INTERNATIONAL JOURNAL OF INTEGRATED ENGINEERING
ISSN: 2229-838X e-ISSN: 2600-7916

IJIE

Vol. 17 No. 9 (2025) 233-254
https://publisher.uthm.edu.my/ojs/index.php/ijie

Inventory Management Policies for Maintenance Spare Parts: Integration of Analytic Hierarchy Process and Multicriteria ABC Classification in the Plastics Industry

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DOI: https://doi.org/10.30880/ijie.2025.17.09.015

Article Info

Received: 6 March 2025
Accepted: 3 November 2025
Available online: 31 December 2025

Keywords

Multicriteria ABC classification, spare parts, spare parts inventories, AHP tool, inventory management, sourcing policies

Abstract

This study establishes supply management policies for maintenance spare parts in a plastics transformation company, using a methodology applicable to any industry managing spare parts inventories. It addresses the challenges of excessive inventory levels and the lack of objective rules for defining stock quantities and parameters by applying a multicriteria approach based on AHP and ABC classification, incorporating expert judgment through the Delphi method. The classification assigned the highest weight to criticality (0.683), followed by supply (0.2) and maintenance (0.117), ensuring a balanced evaluation. Demand analysis revealed that 69% of spare parts exhibit erratic demand, 39% have no recorded demand, and only 145 out of 3,842 items show stable demand, allowing the application of double exponential smoothing forecasting techniques. Based on these findings, a periodic inventory review system was implemented with demand-adjusted policies: (R, S) with safety stock (IS) for class A and B items with stable demand and adjusted IS levels or stock elimination for erratic demand items when justified. This strategy led to a 30% reduction in excess stock and a 15% increase in spare parts availability, optimizing costs and operational efficiency. Additionally, the study highlights the importance of establishing shared indicators between logistics and maintenance, maintaining accurate demand records, and centralizing spare parts storage to enhance decision-making and minimize downtime. These findings contribute to improving inventory management and reducing operational disruptions in industrial environments.

1. Introduction

Logistics constitutes a whole and is considered one of the main activities in the supply chain. Without raw materials, there is no finished product, but without logistics, there is no organization, no supply, storage, transportation, etc (Antún, 2010).

A fundamental object of logistics operations is to manage inventories in companies. Inventories can be defined as all those items or stocks used in production (raw materials and work in progress), support activities (maintenance and repair supplies), and customer service (finished products and spare parts).

Among the different types of inventories that may exist in companies are inventories of raw materials and supplies, work-in-progress inventories, finished goods inventories, and spare parts inventories. Although the first three are directly oriented to meet the needs of customers, the latter represents the possibility of not having to stop production processes for some time due to machinery failures and to use manufacturing resources efficiently. Industries from different sectors establish strategies based on maintaining inventories to guarantee adequate service levels to their customers and consumers. From this perspective, managers make significant investments in inventory, trying to meet proposed service level goals without the capital investments being too high. These decisions are made under considerations related to generating future demands, which usually arise from maintenance needs, either preventively or in response to failures. These demands are difficult to predict and are sometimes based on historical data from previous spare parts usage (Wang, 2012).

Determining inventory levels in a company has been a research problem for decades, with the most relevant studies being related to inventory control models such as Continuous Review (s, Q) and (s, S) and Periodic Review (R, S), which have been successfully applied in controlling raw material and finished product inventories (Khalilinezhad et al., 2021; Wang, 2012). However, when it comes to managing spare parts inventories, this responsibility has often been delegated to maintenance area managers, who define which spare parts should or should not be kept in inventory based on their importance (Cavalieri et al., 2008). Decisions related to spare parts inventories can sometimes lead to parts becoming obsolete or eventually causing a part of a production process to stop because a required spare part is not available. It should be considered that the lack of any spare part can have a very strong impact on production since the downtime of assets can increase due to waiting time if the necessary spare parts are not available. In addition, it is not possible to avoid unforeseen breakdowns, which reduce availability and increase the unreliability of manufacturing systems (Antosz & Ratnayake, 2019).

The determination of spare parts inventory levels should begin with a process related to defining their importance in terms of establishing the impact of their presence or absence in the industry, which may be due to their cost, acquisition difficulty, or any other criterion, leading to the need to find the optimal inventory level (Sgarbossa et al., 2021). This requires a systemic perspective to perform a criticality analysis and prioritize the necessary spare parts to increase the availability and reliability of a manufacturing system (Antosz & Ratnayake, 2019). To determine inventory importance, the traditional criterion based on item value multiplied by its annual usage rate (demand by value) has been used, but this criterion has not proven to be the most suitable. For example, in the case of medicines, their value is related to the well-being of living beings and not their monetary value, or in the case of spare parts, there are items that have had no use.

The common classification of spare parts is typically the ABC classification, where only the criterion of total annual cost, calculated as Demand x Unit Value (Dv), is used. In this classification, type A spare parts are the most important, with a high Dv, while type C parts are the least important, with the lowest Dv. Each resulting group is then managed with an appropriate policy. However, some items in class C may be crucial in terms of availability and criticality, despite their low-cost contribution. Therefore, a multicriteria ABC analysis is more appropriate for classifying these inventories, providing more reliable data. Additionally, during the development of the ABC analysis, verbal assessments are applied for subjective criteria by a group of members directly involved in the process (Gajpal et al., 1994).

In their research (Arrieta et al., 2023), a study is conducted at the company TGV in Colombia, where this issue is addressed through an approach based on ABC Analysis and the Pareto Principle, complemented by a periodic replenishment method that optimizes decision-making regarding suppliers and stock levels, however, these models prioritize inventory management from a cost- and demand-based perspective, without explicitly integrating a multicriteria evaluation that considers the criticality of the spare part, its impact on operations, replenishment lead times, and supplier availability.

In the case of (Paredes-Rodríguez et al., 2019), a methodological approach is proposed based on multicriteria analysis tools and forecasting techniques to optimize spare parts management in industrial inventories; initially, a hierarchical classification was applied using the Fuzzy Analytic Hierarchy Process (FAHP), considering criteria such as total cost and criticality to identify the most representative items within the warehouse. Subsequently, an additional segmentation was carried out to determine the most critical spare parts, complemented by a demand analysis and specific forecasting for the most relevant items (type A), based on these findings, a continuous inventory control policy (s, Q) was established, and its performance was evaluated through a case study applied to a sugar mill and the results obtained highlight the importance of a multicriteria approach for identifying strategic spare parts, enabling cost reduction and improved service levels within the organization.

The research (Serrano González et al., 2024) explores the implementation of the ABC technique for the control and classification of materials in the finished goods warehouse of Grupo Spring S.A. de C.V., demonstrating its impact on resource optimization and operational efficiency, the strategic categorization of products into A, B, and C groups based on cost and volume enabled better resource allocation, a reduction in handling costs, and an overall increase in efficiency, furthermore, the application of the ABC system not only optimized inventory management but also contributed to improvements in workplace organization, cleanliness, and safety, thus highlighting its influence on the company's operational and organizational structure.

The study conducted by (Phruksaphanrat, 2024) evaluates and compares multicriteria inventory classification techniques, including ABC, AHP, and DEA, aiming to optimize management in a refrigerator manufacturing plant, the results indicate that AHP outperforms both ABC and DEA in classifying existing inventories, leading to cost reductions and greater accuracy in category assignment and to classify new items, machine learning (ML) techniques were integrated, with DA and ANN proving to be the most effective, achieving an accuracy rate of 97.7%, the combined use of AHP for existing items and ANN for new ones enhanced inventory control and contributed significantly to operational efficiency.

In (C. P. Teixeira et al., 2019) the authors compare two multicriteria classification methods for spare parts management: rule-based classification and the Analytic Hierarchy Process (AHP). The findings indicate that the rule-based method is easier to implement within organizations, as it does not involve complex calculations, whereas AHP, although more accurate, presents great implementation challenges, especially for users without expertise in the methodology. While AHP allows for a more detailed analysis when multiple criteria are considered, its use in grouping spare parts requires the definition of additional thresholds, which adds to its complexity. Consequently, for classifying and grouping spare parts based on a limited number of criteria, the rule-based approach proves to be simpler and more practical for supporting inventory management decisions.

According to (Kabir & Ahsan Akhtar Hasin, 2011) compares AHP and Fuzzy AHP (FAHP) in the multicriteria classification of inventories, applied to 351 raw materials in an energy engineering company. It highlights that AHP is widely used to evaluate social, economic, and technical criteria through pairwise comparisons, while FAHP allows for the management of uncertainty in decision-making by incorporating fuzzy numbers. The results indicate that FAHP is more effective in environments with imprecise or subjective data, as it better captures the uncertainty inherent in human judgment. The research emphasizes the importance of balancing inventory costs and service levels, noting that proper inventory classification enhances both efficiency and business competitiveness.

In the case of medicines, (Gajpal et al., 1994) propose a classification of spare parts into three categories - vital, essential, and desirable - to determine their importance, while for spare parts, the authors in (Partovi & Burton, 1993) propose a multicriteria method based on Saaty's AHP (Saaty, 1987), considering qualitative and quantitative criteria. The established criteria were unit cost, acquisition cost, annual demand, and lead time.

Based on this, this research presents a hierarchical multicriteria classification process, the main contribution of this work is: 1. Three criteria are considered together to determine the importance of spare parts in an industrial company, which, according to the review carried out, had not been considered together before. In addition, each criterion was carefully defined and subdivided into 18 sub-criteria to evaluate each of the spare parts more accurately and with less subjectivity. 2. A multidisciplinary team of experts was integrated into the process. The inclusion of these experts in decision-making is essential in situations where multiple criteria or factors need to be considered. Multicriteria tools are particularly valuable when addressing complex decisions that encompass both quantitative and qualitative aspects. In this context, experts assessed the relative importance of a wide range of possible alternatives, contributing their specialized perspectives. Subsequently, based on the classification of spare parts, a set of control policies has been proposed that provide a strategic guide for inventory management. The rest of the document is structured as follows: in section 2, the methodology for the classification of spare parts is presented, using the multicriteria tool Analytic Hierarchy Process (AHP) and the ABC classification. In section 3, the results and discussion are presented. In section 4, the conclusions and future research are presented. Finally, in section 5, the bibliographic references are provided.

2. Materials and Methods

The methodology applied in this research is depicted in Table 1, which is developed in four phases: Phase 1. Characterization of the maintenance system. Phase 2. Definition of the AHP process. Phase 3. Expert selection. Phase 4. Application of the AHP tool. Phase 5. Inventory management proposal. An inventory policy is proposed as support for maintenance management for each spare part considering its ABC classification.

Table 1 *Methodology for classification of spare parts inventories*

1. Characterization of the maintenance system.	2. Definition of criteria and feasible alternatives.	3. Expert Selection	4. Application of a multicriteria tool.	5. Proposed inventory policy.
• Description of the maintenance system. • Management of spare parts storage.Management of spare parts supply. • Management of spare parts supply.	• Literature review to define criteria. • Literature review to determine alternatives.	• Identification of Potential Experts. • Assessment of Experience and Skills. • Ongoing Evaluation.	• Scoring Alternatives for each sub-criterion. • Scoring of Criteria and Sub-criteria. • Point Allocation. • ABC Classification.	• Demand analysis. • Demand forecasts for spare parts. • Control strategies for spare parts.

2.1 Phase 1: Characterization of the Maintenance System

In this initial stage, the environment in which the case study is developed is described, investigating the procedure carried out in maintenance activities for each equipment and the established management of spare parts.

2.2 Phase 2: Definition of Criteria and Feasible Alternatives

A literature review of articles that have used multicriteria analysis for spare parts classification was conducted. Based on this review, the process goal is established, criteria and sub-criteria are defined, and the considered alternatives (spare parts) are evaluated.

2.3 Phase 3: Expert Selection

Finally, a group of experts rates the alternatives and assigns a score to each spare part. A group of 7 experts in total, responsible for assigning evaluations to both criteria and sub-criteria, were selected using the Delphi method, with an emphasis on their level of knowledge of the problem and because they also represent the stakeholder group (Escobar-Pérez & Cuervo-Martínez, 2008; García et al., 2013; Zangara & Sanz, 2020). Their level of education and experience were considered, including the plant manager, maintenance manager, maintenance supervisor, plant maintenance technician, spare parts warehouse manager, and production manager.

This approach facilitates consensus-building through structured consultation rounds, reducing individual biases and ensuring well-founded decisions. Its application allows for the integration of expert knowledge from maintenance, logistics, and operations, thereby enhancing the accuracy of criteria weighting, combining the Delphi method with AHP, the robustness of the classification model is strengthened, ensuring inventory management is aligned with the company's operational needs (Montalván-Estrada et al., 2017).

2.4 Phase 4: Application of a Multicriteria Tool

The choice of AHP and Delphi is based on their suitability for contexts in which human expertise is essential for defining decision-making priorities, nonetheless, other methodologies were evaluated prior to their selection; Initially, Fuzzy AHP (FAHP) was considered, as it enables the incorporation of uncertainty in expert judgments through fuzzy numbers. However, this approach entails greater computational complexity, and its added value is marginal when working with highly knowledgeable domain experts, as was the case in this study and the Delphi methodology applied here enabled the collection of consistent evaluations, reducing the need to incorporate FAHP (Heredia et al., 2024).

The Analytic Hierarchy Process (AHP) was selected in this study due to its ability to structure the classification of spare parts by considering multiple key criteria such as criticality, supply, and maintenance, among others, unlike traditional ABC classification, AHP allows for the prioritization of spare parts not only based on cost but also on their operational impact, ensuring a more accurate and strategic inventory management approach. Moreover, its validation through the consistency ratio (CR) index ensures the coherence of expert judgments, thus optimizing decision-making and improving the availability of critical spare parts within the company (Saracoglu & Mifdal, 2024; C. P. Teixeira et al., 2019).

Table 2 *The Saaty scale of judgment*

Numeric Scale	Verbal Scale
1	Equal importance.
3	The element is moderately more important than the other.
5	The element is strongly more important than the other.
7	The importance of the element is very strong compared to the other.
9	The importance of the element is extreme compared to the other.
2, 4, 6, 8	Intermediate values between two adjacent judgments.
Increments of 0,1	Intermediate values between increments (use this scale if you believe your assessment needs a high degree of precision).

To implement this technique, steps mentioned in (Huamaní Huamaní & Eyzaguirre Tejada, 2015; Mendoza et al., 2019) are as follows:

1. Graphically represent the problem hierarchy.
2. Interpret the value judgments according to the Saaty scale presented in Table 2, adapted from Mendoza et al. (Mendoza et al., 2019).
3. Construct the value judgment matrices and normalized matrices, where pairwise comparisons are made for AHP.
4. Calculate the priority and consistency vectors. Calculations are made on the matrices, where expert judgments are loaded and compared one-to-one with the suggested scale.
5. Analyse the results. Finally, the weight of proposed criteria and sub-criteria are calculated and evaluated to decide on the alternative.

Since the AHP method relies on expert-assigned weightings, it is essential to assess the stability of the classification system in the face of potential variations in these judgments, to address this, a sensitivity analysis was incorporated to examine the robustness of the model under reasonable changes in the established weightings, this analysis was conducted in three complementary stages: first, the influence of modifying the weights of the main criteria on the final classification of spare parts was assessed, identifying whether a change in the weighting of a key criterion could significantly alter priorities; second, alternative scenarios were generated by adjusting expert judgments in order to test the consistency and stability of the obtained results; and third, the consistency ratio (CR) index proposed by Saaty was applied to ensure the internal coherence of the comparison matrices and to minimize the risk of bias that could compromise the model's validity.

2.5 Phase 5: Proposed Inventory Policy

In the final phase, the consumption behaviour of the analyzed items for the case study is determined and then control policies are established that are appropriate for each spare part considering its characteristics. First, the demand for each spare part is examined to understand its behaviour in order to determine the system that will forecast demand, and then control policies are defined. This research employs the Analytic Hierarchy Process (AHP) and the Delphi method for spare parts classification in inventory due to their capacity to structure complex decision-making problems and integrate both quantitative and qualitative criteria through expert judgment, these methods enable the evaluation of multiple relevant factors in inventory management, such as spare part criticality, supplier availability, and maintenance costs elements that are typically not addressed by traditional classification methods.

3. Results and Discussion

3.1 Case Study

The company has a standardized procedure that determines what, how, and when to perform maintenance activities for each equipment, as well as the direct responsible and with which indicators the management is tracked.

Among the main responsibilities of the maintenance area are: designing the preventive and predictive maintenance plan for the machines, updating the list of assets of machines and equipment in the plant, complying with indicators and establishing action plans for their improvement, managing through the spare parts warehouse those related to corrective improvement actions, auditing the plant's spare parts stock, defining the minimum, maximum quantities, and reorder points for each spare part and for each machine, making requests for the coding of spare parts according to the plant's needs.

The maintenance area structure consists of a base of electromechanical technical personnel, who are divided into work groups according to specific activities; these, in turn, are led by two engineers who are responsible for managing and coordinating plant management and report to the department head, who in turn reports to management.

3.1.1 Types of Maintenance

The company distinguishes three basic types of maintenance applied in any industry:

- **Preventive maintenance:** Its objective is to extend the life of equipment by preventing excess deterioration (ANSI, 2018).
- **Predictive maintenance:** Involves studying the temporal evolution of certain parameters and associating them with the evolution of failures, in order to determine when that failure will become significantly relevant and thus be able to plan all necessary interventions in advance so that the failure never has serious consequences (Torres, 2014).
- **Corrective maintenance:** Is the necessary intervention to solve a defect or an already occurred failure; in this case, the facilities, machines, or equipment operate with deficiencies or do not function at all (Molenaers et al., 2012).

3.1.2 Spare Parts Storage Management

The company uses the materials management module of its ERP system in which every two weeks the storekeeper reviews the items that are at the order point and issues the list, which is then reviewed by the maintenance department; together they determine which order points are replenished and which are not. The request for the order is generated, whose responsibility corresponds to the supply management area that safeguards and manages the inventory of spare parts.

In the case study, the spare parts warehouse consists of Hardware, Common Parts, Consumables, Specific Parts, and Universal Parts. A total of 6048 SKUs (Stock Keeping Units) have been created; of these, 1,314 are classified as "Non-Rotating," which means they have had no input or output and, therefore, their contribution to the inventory value is $0, only the code has been created; in addition to these, there are 892 codes that correspond to supply items, production consumables, obsolete parts, or machines that are not in use and are not part of this analysis. Table 3 shows the number of SKUs per year of entry and rotation.

Table 3 *Quantity of SKUs in the company's spare parts inventory*

SKUs (Stock Keeping Unit)								
Type of Rotation	Year 1	Year 2	Year 3	Year 4	Year 5	Year 6	Year 7	Total
High	4	8	9	17	23	156	1182	1399
Low	243	257	174	169	200	776	904	2723
Medium	5	5	5	6	23	78	490	612
None		8		3	1	4	1298	1314
Total Overall	252	278	188	195	247	1014	3874	6048

The above means that 4.734 SKUs are the ones that provide value to the spare parts inventory, as shown in Table 4.

Table 4 *Value of inventory by year of entry (Value $USD)*

Rotation	*Year 1*	*Year 2*	*Year 3*	*Year 4*	*Year 5*	*Year 6*	*Year 7*	*Total*
High	$ 31,86	$ 225,19	$ 136,64	$ 103,5	$ 387,29	$ 18.625,5	$ 206.859,1	$ 226.369
Low	$ 10.876,8	$ 13.917,6	$ 28.551,3	$ 6.981,3	$ 18.430,3	$ 120.827,8	$ 142.839,2	$ 342.425
Media	$ 155,36	$ 82,45	$ 31,11	$ 21,98	$ 1.602,97	$ 8.799,4	$ 68.236,3	$ 78.930
Total Overall	$ 11.064	$ 14.225	$ 28.719	$ 7.107	$ 20.421	$ 148.253	$ 417.935	$ 647.724

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The table presents the inventory value of spare parts according to their turnover rate (high, medium, and low) and year of entry. Most of the total value ($647,724) is concentrated in the last two years, particularly in low-turnover items ($342,425), suggesting an accumulation of rarely used parts, high turnover items ($226,369) show a significant increase in year 7, reflecting more recent operational activity, in contrast, medium turnover items ($78,930) account for a much lower value, revealing opportunities to optimize inventory and reduce overstock-related costs.

3.1.3 Spare Parts Supply Management

90% of the machine spare parts required by the company are of foreign origin, which means a variety of delivery times that usually exceed 20 days. This justifies maintaining inventories of these spare parts, particularly those prone to failure for which there is no alternative that can sustain operation until a new one arrives.

Regarding supplier delivery times, it is evident that there are 14 large groups of suppliers, mostly dealing with imported spare parts, whose delivery times depend on variables that cannot be fully controlled in many instances. Table 5 displays the documentation of the different suppliers.

Table 5 *Delivery times by supplier*

Consecutive	Delivery Time (Days)	Consecutive	Delivery Time (Days)
Supplier 1	4	Supplier 8	74
Supplier 2	60	Supplier 9	33
Supplier 3	60	Supplier 10	60
Supplier 4	75	Supplier 11	53
Supplier 5	90	Supplier 12	53
Supplier 6	53	Supplier 13	53
Supplier 7	53	Supplier 14	15

3.1.4 Costs Associated with Supply Management

The elements that affect the costs associated with the supply management of maintenance spare parts are [20]:

- **Acquisition or purchase costs (replenishment):** They depend on the suppliers, item shortages, conditions, shipments, purchase orders, supplier follow-up, receipt of shipped material, procedures, invoice reception, and administrative staff salaries. The cost associated with the acquisition or purchase of a spare part depends on whether it is a local, national, or international purchase.
- **Purchase price of the item:** It depends on the type of spare part to be requested, supplier, and location.
- **Storage cost:** The cost of storing inventory includes all expenses incurred by the company for having stock.

3.2 Phase 2: Definition of Criteria and Feasible Alternatives

The articles that have used multicriteria analysis for the classification of spare parts provide guidance on possible criteria to use to solve the problem at hand. Table 6 summarizes some of them.

Table 6 *Use of criteria by article*

Criterion	Article (s)	Criterion	Article (s)
Supply	(Braglia et al., 2004; Molenaers et al., 2012; Shao et al., 2012)	Maintainability	(Shao et al., 2012)
Storage	(Braglia et al., 2004)	Obsolescence	(Partovi & Anandarajan, 2002)
Low performance	(Gao & Hao, 2012)	Price	(Partovi & Anandarajan, 2002; C. Teixeira et al., 2018)
Maintenance capability	(Shao et al., 2012)	Reparability	(Partovi & Anandarajan, 2002)
Annual usage capacity	(Gao & Hao, 2012)	Residual Risk	(Gao & Hao, 2012)
Characteristics	(Gao & Hao, 2012; Shao et al., 2012)	Substitutability	(Gao & Hao, 2012; Partovi & Anandarajan, 2002)
Reliability / Safety	(Shao et al., 2012)	Usage Rate	(Braglia et al., 2004)

Criterion	Article (s)	Criterion	Article (s)
Plant criticality	(Braglia et al., 2004; Molenaers et al., 2012; Partovi & Anandarajan, 2002)	Type of required response	(Nouri Qarahasanlou et al., 2022)
Facility availability	(Gajpal et al., 1994)	Delivery Time	(Gajpal et al., 1994; Gao & Hao, 2012; Partovi & Anandarajan, 2002)
Demand	(Gajpal et al., 1994; Partovi & Anandarajan, 2002; Partovi & Burton, 1993)		

In addition to the criteria, some of the research that has supported the proposed methodology is related, where the use of various tools is presented. In 2014, in the investigation (Balaji & Kumar, 2014) indicated that the AHP method is used to perform a classification according to location for storage; three alternatives are proposed, which are evaluated based on criteria such as annual usage, unit price, demand, unit weight, and shape. The results show an inventory with considerable improvements in accessibility and traceability.

A classification model for spare parts based on their criticality, based on a multicriteria analysis resolved through AHP. They proposed a list of criteria that are subjected to categorization (vital, essential, and desirable), and these and other parameters are subjected to the AHP decision diagram to assign scores and establish levels of criticality, from level 1, which is highly critical, to level 4, which is not critical. The model was tested in a petrochemical company, achieving a 95.4% accuracy rate (Molenaers et al., 2012).

The decision criteria considered include average monthly demand, spare part delivery time, price, and risk priority number, using AHP, four spare parts reduction policies are proposed as alternatives: conservative policy, moderate policy, strong policy, and aggressive policy, the proposed methodology is applied in an auto parts company with satisfactory results that meet the needs of the company(Rubino et al., 2010).

This investigation (Braglia et al., 2004) propose a new multi-attribute classification model as a tool for spare parts inventory management, using two different methods: Reliability Centered Maintenance (RCM) and AHP. The model combines key aspects of RCM such as line criticality, production losses, among others, and analyzes them from inventory constraints, production loss costs, obsolescence, logistical aspects, etc.

For this case, based on the literature review carried out and the identified needs of the studied company, three macro criteria have been defined, whose evaluation allows defining the importance of the spare part:

• **Criticality**: Refers to the importance of the spare part according to its consequences. These can be critical from a safety, environmental, or performance standpoint and may relate to legal, regulatory, or statutory requirements (ISO, 2014; Molenaers et al., 2012). The defined sub-criteria of criticality are quality, productivity, cost of repair, safety of people, environment, and domino effect.

• **Supply:** It refers to the set of activities aimed at ensuring the availability of necessary resources for an operation (Mendoza Rivadeneira & Ceballos Polanco, 2016; Silver et al., 1998). For the case of interest, supply is associated with all processes aimed at guaranteeing the supply of a spare part in the event of an emergency or for its continued presence in inventory. Sub-criteria such as demand, unit cost, replenishment cost, replenishment time, storage, obsolescence, and number of suppliers are considered.

• **Maintenance:** It is associated with the set of activities aimed at preserving all the assets that make up links in a production or service system (Cavalieri et al., 2008; Sexto, 2018; Wang, 2012). The following sub criteria for maintenance are defined: reparability, type of maintenance, frequency of failure, cannibalism (removal of apart from another machine to continue the operation of the equipment), substitutability, age of the machine, technical specifications, utilization rate, and redundancy (backup).

3.2.1 Identification of Feasible Alternatives

The alternatives that the model can consider are each of the spare parts with their respective weighting. It is necessary to establish which spare parts cannot be kept in stock and the reasons for this. To establish feasible alternatives, it is important to identify all possibilities. For the purposes of the study, the following alternatives are considered:

• **Consumable spare parts:** These are usually low-cost items that are regularly used, such as seals, retainers, fuses, etc. They usually have an established failure rate or are listed in the recommended preventive maintenance schedules by the manufacturer, their replacement depends on the maintenance strategy involved (Molenaers et al., 2012; Rubino et al., 2010).

• **Wear and tear spare parts**: These are normal wear and tear items that need to be replaced after a certain number of operating hours, they usually have an established failure rate or are listed in the recommended preventive maintenance schedules by the manufacturer. Their replacement depends on the maintenance strategy involved (Cedeño Anchundia et al., 2016).

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• **Safety spare parts:** These are spare parts whose impact of not having them in stock can be high, the costs of downtime due to machine stoppage outweigh any other costs and they may or may not have an established failure rate, but their lifespan is subject to the operating conditions of the equipment and its working hours (Paredes-Rodríguez et al., 2019).

3.3 Phase 3: Expert Selection

In order to provide an evaluation consistent with the criteria and sub-criteria for choosing the most feasible alternative in the case study, we opted to select seven experts mentioned earlier, using the Delphi methodology, as follows (García et al., 2013):

• **Plant Manager:** This refers to the person responsible for the overall financial indicator of the plant, which includes maintenance expenses and whether the allocated budget is met. Highlighting their effective asset management and decision-making regarding significant expenses.

• **Maintenance Manager:** The direct overseer of the plant's overall maintenance indicator, associated with the available machine uptime in good operating condition, as well as the prudent use of the allocated budget to ensure it, they possess clarity on internal procedures for spare parts requisition and, being responsible for expenditures, authorize their procurement.

• **Maintenance Supervisor:** Those who coordinate personnel and activities in the area, responsible for resource management, they generate material lists for preventive maintenance and ensure the execution of predictive techniques when responding to recommendations.

• **Plant Maintenance Technician:** Responsible for executing both preventive and corrective maintenance, their extensive knowledge of machinery allows them to educate and lead teams in performing tasks on these machines, their in-depth understanding of the machines enables them to contribute to the significance of a spare part for them.

• **Spare Parts Warehouse Manager:** The person overseeing warehouse spare parts. They initiate replenishment requests for SKUs that have reached the minimum or reorder points and replenish safety stock. Their extensive experience and familiarity with procurement procedures, spare parts, and suppliers make them knowledgeable about the average lead times for each.

• **Production Manager:** Refers to the individual(s) knowledgeable about the production plan, ensuring its execution. They are accountable for productivity and quality indicators. Their production insight enables them to prioritize the importance of machines and draw equivalences among them.

A survey was employed to gather the experts' opinions on the matter, comprising a total of 75 questions distributed as follows: three questions for comparing the criteria to each other, fifteen questions for comparing the sub-criteria established for the criticality criterion to each other, twenty-one questions for comparing the sub-criteria established for the supply criterion to each other, thirty-six questions for comparing the sub-criteria for the maintenance criterion to each other, and a final question requesting the expert to specify their job title or position (García et al., 2013; Mendoza Rivadeneira & Ceballos Polanco, 2016; Zangara & Sanz, 2020).

3.4 Phase 4: Multicriteria Tool Application

By bringing together all the previous aspects into one, the result is the AHP hierarchical model with 4 levels that serves as a guideline for solving the need for classification of spare parts importance as shown in Fig. 1.

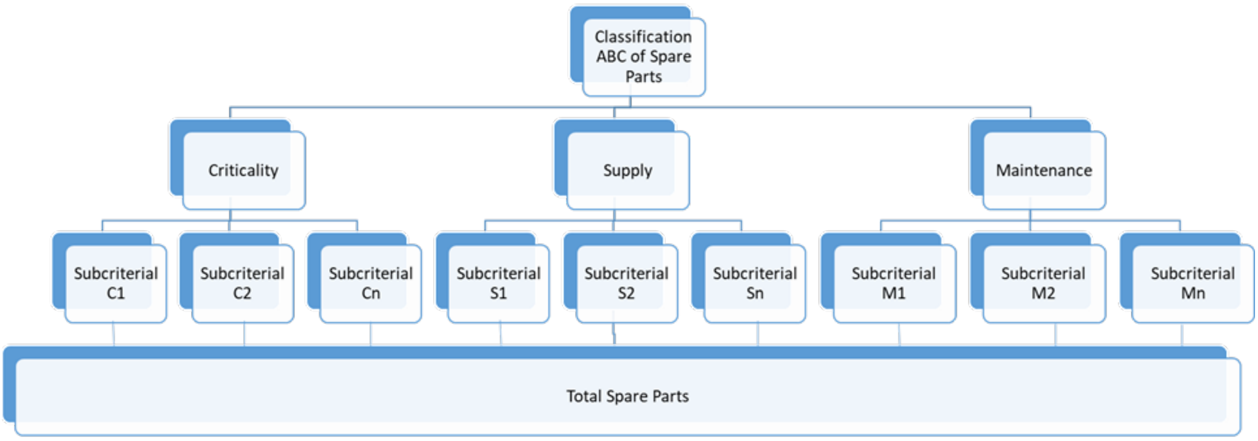

Fig. 1 *Hierarchical model for spare parts classification using AHP*

For the implementation of the AHP tool, the judgments of the aforementioned experts was collected to obtain different hierarchical perspectives, as well as their experience, time, and knowledge of the problem. These aspects are considered in this approach to avoid biases in decision-making within an organization. By including the participation of diverse individuals, a more comprehensive and equitable view is achieved, contributing to more informed and effective decision-making. The method used to gather the expert group's opinion on the criteria and sub-criteria presented in the solution guideline was a survey to generate a numerical weighting, representing the relative importance of each criterion, sub-criterion, and alternative. Since a criteria and/or sub-criteria comparison matrix allows only one rating for each pairwise comparison, the judgments must be treated using the geometric mean (Yamane, 1976), as shown in Equation (1).

$$m_g = (X_1 X_2 \dots X_n)^{\frac{1}{n}} = (\prod_{i=1}^{n} X_i)^{\frac{1}{n}} \quad (1)$$

The resulting averages from the judgments provided by the experts were used to create pairwise comparison matrices, which underwent a process of review and weighting to obtain the final prioritization that determines the global priority. The final result for each alternative is a value between zero and one, where one represents the highest possible importance and zero the lowest (Nantes, 2019; Rezaei, 2015). This allows generating a descending-ranked list based on the overall priority of the analysed dataset. Table 7 shows the weighting of criteria and sub-criteria for SKU 1013 (corresponding to the evaluated SKUs).

The total of analysed alternatives has been gathered into three classification groups: class A items, class B items, and class C items; with class A items being the most important, class B items being of medium importance, and class C items being of lesser importance (Vidal Holguín, 2010). This classification, known as ABC classification, has been performed based on the percentage of items as shown in Table 8.

Table 7 *Calculation of global priority for SKU 1013*

Material	SKU	Result Category	Description	Weight A	Preference eigenvector for subcriteria B	Total weight of subcriteria C:(AxB)	Local Priority D:∑(AxB)	Preference eigenvector for criteria E	Total Priority F: (DxE)	Global Priority G
Criticality	**Quality**	Critical	Between 0 and 85% of products meet quality parameters.	1,000	**0,404**	0,404	0,777	**0,683**	0,531	**0,693**
	Productivity	Critical	Limited productivity between 0 and 85%.	1,000	**0,227**	0,227				
	People safety	Desirable	The failure of the part may cause a minor incident without loss of time.	0,330	**0,183**	0,060				
	Environment	Desirable	No risk to the environment.	0,330	**0,113**	0,037				
	Repair cost	Important	Greater than \$0.9 and less than \$1494.	0,660	**0,042**	0,028				
	Domino effect	Important	Limited effect on productivity. Damage to the spare part affects only one or a few productive parts.	0,660	**0,031**	0,020				
Supply	**Demand**	Result =		0,000	**0,389**	0,000	0,291	**0,200**	0,058	
	Unit Cost	Result =		0,000	**0,252**	0,000				
	Replenishment cost	International repositioning	Management is carried out through foreign trade personnel, although exclusive suppliers always require a quotation.	1,000	**0,105**	0,105				

	Replenishment time	Very high	Lead time > 30 days.	1,000	**0,118**	0,118			
	Storage	Desirable	Minimum storage space required. No special adaptation is required beyond what is already provided for general spare parts storage.	0,330	**0,056**	0,018			
	Obsolescence	Desirable	No obsolescence is presented.	0,330	**0,047**	0,016			
	Number of suppliers	Critical	Only one supplier.	1,000	**0,034**	0,034			
	Repairability	Critical	Non-repairable spare part.	1,000	**0,269**	0,269			
	Maintenance type	Corrective	The spare part or component is not subject to any monitoring. It is used until it fails.	1,000	**0,252**	0,252			
	Failure frequency	Medium	1/5 (event)/year <= f < 1 (event)/year	0,660	**0,167**	0,110			
Maintenance	**Cannibalism**	Important	It is possible to replace the part with another one removed from another machine, but it is not advisable.	0,660	**0,109**	0,072	0,890	**0,117**	0,104
	Substitutability	Critical	It is not standard. It can only be acquired from the machine manufacturer.	1,000	**0,079**	0,079			
	Machine age	Age	t>10 years.	1,000	**0,046**	0,046			
	Technical specifications	Critical	There is no information available about the spare part.	1,000	**0,036**	0,036			
	Utilization rate	Low	Only one is required in the plant.	0,330	**0,024**	0,008			
	Redundancy	High	No redundancy.	1,000	**0,018**	0,018			

The Table 7 presents the evaluation of a spare part using the AHP method, considering the criteria of criticality, supply, and maintenance, along with their respective sub-criteria. The spare part obtained an overall priority of 0.693, indicating high importance, the most influential criterion was criticality (0.683), with key aspects such as quality and productivity standing out, in the supply dimension (0.200), factors like long lead times and the reliance on a single supplier increased its relevance. In terms of maintenance (0.117), non-repairability, corrective usage, and lack of technical information further reinforced its priority, this result supports the prioritization of this item within inventory control due to its operational impact and difficulty of replacement.

Table 8 *Number of items per classification group*

Number of items	3842	
	Percentage	Items per group
Class A Items	20%	768
Class B Items	30%	1153
Class C Items	50%	1921
Total Sum	100%	3842

3.4.1 Sensitivity Analysis of the AHP Model

Since the AHP method relies on subjective judgments provided by experts to assign weights to various criteria and sub-criteria, it is essential to assess the model's robustness against potential variations in these evaluations. To this end, a sensitivity analysis was conducted to examine the stability of spare parts classification when changes are introduced to the established weights. The procedure was carried out in three phases:

3.4.1.1 Evaluation of the Impact of Variations in the Weights Assigned to the Criteria

This phase analyzed how changes in the weights of the main criteria (criticality, supply, and maintenance) influence the overall priority of the items. For this purpose, the weights of each criterion were progressively adjusted (±5%, ±10%, ±15%) while maintaining a total sum of 1. The aim was to observe whether the item's classification within group A, B, or C remained unchanged or was altered. For instance, in the case of SKU 1013 (Table 7), the criticality criterion holds a dominant weight of 0.683, meaning that small variations in this factor have a greater impact compared to supply (0.200) or maintenance (0.117).

3.4.1.2 Simulation of Alternative Scenarios with Modified Judgments

Given the involvement of multiple experts in the development of the AHP model, the geometric mean (Equation 1) was applied to synthesize individual judgments and construct the pairwise comparison matrices. To verify the stability of the results, alternative scenarios were generated by slightly altering the individual values used in the comparisons. These new scenarios made it possible to assess whether global priorities changed significantly or if the items retained their original classification group (Table 8). This process validated the stability of the decisions, even in the presence of minor discrepancies among expert opinions.

3.4.1.3 Consistency Verification Using The Consistency Ratio (CR)

In each scenario generated during the sensitivity analysis, the consistency ratio (CR) proposed by Saaty was calculated to assess the logical coherence of the judgments within the pairwise comparison matrices. A CR value equal to or below 0.10 is considered acceptable, as it indicates that the level of inconsistency in expert evaluations is sufficiently low to ensure reliability.

3.4.2 Alternative Scenarios and Their Feasibility in the Sensitivity Analysis

3.4.2.1 Scenario 1: Increase in the Weight of the Supply Criterion

In the event that the weight of the supply criterion were increased (e.g., from 0.200 to 0.300), items facing logistical challenges such as long lead times, reliance on a single supplier, or high import costs would gain greater overall priority. This shift could result in some items originally classified as class B or C moving into class A.

This scenario would be relevant if the company is experiencing recurrent supply shortages, an overdependence on single suppliers, or logistical constraints that threaten operational continuity. Under such conditions, prioritizing spare parts availability even above functional criticality could be a viable strategy to ensure the steady flow of operations.

3.4.2.2 Scenario 2: Decrease in the Weight of the Criticality Criterion

A reduction in the weight assigned to the criticality criterion, for instance from 0.683 to 0.500, would tend to favor the classification of items that, while not functionally critical, present greater challenges in terms of logistics or maintenance. In this context, such spare parts could move up in the prioritization model.

However, this scenario is not advisable in industrial environments like the one analyzed (plastics transformation), where machine downtime due to the absence of critical spare parts leads to high operational and product quality costs. Lowering the weight of criticality would increase the risk of unexpected failures, potentially resulting in significant losses due to unplanned downtime.

3.4.2.3 Scenario 3: Increased Weight for the Maintenance Criterion

Raising the weight of the maintenance criterion, for example from 0.117 to 0.250, would increase the relevance of items characterized by non-repairability, predominantly corrective maintenance, limited technical documentation, or dependence on cannibalization for recovery. Consequently, certain spare parts that do not have high turnover but are difficult to diagnose or replace could be reclassified.

This scenario becomes meaningful in contexts where the company has identified that low-demand spare parts generate hidden costs due to their technical management complexity or the need for complete replacement. Increasing the weight of the maintenance criterion supports a strategy focused on preventive maintenance and

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the consolidation of technical knowledge, with the aim of reducing the operational impact of hard-to-resolve failures.

3.4.2.4 Scenario 4: More Balanced Distribution Among The Three Criteria

If similar weights were assigned to the three main criteria (e.g., 0.33 for each), the result would be a more neutral classification, with no single criterion prevailing over the others. While this approach might appear fair, in contexts such as the one analyzed where functional and operational criticality plays a central role this scenario may prove less effective. By diluting the true importance of items whose failure compromises operations, it could lead to inaccurate classifications and inefficient logistical decisions.

Table 9 *Sensitivity analysis scenarios in the AHP model*

Scenario	Weight Adjustment	Effect on Classification	Feasibility	Recommendation
1. Increase in Supply Weight	Supply: from 0.200 to 0.300	Items with high logistical difficulty (e.g., long lead time, few suppliers) gain priority; some class C or B items may shift to class A.	Feasible in contexts with supply risks, external dependence, or consolidated purchasing policies.	Applicable when aiming to prevent shortages and optimize bulk procurement.
2. Decrease in Criticality Weight	Criticality: from 0.683 to 0.500	Less functionally critical items gain weight; truly critical items may drop in ranking, increasing operational risk.	Not recommended for industries sensitive to downtime due to missing critical parts.	Avoid this configuration in intensive or highly dependent operational environments.
3. Increase in Maintenance Weight	Maintenance: from 0.117 to 0.250	Items with technical issues (non-repairable, lack of documentation, etc.) are prioritized, even if they are not high-rotation or immediately critical.	Viable when aiming to strengthen technical management, avoid cannibalization, or reduce failures due to poor documentation.	Recommended during technical improvement or maintenance digitalization phases.
4. Balanced Weight Distribution	All criteria weighted approximately 0.33	Results in a more neutral classification may dilute the real importance of critical items and give priority to less relevant ones in demanding operational scenarios.	Less feasible in industries like plastics, where operational continuity depends heavily on criticality.	Useful only for exploratory studies or environments with low operational variability.

The combined use of ABC and AHP enabled the classification of spare parts by simultaneously considering multiple criteria such as criticality, supply, and maintenance which significantly improves the accuracy of classification and the quality of decision-making. In contrast, had a traditional ABC approach been used, only a single criterion typically cost or annual consumption would have been evaluated, thereby limiting the analysis and increasing the risk of misclassification (Paredes-Rodríguez et al., 2019).

Thanks to the multicriteria approach adopted, greater efficiency in inventory management was achieved through better resource allocation, reduced costs associated with storing unnecessary spare parts, and more accurate prioritization of items critical to operations. These results demonstrate that the proposed model offers clear practical and operational advantages over traditional inventory classification methods.

3.5 Phase 5. Inventory Policy

There is a conflict in spare parts inventory decisions, as not having a spare part can significantly affect a production system, while having it without using it represents a wasteful investment in an asset. The use of experts in the Analytic Hierarchy Process (AHP) and decision-making is of utmost relevance and importance for the research and validation of multicriteria tools (López-Zapata et al., 2015). Experts provide specialized knowledge in the various criteria and alternatives being evaluated, ensuring greater accuracy and robustness in the results obtained. Experts can assist in the selection and evaluation of alternatives, providing technical expertise and practical experience in the subject matter.

Their involvement in the decision-making process ensures that the options considered are feasible and viable in the specific context of the research. Costs associated with spare parts and supplies are an important item within the investment and routine maintenance expenses. Companies that develop inventory management policies can achieve savings of more than thirty percent monthly in capital allocated to this (Hodson, 2022; ISO, 2014; Molenaers et al., 2012).

The failure of a critical spare part can stop a company's production for days or even months. Ideally, the replacement part for the component that may fail and cause a machine stoppage should be readily available. Factors such as time, distance, and availability of the spare part justify the existence of inventories, subject to control policies that take into account the responsibilities of the parties involved, associated with availability. On the one hand, the warehouse that must ensure the availability of the part, and on the other hand, maintenance, which must ensure the availability of the production assets (Antún, 2010; Hodson, 2022; Pishdad & Labeau, 2020).

The process followed is to determine the consumption behaviour of the analysed items for the case study and then establish appropriate control policies.

3.5.1 Demand Analysis

To make decisions regarding the management of each item that is part of an inventory, it is necessary to understand their historical behaviour and according to the type of demand presented. For the case study, the historical demand of the 3,842 alternatives was analysed over 72 months using Equation (2), called the coefficient of demand variation. The rule is very general, as mentioned by Vidal [36], but it establishes that if the result is equal to or greater than 1 (100%), the demand can be considered erratic, and for the opposite case, it can be considered non-erratic.

$$\text{C.V of demand} = \frac{\text{Standard deviation of demand}}{\text{Average Demand}} \tag{2}$$

The results after analysing the 3,842 items are presented in Table 9. Although the coefficient of variation rule is very general, it serves as a starting point for analysing each particular case. Table 10 shows the number of items classified by type of demand and ABC classification.

Table 10 *Number of items per demand type*

Class Items	A	B	C	Total
No Demand	240	336	463	1039
Non-Erratic	13	16	116	145
Erratic	515	799	1344	2658
Total	768	1151	1923	3842

The demand analysis was carried out taking into account both its qualitative and quantitative aspects. The quantitative part is related to its coefficient of variation, while the qualitative aspect is related to the behaviour of the curve that describes the demand, in other words, its pattern. According to the table, for item A, the thirteen demands defined as non-erratic are bounded between 0.7366 and 0.9404, and the five hundred fifteen demands defined as erratic are bounded between 1.0075 and 4.2716. In the case of item B, the sixteen demands defined as non-erratic are bounded between 0.5135 and 0.9997, and the seven hundred ninety-nine defined as erratic are bounded between 1.0280 and 4.2716. For item C, the one hundred sixteen demands defined as non-erratic are bounded between 0.3048 and 0.9992, and the four hundred sixty-three demands defined as erratic are bounded between 1.0011 and 4.2716.

The analysis of historical demand is crucial in selecting the forecasting method to be used.

3.5.2 Demand Forecasts for Spare Parts

The demand patterns identified in the previous section represent the general behaviour of each ABC classification group. An article forecast system was established according to the demand pattern presented. Table 9 shows that, out of the total of 3,842 items, 145 present a non-erratic demand pattern: some with a growing trend, others with a decreasing trend, or, failing that, a perpetual demand pattern. Since these are items from the most important groups, a double exponential smoothing forecast system has been selected, recommended for these types of demand considering their importance.

As an explanatory example, item 39 from the case study is taken, with the demand trend graph shown in Fig. 2, with a linear trend and a coefficient of variation = 0.737, classified as A.

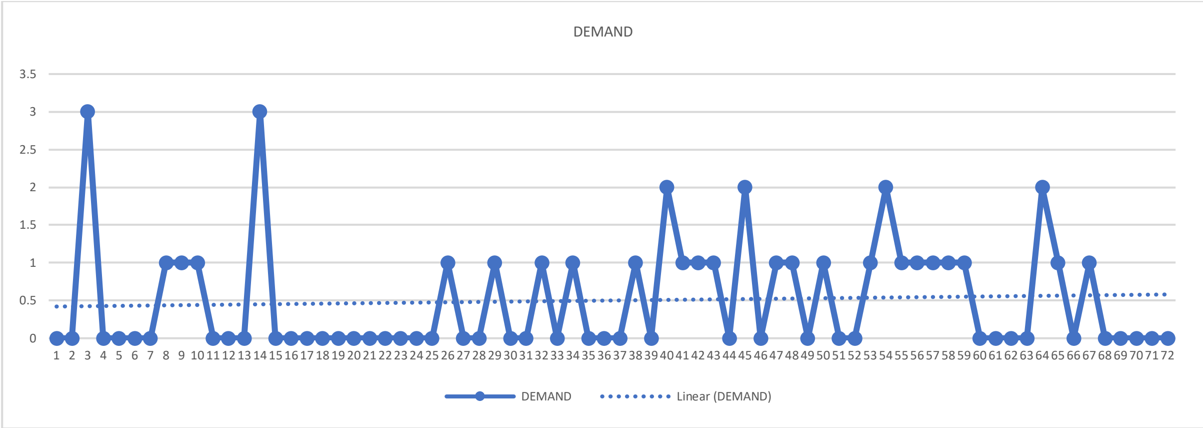

Fig. 2 *Demand for item 39 - A classification group*

As an indicator of the goodness of the forecast and its characteristics, the mean squared error (MSE) is selected, which is a method for evaluating the forecasting technique. Each residual or prediction error is squared, summed, and divided by the number of observations [39]. Equation (3) corresponds to the MSE [36],[40–42].

$$ECM = \frac{\sum_{t=1}^{n}(x_t - \hat{x}_t)^2}{n} \tag{3}$$

The proposed forecasting model was built using a spreadsheet and optimized with the Solver tool to obtain the value of α and β that minimizes the ECM, thus obtaining the value of α = 0.0885539983362672 and β = 0.911446002, as shown in Fig. 3.

PARAMETERS				
a	0,75		Alfa	Beta
b	-0,03		0,088553998	0,911446002
		DOUBLE EXPONENTIAL SMOOTHING		
PERIOD	DEMAND	S_t	$S_t^{[2]}$	X_t

INDICATORS				
	MAD	ECM_t	MAPE	MAPE*
	1	0,484	22,6%	106,2%
e	lel	e^2	lel/X_t	lel/X^*_t

ESTIMATORS				TRACKING SIGNAL	
0,0	W	S_E	C_1		
	0,1	0,7107104	1,12016303		
Average Error	Smoothed Error	Smoothed MAD	Smoothed MSE		
Y(T)	Q(T)	MAD(T)	MSE(T)	Q(T)/MAD(T)	Y(T)/MAD(T)

Fig. 3 *Forecast for SKU 39*

From the analysis of 3,842 items, it was identified that 2,648 exhibit erratic demand. For forecasting purposes, an approach was adopted based on a study of spare parts inventories in chemical plants, which indicates that erratic demand does not follow normal or Poisson distributions, although the occurrence of events can still be modeled as a random Poisson process (Vereecke & Verstraeten, 1994) this characteristic enabled the definition of a specific control policy for items with erratic demand.

As for items with no demand, the main challenge lies in the absence of historical data for generating forecasts. In these cases, the global priority obtained from the AHP analysis will serve as the basis for deciding whether the item should be kept in inventory. Although it is not possible to determine an optimal quantity, the initial strategy will be to maintain one unit as a basic control policy, which will be adjusted according to the item's classification within its importance group.

3.5.3 Control Policies for Spare Parts

Defining a review frequency (R), understood as the replenishment cycle, enables an efficient distribution of the workload associated with managing 3,842 items. It also facilitates the simultaneous purchasing of multiple spare parts from the same supplier, thereby helping to reduce ordering costs. To establish a maximum inventory level, the ordering moment is determined as follows: if, at the time of review, the effective inventory is below the defined maximum, the difference is ordered as the replenishment quantity. The proposed strategy reflects the selected control policy, which is adapted according to the importance group of the spare part and its demand type, resulting in a more efficient and cost-effective management of maintenance inventories.

For class A and B items with perpetual, increasing, and decreasing demand, a periodic system (R, S), also known as the reorder cycle system [36,43]). For both groups, a safety stock defined by Equation (4) is included to cover demand variability, with a specific service level for each. Was established. In this system, every R units of time, the effective inventory is reviewed, and an order is placed for an amount such that this inventory rises to the maximum value S defined by Equation (5).

For class C items with perpetual, increasing, and decreasing demand, a (R, S) system was also established, but using the standard deviation of the average error. The (R, S) inventory control policy developed in Vidal [31] is presented below.

$$Safety\ inventory\ SI\ = k\sigma_{R+L} \tag{4}$$

Where: k = Safety factor dependent on the desired service level.

$$S = d(R+L) + IS \tag{5}$$

Where: d(R+L) = Forecasted demand during the replenishment time L plus the review period.

For items with erratic demand, a safety inventory based on the standard deviation of the average error was established, considering the probability of demand occurrence, taking into account that it follows a Poisson distribution [44].

Table 11 *Parameters for controlling class A, B, and C items*

Parameter	Class A items	Class B items	Class C items
Service level P1	97.5%	95%	90%
Safety factor k	1,96	1,64	1,28
Review period R	30 días	60 días	90 días

The control policies for items with non-erratic demand are defined by the established ABC classification group. There are thirteen items in group A, and their control policy will be as follows: for each review period of R=30 days, the difference between the maximum inventory level S and the effective inventory level will be ordered, with a safety stock level IS that ensures a probability P1=97.5% of not having a stockout during the replenishment cycle. Table 11 shows the established policies for them, where IS and S are obtained by applying Equations (6) and (3), respectively.

$$\sigma_{R+L} = \sigma_1\sqrt{R+L} \tag{6}$$

Where: σ_1= Standard deviation of forecast errors.

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Table 12 *Control policies for class A items with non-erratic demand*

Item	Reorder cycle (days)	Average monthly demand d	Demand R + L	Standard deviation of demand forecast errors	Safety stock IS	S	Policy
444	4	1,233	1	0,914	3	4	Each 30 days, review the inventory and order a quantity Q = (4 * the actual inventory).
38	90	1,014	4	0,771	6	10	Each 30 days, review the inventory and order a quantity Q = (10 * the actual inventory).
39	90	0,986	3	0,711	3	6	Each 30 days, review the inventory and order a quantity Q = (6 * the actual inventory).
408	60	5,726	10	7,100	29	39	Each 30 days, review the inventory and order a quantity Q = (39 * the actual inventory).
476	75	0,877	2	0,897	4	6	Each 30 days, review the inventory and order a quantity Q = (6 * the actual inventory).
489	75	0,685	2	0,720	3	5	Each 30 days, review the inventory and order a quantity Q = (5 * the actual inventory).

Table 12 presents the control policies for six class A spare parts with non-erratic demand. Every 30 days, inventory is reviewed and a replenishment order is placed to adjust the level to the predetermined maximum S (e.g., S = 4, 6, 10, 39, etc.). It is observed that the review cycles (R) vary between 4 and 90 days depending on the SKU, with average monthly demand ranging from 0.685 to 5.726 units, forecast error standard deviations between 0.711 and 7.100, and safety stocks (SS) ranging from 3 to 29 units. The order quantity Q is calculated as Q = S – effective inventory at the time of review. Additionally, joint replenishment of spare parts by grouping orders by supplier, brand, or manufacturer allows for volume discounts, meeting minimum order quantities, and reducing handling costs.

Joint replenishment of spare parts in organizations is a necessary practice due to the following situations: the presence of spare parts of different brands, whose representative is the same supplier, the direct purchase of spare parts from the machine manufacturer, the cost-saving of replenishment that involves handling large volumes, and the minimum order value established by certain suppliers within their sales policies.

3.5.4 Control Policy for Items with Erratic Demand

The cases were analyzed according to the number of demands presented in the evaluation period as shown in Table 13 and the Poisson probability function was applied to determine the possibility of the event occurring. In the event of a failure defined by the probability, the costs incurred due to the high criticality of the items are high compared to the cost of keeping the required spare part in inventory. Equation (7) corresponds to the Poisson probability function Vidal [36].

$$f(x,\lambda) = \sum_{x=0}^{X} \frac{\lambda^x e^{-\lambda}}{x!} \tag{7}$$

Where: λ = Is the average of results per period of time.

x = Is the number of times the phenomenon is expected to occur (probability of failure).

After analysing each case of the 515 items in class A, three policies were established for the set:

• No safety stock should be kept because these are items that present very high demand in a single period.

• Items with SS equal to the mean demand in their single time, with a review period R = 30 and a service level P1 = 97.5%.

• Items with SS calculated using Equation (6) but using the standard deviation of errors in the mean for the analyzed period, a review period R = 30, and a service level P1 = 97.5%.

Table 13 *Demand quantity for erratic class A items*

Number of periods with demand	Number of items	Number of periods with demand	Number of items
1	241	12	8
2	103	13	7
3	39	14	5
4	30	15	4
5	22	16	5
6	12	17	1
7	10	18	1
8	6	19	2
9	6	20	1
10	4	23	1
11	7	Total overall	515

Table 14 *Control policy for class A items with erratic demand*

							Result (x) for X=0,1,2		
Item	Unit value	Lead Time	Average demand d (monthly)	Total demand	Periods with demand	Lambda	0	1	2
38	$ 314.674	90	0,3288	12	1	0,0139	0,986	0,014	0,000
41	$ 428.625	90	0,1644	6	1	0,0139	0,986	0,014	0,000
15	$ 28.456.848	90	0,0548	2	2	0,0278	0,973	0,027	0,000
669	$ 1.758	33	3,3973	124	3	0,0418	0,959	0,040	0,001
337	$ 45.741	33	0,3014	11	5	0,0694	0,933	0,065	0,002
648	$ 49.110	33	3,6438	133	20	0,2778	0,757	0,210	0,029

Table 14 presents the control policies for class A items with erratic demand, characterized by their high unit value and low consumption frequency. A probabilistic model based on the Poisson distribution was applied to estimate the probability of demand occurrences of 0, 1, or 2 units during the replenishment lead time.

For instance, item 38, with a unit value of $314,674 and a lead time of 90 days, has an average monthly demand of 0.3288 units. The probability of no demand occurring during the lead time is 98.6%, while the probability of a demand for one unit is 1.4%. These analyses make it possible to define appropriate safety stock levels, minimizing storage costs without compromising the availability of critical spare parts.

Table 15 *Control policy for class A items with erratic demand part 2*

Item	Backorder cost	Annual holding cost	Safety Stock (SS)	Control policy
38	$ 21.500.000	$ 2.793.271	0	Maintenance major or overhaul. No stock
41	$ 21.500.000	$ 1.902.390	6	SS equal to the average demand per occurrence
15	$ 21.500.000	$ 42.100.542	1	Safety Stock
669	$ 302.900.000	$ 161.254	29	Safety Stock
337	$ 302.900.000	$ 372.190	3	Safety Stock
648	$ 302.900.000	$ 4.831.568	26	Safety Stock

The control policy for class A items with erratic demand (Table 15) is based on cost evaluation and the criticality of each spare part. For items with high backorder costs and significant unit values, such as items 38 and 15, the strategy favors maintaining minimal or even zero safety stock, prioritizing the scheduling of major maintenance or general inspections to avoid unnecessary inventory accumulation. In contrast, for items like 669 and 648, which exhibit more frequent demand and high backorder costs, a substantial safety stock is maintained (29 and 26 units respectively) to ensure availability and minimize the risk of operational disruptions. This strategy balances inventory holding costs with the need to ensure operational continuity, adapting to the specific characteristics of each spare part.

4. Validation

The model represents a part of the system's functioning; therefore, it is mentioned that no model is 100% accurate or valid in its response. As expert-validated data was used, the model was developed using the AHP tool, yielding valid results regarding the inventory problem presented. This made it possible to establish control policies for items and adjust priorities. The model and forecasts were made, presenting coherence in the results obtained in accordance with the supplied data, and were also examined by experts and referenced in the evaluation of the criteria.

5. Conclusions

The implementation of the AHP-ABC model significantly improved the accuracy of spare parts classification by integrating criteria such as criticality, supply, and maintenance, thereby overcoming the limitations of the traditional ABC method, among the most notable results were a 30% reduction in excess inventory and a 15% increase in spare parts availability, contributing to cost optimization and enhanced operational efficiency.

The sensitivity analysis confirmed the robustness of the model, as variations in expert judgments did not substantially alter the final classification. Moreover, control policies were defined according to demand type, enabling a more strategic approach to inventory management.

There is a wide gap between the logistics and maintenance functional areas in a company, which negatively impacts the management of both. On one hand, logistics is in charge of managing the spare parts warehouse and has the knowledge to implement control policies that help increase its service level, while on the other hand, maintenance is the area that knows the spare parts and can help define the parameters for the warehouse to execute controls. This is a product of the most common business model in which the functional areas of a company work and create improvement actions for their own indicators, but there are no shared indicators that require the joint work of these areas.

After applying the AHP model to all analyzed items, there are cases in which the model results differ from the technical group's opinion regarding importance, as well as cases in which the opinion of importance is similar. The point is that there is no quantitative comparison data, so generating the global importance list and performing the ABC classification immediately guides which items to focus on first and allocate more control resources due to the impact their absence produces.

Analysing the demand histories of the case study's spare parts, it is evident what is mentioned in the literature: spare parts have highly erratic demands that do not allow establishing a control system based on a forecast. However, this is not limiting to establishing policies that allow adequate supply management that contributes positively to maintenance work.

There are two aspects to consider in the joint work that the spare parts warehouse and maintenance must do to have accurate demand data for a better analysis:

- Keep track of unmet demand.
- Avoid storing spare parts outside the warehouse (in workshops, for example).

At a practical level, the proposed approach enabled the establishment of differentiated control policies based on demand type (erratic or non-erratic) and ABC classification, allowing for stock level adjustments or the elimination of items when justified, based on the trade-off between stockout cost and inventory holding cost.

As a future line of research, it is recommended to empirically validate this model in other industrial settings, particularly in sectors characterized by high demand variability or critical dependencies it is also suggested to compare its performance with approaches based on artificial intelligence or fuzzy models (such as Fuzzy AHP), which may offer advantages in highly uncertain contexts. Finally, integrating the model with automated inventory management systems (ERP or WMS) could open up opportunities for large-scale and real-time implementation.

Acknowledgement

The work in this document was supported by the author thereof.

Conflict of Interest

The authors declare that they have no conflicts of interest.

Author Contribution

The authors were responsible for data search and analysis, study design, interpretation of results, and manuscript writing.

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