Spare Parts Management 4.0

Standardisation, Performance Indicators and Decision-Support Dashboards for Iberian Manufacturing Plants

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"Move. As far as you can, as much as you can. Across the ocean, or simply across the river. Walk in someone's elses's shoes or at least eat their food. Open your mind, get up off the couch, move".

Anthony Bourdain

Abstract

Spare parts management in multi-plant industrial environments is characterised by the conflict between ensuring operational availability and limiting capital immobilisation. Despite the extensive literature on classification and criticality assessment, their integration into stock control decisions and corporate information systems remains limited, particularly in contexts with heterogeneous data maturity and decentralised practices.

This dissertation develops and demonstrates, through selected case examples, a structured decision-support framework for spare parts management, applied to the four Iberian plants of Sonae Arauco. The research addresses four key dimensions: the quantitative characterisation of the current inventory, the systematic assessment of spare parts criticality, the impact of integrating criticality into stock-based indicators and the translation of the framework into practical decision-support tools aligned with the corporate spare parts management standard ME10, to which this work contributes.

The contribution of this dissertation lies in linking spare parts criticality classification to MRP parameter adjustments in a live SAP S/4HANA environment. The proposed framework combines Power BI diagnostic dashboards, an AHP-based revision of VED(O) weights and a structured decision logic that translates consumption profiles and criticality into reorder point, maximum stock and lot size adjustments.

The framework was applied to selected case examples in Mangualde, identifying approximately 27 400 € of immobilised inventory value that can be released or avoided through stock-level and MRP-parameter adjustments. This corresponds to a one-off reduction in tied-up capital, concentrated in a small number of high-value items, rather than to a recurring saving. The diagnostic dashboards identify a wider application scope across the four Iberian plants, including around 6 M€ of low-turnover inventory, whose optimisation potential can only be quantified once the VED(O) classification is extended to the rest of the inventory.

Overall, this study shows that the gap between spare parts classification theory and inventory practice is primarily one of operationalisation, and provides a documented example of how it can be narrowed in a real multi-plant environment.

Keywords: Spare parts management; Multi-criteria classification; VED(O); Analytic Hierarchy Process; Decision-support dashboards; Maintenance-driven inventory; Industry 4.0.

Resumo

A gestão de peças de reserva em ambientes industriais multi-fábrica é caracterizada pela tensão entre garantir a disponibilidade operacional e limitar a imobilização de capital. Apesar da vasta literatura sobre classificação e avaliação de criticidade, a sua integração nas decisões de controlo de stock e nos sistemas de informação empresariais permanece limitada, particularmente em contextos com maturidade de dados heterogénea e práticas descentralizadas.

Esta dissertação desenvolve e demonstra, através de casos selecionados, um framework estruturado de apoio à decisão para a gestão de peças de reserva, aplicado às quatro fábricas ibéricas da Sonae Arauco. A investigação aborda quatro dimensões: a caracterização quantitativa do inventário atual, a avaliação sistemática da criticidade das peças de reserva, o impacto da integração da criticidade nos indicadores de stock e a tradução do framework em ferramentas práticas de apoio à decisão alinhadas com o referencial corporativo de gestão de peças de reserva (ME10), para o qual este trabalho contribui.

A contribuição desta dissertação reside na ligação entre a classificação de criticidade de peças de reserva e o ajuste de parâmetros MRP num ambiente SAP S/4HANA real. O framework proposto combina dashboards de diagnóstico em Power BI, uma revisão dos pesos VED(O) baseada no método AHP e uma lógica de decisão que traduz perfis de consumo e criticidade em ajustes ao ponto de encomenda, stock máximo e tamanho de lote.

O framework foi aplicado a casos selecionados em Mangualde, identificando aproximadamente 27 400 € de valor de inventário imobilizado passível de ser libertado ou evitado através de ajustes ao stock e aos parâmetros MRP. Trata-se de uma redução pontual de capital empatado, concentrada em poucos artigos de elevado valor, e não de uma poupança recorrente. Os dashboards de diagnóstico identificam um universo de aplicação mais vasto nas quatro fábricas ibéricas, incluindo cerca de 6 M€ de inventário com baixo turnover, cujo potencial de otimização só será quantificável com a extensão da classificação VED(O) ao restante inventário.

De modo geral, este estudo demonstra que o desfasamento entre a teoria de classificação de peças de reserva e a prática de gestão de inventário é essencialmente uma questão de operacionalização, contribuindo com um exemplo documentado da sua redução num ambiente multi-fábrica real.

Ao meu avô Mário,
em memória e saudade.

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Reaching this point has taken time, effort and no small amount of perseverance. From my first day at FEUP to this moment, the journey has been anything but straightforward, with highs worth celebrating and stretches that tested my patience and resolve. Looking back, though, every part of it was worth it, and it is something I am genuinely proud of. Now that this chapter is coming to a close, I want to take a moment to thank those who shared it with me.

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List of Abbreviations

AC	Asset Criticality
ABC	Activity-Based Classification
AHP	Analytic Hierarchy Process
BB	Board Business
CI	Consistency Index
CR	Consistency Ratio
ELECTRE	Elimination and Choice Expressing Reality
EOQ	Economic Order Quantity
ERP	Enterprise Resource Planning
ERV	Estimated Replacement Value
FMEA	Failure Mode and Effects Analysis
FMECA	Failure Mode, Effects and Criticality Analysis
FP	Failure Probability
FSN	Fast, Slow, Non-moving
HB	SAP lot-sizing procedure: Replenish to maximum stock level
KPI	Key Performance Indicator
MDF	Medium-Density Fibreboard
ME02	Corporate Asset Criticality Standard
ME10	Corporate Spare Parts Criticality Standard
MRP	Material Requirements Planning
NBB	Non-Board Business
ND	SAP MRP type: No Planning
OSB	Oriented Strand Board
PB	Particleboard
PD	SAP MRP type: Standard MRP planning
RCM	Reliability-Centered Maintenance
RFA	Repair Feasibility and Alternatives
RI	Random Consistency Index
ROP	Reorder Point
SAP	Enterprise resource planning software (SAP SE)
TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution
UC	Unit Cost
VB	SAP MRP type: Manual Reorder Point Planning
VED(O)	Vital, Essential, Desirable (Obsolete)
XYZ	Demand Variability Classification

Chapter 1

Introduction

1.1 Motivation and Background

Spare parts management plays a critical role in industrial operations, directly influencing equipment availability, production continuity and maintenance costs. One of the most common challenges in industrial environments such as Sonae Arauco is maintaining a balanced spare parts inventory. This situation occurs either when stock levels are too high, leading to increased storage costs, higher risk of obsolescence and unnecessary waste, or when they are too low, potentially causing production delays and missed sales opportunities [1]. Finding the right balance between availability and cost is therefore critical to maintaining operational efficiency while controlling financial and operational risk.

Spare parts management has always been a necessary and complex activity in industrial environments. However, the context in which these decisions are made has changed significantly in recent years. During and after the COVID-19 pandemic, supply chain disruptions reduced the reliability of traditional replenishment models and exposed vulnerabilities associated with supplier-dependent strategies. Many suppliers no longer keep spare parts readily available, resulting in longer and less predictable lead times. As a consequence, manufacturing plants increasingly assume direct responsibility for mitigating operational risk by holding spare parts internally. This helps explain the sustained increase in inventory levels, underscoring the need for more structured, data-driven approaches to support stock-related decisions.

This shift reflects the broader Industry 4.0 trend in spare parts management, where information from systems such as Maximo, SAP (Systems, Applications, and Products in Data Processing) and Power BI is increasingly combined to support real-time decision-making. Despite this potential, the integration of criticality assessment and classification frameworks into the ERP (Enterprise Resource Planning) and business intelligence systems used for everyday inventory management remains limited in practice [2]. To address this limitation, this dissertation incorporates the proposed criticality classification within the existing SAP and Power BI environment instead of developing a separate standalone application. In this context, Industry 4.0 refers to the integration of information systems and data-driven decision support, rather than to technologies such as IoT (Internet of Things) sensors or predictive maintenance.

In addition to external supply chain challenges, the internal situation varies considerably between factories. Each site operates at a different level of process maturity and some inconsistencies are the result of different historical backgrounds, local practices and autonomous decision-making over time. This heterogeneity significantly limits the direct applicability of standardised classification and decision-support models. The absence of a centralised and standardised approach to codification has led to fragmented spare parts data, making it difficult to compare information, consolidate inventories or apply classification models consistently across factories.

At Sonae Arauco, a VED(O) classification exercise, a criticality-based method that classifies spare parts as Vital, Essential, Desirable or Obsolete (Section 2.2.5), was previously carried out for the German plants, covering approximately 4100 spare parts. However, this work was developed independently from the ERP system and was never formally integrated into SAP. With the ongoing transition from SAP R/3 to SAP S/4HANA, this classification information risks being lost, as it is not aligned with the current corporate standard and is not embedded in the system. This risk illustrates how classification initiatives can lose long-term effectiveness and organisational value when they are not embedded into standardised systems and processes.

Another significant concern is the risk of losing critical tacit knowledge. Several employees who have worked with spare parts management for many years, and who possess detailed knowledge about historical decisions, classifications and workarounds, are approaching retirement. Much of this knowledge is not formally documented, and some tools or classifications exist only in personal files or local spreadsheets. If this information is not captured and transferred, there is a real risk that valuable insights will be lost, making it more difficult for future teams to understand past decisions or build consistently on previous work. This reinforces the need for structured, system-embedded decision-support approaches that reduce reliance on individual experience.

In this context, this dissertation focuses on the Iberian plants, that have already completed the migration to SAP S/4HANA. The objective is to analyse the current spare parts landscape and support a more standardised and aligned application of classification principles across factories. By supporting the deployment of the new corporate spare parts management standard and improving data consistency, this work aims to contribute to more effective inventory management, enhanced decision-making and improved operational reliability in an increasingly complex industrial environment.

Despite the existence of several classification and criticality models, including ABC, XYZ, FSN and VED, the gap between classification theory and inventory practice in spare parts management has been consistently identified in the literature. Bacchetti and Saccani [3] found that companies rarely adopt multi-criteria methods and do not systematically link classification outcomes to stock control decisions, treating classification as an end in itself. Hu et al. [4] confirmed a persistent misalignment between theoretical advances and their adoption in corporate ERP systems, which continue to rely on classical methods such as EOQ, reorder point and MRP. More recently, Ifraz et al. [5], in a systematic review of 118 studies, concluded that inventory planning and maintenance planning are still mostly addressed separately.

Despite these findings, existing methods assume that reliable criticality information is already available and consistently applied across all plants, conditions that rarely hold in multi-plant environments with heterogeneous data maturity and incomplete asset-spare part relationships.

Furthermore, decision-support dashboards currently focus on stock performance without establishing a systematic link to item criticality, limiting their value as tools for maintenance-driven inventory management. This dissertation addresses these gaps by making a dual contribution: at the scientific level, it proposes and demonstrates a structured framework that integrates criticality classification with stock analysis in a real ERP environment, a combination absent from the literature; at the practical level, it operationalises this framework in decision-support dashboards aligned with a corporate spare parts management standard, providing a documented example of how the theory-practice gap can be narrowed in a multi-plant industrial context with heterogeneous data maturity.

1.1.1 Spare Parts Inventory Growth

The sustained increase in spare parts inventory levels results from a combination of systemic, operational and human-driven factors. In the SAP system, replenishment decisions are typically based on reorder point calculations that combine average consumption, supplier lead time and safety stock. The safety stock component is influenced by demand variability and by the criticality level assigned to each spare part. Although this logic provides a structured framework, its effectiveness depends on how it is applied in practice.

At plant level, responsibility for spare parts ordering lies with maintenance and planning personnel who operate under pressure to avoid stock-outs and unplanned equipment downtime. To mitigate operational risk, ordering decisions frequently follow a conservative approach, with quantities exceeding those suggested by system parameters in order to "play safe". Over time, this behaviour contributes to a gradual but persistent increase in inventory levels.

This trend is reinforced by the lack of standardisation in spare parts criticality assessment. Criticality levels are often assigned without a unified company-wide methodology and rely on individual judgement and risk perception. As a result, criticality is frequently overstated, leading to higher safety stocks and additional ordering.

In parallel, equipment upgrades and production line changes lead to the accumulation of obsolete spare parts, which remain in inventory until they are sold or written off. Even when not immediately visible, this accumulation contributes to capital immobilisation and reinforces the perception of excessive inventory. Together, these factors highlight the need for improved data visibility and process standardisation to support more balanced spare parts management decisions.

1.1.2 Contribution to Knowledge

Despite the maturity of spare parts classification theory, the literature has consistently failed to bridge the gap between multi-criteria criticality assessment and its operational integration into ERP-based inventory management systems. Existing models typically treat classification as an analytical endpoint rather than as a decision input [3], and empirical studies conducted in real multi-plant environments with heterogeneous data maturity remain scarce [4][5].

The central contribution of this dissertation is the demonstration of how criticality classification can be systematically translated into MRP parameter adjustments within a live ERP environment. This is supported by three complementary elements:

- a structured decision framework applicable under conditions of limited consumption history and incomplete relationships between the assets and their corresponding spare parts;
- a traceable AHP-based procedure for weight derivation within a corporate criticality standard;
- decision-support dashboards that integrate criticality into stock performance measurement.

Each of these contributions is discussed below:

C1 - A structured, auditable translation of spare parts criticality into replen-

ishment policy within a live ERP environment.

While prior work has linked criticality classification to generic stocking policies [6, 7], none has documented the systematic translation of VED(O) criticality scores into specific MRP parameters, namely reorder point, maximum stock level and lot size, within a live SAP S/4HANA environment. This study provides a concrete example of such operationalisation, demonstrating how criticality scores can directly inform replenishment decisions rather than serving as standalone analytical outputs. This translation is governed rather than fully automated, combining category-based replenishment rules with a bounded specialist override (R9) for documented exceptions. It is deliberately conservative: reorder points and maximum stock levels are derived from minimum justified quantities and criticality category rather than from safety-stock calculations, because supplier lead time data was not available for quantitative use (Section 7.2).

C2 - A structured decision framework demonstrated under conditions of data incompleteness.

Existing methodologies implicitly assume data completeness and consistent relationships between assets and spare parts [5, 8, 9]. This study proposes and demonstrates a structured decision framework applicable under conditions of incomplete Bills of Materials, overlapping ERP systems and limited consumption histories, conditions that characterise most real industrial environments but are systematically absent from theoretical models.

C3 - A traceable AHP-based procedure for continuous weight derivation in a corporate criticality standard.

While AHP has been applied to spare parts criticality classification [6, 10], existing applications use it primarily to resolve decision nodes within classification trees. This study instead applies AHP to derive explicit numerical weights for a continuous VED(O) scoring formula embedded in an active corporate standard, supported by full consistency verification and specialist validation. This provides an auditable basis for the weight derivation process in industrial practice.

C4 - Decision-support dashboards that structurally integrate criticality into stock performance measurement.

The absence of decision-support tools linking stock metrics with item criticality has been consistently identified as a gap [3, 11]. This study proposes and implements a criticality-integrated KPI and dashboard layer that changes how conventional stock indicators are interpreted, providing a feedback mechanism between classification outcomes and inventory practice.

Together, these contributions demonstrate that the gap between theory and practice in spare parts management is primarily one of operationalisation, and provide a replicable framework that can be implemented within existing SAP and Power BI infrastructure.

1.2 Company

As illustrated in Figure 1.1, Sonae Arauco is an industrial company operating in the wood-based panels sector, with production units distributed across Portugal, Spain, Germany and South Africa. The company was created as part of a strategic wood-based alliance between two established industrial groups, Sonae Indústria and Arauco, combining long-standing European and South American expertise in the wood-based panels industry. Over time, this partnership gave rise to a diversified international industrial network focused on panel production and related activities [12].

Its operations are highly capital-intensive, relying on complex mechanical and electrical assets to ensure continuous production. Raw materials include both virgin wood and recycled wood, reflecting the company's industrial model and its commitment to resource efficiency and circular economy principles. This makes maintenance activities and the availability of spare parts critical to operational performance, production continuity and risk mitigation.

The company's production system is organised into two main business categories. The Board Business (BB) comprises industrial units dedicated to the production of wood-based panels, such as particleboard (PB), medium-density fibreboard (MDF), oriented strand board (OSB) and decorative panels. The Non-Board Business (NBB) includes facilities responsible for supplying essential inputs to the production process, namely impregnated paper and synthetic resins.

Across the four countries where it operates, Sonae Arauco manages eleven industrial units with different production profiles, equipment configurations and levels of process maturity. This industrial diversity, combined with the geographical distribution of the plants, increases the complexity of spare parts management. It also poses challenges for process standardisation and data consistency, and makes performance monitoring harder to sustain across sites. These challenges are further influenced by the ongoing transition of the company's information systems.

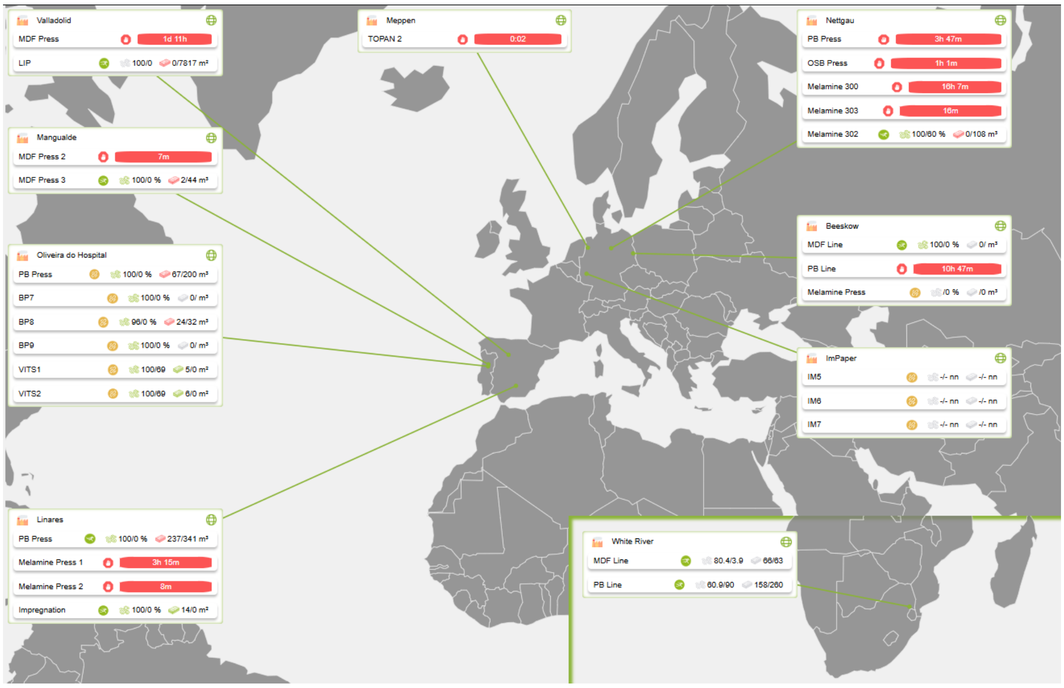

Figure 1.1: Geographical distribution of Sonae Arauco's industrial plants.

The focus of this study is on the Iberian plants, which completed the migration to SAP S/4HANA. Following this transition, several dashboards that were previously available under the legacy SAP system are no longer visible or operational in the Iberian plants, leading to a loss of monitoring capabilities. In Germany, the migration has not yet occurred, and the existing dashboards remain active and continue to be updated.

In addition, the dashboards currently available across the organisation are primarily oriented towards stock management, MRP processes, consumables and procurement activities. While these dashboards are useful from a supply chain perspective, they do not provide detailed or targeted insights into maintenance-related spare parts, such as asset criticality, asset-spare part relationships or operational risk.

The heterogeneity of production plants, systems and data maturity levels described in this section limits the direct applicability of traditional spare parts classification and criticality models, motivating the structured decision-support approach developed in this work.

1.3 Objectives

The objective of this dissertation is to develop and demonstrate the applicability of a structured decision-support framework for spare parts management in multi-plant industrial environments, under conditions of heterogeneous data maturity and incomplete criticality information. This objective is decomposed into four specific objectives:

O1 *Map and benchmark* the spare parts inventory landscape of the four Iberian plants (Linares, Mangualde, Oliveira do Hospital and Valladolid) using quantitative stock analysis, identifying measurable inefficiencies, data quality gaps and inter-plant variation in stock levels.

O2 *Develop and apply* a VED(O) criticality classification framework, with AHP-derived criterion weights, to a targeted set of spare parts selected on the basis of stock value and inter-plant variation, through structured expert sessions with maintenance engineers.

O3 *Quantify* the impact of criticality integration on stock optimisation decisions, by comparing benchmark-based excess stock estimates with criticality-informed recommendations, and estimating the financial value of identifiable optimisation opportunities.

O4 *Design, implement and validate* decision-support dashboards in Power BI that integrate stock performance KPIs with criticality data, aligned with the corporate spare parts management standard (ME10), and endorsed through expert review.

To define the scope of this dissertation, the challenges identified in spare parts management were translated into a set of research questions. Figure 1.2 presents an overview of the study, illustrating how these research questions relate to the main objectives outlined above.

Validation in this study is demonstrative, applied to selected case examples at the Mangualde plant, rather than to the full Iberian inventory. Extending validation to the complete inventory depends on the extension of ME10 classification across the four Iberian plants, which is identified as future work in Section 7.3.

Research Questions

RQ1 What characterises the current spare parts inventory across the Iberian plants, and which structural inefficiencies can be quantitatively identified?

RQ2 How can criticality be systematically assessed and integrated into spare parts inventory decisions in a multi-plant industrial environment?

RQ3 To what extent does the integration of criticality information modify the interpretation of stock-based indicators and the identification of optimisation opportunities?

RQ4 Which decision-support tools can operationalise the proposed framework in alignment with the corporate spare parts management standard?

Targets

T1 Diagnose the spare parts inventory of the four Iberian plants through dashboards integrating stock, consumption, turnover and inter-plant overlap.

T2 Develop a VED(O) criticality framework with AHP-derived weights and apply it through structured expert sessions.

T3 Define a decision framework for adjusting MRP parameters based on criticality and consumption, and quantify the financial impact through case examples.

T4 Design and implement decision-support dashboards in Power BI integrating stock performance with VED(O) criticality, aligned with the ME10 standard.

Implementations

I1 Six Power BI dashboards covering stock diagnostics, temporal evolution, data maturity, movement and turnover, non-moving inventory and inter-plant overlap.

I2 AHP-based weights for the VED(O) classification formula derived through pairwise comparison sessions with four maintenance experts.

I3 Application of the framework to selected case examples, with proposed MRP parameter adjustments and quantification of inventory reduction opportunities.

I4 Criticality-integrated dashboard prototype consolidating the proposed KPIs, together with a conceptual extension of VED(O) integration into existing dashboards.

Figure 1.2: Overview of the study, showing the research questions, targets and implementations.

These implementations are consolidated within a centralised dashboard environment designed to support maintenance engineers in monitoring and decision-making for spare parts management at plant level.

1.4 Methodology

This dissertation adopts an Action Research approach, organised into cycles of planning, acting, observing and reflecting. This iterative structure suited the collaborative nature of the work carried out with specialists at Sonae Arauco throughout the study.

This study began with a diagnosis phase, focused on gaining a comprehensive understanding of the spare parts management practices in the Portuguese industrial plants of Sonae Arauco, located in Mangualde and Oliveira do Hospital. During this initial stage, the production processes and maintenance environments of both factories were analysed. Two on-site visits were carried out to observe how spare parts are managed in practice, including warehouse organisation, spare parts request procedures, registration of material consumption in work orders within the maintenance management system (Maximo), and inbound and outbound warehouse movements.

In parallel, the equipment installed in the plants was examined together with the associated spare parts, providing an initial assessment of how assets and spare parts are linked in practice. This step was essential to understand how maintenance activities, equipment criticality and spare parts inventory are connected in daily operations.

Following this contextual and process-based analysis, an initial data collection phase was undertaken to determine which datasets were available and relevant for the objectives of the study, as well as how they could be reliably obtained from the existing information systems. Throughout this process, several gaps and limitations were identified in the completeness and structure of the data, as well as its consistency across sources. Addressing these issues required interaction with the IT department and a procurement specialist, contributing to a clearer understanding of the available data and its suitability for subsequent analyses.

It should be emphasised that the dashboards developed in this work do not constitute the research objective, but rather the operationalisation of the proposed framework.

Throughout this dissertation, "framework" refers to the proposed decision-support system linking criticality classification to MRP parameter adjustments, presented in Chapter 5, while "methodology" refers specifically to the Action Research approach.

1.5 Outline

Chapter 2 presents the theoretical background that supports this study. It starts with an overview of best practices in spare parts management and then reviews the main spare parts classification and criticality assessment models, covering both qualitative and quantitative approaches, discussing their strengths and limitations. The chapter also addresses inventory performance indicators, data quality issues in maintenance systems and the use of dashboards as decision-support tools in industrial contexts.

Chapter 3 describes the case-study context, including the maintenance and inventory information systems, current spare parts management practices and the data quality constraints that define the analytical scope of the study. The chapter then introduces the ME10 spare parts criticality standard developed with WCMac, covering its purpose and the VED(O) classification methodology. The contribution of this study is presented through the AHP-based derivation of criterion weights.The pairwise comparison procedure and consistency evaluation are detailed first, and the resulting weights are then validated against the Mangualde refiner case.

Chapter 4 presents a structured diagnostic analysis of the spare parts inventory across the Iberian plants. It introduces a set of dashboards covering stock diagnostics, temporal evolution, data maturity, movement and turnover, non-moving inventory and inter-plant overlap, with the objective of identifying structural inefficiencies and patterns requiring further investigation.

Chapter 5 introduces the proposed stock decision framework, which integrates VED(O) criticality, consumption behaviour and current inventory configuration to support MRP parameter adjustments. The framework is applied to selected case examples, illustrating how different inventory situations lead to distinct decision paths and quantifying the impact of the proposed approach.

Chapter 6 proposes a set of key performance indicators that operationalise VED(O) classification for inventory monitoring purposes and presents their integration into a dedicated decision-support dashboard. The chapter also illustrates how criticality information can be embedded into the existing dashboards introduced in Chapter 4, enabling stock indicators to be interpreted in light of operational criticality.

Finally, Chapter 7 concludes the dissertation. It discusses the results obtained from the diagnostic analysis and the application of the proposed framework, examining how the integration of VED(O) criticality modifies the interpretation of stock-based indicators and relating the case-level results to the significant volume of low-turnover inventory identified in Chapter 4. It then discusses the limitations of the study, concerning the data and organisational conditions under which the framework was applied. Finally, it outlines directions for future work: scaling the ME10 classification across the inventory, formalising category-specific stocking rules, and extending criticality integration to additional dashboards.

Chapter 2

Literature Review

This chapter begins by reviewing established best practices in spare parts management, highlighting the particular challenges associated with industrial maintenance environments. It then examines the main approaches used for inventory classification, with emphasis on commonly applied methods and their role in supporting prioritisation and stock control. The chapter further addresses different perspectives on spare parts criticality, exploring how risk, operational impact and maintenance requirements influence inventory decisions. In addition, aspects related to data quality in industrial information systems are discussed, considering their importance for reliable analysis and decision-making. Finally, the chapter explores the use of key performance indicators and dashboards as decision-support tools to improve visibility, consistency and alignment in spare parts management.

2.1 Spare Parts Management in Industrial Environments

Spare parts inventory management differs from traditional inventory management due to its objective and the high level of uncertainty involved [9, 13]. While finished goods inventories are held to meet customer demand, spare parts are stocked to ensure the operational availability of equipment and production systems. Demand for spare parts is typically intermittent and failure-driven, making it more difficult to forecast than demand for final products. Spare parts are also exposed to longer lead times and a higher risk of obsolescence, as they are closely linked to the lifecycle of the supported assets. In addition, spare parts inventories comprise both non-repairable items and repairable components, the latter requiring repair cycles and resources, which further increases management complexity. As a result, inventory policies developed for finished goods are often inadequate for spare parts, whose management aims to ensure operational continuity rather than profit maximisation [14]. In this study, spare parts are distinguished from production consumables such as cutting tools, which are depleted as part of the production process itself rather than through equipment failure or degradation and from operating supplies such as oils and lubricants.

2.2 Spare Parts Inventory Classification

Inventory classification provides a structured way to prioritise spare parts within large inventories, supporting focused decision-making and more effective use of resources [15].

Spare parts can be classified according to different criteria. One common distinction is based on technical characteristics, namely whether components are repairable or non-repairable. Repairable spare parts can be distinguished as rotatable, non-interchangeable or one-of-a-kind items [16]. This distinction is relevant for inventory management, as repairable parts are typically recovered and reused through repair processes, whereas non-repairable parts are usually replaced once a failure occurs.

Another relevant dimension for spare parts classification is the lifecycle phase of the equipment or system. In the initial stage, equipment has recently been introduced and little historical data is available, which increases demand uncertainty. During the normal stage, the equipment is in regular use and sufficient operational history becomes available, allowing for more reliable estimates of spare parts demand and lead times. In the final stage, production of the equipment has ended, while maintenance activities continue. At this stage, spare parts demand is better understood due to the accumulated historical data, but procurement risks increase, as suppliers may discontinue parts or reduce their availability. Consequently, inventory decisions in the final phase are mainly driven by availability constraints rather than demand uncertainty [16].

From a methodological perspective, spare parts classification approaches can be divided into quantitative and qualitative methods [17]. Quantitative approaches are based on numerical information derived from historical data, while qualitative approaches rely on expert knowledge and judgement. Classification methods may also differ in terms of the number of criteria considered, ranging from single-criterion approaches to multi-criteria methods, depending on problem complexity and data availability [18, 19]. Although mathematical optimisation models based on simulation or programming techniques have been proposed, their use in practice remains limited due to their complexity. As a result, simpler classification approaches continue to be widely adopted in industrial spare parts management [20]. Based on these considerations, several inventory classification methods have been developed to support differentiated management of spare parts. The following sections review the most commonly applied value-based, movement-based and criticality-based classification methods.

2.2.1 Value-Based Classification (ABC)

ABC analysis is one of the most used inventory classification methods in the literature and is frequently applied in spare parts management [6]. The method is grounded in the Pareto principle, which suggests that a relatively small proportion of items, accounts for a large share of the total inventory value. In this context, ABC analysis classifies spare parts into three categories according to their relative importance, commonly measured through annual usage value, defined as the product of unit cost and annual demand [21, 22].

In traditional ABC analysis, category A items represent a small proportion of the total number of items but account for a large share of the overall inventory value. Category B items have intermediate importance, while category C items comprise the majority of items but contribute only marginally to total inventory value. Typical classifications indicate that A items constitute approximately 10-20% of items while accounting for 70-80% of total value, whereas C items may represent up to 70-80% of items but only around 10-20% of the total value [21, 23]. Although these thresholds may vary depending on the application context and organizational objectives, the basic reasoning remains the same.

A key advantage of ABC analysis is its simplicity and effectiveness in identifying spare parts with the greatest economic impact. By focusing management effort on a relatively small number of high-value items, organizations can often achieve notable reductions in inventory holding costs [18, 24].

Despite its widespread use, traditional ABC analysis has been criticised in the context of spare parts management. One important limitation is its reliance on a single classification criterion, which does not reflect the diverse characteristics of spare parts [9]. In maintenance environments, spare parts often show highly variable demand and differ in terms of criticality, lead times and functional role. As a result, parts with low demand value may be assigned a low priority, even though their failure could lead to severe operational or financial consequences [25–27].

To overcome these limitations, several extensions of the traditional ABC approach have been proposed in the literature. Some authors suggest including technical or operational criteria, such as mean time to failure or downtime impacts, to better represent spare part criticality [28]. Overall, multi-criteria classification methods that combine economic indicators with maintenance-related factors are well supported in the literature[6, 9]. These approaches aim to reduce the risk of misclassification and improve the relevance of inventory segmentation in complex spare parts environments.

However, ABC classification focuses exclusively on economic value and neglects operational impact, asset dependency and failure consequences. In spare parts management, this may result in low value but operationally critical items, being assigned low priority, limiting the applicability of ABC analysis as a standalone decision-support tool.

2.2.2 Demand Variability-Based Classification (XYZ)

XYZ analysis classifies inventory items based on demand variability over time. Rather than focusing on economic value, it groups items according to how stable or irregular their demand is, supporting inventory decisions in environments with varying demand patterns [29, 30]. Spare parts are classified into three categories: X, Y and Z. X items are associated with stable and predictable demand, Y items exhibit moderate variability and Z items are characterised by highly irregular or sporadic demand, which makes forecasting challenging [29, 31]. XYZ classification relies on statistical measures derived from historical demand data, most commonly the coefficient of variation. Based on threshold values, items are classified as X, Y or Z according to their level of demand variability [32]. This approach enables a distinction between items with predictable and volatile demand and is useful in spare parts inventory management, where demand uncertainty strongly influences forecasting, review frequency and inventory control decisions. Since XYZ analysis focuses on a single dimension, it is often combined with ABC analysis to improve inventory classification[30].

However, XYZ analysis relies on stable historical demand data, which is often scarce or unreliable in spare parts contexts due to intermittent and failure-driven demand. When consumption events are infrequent, the coefficient of variation becomes unreliable as a discriminating metric, and the majority of items tend to be classified as Z, reducing the practical value of the segmentation. Since XYZ analysis focuses on a single dimension, it is often combined with ABC analysis to improve inventory classification [30].

2.2.3 Movement-Based Classification (FSN)

FSN analysis classifies spare parts based on how often they are used over a given period. Items are grouped as fast-moving (F), slow-moving (S) or non-moving (N), depending on their usage frequency [7].

Fast-moving items are used regularly and require closer monitoring, while slow-moving items are consumed less frequently and can be reviewed at longer intervals. Non-moving items show no usage during a defined period and often indicate excess stock or potential obsolescence.

In spare parts management, FSN analysis is mainly used to identify items with low or no movement and to support decisions related to stock reduction or disposal. Since it focuses only on usage behaviour, it is often combined with other classification methods, such as ABC or XYZ analysis [33].

FSN analysis focuses on consumption frequency, providing insight into movement patterns over time, but does not account for economic relevance or operational criticality. In spare parts contexts, this limits its effectiveness when used in isolation, particularly for items with low usage frequency but high operational impact, such as critical motors or major mechanical components whose consumption cycles may span several years. Consequently, FSN analysis is most useful as a complementary tool rather than a primary classification criterion.

2.2.4 Combined ABC-XYZ Classification

ABC-XYZ segmentation combines product classification by consumption value (ABC) with demand variability (XYZ) to support inventory prioritisation [34, 35]. The XYZ dimension classifies items as X (stable demand), Y (moderate variability), or Z (highly irregular demand), resulting in a nine-class matrix that links economic importance with demand behaviour [36, 37].

Empirical studies show that companies tend to prioritise items in categories AX, AY, BX and BY, as these combine higher value with relatively predictable demand, while C-class and Z-class items often receive limited managerial attention [35, 38].

However, the applicability of ABC-XYZ segmentation is limited in spare parts management. Spare parts demand is typically intermittent, low-frequency and driven by random equipment failures, making historical demand patterns poor predictors of future consumption. In addition, the method considers only value and demand variability, neglecting key spare parts characteristics such as operational criticality, downtime impact, long and uncertain lead times and limited substitution possibilities.

Consequently, low-value but critical spare parts may be misclassified as low priority, increasing the risk of equipment unavailability and supply chain disruptions [38]. Therefore, while ABC-XYZ segmentation provides a useful initial overview of inventory structure and control priorities, it is not sufficient as a standalone approach for spare parts contexts and must be complemented with methods that explicitly account for criticality and uncertainty. This observation motivates the review of criticality-based classification methods in the following sections.

2.2.5 Criticality-Based Classification (VED)

VED (Vital-Essential-Desirable) analysis is a qualitative inventory classification method that prioritizes spare parts based on their operational criticality rather than economic value [39]. Items classified as Vital (V) are indispensable for system functioning, as their unavailability can lead to significant production or maintenance disruptions. Essential (E) items support normal operations but allow limited tolerance in case of shortage, while Desirable (D) items have minimal impact on system performance if unavailable.

VED analysis is particularly suited to spare parts management, where the consequences of component failure often outweigh cost considerations. The classification is commonly performed through expert assessment, typically involving maintenance specialists who evaluate the impact of part failure, availability of substitutes, lead times and supply conditions [11, 17]. This allows the method to incorporate multiple criteria that are not captured by purely quantitative approaches [9].

However, the qualitative nature of VED analysis introduces challenges related to subjectivity and consistency. Differences in experience, judgement and local practices may lead to inconsistent classifications, particularly in large organizations operating across multiple plants [17]. As a result, despite its relevance for criticality-driven prioritisation, VED analysis alone does not provide sufficient objectivity or standardisation for robust spare parts inventory decision-making.

Similarly, combined approaches such as ABC-XYZ or ABC-VED, while improving prioritisation, still rely on assumptions of consistent data quality and shared criticality definitions. In complex industrial environments with heterogeneous practices, these assumptions are frequently violated, limiting the practical effectiveness of such methods. These limitations motivate the examination of more structured criticality assessment approaches, discussed in the following sections, which seek to reduce subjectivity and improve consistency across organisational units.

2.3 Spare Parts Criticality

Following the review of single- and multi-criteria spare parts classification methods, the literature consistently identifies criticality as a fundamental concept for prioritising spare parts management decisions. In contrast to value- or demand-based classifications, criticality focuses on the consequences associated with spare part failure or unavailability, which may vary significantly depending on the operational context. Despite its recognised importance, there is no universally accepted definition of spare parts criticality or clear guidelines for its measurement, as criticality is influenced by multiple factors and may be perceived differently under varying conditions [9]. Given this conceptual breadth and its central role in supporting inventory and maintenance decisions, a more detailed examination of spare parts criticality and its determining factors is justified.

2.4 Criticality Assessment Approaches

2.4.1 Failure-Oriented Approaches (FMEA / FMECA)

Failure-oriented approaches, namely Failure Mode and Effects Analysis (FMEA) and Failure Mode, Effects and Criticality Analysis (FMECA), are established techniques used to analyse potential equipment failures in reliability and maintenance engineering. Both methods examine failures at the component level and assess their effects on system operation, allowing the identification of elements whose failure may lead to significant operational consequences [40].

FMEA focuses on identifying possible failure modes and evaluating them based on their likelihood of occurrence, severity of consequences and detectability. These factors are combined into a Risk Priority Number (RPN), which is used to rank failure modes and support maintenance decision-making. However, FMEA focuses on ranking failure modes and does not evaluate their overall criticality at system level [41].

FMECA extends the FMEA framework by incorporating a criticality analysis. In addition to identifying failure modes and their effects, FMECA evaluates the relative importance of failures by considering both their probability and their impact, making it particularly suitable for safety-critical and high-reliability systems [41].

Despite their usefulness, traditional FMEA and FMECA approaches present limitations. The assessment of failure parameters relies on expert judgement, which may introduce subjectivity and lead to inconsistent results. Moreover, different failure modes may receive the same RPN value despite having different likelihood and consequence profiles, which may lead to unclear prioritisation [17]. Nevertheless, failure-oriented approaches provide valuable input for spare parts criticality analysis by linking technical failure behaviour with maintenance priorities. However, the use of the RPN focuses on failure risk prioritisation and does not assess the effectiveness of corrective actions, offering limited support for inventory and stock management decisions. This distinction between failure prioritisation and inventory decision-making is central to the gap addressed in this study.

2.4.2 Reliability-Centered Maintenance (RCM)

Reliability-Centered Maintenance (RCM) is a maintenance decision methodology used to determine which maintenance actions are required to ensure that assets continue to perform their intended functions within a specific operating context. Developed in the aviation industry, RCM emerged as an alternative to traditional time-based preventive maintenance, which often increased maintenance effort without corresponding improvements in system reliability [42].

RCM adopts a function-oriented perspective, focusing on system functions, functional failures and the consequences of failure rather than on individual components alone. Its objective is not to eliminate all failures, but to select maintenance tasks that are technically feasible and economically justified, with priority given to failures that affect safety, environmental integrity and operational availability [43]. Within this framework, failure-oriented techniques such as FMEA and FMECA are used to identify failure modes and assess their effects, supporting the identification of maintenance-significant items and the definition of maintenance policies.

Despite its structured approach, RCM presents important limitations. The analysis requires detailed asset information, specialised expertise and significant analytical effort, which often restricts its application to a limited subset of critical assets. In addition, the asset-by-asset nature of RCM limits its scalability in industrial environments with large numbers of assets and spare parts, making its systematic application across extensive inventories difficult to sustain over time. Moreover, while RCM supports maintenance policy definition, it does not directly address spare parts availability, inventory levels, or sourcing constraints. Simplified RCM variants have been proposed to reduce implementation effort; however, these approaches may rely on generic assumptions and may not fully capture context-specific failure behaviour [44].

Moreover, while RCM supports maintenance policy definition, it does not directly address spare parts availability, inventory levels or sourcing constraints, which are the focus of the present study. The asset-by-asset nature of RCM and its resource-intensive requirements contrast with the need for scalable classification approaches applicable to large multi-plant spare parts portfolios. In the context of the present study, risk matrices are used as a supporting tool within the VED(O) classification workshops, but the final criticality score is derived through a weighted multi-criteria formula with AHP-derived weights, as described in Chapter 3.1.

2.4.3 Risk Matrices for Criticality Assessment

Risk matrices are qualitative tools used for risk and criticality assessment by mapping failure probability against failure consequences into discrete risk categories, typically represented in two-dimensional grids [45, 46]. In maintenance contexts, they are applied to support criticality analysis and prioritisation of assets or components, and are sometimes extended to assist spare parts prioritisation [47].

Despite their intuitive structure, risk matrices present important limitations. Different combinations of probability and consequence may be assigned to the same risk category, even when the underlying risk profiles differ, reducing the clarity of prioritisation [45, 46]. This is particularly relevant in spare parts management, where similar risk classifications may hide differences in failure behaviour.

In addition, risk matrices rely on qualitative judgements represented through low-resolution categorical scales, which reduces their discriminative power and limits consistent prioritisation across large spare parts portfolios [46, 48]. Therefore, while they can support an initial screening of risk and criticality, risk matrices provide limited decision support when used in isolation, motivating the use of more structured and scalable criticality evaluation approaches [47].

2.5 Multi-Criteria Approaches for Spare Parts Criticality

Several multi-criteria decision-making frameworks have been proposed to address prioritisation problems, including AHP, ELECTRE, TOPSIS and weighted scoring models. While these approaches differ in their decision logic and data requirements, they all seek to structure subjective evaluations across multiple criteria. In spare parts criticality assessment, multiple factors such as operational impact, failure behaviour, availability, and supply conditions must be considered simultaneously. Multi-criteria approaches therefore provide a structured way to incorporate expert judgement in a transparent and consistent manner, overcoming the limitations of single-criterion or purely qualitative methods. Among these approaches, the Analytic Hierarchy Process (AHP) is well suited to derive explicit criterion weights from structured expert judgement and is therefore discussed in the next subsection.

2.5.1 Analytic Hierarchy Process (AHP)

Among multi-criteria decision-making approaches, the Analytic Hierarchy Process (AHP) is a well-established and commonly applied method. Originally proposed by Saaty [49], AHP is suitable for decision problems that require the simultaneous consideration of qualitative and quantitative criteria. In the context of spare parts management, AHP has been frequently referenced as a structured approach to support criticality assessment and prioritisation [50].

The AHP methodology is based on the decomposition of a complex decision problem into a hierarchical structure, typically organised as a tree. The hierarchy consists of an overall objective at the top level, followed by evaluation criteria and, where appropriate, sub-criteria. This hierarchical representation allows decision-makers to analyse complex problems in a structured and transparent manner, facilitating the identification of the factors that most strongly influence the decision [49].

Within the AHP framework, the relative importance of criteria is determined through pairwise comparisons. Criteria are compared two at a time, and decision-makers express their judgements using a predefined numerical scale, commonly the Saaty fundamental scale ranging from 1, representing equal importance, to 9, representing extreme importance [51]. These pairwise comparisons enable qualitative judgements to be translated into quantitative assessments and form the basis for deriving the relative weights of each criterion.

One of the main strengths of AHP is its explicit recognition of subjectivity as a natural component of decision-making. Rather than attempting to eliminate expert judgement, AHP incorporates value judgements in a structured and scientifically grounded manner [50].

To improve the reliability of the evaluations, AHP includes a consistency verification mechanism. The logical coherence of the pairwise comparisons is assessed using the Consistency Ratio (CR), which indicates whether the judgements are reasonably consistent. A comparison matrix is generally considered acceptable when the CR is below 0.10, while higher values suggest that the judgements should be reviewed and refined to improve coherence [51, 52].

Despite its structured formulation, AHP has limitations related to expert-based pairwise comparisons. Results are sensitive to expert composition and scalability is limited, as the number of comparisons increases rapidly with the number of criteria. Consequently, AHP is typically applied to a restricted set of predefined criteria, for which it provides a transparent and internally consistent evaluation framework [52].

2.6 Key Performance Indicators

Key Performance Indicators (KPIs) are discussed in the literature as tools used to monitor and assess the performance of spare parts and inventory management systems. By translating operational and logistical processes into quantitative measures, KPIs support performance tracking, benchmarking over time and decision-making in maintenance and asset-intensive environments [53, 54].

The literature identifies a relatively consistent set of KPIs used to evaluate spare parts and storeroom performance. One group of indicators focuses on availability and service performance, reflecting the ability of the inventory system to supply spare parts when required. Indicators such as service level or fill rate, stock-out rate and spare parts availability are frequently used to assess how effectively inventory supports maintenance and repair activities [9, 55].

Another group of KPIs addresses inventory investment and efficiency. Measures such as total inventory value, inventory turnover, holding or carrying costs and the proportion of inactive or obsolete inventory are used to evaluate how financial resources are allocated within spare parts inventories [53, 54]. In storeroom-focused literature, additional indicators such as inventory accuracy (often assessed through cycle counting) and the percentage of inactive items over a given period are highlighted as indicators of inventory control and data reliability [54].

Maintenance and operational support indicators are also discussed, including the parts-to-labour cost ratio, used to analyse the relationship between spare parts inventory investment and maintenance labour expenditure. In parallel, reliability-oriented measures, including mean time to repair (MTTR) and downtime associated with spare parts unavailability, are discussed as indirect indicators of spare parts performance, particularly in asset-intensive systems [55].

In addition, several studies report KPIs associated with demand behaviour and supply characteristics, including consumption rate, demand variability, lead time, emergency purchase frequency and supplier reliability. These indicators are used to characterise uncertainty in spare parts consumption and the responsiveness of the supply process, which are important aspects of maintenance-driven inventory systems [9, 56].

Despite their use in practice, the literature points out limitations in traditional spare parts KPIs. Most indicators focus on cost, volume, or efficiency in isolation and tend to evaluate performance in aggregated terms, without explicitly distinguishing spare parts according to their operational impact or the consequences of unavailability [9, 56]. Inventory performance measurement therefore tends to emphasise how parts are purchased and stored, while providing limited insight into why specific spare parts are held in inventory from a maintenance and operational risk perspective [54]. These limitations motivate the integration of criticality considerations into spare parts performance measurement, as discussed in Section 2.7.

2.7 Final Remarks

The preceding sections have reviewed the main classification methods, criticality assessment approaches and performance indicators used in spare parts management. While each of these areas has received considerable academic attention, the literature has focused predominantly on methodology development, with limited attention to the practical integration of classification outcomes into stock control decisions [3, 11]. Corporate ERP platforms continue to rely on classical methods such as EOQ, reorder point and MRP, with limited adoption of the approaches proposed in the literature [2, 4], and recent systematic reviews confirm that inventory planning and maintenance planning are still mostly addressed separately [2, 5].

Three specific gaps are particularly relevant to the present study. First, although criticality classification methods such as VED and AHP are individually well developed (Sections 2.2.5 and 2.5.1), their integration with stock performance analysis in industrial practice remains scarce, and the few existing models rely on theoretical assumptions that rarely hold in multi-plant environments [8, 9]. Second, decision-support dashboards that combine stock metrics with criticality information have not been addressed in the literature [57]. Third, empirical studies in environments with multiple information systems, incomplete asset-spare part relationships and limited historical data remain absent. The present study addresses these gaps, as summarised in Table 2.1.

Table 2.1: Summary of identified research gaps and the contribution of the present study.

Gap identified	Key references	Addressed in this study
Classification treated as an end in itself, not linked to stock decisions	Bacchetti and Saccani (2012); Roda et al. (2014); Teixeira et al. (2024)	VED(O) classification integrated with stock analysis and stocking policy recommendations
Misalignment between theoretical advances and ERP/software adoption	Hu et al. (2018); Kulshrestha et al. (2024)	Framework designed for a SAP-based environment with real system constraints
Inventory and maintenance planning addressed separately	Ifraz et al. (2025); Scarf et al. (2024)	Dashboards combining stock KPIs with criticality from a maintenance perspective
Theoretical models assume ideal data conditions	Dekker et al. (1998); Huiskonen (2001); Ifraz et al. (2025)	Applied in a multi-plant context with heterogeneous data maturity
No dashboards linking stock metrics with criticality	—	Decision-support dashboards integrating both dimensions

Chapter 3

The Case-Study Company

This chapter outlines the operational context of the present case study, examining the spare parts management practices, information systems and data-related constraints that govern inventory analysis and decision-making. As company background, industrial footprint and site selection criteria have been addressed previously, the present chapter focuses on the factors that define and delimit the analytical scope of the study.

3.1 Maintenance and Inventory Information Systems

Maintenance activities across all plants are managed through IBM Maximo. Assets are organised according to a hierarchical functional location structure that reflects the production process, comprising six levels defined as follows:

- *Plant*: the entire industrial site.
- *Stage*: the main production phases, corresponding to process segments in which production cannot be interrupted without affecting the product in progress.
- *Area*: subdivisions within each stage, representing parallel production routes or sequential processing steps.
- *System*: a group of operations or equipment that function together to perform a specific part of the production transformation.
- *Function*: a specific operational activity carried out within a system.
- *Position*: the exact functional point at which a piece of equipment is installed.

The coding structure associated with this hierarchy is illustrated in Figure 3.1, and the relationship between hierarchical levels and physical equipment is shown in Figure 3.2.

ANNN	–	AAN	–	NNN	–	NNNNN	–	NNNN	–	NNN
Plant		Stage		Area		System		Function		Position

Figure 3.1: Functional location coding structure in IBM Maximo, covering six hierarchical levels across 22 alphanumeric digits.

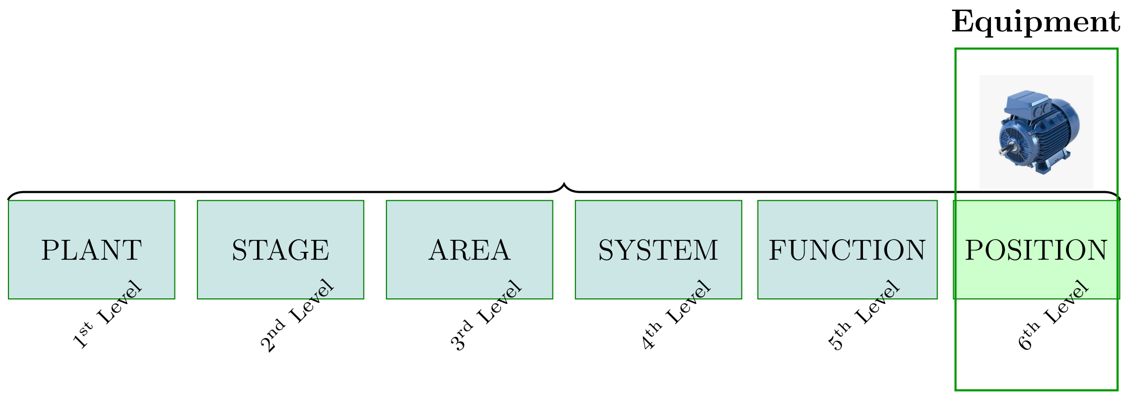

Figure 3.2: Hierarchical levels of the functional location structure and their relationship with physical equipment.

Each equipment item is assigned to a specific position, through which it is linked to all higher levels of the hierarchy. This structure supports maintenance planning, responsibility assignment and criticality assessment. Asset criticality is assigned at the functional location level rather than at the level of individual equipment items or spare parts. This reflects the fact that components can be repaired, replaced, or relocated over time and that their impact on the production process depends on the position they occupy rather than on their individual characteristics. Assigning criticality at the location level ensures that maintenance priorities remain consistent with the functional importance of each position in the process. However, spare parts are not directly linked to functional locations through complete and consistent Bills of Materials. As a result, criticality information cannot be automatically propagated to individual spare parts. This limitation has direct implications for spare parts prioritisation and inventory decision-making, as discussed in the following sections.

Spare parts inventory and procurement activities are managed through SAP, which maintains stock levels, consumption histories, supplier lead times and reorder parameters at plant level. The reorder point is calculated using the standard formula:

$$\text{Reorder Point} = (\text{Average daily consumption} \times \text{Lead time}) + \text{Safety stock} \tag{3.1}$$

3.2 Spare Parts Inventory Management Practices

Spare parts inventories are managed locally at each plant, with replenishment decisions formally supported by SAP reorder point logic based on historical average consumption, lead time and safety stock parameters. In practice, however, these parameters are not reviewed systematically and are frequently adjusted based on operational judgement, with maintenance and planning teams playing an active role particularly for parts associated with equipment perceived as critical for production continuity.

Across manufacturing sites, the responsibility for ordering spare parts lies with specific personnel who frequently adopt a conservative approach, ordering quantities above those recommended by SAP in an effort to avoid stockouts and potential equipment downtime. This behaviour, driven by operational pressure, generates a consistent pattern of overordering that contributes to the gradual increase in inventory levels.

A further contributing factor is the lack of standardisation in criticality assessment. SAP does not incorporate criticality in its replenishment calculations, and the CP levels currently used are assigned without a company-wide method, relying instead on the personal judgement and risk perception of individual planners. This subjectivity tends to cause criticality ratings to be overstated, reinforcing conservative ordering behaviour.

Additionally, when production lines or equipment are discontinued, the associated spare parts may become obsolete and eventually need to be written off, further highlighting the underlying excess in inventory levels. Overall, conservative ordering practices, subjective criticality assessments and the accumulation of obsolete parts result in significant amounts of capital tied up in spare parts inventory, with direct implications for operational efficiency and financial performance.

In response to these challenges, the company has been developing, in collaboration with the consultancy WCMac, a standardised framework for asset criticality assessment known internally as the ME02. Building on this foundation, a dedicated methodology for spare parts criticality classification, referred to internally as the ME10 standard, is currently being developed with the aim of extending a consistent and structured approach to inventory management decisions across all plants. A further objective of this initiative is to capture and formalise the operational knowledge held by experienced employees approaching retirement, much of which currently exists only in personal files or informal practices and risks being lost during workforce transitions. The present study was conducted in the context of this broader initiative, and the contribution to the development of the ME10 methodology is discussed in the Section 3.5.

A more structured approach to spare parts prioritisation has been developed and applied in the German plants by the procurement team. Using a three-year consumption history, items are first classified through the **ABC** method, which ranks parts by annual spend, and the **FSN** method, which categorises them by movement frequency, according to the criteria defined in Tables 3.1 and 3.2.

Table 3.1: ABC classification thresholds applied at Sonae Arauco.

Class	Share of Total Spend
A	80%
B	15%
C	5%

Table 3.2: FSN classification criteria applied at Sonae Arauco.

Category	Rule
F – Fast	Three or more movements per year
S – Slow	Fewer than three movements per year
N – Non-mover	No movements within a three-year period

These two classifications are then combined into a cross-matrix, as illustrated in Figure 3.3, where each segment is associated with a specific set of actions. The AF group (high-spend, fast-moving items) is treated as the highest priority, as these parts simultaneously represent the greatest financial exposure and the highest consumption activity. The AS and BF groups follow as the next targets, progressively moving down the matrix towards lower-spend and slower-moving items. For CN non-movers, the recommended action shifts from MRP optimisation to write-off, relocation or scrap, as these items are unlikely to generate future consumption. This sequencing ensures that the parts with the greatest potential return for the effort expended are addressed first.

	F	S	N
A	**STRATEGIC – PRIORITY 1** • Review MRP • Reduce where possible • Review supply arrangements with vendor • Consider suggested MRP	**TAKE ACTION – PRIORITY 2** • Review MRP • Reduce where possible • Review consump. history	
B	**TAKE ACTION – PRIORITY 4** • RESET MRP to Suggested Levels	**TAKE ACTION – PRIORITY 3** • Review MRP • Reduce where possible • Review consump. history	
C	**TRANSACTIONAL** • RESET MRP to Sug. Levels • Focus on EOQ • Catalogues	**TRANSACTIONAL** • Remove stock where possible • Focus on EOQ • Review consump. history • Catalogues	**Carry out VED analysis** • Keep only V and E items in stock • Transfer to other plants, where possible • Write-Off/Sell/Scrap

Table 3.3: ABC+FSN action matrix defining inventory management priorities and MRP review actions by segment.

Based on this prioritisation, workshops were conducted at each plant to classify the selected items through a **VED(O)** assessment, guided by a risk matrix combining failure probability with production impact, as illustrated in Figure 3.3.

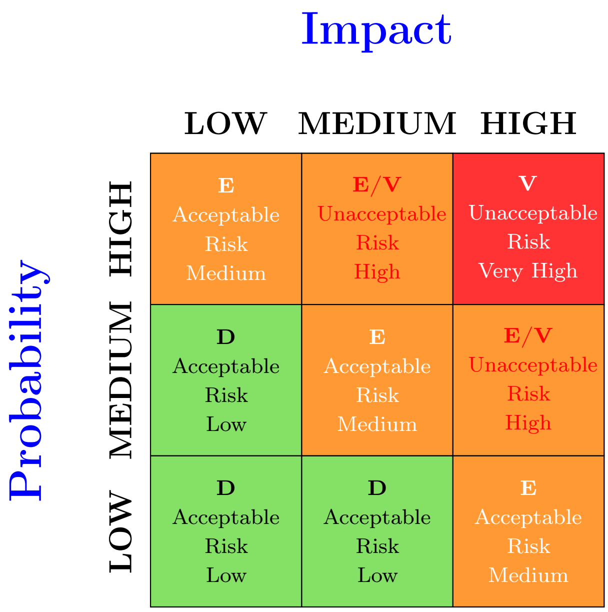

Figure 3.3: Risk matrix used to support VED(O) classification during plant workshops, combining failure probability and production impact.

Each VED(O) category was associated with a set of inventory management guidelines, summarised in Table 3.4, which defined the corresponding stocking policy and MRP parameter adjustments to be implemented in SAP.

Table 3.4: VED(O) classification guidelines and associated inventory management actions.

Category	Meaning	Inventory management guidelines
V	Vital	Must be held in stock; quantities should be minimised through optimisation.
E	Essential	Avoid holding stock where possible; negotiate supplier lead times; keep RO and MAX at minimum levels.
D	Desirable	Do not hold stock; set RO and MAX to zero; replenish only on demand.
O	Obsolete	Segregate in a separate warehouse; transfer to other plants where applicable; sell or scrap.

This process has not yet been extended to the Iberian plants, where spare parts prioritisation remains largely based on operational judgement and experience. This gap motivates the present study, which aims to assess the current spare parts landscape in the Iberian plants and develop a more structured and consistent approach to classification and inventory management.

3.3 Data Quality and Asset-Spare Part Relationships

Data quality represents a significant constraint in spare parts analysis, as incomplete Bills of Materials in Maximo, inconsistent part descriptions and missing asset-spare part relationships reduce visibility into which spare parts support which functional locations. Although functional location criticality is available in Maximo, it cannot be systematically propagated to individual spare parts due to these data gaps, meaning that criticality can only be determined for a limited subset of items for which sufficient data completeness and clear asset association exist.

A further source of inconsistency stems from changes in material coding conventions introduced with the migration to SAP S/4HANA. In the legacy system, spare parts were systematically created under material codes beginning with 411, while codes beginning with 412 were reserved for consumables such as blades and cutting tools. In the new environment, however, spare parts introduced more recently have been assigned 412 codes, meaning that material type alone can no longer be used as a reliable filter to distinguish spare parts from consumables. This overlap complicates data extraction and classification, as any analysis based on material code ranges may inadvertently exclude recently created spare parts or include items of a different nature.

Compounding this, the company is currently operating two SAP environments in parallel. The legacy system, SAP ERP R/3, remains active in the German plants and continues to feed SAP BusinessWarehouse and the associated reporting applications, while the new SAP S/4HANA environment, introduced through the DARWIN migration programme, is already operational in the Iberian plants, supplying data to SAP Datasphere and supporting the updated reporting tools. This overlap exists because the transition is being carried out gradually, site by site: the Iberian plants completed their migration in April 2025, while the German plants are scheduled to transition in the summer of 2026. As each factory migrates, data flows and the integration between Maximo and SAP are adjusted accordingly, which means that the two groups of plants currently operate under different system environments, with potential implications for data consistency and comparability across sites.

Certain data fields relevant to inventory analysis, such as supplier lead times, were not accessible through standard dataset extractions and required direct coordination with the IT department. Although IT support was available throughout the study, access to some system parameters is centrally controlled, which limits the ability of local teams to extract and analyse this information independently. As a result, lead time data could not be systematically incorporated into the quantitative analysis and was considered only where available through other sources, such as procurement records or supplier documentation.

A further limitation concerns the availability of historical consumption data. Company policy restricts the retention of transactional history to a rolling 36-month window, meaning that consumption records beyond this period are not accessible. While this interval is adequate for fast-moving items, it may be insufficient to characterise the demand behaviour of slow-moving or emergency spare parts, such as critical motors or major mechanical components, which may have consumption cycles spanning several years or even decades. For these items, the absence of a longer historical record increases uncertainty in demand estimation and may lead to their misclassification as non-movers, even when they serve a critical function in the production process.

Finally, a subset of items present in the system carry registered stock quantities but no associated monetary value, typically corresponding to project-specific materials that are no longer in active use. These items were identified and treated separately in the analysis, as their inclusion in value-based metrics would distort the results. Their share of the total item population is quantified in Chapter 4.

Taken together, these constraints, incomplete asset-spare part relationships, inconsistent master data, overlapping material coding conventions, an ongoing system migration, restricted access to certain system parameters, a limited consumption history and the presence of unvalued stock items, define the analytical scope of the present study and motivate the use of targeted case examples rather than an exhaustive portfolio-wide assessment.

Data preparation was carried out in Excel. The raw SAP export required several transformations before analysis. Material codes were initially concatenated with their descriptions and material group labels, and leading zeros were removed from the codes. Consumable items recorded in the same warehouse extracts, including chemicals, cleaning and hygiene supplies, construction materials, cutting tools and safety equipment, were outside the spare-parts scope defined in Section 2.2.5 and were therefore excluded. Oils and lubricants were also separated at this stage for the dedicated analysis presented in Appendix A. In addition, a plant-identification table was created to standardise plant references across datasets. No duplicate material codes were identified, which is consistent with the role of material code as a unique key in the SAP extracts. Additional work was required to reconcile the legacy and current SAP environments. Several material groups had been discontinued and absorbed into broader groups, while naming conventions changed from mixed-case abbreviated labels to fully capitalised and less abbreviated forms. These differences were resolved through a manually developed mapping table, ensuring consistent material-group classification across the pre- and post-migration datasets. Missing values for consumption, unit cost and lead time were retained as blank entries and flagged as "no data" rather than imputed, thereby avoiding the introduction of assumptions that could distort subsequent analyses.

3.4 Implications for the Study

The case-study context is characterised by decentralised inventory management, heterogeneous data maturity and limited integration between maintenance and inventory information systems, reflecting a realistic industrial environment in which spare parts decisions are influenced by operational risk, experience-based judgement and data constraints. Within this context, the present study investigates how the integration of structured criticality information, even on a limited scale, can support more informed inventory analysis and identify opportunities for optimisation in the Iberian plants.

3.5 Spare Parts Criticality Standard (ME10)

Sections 3.5.1 and 3.6 describe the ME10 standard, whose development began before this dissertation and continued throughout it. Section 3.7 outlines the classification methodology, while this study's own contribution follows separately, from Section 3.8 onward.

3.5.1 Overview and Purpose

The ME10 standard defines the corporate methodology for Spare Parts Definition and Management within the Asset Management framework of Sonae Arauco. Developed in collaboration with the consultancy WCMac, its purpose is to establish a unified and auditable process for identifying, classifying, codifying and managing spare parts across all industrial sites, ensuring that stocking decisions are grounded in objective technical criteria rather than operational intuition or historical practice.

The standard is designed to be applied in two complementary contexts: the registration of new spare parts and the retrospective classification of items already in the system. For new parts, it defines the process for registration, classification and master data creation in SAP and Maximo, ensuring that all items enter the system with the required attributes and a criticality level formally assigned through the VED(O) methodology. Where historical consumption data is unavailable, reliability analysis techniques such as FMEA may support the estimation of the Failure Probability criterion [58]. At the same time, for existing parts, it provides a structured methodology to review and classify items already registered, with the objective of building a consistent and comparable inventory across all plants, particularly relevant given that significant portions of the existing inventory were registered without a standardised classification process.

The ME10 standard complements the asset criticality framework established by the ME02 standard. While ME02 classifies assets according to their operational criticality, ME10 evaluates each spare part independently, recognising that asset criticality is an input to the classification process rather than its output [6][58]. A supercritical asset may have components that do not require stock, while a non-critical asset may have a component whose failure causes cascading production impacts.

3.6 Development Process and Stakeholder Involvement

The ME10 standard was developed through an iterative process of regular working sessions between the company and WCMac, bringing together representatives from maintenance, supply chain and asset management to ensure that the methodology was both technically sound and practically applicable across plants with different levels of data maturity.

During the development process, the classification categories were initially designated as CP1, CP2 and CP3, but were subsequently aligned with the established VED(O) framework, comprising the categories Vital, Essential, Desirable and Obsolete, which was already familiar to plant teams from previous classification exercises and is consistently adopted in the spare parts criticality literature [59][17].

3.7 VED(O) Classification Methodology

The VED(O) classification assigns each spare part to one of four categories based on the operational impact of its unavailability, each driving a distinct stocking policy. The classification is performed using five criteria, each scored on a scale of 1 to 5, where higher scores indicate higher criticality:

- *Asset Criticality (AC)*: consequence of part unavailability based on the criticality classification of the asset to which the spare part belongs, as defined by the ME02 standard.
- *Lead Time (LT)*: total time elapsed between placing a purchase order and receiving the part in the warehouse, relative to acceptable production downtime.
- *Failure Probability (FP)*: probability that the part will be consumed within a given period, encompassing corrective maintenance, condition-based replacement and

planned time-based interventions, derived primarily from historical consumption data in Maximo and manufacturer specifications.

- *Unit Cost (UC)*: purchase price of the spare part, reflecting the trade-off between capital immobilisation and risk of unavailability.
- *Repair Feasibility and Alternatives (RFA)*: ability to repair the part or mitigate its unavailability through alternatives, including repair feasibility, availability in other plants and existence of preventive maintenance routines that enable anticipation of the need.

An initial weighted formula was proposed by WCMac to combine the five scores into a single VED(O) criticality score. However, following its application, specialists raised concerns that the results obtained did not consistently reflect the operational reality of the plants, suggesting that the original weight distribution required revision. The derivation of revised weights is described in Section 3.8, and the final formula adopted in the ME10 standard is:

$$\text{VED(O) Score} = (AC\times0.419)+(LT\times0.150)+(FP\times0.127)+(UC\times0.163)+(RFA\times0.141) \tag{3.2}$$

The resulting score determines the criticality category and associated stocking policy, as summarised in Table 3.5:

Table 3.5: VED(O) classification thresholds and associated stocking policies.

VED(O) Score	Category	Stocking Policy
≥ 4.0	V – Vital	Mandatory stock with automatic replenishment.
2.5 - 3.9	E – Essential	Conditional stock based on consumption history.
1.5 - 2.4	D – Desirable	No stock; procurement on demand.
0	O – Obsolete	Segregate from active inventory; relocate where possible; sell or scrap.

Unlike the Vital, Essential and Desirable categories, which are obtained directly from the weighted VED(O) score in Equation 3.2, the Obsolete category is determined separately. It is assigned when an item shows sustained non-consumption and therefore does not depend on the Asset Criticality, Lead Time, Failure Probability, Unit Cost or Repair Feasibility scores. For this reason, the value 0 shown in Table 3.5 does not represent a possible result of the weighted formula. Instead, it indicates an independent terminal state. Since all five criteria are scored on a 1-5 scale, the minimum achievable weighted score is 1.0.

3.8 Contribution of the Present Study: AHP-Based Weight Derivation

The AHP method was chosen to derive the criterion weights of Equation (3.2) because, unlike alternatives such as TOPSIS or ELECTRE, it produces explicit weights that can be embedded directly in the VED(O) formula, rather than rankings of alternatives that would not be transferable to the corporate standard. The Consistency Ratio also provides an auditable check on expert judgements, which matters for the ME10 standard since the classification has to remain defensible across plants and over time, and AHP is the method most commonly applied to spare parts criticality assessment in the literature [10, 59, 60].

The VED(O) formula is already multi-criteria, so the AHP exercise is not introducing a new perspective but providing a traceable way to set the weights of that formula, replacing the original WCMac values with weights derived from structured expert judgement.

3.8.1 AHP Structure

The decision problem was structured as a three-level hierarchy [51], as illustrated in Figure 3.4: the overall goal at the top level, the five evaluation criteria at the intermediate level, and the spare parts to be classified at the bottom level.

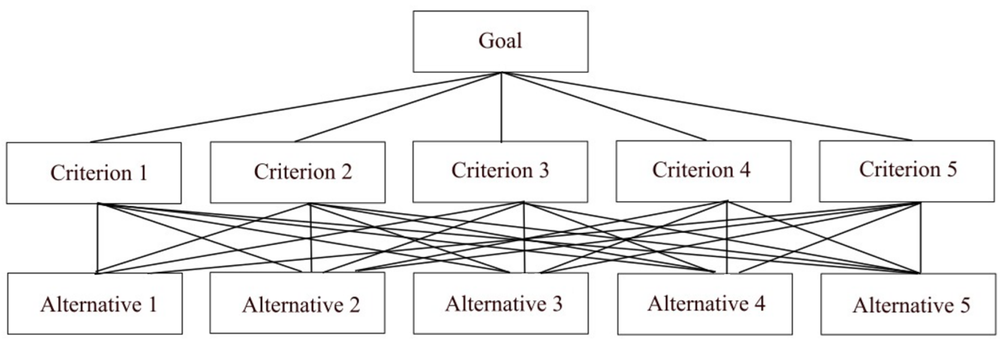

Figure 3.4: Sample hierarchical tree.

3.8.2 Pairwise Comparison Questionnaire

Four internal experts with experience in maintenance and spare parts management independently completed a structured pairwise comparison questionnaire, illustrated in

3.8. Contribution of the Present Study: AHP-Based Weight Derivation

Table 3.6, comparing all possible pairs of criteria, ten comparisons in total, and indicating which criterion is more important and by how much, using the fundamental 1 to 9 scale [49] reproduced in Table 3.7.

Table 3.6: Sample pairwise comparison questionnaire used in the AHP exercise.

Nº	Criterion A	Criterion B	More important (A/B)	Intensity (1-9)
1	Asset Criticality	Failure Probability		
2	Asset Criticality	Lead Time		
3	Asset Criticality	Unit Cost		
4	Asset Criticality	Repair Feasibility/ alternatives		
5	Failure Probability	Lead Time		
6	Failure Probability	Unit Cost		
7	Failure Probability	Repair Feasibility/ alternatives		
8	Lead Time	Unit Cost		
9	Lead Time	Repair Feasibility/ alternatives		
10	Unit Cost	Repair Feasibility/ alternatives		

Table 3.7: Saaty fundamental scale for pairwise comparisons [49].

Rating	Definition	Explanation
1	Equal importance	Two elements contribute equally to the objective.
2	Weak	Between equal and moderate importance.
3	Moderate importance	Experience and judgement slightly favour one element over another.
4	Moderate plus	Between moderate and strong importance.
5	Strong importance	Experience and judgement strongly favour one element over another.
6	Strong plus	Between strong and very strong importance.
7	Very strong importance	An element is favoured very strongly over another.
8	Very, very strong	Between very strong and extreme importance.
9	Extreme importance	The highest possible affirmation of one element over another.

3.8.3 Construction of Pairwise Comparison Matrices

For each expert, the questionnaire responses were used to construct a 5×5 pairwise comparison matrix $\boldsymbol{A}$, where each entry a_{ij} reflects the relative importance of criterion i over criterion j [51]. By the reciprocity rule of AHP:

$$a_{ji} = \frac{1}{a_{ij}}. \tag{3.3}$$

This procedure resulted in four individual 5×5 comparison matrices, one per expert.

3.8.4 Aggregation of Expert Inputs

The individual comparison matrices were aggregated into a single group matrix using the geometric mean of corresponding elements, as recommended for group AHP applications [51]. For the four experts, the aggregated entry for each pair (i, j) is given by:

$$a_{ij}^{\text{group}} = \left(a_{ij}^{(1)} \times a_{ij}^{(2)} \times a_{ij}^{(3)} \times a_{ij}^{(4)}\right)^{\frac{1}{4}}. \tag{3.4}$$

3.8.5 Derivation of Criterion Weights

The criterion weights were derived from the principal right eigenvector of the aggregated matrix by solving [51]:

$$\boldsymbol{A}\mathbf{w} = \lambda_{\max}\mathbf{w}, \tag{3.5}$$

where $\boldsymbol{A}$ is the aggregated comparison matrix, $\mathbf{w}$ is the non-negative eigenvector, and $\lambda_{\max}$ is the maximum eigenvalue of $\boldsymbol{A}$. The resulting eigenvector was normalised so that the sum of all criterion weights equals one.

3.8.6 Consistency Verification

The logical coherence of the pairwise comparison matrices was assessed using the Consistency Index (CI) and the Consistency Ratio (CR), defined as [51]:

$$CI = \frac{\lambda_{\max} - n}{n - 1}, \tag{3.6}$$

$$CR = \frac{CI}{RI}, \tag{3.7}$$

where RI is the Random Consistency Index for a matrix of size n, presented in Table 3.8 [61]. For $n = 5$, $RI = 1.1159$ [51]. A comparison matrix is considered acceptably consistent when $CR < 0.10$ [49, 62]. The consistency results for each individual and aggregated matrix are presented in Table 3.9.

Table 3.8: Random Consistency Index (RI) values by matrix dimension [61].

Dimension	RI
1	0.0000
2	0.0000
3	0.5799
4	0.8921
5	1.1159
6	1.2358
7	1.3322
8	1.3952
9	1.4537
10	1.4882

Table 3.9: Consistency verification of individual and aggregated pairwise comparison matrices.

Matrix	$\lambda_{\max}$	CI	CR	Interpretation
Expert 1	5.365	0.091	0.082	Consistent
Expert 2	6.166	0.292	0.260	Not consistent
Expert 3	6.226	0.307	0.274	Not consistent
Expert 4	5.302	0.076	0.067	Consistent
Aggregated	**5.311**	**0.078**	**0.070**	**Consistent**

Although two individual matrices exceeded the accepted consistency threshold, this outcome is common in expert judgement exercises [62] and does not invalidate the approach, as it is the aggregated matrix that is used to derive the final criterion weights [51]. No individual matrix was returned to the corresponding expert for revision, since doing so would have required an additional round of sessions across four geographically dispersed plants and risked reducing the functional representativeness of the panel (each expert represents a distinct site and role). The aggregated matrix, rather than individual revision, was therefore used as the basis for weight derivation, consistent with standard practice in group AHP applications [49, 51]. The aggregated matrix yielded a consistency ratio of 0.070, confirming that the group judgements are methodologically valid. A sensitivity analysis on this point is presented in Section 3.8.8.

3.8.7 Results and Comparison

Table 3.10 compares the criterion weights obtained through the AHP process with those defined in the original WCMac proposal.

Table 3.10: Comparison of criterion weights: original WCMac proposal and AHP-derived weights.

Criterion	WCMac (original)	AHP-derived
Asset Criticality (AC)	0.350	0.419
Lead Time (LT)	0.300	0.150
Failure Probability (FP)	0.200	0.127
Unit Cost (UC)	0.100	0.163
Repair Feasibility and Alternatives (RFA)	0.050	0.141

The comparison reveals differences between the AHP-derived weights and the original WCMac proposal. The initial formulation assigned a comparatively high weight to Lead Time and lower weights to Unit Cost and Repair Feasibility, reflecting a prioritisation dominated by supply chain considerations. In contrast, the AHP results reduced the weight of Lead Time while increasing the relative importance of Unit Cost and Repair Feasibility, and further reinforced the role of Asset Criticality.

To validate the revised weights, the updated formula was applied to a set of spare parts associated with the refiner equipment at the Mangualde plant, covering components across multiple functional positions. The resulting VED(O) classifications were reviewed by the maintenance specialists involved in the development process and considered consistent with the operational reality of the equipment. Items such as the screw conveyor body and the DC motor, which are critical for production continuity and have long lead times, were correctly classified as Vital, while components with shorter lead times or available alternatives received Essential or Desirable classifications. The resulting classifications were considered by the specialists to accurately reflect the operational reality of the equipment, confirming the validity of the AHP-derived weights.

3.8.8 Sensitivity Analysis

To assess the influence of the two experts whose individual pairwise comparison matrices exceeded the consistency threshold (Experts 2 and 3 in Table 3.9), the criterion weights were recomputed using only the two experts whose individual matrices satisfied the threshold (Experts 1 and 4, with $CR = 0.082$ and $CR = 0.067$ respectively). The aggregated matrix obtained from these two experts produced an even more consistent group judgement, as reported in Table 3.11.

Table 3.11: Consistency comparison between the four-expert and the two-expert aggregations.

Aggregated matrix	$\lambda_{\max}$	CI	CR
Four experts (baseline)	5.311	0.078	0.070
Two consistent experts (Experts 1 and 4)	5.136	0.034	0.031

3.8. Contribution of the Present Study: AHP-Based Weight Derivation

The resulting weights are compared with the baseline weights in Table 3.12.

Table 3.12: Comparison of criterion weights derived from the four-expert aggregation and from the two-expert robustness check.

Criterion	Four experts	Two consistent experts	$\|\Delta\|$
Asset Criticality (AC)	0.419	0.492	0.073
Lead Time (LT)	0.150	0.132	0.018
Failure Probability (FP)	0.127	0.202	0.075
Unit Cost (UC)	0.163	0.132	0.031
Repair Feasibility and Alternatives (RFA)	0.141	0.042	0.099

The deviations between the two configurations range from 0.018 (LT) to 0.099 (RFA). Asset Criticality remains the dominant criterion in both configurations and Lead Time, Failure Probability and Unit Cost form a middle group whose internal ordering shifts but whose combined weight remains stable (0.440 in the four-expert aggregation against 0.466 in the two-expert aggregation). The most significant deviation occurs in Repair Feasibility and Alternatives, which drops from 0.141 to 0.042 when the two less consistent experts are excluded.

The weights derived from the four-expert aggregation are retained for the remainder of the study. The aggregated matrix satisfies the $CR < 0.10$ requirement, which is the relevant criterion for group AHP applications [49, 51], and excluding two of the four experts would lose part of the operational perspective that the exercise was designed to capture, since the four experts represent different sites and functional roles. The classifications obtained when these weights were applied to the Mangualde refiner components (Section 3.8) were also reviewed by the specialists involved in the ME10 standard and considered consistent with operational reality.

Chapter 4

Stock Diagnostics and Decision-Support Dashboards

This chapter presents the dashboards developed to analyse the spare parts inventory of the four Iberian plants, based on data from SAP S/4HANA (Datasphere) covering March 2025 to March 2026. For analyses requiring a longer consumption history, pre-migration data from SAP R/3 was also considered. As defined in Section 2.1, the analysis covers all materials held in the maintenance warehouses to support equipment availability. Oils and lubricants were treated separately (Appendix A).

These dashboards are diagnostic, built directly on SAP S/4HANA data. As shown in Table 2.1, ERP practice and theoretical models remain misaligned in the literature. Criticality is introduced only in Chapters 5 and 6, once the diagnostic baseline identifies which items and plants need closer assessment. Each dashboard below is framed around the management decision it supports, the diagnostic question it answers and the action it triggers. This structure is repeated for every dashboard in the chapter to allow direct comparison between them. The bullet points give a short summary, and the paragraphs that follow explain the underlying data and reasoning.

4.1 Initial Stock Diagnostics

This dashboard addresses the following:

- **Decision supported:** which factories and product groups warrant deeper investigation.
- **Question answered:** is stock concentration proportional to each factory's asset base?
- **Action triggered:** Valladolid's disproportionate stock-to-ERV ratio (2.41%, the highest

of the four plants despite the smallest absolute stock value) is flagged for closer review in subsequent dashboards.

An overview dashboard was developed to provide a structured overview of the spare parts inventory system and to establish a baseline for subsequent analyses. The dashboard supports a high-level assessment of stock distribution across factories and enables the identification of structural differences that justify more detailed investigation.

At this stage, inventory data were aggregated by *product groups*, such as bearings, conveyor systems, motors and electrical materials. This functional grouping reduces analytical complexity and allows an initial identification of categories exhibiting disproportionate stock levels, before progressing to more detailed spare part-level analyses in subsequent dashboards.

To contextualise inventory levels, the *Estimated Replacement Value* (ERV) was included as a reference indicator. ERV represents the estimated replacement value of the installed production assets and provides a proxy for the scale of each factory. Relating spare parts stock value to ERV enables a proportional interpretation of inventory levels with respect to the underlying asset base.

All inventory indicators were designed to be analysed both in monetary terms (€) and in physical units. Value-based analysis supports the assessment of capital tied up in stock, while quantity-based analysis enables the identification of accumulation patterns and logistical complexity. This separation is necessary due to the existence of articles recorded with non-zero quantities but zero accounting value, which represent approximately 5% of total stock in quantity terms across the four Iberian plants, with Valladolid (9.2%) and Mangualde (9.0%) exhibiting the highest proportions. Such zero-value situations arise from specific operational and accounting processes, including materials regularised without assigned value, items introduced through non-standard internal movements and repaired components returned to stock without accounting value.[1] To avoid distortion of financial interpretations, value-based and quantity-based analyses are therefore treated separately throughout the dashboards.

Additionally, a unit price filter was incorporated following exploratory data analysis. Approximately 37% of items have a unit price below 10 €, representing 2.3% of total stock value but a significant share of total quantity. While operationally relevant, these items can obscure the identification of inventory reduction opportunities with significant financial impact. The price filter allows the analysis to be adapted to different decision objectives, distinguishing between financial optimisation and operational coverage

[1] Examples include SAP movement type 501, which registers goods receipts without purchase order, and the return of repaired components where accounting value is not restored upon re-entry into stock.

considerations.

Figure 4.1 presents the initial diagnostic dashboard, illustrating stock distribution by factory and product group, together with ERV contextualisation and flexible analysis options.

All inventory, consumption and asset-related values presented in this chapter correspond to a data snapshot from March 2026, reflecting a stable operational period following the SAP system transition.

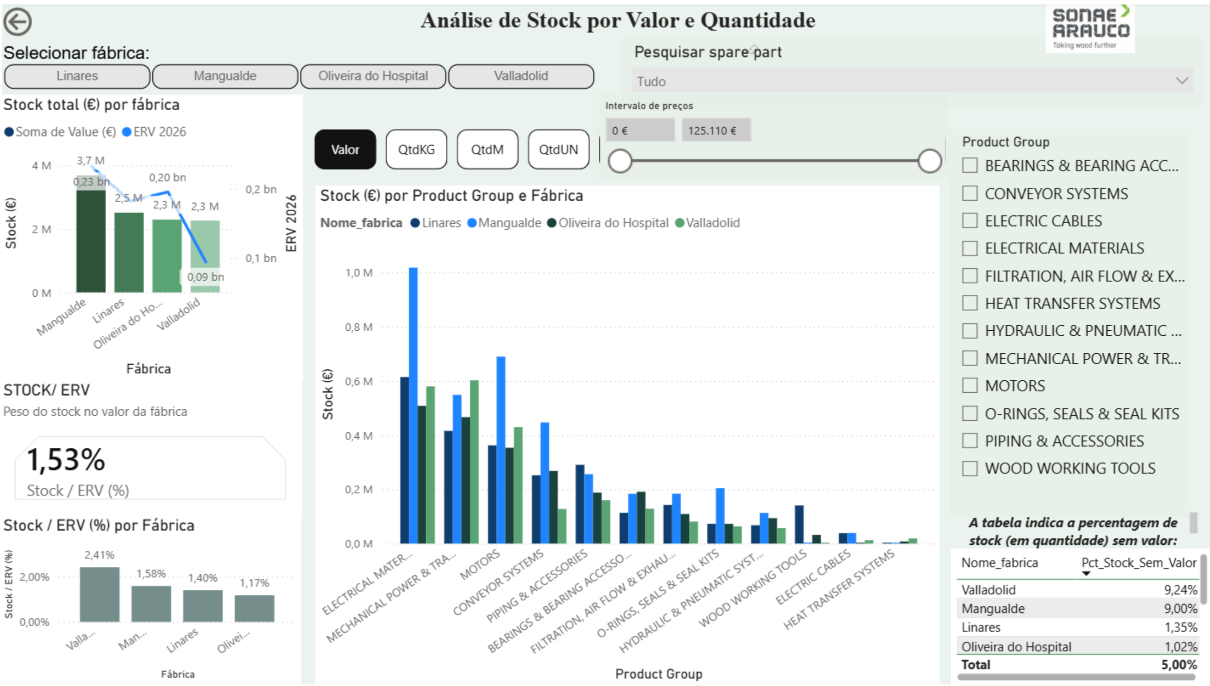

Figure 4.1: Initial diagnostic dashboard: Stock analysis by value and quantity, segmented by factory and product group, with ERV contextualisation and interactive filtering options.

The March 2026 snapshot reveals clear differences in inventory scale across factories. Mangualde concentrates the highest total stock value (approximately 3.7 M€), followed by Linares (2.6 M€), Oliveira do Hospital (2.3 M€) and Valladolid (2.3 M€). When expressed as a percentage of ERV, Valladolid exhibits the highest ratio (2.41%), followed by Mangualde (1.58%), Linares (1.40%) and Oliveira do Hospital (1.17%). This indicates that Valladolid, despite having the smallest absolute stock value, carries a disproportionately high inventory relative to its asset base, confirming the disproportionate stock-to-ERV ratio flagged at the start of this section.

Despite these differences in magnitude, the composition of inventory by product group is largely consistent across factories, with Electrical Materials, Mechanical Power & Transmission Systems and Motors accounting for a significant share of total stock value at all sites. The comparison between value-based and quantity-based representations confirms that product groups with the highest quantities do not necessarily correspond to the highest financial impact. This diagnostic analysis highlights structural differences in scale and proportionality, motivating subsequent analyses that incorporate stock movement and turnover to assess inventory alignment with actual usage.

4.2 Stock and Consumption Evolution

This dashboard addresses the following:

- **Decision supported:** whether current stock growth requires intervention, and where.
- **Question answered:** is stock growing faster than consumption, and at which plants?
- **Action triggered:** Mangualde's growth of approximately 215 k€ (the largest absolute increase across the four plants) and the 65-81% of items with no 12-month consumption motivate the criticality-based distinction introduced in Chapter 5.

A temporal analysis dashboard was developed to examine the evolution of spare parts stock and consumption between March 2025 and March 2026, corresponding to the first year of operation under SAP S/4HANA. Stock data are available for the entire 13-month period, as inventory balances were carried forward from the legacy system. In contrast, consumption data are only available from April 2025 onwards (12 months), since the dashboard relies exclusively on SAP S/4HANA records and consumption data prior to the migration remained in the legacy SAP R/3 system. Consequently, the March 2025 data point includes stock information but no corresponding consumption value. The dashboard provides two complementary perspectives: a combined stock and consumption view (Figure 4.2), which displays monthly consumption alongside stock evolution, and a quantity-based view (Figure 4.3), which focuses on stock accumulation patterns independent of monetary effects. Both views support filtering by factory, product group, and spare part code or description.

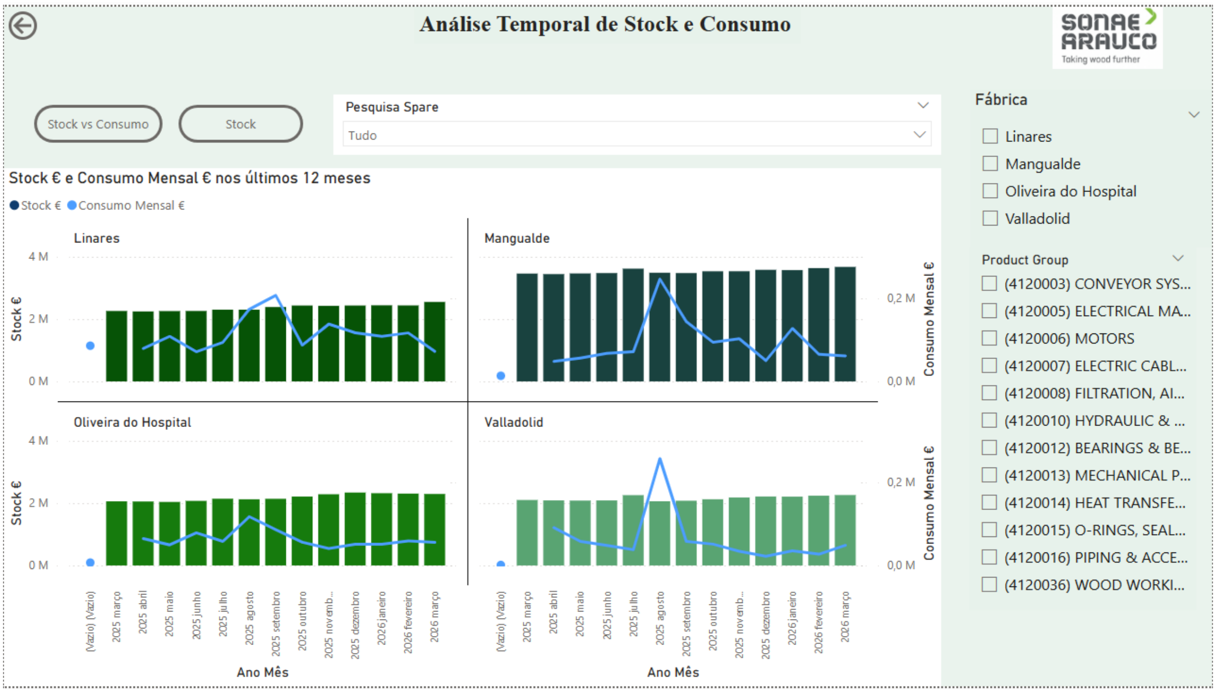

Figure 4.2: Stock and consumption evolution: monthly stock value (bars) and consumption value (line) by factory (March 2025 - March 2026).

Over this period, total spare parts stock across the four plants increased from approximately 9.9 M€ to 10.8 M€, representing a growth of 9.1%. All four factories exhibit a consistent upward trend in stock value. Linares recorded the highest relative increase (+12.9%), followed by Oliveira do Hospital (+11.5%), Valladolid (+7.6%) and Mangualde (+6.2%). In absolute terms, Mangualde contributed the largest increase (approximately 215 k€), consistent with its position as the largest inventory in the Iberian scope. This sustained growth pattern is consistent with the factors discussed in Section 1.1.1, namely conservative ordering practices, subjective criticality assessment and the accumulation of parts associated with discontinued equipment.

As illustrated in Figure 4.2, the comparison between stock and consumption enables the identification of two distinct inventory behaviours. A significant proportion of spare parts held in stock recorded no consumption over the 12-month period. Across the four plants, this subset represents between 65% and 81% of stocked items depending on the factory, and between 62% and 82% of stock value. In contrast, a smaller subset of 608 spare parts recorded consumption without holding stock at the end of the analysis period, representing between 22% and 41% of total consumption value depending on the factory. These items may follow an order-on-demand procurement approach or may correspond to cases where previously held stock was fully depleted during the period. Together, these two patterns point to a structural imbalance: a large share of capital is tied up in items with no recent usage, while a portion of actual maintenance demand is met without permanent stock holding. However, this observation alone does not distinguish between justified insurance stock for critical assets and genuine excess inventory, a distinction that requires the integration of criticality information.

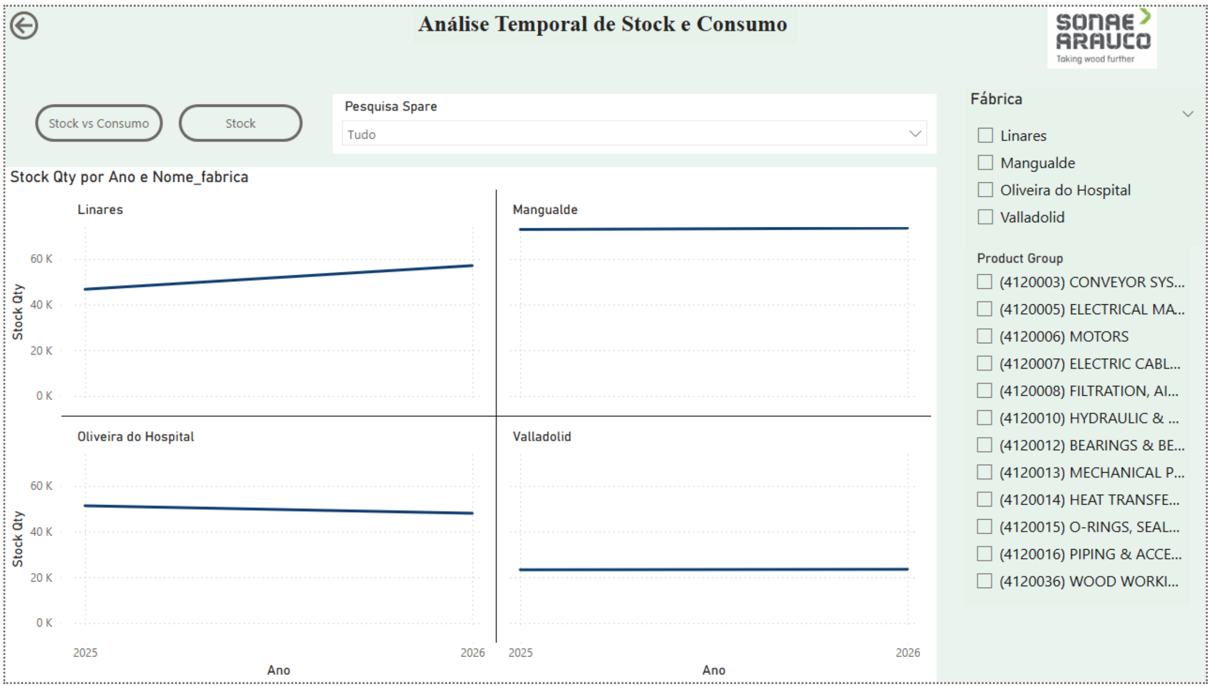

Figure 4.3: Stock quantity evolution by factory (March 2025 - March 2026).

The quantity-based view presented in Figure 4.3 reveals that stock growth is not uniform in nature across factories. At Oliveira do Hospital, stock value increased by 11.5% while quantity decreased by 3.5%, indicating that growth is driven by the accumulation or revaluation of higher-value items rather than by a general increase in the number of parts. Conversely, at Mangualde, quantity grew by 9.4% while value increased by only 6.2%, suggesting a broader accumulation of lower-value items. Linares exhibits growth in both dimensions (value: +12.9%, quantity: +14.5%), indicating a generalised expansion of inventory. These differences suggest that the drivers of inventory growth vary across plants, reinforcing the need for site-level analysis when defining inventory reduction strategies.

4.3 Maturity Overview Dashboard

This dashboard addresses the following:

- **Decision supported:** whether asset-spare part data is mature enough, at each plant, to support criticality-based classification.

- **Question answered:** which assets lack a documented link to their spare parts?
- **Action triggered:** the 80-90% of assets without associated spare parts across the Iberian plants identifies data-quality remediation as a precondition for scaling VED(O) classification, ahead of the financial optimisation addressed in later dashboards.

A maturity overview dashboard was developed to assess the completeness of the asset-spare part data structure, which influences the feasibility of criticality-based inventory management. The dashboard focuses on the identification of assets without associated spare parts, representing structural gaps that may compromise maintenance planning and inventory decision-making.

Although the analytical scope of this thesis focuses on the Iberian plants, this dashboard was extended to include Germany and South Africa at the request of the company, reflecting a corporate-level need to evaluate data consistency across regions. The dashboard is therefore not used for quantitative comparison between sites, but to provide contextual insight into system-wide data maturity.

The dashboard enables the visualisation of assets without associated spare parts by factory. Within this subset, users can further filter assets by maintenance criticality (critical and supercritical) and by operational status. Hierarchical drill-down by area and position is also available. Assets classified as scrap or inactive in IBM Maximo were excluded, as they do not represent current operational requirements.

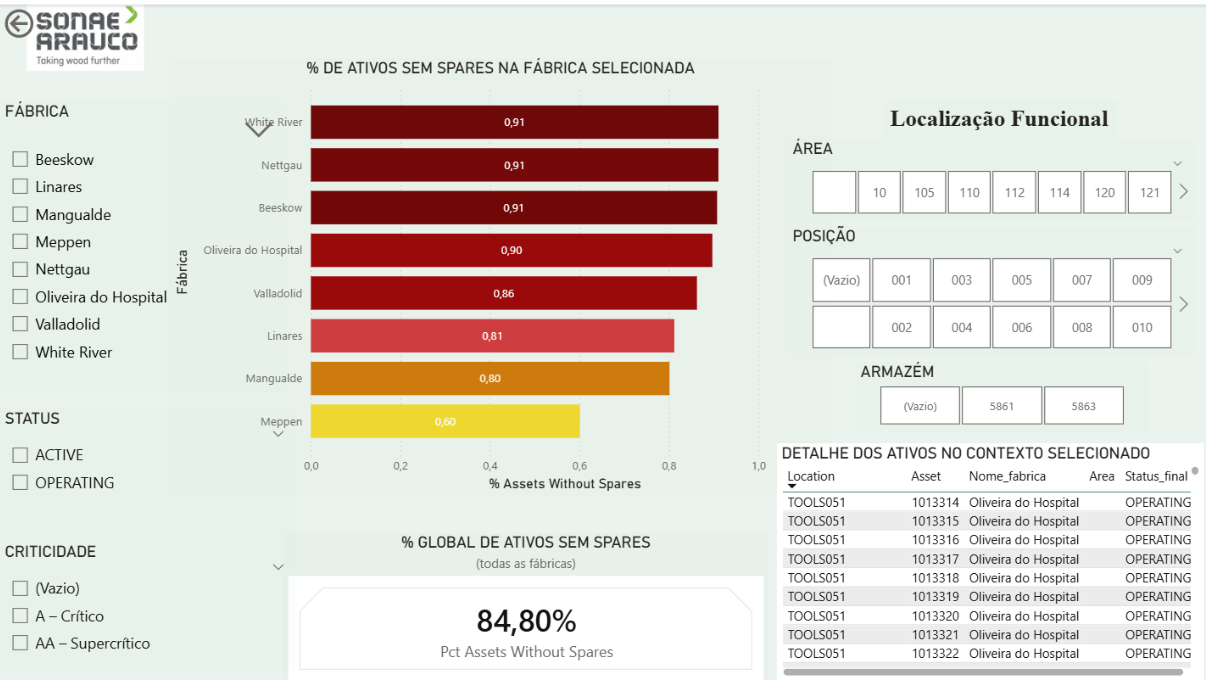

Figure 4.4: Maturity overview dashboard: assets without associated spare parts, criticality assignment, operational status, and hierarchical drill-down by area and position.

4.3. Maturity Overview Dashboard

Within the Iberian scope, relevant differences are observed between factories. Oliveira do Hospital presents the highest percentage of assets without associated spare parts (approximately 90%), exceeding Valladolid (86%), Linares (81%) and Mangualde (80%). However, Oliveira do Hospital also exhibits the highest coverage of criticality classification within this subset, with approximately 11% of assets classified as critical and 20% as supercritical, significantly higher than the remaining plants where criticality coverage is limited or absent. This pattern reflects the historical context of IBM Maximo implementation, as Oliveira do Hospital was the first site where the system was deployed, leading to more rigorous asset registration practices. Observed differences should therefore be interpreted as a reflection of heterogeneous implementation timelines rather than of operational performance.

The completeness of asset-spare part linkages is further influenced by changes in data capture practices over time, as discussed in Section 3.3. These structural gaps in the data represent a precondition that must be addressed prior to the full-scale implementation of criticality-based inventory strategies. The maturity overview dashboard provides the visibility required to prioritise data quality improvement actions at specific asset and location levels.

To complement the maturity assessment, a spare parts diversity indicator was developed, defined as the ratio between the number of distinct spare part codes and the number of active assets at each factory (Figure 4.5). Linares, Mangualde and Valladolid exhibit similar ratios (0.69-0.72), while Oliveira do Hospital presents a notably lower value (0.48). This result is consistent with the higher proportion of assets without associated spare parts observed at this factory, and is partly explained by different asset registration practices. At Oliveira do Hospital, components such as motors and reducers were registered as separate assets from the early stages of IBM Maximo implementation, whereas other plants tend to register assemblies as single assets. This finer registration granularity increases the total number of assets in the system without a proportional increase in spare part associations, resulting in both a lower spare-to-asset ratio and a higher proportion of assets without linked spare parts. This example illustrates how differences in registration practices directly affect inventory indicators and reinforces the need for caution when comparing metrics across plants.

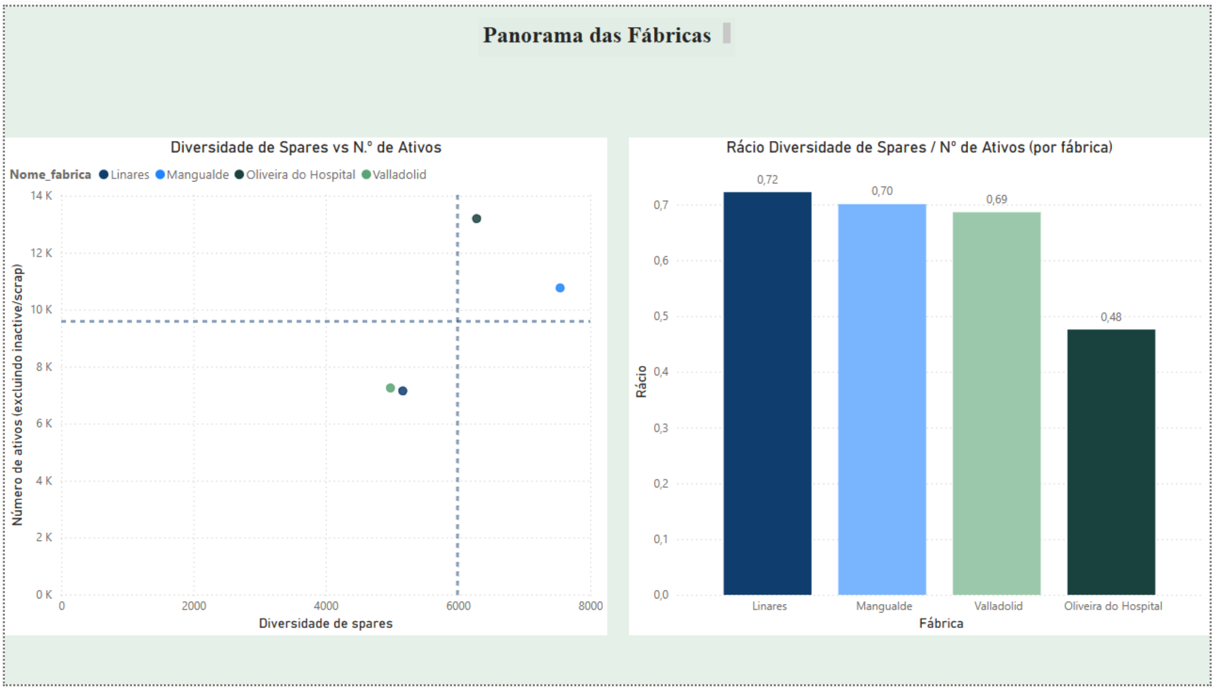

Figure 4.5: Factory overview: spare parts diversity versus number of assets (left) and spare-to-asset ratio by factory (right).

4.4 Spares by Movement and Stock

This dashboard addresses the following:

- **Decision supported:** which specific spare parts should be prioritised for detailed criticality review.
- **Question answered:** which items combine high stock value with low turnover?
- **Action triggered:** 1 572 items, representing approximately 6.0 M€ (56% of total inventory value), are identified as priority candidates and carried forward into the selection process described in Chapter 5.

To support the identification and prioritisation of inventory reduction opportunities, two complementary dashboards analysing the relationship between spare parts stock and movement were developed, providing both a factory-level assessment and a detailed spare part-level analysis.

The analysis is grounded on the principle that total inventory value at factory level should be proportionate to the annual movement of that inventory, a relationship commonly used in inventory management to assess stock efficiency [24]. In this work, the relationship was expressed using the ratio Consumption / Stock. Values closer to 1 indicate a balanced alignment between inventory levels and usage, while values significantly below 1 suggest that stock levels may be disproportionate relative to actual consumption. Values above 1 would indicate high turnover, where annual consumption exceeds average stock. Although this indicator constitutes a coarse approximation, it is suitable for comparative assessment across factories operating within the same industrial sector.

Factory-level overview

The first dashboard, presented in Figure 4.6, provides a factory-level overview through a scatter plot relating total stock value to total consumption value, complemented by inventory turnover by factory. Consumption corresponds to the last 12 months of recorded movements, while stock values represent the average stock value over the same period. This approach reduces the impact of short-term fluctuations and ensures consistency with the post-SAP operational period.

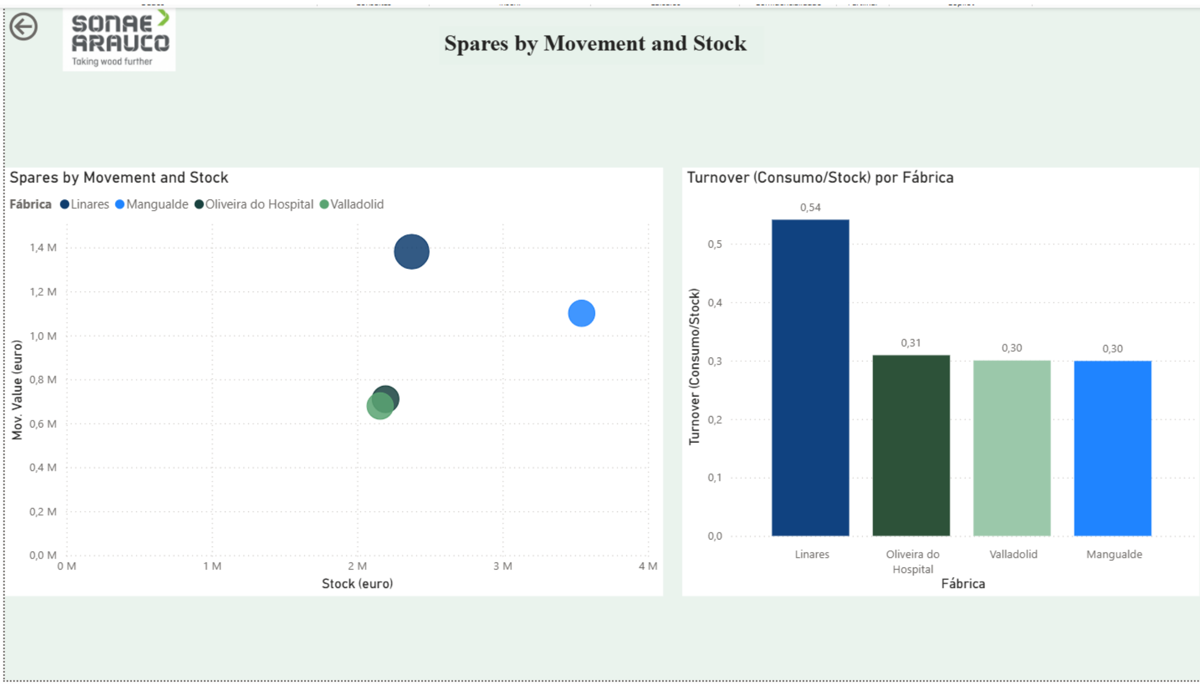

Figure 4.6: Factory-level dashboard: spare parts stock versus movement and turnover by factory.

The results show that all four sites exhibit a Consumption/Stock ratio below 1, confirming that inventory levels exceed annual consumption across the Iberian plants. Linares presents the highest ratio (0.53), followed by Oliveira do Hospital (0.27), while Mangualde and Valladolid both record ratios of 0.21. Mangualde and Valladolid thus combine the lowest turnover with, respectively, the highest absolute stock value and the highest stock-to-ERV ratio, suggesting that these factories concentrate a larger share of potential inventory reduction impact.

Spare-level analysis

The second dashboard, shown in Figure 4.7, complements the aggregated analysis by enabling a spare-level assessment. A Stock versus Consumption scatter plot is used, where each data point represents an individual spare part. Bubble size corresponds to turnover Consumption / Stock, allowing the simultaneous evaluation of stock value, consumption behaviour and turnover efficiency.

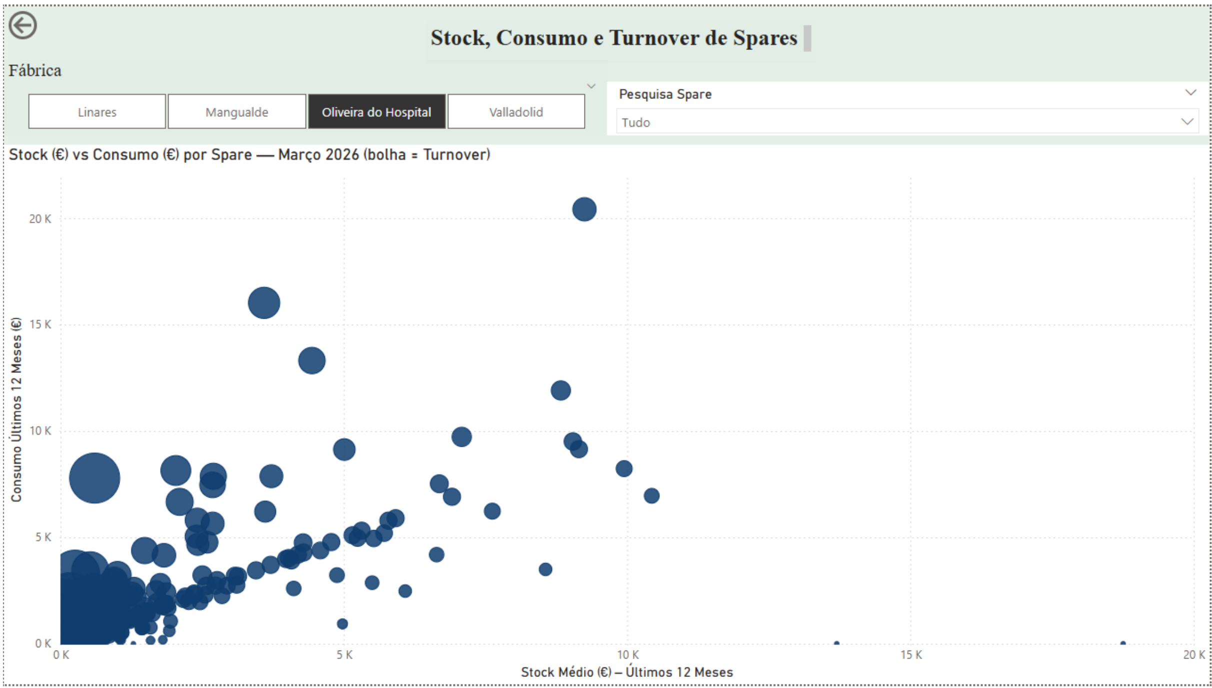

Figure 4.7: Spare-level dashboard: stock versus consumption per spare part, with turnover represented by bubble size.

This representation supports the identification of spare parts characterised by high stock value, low consumption and low turnover. Applying a threshold of stock value above 1 000 € and turnover below 0.1, a total of 1 572 spare parts were identified across the four plants, representing approximately 6.0 M€ in stock value, or 56% of total inventory. At a higher threshold of 5 000 €, 296 items still account for 3.4 M€ (31.6% of total stock value). These spare parts constitute prioritised candidates for subsequent detailed evaluation, where maintenance criticality and operational constraints are introduced to validate and refine inventory optimisation decisions, as described in Chapter 5.

4.5 Non-Moving Inventory and Potential Obsolescence

This dashboard addresses the following:

- **Decision supported:** which items are candidates for obsolescence review, write-down or disposal.
- **Question answered:** which items have recorded no consumption over 12 or 24 months?
- **Action triggered:** 3 150 items, representing approximately 1.6 M€ in stock value (13.1% of total inventory), are routed into the review workflow proposed in Section 7.3.

To support the identification of spare parts that may require review or reclassification, a dedicated dashboard was developed for items with no recorded consumption over a 24-month period (Figure 4.8). The construction of this 24-month consumption window required the integration of data from both the legacy SAP R/3 environment, covering the period prior to the migration, and the current SAP S/4HANA system, operational since April 2025. The 12-month consumption flag, based exclusively on post-migration data, was included alongside the 24-month flag for two reasons. First, it enables users to distinguish between items with no consumption in either period, which are stronger candidates for obsolescence review, and items consumed only within the most recent 12 months. Second, spare parts introduced under material codes beginning with 412 were created in the new system and could not, by definition, have accumulated 24 months of consumption history. For these items, the 12-month flag provides the only meaningful consumption indicator.

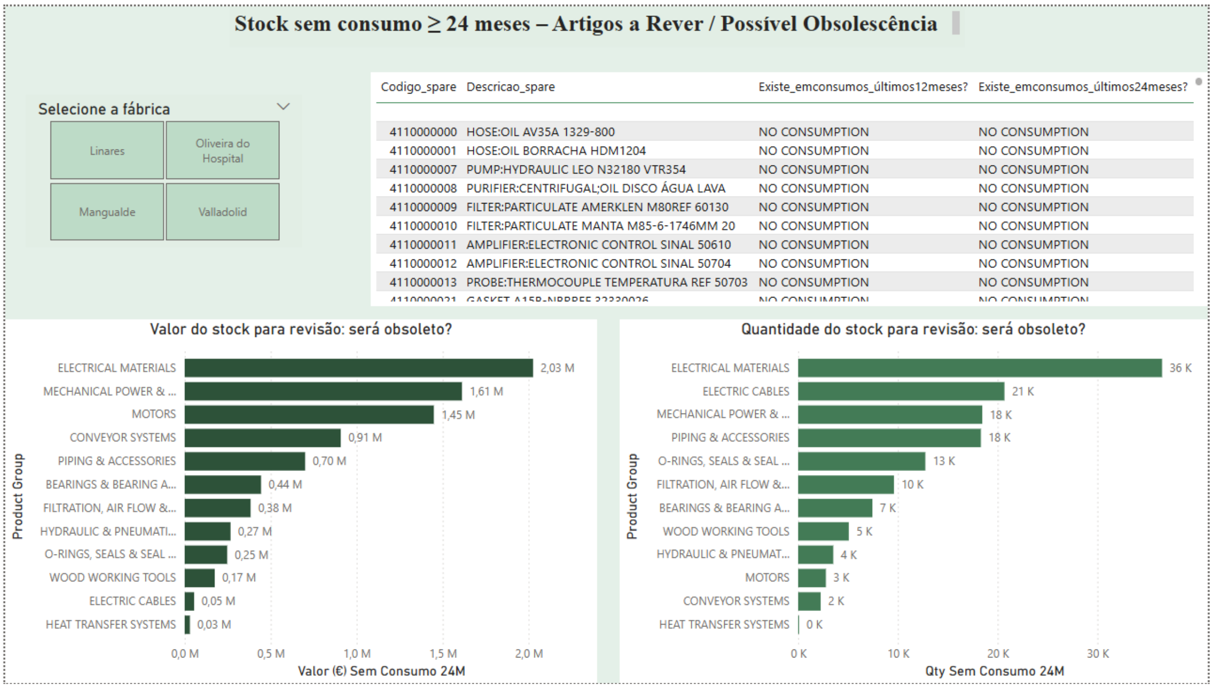

Figure 4.8: Non-moving inventory dashboard: spare parts without consumption in the last 24 months, by product group (value and quantity), with 12-month and 24-month consumption flags.

Items flagged as non-moving under the relevant window, 24 months for items with sufficient consumption history, or 12 months for items introduced under the 412 material code prefix, are candidates for the formal Obsolete category defined in Section 3.7; items flagged here are therefore review candidates rather than automatically reclassified as Obsolete.

Across the four Iberian plants, 3150 items (13.1% of total inventory) recorded no consumption over the 24-month window, representing approximately 1.6 M€ in stock value (15.3% of total). The distribution across factories is not uniform. Mangualde concentrates the largest share, with 1612 items (21.4% of its inventory) accounting for 1.2 M€ (32.3% of its stock value), significantly above the levels observed at the remaining plants. Valladolid presents 829 items (16.7%) but with a comparatively low associated value (60 k€, 2.7%), suggesting that its non-moving stock consists primarily of low-value items. Oliveira do Hospital and Linares exhibit the lowest proportions (4.6% and 8.2% respectively), although Oliveira do Hospital concentrates a higher value per non-moving item (264 k€ across 287 items).

The comparison between the 12-month and 24-month indicators reveals a significant difference: 76.5% of items show no consumption over 12 months, compared to 13.1% over 24 months. This gap is largely explained by the SAP system transition. The 12-month flag relies exclusively on post-migration data, meaning that items consumed in the legacy system but not yet consumed since April 2025 appear as non-movers under this indicator. The 24-month flag, which integrates pre- and post-migration records, provides a more reliable basis for identifying truly inactive stock.

By product group, Electrical Materials (446 k€), Motors (412 k€) and Conveyor Systems (290 k€) account for the largest share of non-moving stock value. Motors, despite representing fewer items, exhibit a high concentration of value, indicating the presence of individual high-cost components without recent usage.

At the time of this study, no formalised process existed within the company for the periodic review of potentially obsolete spare parts. Decisions to write off, transfer or dispose of non-moving items were taken reactively and on an ad hoc basis, without a defined review frequency or standardised criteria. This dashboard was designed to support the introduction of such a practice, and the establishment of a periodic obsolescence review cycle is proposed as a recommendation for integration into the ME10 spare parts management standard (Chapter 3.5).

Using this dashboard as a screening tool comes with an important caveat: the absence of consumption does not necessarily indicate obsolescence. A motor without movement in 24 months may be a vital spare for a supercritical production asset, or it may correspond to discontinued equipment. Without criticality information, it is not possible to distinguish between justified insurance stock and genuine excess. This distinction is addressed through the integration of VED(O) criticality classification in the following chapter.

4.6 Inter-Plant Spare Parts Overlap

This dashboard addresses the following:

- **Decision supported:** whether an item flagged for reduction at one plant should be transferred rather than written off.
- **Question answered:** is a given spare part also stocked at another Iberian plant?
- **Action triggered:** enables the cross-plant transfer decision (rule R5 of the framework, Section 5.1.4) as an alternative to write-off, and supports urgent internal sourcing before external procurement.

An overlap analysis was conducted to determine how many spare parts are shared across the Iberian plants. Of the 23 079 distinct spare part codes, 22 295 (96.6%) are stocked at a single factory. Of the remaining items, 784 items (3.4%) are present at two or more sites, 87 (0.4%) at three or more and 20 (0.1%) at all four plants.

This low overlap reflects the decentralised inventory management described in Section 3.2, where each plant manages spare parts independently. While limited commonality is partly expected due to differences in installed equipment, it also limits opportunities for cross-plant transfer of non-moving or excess items.

In practice, when maintenance engineers needed to check whether a spare part existed at another factory, they had to search for the code in SAP and verify each plant individually. To simplify this, a lookup dashboard was developed (Figure 4.9) where users can search by spare part code and see which factories hold it. This is useful both for stock reduction decisions, where a part flagged for write-off at one plant may still be needed at another, and for urgent situations, where a part can be sourced internally before ordering from a supplier.

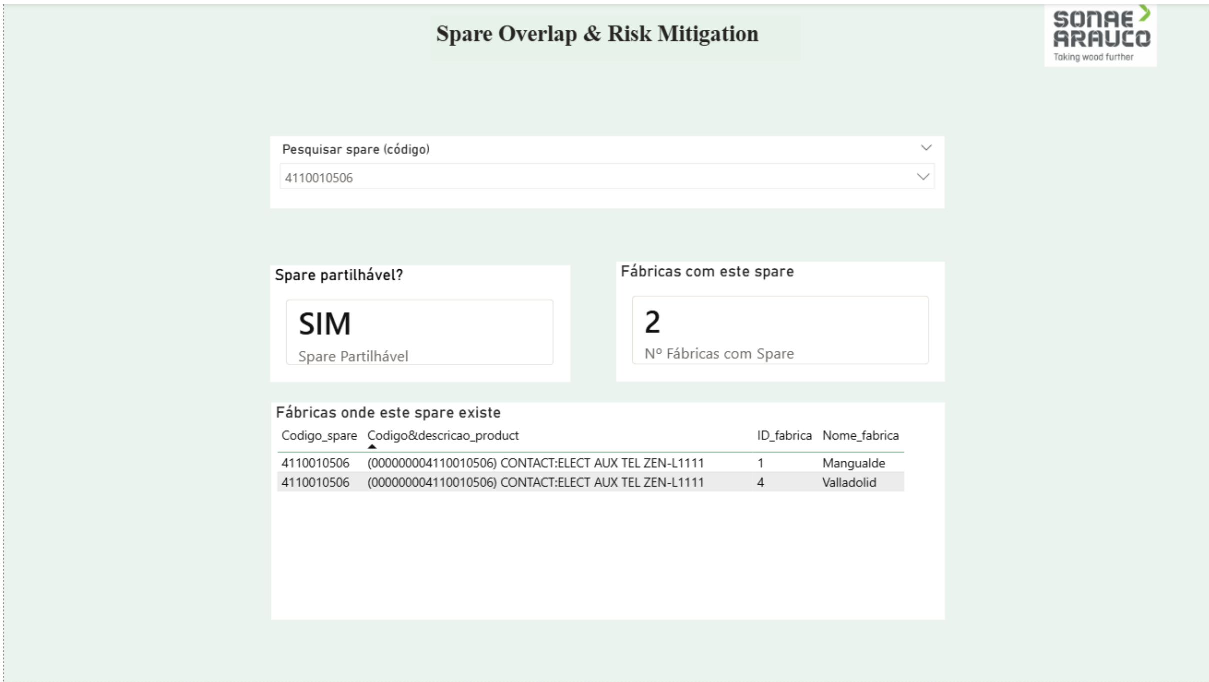

Figure 4.9: Spare overlap and risk mitigation dashboard: spare part lookup showing cross-plant availability.

The identification of shared items is also relevant for the Obsolete category in the VED(O) classification, where transfer to other plants is a recommended action before write-off (Chapter 3.5).

The dashboards presented in this chapter were developed with iterative input from a procurement specialist and maintenance specialists from the Mangualde and Valladolid plants, all experienced in working with dashboards and company data. Their feedback, collected as the dashboards were being built, led to concrete adjustments before finalisation.

Chapter 5

Stock Decision Framework and Application

This chapter operationalises the diagnostic findings of Chapter 4 into a structured decision framework. It first describes the selection of spare parts for detailed criticality assessment, the framework itself, and its translation into concrete MRP parameters. The framework is then applied to selected case examples, reporting the resulting stock adjustments and their financial impact. This addresses the first gap in Table 2.1: classification treated as an analytical endpoint rather than an input to stock decisions, accounting for the incomplete data described in Section 3.3.

5.1 Selection of Spare Parts for Criticality Assessment

The dashboards presented in Chapter 4 revealed inventory imbalances across the four Iberian plants, but the underlying analyses rely on financial and movement-based indicators alone. Stock value, turnover and consumption history do not reflect whether a given spare part is operationally critical or not. To address this limitation, a subset of items was selected for the application of the proposed framework, integrating criticality, consumption behaviour and current inventory configuration.

The items selected for detailed analysis were not chosen simply because they presented the lowest turnover or largest stock imbalances identified in Chapter 4. Instead, they were selected to represent different inventory situations and decision contexts addressed by the proposed framework, including cases with active demand, intermittent consumption, non-moving stock and low-value items. This allows the framework to be illustrated across a range of realistic operational scenarios, rather than focusing only on the most extreme cases of excess inventory.

The selection was based on the stock and consumption dashboards, starting from items with high stock value, quantities above one unit, or no consumption over 24 months, and excluding items with a negligible unit value. Each item was then examined in relation to the equipment it supports, since the same spare part may be justified at one factory and excessive at another depending on the associated asset and location. For items stocked at more than one plant, the inter-plant analysis, supported by a dedicated dashboard (Section 4.6), was used to compare quantities across sites and identify discrepancies.

The focus was on items where criticality information could lead to a different stock decision, rather than on covering as many items as possible. A total of 6 items were selected for detailed analysis at the Mangualde plant, covering motors, pumps, seals, conveyor components and electrical materials. For each item, the current stock quantity, value and consumption history were recorded as a baseline for the criticality assessment described in Section 5.1.1.

5.1.1 VED(O) Classification Session

One remote session was conducted to classify the selected items, involving a specialist from Mangualde.

For each item, the stock data documented in the selection phase was presented and the specialist assessed its operational relevance based on their experience with the equipment and production process. Then, the specialist scored each item on the five ME10 criteria (Asset Criticality, Lead Time, Failure Probability, Unit Cost and Repair Feasibility and Alternatives) on a scale of 1 to 5. The VED(O) score was calculated using the AHP-derived formula (Section 3.8) and classified according to the thresholds in Table 3.5. At the time of writing, the classification has been completed for a subset of the selected items, with the remainder pending additional sessions as the ME10 standard is deployed across the Iberian plants.

5.1.2 Stock Decision Framework

The ME10 standard defines stocking policies for each VED(O) category, including MRP type, reorder point logic, safety stock levels and order policy. These rules provide clear guidance for configuring newly classified items in SAP. In practice, however, inventory management often involves a different situation: items already in stock, with an existing quantity and a known consumption history, which still need to be reviewed and managed. The ME10 standard does not provide explicit guidance on how to handle these cases. To complement the classification with structured recommendations, a decision framework is proposed to support the review and adjustment of MRP parameters for spare parts already in stock, integrating criticality, observed consumption behaviour and current system configuration.

The objective is not to optimise theoretical stock levels, but to identify and correct misalignments between system-driven parameters and the actual operational behaviour of spare parts.

5.1.3 Inputs and Item Screening

For each spare part, the following inputs are considered:

- VED(O) classification, representing the criticality level
- Historical consumption
- Current stock quantity
- Current MRP parameters defined in SAP

These inputs provide both a risk-based and a behaviour-based perspective on inventory management.

In a population of approximately 24 000 active items across the Iberian plants, applying the framework exhaustively is not feasible. This total corresponds to 23 079 distinct spare part codes, some of which are held at more than one plant, as discussed in Section 4.6. Instead, items are pre-screened using the diagnostic dashboards developed in Chapter 4. The screening targets items that exhibit potential signs of misalignment, namely:

- items with a stock value disproportionate to their consumption level, identified through the stock-versus-consumption dashboard (Section 4.2);
- items with low turnover ratios, identified through the turnover analysis included in the dashboard from Section 4.4, which highlights cases where annual consumption is significantly below the average stock value;
- items without recorded consumption over 24 months but with a current stock quantity greater than zero, identified through the non-moving inventory dashboard (Section 4.5);
- items present in multiple plants with imbalanced stock profiles between them, identified through the overlap dashboard (Section 4.6).

Items selected through this screening are then segmented according to two dimensions, criticality and consumption behaviour, which determine which branch of the decision logic is applied. The case examples discussed in Section 5.2 were selected through this screening process. The tachometer and the sealing ring cases originated from stock-versus-consumption and turnover analysis, the fuse case from low-value pattern detection in the consumption history, and the vacuum pump and conveyor belt cases from the non-moving inventory dashboard.

5.1.4 Decision Logic

The decision logic is organised in two pathways, distinguished by the analytical approach they require: a demand-based pathway, for items with recorded consumption events, and a risk-based pathway, for items without recorded consumption. For items held in more than one unit, a preliminary technical assessment (Step 0) is applied to both pathways before the pathway-specific analysis takes place. A transversal economic dimension is then applied to refine procurement decisions for items with very low unit value.

Step 0 (preliminary): Technical assessment of the existing quantity

For items currently held in more than one unit, the technical justification for the existing quantity is reviewed before proceeding with the rest of the analysis. This preliminary step applies to both branches and distinguishes between four situations:

- **Group replacement:** the component is replaced as part of a set or kit, where several units are consumed together during a single maintenance intervention (e.g., a set of seals for a hydraulic cylinder). In these cases, the existing quantity is technically justified by the size of the replacement set;
- **Physical redundancy:** the equipment includes multiple identical positions where the same spare part is installed (e.g., several identical hydraulic cylinders in the same group). The required stock level may then reflect the number of installed positions, although simultaneous failure is typically rare and a single insurance unit may still be sufficient;
- **Wear component with scheduled bulk replacement:** the component is consumed in batches as part of a planned intervention (e.g., conveyor knives replaced in full sets during planned shutdowns);
- **Unjustified accumulation:** the existing quantity cannot be explained by any of the above and reflects over-cautious procurement, duplicated orders or historical purchases without operational support. This is the typical case for reduction.

The assessment is performed in consultation with the maintenance specialist, who provides the operational context that the data alone cannot reveal. Items for which the existing quantity is technically justified are excluded from further reduction; items classified as unjustified accumulation proceed to the subsequent analysis steps.

Demand-based pathway: Items with consumption

For items with recorded consumption events, the analysis focuses on the alignment between consumption behaviour and the configured MRP parameters. Following the technical assessment in Step 0 when applicable, the diagnostic identifies three main types of misalignment:

- current parameters lead to stock levels higher than the observed demand profile justifies;
- manual replenishment decisions override the configured logic, leading to stock levels that the system parameters did not trigger;
- procurement is fragmented into multiple small orders, generating administrative effort disproportionate to the value moved.

In all three cases, the adjustment consists of recalibrating the MRP parameters: reorder point, maximum stock and lot size, to reflect the actual consumption pattern, while preserving the level of availability required by the item's criticality.

Risk-based pathway: Items without consumption

For items without recorded consumption, the decision logic shifts from a demand-based to a risk-based evaluation. The absence of demand does not in itself imply that the spare part is not required: in industrial environments, certain components associated with rare but high-impact failures may remain unused for extended periods while still being operationally critical. For this reason, the absence of consumption is treated not as evidence of obsolescence, but as a trigger to reassess whether the existing stock is justified.

Two time horizons are considered. When consumption has occurred within the last 24 months but not within the last 12, the item is treated as intermittently demanded: stock is justified but is maintained at a reduced level through a conservative MRP configuration with low reorder points and unitary lot sizes.

When no consumption has been observed over a 24-month period, the assessment follows three sequential steps that assess the legitimacy of holding stock at all. Step 0 is applied first whenever the existing quantity exceeds one unit, to filter out situations of legitimate redundancy that should be excluded from reduction.

Step 1: Cross-verification of inactivity

The absence of consumption is confirmed against the detailed transactional records before any decision is taken. Aggregated SAP flags may overestimate inactivity, as items with consumption events that were subsequently replenished within the 24-month window may still appear as inactive.

The 12-month and 24-month horizons act as triggers for the analysis rather than rigid cut-offs. Whenever the available data supports it, the consumption record is examined further back in time, up to the earliest reliable consumption data available (early 2023, corresponding to approximately 36 months of history). This extended verification is particularly relevant for high-value or highly critical items, where demand events may be separated by several years and where a strict application of the 24-month window could misclassify an active spare part as inactive. The boundary at early 2023 is itself a consequence of the data quality constraints discussed in Chapter 3: beyond this point, the combination of pre-migration records from SAP R/3 and post-migration records from SAP S/4HANA becomes less reliable, and consumption history cannot be examined with the same confidence.

Step 2: Cross-plant verification

Before considering reduction or elimination at plant level, the inter-plant overlap dashboard is used to verify whether the same item is consumed at another plant. When this is the case, the excess stock is treated as a candidate for transfer rather than write-off, preserving the operational value of the existing inventory while addressing the local imbalance.

Step 3: Criticality-based decision

For items confirmed as inactive and without transfer opportunity, the decision is informed by the VED(O) classification, while recognising that the final stock level is determined in consultation with the maintenance specialist:

- **Vital items** are kept at a minimum technically justified quantity, ensuring protection against low-probability but high-impact events. The MRP configuration uses reorder-point-based planning, typically with a maximum stock of one unit and unitary lot sizing.
- **Essential items** are reduced to a minimal level and flagged for periodic review, acknowledging the uncertainty regarding future requirements. MRP parameters limit replenishment quantities while preserving the system's ability to respond if demand reappears.
- **Desirable items** are candidates for stock reduction or elimination, given the combination of prolonged inactivity and limited operational impact. The recommended quantity depends on contextual factors that the system

> alone cannot evaluate, such as the residual operational value of holding a small quantity, the unit cost of the item, or the existence of planned interventions. The MRP configuration is adjusted to prevent automatic replenishment.

This sequence (combining the technical justification of Step 0, the cross-verification of inactivity, the cross-plant availability check and the criticality-based decision) ensures that decisions for items without consumption are grounded in an explicit evaluation of stock legitimacy, rather than relying solely on historical demand. **Throughout the framework, the VED(O) classification is positioned as a structured input to the decision rather than as a deterministic rule, preserving the role of expert judgement when contextual factors are not fully captured by the available data.** This principle is applied consistently across all case examples in Section 5.2.

Economic dimension: Low-value items

Independently of the branch followed above, an additional dimension is considered for items with very low unit value. In these cases, inefficiencies are typically not associated with excess inventory, but with procurement processes: small order quantities trigger frequent replenishment cycles that generate administrative effort disproportionate to the value moved. The optimisation goal shifts accordingly. Rather than reducing stock levels, the MRP configuration is adjusted to increase lot sizes, consolidating demand into fewer transactions while maintaining adequate availability. This adjustment is applied whenever the unit cost is sufficiently low for the administrative overhead of procurement to exceed the holding cost of larger replenishment batches.

5.1.5 MRP Translation and Validation

The decisions obtained through the framework are translated into recommended MRP configurations through the adjustment of four parameters: MRP type, reorder point, maximum stock level and lot size or rounding value. The selection of MRP type follows the decision pathway: a reorder-point logic (VB) is the default for items requiring stock availability, while a no-planning logic (ND) is appropriate for items where automatic replenishment is no longer desired, typically Desirable items flagged for elimination. Reorder point and maximum stock are set according to the recommended quantity, and lot size is configured to match the operational pattern, unitary lots for low-frequency items, fixed lots aligned with annual demand for low-value high-frequency items.

The validation of each decision is performed through the comparison between current and proposed configurations along four dimensions: changes in MRP parameters, changes in stock levels in units and value, total reduction in inventory value, and consistency between the proposed decision, the criticality classification and the observed consumption behaviour. For items with consumption, this validation is quantitative, based on before-and-after measurements. For items without consumption, the verification is based on logical consistency between the four steps of the decision logic, complemented by preservation of operational risk coverage. The application of the framework to selected case examples is presented in Section 5.2. The complete workflow, together with the corresponding decision rules, is summarised in Figure 5.1 and Table 5.1

5.1. Selection of Spare Parts for Criticality Assessment

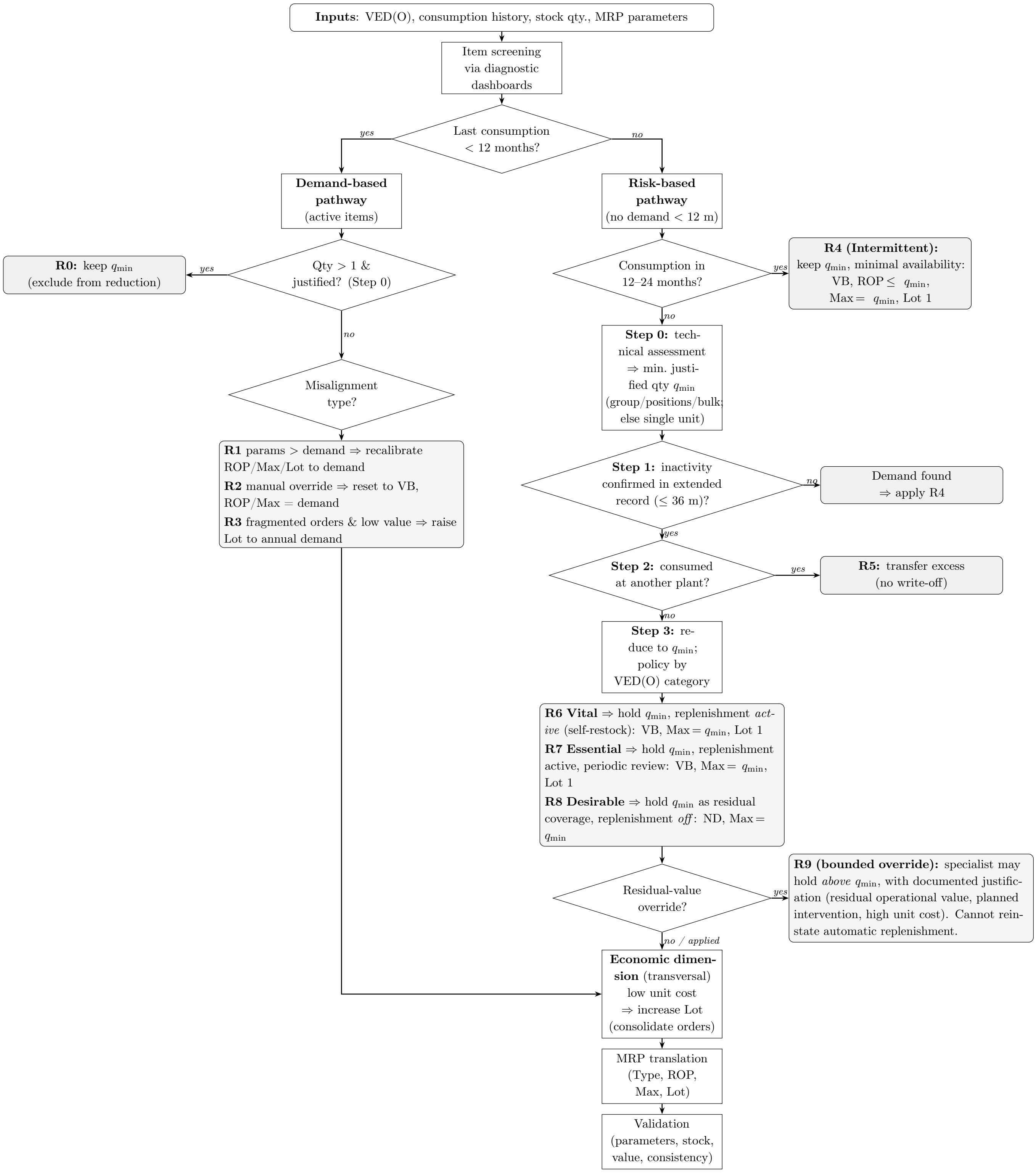

Figure 5.1: Proposed decision framework for adjusting MRP parameters of spare parts *already held in stock*. Each leaf routes to an explicit decision rule (R0-R9) defined in Table 5.1. The retained quantity is the minimum justified quantity $q_{\min}$, established by the Step 0 technical assessment (group replacement, installed positions or scheduled bulk; a single unit when none applies); the VED(O) category sets the replenishment policy around $q_{\min}$, and expert judgement enters only through the bounded override R9.

Table 5.1: Decision rules of the framework, applied to spare parts *already held in stock*. Conditions are evaluated in the order imposed by Figure 5.1. $q_{\min}$ denotes the minimum justified quantity set by the Step 0 technical assessment (a single unit unless group replacement, installed redundancy or scheduled bulk applies). The MRP configuration column states the resulting SAP parameters (MRP type, reorder point, maximum stock, lot size).

Rule	**Step / branch**	**Condition (IF)**	**Decision (THEN) – MRP config**
R0	Step 0	Existing qty equals the technically justified qty $q_{\min}$ (kit, installed redundancy or scheduled bulk)	Retain $q_{\min}$; exclude from reduction. *MRP unchanged*
R1	Demand	Parameters drive stock above the demand profile	Recalibrate to demand. *VB; ROP, Max from demand; Lot demand-based*
R2	Demand	Manual replenishment overrides the configured logic	Reset to reorder-point logic. *VB; ROP = 1; Max = demand; Lot = 1*
R3	Demand	Low unit value and procurement fragmented into many small orders	Consolidate procurement. *VB; Lot = annual demand*
R4	Intermittent / Step 1	Demand exists but is infrequent (12–24 m, or found in extended record)	Minimal availability. *VB; ROP* $\leq q_{\min}$*; Max*$= q_{\min}$*; Lot = 1*
R5	Step 2	Item consumed at another Iberian plant	Transfer excess; no write-off. *Relocation (no parameter change)*
R6	Step 3 – Vital	No demand $\geq$ 24 m, qty above $q_{\min}$, no transfer; **Vital**	Reduce to $q_{\min}$; keep replenishment active (self-restock on consumption). *VB; Max*$= q_{\min}$*; Lot 1*
R7	Step 3 – Essential	idem; **Essential**	Reduce to $q_{\min}$, flag periodic review; replenishment active. *VB; Max*$= q_{\min}$*; Lot 1*
R8	Step 3 – Desirable	idem; **Desirable**	Reduce to $q_{\min}$ as residual coverage; disable automatic replenishment. *ND; Max*$= q_{\min}$
R9	Override (gated)	A Step-3 default applies **and** (residual operational value $\vee$ planned intervention $\vee$ high unit cost)	Specialist may hold *above* $q_{\min}$, with documented justification; cannot reinstate auto-replenishment. *Max*$> q_{\min}$ *(documented)*
L	Economic (transversal)	Very low unit cost (admin. cost of ordering > holding cost of larger batch)	Increase lot size to reduce ordering frequency. *Lot* $\uparrow$

Because reliable supplier lead-time data could not be retrieved from SAP (Section 7.2), the reorder points and maximum-stock levels proposed in this section are not derived from a lead-time-based safety-stock calculation. For this reason, the reduction of Vital and Essential items to a single insurance unit is never applied automatically. It is confirmed with the maintenance and procurement specialist, who weighs supplier responsiveness against the consequences of a stock-out, and the bounded override R9 exists precisely to retain additional units when the lead-time risk justifies it.

5.1.6 Sensitivity of the Decision Logic

The decision logic relies on three time-based thresholds: 12 months to separate active from inactive demand, 12 to 24 months for the intermittent classification (R4), and 36 months for the extended verification used in the risk-based pathway (Step 1). These thresholds were not derived from statistical analysis. They follow the 36-month data retention limit described in Section 3.3, the maximum consumption history the SAP system keeps, rather than a value chosen specifically to separate active from inactive items. Items whose last consumption falls close to one of these windows are therefore the ones most likely to change classification if the thresholds were set differently, for example an item with 20 months since its last consumption event, just below the 24-month cut-off.

None of the six case examples in Section 5.2 sits at one of these boundaries, since they were chosen to illustrate clear-cut situations rather than borderline ones. This is itself a limitation: the cases demonstrate how the framework behaves, but not how sensitive its outcomes are to the exact threshold values.

The rules themselves can also shift outcomes near their boundaries. Choosing between R1 and R2 depends on whether a misalignment comes from system parameters or from a manual replenishment decision, and this is not always clear from the data alone. In Step 3, the boundary between Vital and Essential matters for the same reason: since it comes directly from the AHP weights, the weight sensitivity already shown in Section 3.8.8 would carry over into a different stock recommendation for any item close to that boundary. The R9 override offers a partial safeguard, letting a specialist correct a rule-based outcome that conflicts with operational knowledge. A full sensitivity analysis, re-screening the item population under alternative thresholds, is left as future work (Section 7.3).

5.2 Application and Results

This section presents the application of the proposed framework to a selected set of spare parts and the corresponding results obtained. The objective is to evaluate its impact in adjusting inventory management parameters and improving overall stock efficiency.

For most analysed items, "where used" information in Maximo was not available due to incomplete asset-spare part relationships. Therefore, stock decisions were validated with a maintenance specialist from the Mangualde plant. However, for some items (e.g. the sealing ring, Item 4110174135, and the tachometer, Item 4110047428), asset-level information was available and used to support the stock decision.

The proposed framework was applied to a selected set of spare parts identified as having potential optimisation opportunities. These included items with high stock levels compared to consumption, items without consumption over a 24-month period, and cases where inconsistencies were observed between current stock levels and MRP parameters.

Throughout this section, the reported impact corresponds to the reduction in immobilised inventory value (current value minus proposed value), that is, the capital released or whose future commitment is avoided. Two situations are distinguished: for items whose future replenishment is avoided, the value represents an avoided expenditure; for items already received and held without consumption, the reduction is realised through write-down and therefore represents a recovery of previously committed capital rather than a forward saving. The figures are one-off effects, not recurring annual savings.

The six examples that follow share the same structure: diagnosis, proposed decision, and inventory and MRP impact, reported under consistent subheadings.

5.2.1 Case example: misaligned reorder parameters

This case concerns a tachometer (Item 4110047428), classified as a Vital spare part with very high operational impact and currently managed using a reorder-point-based MRP configuration. The evolution of stock and consumption over a 36-month period, integrating data from both the legacy SAP R/3 system and the current SAP S/4HANA environment, is presented in Figure 5.2.

5.2. Application and Results

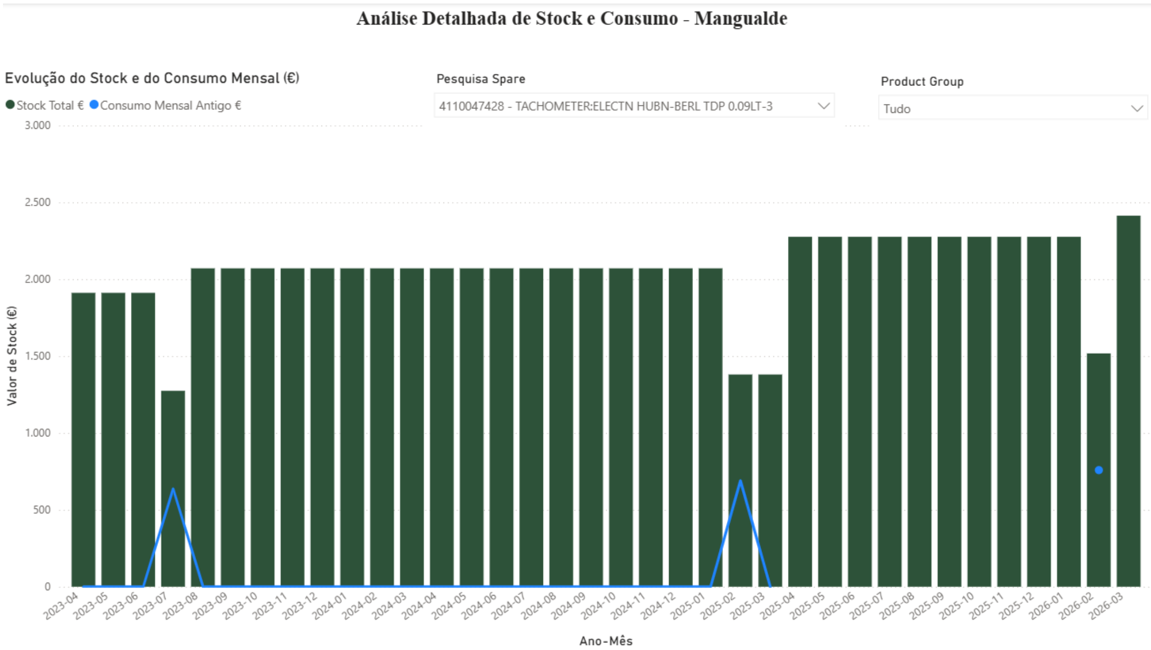

Figure 5.2: Stock and consumption evolution for the tachometer (4110047428), April 2023 to March 2026. The difference in visual representation between the continuous line (pre-migration) and the isolated point (post-migration) reflects the change in how months without consumption are recorded across SAP systems.

Three consumption events are observed over the 36-month window, each corresponding to a single unit, which characterizes an intermittent demand pattern as defined in the framework. Despite this, the system is configured with a reorder point of two units, resulting in stock levels maintained at approximately three units throughout the period. The pattern persists consistently across the SAP transition in April 2025, indicating that the misalignment is not system-related but rather linked to the parameter configuration itself.

Additionally, the Maximo "where used" record shows that the tachometer is installed in a single asset ("1001433 - MOTOR S/FIM ALIMENT. PRE-AQUECEDOR M51") at the Mangualde plant, with a required quantity of one unit. This technical configuration supports the proposed reduction to a single unit in stock.

Inventory impact

Table 5.2: Impact of proposed stock adjustment.

Item	Criticality	Current Qty.	Current Value (€)	Proposed Qty.	Released Capital (€)
4110047428	Vital	3	2 413	1	1 608

Maintaining three units in stock is not supported by the observed consumption pattern, as demand occurs in single units and at low frequency, with inter-event intervals exceeding twelve months. The additional stock does not provide significant protection against demand variability but instead ties up unnecessary capital.

MRP parameter adjustment

Table 5.3: Current and proposed MRP configuration.

Parameter	**Current**	**Proposed**
MRP Type	VB	VB
Reorder Point	2	1
Maximum Stock Level	3	1
Lot Size	HB	1

Applying the proposed framework, the item is classified as intermittent demand with high criticality. In this context, maintaining availability is essential, but stock levels should remain minimal. The reduction from three units to one corresponds to a decrease of approximately 66% and a potential saving of 1 608 €, without compromising operational reliability. This example illustrates how inefficiencies can arise from misaligned parameter settings rather than from demand uncertainty.

5.2.2 Case example: misalignment due to manual replenishment

This case concerns a sealing ring (Item 4110174135), classified as Essential, analysed in order to illustrate how manual interventions can lead to inconsistencies in inventory management.

Historically, the item was maintained at a stock level of one unit, which proved sufficient over time, as only one consumption was recorded during the analysed period, corresponding to an intermittent demand pattern as defined in the framework. Additionally, the Maximo "where used" record shows that the sealing ring is installed in a single asset ("1001437 - ESPREMEDOR ESTILHA") at the Mangualde plant, with a required quantity of one unit. This provides a clear technical basis for retaining a single unit in stock and confirms that the current stock level exceeds operational requirements.

However, following a system transition, the stock level increased to three units, without any corresponding change in the defined MRP parameters. As a result, the current inventory level is not supported either by historical consumption or by the logic embedded in the system.

Inventory impact

Table 5.4: Impact of proposed stock adjustment.

Item	Criticality	Current Qty.	Current Value (€)	Proposed Qty.	Proposed Value (€)	Released Capital (€)
4110174135	Essential	3	30 000	1	10 000	20 000

Given that one unit has historically been sufficient, the current level of three units represents excess inventory, tying up capital without a clear operational justification.

MRP parameter adjustment

Table 5.5: Comparison between current and proposed MRP configuration.

Parameter	Current	Proposed
MRP Type	PD	VB
Reorder Point	0	1
Maximum Stock Level	1	1
Lot Size	-	1

The current configuration, based on standard MRP logic (PD), did not prevent the increase in stock, as it was overridden by manual intervention.

According to the proposed framework, the item should be managed using a reorder-point approach (VB), with a reorder point of one unit and unitary lot sizing. This ensures that replenishment is only triggered when the item is effectively used, while maintaining the required level of availability.

Reducing the stock from three units to one unit corresponds to a decrease of approximately 67%, resulting in a potential saving of 20 000€, without affecting operational reliability.

This case highlights that inefficiencies are not solely a consequence of uncertain demand, but often arise from the lack of structured decision rules and criticality parameters, guiding inventory management.

Although the resulting stock levels are similar in both cases, the reasoning behind each decision differs, reflecting the flexibility of the proposed framework in adapting to different types of inefficiencies while maintaining consistency in outcomes.

5.2.3 Case example: improving efficiency for low-value items

This case concerns a fuse (Item 4110045620, FUSE: CERAMIC SILIZED 16A500V GR5SD420), classified as Vital and with a unit cost of 4.5 € and a stable consumption pattern over time. While its criticality requires continuous availability, the low unit value implies that optimisation efforts should focus on efficiency rather than reducing inventory levels.

The evolution of stock and consumption, based on data from the new SA system, is shown in Figure 5.3. The graph reveals a recurring pattern in which stock decreases gradually as a result of regular usage and is then replenished in larger quantities.

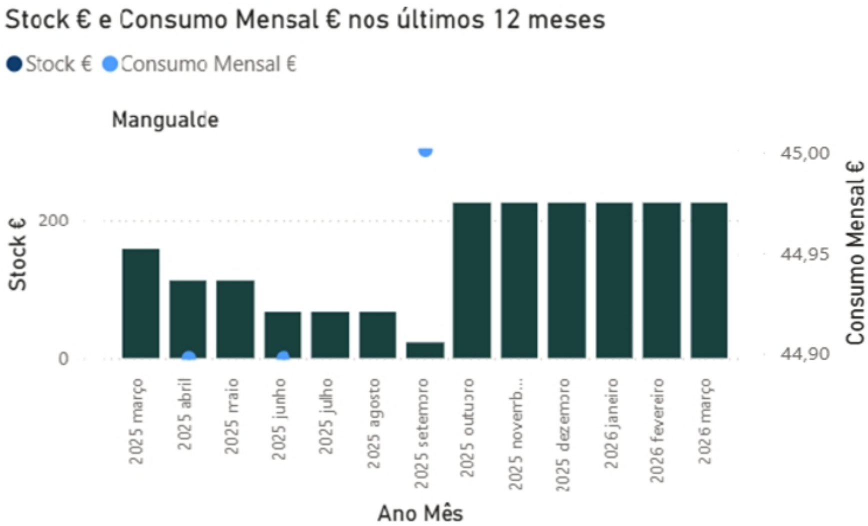

Figure 5.3: Stock and monthly consumption evolution over the last 12 months.

More specifically, three main consumption events can be identified, each corresponding to 45 € (10 units). This indicates a relatively stable and predictable demand, equivalent to an annual consumption of approximately 30 units. This behaviour is consistent with the patterns previously observed in the legacy SAP system, confirming that the demand structure remains stable across both systems.

Despite this predictability, the replenishment pattern is not fully aligned with the observed demand. As shown in Table 5.6, multiple orders were placed within a short time interval, indicating that replenishment decisions are triggered reactively rather than following a structured logic.

Replenishment behaviour

Table 5.6: Observed replenishment pattern.

Date	Quantity	Value (€)	Observation
10/10/2025	5	22.50	Reactive order
21/10/2025	40	180.00	Follow-up replenishment

Although the total quantity ordered is aligned with annual consumption, the fragmentation of procurement into multiple orders increases administrative effort without improving availability. This same pattern is also observed in the legacy SAP system, where stock cycles follow a similar structure, confirming that the inefficiency is not system-dependent but related to procurement logic.

MRP parameter adjustment

Table 5.7: Current and proposed MRP parameters.

Parameter	Current	Proposed
MRP Type	VB	VB
Reorder Point	10	5-10
Maximum Stock Level	50	40
Lot Size	HB (replenish to max)	∼40 units

Applying the proposed framework, the item is classified as having active consumption, high criticality and low unit value. In this context, maintaining availability is essential, and therefore inventory reduction is not the primary objective. Instead, optimisation focuses on improving replenishment efficiency through better alignment between demand and ordering decisions.

The proposed adjustment consists of defining a structured lot size aligned with annual demand, estimated at approximately 40 units (180 €). This value reflects the observed consumption pattern, while also providing a margin to accommodate variability.

By replacing the current maximum-based replenishment logic with a fixed lot size, demand can be consolidated into a single planned replenishment cycle. From an operational perspective, this represents a reduction of approximately 50% in ordering frequency, shifting from multiple transactions to a single annual order, while maintaining adequate stock availability.

Overall, this example highlights that inefficiencies may arise not only from excessive inventory, but also from the way replenishment decisions are defined. More broadly, it confirms that, for low-value items, optimisation opportunities often lie in increasing lot sizes to reduce ordering frequency, even when inventory levels themselves are not excessive.

5.2.4 Case example: reducing excess stock of a vital item without consumption

This case concerns a vacuum pump (Item 4110196181, PUMP SIHI AKHX 3104 NA RB 001 OA TAM) at Mangualde, classified as a Vital spare part and currently held in stock without recent consumption activity.

The transactional history of the item shows that one unit was received in April 2023 and consumed in June 2023. Following this event, two additional units were received in February 2025, despite no further consumption being recorded. The current stock therefore stands at three units, none of which have been consumed in the last 12 months, and no consumption has been observed in any other Iberian plant. The evolution of stock and consumption over the 36-month period is shown in Figure 5.4.

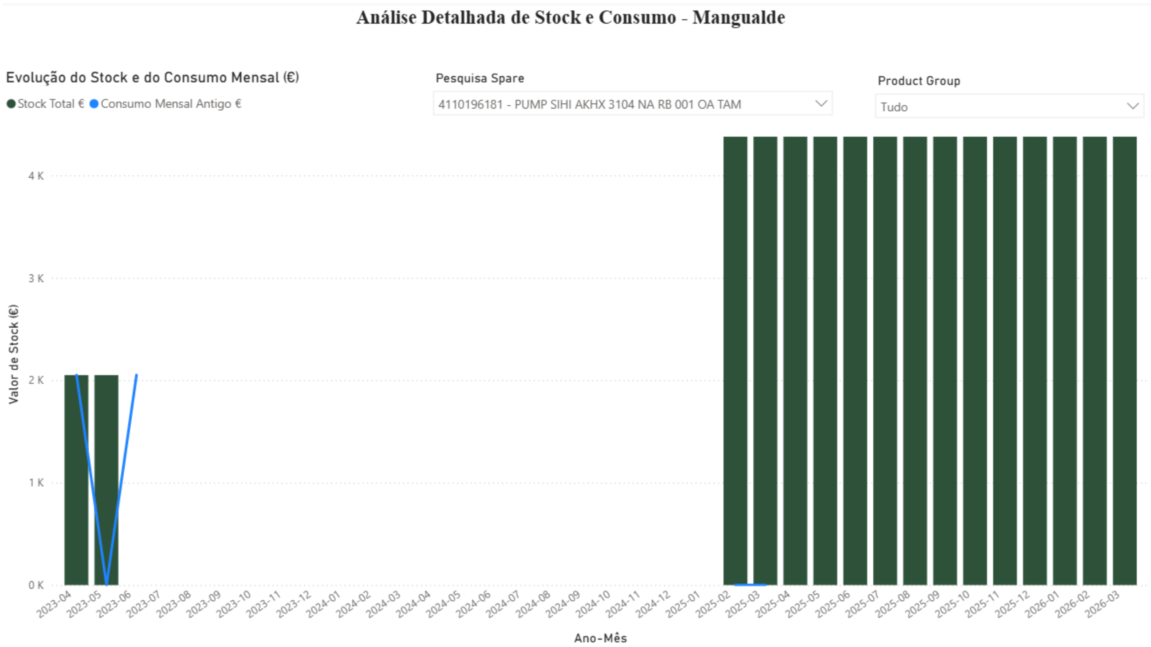

Figure 5.4: Stock and consumption evolution for the vacuum pump (4110196181), April 2023 to March 2026. A single consumption event is observed in June 2023, followed by approximately 20 months of zero stock until the replenishment in February 2025. No further consumption has been recorded since.

Cross-verification between the aggregated consumption flag and the detailed movement records confirmed that this item meets the criterion of prolonged inactivity defined in Section 5.1.2. The analysis also extends beyond the standard 24-month horizon, since the only recorded use of this item dates back to June 2023, more than 30 months before the analysis period.

The VED(O) classification of the item, validated with the maintenance specialist at Mangualde, resulted in the category Vital, reflecting the high operational impact associated with a potential failure of the supported equipment. The specialist further confirmed that the item is required as insurance stock, but that maintaining three units is not justified by the operational profile of the equipment.

Inventory impact

Table 5.8: Impact of proposed stock adjustment for the vacuum pump.

Item	Criticality	Current Qty.	Current Value (€)	Proposed Qty.	Proposed Value (€)	Released Capital (€)
4110196181	Vital	3	4 378	1	1 459	2 919

MRP parameter adjustment

Table 5.9: Current and proposed MRP configuration for the vacuum pump.

Parameter	Current	Proposed
MRP Type	VB	VB
Reorder Point	0	0
Maximum Stock Level	1	1
Lot Size	-	1

A relevant observation in this case is that the current MRP parameters already specify a maximum stock level of one unit, consistent with the stocking policy associated with a Vital item without recent consumption. The actual stock of three units is therefore not the result of a misconfiguration of the system, but rather of manual replenishment decisions taken independently of the configured logic. The recommended action is the alignment of the physical stock with the existing parameters, through the consumption or write-down of the excess units, rather than a parameter adjustment. The corresponding 2 919 € therefore represents recovery of previously committed capital rather than an avoided expenditure.

This example illustrates the methodological argument that the VED(O) category determines whether stock should be held, not how much. A Vital classification mandates the availability of one unit at all times for replenishment-protected operation, but does not in itself justify higher quantities. The case also illustrates the importance of examining consumption history beyond the standard 24-month window: a rigid application of the

24-month trigger would have classified this item simply as inactive, missing the operational evidence from June 2023 that supports the Vital classification.

5.2.5 Case example: reducing stock of a desirable item without consumption

This case concerns a conveyor belt (Item 4110056841, BELT:CONVEY HABAS HAT12P 200X18315) at Mangualde, analysed in order to illustrate the application of the framework to items in the Desirable category.

The transactional history of the item shows no recorded consumption events over a three-year period, and the original receipt of the current stock dates back more than four years. The item is therefore well beyond the 24-month inactivity horizon defined in the framework. Cross-plant verification confirmed that the item is not consumed at any other Iberian plant, ruling out transfer as a mitigation option.

The VED(O) classification, validated with the maintenance specialist at Mangualde, resulted in the category Desirable, reflecting both the prolonged absence of demand and the limited operational impact associated with the item.

Inventory impact

Table 5.10: Impact of proposed stock adjustment for the conveyor belt.

Item	**Criticality**	**Current Qty.**	**Current Value (€)**	**Proposed Qty.**	**Proposed Value (€)**	**Released Capital (€)**
4110056841	Desirable	3	1 786	2	1 191	595

MRP parameter adjustment

Table 5.11: Current and proposed MRP configuration for the conveyor belt.

Parameter	**Current**	**Proposed**
MRP Type	VB	VB
Reorder Point	1	0
Maximum Stock Level	3	2
Lot Size	-	1

The current MRP parameters specify a maximum stock level of three units with a reorder point of one, a configuration that does not align with the policy defined for Desirable items in the ME10 standard, where stock is typically reduced or eliminated. The combination of a Desirable classification and four years of inactivity supports the reduction of stock to two units, with the corresponding adjustment of the MRP parameters to prevent automatic replenishment. The proposed configuration keeps the reorder-point type (VB) with a reorder point of zero, so automatic replenishment is never triggered, functionally equivalent to the no-planning policy (ND) prescribed by R8, while keeping the item visible in the standard reorder-point reporting. Retaining two units rather than one is a documented R9 override.

This example highlights a different type of inefficiency from those discussed in the previous case examples. The misalignment is not between system parameters and operational behaviour, but between system parameters and the criticality classification of the item. The decision to retain two units rather than reducing further reflects the role of expert judgement: although the Desirable classification combined with four years of inactivity would technically support further reduction, the specialist considered contextual factors such as the residual operational coverage value and the limited financial cost of holding the item, a clear application of the principle established in Section 5.1.2.

Together, the two case examples for items without consumption demonstrate that the proposed framework produces consistent decisions across distinct operational situations: a Vital item where the system parameters were correctly configured but the physical stock was not, and a Desirable item where both the parameters and the stock required adjustment. In both cases, the integration of criticality and inactivity information enabled a structured decision that the previous stock-based dashboards alone could not support.

5.2.6 Case example: reducing stock of an essential item without consumption

This case concerns a gearbox (Item 4110198785, GEARBOX SEW FA97/G DRN112M4) at Mangualde, classified as an Essential spare part and currently held in stock without recent consumption activity.

The transactional history of the item, examined across both the legacy SAP R/3 system and the current SAP S/4HANA system, shows that two units have been held in stock at a constant value of 4 553.93 € since March 2023, without any consumption event recorded during the 36-month period covered by the available data. Cross-plant verification confirmed that the item is not consumed at any other Iberian plant, ruling out transfer as a mitigation option.

The VED(O) classification of the item, validated with the maintenance specialist at Mangualde, resulted in the category Essential. The score reflects the role of the gearbox in mechanical transmission (asset criticality 4) combined with three mitigating factors: the relatively short lead time provided by SEW Eurodrive for catalogue gearboxes (lead time

2), the established repairability and availability of dimensionally compatible alternatives from other manufacturers such as Nord and Bonfiglioli (repair feasibility and alternatives 2), and the low historical failure probability of the component (1).

The technical assessment described in Step 0 of the framework could not establish the exact number of installed positions, as the equipment-to-spare-part mapping is not documented in either Maximo or SAP. According to the maintenance specialist, no record allows confirming whether the SEW FA97 is installed in a single position or in two identical positions, which corresponds to the data quality gap discussed in Chapter 3. In the absence of evidence of physical redundancy or group replacement, the existing quantity of two units is treated as unjustified accumulation, and the recommendation is to retain one unit as insurance stock, a conservative decision that preserves operational coverage while eliminating the excess. Should the specialist later confirm the presence of two identical installed positions, the recommendation would shift to retaining two units (one insurance unit per position), without altering the underlying framework.

A particular feature of this case is that the current MRP parameters in SAP indicate that the item is not being actively managed by the replenishment logic. The reorder point is set to zero and no maximum stock level is defined, despite the economic order quantity having been set to one unit. With the reorder point at zero, automatic replenishment is never triggered, regardless of the configured order quantity. The two units in stock therefore exist outside the system's replenishment logic, which is consistent with the prolonged inactivity observed in the transactional history.

Inventory impact

Table 5.12: Impact of proposed stock adjustment for the SEW gearbox.

Item	Criticality	Current Qty.	Current Value (€)	Proposed Qty.	Proposed Value (€)	Released Capital (€)
4110198785	Essential	2	4 554	1	2 277	2 277

MRP parameter adjustment

Table 5.13: Current and proposed MRP configuration for the SEW gearbox.

Parameter	Current	Proposed
MRP Type	-	VB
Reorder Point	0	0
Maximum Stock Level	0	1
Lot Size	1	1

The proposed configuration activates the reorder-point-based MRP logic (VB) by setting a maximum stock level of one unit, while keeping the reorder point at zero and the lot size at one. This change reflects two complementary objectives: reducing the existing physical stock to one insurance unit, and establishing a replenishment logic that effectively triggers an order once the remaining unit is consumed. Under the proposed configuration, the consumption of the remaining unit will automatically trigger a new order, restoring the insurance stock without manual intervention, a behaviour that the current configuration, despite having a defined order quantity, does not produce.

Table 5.14 consolidates the financial impact of the five case examples for which a stock-level reduction was recommended; the fuse example (Section 5.2.3) is excluded, as its optimisation concerns replenishment efficiency rather than stock value.

Table 5.14: Summary of financial impact across case examples.

Item	**VED(O) Category**	**Case**	**Released Capital (€)**
Tachometer (4110047428)	Vital	Sec. 5.2.1	1 608
Sealing ring (4110174135)	Essential	Sec. 5.2.2	20 000
Vacuum pump (4110196181)	Vital	Sec. 5.2.4	2 919
Conveyor belt (4110056841)	Desirable	Sec. 5.2.5	595
Gearbox (4110198785)	Essential	Sec. 5.2.6	2 277
Total			**27 399**

This total corresponds to a one-off reduction in tied-up capital rather than to a recurring saving. It is strongly concentrated in a single item, the sealing ring, which alone accounts for 73% of the released capital. Excluding it, the remaining four cases still release approximately 7 400 € across items with otherwise modest individual impact.

Chapter 6

Proposed KPIs and Dashboard Integration

The dashboards developed in Chapter 4 provide visibility over stock levels, consumption patterns and inter-plant variation across the Iberian plants. However, as discussed in Section 2.7, they do not differentiate items by criticality, so the same stock indicator can point to genuine excess or to a deliberate safeguard, depending on the item. The same observation applies in the literature: most spare parts performance metrics emphasise cost, volume or efficiency in isolation, without explicitly distinguishing items according to the consequences of their unavailability.

The VED(O) classification framework introduced in Chapter 3 addresses this gap at the item level, but its operational value depends on its integration into the decision-support layer. This chapter proposes a set of indicators that operationalise VED(O) information for inventory monitoring purposes. The indicators are designed to be integrated into the existing dashboard infrastructure, complementing rather than replacing the stock-based KPIs already in use, and to scale progressively as the ME10 standard is deployed across the inventory.

6.1 Proposed Indicators

Stock value distribution by VED(O) category

This indicator breaks down total stock value by criticality category, calculated as:

$$\text{Value share}_k(\%) = \frac{\sum_{i \in k} V_i}{\sum_i V_i} \times 100, \tag{6.1}$$

where V_i is the stock value of item i and k the VED(O) category. When applied at scale, a high share of value in Desirable items would signal capital tied up with limited operational justification, while a low share of value in Vital items may indicate insufficient protection against high-impact failures.

Stocking policy compliance

The ME10 standard defines general stocking policies per category, including zero stock for Desirable items. In practice, the specialists recommended maintaining reduced quantities for some Desirable items, considering factors such as lead time and availability of alternatives, which are already reflected in the VED(O) score. The compliance indicator therefore measures whether each item's current stock is at or below the quantity recommended during the classification sessions:

$$\text{Compliance (\%)} = \frac{N_{\text{compliant}}}{N_{\text{classified}}} \times 100, \tag{6.2}$$

where an item is compliant if $Q_i \leq Q_i^{\text{rec}}$. This indicator captures whether the outcomes of the VED(O) classification sessions are effectively translated into stock-level adjustments, distinguishing between items where the classification has been operationalised and items where it remains on paper. The formalisation of category-specific stocking rules, supported by a larger classified sample, is identified as a direction for future work.

Excess stock value by VED(O) category

The value of stock above the recommended quantity, segmented by category:

$$\text{Excess}_k = \sum_{i \in k} (Q_i - Q_i^{rec}) \times P_i, \tag{6.3}$$

where Q_i is the current quantity, Q_i^{rec} the recommended quantity and P_i the unit price. This indicator quantifies the financial margin available for inventory adjustment and supports the prioritisation of action across criticality categories, as different categories may concentrate excess stock for different reasons: high-value Vital items where even small quantity reductions yield significant savings, or low-value Desirable items that accumulate without operational justification.

Vital items without stock

The number of items classified as Vital with current stock quantity equal to zero represent situations where the most critical spare parts are not available in the warehouse. The financial relevance of this indicator can be contextualised by the production line stoppage costs: at Oliveira do Hospital, a press stoppage costs approximately 4 455 €/h, while finishing line stoppages reach 5 265 €/h. A missing Vital spare part for these lines can generate losses that far exceed the cost of holding the item in stock, which makes the visibility of stock-out situations a particularly important monitoring dimension as the VED(O) classification is rolled out.

Classification coverage

Percentage of items in stock with a VED(O) classification:

$$\text{Coverage (\%)} = \frac{N_{\text{classified}}}{N_{\text{total}}} \times 100, \tag{6.4}$$

This KPI monitors the deployment of the ME10 standard over time. As coverage increases, the remaining indicators become progressively more representative of the full inventory.

Together, these indicators address operational risk (Vital items without stock), inventory efficiency (excess by category, value distribution and compliance) and implementation progress (coverage). They are designed to be integrated into the existing dashboard infrastructure and to scale as the VED(O) classification is extended to larger portions of the inventory.

6.2 Dashboard Integration

The five indicators are consolidated into a single dashboard, shown in Figure 6.1. The layout follows the same visual conventions used in Chapter 4, so that maintenance engineers already familiar with the existing dashboards do not need to learn a new interface.

The dashboard is organised in three blocks. The top row contains four KPI cards, each addressing a distinct decision need: coverage tracks how far ME10 deployment has progressed; compliance shows how often current stock levels match the recommendations from the classification sessions; the count of Vital items without stock flags situations of immediate operational risk; and total excess quantifies the financial margin available for inventory adjustments. Below the cards, two charts give the user a sense of distribution. A donut chart breaks down stock value across VED(O) categories, making visible whether capital is concentrated in critical or non-critical items. A bar chart shows excess value per category, indicating where adjustment efforts are likely to be more productive. A detail table at the bottom allows drill-down to individual items, which is the level at which decisions are ultimately made.

The values in Figure 6.1 are based on an illustrative dataset, not on current inventory data, since ME10 classification is still in progress. As more items are classified, the indicators gradually become representative of the full inventory. The dashboard supports filtering by plant and by VED(O) category, so it can be used both for a consolidated view across the Iberian scope and for site-specific analysis.

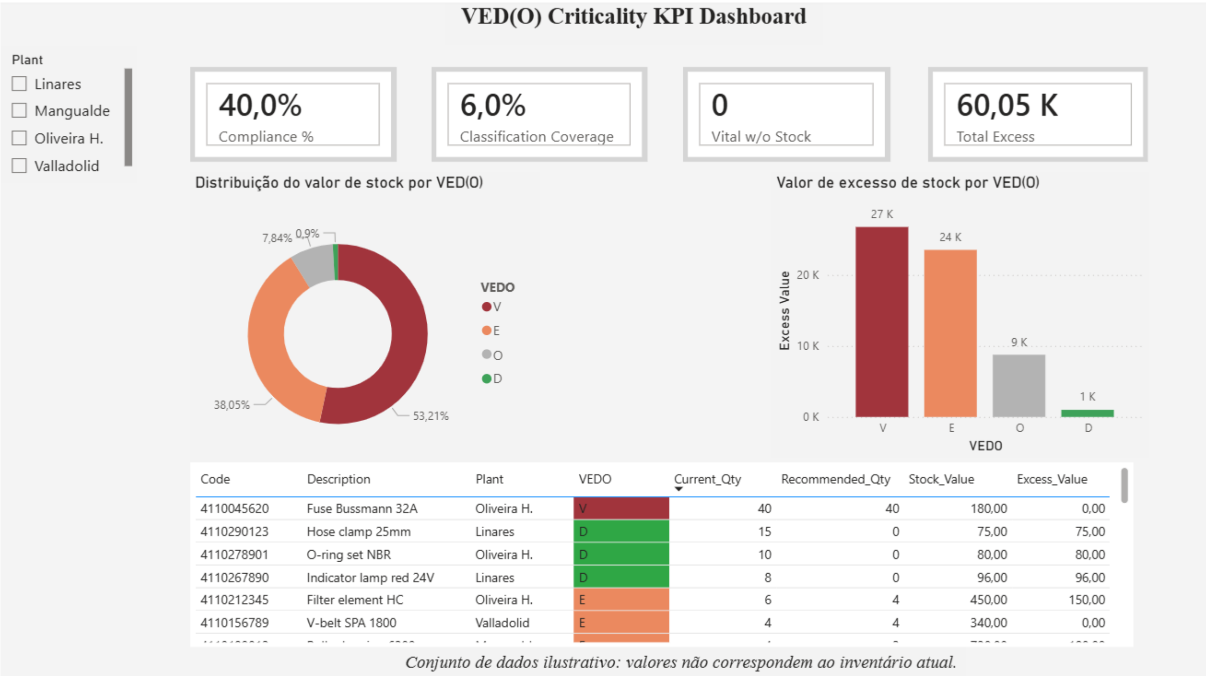

Figure 6.1: Proposed VED(O) KPI dashboard, consolidating the five indicators defined in Section 6.1. The values shown are illustrative; the dashboard becomes operational as ME10 classification is scaled across the Iberian plants.

6.3 Extending Criticality Integration to Existing Dashboards

The dashboard presented in Section 6.2 consolidates the new criticality indicators into a dedicated view. A second, complementary use of VED(O) classification is to enrich the dashboards already introduced in Chapter 4, by adding criticality as an additional dimension of analysis. This section illustrates the approach through the spare-level dashboard from Section 4.4. This dashboard was chosen because the simultaneous representation of stock, consumption and turnover at item level provides a clear visual context for demonstrating how criticality changes the interpretation of stock indicators.

Figure 6.2 shows the same scatter plot with two additions: a VED(O) slicer placed alongside the existing filters, and colour coding of the data points by criticality category. Items not yet classified retain the original colour. The resulting view modifies the way the chart is interpreted. A point located in the region of high stock and low consumption no longer corresponds, by itself, to a reduction candidate: for a Vital item, this position may correspond to deliberate insurance stock against high-impact failure rather than to excess inventory, whereas for a Desirable item it is more likely to indicate stock that exceeds the policy recommendation. The slicer enables the user to isolate one or more categories and to direct the analysis towards the subset of items for which action is meaningful.

By construction, the dashboard plots only items using recorded consumption in the last 12 months. The analysis of items without recorded consumption is supported by a separate dashboard (Section 4.5), whose integration with VED(O) is discussed as a direction for future work in Chapter 7.

The values and category assignments shown in Figure 6.2 are illustrative, representing how the dashboard would behave once ME10 classification is scaled across the inventory. The same approach can be applied to the remaining dashboards developed in Chapter 4, with the specific extensions and their expected benefits discussed in Chapter 7.

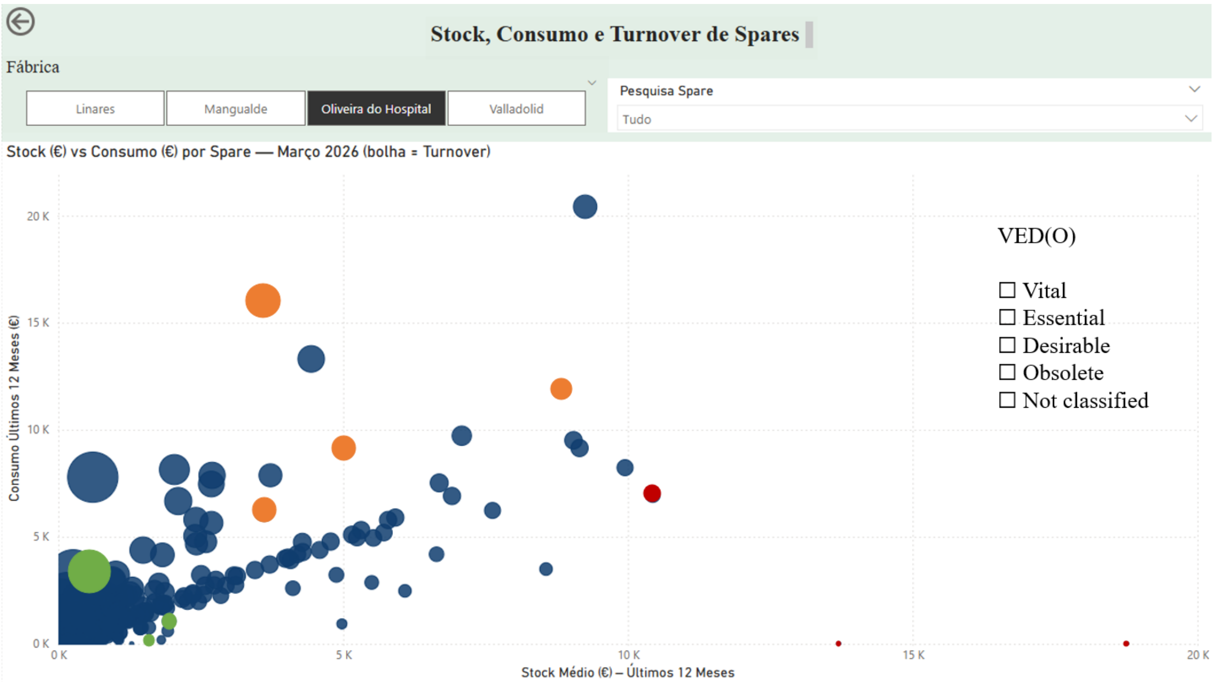

Figure 6.2: Conceptual integration of VED(O) classification into the spare-level stock-versus-consumption dashboard. Category assignments and colours are illustrative; the integration becomes operational as ME10 classification progresses.

Chapter 7

Conclusions, Limitations and Future Work

7.1 Conclusions

Figure 7.1 presents the conceptual framework that operationalises the central contribution of this study: the closed loop between criticality classification and MRP parameter adjustment in a live ERP environment. The three supporting contributions are positioned as enabling layers rather than parallel contributions. Diagnostic analytics provide the visibility on which decisions are based, AHP-based weight derivation grounds the criticality scores and criticality-integrated dashboards feed the outcomes back into routine inventory monitoring. Together, they reflect the argument that the theory-practice gap in spare parts management is primarily one of operationalisation, not of methodological development.

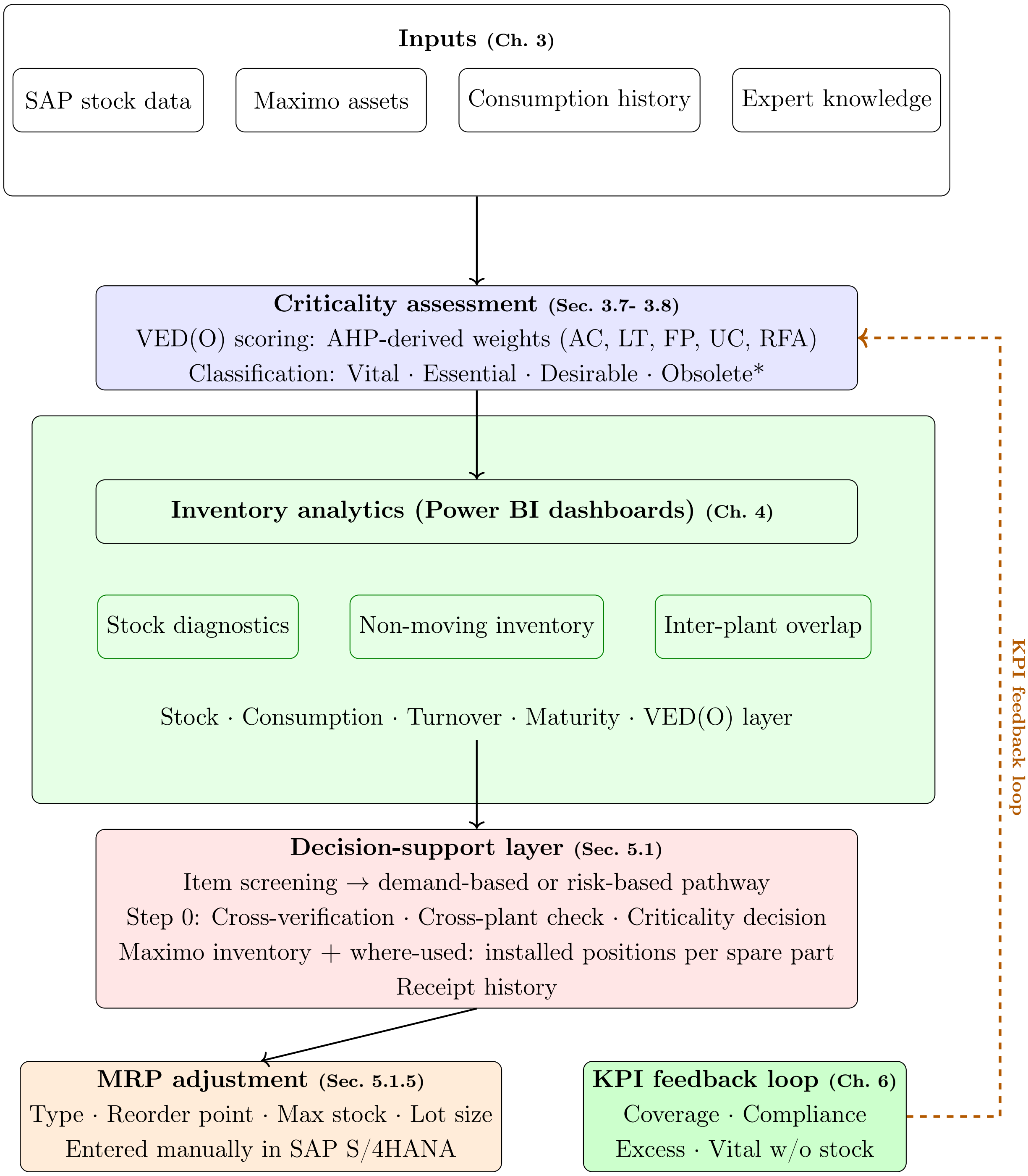

Figure 7.1: Conceptual framework for criticality-integrated spare parts management, comprising five layers from data inputs to KPI feedback. *Obsolete is not derived from the weighted VED(O) score in Equation 3.2; candidates are identified through the 12/24-month non-consumption criterion of the non-moving inventory dashboard (Section 4.5), subject to review before reclassification.

7.1. Conclusions

The diagnostic analysis confirmed a consistent structural imbalance across all four Iberian plants: inventory levels grow steadily while Consumption/Stock ratios range from 0.21 to 0.53, driven by conservative ordering behaviour, subjective criticality assessment and accumulation of parts associated with discontinued equipment **(addressing RQ1 and O1)**. These patterns are consistent with the drivers discussed in Section 1.1.1, but the more substantive finding is that conventional stock indicators are insufficient to support inventory optimisation decisions in maintenance contexts without criticality information. This insufficiency is not merely empirical. The 3 150 items with no consumption over 24 months cannot be correctly evaluated through financial or movement-based metrics alone, because the same stock pattern can correspond to either justified insurance stock or genuine excess depending on the criticality of the item. The case examples in Chapter 4 illustrate this: without criticality information, a Vital vacuum pump and a Desirable conveyor belt would be flagged as reduction candidates on identical grounds. With criticality information, the reduction logic differs fundamentally, as the vacuum pump is retained at a minimum justified quantity while the conveyor belt is reduced based on its limited operational impact **(addressing RQ2 and O2, through the VED(O) framework applied in Section 5.1)**.

The integration of VED(O) criticality does not merely refine these decisions: it structurally changes what the indicators measure **(addressing RQ3 and O3)**. Excess stock segmented by criticality category redefines what counts as excess. Vital items without stock introduces an operational risk dimension absent from conventional KPI frameworks [53, 54]. This operationalises the argument of Bacchetti and Saccani [3] that classification should function as a decision input rather than an analytical endpoint, and demonstrates its feasibility within existing SAP infrastructure without system modifications.

The case examples further reveal that the primary source of inefficiency in the Iberian plants is not demand uncertainty but misconfiguration: parameters misaligned with consumption patterns, manual overrides of system logic and stock quantities that exist outside any replenishment rule. These findings are consistent with Hu et al. [4], who identify the persistence of classical ERP methods as the central barrier to criticality-informed inventory management, and with Kulshrestha et al. [2], who confirm that the integration gap between classification theory and ERP practice remains unresolved in Industry 4.0 contexts.

The decision framework positions VED(O) as a structured input rather than a deterministic rule, reflecting a finding that emerged consistently across the case examples: the data alone is insufficient to determine the correct stock level without expert judgement. This is not a limitation of the study but a characteristic of spare parts management in industrial environments, where relevant information is distributed across ERP systems, maintenance records and operational experience. The framework makes this explicit and traceable, integrating maintenance and inventory perspectives at each decision node in response to the gap identified by Ifraz et al. [5]. The approximately 27 400€ of immobilised capital released across the Mangualde case examples, a one-off effect concentrated in a few high-value items, provides initial evidence that this integration yields financially material decisions even at small scale.

The primary barrier to criticality-based inventory management identified in this study is not analytical complexity but operationalisation: the absence of standardised classification, the lack of integration between classification outcomes and MRP parameters and reliance on undocumented individual experience. This is consistent with Bacchetti and Saccani [3], who identify company maturity and knowledge accumulation as key factors in the research-practice gap. The analytical frameworks exist in the literature [6, 11]; the challenge is embedding them into operational systems under real data and resource constraints. The framework proposed in this study represents one documented and replicable approach to this challenge **(addressing RQ4 and O4, through the Power BI dashboards developed in Chapter 4 and the criticality-integrated KPIs proposed in Chapter 6)**.

The four research questions and objectives presented in Section 1.3 were addressed through the analysis of the selected case examples. However, the extent to which they could be fully examined was constrained by data availability and the level of detail provided by the ME10 classification, as discussed in Section 7.2.

7.2 Limitations

The limitations discussed below concern the data and organisational conditions under which the framework was applied, rather than the AHP, VED(O) or MRP methods on which it builds. This reflects the central claim of the study: the contribution lies in applying these methods together in a real ERP environment, not in developing new ones.

Several limitations of the present study should be acknowledged, as they bound the interpretation of the results and the generalisability of the proposed methodology.

Lead time data and replenishment policy
Although lead time was incorporated as a scoring criterion within the VED(O) classification framework, reflecting its role as a determinant of operational risk, actual lead time data was not available for quantitative use. Supplier lead times could not be retrieved from SAP in a complete and reliable form. As a consequence, the MRP parameter recommendations, specifically safety stock levels and reorder points, were derived without incorporating lead time variability, which is a recognised determinant of optimal inventory levels in spare parts management [63, 64]. Safety stock levels calculated without lead time data may therefore

systematically underestimate the buffer required to achieve target service levels. The incorporation of lead time data, once made available, is identified as a priority refinement of the proposed framework. This absence of lead time data directly bounds contribution C1 (Section 1.1.2): the translation from criticality to replenishment policy relies on minimum justified quantities and category-based rules rather than on safety-stock calculations, with the bounded R9 override providing the mechanism for specialist correction where this is insufficient.

Material coding inconsistencies
A further data limitation arises from the SAP S/4HANA migration, which introduced structural inconsistencies in the material master data that affected the comparability of pre- and post-migration consumption records. Material group classifications were reorganised during the migration: categories that existed as distinct groups in the legacy system, such as *Pumps* and *Sensors*, were consolidated into broader groups in the new system, being absorbed into *Motors* and *Electrical Materials* respectively. Additionally, material group naming conventions changed, with the legacy system using mixed-case labels and the new system adopting capitalised formatting, requiring manual reconciliation to enable cross-system comparisons. Furthermore, spare parts registered in the new SAP environment were assigned material codes beginning with the prefix 412, replacing the legacy prefix `411`, meaning that newly created materials could not be directly matched to historical consumption records. These inconsistencies limited the depth of longitudinal analysis and introduced uncertainty in the aggregation of consumption data across the full study period, particularly for items whose classification or coding changed during the transition. Resolving these inconsistencies through a documented reconciliation between legacy and current material codes is identified as a data-quality priority for future work (Section 7.3).

Asset-spare part linkage and consumption history depth
Significant data quality constraints limit the analytical scope of the study. Incomplete asset-spare part relationships in IBM Maximo, inconsistent material coding conventions following the SAP S/4HANA migration and a consumption history restricted to 36 months introduce uncertainty in the classification of slow-moving and intermittently demanded items. These constraints are not specific to this study but characterise a large proportion of real industrial environments, which reinforces the relevance of the proposed framework while limiting the precision of individual decisions. Completing asset-spare part relationships in Maximo, in particular Bills of Materials, is identified as a foundational step for future work (Section 7.3), as it would allow criticality to be propagated automatically from functional locations to individual spare parts, rather than relying on manual expert validation for

each item.

Expert judgement in AHP and VED(O) scoring
The AHP exercise involved four internal experts, two of whom produced inconsistent pairwise comparison matrices. Although the aggregated matrix met the accepted consistency threshold, the results remain sensitive to expert composition. A different panel, or a larger one, could yield different weights. As discussed in Section 3.8.6, individual matrices were not returned for revision due to the logistical constraints of a four-plant panel; this trade-off is reflected in the sensitivity analysis of Section 3.8.8 rather than in a revised, fully consistent expert set. Similarly, VED(O) scores depend on specialist judgement for criteria such as Asset Criticality and Repair Feasibility, introducing subjectivity that cannot be fully eliminated through the scoring formula. This is an inherent characteristic of expert-based classification methods [17, 49], but it implies that classifications may not be fully reproducible across different evaluators or time periods. Periodic reassessment of the AHP panel, through expert rotation or an expanded panel, is proposed as future work to monitor and validate the stability of the derived weights over time (Section 7.3).

Demand modelling approach
The study does not incorporate probabilistic demand modelling or stochastic analysis of failure rates. This reflects a deliberate methodological choice grounded in the nature of the available data: for items with intermittent or historically absent consumption, parametric forecasting methods are known to underperform due to data sparsity and the irregular, maintenance-driven character of spare parts demand [3, 65]. Under these conditions, structured expert judgement provides a more reliable basis for inventory decisions than quantitative demand models requiring consumption histories of sufficient length and statistical regularity, a constraint directly analogous to that observed in comparable industrial studies [66, 67]. In particular, the methods specifically designed for intermittent demand, such as Croston's method and its Syntetos-Boylan approximation (SBA), still require a minimum number of demand occurrences to estimate inter-arrival intervals reliably. For the items addressed here, with at most three demand events (or none) over the available 36-month window, these conditions are not met. This is why structured expert judgement was preferred over parametric forecasting. As consumption histories lengthen beyond the current 36-month window, revisiting probabilistic demand modelling for high-value intermittent items is identified as a natural extension of this work (Section 7.3).

Dashboard validation was limited to iterative review by three specialists (procurement, and maintenance at Mangualde and Valladolid); broader validation with plant-level end users across all four plants remains future work.

7.3 Future Work

The limitations identified in Section 7.2 define the most immediate directions for future research.

Lead time integration for replenishment policy
Once reliable supplier lead time data becomes available, incorporating it into the safety stock and reorder point calculations is identified as a priority refinement, allowing the framework to move from criticality-based minimum quantities to statistically grounded safety stock levels.

Strengthening data quality across SAP and Maximo
Two data-quality actions at system level are recommended to strengthen the foundation for scaling the framework:

- reconciling the legacy and current material group taxonomies in SAP, which differ in both naming convention and category structure, is recommended to the IT department as a tractable, one-off exercise given the limited number of distinct groups; for the present study, this reconciliation was instead performed manually for the purpose of dashboard construction and analysis, which is not a scalable solution;
- completing Bills of Materials and asset-spare part relationships in IBM Maximo would allow criticality to be propagated automatically to individual spare parts, reducing reliance on manual expert validation.

AHP panel reassessment and sensitivity analysis
Three methodological refinements are proposed as data and organisational conditions evolve:

- a periodic reassessment of the AHP-derived criterion weights, through an expanded or rotating expert panel, would monitor their stability over time;
- a quantitative sensitivity analysis of the decision logic thresholds (Section 5.1.6), re-screening the item population under alternative time windows;
- as consumption histories lengthen, revisiting probabilistic demand modelling, such as Croston's method or its Syntetos-Boylan approximation, becomes viable for high-value intermittent items once a sufficient number of demand occurrences is available.

Scaling ME10 classification across the Iberian inventory

The most immediate priority is the scaling of ME10 classification across the full Iberian inventory. As criticality coverage increases, the proposed KPIs and dashboards become progressively more representative and operationally useful. A structured programme for classification sessions, prioritising high-value and low-turnover items identified through the diagnostic dashboards, would provide the data foundation required for full deployment of the framework.

Extending dashboard validation to the remaining plants

The decision framework should be extended and validated across the remaining Iberian plants, moving dashboard validation beyond the current expert review (Section 7.2) towards structured feedback from end users at each site. Applying the framework at Linares, Oliveira do Hospital and Valladolid would test its robustness under different equipment profiles, data maturity levels and operational contexts, and provide a more comprehensive assessment of its generalisability within the organisation.

Completing VED(O) integration across the remaining dashboards

The integration of VED(O) criticality into the remaining dashboards developed in Chapter 4, specifically the non-moving inventory dashboard and the inter-plant overlap dashboard, represents a natural extension of the work presented in Chapter 5. These integrations would complete the criticality layer across the full dashboard environment and enable more comprehensive monitoring of inventory risk.

Formalising an obsolescence review cycle

A further direction concerns the operationalisation of the non-moving inventory dashboard as a periodic review tool at plant level. At present, no formalised process exists within the organisation for the systematic review of potentially obsolete spare parts, with decisions taken reactively and on an ad hoc basis. A structured obsolescence review cycle, supported by the non-moving inventory dashboard, would enable maintenance engineers at each plant to periodically identify items without consumption, assess the equipment they support, review current stock quantities and evaluate disposal, transfer or retention options in a documented and consistent manner. The formalisation of this cycle, including review frequency, responsible roles and decision criteria, is proposed as a recommendation for integration into the ME10 spare parts management standard.

Warehouse-level validation of inventory records

An additional line of future work would be to validate the accuracy of the inventory data by comparing the system records with the actual stock in the warehouse. During the analysis, some items appeared to have increasing stock levels without any corresponding consumption, which may point to issues such as missing consumption entries or irregular stock adjustments. Checking these cases directly at warehouse level would help to understand whether the materials are actually available or if there are discrepancies between the system and reality, and could highlight weaknesses in inventory control practices. An initial attempt was made to explore this, but it was not possible to validate these situations within the scope of this study.

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Appendix A

Oils and Lubricants Analysis

A dedicated set of dashboards was developed for oils and lubricants at the request of the company. As these items are classified as operating supplies rather than spare parts, they fall outside the scope of the VED(O) criticality classification and are presented separately.

Figure A.1 shows the monthly evolution of oil stock and consumption by factory. Figure A.2 compares monthly oil consumption across the four plants. Linares, Mangualde and Oliveira do Hospital exhibit similar levels of monthly variability, while Valladolid presents a more stable consumption pattern.

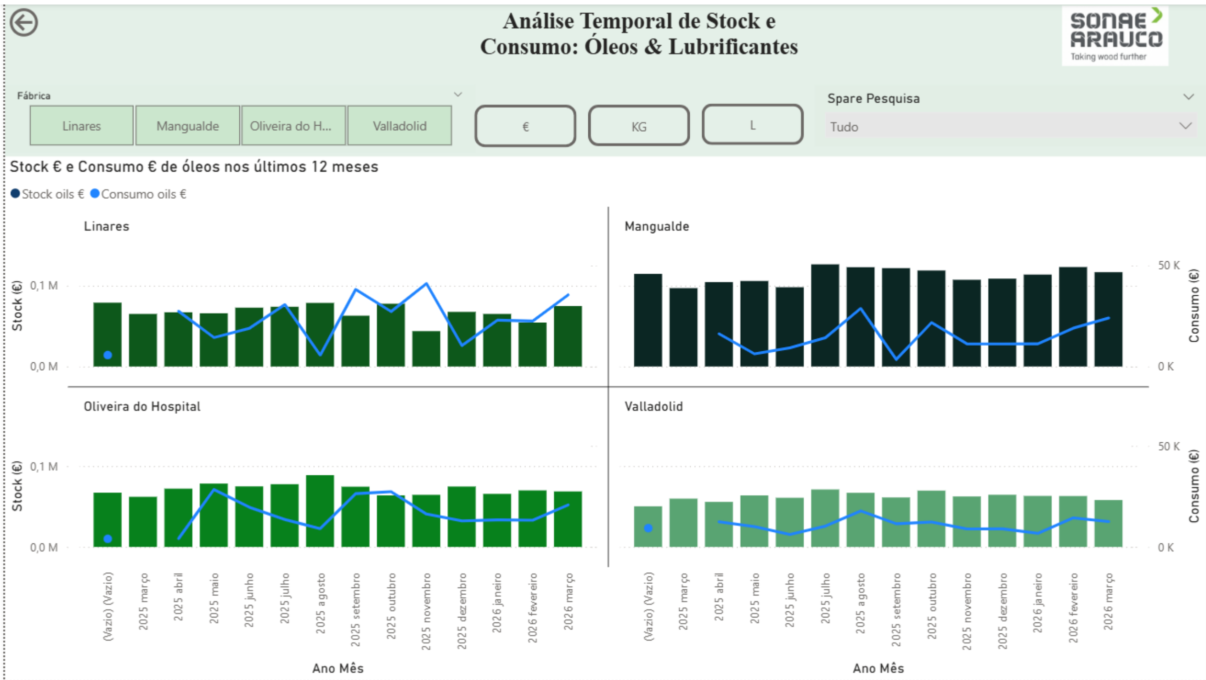

Figure A.1: Oils and lubricants: stock and consumption evolution by factory.

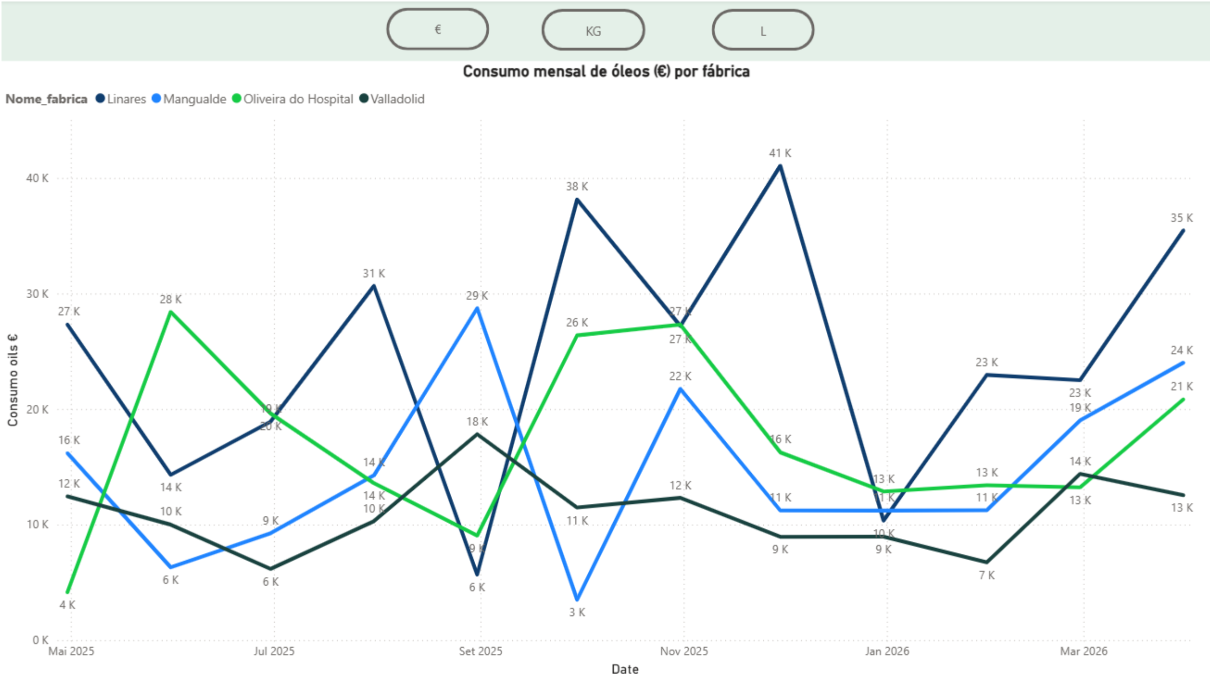

Figure A.2: Monthly oil consumption by factory.

To normalise consumption across factories of different scales, a consumption intensity indicator was defined as total oil consumption divided by the number of active assets (Figure A.3). Linares presents a notably higher value (41 €/asset) compared to the remaining factories (16-18 €/asset), suggesting differences in lubrication practices or equipment characteristics that may warrant further investigation.

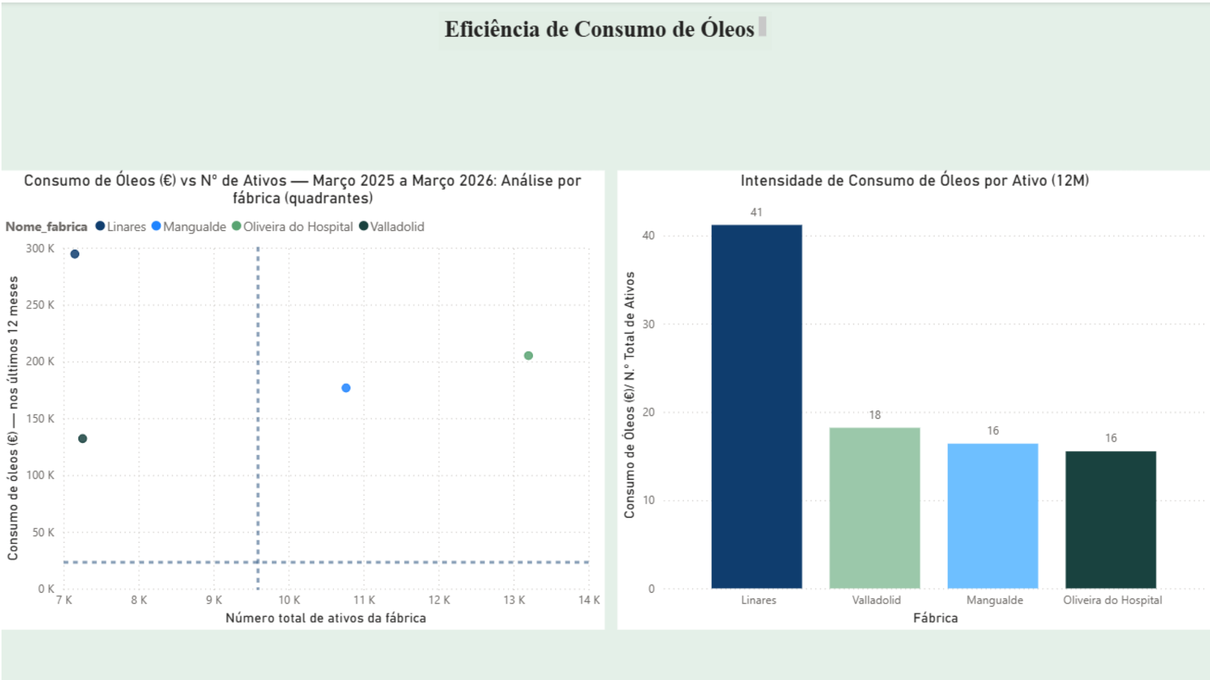

Figure A.3: Oil consumption efficiency: total consumption versus number of assets (left) and consumption per asset by factory (right).