A novel approach for spare parts dynamic deployment

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Abstract: Efficient spare parts management is fundamental for service organizations. Optimal strategies in procurement, stocking, and supply increase the competitive advantage of service-oriented firms. Therefore, a dynamic asset deployment (DAD) strategy should be used to determine what items allocate throughout the geographical hierarchy of company service support locations. That policy should define whether to centralize or decentralize the management of Stock Keeping Units (SKUs), aligning spare parts storage and distribution chain closely with the equipment users' operations. A successful heuristic strategy should consider individual item criticality while remaining flexible with respect to demand fluctuations. A popular methodology for the hierarchical classification of assets is the multi-criteria ABC analysis, which has been widely applied to plan the optimal supply of spare parts in a single warehouse. This paper compares two heuristic approaches that exploit ABC analysis to solve a multi-item, multi-location problem, indicating how to deploy SKUs in different warehouses and configuring the distribution network. First, a literature approach is shown. Then, considering the first approach, a renewal-based model is derived to overcome the identified weaknesses. Both methodologies are applied to the case study of an Italian trucking company. Using historical data of demand, that occurred in the company is compared with what would have happened using the two approaches. Results prove that both ABC strategies allow rationalizing the use of economic resources, thus achieving benefits in terms of stock levels and number of orders. However, the derived approach is not affected by subjectivity and can be applied to manage thousands of different items. Moreover, the results highlight the differences between the compared approaches in terms of centralization and decentralization.

Keywords: spare parts management, ABC multi-criteria, two-echelon network, dynamic asset deployment.

1. Introduction

During the last decade, many firms shifted their focus from products to customers, thus adopting a customer-centric perspective (Cohen et al., 2006). As managing the needs of clients in supply chains has become increasingly important, logistics companies have recognized customer orientation as a critical aspect of their success (Giannikas et al., 2019). In this context, it has become essential for after-sales companies to align supply chains and logistics activities closely with the equipment users' operations, optimally configuring their network of resources. As stated by (Stoll et al., 2015), when it comes to increasing the serviceability of spare parts networks, designing the optimal allocation and distribution of items plays a crucial role. A common challenge in configuring a supply chain boils down to reducing inventory costs while delivering high service levels (Jiang et al., 2019). On the one hand, customers facing stock-outs typically abandon their purchases, switch retailers, and seldom gone back (Fitzsimons, 2000). To avoid this by ensuring reliable and rapid response to demands, multiple local distribution centers (DCs) should be established, configuring a decentralized logistics system, where each DC holds inventory based on the needs of its specific customers (Cohen et al., 1992). On the other hand, keeping high inventory levels increases warehouse costs. Therefore, it would be preferable to configure a centralized system, where all spare parts are stored in a single DC and, if necessary, delivered to clients (Milewski, 2020). According to (Cavalieri et al., 2008), a valuable way to balance these needs is to build a multi-echelon network, in which SKUs can be stocked at different inventory holding points that might belong to different levels (echelons), where the higher echelons of the network supply the lower ones. In such a structure, local DCs close to customers guarantee fast delivery, while a single central location facilitates low safety stocks, thus reducing holding costs due to the risk-pooling effect (Alvarez and van der Heijden, 2014). (Cohen et al., 1997) reported that a high number of echelons (more than three) rarely occur in practice, while frequent networks are those made by two levels (base-depot structures). In this case, several sites (bases) close to customer clusters satisfy local demands by keeping decentralized stocks. Then, emergency shipments from the central depot are used only to replenish the bases in case of stock-outs (Alvarez and van der Heijden, 2014).

To define the most cost-effective and service-effective way of providing a spare parts service, it is useful to adopt structured approaches for configuring the supply and distribution chain. Typically, these approaches consist of two steps (Gregersen and Hansen, 2018). First, the network configuration is decided, determining for each SKU whether to opt for a centralized, decentralized, or hybrid (multi-echelon) management. Next, it is decided the inventory control policy, planning which SKU to procure and which to order on request, and also defining how to deploy them in different warehouses (Caron and Marchet, 1996). Since spare parts are subject to volatile and uncertain demands, static management approaches are inefficient, while flexible strategies called Dynamic Asset Deployment (DAD) approaches are preferable (Cohen et al., 2006). Using DAD approaches for determining what items allocate throughout the geographical hierarchy of company service support locations results in numerous benefits. Among these are included the achievement of the desired customer service level, the ability to respond to volatile demands, the reduction of investment in non-critical parts, the simplification of business processes, and the establishment of a form of large-scale corporate coordination (Cohen et al., 1999). The literature offers three types of DAD approaches to configure logistics networks (Muckstadt, 2004). The firsts are operational research (OR) optimization models, in which an objective function is solved according to constraints. The seconds are the heuristic approaches, which aim to find a trade-off between costs, revenues, and service level, providing a near-optimal solution. Finally, the thirds are the approaches based on the development of simulative models and the study of "what if" scenarios. Historically, the first developed approaches are those of OR (Sherbrooke, 1968). However, as emphasized by other authors (Gregersen and Hansen, 2018; Mintzberg, 1989), they are computational challenging, whereas there is a need for more efficient strategies. To this end, algorithmic and heuristic approaches were developed (Cohen et al., 1990, 1988). Focusing on heuristic approaches, usually, the core of DAD systems is spare parts classification. According to (Persson and Saccani, 2007), a successful DAD strategy should consider individual item criticality based on multiple characteristics. Then, the ranking methodology should be used to define stocking lists for each DC, thus determining where parts should be stored. One of the most popular methodologies for the hierarchical classification of assets is the multi-criteria ABC analysis. As literature shows (Roda et al., 2014), this approach has been widely applied in the field of inventory management, mainly to plan the optimal supply of spare parts in a single warehouse. Despite ABC is renowned for its ease of application (Ng, 2007), to the best of the authors' knowledge, the literature offers only one paper that uses ABC to solve DAD problems (Stoll et al., 2015). This approach is based on a three-dimensional classification. Two dimensions are used to estimate the value and predictability of SKUs with the help of an ABC and XYZ analysis. Instead, the third dimension is a VED-AHP analysis, which ranks items according to six criteria related to maintenance and production aspects. However, the author himself states that his approach is affected by weaknesses that represent barriers to the application of the methodology. In light of this, the present paper shows a renewal-based model derived by (Stoll et al., 2015) through the elimination of its critical aspects. The aim is to compare the performance of two heuristic ABC approaches, thus verifying how the changes impact the DAD results. The contribution of this paper is twofold. At a theoretical level, it is to show that barriers to the application of ABC DAD strategies highlighted by (Stoll et al., 2015) can be overcome, giving rise to a structured approach not affected by subjectivity and able to handle thousands of different SKUs simultaneously. In this sense, a case study is used to show the performance of the proposed approach, comparing its effectiveness against the literature approach. On a practical level, the outcome of this article is to provide companies with a user-friendly DAD approach that can be used to design two-echelon supply chains in service organizations, rationalizing the use of economic resources, and achieving benefits in terms of stock levels, and the number of replenishment orders. Overall, the novelty of this article lies in facilitating the deployment of the ABC tool not only for the classification of spare parts in a single warehouse but also in the area of spare parts distribution chain configuration. The remainder of the present paper is as follows: after providing a literature review regarding DAD (Section 1.1), Section 2 describes the functioning of the two heuristic approaches. First, the literature-based methodology is shown (Section 2.1). Then, the derived approach is proposed (Section 2.2). Subsequently, the different choices in terms of inventory levels and distribution networks suggested by the two strategies are evaluated using a common case study of an Italian trucking company (Section 3). Using demand historical data, that occurred in the company is compared with what would have happened using the two approaches. Finally, Section 4 offers a discussion on the results and some conclusions.

1.1 Literature review

The first practical application of DAD theory is the METRIC model by (Sherbrooke, 1968). It is an OR model capable of determining base and depot stock levels for a group of recoverable items. Its main purpose is to optimize the performance of a multi-item, multi-warehouse, two-echelon system by minimizing the sum of expected backorders, which are convex functions of base stock levels that exist if there is an unsatisfied demand at a base level. Several extensions and modifications of METRIC have been proposed since 1968. Among these, just a few examples are the following. (Muckstadt, 1973) revisits the METRIC model to keep under consideration the logistics relationship between an assembly and its subassemblies. (Muckstadt and Thomas, 1980) propose a two-echelon inventory system with no lateral resupply, which is particularly appropriate for managing inventories with low-demand items. Finally, (Alfredsson and Verrijdt, 1999) consider a two-echelon network with lateral transshipments between bases and direct deliveries from external suppliers. Given the prevalence of two-echelon networks compared to multi-level ones (see Introduction), most scientific efforts focused on developing approaches to solve such problems. No generality is lost by considering two-level methods because they can easily be extended into multi-level cases if the depot of one layer is considered the base of the previous one (Ding and Kaminsky, 2018). According to (Cohen et al., 2006), DAD OR models are formulated as nonlinear, integer, combinatorial, stochastic, non-stationary optimization models. These formulations, as stated by (Cohen et al., 1990; Mintzberg, 1989), are computationally challenging and difficult to solve, while there is a need for computationally efficient ways for finding solutions. For this reason, several mathematical approximation approaches were developed. Two of them are as follows. (Graves, 1985) shows an approach in which failures are assumed to follow a compound Poisson process and the shipment time from the repair depot to each site is supposed to be deterministic. (Cohen et al., 1988) presents an algorithm to simplify the METRIC model and compute stock levels in a two-echelon system with multiple prioritized demand classes and lost sales of excess demand. According to (Alvarez and van der Heijden, 2014), the algorithmic approaches (often based on iterative cycles), although being reasonably accurate, may not lead to convergence, for example, in the case of expensive slow-moving items for which a lot of stock is kept at the depot, with little stock kept locally. Hence, other DAD methods were developed based on the execution of simulations or the multi-criteria classification of spare parts. In the case of simulation, different network scenarios are hypothesized (i.e., total decentralization, centralization, or hybrid configurations), the costs and benefits of each scenario are evaluated, and, the optimal case is selected among those considered. Some resolutions of DAD problems using simulations were shown by (Confessore et al., 2003; Mofidi et al., 2018). In the case of classification approaches, on the other hand, a range of attributes is considered, such as critical factors related to individual SKUs (unit cost, expected demand rate, and delivery time). Item classification groups are created. Then, group membership is used to guide rule-based asset distribution decisions (Teunter et al., 2010). Literature offers approaches of this type based on qualitative (Gregersen and Hansen, 2018) or quantitative criteria (Caron and Marchet, 1996; Cavalieri et al., 2008). Even though multi-criteria ABC analysis is a well-known tool for parts classification (Van Wingerden et al., 2016), to the best of the authors' knowledge, only one author proposed a heuristic DAD approach based on it (Stoll et al., 2015). This approach is the starting point of the present study.

2. Methodology

This section describes two ways of using ABC multi-criteria analysis as a DAD approach in a multi-item, multi-location company which aims to align distribution strategies with customers. The first way (Section 2.1) is the literature methodology by (Stoll et al., 2015). The second (Section 2.2) is an approach here proposed for the first time, which derives from the previous one and seeks to reduce negative aspects underlined by the author himself.

2.1. Literature-based approach

The approach by (Stoll et al., 2015) involves performing, in each company warehouse, a classification of spare parts according to three dimensions. For the first dimension, a typical ABC analysis is conducted (Van Wingerden et al., 2016), where SKUs are sorted according to their cost into critical (A, first 80% of the ranking), moderately critical (B, next 15%), and non-critical (C, remaining 5%). For the second dimension, the demand for SKUs is considered by performing an XYZ analysis. The criterion analyzed is predictability, estimated as the coefficient of variation of the demand for each SKU ($\theta(x)$), i.e., the ratio between the standard deviation of demand ($\sigma(x)$) and its mean value ($\bar{x}$). In this case, the separation limits of classes were determined and validated through surveys submitted to a panel of maintenance experts (Table 1).

Table 1: XYZ-categories by (Stoll et al., 2015).

Category	Description	Condition
X	Uniform, constant course of demand	$\theta(x) < 1.5$
Y	Average prediction accuracy	$1.5 < \theta(x) \leq 3$
Z	Random course of demand	$\theta(x) > 3$

Finally, for the third dimension, a VED classification is performed. Unlike ABC and XYZ, VED is not described by a single indicator but results in a multi-criteria analysis. Items are divided into vital (V), essential (E), and desirable (D) based on six criteria defined in agreement with experts. These criteria are failure frequency, lead time, installation time, machine priority (which considers whether the machine is redundant or its fault stops production), equipment availability, and shift plan. The first three criteria relate to the area of maintenance, while the remaining ones relate to the production process and should be considered if the company does not only sell spare parts to external customers but uses them to repair its manufacturing plants. According to Figure 1, SKUs are subjected to a VED analysis for each of the six criteria. To obtain a single criticality class, the six VED evaluations performed for each SKU are entered into a decision tree, whose nodes represent the defined criteria. Besides, an analytic hierarchy process (AHP) is used to solve multi-criteria classification problems in the different nodes of the tree (Figure 2). Using the AHP, by weighting through a pairwise comparison, rational consideration of individual criteria at each level is achieved. Then, the aggregated weighted criteria (global priority, $P_{h,i}^{global}$) of each category h in terms of criterion i is calculated by multiplying the weighting of the individual VED category (v^h) with the weighting of the criteria at the next higher level of the tree (v^i). By summing up all global priorities of one level in the hierarchy, which consists of several criteria i, the overall priority of that category is obtained (P_h^{total}, (1)). Then, sorting SKUs according to decreasing P_h^{total} values, the first 80% of them is placed in global class V, the second 15% in class E, and the remaining 5% in class C.

$$P_h^{total} = \Sigma_i \left(P_{h,i}^{global}\right) = \Sigma_i \left(v^h * v^i\right) \quad (1)$$

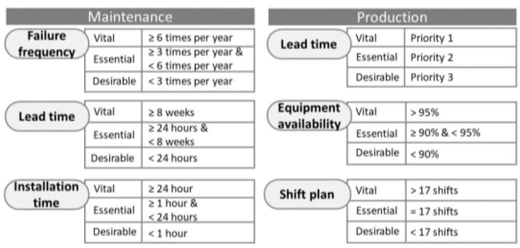

Figure 1: VED ranking for six criteria by (Stoll et al., 2015).

Having performed the 3 classifications, each SKU is categorized into a cell of a 3x3x3 matrix (Figure 3). For each quadrant, a deployment strategy is suggested (Table 2). For the darker quadrants, centralization is efficient, and the depot answers both to the demands of local customers and peripheral bases. For white quadrants, no stock should be held, and SKUs should be ordered when required. Those quadrants contain vital items with low economic value and bad predictability. Finally, for the remaining quadrants, the decentralization in the bases is suggested since they are desirable items, with good predictability and high economic value.

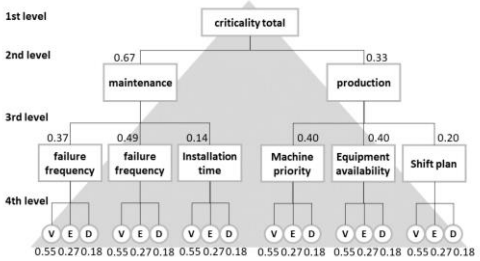

Figure 2: VED-AHP decision tree by (Stoll et al., 2015).

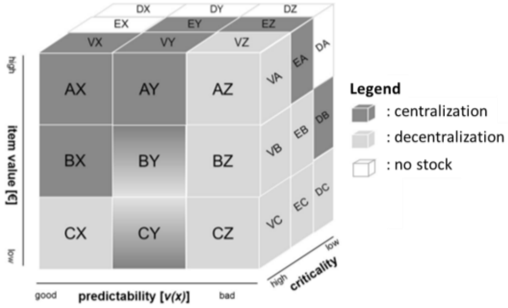

Figure 3: 3-dimensional classification by (Stoll et al., 2015).

Except for SKUs not requiring stock, inventories are managed by defining reorder levels (*RL,* (2)) and optimal reorder quantities using Wilson's formula (*EOQ,* (3)).

$$RL = (\bar{x} * LT) + SS = (\bar{x} * LT) + Z * \sqrt{LT} * \sigma(x) \tag{2}$$

$$EOQ = \sqrt{\frac{2C * D}{hc}} \tag{3}$$

C is the order fixed cost, *hc* is the variable holding cost, *D* is the total demand in the analysis period, and *SS* is the safety stock calculated for the desired service level (*Z*), the procurement lead time (*LT*), and the standard deviation of lead time *σ(LT*)). As emphasized by the author himself (Stoll et al., 2015), this approach suffers from some weaknesses. First, the use of an AHP makes VED results subjective, which depend on pairwise comparisons and the ratings that a set of experts assigns to the six criteria. Second, AHP prevents the method from subsequent modifications. Regressions during development are only partially possible or associated with high modification effort. Third, X, Y, and Z class boundaries are subjective, being established by operators. Finally, in the case study by (Stoll et al., 2015), the VED allowed classifying only 50,000 out of 115,000 spare parts due to the complexity of the amount of data required for evaluating the six criteria.

Table 2: deployment strategies (DS) for matrix quadrants.

Criticality classes	Suggested DS
AXV, AYV, BXV, BYV, CYV, AYE, AZE, BYE, CXE, CYE, BYD, BZD, CYD	Centralization
AZV, BZV, CXV, CZV, BZE, CZE, CZD	Decentralization
AXE, BXE, AXD, AYD, AZD, BXD, CXD	No stock

2.2 Proposed approach

Seeking to reduce weaknesses in the methodology, a DAD approach derived from (Stoll et al., 2015) was developed. This approach involves performing a two-dimensional classification, not needing to implement the VED to avoid subjective and time-consuming analyses. The first classification is an ABC analysis performed like the one described in Section 2.1. The second classification is an XYZ, which, instead of being carried out by considering the coefficient of variation of demand, evaluates the number of supply orders for each item in the period of analysis. This choice was made because the demand for spare parts typically follows a Poisson distribution, whose deviation and expected value are already considered in the calculation of RL. Therefore, it is not necessary to evaluate these aspects twice. Both ABC and XYZ classes are divided into percentages 80%, 15%, and 5% according to Pareto principle, so a 3x3 matrix is obtained, whose quadrants, based on (Flores and Whybark, 1987), are grouped and reclassified into three main categories (α, β, and γ) to obtain a mono-dimensional ABC (Figure 4). To this end, SKUs belonging to AA, AB, or BA matrix cells are included in the highest criticality class (α). Indeed, if an element is critical in at least one of the two classifications (ABC and XYZ), then it will be critical also in the final ranking. Conversely, CB, BC, and CC articles are included in the lowest criticality class (γ). The remaining items are classified in the β class. Then, the suggested deployment strategy is as follows. Critical elements (α class) are kept close to the final customer to avoid high delivery times. Therefore, their management remains decentralized. These SKUs are the most critical, so they need higher care, and it is mandatory to find the optimal lot-sizing and reordering frequencies for them. Similarly, articles of moderate importance (β class) should be left in the peripheral bases because their annual demand is not negligible. SKUs of β class deserve an intermediate level of attention and can be managed by means of standard procurement policies. On the contrary, non-critical articles (γ class) can safely be centralized to benefit from the risk-pooling effect. These articles are rarely required, and they will be distributed to users only when needed, with a higher delivery time, but without deteriorating the overall service level. γ items are not relevant, especially those coming from CC class, hence they should be managed to simplify the procurement and stocking process as much as possible. Therefore, their demand will be neglected in the peripheral bases and cumulated in the centralized depot, where the inventories of these items will be managed. Even in this DAD approach, inventories are managed by calculating *RL* and *EOQ*. As an example, Figure 5 shows the application of the proposed approach to the case study of a company with 3 warehouses. Assuming that, initially, the 3 warehouses are independent (each managing a certain inventory of SKUs), the starting scenario corresponds to decentralization. Supposing that warehouse WH2 is designated for centralization and applying the DAD approach, first, the bi-criteria ABC analysis is carried out in the peripheral bases (WH1 and WH3), classifying the respective SKUs in α, β, and γ. Then, α and β items are deployed and managed in the bases, while the demand for γ items is centralized and cumulated in the depot, where the bi-criteria ABC classification is, then, carried out. Finally, items found to be α and β in the depot are kept in stock and ordered with appropriate inventory policies, while no stock is kept for γ items, which are non-critical both in the bases and the depot.

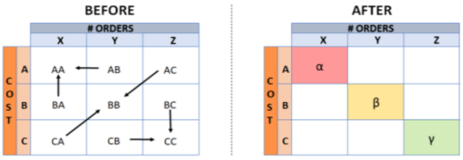

Figure 4: transformation of the bi-dimensional classification (before) into a mono-dimensional one (after).

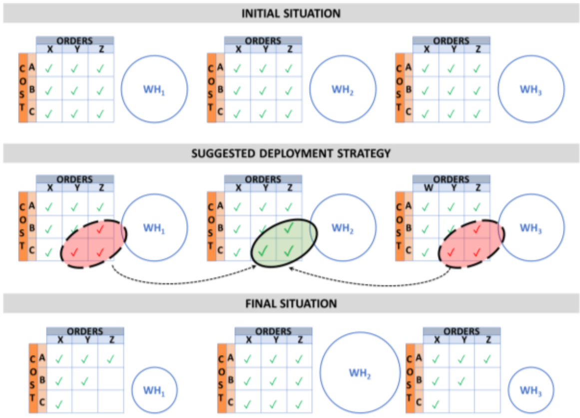

Figure 5: initial decentralized scenario (up), application of DAD strategy (middle), and final 2-echelon solution (down). Circle diameters symbolize stock levels in WHs.

Finally, based on (Alvarez and van der Heijden, 2014), to prevent ordering expensive slow-mover items or obtaining excessive *EOQs*, the following constraints are introduced.

- **If** $EOQ > 2 * D$, then $EOQ' = D$, **else** $EOQ' = EOQ$;
- **If** *number of orders in the analysis period* ≤ *1* and *quantity ordered* ≤*1*, no stock is kept for that SKU, **else if** *number of orders* ≤ *1* and *average unit cost* **>** *limit cost* (established by the company), then no stock is kept, **else** $RL'=RL$.

3. Case study

Both approaches of Section 2 were applied to the case study of a public transport company. The company owns about 600 buses, including city, suburban, and intercity buses, school buses, tourist, and rental vehicles. Besides, the company offers after-sale services, selling spare parts to external customers. 5 warehouses are used to stock more than 3000 types of SKUs. The warehouses are currently managed according to total decentralization and the supply of items is in charge of warehouse managers who define DAD policies based on their algorithms and experience. The inventory management is not completely satisfying. Sometimes order errors prevent customer needs to be fulfilled. Other times stocks are excessive, as in the example provided in Figure 6. The company aimed to improve the performance of its warehouses, assuring a fill rate of 95% while minimizing inventory costs. In this context, the two ABC DAD approaches were implemented, extracting the necessary input data from the company databases. For each SKU, the information collected was SKU identifier (*ID*), description, average unit cost, total annual demand in each warehouse (*D*), quantity unloaded every day from each warehouse and, average demand over the lead time (*LT*). For privacy and industrial reasons, the costs of SKUs were all changed adding a coefficient *k*. To run the model, *C* was evaluated in 26.10 €/order, while *hc* was considered 9.87% of the cost of each SKU.

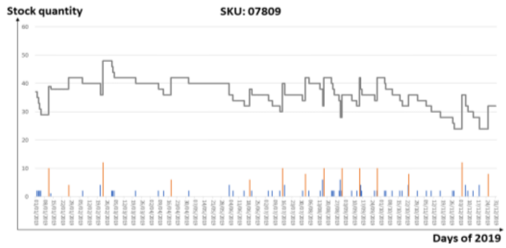

Figure 6: for article 07809 in WH_2, orange lines are orders placed. Blue lines are historical withdrawals (customer requests). Grey line is the stock trend occurred in 2019.

The results of the two approaches are shown below. Table 3 shows for a sample of 4 SKUs contained in WH_3 the following information. ID, description, 2019 annual demand (AD), 2019 annual cost (AC), coefficient of demand variation, criticality classification (CrC) and deployment strategy (DS) by (Stoll et al., 2015), and same information by the derived approach. Table 3 highlights differences in terms of criticality classes and consequent allocation policies obtained through 2 or 3-dimensional classifications and studying either the coefficient of variation in demand or the number of orders. Since WH_1 had a large physical size and a central location with respect to all external customers, it was decided to use this warehouse for centralization purposes.

SKU ID & description	AD	AC	$\theta(x)$	CrC by literature approach	DS by literature approach	CrC by derived approach	DS by derived approach
00682 motor belt	18	828.2	19.4	BZE critical	Decentralization	BX moderate	Decentralization
00047 diesel filter	2	126.4	0	CXV critical	Decentralization	CY non critical	Centralization in WH_1
62733 lateral bar	0	0	-	-	No stock	-	No stock
96047 water filter	39	2486.6	15.3	AZV critical	Decentralization	AX critical	Decentralization

Table 3: literature and derived approach outcomes for a sample of 4 SKUs in WH_3.

For the same sample of 4 SKUs, Table 4 illustrates the inventory policy outcomes for different warehouses. For 1 out of 4 SKUs (62733), the two approaches give similar results, while for the remaining SKUs they give different *RL* and *EOQ* values. For SKU 00047, the literature approach opts for centralization in WH_1, while the other prefers decentralization. For SKUs 00682 and 96047, the opposite consideration applies. Given the number of SKUs unloaded in 2019 from each warehouse, if a model suggests centralization, the demand of that SKU is cumulated in WH_1 to satisfy customer requests through the risk pooling strategy. Conversely, if the model suggests decentralization, that demand is maintained inside the local base, setting the inventory to satisfy customers at least with a service level equal to the one imposed.

Table 4: comparison of inventory policies for a 4 SKU set.

(*RL, EOQ*) by literature-based approach					
ID	**WH$_1$**	**WH$_2$**	**WH$_3$**	**WH$_4$**	**WH$_5$**
00682	(2, 18)	No stock	(3, 14)	No stock	No stock
00047	(1, 5)	No stock	(1, 4)	No stock	No stock
62733	(1, 3)	(2, 4)	No stock	No stock	No stock
96047	(3, 20)	No stock	(4, 18)	No stock	No stock
(*RL, EOQ*) by derived approach					
ID	**WH$_1$**	**WH$_2$**	**WH$_3$**	**WH$_4$**	**WH$_5$**
00682	(3, 19)	No stock	(3, 14)	(3, 12)	No stock
00047	(1, 7)	No stock	No stock	No stock	No stock
62733	(1, 3)	(2, 4)	No stock	No stock	No stock
96047	No stock	No stock	(4, 18)	(3, 15)	(3, 15)

As illustrated in Table 5, the annual quantities withdrawn for every SKU (calculated as the sum of withdrawals in each warehouse) are equal in both approaches since they are historical values. However, looking at the warehouse in which they are placed, we can see if that approach imposed centralization or decentralization. Overall, the derived approach decentralizes inventories more than the literature one. That decentralization orientation is confirmed by the results in Figure 7. Due to the risk-pooling, by applying the literature approach in 2019, the firm would have obtained a decrease in the average stock and the number of orders. Figure 7 also shows that, while providing different results, the heuristic approaches perform better in terms of average inventory and number of orders than the historical data. Furthermore, these approaches, unlike the historical scenario, ensure a minimum service level of 95%, preventing excessive stock-outs.

Table 5: comparison of annual quantity of withdrawals.

Annual quantity of withdrawals by literature-based approach						
ID	**WH$_1$**	**WH$_2$**	**WH$_3$**	**WH$_4$**	**WH$_5$**	**Sum**
00682	31	2	18	16	5	72
00047	3	0	2	0	0	5
62733	3	5	0	0	0	8
96047	55	0	39	0	0	94
…	…	…	…	…	…	…
Sum	**402,612**	**13,630**	**43,881**	**22,446**	**29,504**	**512,073**
Annual quantity of withdrawals by derived approach						
ID	**WH$_1$**	**WH$_2$**	**WH$_3$**	**WH$_4$**	**WH$_5$**	**Sum**
00682	38	0	18	16	0	72
00047	5	0	0	0	0	5
62733	3	5	0	0	0	8
96047	0	0	39	27	28	94
…	…	…	…	…	…	…
Sum	**208,951**	**24,621**	**158,212**	**54,345**	**65,944**	**512,073**

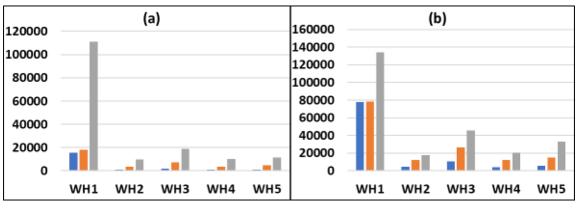

Figure 7: number of replenishment orders (a) and average stock (b) obtained historically (grey), and through literature (blue) and derived approach (orange).

4. Discussion and conclusions

Warehouse logistics can determine a company's success both in terms of performance (Cantini et al., 2020) and service level. Designing a distribution chain aligned with customer needs can improve the performance of after-sales companies, so it is essential to establish optimal strategies for allocating spare parts in warehouses, determining whether to centralize or decentralize their management. Although multi-criteria ABC analysis is a well-known classification tool, the literature offers only one ABC technique to define an effective DAD procedure. Starting from that methodology, the present paper proposes a renewal-based strategy. Both approaches are applied to a common case study of a transport company and then compared. The methodologies classify items, manage their allocation according to their criticality, and set inventory policies by calculating *RL* and *EOQ*. Both, moreover, aim to leave the most critical SKUs decentralized, while centralizing the less critical ones. The main differences between the approaches lie in the classification modalities. The literature methodology is three-dimensional and considers 8 classification criteria, including cost, coefficient of demand variation, failure frequency, lead time, installation time, machine priority, equipment availability, and shift plan. The classification is performed with ABC, XYZ, and a six-criteria VED. On the other hand, the derived strategy is two-dimensional, eliminating the VED analysis and limiting the elements of subjectivity and time consumption. This approach involves performing ABC, XYZ, and using two boundary conditions to limit inventory replenishment values. Both approaches do not ensure the achievement of optimal solutions, rather they provide near-optimal results. However, their implementation requires collecting data generally available in all companies. The case study here provided confirmed the applicability of methodologies in a real context, emphasizing that both approaches are effective as they significantly improve the initial situation, but highlighting their differences. Since the analyzed company does not produce spare parts in-house, the literature approach was based only on 5 out of 8 classification criteria, not considering production aspects. This was not a limitation because, as stated by (Zijm et al., 2019), most components in service companies are ordered from external suppliers. The literature approach showed advantages in terms of average stock and annual orders, favoring the centralization scenario, issuing frequent supplies in small lots, and benefiting from risk pooling. However, it was affected by subjectivity and its application was time-consuming because, to apply the VED analysis, it was necessary to transform the classification into a decision tree, perform an AHP, and consult experts to transform the evaluations of the 8 criteria into a single score. The derived approach, in contrast, involved a more decentralized scenario, increasing proximity to the customer and decreasing the time and distance required to deliver SKUs. The main advantages of the derived method are as follows. It gives objective results, being based on data extracted from databases and not needing to consult expert personnel. It is less time-consuming, and consequently, it allows thousands of different SKUs to be handled simultaneously. There is no need to reduce the set of SKUs to be managed (unlike what was done in the case study reported by (Stoll et al., 2015)), and for each SKU the optimal deployment policy is established. Overall, the weaknesses and barriers for the application of ABC DAD approaches highlighted by (Stoll et al., 2015) are overcome. However, as a disadvantage, it considers fewer analysis criteria, looking at demand, the historical number of orders, and the cost of items. Moreover, it resulted in higher average inventory and number of orders, while also promoting higher *RL* and *EOQ* values, larger purchase batches, and more sporadic orders. Both approaches turned out satisfactory in respect to the initial (decentralized) situation. Indeed, they showed improvements in terms of average stock (and inventory cost) and the number of orders, while maintaining the desired service level (95%). The results of this article can be useful to support the staff of a multi-warehouse company in their complex decision-making processes related to distribution network configuration and procurement management. First, based on (Gregersen and Hansen, 2018), the company can identify its optimal degree of centralization. Therefore, based on this index, it can select the best ABC DAD approach, preferring the literature one to obtain centralization or the derived one in the other case. Since the literature does not offer many studies comparing different DAD techniques, this article lays the foundation for future studies. In this perspective, future analyses could compare the results of the two approaches here described with other methods, even non-heuristic ones. Finally, other future steps of this research could be to apply the approaches to a company producing spare parts to see if the considerations about the results change; and to evaluate the transport costs related to transshipments between depot and bases and the delivery to final customers, which were not considered here.

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