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# Multi-criteria Inventory ABC Classification Approach Using Gaussian AHP

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**ABSTRACT**

The ABC analysis is a technique widely used by companies to manage inventory items. Usually, ABC analysis classifies items into three categories: A, B, or C, based on annual dollar usage, where A are the most important items, B are moderate items, and C are less important items. From this perspective, to add efficiency to inventory control and determine planning policies, multi-criteria ABC is used. This paper proposes a new ABC classification approach, based on an extension of the Analytic Hierarchy Process (AHP), called Gaussian AHP. The proposed Gaussian AHP methodology uses the normal curve to determine the weights of criteria without dealing with qualitative aspects for distributing the weights. The methodology is applied to a dataset from a Hospital Respiratory Therapy Unit and also from a major aeronautical manufacturer, and the results demonstrate a new categorization of items that enhances inventory management by integrating multi-criteria in a systematic way.

**KEYWORDS. Gaussian Analytic Hierarchy Process. Multi-criteria Inventory ABC Classification. Inventory management.**

**Paper topic: ADM - Multicriteria Decision Making/Aiding**

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## 1. Introduction

ABC analysis is an important technique in inventory management, used to classify items into three categories: category A includes the most important items, category B includes moderately important items, and category C includes the least important items. This method is intrinsically linked to the Pareto principle, or the 80/20 rule [Pareto et al., 1971]. ABC analysis is usually based on the annual monetary consumption of items and is used by various companies to classify inventories. It was first used by General Electrics in 1951 for inventory control [Dickie, 1951]. In general, ABC analysis is a widely used tool due to its ease of understanding.

Several authors have explored ABC analysis in an improved way, adding criterias to make the classification of inventories more precise and in line with operational needs. In addition to the annual consumption figure traditionally used, factors such as lead time, reparability of items, distribution of demand, level of criticality and availability of suppliers are often taken into account. These approaches allow for a more holistic view of inventory management, making it easier to prioritize not only on the basis of cost, but also on the speed of replenishment and the impact of possible shortage. From this perspective, multi-criteria ABC analysis becomes a powerful tool for optimizing stock levels and ensuring the continuity of operational processes, avoiding unwanted downtime and reducing costs related to the unavailability of essential materials.

In this context, the integration of ABC analysis with advanced decision-making methods, such as the Analytic Hierarchy Process (AHP), fuzzy logic, and multi-criteria decision-making (MCDM) techniques, has gained prominence in the literature. These approaches enable the incorporation of both quantitative and qualitative factors, mitigating the limitations of the traditional single-criterion approach. By combining ABC analysis with such methodologies, inventory managers can derive classifications that are not only cost-oriented but also aligned with strategic objectives. This evolution reflects the growing complexity of modern supply chains and highlights the need for inventory classification systems that are adaptable, data-driven, and capable of supporting long-term competitiveness.

## 2. Related Research

Flores and Whybark [1986, 1987] were the first to consider a multi-criteria analysis of inventory items to classify them into ABC categories. Following these articles, numerous methods have been published providing solutions for inventory classification. In their approach, Flores and Whybark [1986, 1987] use a bi-criteria matrix where annual dollar usage is evaluated alongside another criterion within a joint-criteria framework. From this perspective, this method has some limitations, such as the fact that it only uses two criteria and that the weights for both criteria are the same.

Partovi and Burton [1993] proposed a method that applies the Analytic Hierarchy Process (AHP) to ABC analysis, integrating both quantitative and qualitative criteria. Their approach illustrates the use of AHP in a real-world pharmaceutical industry context, highlighting its effectiveness for multi-criteria decision-making. Partovi and Anandarajan [2002] explored the use of artificial neural networks (ANNs) for ABC classification in the pharmaceutical industry. Their approach applied two learning methods-backpropagation (BP) and genetic algorithms (GA) and included a comparative analysis of the two.

Ramanathan [2006] proposed a simple classification scheme based on weighted linear optimization. The model uses a weighted additive function to aggregate the performance of inventory items across different criteria (hereafter referred to as the R-model). Zhou and Fan [2007] extended this classification approach and proposed a new model based on the R-model, using a convex combination of two weights to generate a score for each criterion (ZF-model). Ng [2007] introduced a method where the decision-maker can add constraints to express a priority order, after simplification, the model can be represented in canonical form with a single equality constraint (NG-model).

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Chen et al. [2008] proposed a case-based distance model for ABC analysis using multi-criteria tools. Their study employed weighted Euclidean distances to support decision-making. In the same year, Chu et al. [2008] developed a new inventory control method called ABC-fuzzy, which allows for the incorporation of both quantitative and qualitative variables based on managerial experience.

Based on the NG-model, Hadi-Vencheh [2010] proposes an improvement to this model using Nonlinear Programming (NLP) so that the final scores of the items are not independent of the weights of the criteria, making the final classification of the ABC analysis more assertive and accurate (hereafter called H-model). Later, Chen [2011] have used a peer-estimation for multi-criteria inventory classification (MCIC). The approach determines two commom sets of criteria weights and aggregates the resulting.

Hadi-Vencheh and Mohamadghasemi [2011] proposed a classification approach based on an integrated fuzzy analytic hierarchy process-data envelopment analysis (FAHP-DEA) for multi-criteria ABC inventory classification. The integrated FAHP-DEA methodology is illustrated by means of a real case study.

Chen [2012] proposed alternative method for multi-criteria inventory classification (MCIC) introduces two virtual items and integrates the TOPSIS technique. This approach enhances previous methods by offering a more objective and comprehensive performance index, resulting in an unbiased classification.

Yu [2011] have used artificial intelligence (AI) techniques such as support vector machines (SVMs), backpropagation networks (BPNs), and the k-nearest neighbor (k-NN) algorithm and makes a comparison between these three methods to determine which is the most efficient. In this same context, Zowid et al. [2019] also uses AI techniques to categorize inventory, in this research they used the Gaussian mixture model (GMM) to deal with this classification.

In Douissa and Jabeur [2020], a novel method for ABC classification is proposed, which leverages a non-compensatory aggregation procedure based on a simplified version of the ELECTRE III method. This approach is designed to handle multiple criteria without allowing trade-offs between them, ensuring that the decision-making process remains consistent with real-world constraints. The study also includes a comprehensive comparative analysis using two real-world datasets, where the results consistently showed that the proposed method outperformed other classification models, leading to the lowest total inventory cost in both cases (hereafter called ELIII-CVNS model).

With the most diverse approaches to inventory classification following multi-criteria, this article considers the ABC classification proposal based on the Gaussian AHP method, an extension of the AHP method developed by Santos et al. [2021]. Several studies have explored the Gaussian AHP method for decision-making in different areas, such as agriculture, defense, energy, investments, inventory management, and logistics [Santos et al., 2021; Silva et al., 2022; Almeida et al., 2022; Pereira et al., 2023a; Gomes et al., 2021; Rodrigues et al., 2024]. This method has proven to be effective in dealing with multi-criteria, allowing an accurate assessment and classification of items according to their most relevant characteristics.

Therefore, this article proposes a new approach to ABC classification, based on the Gaussian AHP method, with the aim of improving accuracy and efficiency in inventory management. The aim is to optimize the allocation of resources and the definition of inventory policies, offering a robust solution to the challenges faced by companies that deal with a wide variety of items and need to make quick decisions based on multiple factors.

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## 3. Gaussian AHP Method

The Gaussian AHP method represents an improved extension of the Analytic Hierarchy Process (AHP), offering an approach that allows the weights to be determined and the alternatives to be ranked based on a Gaussian factor. This technique eliminates the need to make direct comparisons between alternatives and criteria, simplifying the multi-criteria decision-making process and maintaining the consistency of the results [Santos et al., 2021].

The method developed by Santos et al. [2021], follows seven steps which are represented in Figure 1.

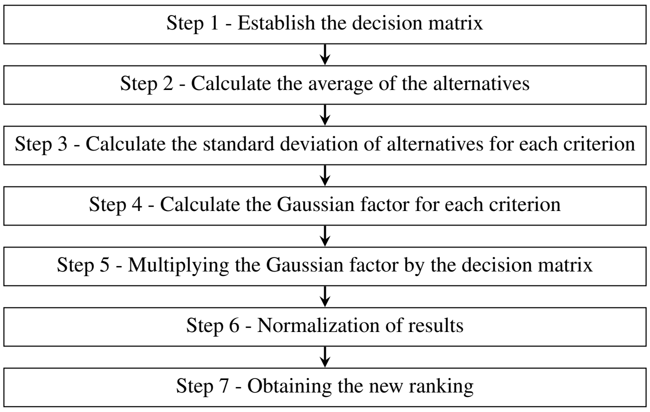


Figure 1: Steps for Gaussian AHP [Santos et al., 2021]

Let $A = \{a_i \mid i \in I\}$, with $|I| = n$, be the finite set of possible actions or options, and $G = \{g_j \mid j \in J\}$ and $|J| = m$, the set of criteria evaluated for preference modeling, where $g_j$ represents a criterion, with $g_j : A \to \mathbb{R}, \forall j \in J$, is an interval scale measure such that $g_j(a)$ represents the evaluation of action $a$ for the $j$-th criterion. The result of this step is the decision matrix [Silva et al., 2022].

After applying the definition of the decision matrix, a normalized factor for a common interval between 0 and 1 can be obtained, such that the normalized factor $x_{ij}$ generates a new matrix. Equation 1 should be used when the criterion $g_j \in G$ has a maximizing criterion and Equation 2 should be used when it has a minimizing criterion [Silva et al., 2022].

$$x_{ij} = \frac{a_{ij}}{\sum_i a_{ij}} \; \forall \max g_j \tag{1}$$

$$x_{ij} = \frac{a_{ij}^{-1}}{\sum_i a_{ij}} \; \forall \min g_j \tag{2}$$

With the $g_j$ criteria from the decision matrix, the average ($\bar{x}$), standard deviation ($\sigma$) are calculated for all criterias, and the Gaussian factor (standard deviation divided by the mean) are calculated, and, finally, the Gaussian factor normalized or, in this context, weight ($w$), is multiplied by the decision matrix in such a way that a rank is obtained.

The Gaussian AHP method has two main limitations [Pereira et al., 2023b]. The first is the impossibility of using negative numbers, due to the need to respect the axiomatic aspects of modeling [Saaty, 1987]. The second limitation is related to the nature of the data, which is obtained exclusively quantitatively. This method restricts the inclusion of qualitative aspects, although it is possible to convert this data into quantitative scales for application in the models. However, it is necessary to carefully evaluate this approach to avoid subjective biases that unduly favor a specific criterion [Almeida et al., 2022].

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## 4. Experimental Results

To illustrate the proposed classification and validate the results with other classifications, two datasets were used: the dataset proposed by Reid [1987] and real data from spare parts from an aeronautical industry.

### 4.1. Experimental results with Reid's dataset

The first dataset includes 47 inventory items used in a Hospital Respiratory Therapy Unit (HRTU) and evaluated according to four criteria: (1) the Annual Dollar Usage (ADU), (2) the Average Unit Cost (AUC), (3) the Lead Time (LT) and (4) the Critical Factor (CF). The Critical Factor (CF) is usually ignored in these studies. This study compares the ABC classification with other models, namely R-model [Ramanathan, 2006], ZF-model [Zhou and Fan, 2007], Peer-model [Chen, 2011], NG-model [Ng, 2007], H-model [Hadi-Vencheh, 2010], TOPSIS-based model [Chen, 2012], and ELIII-CVNS [Douissa and Jabeur, 2020].

Based on these classifications, the Gaussian AHP method is used for ABC analysis. The implementation uses some intrinsic characteristics of the criteria that are presented in Table 1.

Table 1: Criteria weights analysis through the Gaussian Factor on Reid [1987] dataset

| Criteria of the model | $\bar{x}$ | $\sigma$ | $\sigma/\bar{x}$ | $w$ |
|---|---|---|---|---|
| AUC | 0.021277 | 0.015074 | 0.708482 | 0.276192 |
| ADU | 0.021277 | 0.030380 | 1.427852 | 0.556628 |
| LT | 0.021277 | 0.009124 | 0.428848 | 0.167180 |

It can be seen that the weight of Annual Dollar Usage (ADU) is the most important when compared to Average Unit Cost (AUC) and Lead Time (LT), but the AUC and LT criteria are equally important for the construction of the multi-criteria method. It is important to note that all the criteria evaluated adopted the maximizing criterion, in which higher values reflect greater importance attributed to the criteria considered.

According to Flores et al. [1992], the ABC classification is based on annual dollar usage, where the first 10 items are classified as A, 14 items are classified as B and the remaining 23 are classified as C. Note that Table 2 summarizes the information on the classes and their respective percentages.

Table 2: Classification of materials according to the parameters of Flores et al. [1992]

| Item Class | A | B | C |
|---|---|---|---|
| Number of items | 10 | 14 | 23 |
| % Items | 21.3% | 29.8% | 48.9% |
| ADU | 73.6% | 18.9% | 7.5% |

In this study, the same classification will be used for the materials following the classifications provided by the Gaussian AHP method. Based on this information, Table 3 presents the results obtained for the ABC classifications as described by [Douissa and Jabeur, 2020].

From the information in Table 3, it is possible to calculate the Rate of Items that are Identically Classified (RIIC) by each pair of tested classification models, as in the article by Douissa and Jabeur [2020]. In addition, it can be noted that each classification provides a different ABC classification following specific criteria that are intrinsic and natural to each model. The comparison between each of the classification pairs is expressed in Table 4. It can be seen that the models with the highest similarity index are the H-model and the NG-model, which show a degree of similarity of 95.7%, this result can be explained by the fact that the method developed by Hadi-Vencheh [2010] is a direct improvement on the method proposed by Ng [2007]. In contrast, the Gaussian AHP showed the lowest similarity index compared to the R-model, with only 48.9%, which can be

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Table 3: A comparison of ABC classification using Gaussian AHP and differents models on Reid [1987] dataset

| Item | AUC | ADU | LT | Tested classification models based on Douissa and Jabeur [2020] | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | Gaussian AHP | R | ZF | Peer | NG | H | TOPSIS | ELIII-CVNS |
| 2 | 210 | 5670 | 5 | A | A | A | A | A | A | A | A |
| 1 | 49.92 | 5840.64 | 2 | A | A | A | A | A | A | A | A |
| 3 | 23.76 | 5037.12 | 4 | A | A | A | A | A | A | A | A |
| 4 | 27.73 | 4769.56 | 1 | A | B | C | B | A | A | B | A |
| 10 | 160.5 | 2407.5 | 4 | A | B | A | A | A | A | A | A |
| 5 | 57.98 | 3478.8 | 3 | A | B | B | B | A | A | B | A |
| 9 | 73.44 | 2423.52 | 6 | A | A | A | A | A | A | A | A |
| 8 | 55 | 2640 | 4 | A | B | B | B | B | B | A | A |
| 6 | 31.24 | 2936.67 | 3 | A | C | C | B | A | B | B | A |
| 7 | 28.2 | 2820 | 3 | A | C | C | B | B | B | B | A |
| 13 | 86.5 | 1038 | 7 | B | A | A | A | A | A | A | B |
| 14 | 110.4 | 883.2 | 5 | B | B | A | B | B | A | A | B |
| 29 | 134.34 | 268.68 | 7 | B | A | A | A | A | A | A | C |
| 15 | 71.2 | 854.4 | 3 | B | C | C | C | C | C | B | B |
| 12 | 20.87 | 1043.5 | 5 | B | B | B | B | B | B | C | B |
| 23 | 86.5 | 432.5 | 4 | B | C | B | C | B | B | B | B |
| 28 | 78.4 | 313.6 | 6 | B | A | A | A | B | B | A | C |
| 18 | 49.5 | 594 | 6 | B | A | A | B | B | B | B | B |
| 16 | 45 | 810 | 3 | B | C | C | C | C | C | C | B |
| 19 | 47.5 | 570 | 5 | B | B | B | B | B | B | B | B |
| 22 | 65 | 455 | 4 | B | C | B | C | C | C | B | B |
| 20 | 58.45 | 467.6 | 4 | B | C | B | C | C | C | C | B |
| 31 | 72 | 216 | 5 | B | B | B | B | B | B | B | C |
| 11 | 5.12 | 1075.2 | 2 | B | C | C | C | C | C | C | B |
| 27 | 84.03 | 336.12 | 1 | C | C | C | C | C | C | C | C |
| 17 | 14.66 | 703.68 | 4 | C | C | C | C | C | C | C | B |
| 39 | 59.6 | 119.2 | 5 | C | B | B | B | B | B | B | C |
| 40 | 51.68 | 103.36 | 6 | C | B | B | B | B | B | B | C |
| 33 | 49.48 | 197.92 | 5 | C | B | B | B | B | B | B | C |
| 38 | 67.4 | 134.8 | 3 | C | C | C | C | C | C | C | C |
| 21 | 24.4 | 463.6 | 4 | C | C | C | C | C | C | C | B |
| 35 | 60.6 | 181.8 | 3 | C | C | C | C | C | C | C | C |
| 24 | 33.2 | 398.4 | 3 | C | C | C | C | C | C | C | B |
| 45 | 34.4 | 34.4 | 7 | C | A | B | A | B | B | B | C |
| 26 | 33.84 | 338.4 | 3 | C | C | C | C | C | C | C | C |
| 32 | 53.02 | 212.08 | 2 | C | C | C | C | C | C | C | C |
| 37 | 30 | 150 | 5 | C | B | B | B | C | C | C | C |
| 30 | 46 | 224 | 1 | C | C | C | C | C | C | C | C |
| 34 | 7.07 | 190.89 | 7 | C | A | B | A | B | B | C | C |
| 25 | 37.05 | 370.5 | 1 | C | C | C | C | C | C | C | C |
| 36 | 40.82 | 163.28 | 3 | C | C | C | C | C | C | C | C |
| 44 | 48.3 | 48.3 | 3 | C | C | C | C | C | C | C | C |
| 43 | 29.89 | 59.78 | 5 | C | B | C | C | C | C | C | C |
| 42 | 37.7 | 75.4 | 2 | C | C | C | C | C | C | C | C |
| 46 | 28.8 | 28.8 | 3 | C | C | C | C | C | C | C | C |
| 47 | 8.46 | 25.38 | 5 | C | B | C | C | C | C | C | C |
| 41 | 19.8 | 79.2 | 2 | C | C | C | C | C | C | C | C |

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attributed to the difference in the way the weights are generated for each criterion. The Gaussian AHP uses a method based on normal distribution to establish the criteria, resulting in significant variations compared to traditional approaches. However, it should be noted that for ELIII-CVNS, the Gaussian AHP showed a high similarity index, reaching 87.2%, with no significant changes when compared only to category A. It should also be noted that the other methods did not show such high similarity indices when compared to the Gaussian AHP.

Table 4: Rate of Items that are Identically Classified (RIIC) by each pair of tested classification models on Reid [1987] dataset

| | Gaussian AHP (%) | R (%) | ZF (%) | Peer (%) | NG (%) | H (%) | TOPSIS (%) | ELIII-CVNS (%) |
|---|---|---|---|---|---|---|---|---|
| Gaussian AHP | - | 48.9 | 59.6 | 57.4 | 70.2 | 66.0 | 66.0 | 87.2 |
| R | | - | 78.7 | 87.2 | 72.3 | 70.2 | 68.1 | 40.4 |
| ZF | | | - | 78.7 | 78.7 | 80.9 | 78.7 | 51.1 |
| Peer | | | | - | 83.0 | 83.0 | 80.9 | 48.9 |
| NG | | | | | - | 95.7 | 78.7 | 59.6 |
| H | | | | | | - | 83.0 | 55.3 |
| TOPSIS | | | | | | | - | 57.4 |
| ELIII-CVNS | | | | | | | | - |

### 4.2. Experimental results with data from an aeronautical industry

The second empirical investigation for this study was conducted using real-world data provided by a major aeronautical manufacturer located in southeastern Brazil. The dataset obtained for this case study are from aeronautical spare parts items that do not have a defined forecast, so it is important to classify a multi-criteria methodology for policy definition in the ERP system. Due to confidentiality agreements, actual component identifiers have been anonymized.

This approach is applied to a set of 574 items, each with distinct and specific characteristics. To obtain the necessary data, factors such as historical consumption and the monetary value of the materials in dollars are taken into account. These parameters allow for a comprehensive and detailed analysis, making it easier to identify patterns in the behaviour of items and ensuring that decisions are based on accurate and relevant information.

The criteria selected to implement the Gaussian AHP method were: Annual Dollar Usage (ADU), Average Unit Cost (AUC) and Lead Time (LT). Annual dollar usage is a criterion widely used in multi-criteria ABC classification problems, as it makes it possible to identify materials with the greatest financial impact. The unit price of each material is relevant for assessing the individual economic representativeness of the items. Lead time represents the time required between the order being requested and the material arriving in stock, and is an essential factor for efficient supply chain management and for avoiding stock-outs.

As shown in Table 5, the weights of annual dollar usage and material unit price play a significant role for the criteria, while the lead time criterion, in this study, is not so important for the classification, this is due to the low variability of LT in this study.

Table 5: Criteria weights analysis through the Gaussian Factor

| Criteria of the model | $\bar{x}$ | $\sigma$ | $\sigma/\bar{x}$ | $w$ |
|---|---|---|---|---|
| ADU | 0.001742 | 0.008040 | 4.615245 | 0.542907 |
| AUC | 0.001742 | 0.005864 | 3.366158 | 0.395973 |
| LT | 0.001742 | 0.000905 | 0.519579 | 0.061120 |

Furthermore, a comparison is made with the traditional method of ABC analysis, considering the classification based exclusively on traditional dollar usage. In this classic method, items

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are categorized into classes A, B or C based on their cumulative financial impact, which often results in a simplified approach that can neglect other critical factors. Although this approach is widely used due to its simplicity and effectiveness in less complex scenarios, it can fail to capture the complexity of modern inventory management environments. In order to maintain a standard in class sizes, a standardization was made following the ADU criterion which is shown in Figure 2.

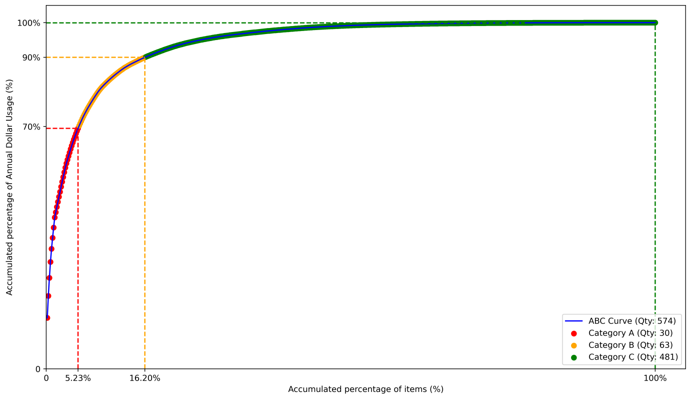


Figure 2: Tradiotinal ABC analysis

Based on the information provided by the Figure 2, the first 30 items are classified as category A (about 5.2% of total items), 63 items are classified as category B (about 11.0% of total items) and 481 items are classified as category C (about 83.8% of total items). This same criterion is established from the classification using the Gaussian AHP method, i.e. the first 30 items are classified as A, then the B items and finally the C items.

With this information, it is possible to carry out a comparative study between the traditional ABC analysis method and the Gaussian AHP method. It is clear that there are differences between the methods and considering the Rate of Items that are Identically Classified (RIIC) by each pair of tested classification models is 89.5%. The multi-criteria approach takes a more realistic view of dealing with highly complex inventories, such as those in the aeronautics sector.

However, fixing the number of materials can cause deviations in the process, so another approach is taken by leaving the number of materials unfixed and determining the materials following the cumulative percentages provided by the AHP Gaussian method. The Figure 3 shows the result of this analysis following the same categorization criteria.

Therefore, Table 6 compares the quantities of materials in relation to the classifications following the standards of the traditional ABC method and the method following the Gaussian AHP criteria. In this way, the cumulative percentage is set at 70% for category A items, between 70 and 90% for category B items and the rest for category C. With this definition, the Gaussian AHP method results in 58 itens (about 10.1% of total items) in category A, 118 in category B (about 20.6% of total items) and, finally, 398 items in category C (about 69.3% of total items).

Table 6: A comparative table of classification results from two different methods

| Method | Group | | |
|---|---|---|---|
| | A | B | C |
| ABC Analysis | 30 (5.2%) | 63 (11.0%) | 481 (83.8%) |
| ABC-Gaussian AHP | 58 (10.1%) | 118 (20.5%) | 398 (69.3%) |

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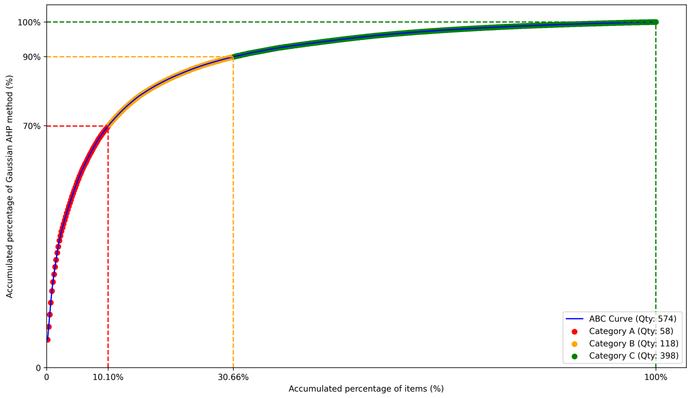


Figure 3: ABC-Gaussian AHP analysis

This analysis reveals that the Gaussian AHP method incorporates a greater number of criteria compared to the traditional approach, thus providing a more comprehensive view in line with the complexity of inventory control. In this context, it becomes possible to define specific policies for items in categories A, B and C, ensuring a more efficient allocation of resources and management efforts. Policies can be adjusted according to the relative importance of each group, ensuring that critical items receive greater attention, while less relevant items are treated proportionally. This results in better-informed decisions, contributing to more efficient, balanced stock management adapted to the specific dynamics of each logistics operation.

## 5. Conclusions

In a scenario of high complexity and volatility, dealing with inventory is a complex task, since you have to deal with critical shortages and the total cost of inventory. In this context, having essential items in stock is of paramount importance in order to meet customer needs. In this paper, a new inventory control approach combining ABC with Gaussian AHP classification has been proposed to use a multi-criteria approach without subjective variables.

To validate the results, two different datasets were used and compared with different classification methods. The first dataset used was provided by Reid [1987] and consists of 47 items. This dataset is widely recognized and often used by various researchers as a reference for testing and validating classification techniques in inventory control.

In addition to this dataset, we also used a dataset from a real application, provided by a large aeronautical manufacturer located in southeastern Brazil. Using this data, a comparative study was conducted between the Gaussian AHP method and the traditional ABC analysis approach. This study makes it possible to establish inventory management controls and policies that consider a broader set of criteria, going beyond the simple “annual dollar usage” metric. In this way, the decision-making process becomes more robust and adapted to operational complexity, ensuring more efficient inventory management in line with the specific demands of the sector.

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