Improvement of logistical processes in a medical equipment warehouse based on a multicriteria ABC classification:
a Case Study of a Technical and Scientific Organisation

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Keywords: SKU, ABC classification, VED analysis, XYZ classification, Analytic Hierarchy Process (AHP), service level and inventory management policies.

Abstract: The company under study is technical and scientific organisation that sells equipment for laboratory, scientific research and industrial quality control. It operates with a wide range of business segments and different products and provides technical assistance services for its customers. The main goal is to develop a multicriteria classification model to give support in the formulation of differentiated stock management and control policies for each SKU (Stock Keeping Unit) in order to maximize the service level provided by the company under analysis and to minimize both inventory holding costs and the loss generated by an insufficient inventory management system. The company handles an extensive number of SKU and it's extremely difficult to define which SKU to keep in stock, in what periods, and how much to ensure that is available from each one. For that purpose, and for the development of the multicriteria classification model, three key criteria were defined: sales volume, criticality and demand variability. Regarding the second criterion, it's divided into three subcriteria: lead time, lead time variability and number of suppliers. A multi-methodology was built to create a multicriteria classification model. This classification model is based on a tradicional ABC classification, on a criticality analysis (VED) and on an XYZ classification that measures the demand variability. In order to solve the multicriteria problem, the Analytical Hierarchical Process (AHP) was used to obtain the criteria weights and the global score for each of the thirty two SKU and, finally, divided the SKU by the three different categories. .

1 INTRODUCTION

Technological equipment retail companies constantly deal with inventories that can contain thousands of articles. Nevertheless, the resources available to maintain them are often limited. In order to gain operational effiency in managing inventory, one must try to use the resources in the best possible way. (Hatefi et al., 2013)

The management of spare parts, for the purpose of preventive or corrective maintenance of integral equipment, contributes considerably to the total revenue and sales volume of the modern organizations. However, according to (Hu et al., 2017), this management is often neglected for the management of final produtcs. This results in the adoption of undifferentiated management techniques for spare parts from those used for final products.

Also, the cost associated with the lack of certain spare part generally imples losses in terms of quality of the service provided, which are difficult to quantify. The risk associated with the lack of a certain spart part also entails associated costs that are not easily determined. For some type of SKU, namely spare parts for corrective maintenance purposes, their lack in inventory implies a high cost which justify an increased attention.

According to (Teunter et al., 2010), there are many companies that use the ABC classification, based on sales volume, to group SKU into different categories. For each category, management strategies are defined and basic requirements and service levels are stipulated according to the importance of each category.

However, for the company under study, it makes sense to consider other criteria besided the typical sales volume. In the present paper it was considered a criticality analysis (VED) and a demand variability classification (XYZ). For the purpose of the resolution of the multicriteria problem, the Analytical Hierarchical Process (AHP) tool used with the support of the decision makers envolved in the development of the model in order to set criteria and weight them.

2 LITERATURE REVIEW

In the last few decades, the management of spare parts has gained a great interest in reseracher operating in this area.

Due to the ambiguous tendency of the spare parts characteristics, their careful and thorough classification is considered to be a viable solution for the correct and appropriate development of management policies of different materials in an industrial context. (Molenaers et al., 2011)

It is important to mention that the quality of the logistics inherent, mainly in the spare parts field, plays a crucial role in regard to increasing the service level in retail industries of this kind of stock materials. On one hand, spare parts must be provided at a reduced cost, on the other hand they must be highly available. While the unavailability of spare parts causes interruptions in industrial processes, excess stock generates high inventory holding costs. (Lanza & Behmann, 2011)

To remedy these shortcomings in terms of spare parts management, and according to (Cavalieri et al., 2008), the management process can be organized following different stages: identification of spare parts, through partial coding and SKU classification; forecasting requirements for spare parts (e.g. demand volume); identification and development of stock management policies and systems for inventory control; testing policies adopted in order to achieve continuous improvement in terms of global performance and service level.

The application of classification frameworks as tool for inventory management is a very popular and common approach in the industrial world. The ABC classification, which follows the Pareto principle, is the best known and applied to adress these kind of issues. (Çelebi et al., 2008)

APICS (American Production and Inventory Control Society) defines the ABC classification according to the following guideline: "The classification of a group of items in a decreasing order of annul purchase cost value or other relevant criteria. Therefore, SKU are divided into three different categories, called A, B and C. (Cox & Blackstone, 2008)

It is important to mention that, in the traditional ABC analysis, there is a widely exposed prespective that is based on the Pareto principle. Basically, stating that 80% of total annual revenue comes from only 20% of the total number os SKU. This rule logically implies that the number os SKU inserted in category A corresponds to the smallest fraction of the total number of SKU handled by the companies.

However, with the increase in demand for a wider range of products, one should increase the variety of inventory articles. (Rezaei & Dowlatshahi, 2010) The characteristics and attributes of the spare parts may differ from one another, in terms of other parameters, so the ABC classification model may prove to be insufficient. Despite a certain article has a high purchase cost, its demand can be punctual or predictable. Also, criticatlity associated to a spare part is widely addressed in literature and a clear understanding of the concept dependes directly on different factors and, therefore, it's difficult to measure criticality in a consensual, uniform and transversal way across all organizations. (Molenaers et al., 2011)

For instance, according to (Roda et al., 2014), spare parts whose stock unavailability results in serious consequences for a certain production center, both from an operational and generating losses point of view, are considered critical by maintenance activities. On the other hand, from a logistical prespective, other parameters should be considered such as storage and operating costs when delevoping management policies. Some examples of criteria that are used in criticality assessment are presented: lead time, production failure, quality problems, consumption rate, price, substituiability, communality, number of suppliers.

The criticality analysis that is carried out in these contexts depends on a wide range of criteria. The negative impact of the unavailability of a certain spare part can be considerably more relevant than its commercial value. A spare part that is needed immediately, that is out of stock, causes issues regarding criticality concept. The lead times associated may or may not be able to address the problem in time. (Huiskonen, 2001).

Many autors apply the VED ("Vital"; "Essential"; "Desirable") analysis to tackle criticality classification. In this model, the "Desirable" category indicates that a certain part will have a preferential overall performance when evaluated in terms of criticality based on a certain criterion. The opposite is true for the "Vital" category. (Roda et al., 2014) Exemplifying, in term of lead time, the ideal scenario and, therefore, "Desirable" for a certain part is that it can be supplied immediately. The lead time becomes "Essential" if it the spare part is only supplied, for instance, in two weeks. In the case that the lead time adopts an extremely high value, it makes this spare part "Vital" for the company. (Roda et al., 2014)

Additionally, other criteria should be considered in the development of a framework to classify spare parts, resulting in a multicriteria model. For instance, production and distribution methods based on demand variability provides tools to improve operational efficiency. It also becomes possible to optimize service levels, while keeping inventories at a minimum, and stock levels can be defined based on this demand profile. (Bacchetti & Sacanni, 2012)

As said before, considered just on criterion results in a insufficient approach to address spare parts classification. In that sense, several authors have used AHP as a methodoly to support VED analysis in which are considered multiple criteria. (Braglia et al., 2004) An evident advantage lies in the possibility of considering multiple criteria, both qualitative and quantitative, in order to describe and quantify levels of criticality as the basis for the SKU classification. Through weighting and hierarchy of criteria, AHP provides a realistic representation of the decision-making problem. (Saaty, 1980)

The AHP method is proposed to solve multicriteria problems. The hierarchical analytical proves is based on expert judgements and peer comparisons, assigning weights to different attributes. The decision makers must determine which criteria and alternatives are most important. It is also important to mention that one must identify differences in terms of importance of the elements under analysis based on a ratio scale and respective representation in a judgement matrix. (Molenaers et al., 2011)

3 RESEARCH METHOD

This work combined action research with a case study in technical and scientific organisation in Portugal. This approach had the main objective of supporting a more structured approach in classifiying SKU in order to develop management policies and inventory control systems.

Due to difficulties in spare parts management, namely the perceived misalignment between purchasing strategies and corrective maintenance activities, the decision makers involved in the process were invited to define the fundamental criteria that should be inserted in the multicriteria classification model.

The company under study, and its success, depends directly in how the spare parts are classified and managed. It's necessary to emphasize, once again, the importance of inventories of spare parts, which is based on the responsibility of assisting corrective maintenance and repair activities, ensuring that certain equipment is in constant operating condition. (Roda et al., 2014)

Given the mentioned responsibility, and according to (Bošnjaković, 2010), countless questions arise regarding spare parts management, such as: "Should a company ensure that all spare parts are available in stock?"; "How much to order from the supplier and when?"; "How many units of each spare part should be in stock?". In short, the critical problem facing by the company under analysis lies in the uncertainty associated with the corrective maintenance activities, as it is unknown when they will be requested by a customer and what quantities of a certain spare part will be required. This results in a decrease in the service level and the quality of the response to orders and requestes for technical assistance.

The research process required close collaboration between the decision makers and several sessions were held for data collection, criteria definition, development and results validation. In the sessions, the warehouse controller, the responsible for the purchasing department and the technical assistance manager had equal weight in decision-making processes in order to evaluate the alternatives (SKU) under the previously defined criteria.

The list of spare parts handled by the company is extremely large, so the multicriteria classification model considered thirty-two SKU classes. Thus, an ABC analysis was carried out to classify the importance of SKU by sales volume.

Additionally, a criticality analysis (VED) was carried out too in order to evaluate the SKU taking into account three subcriteria: lead time, lead time variability and number of potential suppliers. Also, since the demand volume for each SKU is extremely heterogeneous, the decision makers considered that a third criterion should be inserted in the multicriteria model: demand variability that follows a XYZ classification based on varitation coefficient.

To solve the multicriteria problem, as said before, the AHP was used to obtain the criteria weight and a overall score for each SKU. Lastly, it was possible to divide the thirty-two SKU into three different categories, according to the overall performance in the developed model.

4 ANALYTICAL HIERARCHICAL PROCESS APPLICATION

To apply the classification model is required the use of a multiple criteria decision-making tool, which is essential in problem-solving characterized by various actors, criteria, and objectives (Kumar et al., 2017). These tools' main goal is to support decision-makers as there is usually not only one optimal solution for problem-solving, and it's required to differentiate existing solutions (Saaty, 1980).

AHP is a technique that supports reducing the uncertainty in subjective evaluations (Saaty, 1980). Complex decision making needs the establishment of different "trade-offs" between criteria. The decision elements are compared with each other and weights assigned to define the priorities in the decision-making process (Ramanathan, 2006)

Table 1 – SKU classes and designation.

SKU class	Designation
1	Spare parts for climatic chambers
2	Diverse solutions
3	Diverse weights
4	Batteries/electric spare parts
5	Electric components Memmert
6	Universal components Memmert
7	Incubation material
8	Small engines
9	Water bath
10	Refrigerator spare parts
11	Weighting spare parts/calibration
12	Thermogenesis bags
13	Thermogensis spare parts
14	Freezing spare parts
15	Memmert spare parts (>dimension)
16	Memmert valves
17	Memmert spare parts (<dimension)
18	IT spare parts
19	Mugs
20	Tinius Olsen Load cells
21	Tinius Olsen spare parts
22	Laboratorial material
23	Measure equipment %H2O/CO2/PH
24	Regrigerator equipment
25	Rubbers/seals/support spare parts
26	Piping climatic chambers spare parts
27	Vital solutions
28	Resin
29	Biological material
30	Diverses
31	Lasers
32	Traction/Elongation spare parts

In the present work, an AHP model with four levels gives support to the development of the multicriteria classification model (Figure 1).

At Level 1, the main goal provides the overall score for each SKU in terms of three criteria that were considered determinant to evaluate the alternatives. The criteria that the experts give as input for the model for measuring the performance of each SKU are located at Level 2 and they are: sales volume, criticality and demand variability. Level 3 contains the rating scale for measuring and evaluate each SKU in each criterion. Finally, Level 4 includes de alterantives themselves, that are thirty-two families of SKU.

In order to calculate the relative weight of the criteria, pair-wise comparisons based on a "1 to 9" relative importance scale were utilized (Table 2). To score each alternative (Family of SKU) for each criterion, a direct measurement was performed, which is an advantage over pair-wise comparisons, which would require a high number of comparisons. (Thomas L. Saaty Katz, 2008) Also, the AHP was used two times, one to solve the multicriteria problem associated with the three subcriteria of criticality. Second, to address the multicriteria problem that results from the estipulation of three fundamental criteria: sales volume, criticality and demand variability.

The company aims to develop management and inventory control policies according to the results of the multicriteria classification model.

4.1 Criteria selection and rating

The selection of the criteria to evaluate the alternatives in the multicriteria classification model has been a hard task to accomplish. However, this work relied on the experts experience and knowledge in order to select the criteria that better evaluate the SKU and to create a respective assessment scales.

From criteria found in the multicriteria models available in the literature, experts selected a set of three criteria as appropriate for classifying the SKU.

Sales Volume (ABC Classification)

The first criterion is based on sales volume (in Euros), whether obtained by direct sales or by corrective maintenance activities and the SKU are classified according to an ABC classification.

It is a frequently used criterion (sometimes it's considered the purchase volume) and has a considerable impact to the company as the SKU classes have extremely different selling prices. (Cavalieri et al., 2008)

The distribution of the thirty-two SKU was performed following the Pareto Principle, already presented before. To complete the definition of the first criteria, the experts were requested to develop a rating scale based on the category A, B or C (Table 3). It is an evaluation scale in which is given to the category A the maximum score, due to its substantial importance in terms of sales volume generated for the company. Regarding those SKU that belong to category B and C, they are assigned 70% and 20% of the maximum score (1), respectively.

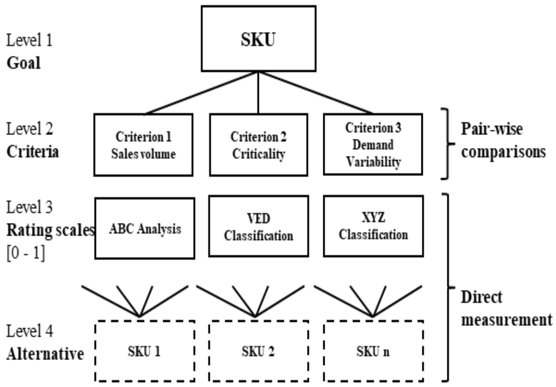

Figure 1 – AHP model for the multicriteria classification model development (adapted from (Thomas L. Saaty Katz, 2008))

Table 2 - Pair-wise comparisons "1 to 9" scale for AHP (adapted from Saaty (2008)).

Intensity of importance	Definition	Explanation
1	Equal importance	Two criteria contribute equally to the objective
3	Moderate importance	Experience and judgment slightly favor one over another
5	Strong importance	Experience and judgment strongly favor one over another
7	Very strong importance	A criterion is strongly favored, and its dominance is demonstrated in practice
9	Absolute importance	The importance of one over another recognized unassailably.
2, 4, 6, 8	Intermediate values	Used to represent a compromise between the priorities listed above
Reciprocals of above	If criterion *i* has one of the above non-zero members assigned to it when compared with criterion *j*, then *j* has the reciprocal value when compared with *i*.	

Table 3 – Criteria score scale of the Sales Volume (ABC classification)

Category	Score
A (15% total SKU)	1,00
B (30% total SKU)	0,70
C (55% total SKU)	0,20

Criticality (VED analysis)

In the criticality criterion were considered three subcriteria, namely: lead time, lead time variability and number of potential suppliers that are able to supply a certain SKU.

For classifying the SKU into the three VED categories, was necessary to develop evaluation scales for each subcriterion that are presented in Table 4, Table 5 and Table 6.

The first subcriterion, experts agreed that the 'leadt time' is key, since, the company deals with a large range of suppliers that are geographically spread around the world. The second, 'lead time variability' was chose because the company struggles to predict how much long it will take since the first contact with the supplier and the arrival of the goods at the warehouse. Finally, 'number of suppliers' had to be considered since many SKU are supplied by multiple entities, while other are supplied by a single entity.

Table 4 – 'Lead time' Evaluation scale

Lead time (nºdays)	Category VED
$\leq 10\ days$	Desirable (D)
$> 10\ days\ and \leq 30\ days$	Essential (E)
$> 30\ days$	Vital (V)

Table 5 – 'Lead time variability' Evaluation scale

Lead time variability (%)	Category VED
$\leq 10\%$	Desirable (D)
$> 10\%\ and \leq 65\%$	Essential (E)
$> 65\%$	Vital (V)

Table 6 – 'Number of suppliers" Evaluation scale

Lead time variability (%)	Category VED
$> 3\ suppliers$	Desirable (D)
$> 1\ supplier\ and \leq 3\ suppliers$	Essential (E)
$1\ supplier$	Vital (V)

Important to mention that, like the first criterion, the VED categories were converted into a numerical scale. To SKU classified as 'Vital' was given the maximum score of 1. Categories 'Essential' and 'Desirable' were assigned 60% and 20% of the maximum score, respectively.

Demand variability (XYZ classification)

Regarding the demand variability, there are four types of variability structures according to (Çelebi et al., 2008): steady demand that refers to items with constant demand from one period to next; trend demand, that indicates that the demand is increasing or decreasing with a constant rate of change; items with a variable demand structure but with a repeating pattern are grouped under seasonal demand; finally, items with a discontinuous and nonuniform demand structures are grouped under lumpy category. For the company under analysis, two types of demand structure are identified, namely seasonal demand and discontinuous demand.

In order to quantify the variation observed regarding demand, the calculation of the variation coefficient (CV) is carried out. Then, an evaluation scale is defined to assign one of the categories of the XYZ model. The scale is presented in Table 7.

Table 7 – 'Demand variability' Evaluation scale

Demand variability (%)	Category XYZ
≤ 25%	Z – Best outcome
≤ 75%	Y – Intermediate outcome
> 75%	X – Worst outcome

Once again, like the preivous criteria, the XYZ categories were converted into a numerical scale. To SKU classified as 'X' was given the maximum score of 1. Categories 'Y' and 'Z' were assigned 70% and 20% of the maximum score, respectively.

4.2 Criteria Prioritization

The next step was determining the relative weights of each criterion, which must reflect their "importance" in the multicriteria classification model. For calculating the weights, the pair-wise comparisons inherent in the AHP application were carried out as a team exercise in sessions with the decision makers involved in the process. The final results were reached by consensus and can be found in Tables 8 and 9.

The development of the multicriteria classification model faced the need to apply AHP method in two nodes of the decision diagram. First, to calculate the relative weights for the three criticality subcriteria. Then, to determine the relative weights of each criterion and to obtain the final score for each class of SKU.

It turns out, as expected, that the most relevant subcriterion for the company is the 'lead time'. It obtained the maximum weight, 69.6%, since the company deals with multiple suppliers located geographically spread around the world, many of which fail to ensure a fast and efficient shipping and delivery service. Secondly, there is the subcriterion 'lead time variability' which has a weight of 22.9% and translates into how the lead time vary for each class of SKU. Finally, not so important, the subcriterion 'number of suppliers' apperars with a weight of 7.5%. This outcome would be expected since, for the decision makers, the number of suppliers available doesn't have as critical impact as the other criteria, expect logically the case where a SKU is only supplied by one entity.

The consistency ratio (CR) for the criticality subcriteria is 8.0%, which is acceptable once it is less than the threshold of 10% (Saaty, 1980).

Table 8 – Relative weights of the subcriteria (criticality criterion)

Criteria	(1)	(2)	(3)	Weight
(1) Lead time	1	4	7	69.6%
(2) Lead time variability	1/4	1	4	22.9%
(3) Number of suppliers	1/7	1/4	1	7,5%
Consistency Ratio (CR) = 0,080				

Table 9 – Relative weights of the major criteria

Criteria	(1)	(2)	(3)	Weight
(1) Lead time	1	2	7	59.2%
(2) Lead time variability	1/2	1	5	33.3%
(3) Number of suppliers	1/7	1/5	1	7,5%
Consistency Ratio (CR) = 0,015				

Concerning the three fundamental criteria, and using the AHP mehod once again, it's possible to obtain the relative weights for each one: 'sales volume'; 'criticality' and 'demand variability'. Then, the criteria mentioned are compared in order to obtain their relative weights. The most important criterion is the 'sales volume', so it obtained the maximum weight of 59.2% since the company manages SKU that are quite different in terms of commercial value. The partial or total lack of a certain SKU has an intense and direct impact on sales volume generated by the company. Secondly, there is the criterion 'criticality' which has a weight of 33.3%. Finally, and not so important, there is the 'variability demand' with a weight 7.5%.

In the major criteria AHP analysis, CR is 1.5%, which is an acceptable value once it is less than 10%. (Saaty, 1980)

5 RESULTS AND DISCUSSION

Once the criteria and prioritization of of their weights have been defined, the next step is to classify all thirty-two classes of SKU using the Pareto principle for the ABC classification and the rating scales presented in the Tables 4-7 for the VED analysis and XYZ classification. Then, for each SKU, a numerical score was assigned according to the category obtain in the three criteria and the final score was calculated to split the SKU into the three categories of the multicriteria classification model: A final, B final and C final.

After accounting for the weights of the subcriteria defined for the criteria 'criticality' it was possible to obtain the global score for the VED analysis according to the Equation (1).

$$VED\ score = \sum_y Subcriterion\ weight_y \times SKU\ score_y \quad (1)$$

The equation (1) is nothing more than a multiplication of the numerical score (1; 0.6 or 0.2) obtained according to the category by the weight of the corresponding subcriterion. Thus, the variable y can be any one of the subcriteria considered; 'Lead time', 'Lead time variability' and 'Number of suppliers'. The major results are presented in Tables 9-11.

Table 9 - Results for subcriterion 'Lead time'

	Vital	Essential	Desirable
N. of classes	16	16	0

Table 10 - Results for subcriterion 'Lead time variability'

	Vital	Essential	Desirable
N. of classes	11	17	4

Table 11 - Results for subcriterion 'Number of suppliers'

	Vital	Essential	Desirable
N. of classes	19	9	4

Then, according to the numerical score obtained for each subcriterion, it was possible to calculate the final VED score, through Equation (1), to insert in the multicriteria classification model.

Regarding the ABC classification, the main results are presented in the Table 12.

Table 12 – Results for criteria 'Sales volume'

	A	B	C
N. of classes	5	10	17

Finally, with the XYZ classification it was possible to distribute all classes of SKU into the three categories considered. The main results can be found in Table 13.

Table 13 - Results for criteria 'Demand variability'

	X	Y	Z
N. of classes	29	2	1

By analyzing the results obtained through the XYZ classification, it is easily verified that twenty-nine of the thirty-two classes of SKU have benn placed in category X, since the coefficient of variation calculated for them adopts very high values.

For the purpose of developing inventory control and management policies, was consensual for the decision makers that any of these classification, ABC, VED and XYZ, by itself, would not serve as a definitive classification tool for the company. In that sense, and using the AHP, it was possible to obtain the relative weights os each criteria and then the overall scores for each of the thirhy-two classes of SKU. For the calculation of the global score and consequent insertion in one of the final categories, the equation (2) was applied.

$$Final\ score = \sum_x Criterion\ weight_x \times SKU\ score_x \quad (2)$$

This equation (2) is nothing more than a multiplication of the numerical score obtained by each class of SKU in each of the criteria considered by the weight of the corresponding criterion. The final score is the the multicriteria model score based on the three parameters. Thus, the variable x can be any of the three criteria: 'Sales volume'; 'Criticality' and 'Demand variability'.

The main and final results are presented in Table 14.

Table 14 – Classification of classes of SKU through multicriteria classification model

Class of SKU	Partial scores			Final score	Final category
	ABC (0.592)	VED (0.333)	XYZ (0.075)		
5	1	1	0.91	0.99	A
13	1	1	0.91	0.99	A
24	1	1	0.63	0.97	A
1	1	0.7	0.97	0.90	A
6	0.7	1	0.91	0.82	A
7	0.7	1	0.91	0.82	A

Class of SKU	Partial scores			Final score	Final category
	ABC (0.592)	VED (0.333)	XYZ (0.075)		
10	0.7	1	0.91	0.82	A
14	0.7	1	0.88	0.81	A
15	0.7	1	0.82	0.81	A
18	0.7	1	0.72	0.80	A
27	0.7	1	0.60	0.79	B
29	0.7	1	0.60	0.79	B
31	0.7	1	0.54	0.79	B
32	0.7	1	0.26	0.77	B
12	1	0.2	0.91	0.73	B
2	0.3	1	0.94	0.58	C
3	0.3	1	0.94	0.58	C
8	0.3	1	0.91	0.58	C
9	0.3	1	0.91	0.58	C
11	0.3	1	0.91	0.58	C
16	0.3	1	0.82	0.57	C
17	0.3	1	0.72	0.56	C
19	0.3	1	0.69	0.56	C
20	0.3	1	0.69	0.56	C
21	0.3	1	0.69	0.56	C
22	0.3	1	0.66	0.56	C
23	0.3	1	0.66	0.56	C
25	0.3	1	0.63	0.56	C
26	0.3	1	0.63	0.56	C
28	0.3	1	0.60	0.56	C
30	0.3	1	0.60	0.56	C
4	0.3	0.7	1.00	0.49	C

After the distribution obtained according to the ABC classification, the VED analysis and the XYZ classification, the global results panorama in terms of category shifts are shown in the Figure 2.

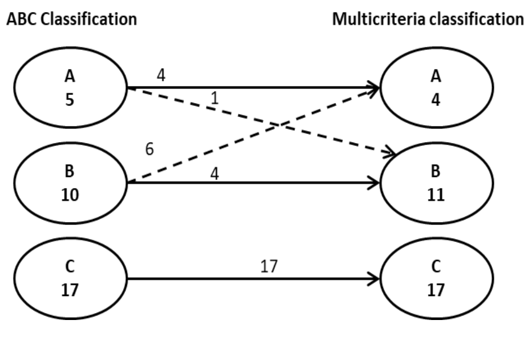

Figure 2 - ABC classification results versus Multicriteria classification results

By analyzing the results obtained after applying the multicriteria classification model there were some major changes. Six classes that, according to the ABC classification, belong initially to category B started to integrate the final category A, the most important for the company in terms of spare parts management. It also should be noted that, after applying the multicriteria model, the opposite also occurred for a classe of SKU that passed from category A, according to traditional ABC classification, to the final category B.

These movements between the ABC classification categories and the multicriteria categories are in accordance with the results reported in the literature. For example, (Flores et al., 1992) noted that two SKU that initially had been classified as A, according to the tradicional ABC classification, started to integrate category B. On the other hand, six SKU that were classified as B become part of the most important category, A. (Balaji & Kumar, 2014), after applying the multicriteria model, also obtained results quite different from those obtained initially, since ten SKU that were classified as B then, after running their multicriteria model, were insered in category A. On the other hand, two SKU initially classified as A, were introduced in the category A of the multicriteria classification model.

It should be mentioned that the usefulness of the multicriteria classification model developed for the company under study is not only related to the conclusions drawn from the overall scores obtained, but also individually, criterion by criterion. An example of this is the five classes of SKU belonging to the final category B, but which are vital in terms of criticality and have extremely oscillating demand. These fice classes undoubtedly deserve more attention when compared, for instance, with the remaining seventeen classes members of the final category C.

Additionally, six classes of SKU would be underestimated if only the traditional ABC classification was applicated, since they were integrated in category B. However, the multicriteria model showed that, despite not having sale volumes as high as the other five classes classified as A by the ABC classification, that six classes are critical to the company for which they were inserted in the final category A of the multicriteria model. On the other hand, if the company only considered the reslust obtained through the ABC classification, would be considering the class of SKU n.12 as deserving of the higher level of importance (category A). Nevertheless , after applying the multicriteria model this class of SKU was classified as B.

Finally, it is also necessary to adopt a critical approach and carry out a review of the results for the SKU classes which, despite not having been inserted in the final category A, obtained considerably high scores. Are examples of this the classes 27, 29 and 31 (final score 0.79). For that reason, even showing sales volumes not as high as the classes classified as A according to the multicriteria model, should be managed with more proximity and control. So, when formulating inventory control policies and monitoring and management strategies, definition of safety stock levels, or stipulation of any other parameter, these three classes must be approached and analyzed closely.

6 CONCLUSION

The present study carried out showed, in first instance, the complexity and operational effort associated with the control and management of spare parts in inventory. The way in which SKU are managed, and the effiency of those management strategies, substantially influence the sales volume generated by companies and the service level provided to its customers.

The kind of spare parts sell by the company differ form each other in terms of specificities, sale price, volumes requested, supply opportunities, among other parameters. Nowdays, the way companies manage and deal with this kind of inventory articles is decisive for the quality of corrective maintenance services offered by the company.

In order to overcome the problems that arise from the current insufficient control inventory system and from the fact that there are no policies and strategies according to the importance of SKU, together with the decision makers, a multicriteria classification model was developed. First, to divide the SKU into categories, according to a set of relevant criteria. And, therefore, to adjust the existing inventory management policies to the specificities of each class of SKU.

Then, a SKU classification tool was created based on three criteria considered by the decision makers as determinants in an inventory classification problem of this nature. They are the 'sales volume', 'criticality' and 'demand variability'. The second one is based on three distinct subcriteria: 'lead time', 'lead time variability' and 'number of suppliers'. Since the company is dealing with multiple criteria, in order to solve the multicriteria problem, the AHP was used to address the two nodes of the decision diagram.

Despite the complex scenario experienced by the company taking into account the large number of inventory items that the company has to manage and deal, it is clear that a classification system based on multiple criteria is a crucial tool for contemporary organizations. On one hand, from a more particular prespective, this kind of model will contribute continuously to operations optimization, as it can always be updated as needed. On the other hand, and considering the limitations in terms of stock management, the company can use this model to define inventory control strategies and focus the attention on the ten classes belonging to the final category A that should be controlled on a daily basis.

For these, minimum stock levels must be maintained and constantly reviewed, depending on the average quantity ordered, demand variability profiles, number of suppliers. For the classes inserted in the final category A, should be taken into account the various parameters considered in the multicriteria classification model and not only the final result.

Additionally, since the company's warehouses need physical and organizational restructuring, the model created could serve as a basis for that purpose if other criteria were considered, such as inventory turnover number, dimensions and weight of spare parts, or other relevant criteria. Thus, it is possible to define physical regions for SKU to be stored according to relevant criteria.

Finally, there was a consensus on the applicability of the mulitcriteria classification model and the quality of the results obtained, in terms of optimizing the logistics activities and increasing stock management quality.

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