Hindawi
Journal of Engineering
Volume 2023, Article ID 7661628, 11 pages
https://doi.org/10.1155/2023/7661628

Research Article

Fuzzy AHP TOPSIS Methodology for Multicriteria ABC Inventory Classification

Andrés Mauricio Paredes Rodríguez,[1] **Juan José Bravo Bastidas**,[2] **Juan Carlos Osorio Gómez**,[2] **Diego León Peña Orozco**,[1] **and Jesús González Feliu**[3]

[1]*Department of Industrial Engineering, Corporación Universitaria Minuto de Dios, Buga, Colombia*
[2]*School of Industrial Engineering, University of Valle, Santiago de Cali, Colombia*
[3]*Supply Chain, Purchasing and Project Management, Excelia Group, La Rochelle, France*

Correspondence should be addressed to Andrés Mauricio Paredes Rodríguez; andres.paredes@correounivalle.edu.co

Received 16 September 2023; Revised 10 November 2023; Accepted 16 December 2023; Published 22 December 2023

Academic Editor: Natt Makul

Products' classification according to their importance has been a topic addressed by academia and industry for many years, mainly due to the great importance of this process to obtain efficient inventory policies that reduce lost sales while reducing inventory maintenance costs. This research has to perform an ABC inventory classification in a medium-sized company that sells hardware goods and construction materials, considering multiple quantitative and qualitative criteria. AHP fuzzy TOPSIS multicriteria tool was used as a methodological approach which implies the definition and initial weighting of a set of relevant criteria for the study based on the AHP fuzzy methodology, to obtain an inventory products' importance assessment according TOPSIS technique procedure. After applying the technique, it is possible to obtain that 0.26% of the inventory was classified as highly critical. Likewise, 5.45% represents products of medium relevance to the organization. Finally, it is observed that many of the products (approximately 94%) have little or almost no impact within the company under study. This methodology was used in a practical case where some criteria were taken from the reviewed literature. In addition, the criticality criterion was used from a financial perspective.

1. Introduction

In today's global competitive business environment, companies develop tools to support the decision-making process [1–3], looking to anticipate that different situations may affect their performance in market [4–6]. Logistics decisions in organizations have a direct influence on profitability and competitiveness, so mechanisms must be established to ensure effective decision-making [7]. Inventory management is one of the most important logistic decisions in companies [8], which has led to the detailed study of different policies that guarantee an efficient administration of this resource.

The products' ranking establishment according to their importance has helped companies get greater efficiency in managing focusing efforts on the most representative items into the inventory. One of the most widely used schemes for prioritizing products in an inventory is known as the ABC analysis [9], which is carried out in two ways: with a single criterion or with multiple criteria. The traditional ABC classification, which only considers the sales volume criterion, has as its main limitation the fact that the items to be analyzed must be homogeneous with each other, which in reality is not always true [9]. For this reason, authors such as [10–12] affirm that traditional ABC analysis is not recommended in practice. In other words, monocriterion ABC analysis based on sales or stock levels only does not always fit the service goals or required product classification. In this sense, a more suitable problem structuring is required to transform those goals into a representative decision problem to solve [13, 14]. On the contrary, multicriteria methods have as their main advantage the assessment of the importance of a product through multiple quantitative and qualitative criteria such as delivery time, product criticality, durability, and the size of the order, among others [15]. A search carried out in the Scopus database about research works in ABC multicriteria allows us to observe a growing trend on this field in the last 50 years, which is increasing since 2006 (Figure 1), which validates its importance and impact worldwide.

To enhance the robustness of ABC analyses, mathematical programming models proposed to choose and validate a set of criteria used in prioritization. They are made up of linear or nonlinear optimization models that seek to maximize the performance of each item through a weighted score [16]. The author in [9] was the first to develop a multicriteria ABC classification model with linear programming. Furthermore, the authors in [17] propose a mixed integer linear programming model with multiple objectives: to optimize the number of inventory groups, their service levels, and the allocation of products to each group, under a limited inventory expense budget. The model was tested in real life, obtaining better results than the traditional ABC classification. As an extension of the previous work, the authors in [18] develop a mixed integer linear programming (MILP) model that integrates the problem of inventory classification and control in a multiperiod environment with a nonstationary demand. The proposed model aims to maximize the net present value (NPV) of earnings subject to an inventory budget constraint for each period.

To those, can be ascribed the heuristic and metaheuristic methods contribution to evaluate products, considering the interaction among criteria. However, the number of criteria in these models is limited, and it is not recommended when there are qualitative attributes [19]. A hybrid algorithm is proposed in [20] that involve ant colony and bee swarm metaheuristics in order to perform an ABC classification. The model was used in a hypothetical case and yielded a performance comparable to the best results presented in the literature. Likewise, the authors in [10] present an ABC classification performed in the pharmaceutical industry based on the use of neural networks.

Both the mathematical programming models and the heuristic methods are based on objective and deterministic considerations, and the subjective, qualitative, and fuzzy aspects are not easily approachable. Multicriteria decision techniques incorporate human judgments, and it is possible to find contradictory suggestions regarding the products' classification which are induced by the heterogeneity in the measurement scales and factors (qualitative and quantitative aspects) [16]. The authors in [21] use TOPSIS technique to make an initial inventory classification, and then machine learning methods are employed to forecast the class of newly added inventory items and reclassify existing inventory. The author in [22] develops a hybrid methodology for inventory classification based on metaheuristics and TOPSIS technique. The authors in [23] propose an ABC classification using a multicriteria scoring method and define inventory policies based on a fuzzy strategy; a model is probed in a real multinational company.

One of the most widely used multicriteria decision methods is the analytic hierarchy process (AHP), which is mainly used when trying to qualify the importance of items through a subjective opinion considering criteria and subcriteria [9]. The authors in [19] use the AHP to determine the weight of the selected criteria, considering that criteria evaluation was performed with linguistic terms typical of fuzzy logic. The authors in [24] develop a hybrid AHP model where items not well valued or with a low AHP score on some criteria could end up being included in the best class since bad scores are compensated. Fuzzy logic is normally used to mathematically represent uncertainty and provide formal methods for dealing with it [25]. Additionally, fuzzy logic complements well with multicriteria tools such as AHP and TOPSIS [26]. In ABC classification, fuzzy logic is used to quantify qualitative criteria, which do not have an accurate measurement scale [27]. The authors in [15] develop an ABC-fuzzy classification, in which they include quantitative and qualitative criteria that are valued based on experience.

Currently, there is a research gap in regard with considering uncertainty in the multicriteria decision tools' application [28] combining fuzzy logic, AHP, and TOPSIS techniques. This research aims to answer this research gap. Likewise, the AHP fuzzy TOPSIS methodology is used in this work as a strategy to classify products within an inventory, considering quantitative and qualitative criteria. A process of criteria weighing using the AHP fuzzy method is initially considered to introduce the uncertainty. Then, an importance products' order is proposed using the TOPSIS technique. Those results show a potential improvement of ABC classification to have models closer to decision makers' goals, which can be expressed quantitatively or qualitatively. This research aims to generate a methodological framework to establish inventories' classification considering quantitative and qualitative criteria, which can be used by organizations.

To do that, it is important to propose bottom-up approaches. Indeed, since the aim of ABC classification models is to support tactical or operational decisions, their suitability and relevancy are strongly related to the field they are to be applied. Moreover, to represent the objectives of decision makers, it is necessary to know them and interact with those decision makers, and only field-related or case-related research allows doing it [29]. Therefore, it was chosen to focus on the hardware sector in Colombia for the following reasons. Hardware sector is a great driver in the Colombian economic activity. According to the National Merchants Federation in Colombia (FENALCO), 450 thousand jobs were generated in this industry and contributed 2.5% at GDP in 2019. In Colombia, 34,129 legally constituted companies are registered within this economic activity in the same year. According to the Colombian Confederation of Chambers of Commerce (CONFECAMARAS), 5,528 additional companies were registered in 2021.

As a result, having been posed by the COVID-19 pandemic challenges, where this country, like many others, had to resort to confinement, the need arose to assume virtualization as a strategy to maintain business activity. However, logistics processes' weaknesses were revealed, and some of them were related to the inventory large investment.

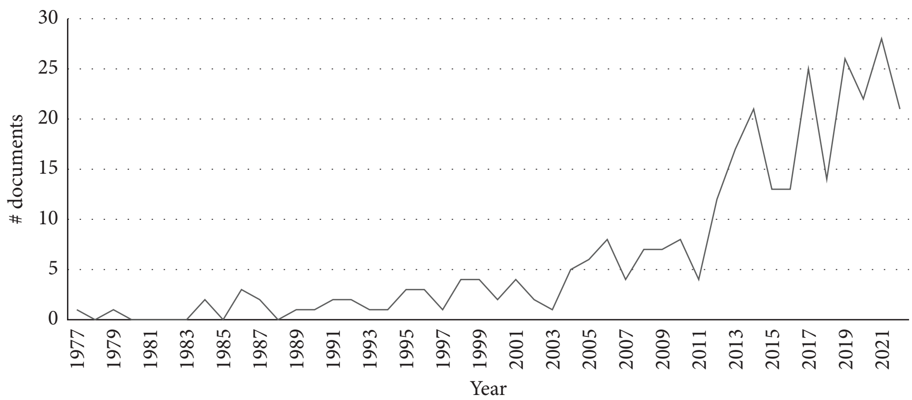

Figure 1: Evolution of research related to ABC multicriteria classification (the search was made in August 2022).

Goods without adequate rotation and its relationship with profitability become more sensitive in a restricted markets scenario and with supplier trade measures in payment condition terms have required organizations to focus on decision-making strategies to improve the inventory throughput. This is not a minor problem in a hardware store where thousands of items are handled, which must maintain a balance between availability and the service level wanted. In addition to strengthen the digitalization processes, it also became necessary to control the investment required in inventory.

A medium-sized hardware company taken as a case study in recent years has implemented a continuous review inventory policy (s, S) in order to reduce the negative effects generated by poor purchasing management. Some main causes in the supply management in the study case are related to the poor demand forecast systems' accuracy. The enterprise is made up of a central warehouse that supplies its own point of sale and different wholesale and retail customers geographically dispersed in its coverage area. However, the enterprise under study suffers from the most common problem in the inventory area, to have excesses of products with lower turnover and shortages of products with higher turnover. Company manages the moving average as only forecast system, assuming erroneously the same demand behaviour for all products in the inventory. In addition, a high supplier's delivery times' variability is identified, a great complexity factor because it depends on aspects that cannot be controlled by the company such as supplier production scheduling problems or dispatch planning. The above makes it very difficult to establish a safety inventory. Another important point is related to the effectiveness lacking in the inventory review system. In this sense, the company manages more than 18,000 references distributed among 150 suppliers, where the current policy involves an item-by-item inventory review, which makes it complex to generate a consolidated order and increases the risk of out-of-stock products. Although the company has a monocriterion ABC classification system (rotation by margin), type A products repeatedly present out-of-stock inventory. An additional complexity is the lack of knowledge from the purchasing staff about the company's storage restrictions. Warehouse capacity has a great impact on the logistics process because supplying products that occupies a space of 0.001 m^3 per unit is not the same as entering product in pallets that on average occupies 2.6 m^3 in storage area. The inventory saturation has generated damaged product estimated in eight periods taken as sample near at U$3,112 per month (See Figure 2).

Likewise, the excess product in warehouse generates congestion which causes greater setup times because the collection time depends on the route length, the product location, and the forklift speed. Finally, there is inadequate order consolidation to meet minimum order sizes. Approximately 55% of the products come from suppliers, whose policy is to issue a minimum order size either in packaging unit or minimum purchase value. Difficulty lies mainly in the product consolidation criterion absence since if the buyer staff does not make adequate item allocation, an excess inventory is produced, which translates into low turnover.

In this sense, it is necessary to develop tools to help the sector through the company, taken as a study case, improve in competitiveness and sustainability. The company addressed is supported by its logistics storage and distribution processes' management, where making adequate decisions about inventory management becomes crucial to be profitable. Tools such as multicriteria ABC, AHP, and TOPSIS allow the product prioritization availability, based on the market sensitivity measurement in terms of order-generating criteria and implication about making the decision on which products to keep in stock. All of this must be performed in the investment setting, profitability, and customer service level desired.

Nevertheless, the most frequent discussion in business scenarios has to do with the additional criteria that need to be considered when making the replenishment decision. These criteria should contribute to the inventory control policy, where it is possible to consider quantitative and qualitative aspects in making inventory decisions. For the company under study, it is relevant to explore the inventory policies' definition that involves these aspects, seeking to improve the customer service level and sales, which will be reflected in better income.

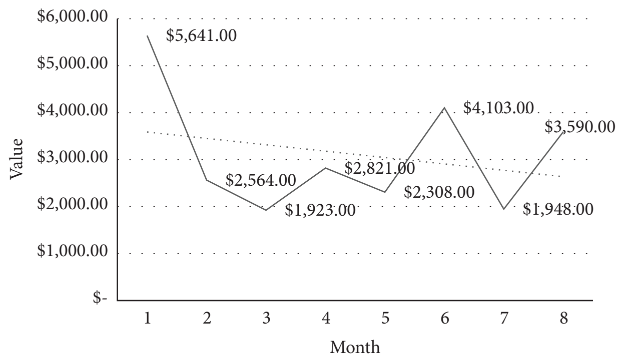

Figure 2: Damaged product costs per month expressed in American dollars.

This paper proposes a fuzzy multicriteria decision analysis (fuzzy-MCDA) methodology for inventory classification constructed using field data from the hardware industry and applied to a real Colombian company on that field. The novel used approach involves a combination of the fuzzy AHP strategy with the TOPSIS multicriteria method, implemented in a real case.

This document presents the methodology section, where an operational approach to the AHP, FUZZY, and TOPSIS tools is made, starting with conceptual definitions. Subsequently, a section of results and discussion is presented, where in a structured manner, the case study is described, the results obtained are analyzed once the methodology has been applied to the case study, and a generalization approach is made. This is performed considering that, in this country, medium-sized hardware companies maintain a similar profile. Finally, conclusions and future work are presented.

2. Methodological Framework

2.1. Problem Definition and General Methodology. Today, small and medium companies lack an inventory control system that allows for a timely supply of merchandise, so it is very common purchasing through intuition and generate an imbalance in inventories which means that there are many warehoused products with low turnover and there are out of stock of especially important references. One of the main causes of the inefficient inventory policy lies in the lack of prioritization of items within the inventory; therefore, this document proposes a multicriteria methodology to perform an ABC classification of the inventory.

The AHP fuzzy methodology has proven to be a tool with great potential when evaluating alternatives, taking into account quantitative and qualitative criteria in cases where there is high vagueness and uncertainty in the decision makers [30]. Some reference studies that show the application of the tool is [31] where the fuzzy analytical hierarchy process (FAHP) is used to classify the challenges identified for cloud-based external software development projects. In contrast, [28] integrates the AHP fuzzy methodology with TOPSIS seeking to assess the barriers to implementation of renewable energies in Iran. Also, the authors in [32] use AHP fuzzy TOPSIS with a novel fuzzy scale, where they selected an advanced manufacturing system and were able to conclude that this methodology is effective in managing uncertainty in decision-making and leads to solid and competitive results compared to conventional approaches: state-of-the-art multicriteria decision-making system. The AHP fuzzy methodology has the advantage over other similar techniques such as AHP or ANP because a linguistic scale is used for the criteria evaluation process, treating uncertainty present in the expert's decision in a much more convenient way.

In this research, an ABC multicriteria classification is carried out using the fuzzy AHP method combined with TOPSIS. The methodological framework is presented in Figure 3, where initially, a systematic literature review is conducted in different databases to identify those criteria most used in inventory classification. Keywords such as inventory, classification, and multicriteria decision methods are used as search equations. After this search, a criterion list is obtained to be analyzed in the company board. The influence that each criterion has in the inventory is evaluated through the survey. A Likert scale from 1 to 5, where 1 represents a very low importance and 5 a very high relevance, is used. Only those criteria that obtain 4 as an average value remain. However, at this stage, it is possible to add some specific criteria that are not considered in both previous search and research studies. Once a definitive criterion list is available, a decision hierarchy to use in the model is created, using a diffuse scale that allows uncertainty to be considered in the weighting process. It should be noted that four experts from the company were consulted, due to their experience and direct relationship with inventory decisions. After having the criteria final weighting supported in fuzzy AHP multicriteria tool, a decision matrix is built collecting information about each inventory item regarding the criteria defined previously. In addition, two classifications are used: the first considers the consolidated products in subgroups as a products line, in order to know line relevance within the total inventory and a second classification focused on the item's relevance within each subgroup or lines defined. In both scenarios, the TOPSIS multicriteria tool is used to obtain importance ranking subgroups and products. Subsequently, with the values obtained, once a technique is applied, a scale is established to determine the category of each subgroup and product. Those items and/or subgroups with a score higher than the 90th percentile would be considered product A, and category B would also be granted to those products or subgroups whose valuation is within the 50th and 90th percentile, and finally, the C category would be those that obtained a rating below the 50th percentile. As the last consideration in the proposed model, it is established that the most critical items will be both products and subgroups included simultaneously within category A.

2.2. Methodology for the Application of the AHP -FUZZY Technique. The analytical hierarchy process (AHP) was introduced by Thomas Saaty in 1970. This technique is mainly used when it is intended to qualify the importance of the items through a subjective classification of the criteria

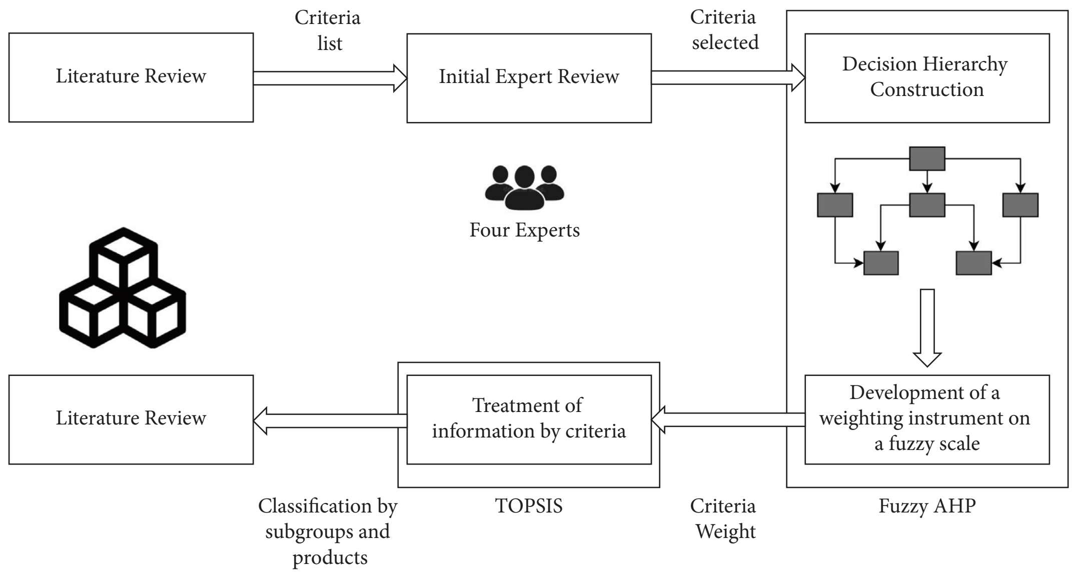

Figure 3: Methodological framework for the application of AHP fuzzy TOPSIS for inventory classification.

and/or subcriteria [9]. The authors in [19] use the analytical hierarchy to determine the weight of the criteria, considering that the evaluation of the criteria was carried out with linguistic terms typical of fuzzy logic. The authors in [24] develop a hybrid AHP model where items rated low on some criteria could end up included in the best class since poor scores are compensated.

Step 1. Definition of the decision criteria in the form of hierarchical objectives, where it is structured at different levels. It is necessary to consider that there is no limit to the number of levels that the hierarchical structure can contain.

Step 2. Evaluation of the decision criteria: in this phase, a series of experts on the subject are consulted, who must assess the importance of each criterion by making a paired comparison between the defined attributes. The AHP compares n elements, $C1, \ldots, Cn$, denoting the relative weight (priority or significance) of Ci with respect to Cj by the ratio aij. Such comparisons are in a square matrix of order n that must meet certain restrictions: $aij = 1/aji$, for i different from j and $aii = 1$ for all i

This section is where fuzzy logic is included since the AHP method traditionally uses the Saaty scale, but for a better understanding of the group of experts, a linguistic scale is usually built based on triangular fuzzy numbers that allows considering the uncertainty itself in the evaluations of the team that makes the decision.

Step 3. Evaluation of the consistency of the evaluations: it is necessary to guarantee that the expert's opinion is not biased or presents contradictory evaluations; for this reason, the consistency coefficient (CC) is calculated (see equation (1)), which is obtained from the comparison of the consistency of the matrix (IC) with the value obtained in a random matrix (IA)

$$CC = \frac{IC}{IA} \quad \text{donde } IC = \frac{\gamma - m}{m - 1}, \; m = \text{matriz order}. \tag{1}$$

Step 4. Obtaining the weight of the criteria: once the matrix of paired comparisons is prepared and its consistency is validated, what is called the priority of each of the criteria can be calculated.

2.3. Methodology for the Application of the TOPSIS Technique. The technique for order preference by similarity with the ideal solution (TOPSIS) is a method for multiple attributes that identifies solutions from a finite set of alternatives. The methodology attempts to choose alternatives that simultaneously have the shortest distance from the positive ideal solution and the furthest distance from the negative ideal solution [33]. The ideal solution is the one that maximizes the benefit criteria and minimizes the cost, while the counterpart is known as the negative ideal solution, in which the cost is maximized, and the benefit criteria are minimized. According to [34], the application of the method is as follows:

Step 1: obtain a decision matrix based on the performance ratings assigned to each alternative with respect to each attribute as shown in the following equation:

$$D = \left[X_{ij}\right]_{\text{mxn}}. \tag{2}$$

Step 2: choose the importance weight of each attribute $((Wj))$ given by the experts such that (equation (3)).

$$\sum_{j=1}^{n} \text{Wj} = 1. \tag{3}$$

Step 3: normalize the decision matrix to transform various attribute dimensions into comparable dimensions as shown in the following equation:

$$r_{\mathrm{ij}} = \frac{X_{ij}}{\sqrt{\sum_{i=1}^{m}\left(X_{\mathrm{ij}}\right)^2}}, i = 1, 2, \ldots m;\ j = 1, 2, \ldots n. \quad (4)$$

Step 4: construct the weighted normalized decision matrix as shown in the following equation:

$$V = \left[V_{\mathrm{ij}}\right]_{\mathrm{mxn}}, \quad (5)$$

where

$$V_{\mathrm{ij}} = W_{\mathrm{ij}} * r_{\mathrm{ij}}, i = 1, 2, \ldots m;\ j = 1, 2, \ldots n. \quad (6)$$

Step 5: determine the positive ideal solution (+) and the ideal negative solution (−) (equations (7) and (8))

$$\begin{aligned} A^+ &= \left(V_1^{\,+}, V_2^{\,+}, \ldots, V_n^{\,+}\right) \\ &= \left\langle\left(\max V_{ij} \mid j \in \varphi_B\right), \min\left(V_{\mathrm{ij}} \mid j \in \varphi_B\right)\right\rangle, \end{aligned} \quad (7)$$

$$\begin{aligned} A^- &= \left(V_1^{\,-}, V_2^{\,-}, \ldots, V_n^{\,-}\right) \\ &= \left\langle\left(\min V_{\mathrm{ij}} \mid j \in \varphi_B\right), \max\left(V_{\mathrm{ij}} \mid j \in \varphi_c\right)\right\rangle, \end{aligned} \quad (8)$$

where φ_{B} and φ_{C} are associated with cost and benefit attribute sets.

Step 6: calculate the Euclidean distance of each alternative from the negative ideal solution and positive ideal solution (equations (9) and (10)).

$$d_i^{\,+} = \sqrt{\sum_{j=1}^{n}\left(V_{\mathrm{ij}} - V_j^{\,+}\right)^2}, \mathrm{i} = 1, 2 \ldots, \mathrm{m}, \quad (9)$$

$$d_i^{\,-} = \sqrt{\sum_{j=1}^{n}\left(V_{\mathrm{ij}} - V_j^{\,-}\right)^2}, \mathrm{i} = 1, 2 \ldots, \mathrm{m}. \quad (10)$$

Step 7: calculate the coefficient of proximity to the ideal solution (R_i) for each alternative. See the following equation:

$$R_i = \frac{d_i^{\,-}}{d_i^{\,-} + d_i^{\,+}}, 0 \leq \mathrm{Ri} \leq 1, i = 1, 2, \ldots m. \quad (11)$$

Step 8: determine the ranking preference order of the alternatives in decreasing order. An alternative that is closer to the positive ideal solution and further from the negative ideal solution.

3. Results

3.1. Case Study. The proposed method has been designed and applied considering the needs and goals of a hardware company in Colombia. The company sells approximately 8,000 references of products for construction, remodeling, and home finishing.

In order to assess the suitability of the proposed method, a before-after analysis is proposed [35]. To do that, it is important to first define a baseline scenario, known as "before scenario," which will represent here the current method (or the one that is the closest to reality) used to classify products in this company. This method is a monocriterion and follows the classical ways of classifying products in a company. Then, a new scenario, known as "after scenario," is assessed, in this case using the proposed methodology. The change that this scenario adds to the baseline is that of including various criteria. To do that, it is required to identify a set of potential criteria, and then using the proposed methodology, select those suitable for the proposed classification, to finally compute a prioritization of products that will lead to a final classification.

First, it is important to analyze the current situation. The inventory current ABC classification under analysis was made by using the indicator of turnover times contribution margin. This approach can cause some products with low margin but have crucial importance in the sales and are not classified within the appropriate category. Currently, approximately 5% of its main references are out of stock (Figure 4), generating lost sales. In addition, the inventory excess is approximately 30% of sales, which generates a high capital investment, whose recovery is slow and generates a decrease in the cash flow.

In turn, as Figure 5 shows, the inventory days' indicator in the last year has remained above the target value, which was set at 25 days, and this is justified because of the company's cash needs and the need of inventory to meet sales forecast, offering a 99% service level.

It should be considered that due to the references' large volume handled by the company (more than 18,000), the ABC multicriteria classification problem was divided into two steps. First, a grouping of products into subgroups was carried out, to identify the most critical subgroup, and afterwards, an ABC classification was made for each product within the main subgroups or type A.

3.2. Result Analysis and Discussion. For generating the sets of products to be evaluated, 196 sublines of products were first taken as a basis, and within each subline, some subgroups were created which considered the brand to which they belonged. For example, in the cladding subline, three subgroups were created related to each brand that is currently handled. After this product grouping, 89 alternatives were obtained, which will be ordered depending on the criteria to be evaluated. The next step was to search for the criteria useful to define the ranking of products in the inventory. To meet this objective, an analysis of papers dealing with ABC classification was carried out. The selected papers were extracted from the first selection that led to the construction of Figure 1, refining it by considering only those that were relevant to the present research. Figure 6 shows the most used criteria to prioritize inventories based on 40 selected reviewed articles.

As we can observe, Figure 6 shows criteria such as annual sales at cost, delivery time, and criticality, among others. These three criteria were initially selected for the subgroup's definition, while the unit cost criterion was later added for the ABC classification. The concept of criticality will be understood as the commercial importance of the product for the company. After this criterion definition, the selected experts of the company suggested to change the sales at cost

Figure 4: Behavior of out-of-stock products in the inventory under study.

Figure 5: Variation of the days of inventory indicator in the company under study.

(used in the literature) with the profit. Likewise, they also suggested adding a new criterion associated with the impact of the product in the warehouse. Once the alternatives (subgroups) and criteria are available, the evaluation of the criteria is carried out with the AHP diffuse method, and the evaluation of alternatives ranking will be developed supported by the TOPSIS methodology (Figure 7)

For the evaluation of criteria, four experts, who have a different vision of the problem, were considered. Their backgrounds are as follows:

(1) The buyer with 10 years of experience in this process

(2) The head of integrated systems, who has led the continuous improvement project and designed the current company's ABC classification

(3) The commercial manager, who is especially important when talking about the criteria of commercial criticality of a product

(4) The logistics manager, whose opinion regarding warehousing impact of a product is especially relevant

The experts compared the criteria using the linguistic variables defined in Table 1. The methodology defined by [37] was used. The opinions of the four experts were consolidated using the geometric mean, with which a new consolidated matrix is formed as shown in Table 2.

According to Buckley et al. [37], the geometric mean of the fuzzy comparison values of each criterion is calculated to obtain *Ri*. The fuzzy weight of each criterion is shown in Table 3.

To validate the fact that the weights are coherent for the analysis, the consistency coefficient of the final comparison matrix is obtained by calculating both the inconsistency index (IC) and the randomness index (IA) as shown in Table 4. The resultant coefficient is 0.097 which is allowed by the methodology (less than 0.1)

The evaluation of the alternatives was carried out with the TOPSIS method. For doing this, data collection was conducted associated with each criterion for each alternative (subgroup) during the last year. It is necessary to clarify that both the criticality and storage impact criteria are qualitative criteria that were evaluated with a defined scale (Table 5). Once the decision matrix is obtained, it is normalized as indicated by (4). Then, the resulting matrix is multiplied by the weight of each criterion.

Once we have the weighted normalized matrix, we proceed to find the positive ideal values (A+) and negative ideal values (A−) depending on the objective of each criterion. In the case of study, all criteria are of maximization since it is considered that the most critical subgroup is the one with the best sales, delivery time, criticality, and storage impact. Table 6 summarizes the values found for each criterion.

Finally, the distance of each alternative from the ideal and antiideal value is calculated, and based on the formula presented in (11), the ranking of subgroups is established. For the ABC classification, in order to determine subgroups A, B, and C, we reviewed in the literature what strategies have been used to establish the cuts when using the TOPSIS methodology. The authors in [38] carry out the assignment of items to each class without any particular methodology. Furthermore, the authors in [39] use the Pareto rule to make the respective assignment.

In this article, the *Ri* value, obtained after applying TOPSIS, will be taken as a classification criterion, where the type-A subgroups will be those that have obtained a *Ri* score greater than the 90th percentile of the sample of 89 analyzed subgroups. Likewise, the type-B subgroups will be made up of those alternatives that have obtained a *Ri* score below the 90th percentile and above the 50th percentile. Finally, the type-C subgroups will be those that obtain a *Ri* value below the 50th percentile. Table 7 shows the subgroups classification or the number of subgroups that were included in each inventory class.

In order to check how sensitive, the results are, it was decided to vary the weight of the criteria. In the first scenario, we set the same weight for all of them (25%); in the second, a weight of 100% is given to the sales criteria, as proposed by the traditional ABC classification; finally, it was decided to place a greater weight (35%) on the qualitative criteria (storage impact and criticality) and a weight of 15% on the criteria of delivery time and sales. Table 8 presents the summary of the sensitivity analysis, where seven of the nine subgroups classified as type A remain in each proposed scenario.

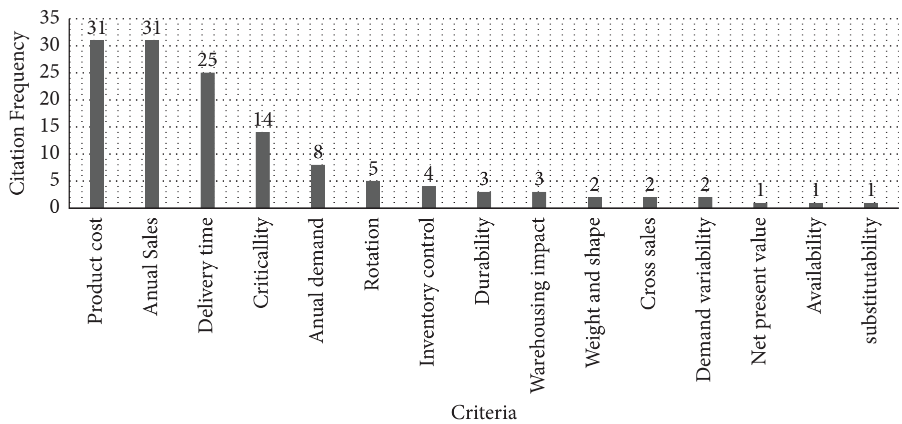

Figure 6: Most used criteria for inventory classification.

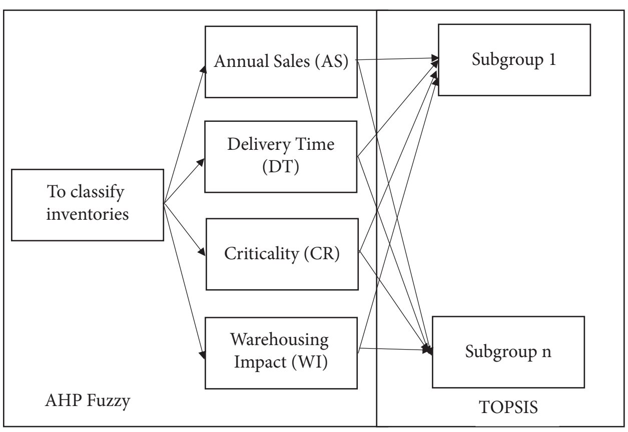

Figure 7: Problem hierarchy and methodology.

Table 1: Linguistic variables used for the evaluation of criteria.

Linguistic variables	Triangular fuzzy number
Absolutely more important	8, 9, 9
Strongly more important	6, 7, 8
Much more important	4, 5, 6
Weakly more important	2, 3, 4
As important	1, 1, 1
Weakly less important	1/2, 1/3, ¼
Much less important	1/6, 1/5, ¼
Strongly less important	1/8, 1/7, 1/6
Absolutely less important	1/9, 1/9, 1/8

Source: [36]. *Notes*. Table 1 presents the linguistic scale used to assess the criteria.

Table 2: Consolidated comparison matrix.

Criteria	AS			DT			CR			WI		
AS	1	1	1	2.8	3.9	4.9	0.3	0.4	0.5	0.8	1.1	1.4
DT	0.2	0.3	0.4	1	1	1	0.2	0.2	0.3	1	1.2	1.4
CR	2	2.6	3.1	3.5	4.6	5.7	1	1	1	1.9	2.1	2.4
WI	0.7	0.9	1.2	0.7	0.8	1	0.4	0.5	0.5	1	1	1

*AS: annual sales, DT: delivery time, CR: criticality, and WI: warehousing impact. *Notes*. Table 2 shows the consolidated assessment matrix for the 4 criteria used in the study.

Table 3: Criteria's weight.

Criteria	Weight (%)
AS	24.4
DT	11.1
CR	47.9
WI	16.6

Notes. Table 3 presents the weights of each criterion obtained after applying the AHP fuzzy tool.

Table 4: Consistency coefficient calculation.

Inconsistency index (IC)	Random index (IA) 4 × 4 matrix	Consistency coefficient (IC/IA)
0.086	0.890	0.097

Notes. Table 4 shows the consistency coefficient of the AHP fuzzy process, where it can be validated that the assessment made is valid because the indicator is less than 0.1.

Table 5: Proposed scale to measure the criticality and warehousing impact criteria.

Scale	Criticality criteria	Warehousing impact criteria
5	Absolutely important	Very high
4	Strongly important	High
3	Very important	Medium
2	Weakly important	Low
1	Less important	Very low

Notes. Table 5 shows the scales constructed for the two qualitative criteria used in the study, such as criticality and warehousing impact.

Table 6: Positive and negative ideal values by criteria.

	Maximize			
	Annual sales	Delivery time	Criticality	Warehousing impact
A+	0.14	0.02	0.07	0.03
A−	0.00	0.00	0.01	0.01

Notes. Table 6 shows the values obtained for the positive and negative ideal solutions for each criterion.

Table 7: ABC classification of subgroups with the TOPSIS methodology.

Classification	Number of subgroups
A	9
B	35
C	45

Notes. Table 7 shows the results obtained after applying the TOPSIS method for the company's inventory subgroups, where 9 belongs to category A, 35 to B, and 45 to C.

Table 8: Sensitivity analysis of the ABC multicriteria classification.

Classification	Number of subgroups			
	Initial solution	25% each criterion	100% AS	CR-WI (35%) + AS-DT (15%)
A	9	7	7	8
B	35	37	36	36
C	45	45	46	45

*AS: annual sales, DT: delivery time, CR: criticality, and WI: warehousing impact. *Notes*. Table 8 shows how the results obtained in the TOPSIS method vary by varying the weight of the criteria, where the groups classified as A continue to hold in the different scenarios.

After having carried out the classification by subgroups, a prioritization will be made for the type-A and type-B subgroups. For the type-A subgroups, a multicriteria classification approach will be used. In contrast, type-B subgroups will be ordered according to a traditional ABC classification based on sales profit and demand. At the end of the respective classifications, seven product categories will be obtained that will define how critical, for the organization, the product is (Table 9).

The prioritization of items that are within the alternatives (subgroups) classified as A began with the selection of the criteria that will be considered for this new classification, and this needed again the information found in the literature review which is shown in figure V. The selected criteria in this case are unitary product cost (CU), annual sales (from the profit approach -UT), demand (DM), complementarity (CM) (understood as the need to buy one product in order to use another), and variability of demand (DV). The last one has not been frequently used in the literature, but it was selected for its relevance in this case.

Once the criteria were defined, a weighting process was performed using the fuzzy AHP multicriteria method, as was performed in the prioritization of subgroups. Table 10 presents the weights obtained after applying the methodology.

Considering the weight of the selected criteria and the information collected from the products of each type-A subgroup, the TOPSIS multicriteria tool was applied (using the same procedure for the initial subgroup classification) to obtain the final prioritization of the items in each critical subgroup. After this, the products are assigned to the seven categories defined in Table 9, as shown in Table 11.

Table 11 shows that only 0.26% of the inventory was classified as highly critical. Likewise, 5.45% represents products of medium relevance to the organization. Finally, we observe that many of the products (approximately 94%) have little or almost no impact within the company under study.

Table 9: Product categorization.

Category	Subgroup	Product
High	A	A
Medium	A	B
	B	A
Low	A	C
	B	B
	B	C
None	C	

Notes. Table 9 represents the criticality proposal of the categories according to the results obtained in the ABC classification of subgroups and individuals.

Table 10: Weighting of criteria for product classification of subgroups A.

Criteria	Weight (%)
UT	27.8
DM	32.9
CM	17.6
VD	17.3
CU	4.3

Notes. Table 10 shows the weight of the criteria used for the individual classification of products within the inventory.

Table 11: Final categorization of products.

Criticality	Category	Number of items	Inventory (%)
High	AA	4	0.05
	AB	17	0.21
Medium	BA	447	5.45
Low	AC	1049	12.79
	BB	603	7.35
	BC	905	11.04
None	C	5175	63.11

Notes. Table 11 represents the final classification of the products within the inventory, where 4 of them are considered highly critical.

3.3. Generalization and Practical Implications. The structure methodological to an inventory general classification presented in this research is applicable to any product type (raw material, finished product, and spare parts). Its implementation is versatile and can be carried out using Microsoft Excel, a tool widely used in most organizations today, regardless of their size. As it has been previously discussed, the hardware sector in the country where this case study is located has a similar organizational profile. In this sense, this methodology can be implemented in small and medium-sized hardware companies' network, promoting better decision-making and improving the supply management in order to guarantee greater competitiveness in the market.

3.4. Future Research. As future research, observing very companies including new products in its portfolio, it is expected to propose a methodology that allows us inferring the classification of new products once entering the warehouse, and although these new products do not have data to support their valuation with the selected criteria, it is necessary to enter a category to track the behavior of the product in the inventory. Similarly, it is interesting to develop a tool which guarantees a continuous evaluation of the importance of the criteria because, depending on the context of the organization, criterion weights may vary over time and affect inventory classification.

4. Conclusions

Currently, the traditional ABC classification that only considers the criterion of sales volume could not be a useful tool because of its limitation to prioritize items in complex organizations. For this reason, multicriteria classification methods emerge that incorporate a set of quantitative and qualitative attributes that provide a more accurate classification of those products that have high criticality indexes for the organization.

The literature showed a growth in the research related to inventory classification methods, and it was possible to establish those criteria that have greater relevance when prioritizing items in inventories. However, it should be clarified that there are attributes that are particular of the type of inventory and of the role of that inventory into the organization, and therefore, the selection and weighing of criteria must always be done with experts from the company.

Due to the high number of items handled by the company under study, in this research, two classifications were made, the first associated with identifying those most important subgroups and the second was finding out which items within the subgroups had a higher priority degree. At the end of the application of the methodology, it was found that only 0.26% of the products in the inventory are highly critical.

This paper raises a set of considerations, for both research and practice. The first is that by considering various criteria, the needs of decision makers are better represented. However, computing a multicriteria analysis can be long and need a validation of decision makers on the number of criteria and their importance. In that sense, the proposed method allows to propose a set of criteria from which decision makers can choose and examine the potential of multicriteria methods in being closer to the decision makers' needs. Another important point is that this classification includes a measure of criticality, allowing it to identify by computation of the set of most critical products (which represents a very small percentage in the number of references but is in general difficult to identify based on objectively defined criteria). Finally, by adding uncertainty and fussy logic to the construction of the categorization, this paper deals with potential risks and unexpected issues, having higher anticipation capabilities than classical, deterministic approaches.

Data Availability

The data used to support the findings of this study are available on request from the corresponding author.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

This work was supported by the Government of Valle, Colombia, and by the University of Valle, Cali, Colombia.

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