA Journal of Management Mathematics*, vol. 21, issue 3, pp. 227–237, July 2010.

Chawla,G., Miceli,VM.(2019). Demand Forecasting and Inventory Management for Spare Parts. Available: https://dspace.mit.edu/handle/1721.1/121291**,** March 2021.

Jin, T., *Reliability Engineering and Services*, John Wiley and Sons, 2019.

Millstein, M., Yang, L., Li., H., Optimizing ABC inventory grouping decisions, *Int. J. Production Economics*, vol. 148, pp. 71–80, 2014.

Rezaei, H., Baboli, A., Shahzad, M. K., Tonadre, R., A new methodology to optimize target stock level for unpredictable demand of spare parts: A case study in Business Aircrafts Industry, *IFAC Symposium on Information Control Problems in Manufacturing*, vol 51, issue 11, pp. 538-543, 2018.

Teunter, R, H., Babai, M. Z., Syntetos, A. A., ABC Classification: service levels and Inventory Costs, *Prod.Oper.Manage*, vol. 19, no. 3, pp. 343–352, 2010.

Vaez-Alaei, M., Atashbar, N. Z., Baboli, A., and Tonadre, R., Target stock level and fill rate optimization for worldwide spare parts inventory management: A case study in business aircraft industry, *2018 IEEE International Conference on Technology Management, Operations and Decisions (ICTMOD)*, pp. 282-287, 2018.

Yang, L., Li, H., Campbell, J. F., and Sweeney, D. C., Integrated multi-period dynamic inventory classification and control, *International Journal of Production Economics*, vol. 189, 2017, pp. 86-96, 2017.

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